Asia Pacific Science Press

Asia Pacific Economic and Management Review
ISSN(O):3005-9275
ISSN(P):3005-9267
Vol. 2 No.4 (2025)

Impacts of Food Delivery Culture on Dietary Health Among Young Adults in Shanghai

Tao Yang*

College of Business and Public Management, Wenzhou-Kean University, Wen'zhou, Zhejiang, 32500, China

Corresponding author: Tao Yang, 1308156@wku.edu.cn

Copyright: 2025 Author(s). This is an open-access article distributed under the terms of the Creative Commons Attribution License (CC BY-NC 4.0), permitting distribution and reproduction in any medium, provided the original author and source are credited, and explicitly prohibiting its use for commercial purposes.

Abstract: This study investigates the effect of delivery culture on diet health among young adults in Shanghai, motivated by increased reliance on delivery platforms and their associated health consequences. The study contrasts dietary intake, nutrition knowledge, and convenience-manipulated behavioral determinants. A mixed-methods study design involved a structured survey (n = 196) supported by semi-structured interviews (n = 15). Quantitative data were analyzed with descriptive statistics, correlation, and regression, and qualitative answers were coded thematically using NVivo. Sampling was conducted with stratified random and purposive sampling to obtain representativeness according to age, gender, and delivery use behavior. Correlation analysis results showed a small but statistically significant ($r = 0.35$, $p < 0.001$) correlation between the frequency of food delivery and perceived health deterioration. Regression analysis picked convenience as the strongest predictor for higher consumption, while nutrition awareness did not find a statistically significant protective factor. Descriptive statistics showed that while 61.23% believe they care about nutrition while ordering, 30.62% order healthy food frequently. Platform suggestions, price, and habit strongly predict poor interview options. The study summarizes that while consumers self-report being aware of nutritional issues, online influence and behavioral inertia thwart healthy intentions. It recommends mandatory nutritional labeling, AI-supported healthy recommendations, and reward-based platforms on delivery apps. The main limitations are self-reported measures, the threat of sampling bias, and the geographic location of Shanghai. Future studies should examine the impacts of longitudinal health and sample the population in other Chinese cities.

Keywords: Food Delivery; Dietary Health; Young Adults; Behavioral Determinants; Digital Nutrition

Published: Jun 17, 2025

DOI: https://doi.org/10.62177/apemr.v2i4.450

1.Introduction

1.1 Background of the study

The intersection of technology and food consumption has had spectacular changes in eating habits globally, particularly in cities. The fast pace of digitalization in daily life and busy work and learning schedules have fueled the mass appeal of food delivery applications across most countries. Algorithmic recommendation, real-time convenience, and affordable prices have driven these applications to reshape modern mealtime habits. Globally, youth are using more apps to obtain food instead of preparing it or dining out in restaurants, a situation prevalent in developed and developing countries (Buettner et al., 2023). However, food delivery offers economic opportunities and makes the availability of different cuisines possible. Researchers and public health professionals have raised concerns regarding its dietary consequences for providing energy-dense, nutrient-poor foods (Dai et al., 2022).

Such change is evident in mushrooming urban areas like Shanghai. Food delivery's convenience influences new adult eaters' choices, not necessarily for the better. Research showed that frequent use of food delivery services was related to excessive consumption of sodium, fat, and sugar, along with the restriction of diet diversity and lack of nutritional knowledge (Mehta et al., 2022). Additionally, digital platforms employed marketing ploys and reward system techniques to subtly nudge selection toward less healthy choices (Li, 2023). However, little is known about the behavioral and health impacts of food delivery among young adults in urban China. We analyzed how the food delivery environment impacted the dietary quality of young Shanghai adults to offer insight for future action in nutrition policy, consumer education, and digital health promotion.

1.2 Problem statement

The growing popularity of food delivery culture in Shanghai has brought about changes in dietary patterns among young people. This culture not only brings convenience to everyday lives but also causes adverse health outcomes such as obesity and poor nutrition. A study evaluating the nutritional quality of popular online food delivery set meals in China found that 89.56% scored below 50 out of 100, reflecting serious problems to be solved (Dai et al., 2022). Mass consuming these cost-effective diets may result in high oil, salt, and sugar consumption, contributing to overweight and high serum lipid levels (Mehta et al., 2022). In addition, another study indicated that young adults in Shanghai reported a higher intake of animal over plant proteins, but consumption of plant proteins increased (Fu, 2021). This kind of diet and the existence of food delivery apps can lead to poor nutrition and possible health issues (Buettner et al., 2023). Moreover, the development of the food delivery sector concerns the population's health, workers' well-being, and environmental safety in Shanghai (Cai et al., 2021). Based on the existing literature, the research has not covered several aspects: late effects on health, cultural changes in eating patterns, and behavioral and psychological issues. Thus, to address these issues, the current study was conducted to raise the problems, promote the healthy alternative of food delivery, and suggest a change towards balanced eating among young adults in Shanghai. Solving for this was critical to providing long-term health and wellness in a time of convenience-based consumption.·

1.3 Aims of the research

This study aimed to emphasize the issues of long-term health and cultural changes in eating behaviors and psychological or personal factors, propose healthier delivery meal options, and promote the transition to more balanced weight behaviors among young adults in Shanghai. Dealing with this problem was crucial for supporting a healthy lifestyle in the age of convenience-oriented consumption.

1.4 Objectives of the research

This study aimed to investigate the roles of food delivery culture on diet-related health of young adults in Shanghai by examining the nutritional quality of online food delivery set meals, young adults‘ food consumption, and the determinants of food choices. It aimed to discuss how healthier food delivery initiatives may be encouraged to safeguard young adults' and society's future health.

1.4.1 Supporting Objectives

To guide this investigation, the following supporting objectives have been formulated:

To explore the nutritional quality of food delivery meals consumed by young adults in Shanghai;

To explore young adults' dietary habits and preferences when they use food delivery services in Shanghai;

To ascertain the factors that impede healthy eating habits among young adults using food delivery services in Shanghai;

To assess the impact of frequent food delivery consumption on the long-term health of young adults in Shanghai, and

To explore strategies to promote healthier food delivery options and encourage balanced eating habits among young adults in Shanghai.

1.4.2 Research Questions

These objectives are achieved by providing answers to the following questions:

What do young adults in Shanghai consume in their food delivery meal diets?

How are food intakes and eating habits among young adults who frequently use online food delivery in Shanghai different?

What impedes healthy consumption among young adults who frequently use food delivery in Shanghai?

What are the long-term health implications of habitual food delivery consumption among Shanghai's young adults? and

What policies may be implemented to promote healthier food delivery and get young adults in Shanghai to eat healthy food?

1.5 Significance of the study

Although food delivery has brought convenience, it has also promoted unhealthy dietary choices, leading to health problems such as obesity and poor nutrition. Many people place a higher value on taste and price but neglect health conditions and are unaware of long-term risks. Since fewer people cook at home, their dependence on fast food has intensified. This research, however, aimed to increase awareness, advocate healthier food delivery choices, and encourage more balanced eating habits.

1.6 Delimitation and Scope of the Study

This study is delimited to young adults aged 18 to 35 residing in Shanghai, China, who actively use food delivery platforms at least once per week. The focus is primarily on food consumption patterns of urban consumers fueled by online food delivery platforms in the online space, and results must not be extrapolated to rural residents or Chinese cities beyond Guangzhou. The goals are to assess the nutritional value of online food delivery meals, food consumption patterns, drivers like platform ease of use and convenience, and health impacts as self-reported. It does not involve children and adolescents, older adults, and customers of specialized health-related delivery applications. It also does not have the perspective of food hawkers or delivery personnel. The study employs mixed methods, combining quantitative questionnaires and qualitative interviews, to better understand things in the stated geographic and demographic regions.

Summary

This chapter presents the growing influence of delivery culture among young urban Chinese, especially in Shanghai, and its profound impact on eating habits and health. The question statement points out that the rise of the take-away culture in Shanghai, although practical, also has adverse health effects, such as obesity and malnutrition. The research aims to promote healthy delivery options and support a healthy lifestyle in the age of consumption. This study was limited to Shanghai youth aged between 18 and 35 who use the delivery platform weekly. The study does not cover rural residents, other cities, children, older adults, or specialist health delivery platforms and delivery staff users.

2.Literature Review

2.1 Introduction

This section summarizes literature pertinent to this study of food delivery culture's impact on eating well-being among young Chinese adults in Shanghai. There is an empirical review organized by themes for the research questions and theoretical and conceptual frameworks on which this study rests. A summary of key findings from the literature is provided to highlight gaps and set a foundation for further research.

2.2 Theoretical framework

Such a theory has underlain the dynamic nexus of domestic and foreign culture and, later, the dietary wellness of Shanghai adolescents. Two main theories have been used in this study:

Social Cognitive Theory (SCT)

Bandura (1986) used social cognitive theory to explain how individuals learn behaviors through observation, imitation, and reinforcement. According to the theory, in the case of takeaway culture, for young adults, eating behaviors are primarily shaped by digital exposure, peer influence, and behavioral reinforcement by marketing strategies. App-based convenience and promotions can further solidify habitual unhealthy food choices, as users are guided by their environmental surroundings, such as targeted food ads recommended by peers, to order the same greasy food repeatedly.

Theory of Planned Behavior (TPB)

According to Ajzen's (1991) theory of behavioral planning, attitudes, subjective norms, and perceived behavioral control affect a person's intention to engage in a particular behavior. Regarding food delivery, ordering healthier food is driven by factors such as attitudes (perceptions of nutrition), subjective norms (social expectations), and perceived behavioral control (the need to make healthy food choices even when habit does not dictate so out of convenience). This theory is a groundwork for probing how AI-based meal suggestions and digital health ratings could enhance dietary choices by altering the aforementioned influencing factors.

These theories are also consistent with global health perspectives, such as the WHO (2024), which emphasizes that environmental design is pivotal in enabling or constraining healthy behavior, particularly in digital food systems.

2.3 Empirical review

The empirical review focuses on the key variables related to this study and is consistent with the research questions. The following themes are organized around significant aspects of food delivery culture and its influence on dietary health.

2.3.1 Nutritional Quality of Food Delivery Meals

Nutritional quality has always been an essential concern since it directly results in health outcomes. However, due to the high content of fats, salt, and sugar brought by takeaway, people's dietary health has been at risk in recent years (Monteiro et al., 2013). Studies comparing the nutritional content of best-selling Chinese online set meals revealed that 89.56% contained less than 50 points out of 100, which means significant problems must be solved (Dai et al., 2022). Moreover, bulk consumption of these meals would also lead to a high intake of oil, salt, and sugar, contributing to weight gain and blood lipid profiles (Mehta et al., 2022).

2.3.2 Dietary Habits and Preferences of Young Adults

Food delivery culture has affected the dietary habits and preferences among young adults. Research has suggested that young adults in Shanghai consume more animal than plant proteins, although the shift toward plant proteins has begun (Shu et al., 2019). The availability of food delivery apps can lead to disparate nutritional and health consequences. Both economic and cultural determinants of food selection were also found in the research. Tahim et al. (2024) also mentioned that food delivery apps are a consumption habit, car and mobile convenience, and promotional strategies affect the consumption of unhealthy food.

2.3.3 Factors Preventing Healthy Eating Habits

Several factors are responsible for improper food eating habits among users of food delivery services. They encompass financial constraints, advertising impacts, and behavioral and psychological predispositions for poor eating habits.

2.3.3.1 Economic Constraints

Financial factors have played a significant role in food selection, with most nutritional value for food delivery meals being influenced by what one can afford.

2.3.3.1.1 Price Sensitivity

The majority of teens prefer low prices over nutritional quality. Research has proven that inexpensive meals contain unhealthy fat, sugar, and salt (Tufts Health & Nutrition, 2019).

2.3.3.1.2 Subscription-Based Discounts and Promotions

Food delivery platforms have discounts, meal bundles, and subscription offers that encourage eating more fast food than healthy food.

2.3.3.1.3 Socioeconomic Disparities in Food Access

Low-income people's economic ability does not support them in buying nutritious, high-quality food, and they only order cheap food through delivery platforms, reducing their opportunity for healthy meals (Chadwick, 2024). Consequently, poor health outcomes such as overweight, diabetes, and other chronic diseases emerge (Malik et al., 2010). In addition, reliance on cheap, low-quality foods has continued to drive food insecurity and diet disparities, which have increased socioeconomic and health disparities among poor populations (Darmon & Drewnowski, 2008).

2.3.3.2 Digital Marketing and Influence

Market and advertising theory show that marketing strategies influence consumer decisions on food delivery sites. Through persuasive advertising and user engagement strategies, users are encouraged to order unhealthy food online and avoid healthy eating habits.

2.3.3.2.1 Targeted Digital Advertising

Food delivery software analyzes users' preferences through big data and constantly pushes content and ingredients matching their tastes (Li et al., 2024). For example, once a user orders a hamburger, the platform continues to push fast food content, making it harder for users to resist unhealthy eating temptations.

2.3.3.2.2 Gamification and Reward Systems

Numerous small lottery games and cash red envelope rewards, such as meal discounts and platform incentives through consumption records and amounts, have encouraged consumers to keep spending on delivery platforms, distancing them from nutritious and healthy food (Chan et al., 2017).

2.3.3.2.3 Social Media Influence on Food Choices

Most food bloggers gain popularity by overindulging and promoting high-calorie, desirable but low-nutrient foods, leading people to develop incorrect eating habits (Roorda & Cassin, 2025).

2.3.3.3 Behavior and Psychological Determinants

Cognitive illusions and habitual behavior have greatly influenced food choices, generally favoring convenience over nutrition (Wansink & Chandon, 2006).

2.3.3.3.1 Emotional and Stress-Induced Eating

To conserve time and keep work simple, most youths take advantage of online takeaway services during hectic periods, i.e., overtime and examination periods, exchanging healthy meals for plain bento to save time. This has resulted in nutritionally unbalanced food composition and chronic malnutrition (Zhang et al., 2024).

2.3.3.3.2 Lack of Knowledge on Nutrition

Food delivery platforms don't provide transparent ingredient details, portions, and nutritional values. Customers ultimately rely on vague descriptors like "healthy" or "balanced" without precise dietary information. Furthermore, ingredient sources and preparation methods remain undisclosed, and individuals become misinformed regarding the actual healthiness of meals (Pomeranz et al., 2022). Consequently, customers incorrectly assign food delivery meals' nutritional and calorie value (Sharib et al., 2024).

2.3.3.3.3 The Building of Habits and Culture of Convenience

Customized food ordering contributes to unhealthy habitual eating, trapping the consumers in a destructive loop in which convenience is paramount (Zhang et al., 2024).

2.3.4 Impact of Frequent Food Delivery Consumption on Long-Term Health

Frequent consumption of takeout food causes poor physical health, increasing healthcare costs over time, especially among adults in their twenties who use food delivery apps. Compared to undelivered food, most food delivery meals have high calories, harmful fats, sodium, and added sugars that may lead to obesity, cardiovascular disease, and metabolic disorders in the long term (Garone, 2024). Furthermore, dependence on quick and processed foods has replaced the major nutrients like fiber, vitamins, and minerals required for health maintenance (Steele et al., 2016).

In addition, studies have determined that frequent use of food delivery promotes unhealthy actions such as late food intake or higher portions. Convenience in application and food mode when on delivery may lead to nutritional imbalance and health impacts. Economic and cultural determinants of food choice factors were also examined in the study. Food ordering apps are a consumption behavior, a mode, and a mobility convenience, and promotion behavior was also the finding of Tahim et al. (2024), which influenced unhealthy food consumption. They contribute to weight gain and metabolic disorders (Gu et al., 2020). Preparation of foods, in which individuals are usually not in command, has been linked with increased intake of preservatives and additives, resulting in hypertension and susceptibility to type 2 diabetes (Dai et al., 2022).

The World Health Organization (2024) also cautioned against the systemic impacts of convenience-based food venues and their contribution to degrading world diet quality and the acceleration of non-communicable diseases. These convenience-based food venues, where food-delivery chains dominate, compromise user control, facilitate overindulgence, and minimize exposure to nutritional balance. This concurs with the trends in young people's health in Shanghai and contributes to the need for structural and policy-driven interventions.

2.3.5 Enabling Healthier Eating and Balanced Diet

Different strategies have been created to promote healthier provisions and enable balanced consumption. Policy intervention, technological advancement, educational consumerism, and industrial involvement are the most critical areas.

2.3.5.1 Policy and Regulatory Approaches

Healthy eating and food safety concerns should be promoted through government regulation and intervention policies.

2.3.5.1.1 Mandatory Nutritional Labeling

Visible nutrition labels on packaging and the proportion of each element should enable consumers to accurately assess food's nutritional value and alert those who need to avoid substances like cholesterol, promoting healthier eating habits (Campos et al., 2011). Substances such as calorie content, macronutrients, and additives significantly impact human health (Cecchini & Warin, 2016). Business integrity, truthful reporting, and inspection by the Market Supervision Bureau should be necessary for quality assurance.

2.3.5.1.2 Taxation on Unhealthy Food Options

Taxes on unhealthy food can prevent the circulation of junk food and encourage people to avoid such items. For example, the high sugar tax on soft drinks has changed marketing strategies and increased consumer awareness of food safety and responsibility (Singleton, 2024).

2.3.5.1.3 Partnership between Food Delivery Platforms and Health Organizations

Food delivery services can collaborate with government agencies, health organizations, nutrition experts, and doctors to design eating guidelines for healthy meals. These collaborations included personalized health counseling columns and customized meals according to personal nutritional needs (Yang et al., 2024). Physicians and nutritionists participated in meal preparation guidance to preserve healthy foods, improve ingredient authenticity, and promote healthier consumption (Triyuni et al., 2021).

2.3.5.2 Technological Developments in Food Ordering Services

Digital technology can promote healthier eating via AI-generated recommendations, app adjustments, and portion management.

2.3.5.2.1 Healthy Meal Ideas via AI

With AI algorithms, delivery platforms can capture gigantic customer data, track the buying habits, food preferences, and previous orders, and automatically offer healthier meal options (Yang et al., 2024). These AI-powered recommendation systems can be personalized based on users' eating habits and have incorporated health experts' advice to encourage users to make healthier choices or meal options like low salt, low sugar, high protein, or rich dietary fiber foods. Aside from this, unwittingly, consumers also receive AI-driven recommendations that nudge them toward healthier meals, as research has proven (Dobbyn, 2024). AI technology can also conduct this analysis live, using market data, to forecast consumer need for healthy food (and how quickly this would shift due to product innovation or price) and recommend menu design, to make each meal as appealing and nutritious as possible.

2.3.5.2.2 Portion Control and Customizable Meals

Takeout is big, and it is a call to overeat. Options for customized portion sizes can be a feature of platforms; a user might choose smaller, more balanced meals. Even partial control may attenuate the risk for high calorie intake (McKay et al., 2023).

2.3.5.2.3 Digital Badges and Ratings of Health Score

For instance, the health score of food can be awarded to a delivery portal, and the rating system can be employed. Consumers concerned about health were likely to order the food type when given a good label and health score (Grummon et al., 2023).

2.3.5.3 Consumer Education and Behavioral Changes

Education interventions can enhance the dietary care of consumers and help with a healthy diet.

2.3.5.3.1 Food Delivery Apps Public Health Campaigns

Public health organizations can use food delivery apps to remind people of unhealthy consumption and provide health tips. Studies have proven that providing health information deliberately online can enhance eating (Seid et al., 2024).

2.3.5.3.2 Nutrition Literacy Programs for Young Adults

These nutrition literacy interventions, such as consumer education for food label reading, are possible at the community level. Workshops, online platforms, and mobile apps enable access to a youth population with live tools to assess the quality of meals and increase purchasing ability." Research has proven that individuals with higher nutrition literacy function better in selecting healthy food intake (Taylor et al., 2019).

2.3.5.3.3 Reward Systems for Healthy Choices

Meal delivery sites can create reward programs that give points or incentives to customers for healthier meals. Healthy meal ordering gives points or discounts for healthy dietary changes.

2.4 Conceptual framework

The conceptual framework depicts the relationship between the key variables of this study, i.e., food delivery culture, consumer behavior, and dietetic health outcomes.

Key Variables

This literature review operationalizes independent variables by explaining food delivery culture (e.g., usage frequency, marketing type, platform algorithms).

Mediating Variables

Food practice of the consumer (defined by economic status, behavior practice, and marketing exposure).

Dependent Variable

Influence of diet on health (nutritional value of consumed meals, long-term health risk).

Variable Relationships

From Food Delivery Habits to Diet of the Population

More exposure to digital marketing and promotions leads to ordering unhealthy meals as a habit. Economic factors, such as price sensitivity and discount incentives, have nudged consumers towards lower-cost, energy-dense meals.

From Consumer Dietary Culture or Habits to Dietary Health Outcomes

Repeated intake of an energy-dense, high-salt diet is associated with increased risk of obesity and related disorders, including cardiovascular diseases and metabolic disorders. Improper nutritional knowledge and misleading packaging have made people underestimate caloric intake.

From Strategies for Interventions to Customary Eating Behavior

Concerning consumer awareness and serviceability, implementations like AI-driven meal recommendations, public health campaigns, or nutrition labeling enhance consumer awareness and decision-making. Taxation of unhealthy food and mandatory transparent nutrition labels have been examples of policy interventions that help improve bad dietary habits.

Summary

This literature review has focused on the relationship between food delivery culture and dietary health among young adults in Shanghai. Social Cognitive Theory and the Theory of Planned Behavior have provided theoretical perspectives on behavioral reinforcement, implicit behavior control, and dietary choice. The conceptual model has illustrated the influence of food delivery platforms on consumer behavior and long-term dietary health outcomes. Policy interventions, technological innovations, and consumer education must address these challenges and promote healthier foods and balanced eating. By emphasizing these points, this review has shown future trajectories in this nascent area, the effectiveness of the AI-based recommendations, and the different regulatory actions.

3.Methodology

3.1 Introduction

This section explains the methodology development process for examining the influence of food delivery culture on young adults' dietary health. It describes the research design, the sampling method, the tools for data collection, and the data analysis method selected. Issues of data quality and protection of participants are noted as well. The study design ensures reliability, validity, and ethics throughout the research.

3.2 Study Design

Research design is an action plan linking research questions to data collection, measures, and analysis (Creswell & Creswell, 2017). It integrates various parts of the research logically and consistently to ensure its credibility and dependability. This is a mixed-methods research design study. This approach integrated quantitative and qualitative procedures to investigate the research problem (Creswell & Clark, 2017). Quantitative and supplementary qualitative data offer complementary statistical, generalizable findings and contextual, nuanced understandings. This survey-based study used quantitative methods to determine the trends and patterns of food delivery use and dietary health. On the other hand, qualitative procedures via interviews sought to investigate participants' motives, behavior, and influences in greater detail. While purely quantitative or qualitative approaches might have contributed to specific insights, they also had the danger of sacrificing statistical generalizability or contextual detail. Therefore, a mixed-method design was particularly well fitting given the research question: The Impact of Food Delivery Culture on Dietary Health among Young Adults in Shanghai, which involves behavioral complexity and visible trends. Mixed-methods designs beyond the spatially remote cases have been particularly well-suited to field studies in social phenomena, where no single number can describe human behavior (Tashakkori, 2010). Quantitative tools were needed, for instance, to understand how often young adults ordered via food delivery apps. However, knowing how they selected foods or what they thought about their health required understanding attitudes, beliefs, and context, qualities best captured with qualitative methods. This integration enhanced the scope and depth of the findings, yielding insights that have been comprehensive and actionable (Greene et al., 1989).

3.3 Population and target population

The study population is the larger group from which data can be collected (Creswell & Creswell, 2017). While the study population included all urban young adults in China using food delivery services, this research narrowed its focus to a more specific group. The participants in the present study were young adults aged 18–35 years in urban China who accessed and utilized food delivery services. This group was particularly relevant because food delivery platforms were widely used among digitally connected urban youth, and this age group was critical for establishing long-term dietary habits (Ho et al., 2019). The target population refers to a particular portion of the entire population on which the study focuses. The target population for this research was young adults aged 18–35, who were living in Shanghai and already used food delivery platforms regularly (i.e., once per week or more). Shanghai was chosen thanks to its sound internet infrastructure, fast pace of life, and high incidence of food delivery service usage. These characteristics made Shanghai appropriate for studying how food delivery culture might influence diet and health. Differentiating between the broader and target populations enhanced the precision and applicability of the study's findings.

3.3.1 Sample size and sampling technique

The study included 196 participants, consisting of 196 participants for the quantitative survey and 15 for the qualitative interviews. The survey participants were distributed across age groups: 18–22, 23–26, 27–30, and 31–35. Gender distribution was also approximately balanced. Two sampling methods were applied, consistent with the mixed-methods approach. Stratified Random Sampling involves dividing the population into distinct subgroups (strata) based on age and gender and randomly selecting participants from each subset. The Stratified Random Sampling technique ensures proportional representation and reduces sampling bias (Etikan & Bala, 2017). Participants from all the strata were first invited and assessed by the researcher from Shanghai-based universities, the government sectors, and users of food delivery apps. A random number generator was used to select participants from within each subgroup. Purposive Sampling is a non-probability sampling approach in which the sampling is conducted based on set characteristics and relevance of the individual (Palinkas et al., 2015). Purposive sampling was also used to select participants with different frequencies of use of food delivery platforms and different levels of awareness of healthy and unhealthy food. The combined sampling approaches strengthen the quantitative component's statistical reliability and the qualitative insights' contextual depth, consistent with a "fully integrated" design in mixed methods (Creswell & Clark, 2017)—this opportunistic sampling results in a study that retains measurable trends and individual perspectives germane to the research issue.

3.4 Data Collection Instrument

The primary data gathering tools used according to the mixed methods design of the study were a structured questionnaire for the quantitative phase and a semi-structured interview guide for the qualitative phase.

3.4.1 Structured Questionnaires

The questionnaire was designed to capture the quantifiable information related to food delivery behaviors, dietary habits, health conditions, health perception, and other determinants of food delivery (DeVellis & Thorpe, 2021). It was selfadministered and administered online (on platforms like WeChat, Wenjuanxing, and university mailing lists). Personal details such as age, gender, occupation, and income were reported in the questionnaire in addition to five sections including: food delivery use (frequency of ordering, platform, and type of meals ordered), nutritional knowledge about labels and perceptions of healthiness, behaviors (convenience and marketing practices rated on a 5-point Likert scale from "Strongly disagree" to "Strongly agree"), and self-reported health outcomes such as weight changes, energy levels, and health problems like gastrointestinal problems or hypertension. The survey was also quantitative, supporting the examination of trends or relationships between variables (e.g., the relationship between delivery frequency and self-reported dietary health).

3.4.2 A Semi-Structured Interview Guide

In-depth interviews based on the interview guide were conducted to investigate the motivations, feelings, and social forces of using food delivery. This qualitative approach was necessary to uncover the nuanced, lived experiences that were invisible in the surveys (Creswell, 2014). Interviews were audio-recorded in person or via Zoom with the participants' permission. The guide included open-ended questions categorized by key thematic areas: motives to use food delivery (e.g., convenience, social influence); knowledge and attitudes about nutrition (e.g., how participants defined "healthy food"); perceived impacts of food delivery on health (e.g., changes in diet energy or well-being); emotional and behavioral triggers (e.g., stress eating, late-hour ordering); and suggestions for healthier choices (e.g., digital labels, platform changes). The semi-structured format allowed for flexibility and depth, enabling follow-up questions and a more thorough exploration of individual experiences. By leveraging the strengths of both instruments, the study combined breadth with depth, as quantitative and qualitative data complemented each other to generate a holistic analytical picture of how food delivery culture influenced young adults' dietary health in Shanghai.

3.5 Pilot test

A pilot study assesses research instruments' understandability, usability, and reliability (Van Teijlingen & Hundley, 2001). A standard questionnaire and a semi-structured interview guide were used before using the main data collection. Pre-test served multiple critical roles: it clarified and corrected imprecise or unclear wording of the interview questions or questionnaire; confirmed that each instrument had an appropriate length, structure, and sequence; piloted the questionnaire in terms of internal consistency and reliability; and assessed if the interview guide resulted in significant, pertinent responses in direction of the research (Van Teijlingen & Hundley, 2001). The pilot survey was conducted with 10 young adults from the target population, while the pilot interviews were conducted with two participants at different levels of food delivery use. After participants answered the questionnaire, each was asked to provide feedback on the clarity, relevance, and language used in the questions. Participants who underwent the interviews then discussed how natural or unnatural the questions felt and whether they felt free to express themselves. The study used Cronbach's Alpha to assess internal consistency, with a threshold of 0.7 or higher considered acceptable for Likert-scale items measuring the same construct (e.g., health awareness, stress-related eating, or food delivery behavior) (DeVellis & Thorpe, 2021). The feedback further facilitated construct reliability by confirming that particular items consistently measured underlying variables. Due to the pilot, unclear, unrelated, or redundant questions were edited. The order of questions in certain sections was structured better to maintain respondent engagement throughout the survey until the end, before interest was lost. This pre-test phase provided a window for the instrument sharpening and piloting, which rendered them reliable and valid and enhanced the accuracy and reliability of the findings.

3.6 Data collection, coding, analysis, and interpretation

According to the mixed-methods design, the data were collected through an online survey and semi-structured interviews. An online survey was established on a secure online survey site (i.e., Wenjuanxing or Google Forms). The survey URL was posted on social media websites (WeChat, Weibo), university email listservs, and the Shanghai-based online food delivery forum. A brief cover letter describing the aim of the study and an estimated completion time was sent, along with a consent form, to maximize response rates. In-depth semi-structured interviews were conducted face-to-face and by Zoom, based on participant preference and availability. Interviews took approximately 30–45 minutes each and were audio-recorded with the participant's consent. Responses from the survey were auto-collected and saved in a password-protected spreadsheet (Google Sheets or Excel). The interviews were recorded digitally and safely stored in an encrypted password-protected cloud drive asset and hand-transcribed for analysis. The participants were de-identified to ensure anonymity. Participants were assigned a unique coded ID (e.g., Q001, I005). Data analysis entails systematically using statistical or logical operations to describe, summarize, and compare data to draw meaningful conclusions (Creswell, 2014). The closed-ended question responses were coded numerically. The Likert scale responses are scored from 1 (Strongly Disagree) to 5 (Strongly Agree) (Joshi et al., 2015). Statistical analysis was conducted with SPSS. Descriptive statistics of frequency, relative frequency, and cumulative relative frequency were applied to describe the participants' demographic information and food delivery behaviors. The relationships between the frequency of food delivery, economic factors, and perceived health were examined using correlation analysis and regression analysis to identify predictors of adverse dietary health outcomes. The cross-tabulation analysis explored deeper relationships between key demographic variables, especially food delivery frequency, and behavioral variables from the questionnaire. Texts of interviews are transcribed and processed in NVivo, a qualitative data analysis software (Goyal & Deshwal, 2023). The research data were coded thematically into categories of other patterns, such as platform influence or health concerns. The findings were triangulated with the survey findings, comparing themes to see where qualitative insights confirmed or diverged from quantitative trends. Data analysis and communication of conclusions, combining quantitative and qualitative data, helped draw a holistic picture of the research issue. Findings were grouped along thematic lines (e.g., behavioral drivers, nutritional awareness, marketing effects) and connected to the study's theoretical framework. The concluding research report integrated the findings using charts, graphs, and written summaries. Observations were drawn from available literature to determine similarities, gaps, or contradictions that may guide future research or policy recommendations.

3.7 Reliability and Validity

3.7.1 Reliability

Reliability is the consistency or steadiness of a measuring instrument and the ability to have similar measurements under similar conditions (Heale & Twycross, 2015). This meant the instrument yielded consistent results when administered repeatedly under identical conditions. To ensure the data collection instruments were reliable, multi-item scales, such as those measuring dietary behavior and nutritional awareness using Likert items, were pilot-tested using Cronbach's Alpha to ensure internal consistency. A satisfactory cutoff of 0.7 and above was used. Fellow academics did a peer review of the questionnaire to ascertain reasonable sequencing of items, question clarity, and compliance with research objectives. Standardized methods were used in collecting data to allow standardized delivery and understanding of the questions.

3.7.2 Validity

Validity indicates the degree to which a measurement tool measures the concept it was constructed to measure (Creswell & Creswell, 2017). Assured validity contributed to general study rigor by linking study inferences to real-world phenomena. The study quantified different types of validity. For Content Validity, behavioral science and public health professionals piloted the interview guide and questionnaire to ensure that all the significant concepts in the literature (e.g., nutritional awareness, marketing exposure, emotional eating, etc.) were included (Haynes et al., 1995). For Construct Validity, questionnaire items to measure perceived behavioral control and subjective norms were derived from the Theory of Planned Behavior constructs (Ajzen, 1991), and observational learning and self-efficacy were taken from Social Cognitive Theory (Bandura, 1986). For Face Validity, pilot testing helped to create a basis on which it was ensured that the instruments seemed to be measuring what they should from the respondent's perspective (Heale & Twycross, 2015).

3.8 Ethical considerations

Participants read briefly about the purpose, procedures, and rights before participating. Electronic informed survey consent was collected, and verbal informed consent for interviews was noted. All participants provided their consent willingly and were told they could leave without penalty. Data collected from study participants was treated under absolute confidentiality measures. No identifying information was collected, and each participant received a unique code. Participant responses were saved as an encrypted file to which the researcher was the only one with access. For the analysis, audio files were transcribed verbatim while removing identifying features of participants. Although this study posed little risk, a few participants may have felt discomfort discussing personal dietary habits or health concerns. To prevent this, participants were allowed to skip any question and received a short debrief, with links to mental health and nutrition resources, following their participation. The research findings were reported as they were; no data was falsified or manipulated. Quantitative and qualitative results, including limitations and contradictory responses, were shared to ensure transparency and academic integrity. The data collected was utilized solely for educational purposes concerning the research. All the logs were securely stored and not retained for over six months following project closure, upon which all records were permanently deleted. There was no unauthorized access, and data handling was by China's Personal Information Protection Law.

Summary

This chapter elaborates on the research approach in examining the impact of food delivery culture on the health of young Chinese people in Shanghai. The research employed a mixed approach using quantitative questionnaires and qualitative interviews to collect statistical patterns and individuals' in-depth summaries. By combining purposeful and stratified random sampling, diversity and representativeness of the sample were guaranteed. Data collection tools comprised a pre-tested structured online questionnaire and a pre-tested semi-structured interview guide. Quantitative data were then analyzed with SPSS, while qualitative data were coded thematically in NVivo. The chapter includes measures taken to ensure the reliability, validity, and ethical compliance of all data used during research, such as informed consent, confidentiality of data, and adherence to relevant data protection laws.

4.Analysis And Interpretation Of Data

4.1 Introduction

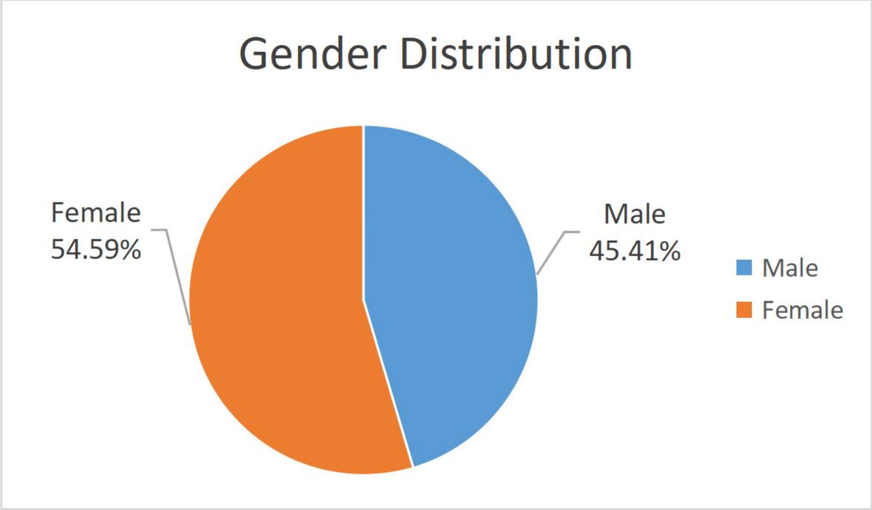
This chapter presents the findings of the mixed-method study, with quantitative data extracted from an online survey and qualitative findings from semi-structured interviews. Results have been reported in two parts: demographic profile of participants and thematic analyses of research questions. Quantitative data were analyzed descriptively and inferentially with SPSS, while interview data were analyzed thematically with NVivo. Findings are presented graphically and supplemented by reliability measures and correlation between key variables.

4.2 Analysis of Demographic Data

This study involves 196 participants. The data obtained on the study's Gender Groups is displayed in Figure 1 below.

Figure 1: Gender Distribution

Source: Survey Data

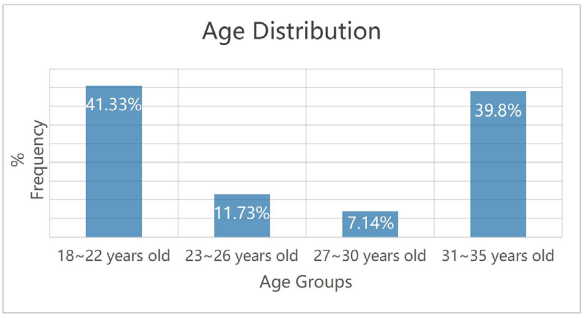


As observed in Figure 1 above, participants are grouped under two general gender categories: male and female. Of the 196 respondents, 54.59% were female and 45.41% were male. This virtually identical percentage ensures both genders are well represented in the study. The moderate percentage difference (9.18%) suggests that gender responses cannot be anticipated to have a large impact on final outcomes. The relative cumulative frequency sustains the observation that the data reflect almost identical engagement by sex, sustaining also the veracity of comparative analysis of food intake behaviour, food delivery behaviour, and health perceptions among respondents by gender.

The data obtained on the study's Age Groups is displayed in Figure 2 below.

Figure 2: Age Distribution

Source: Survey Data



In Figure 2 above, the participants are grouped into four categories: 18~22, 23~26, 27~30, and 31~35. Only 7.14% of the participants are in the 27~30 age group. This relatively low percentage might be attributed to the specific population under investigation. As shown in Figure 2, most participants are concentrated in the 18~22 and 31~35 age groups, accounting for 41.33% and 39.8% respectively. The cumulative relative frequency indicates that nearly 60% of participants are 30 or younger, while almost all are 35 or younger.

The data obtained on the occupation created by the survey is displayed in Figure 3 below.

Figure 3: Occupation Distribution

Source: Survey Data

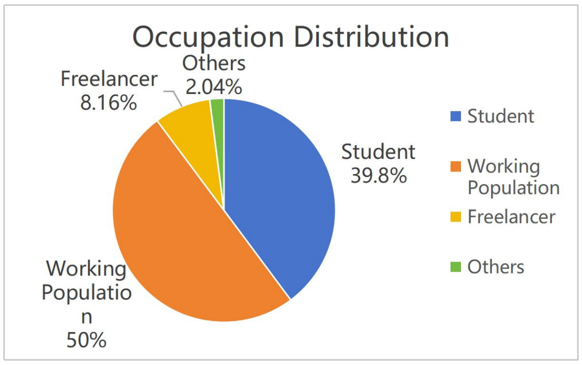


Figure 3 above investigates four job categories: Student, Working population, Freelancers, and Others. The data reveals that the working population constitutes the largest group, accounting for 50% of the participants. This unusually high proportion suggests that the findings primarily represent urban working individuals. Students represent the second largest group, with a relative frequency of 39.8%. Freelancers and others in the 'Other' category constitute smaller proportions of the sample, at 8.16% and 2.04% respectively. The cumulative relative frequency indicates that nearly 90% of the participants are either students or working professionals, highlighting these as the primary occupation groups in the study.

The data obtained from the Source of Income created by the survey is displayed in Figure 4 below.

Figure 4: Source of Income Distribution

Source: Survey Data

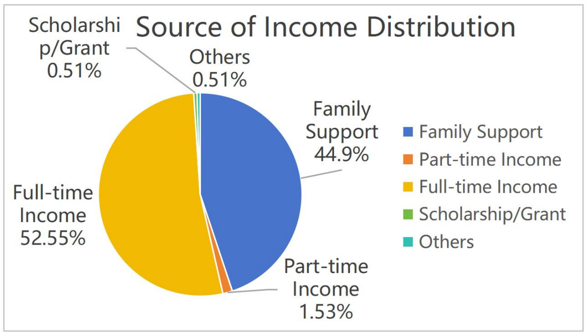


Figure 4 presents the source of income distribution of the participants: Family Support, Part-time Income, Full-time Income, Scholarship/Grant, and Others. The data reveals that full-time income is the primary source of financial support for most participants, accounting for 52.55%. Family support is the second largest source, with a relative frequency of 44.9%. Part-time income, scholarships/grants, and other sources constitute tiny proportions of the sample. The cumulative relative frequency indicates that nearly 99% of participants rely on either family support, part-time income, or full-time income as their primary source of financial support.

The data obtained on the Order Frequency as created by the survey is displayed in Figure 5 below.

Figure 5: Order Frequency Distribution

Source: Survey Data

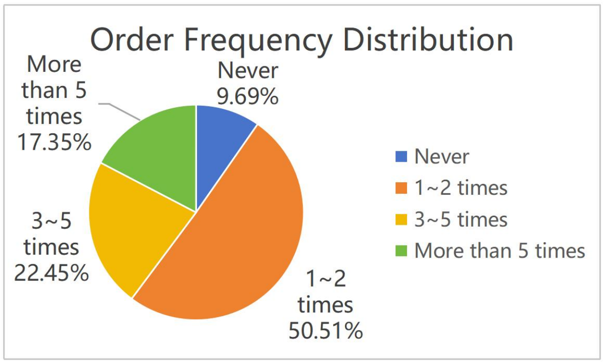


Figure 5 presents the participants' average weekly food delivery order frequency: Never, 1~2 times, 3~5 times, and More than 5 times. The data reveal that most participants (50.51%) use food delivery services 1~2 times weekly. A significant proportion (22.45%) use it 3~5 times per week, while a smaller proportion (17.35%) use it more than 5 times per week. Only a small proportion (9.69%) of participants never use food delivery services. This relatively low percentage indicates that food delivery usage is nearly universal among the surveyed population. The cumulative relative frequency suggests that over 80% of participants use food delivery services at most 5 times per week, with nearly all participants using them at least occasionally.

The data obtained on the Time of Use as created by the survey is displayed in Figure 6 below.

Figure 6: Time of Use Distribution

Source: Survey Data

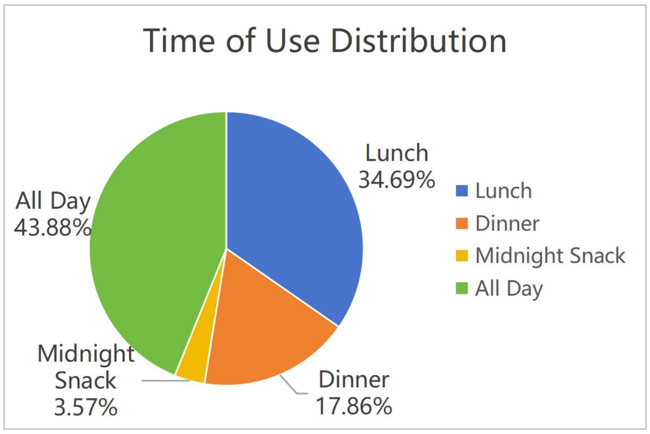


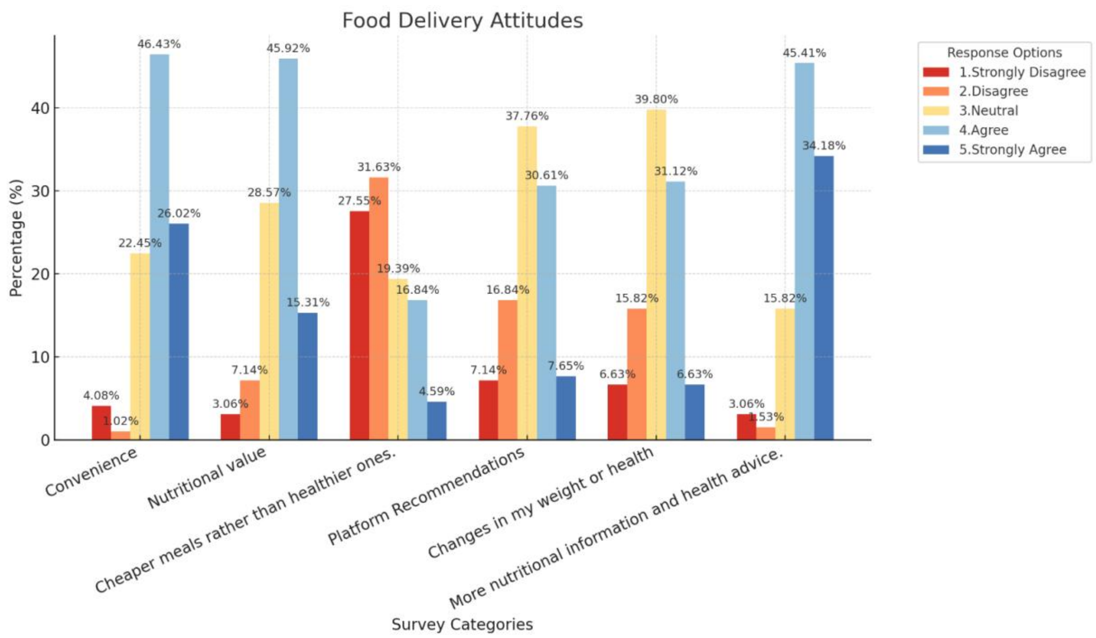
Figure 6 presents the usual times food delivery service use among the participants: Lunch, Dinner, Midnight Snack, and All Day. The data reveals that food delivery is most commonly used throughout the day (43.88%), followed by lunchtime (34.69%). A significant proportion of participants also use food delivery for dinner (17.86%), while a small proportion use it for midnight snacks (3.57%). This minimal percentage suggests that late-night ordering is relatively rare among young adults in this sample. The cumulative relative frequency indicates that over 56% of participants use food delivery at lunch, dinner, or as a midnight snack, with nearly all participants using it at some point during the day.

4.3 Empirical Analysis

This study involves 196 participants. The data obtained on the Perceptions of Food Delivery Attitudes as created by the survey is displayed in Figure 7 below.

Figure 7: Food Delivery Attitudes

Source: Survey Data



In Figure 7 above, the survey results indicate that most respondents find food delivery more convenient than cooking, with over 72% agreeing or strongly agreeing. Nutrition is a notable consideration, as more than 61% of participants consider it when ordering. However, cost is also strongly influenced—59% disagreed or strongly disagreed with prioritizing healthy meals over cheaper options. Platform recommendations appear moderately influential, with 30.61% agreeing and 37.76% remaining neutral. Regarding the health impact of using delivery services, opinions are more mixed, though about 38% reported some perceived effects on weight or health. Importantly, there is substantial demand (79.59%) for food delivery platforms to provide more nutritional labels and health-related guidance, highlighting a growing health awareness among users.

4.4 Reliability and Validity

4.4.1 Reliability

Reliability analysis is used to evaluate the stability and consistency of the questionnaire. In this study, we used the Cronbach's Alpha coefficient to assess the internal consistency of the questions in Section C (Dietary Habits and Health Cognition) of the questionnaire. This study involves 196 participants. The data obtained on the Cronbach's Alpha coefficient as created by the survey is displayed in Table 8 below.

Table 8: Cronbach's Alpha coefficient

Sample Size	Number of Items	Cronbach's Alpha Coefficient
196	6	0.556

Source: Survey Data

In Table 8 above, the data presented shows a sample size of 196 and six items. The Cronbach's Alpha coefficient is reported as 0.556, indicating a moderate internal consistency among the items. Generally, a Cronbach's Alpha value between 0.5 and 0.7 is considered acceptable, but it suggests that there may be room for improvement in the reliability of the measurement tool. While the value shows some degree of consistency, further refinement may be needed to enhance the cohesiveness of the items.

4.4.2 Validity

Validity analysis is used to assess the effectiveness and accuracy of questionnaires. In this study, we evaluated the questionnaire's validity through structural validity and content validity.

Construct Validity

The data obtained on the Construct Validity, as created by the survey, is displayed in Table 9 below.

Table 9: Construct Validity

Item	Factor 1	Factor 2	Factor 3	Factor 4	Commonality
Gender	-0.11	0.26	-0.31	0.04	0.173
Age Group	0.90	0.03	-0.13	-0.03	0.828
Occupation	0.87	-0.03	-0.11	-0.08	0.779
Source of Income	0.87	0.03	-0.04	0.02	0.762
Order Frequency	-0.06	0.39	-0.07	0.62	0.543
Time of Use	0.02	-0.14	0.09	0.78	0.645
Convenience	-0.15	0.57	0.08	0.45	0.558
Nutritional Value	0.00	0.78	-0.01	-0.18	0.645
Cheaper meals rather than healthier ones.	-0.31	-0.23	0.69	0.08	0.632
Platform Recommendations	-0.17	0.14	0.75	0.09	0.617
Changes in my weight or health	0.01	0.40	0.63	-0.05	0.553
More nutritional information and health advice.	0.19	0.72	0.08	0.22	0.606
Characteristic root values (before rotation)	2.82	2.15	1.28	1.10	-
Variance explained rate (%) (before rotation)	23.51%	17.90%	10.63%	9.14%	-
Cumulative variance interpretation rate %(before rotation)	23.51%	41.41%	52.04%	61.18%	-
Characteristic root values (after rotation)	2.53	1.92	1.58	1.31	-
Variance explained rate (%) (after rotation)	21.07%	16.04%	13.14%	10.93%	-
Cumulative variance explained rate (%) (after rotation)	21.07%	37.11%	50.25%	61.18%	-
KMO value	0.697				-
Bart's spherical value	568.133				-
df	66.000				-
P value	-				-

Source: Survey Data

Table 9 shows the solution to factor analysis for all items and factor loadings, commonality, and variance explained by each factor. Gender, occupation, income, and age category items all load high on Factor 1, with a significant contribution to the factor (loadings of 0.90, 0.87, and 0.87, respectively). They are highly similar to socio-demographic characteristics, therefore loading high on this factor. Food delivery usage behavior items (e.g., frequency, time of day) load variably across factors. Factor 4 loads moderately for frequency of delivery (0.62) and Factor 4 loads heavily for use at various times of the day (0.78). Food-related health and nutritional products, such as considering nutritional value when purchasing food, choosing cheaper meals over healthier ones, and the influence of platform recommendations, impact heavily on Factor 2 and Factor 3, which would imply that these are more linked with food choice, health awareness, and platform influence. Commonality values are the common variance shared by items and factors, and the items all fall between moderate to highly correlated (0.553 to 0.828) with one another, that the factors account for the bulk of the response variance. Factor 1 is responsible for the largest amount of variance before rotation (23.51%), followed by Factor 2 (17.90%), Factor 3 (10.63%), and Factor 4 (9.14%). Upon rotation, the percentage of the variance explained by each factor is altered slightly such that Factor 1 accounts for 21.07%, Factor 2 accounts for 16.04%, Factor 3 accounts for 13.14%, and Factor 4 accounts for 10.93%. The cumulative variance is 61.18% after rotation, indicating that the four factors account for much of the variance in the data. Kaiser-Meyer-Olkin (KMO) value of 0.697 shows that the data is suitable for factor analysis, as values above 0.6 are deemed satisfactory. Bartlett's Test of Sphericity is significant with a p-value (less than 0.05), which confirms that the correlation matrix is not an identity matrix and that there are sufficient correlations in the data to conduct factor analysis. The analysis reveals that the items can be classified into four factors, each accounting for a distinctive dimension of the respondents' food delivery behaviors and attitudes, health consciousness, and socio-demographic characteristics.

Content Validity

The data obtained on the content validity, as created by the survey, is displayed in the table 10 below

Table 10: Content Validity

Item Description	Highest Factor Loading	Communality	Content Validity	Justification
Gender	Factor 2 (0.26)	0.173	Low	Low communality; weak association with any factor (<0.3). Gender is demographic, not central to delivery-health link.
Age Group	Factor 1 (0.90)	0.828	High	Very strong loading and communality; age directly affects health awareness and delivery behavior.
Occupation	Factor 1 (0.87)	0.779	High	Strong link to socioeconomic status and lifestyle, which are highly relevant to dietary health patterns.
Source of Income	Factor 1 (0.87)	0.762	High	Income source influences food affordability and
				choices; high communality confirms this is a key construct.
Order frequency	Factor 4 (0.62)	0.543	High	Strong behavior-based factor; direct proxy of food delivery habit intensity.
Time of use	Factor 4 (0.78)	0.645	High	Reflects variability in meal timing habits— relevant to understanding eating behavior disruption.
Convenience	Factor 2 (0.57)	0.558	Medium–High	Reflects attitude towards food sourcing; moderate communality, tied to convenience-driven behavior.
Nutritional value	Factor 2 (0.78)	0.645	High	Measures health awareness; strong alignment with dietary health construct.
Cheaper meals over healthier ones	Factor 3 (0.69)	0.632	High	Indicates value vs. health trade-offs; strong factor loading supports its validity.
Platform recommendations	Factor 3 (0.75)	0.617	High	Shows susceptibility to external influence; strongly behavioral, well loaded.
Changes in health or weight	Factor 3 (0.63)	0.553	High	Directly captures health outcome perception; good communality and interpretability.
More nutrition info and health advice	Factor 2 (0.72)	0.606	High	Reflects consumer expectations for health guidance; well aligned with health attitudes.

Source: Survey Data

The results show that the majority of the items in the survey are very content valid because significant factor loadings (usually >0.6) and communalities (>0.5) are experienced. Significant demographic items like occupation, source of income, and age group load considerably on Factor 1 because they are used in socioeconomic determinants of diet health. Items like frequency of weekly food ordering and usage time also have high loadings (0.62 and 0.78, respectively), thus bearing witness to their significant role in measuring actual usage patterns. Items measuring attitude and perception—e.g., regard for nutritional content, lower meal cost preference, influence of platform recommendation, and perceived changes in health/weight—are similarly well-loading on Factors 2 and 3 and positively contributing to health consciousness and behavior influence constructs. While gender is of low communality (0.173) and low factor relation, suggesting that it is not a significant factor in the underlying structure and therefore is of low content validity. The tool has a good structural foundation and a valid representation of prominent health-related dimensions.

4.5 Correlation Analysis

Correlation analysis explores the degree of association between different questions or variables in the questionnaire. The data obtained in Table 11 below shows the correlation analysis results (expressed in Pearson correlation coefficient) between the questions in Section C and other parts (such as the behavior of using food delivery services):

Table 11: Correlation Analysis

Item	Mean	Standard Deviation	Convenience	Nutritional value	Cheaper meals rather than healthier ones.	Platform recommendations	Changes in my weight or health
Convenience	3.89	0.94	1				
Nutritional value	3.63	0.93	0.30**	1			
Cheaper meals rather than healthier ones.	2.39	1.19	0.06	-0.17*	1		
Platform Recommendations	3.15	1.02	0.22**	0.06	0.41**	1	
Changes in my weight or health	3.15	0.99	0.10	0.23**	0.18**	0.32**	1
* p<0.05 ** p<0.01							

Source: Survey Data

Table 11 presents the means, standard deviations, and correlation matrix for a few food delivery behavior items, with level of significance presented as p-values. The items have varying means, revealing overall patterns in response. For example, "I think ordering takeout is more convenient than cooking" has a mean of 3.89 and a standard deviation of 0.94, suggesting most respondents agree that ordering takeout is more convenient. Other items, like "I tend to choose cheaper meals rather than healthier ones," have lower means (2.39), indicating less agreement with this statement. There is a positive and significant correlation ($p < 0.01$) between "I think ordering takeout is more convenient than cooking" and "When I order takeout, I consider the nutritional value of the food" (0.30), suggesting that people who find takeout more convenient also tend to consider the nutritional value of the food they order. The item "I tend to choose cheaper meals rather than healthier ones" has a negative and significant correlation ($p < 0.05$) with "When I order takeout, I consider the nutritional value of the food" (-0.17), suggesting that those who prioritize price tend to care less about nutritional value. There are positive and significant correlations between "I tend to choose cheaper meals rather than healthier ones" and "The recommendations on takeout platforms influence my food choices" (0.41) and "I have noticed changes in my weight or health after using takeout services"

(0.18), suggesting that price sensitivity may influence both the role of platform recommendations and perceived health changes. The correlation between “The takeout platform recommendations influence my food selection” and “I have had fluctuations in health or weight after consuming takeout” is strong and very positive (0.32), which indicates that those whose food selection is driven by platform recommendations have fluctuations in weight. Convenience, nutritional needs, expense, platform recommendations, and perceived health drive delivery behavior and food attitude, as the associations elucidate.

4.6 Regression Analysis

Regression analysis is a statistical method of establishing the relationship between an independent variable and one or more dependent variables. The current study determined how behavior and perception variables such as convenience, nutrition consciousness, cost sensitivity, and algorithmic power predict change in self-reported measures of food delivery consumption. Regression Analysis statistics from the survey appear in Table 12 below.

Table 12: Regression Analysis

Item	Regression Coefficient	t value	p value	VIF
Constant	0.98	2.75	0.007**	-
Convenience	0.35	5.16	0.000**	1.16
Nutritional value	-0.00	-0.04	0.964	1.22
Cheaper meals rather than healthier ones.	-0.03	-0.59	0.555	1.27
Platform Recommendations	-0.02	-0.29	0.774	1.35
Changes in my weight or health	0.09	1.36	0.174	1.19
Sample Size	196			
R^2	0.149			
Adjust R^2	0.126			
F	F(5,190)=6.648,p=0.000			
* p<0.05 ** p<0.01				

Source: Survey Data

Table 12 presents the result of a multiple regression analysis of the relationships between factors explaining food delivery behavior and outcomes for health. Regression Coefficients describe the size and direction of each predictor’s relationship with the dependent variable. For example, the value of “I find ordering takeout more convenient than cooking” is 0.35, meaning that with every unit increase in convenience, the dependent variable increases by 0.35 units. The effect ($p < 0.01$) indicates a very strong positive effect. The t-value reflects the strength of the effect of the oscillation of the sample data, and the p-value indicates the significance of the effect. Utterances such as “I think ordering takeout is more convenient than cooking” have a very strong positive effect ($p < 0.01$). On the other hand, other statements, like “When ordering takeout, I consider the nutritional value of food” ($p = 0.964$), “I will order less expensive meals rather than more healthy meals” ($p = 0.555$), and “Recommendations of takeout websites influence my food choice” ($p = 0.774$), are not significantly different from zero ($p > 0.05$), that is, there is no significant effect on the dependent variable. VIF is also examined for multicollinearity, and every value above 10 indicates the issue of multicollinearity between highly correlated predictor variables. In this study, all VIF values are below 2, indicating no issue of multicollinearity between the predictors. R^2 (0.149) shows that the predictors in the model predict about 14.9% of the dependent variable’s variance, indicating it as moderate. Adjusted R^2 (0.126) is corrected for the number of predictors and indicates poorer fit when the number of variables is involved. The F-statistic ($F(5,190)=6.648$, $p = 0.000$) is significant and suggests that the model is statistically significant and that predictors impact the dependent variable. The regression process indicates the importance of convenience on the dependent variable. Predictors like price sensitivity, platform recommendations, and nutrition knowledge do not have any relevant role to play in this model. The model fit is perfect, and predictors explain modest variance.

4.7 Cross-Tabulation Analysis

The cross-tabulation analysis explores deeper relationships between key demographic variables, especially food delivery frequency, and behavioral variables from the questionnaire. The data obtained on how food delivery frequency affects perceived health change is displayed in Table 13 below.

Table 13: Food Delivery Frequency X Perceived Health Change

Frequency/ Change	1. Strongly Disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly Agree	Total
Never	3(15.79%)	2(10.53%)	11(57.89%)	2(10.53%)	1(5.26%)	19
1~2 times	4(4.04%)	18(18.18%)	39(39.39%)	34(34.34%)	4(4.04%)	99
3~5 times	3(6.82%)	9(20.45%)	15(34.09%)	14(31.82%)	3(6.82%)	44
More than 5 times	3(8.82%)	2(5.88%)	13(38.24%)	11(32.35%)	5(14.71%)	34
Total	13	31	78	61	13	196

Source: Survey Data

The cross-tabulation results indicate a clear relationship between the frequency of food delivery and the attitude towards change in health. Among participants who “never” utilized food delivery services, 57.89% were neutral in attitude, while only 5.26% strongly agreed that they had noticed a health change. Among 1–2 times a week order participants, 34.34% said they agreed their health had been altered, 39.39% stayed neutral, and a mere 4.04% strongly agreed. Among 3–5 times a week delivery users, 31.82% agreed and 6.82% strongly agreed to have been affected by health impacts, 34.09% of whom remained neutral. The highest perception change was observed in the group that utilizes delivery services more than 5 times a week, where 32.35% agreed and 14.71% strongly agreed that their health influenced them. Meanwhile, 38.24% were neutral. These figures suggest that with increased frequency of delivery, both awareness and health concern increase, but a significant majority of users remain indifferent. This conflicted trend partially supports the assumption that frequent food delivery can contribute to perceived health deterioration. Also, it indicates that awareness can be influenced by other factors such as personal lifestyle, age, or food content.

The data obtained on how food delivery frequency affects nutrition value consideration is displayed in the Table 14 below

Table 14: Food Delivery Frequency X Nutrition Value Consideration

Frequency/ Consideration	1. Strongly Disagree	2. Disagree	3. Neutral	4. Agree	5. Strongly Agree	Total
Never	4(21.05%)	0(0.00%)	7(36.84%)	8(42.11%)	0(0.00%)	19
1~2 times	0(0.00%)	9(9.09%)	27(27.27%)	49(49.49%)	14(14.14%)	99
3~5 times	1(2.27%)	1(2.27%)	15(34.09%)	20(45.45%)	7(15.91%)	44
More than 5 times	1(2.94%)	4(11.76%)	7(20.59%)	13(38.24%)	9(26.47%)	34
Total	6	14	56	90	30	196

Source: Survey Data

Table 14 illustrates the relationship between food delivery frequency and consideration of nutritional value. Among those who never use food delivery services, a majority (42.11%) agree that they consider nutritional value, with no respondents strongly agreeing or disagreeing. With more frequent orders, the overall pattern is one of greater agreement for nutrition awareness. For instance, among those who order 1–2 times a week, nearly two-thirds (63.63%) agree or strongly agree with nutrition considerations. This proportion is relatively high for the group ordering 3–5 times a week (61.36%), and yet goes up with those ordering more than 5 times a week (64.71%). Most notably, the highest concordance (26.47%) is found at the “more than 5 times” category, suggesting that frequent users of food delivery pay more attention to nutritional content, possibly because they are exposed more or because they are picking and choosing what to order. The figures reveal a positive relationship between the frequency of food delivery and nutrition attention.

The data obtained on how food delivery frequency affects food delivery convenience is displayed in the Table 15 below

Table 15: Food Delivery Frequency X Food Delivery Convenience

Frequency/ Convenience	1. Strongly Disagree	2.Disagree	3. Neutral	4. Agree	5. Strongly Agree	Total
Never	7(36.84%)	0(0.00%)	5(26.32%)	6(31.58%)	1(5.26%)	19
1~2 times	1(1.01%)	2(2.02%)	27(27.27%)	47(47.47%)	22(22.22%)	99
3~5 times	0(0.00%)	0(0.00%)	7(15.91%)	24(54.55%)	13(29.55%)	44
More than 5 times	0(0.00%)	0(0.00%)	5(14.71%)	14(41.18%)	15(44.12%)	34
Total	8	2	44	91	51	196

Source: Survey Data

Table 15 presents the relationship between food delivery frequency and the perception of its convenience. There is a strong trend; indeed, the higher the frequency of ordering food delivery on the part of a respondent, the more they find it convenient. Thus, among those ordering it never, as many as 36.84% agree or strongly agree with the convenience statement, with an impressive 36.84% seriously disagreeing. Against that background, the number of agreements reaches 69.7% of those ordering 1–2 times a week and as high as 84.1% among those ordering 3–5 times.. Most strikingly, 85.3% of those ordering more than 5 times a week agree or strongly agree that food delivery is convenient, with 44.12% strongly agreeing. The absence of variance between the higher-frequency groups suggests that frequent users all perceive food delivery as convenient, validating the assertion that convenience is a key stimulus for repeated use.

4.8 Qualitative Questions Analysis

4.8.1 Perceived Health Impact of Food Delivery Services

This study involves 196 participants. The data obtained on the Perceived Health Impact of Food Delivery Services created by the survey is displayed in Table 16, 17, 18 and 19 below.

Table 16: Negative Health Perceptions

Node	Sample Coded Reference (Complete Answer)	Frequency
Excess Oil & Salt	"Takeout food contains too much oil and salt."	3
Weight Gain	"Ordering food causes me to gain weight."	2
Food Safety Concerns	"There are potential food safety issues."	2
Overuse of Spices	"Too spicy/salty, not suitable for regular intake."	2
Unhealthy Advertising	"The platform promotes unhealthy food."	2
Health Impact (General)	"Food delivery negatively affects my health."	3

Source: Survey Data

Table 16 documents respondents' self-reported negative health impacts of food delivery services. The most frequently mentioned issue was the high oil and salt content in takeaway food, noted by three participants, indicating high concern over the nutritional quality of meals ordered online. Similarly, several participants indicated overall health problems and weight gain, indicating a perception that regular food delivery is part of an unhealthy lifestyle pattern. Other issues were the potential threat to food safety, overuse of spices, and platforms creating unhealthy options through promotion, which happened more than once. All of these responses refer to an underlying theme of diet risk and distrust, suggesting that most users feel that food delivery is potentially unhealthy to their well-being in terms of ingredients employed as well as the promotion strategies of platforms.

Table 17: Health-Neutral Views

Node	Sample Coded Reference (Complete Answer)	Frequency
Balanced Habits	"The impact on health is general."	1
Personal Choice	"I already choose healthy options myself."	1
Mitigation Strategies	"I can avoid unhealthy choices."	2
Cooking Preference	"I prefer to cook for better control."	1

Source: Survey Data

Table 17 illustrates the participants' health-neutral perceptions regarding food delivery services. While not denying potential health impacts, these accounts are more middle-of-the-road or self-controlled. Some participants reported that the effect of food delivery on their health is general or none. Others, however, pointed out agency, with them having the option to select healthy food when ordering or to have home meals to enjoy what they desire. The most commonly cited neutral stance was mitigation strategies, with participants sure of taking steps voluntarily to avoid unhealthy food. These responses suggest that a population of users knows possible risks but feels they can manage them. Hence, they suggest both individual agency and choice in refusing the convenience of food delivery.

Table 18: Positive Health or Lifestyle Outcomes

Node	Sample Coded Reference (Complete Answer)	Frequency
Convenience	"Delivery is very convenient."	3
Saves Time / Effort	"It saves me cooking time."	2
Health-Conscious Choices	"I can order healthier food if I choose."	2
Eating Routine Improvement	"It helps me eat more regularly."	2

Source: Survey Data

Table 18 illustrates the lifestyle or health benefits that participants in food delivery services saw. The convenience factor was the most frequent advantage cited by respondents, who appreciated ease and accessibility in having meals. Other participants also identified food delivery as saving effort and time, particularly by minimizing the amount of work needed in meal preparation, which could be pretty helpful to individuals with a busy lifestyle. Significantly, consumers said they can selectively make healthier choices by ordering more nutritious foods on delivery platforms. Some added that delivery services enable them to eat more frequently, suggesting increased daily food intake. These insights reflect a group of users who view food delivery as a tool that can support efficient and potentially healthier lifestyle habits when used intentionally.

Table 19: Data Summary Matrix

Node	Number of Nodes	Frequency Total
Negative Health Perceptions	6	20
Neutral / Agency Perspectives	4	6
Positive Outcomes	4	14

Source: Survey Data

Table 19 summarizes the thematic coding across all participant responses regarding the perceived health impact of food delivery services. The theme of Negative Health Perceptions had the highest frequency, with six distinct nodes and 20 coded responses, indicating that concerns about nutritional quality, weight gain, and food safety were dominant among respondents. In contrast, the Neutral / Agency Perspectives theme included four nodes and six responses, reflecting a smaller group that acknowledged potential impacts but emphasized personal responsibility and choice in mitigating adverse effects. The Positive Outcomes theme, comprising four nodes but with a higher frequency total of 14, showed that many participants recognized convenience, time efficiency, and the ability to make health-conscious choices as key benefits of food delivery. This distribution highlights a complex relationship: while negative perceptions are most prevalent, a significant portion of users see value in food delivery when used mindfully and strategically.

4.8.2 Perceived Platform Measures for Healthier Food Choices

The data obtained on the Perceived Platform Measures for Healthier Food Choices created by the survey is displayed in Table 20, 21, 22, 23 and 24 below.

Table 20: Negative Perceptions of Platform Measures

Node	Sample Coded Reference (Complete Answer)	Frequency
Self-cooking as Alternative	"I prefer cooking myself."	1
Reduce Prepared Meals	"Limit processed food vendors."	1
Implementation Difficulty	"These measures are hard to execute."	1
Platform Profit Priority	"Platforms prioritize profits over health."	1
Avoid Big Data	"Stop using algorithms to push unhealthy options."	1

Source: Survey Data

Table 20 presents the negative perceptions of platform-level measures that promote healthier food choices. All nodes were cited once, indicating a heterogeneous but low-frequency set of concerns. Some participants chose self-cooking as a better choice, indicating a lack of faith in the effectiveness of any platform intervention. Others lamented the overwhelming availability of processed food on delivery platforms and suggested limiting such products. Some responses indicated ambivalence towards making actual changes, citing operational or technical challenges. Specifically, respondents believed that the platforms are more interested in profit than public health, and a respondent was clear in requesting a reduction in reliance on big data algorithms, which they believed encouraged unhealthy consumption habits. These views express an attitude of distrust or cynicism about the platforms' willingness or capacity to deliver real improvements in health.

Table 21: Neutral/Pragmatic Perspectives

Node	Sample Coded Reference (Complete Answer)	Frequency
Unaware of Measures	"I don't know what they're doing."	7
Advertising Neutrality	"Ads exist but don't influence me."	4
Conditional Approval	"Measures depend on context."	2
Basic Labeling	"Calorie tags are useful."	3

Source: Survey Data

Table 21 consolidates the pragmatic or neutral reflections provided by the participants regarding the role of food delivery platforms toward promoting healthier consumption. The most frequent answer was not knowing, seven participants affirming they had no clue what the platforms were doing in this direction, illustrating disconnection or transparency of health efforts. Some expressed advertising neutrality, affirming the presence of advertising but stating that they had little effect. Others gave qualified support, suggesting that whatever success a health campaign might have would depend on how it was carried out. In addition, straightforward nutritional labeling, such as calorie stickers, was positively identified by three participants as potentially useful. These responses are more balanced in tone—neither entirely favorable nor categorically unfavorable—anticipating better, more observable, and user-centric health promotion practices from sites.

Table 22: Constructive Suggestions

Node	Sample Coded Reference (Complete Answer)	Frequency
Health Topic Sections	"Create dedicated healthy food zones."	3
Nutritional Labeling	"Require detailed calorie/nutrient tags."	6
Balanced Recommendations	"Suggest lighter meal combinations."	3
Quality Control	"Strict vendor screening needed."	2

Source: Survey Data

In Table 22, the qualitative results point to nutritional labeling as the most deeply concerned, with six references expressing a need for complete calorie and nutrient labels, reflecting the high demand level from stakeholders for information and nutritious food choice. Balanced advice and health topic areas were referred to three times each, highlighting a mid-point need for healthier eating environments and lower calorie-content meals. Less often named (twice), quality control then signals inherent problems with vendor consistency and food safety. Overall, the information indicates that the top priority is consumer empowerment via information, besides environmental cues and government regulation.

Table 23: Positive Framing of User Agency

Node	Sample Coded Reference (Complete Answer)	Frequency
Personal Responsibility	"Users choose their own meals."	3
Control Through Choice	"I select healthy options if available."	3

Source: Survey Data

Table 23 presents positively phrased answers on personal responsibility and user control in choosing healthier foods. Two shared nodes existed. First, the theme of personal responsibility was observed in answers that stated that users decide what they wish to eat, regardless of platform design. Nodes are stated three times, suggesting that individual choice is essential in influencing health. Second, control by choice was a theme that arose frequently, with users explaining that they can make healthy choices if those choices are present on the platform. These instances illustrate a user population that sees itself as active agents, not passive consumers, choosing autonomy and self-directed decision-making over being regulated by external means or platform-driven guidance.

Table 24: Summary Coding Matrix

Node	Number of Nodes	Frequency Total
Negative Perceptions	5	5
Neutral/Pragmatic Views	4	16
Constructive Suggestions	4	14
Positive User Agency	2	6

Source: Survey Data

Table 24 presents a thematic summary of user reactions to platform efforts towards promoting healthier food choices. The Negative Perceptions theme contains five nodes with a total frequency of 5, indicating that although there is some distrust or skepticism regarding platform intentions and capability, such attitudes do not dominate. The most frequent answers were under Neutral/Pragmatic Views, which added up to 16 nodes in frequency. These convey a more guarded stance, wherein users are either unaware of existing measures or provide condition-based, intermediate comments based on actual implementation. Constructive Suggestions were also significant, represented by 14 occurrences over four nodes, showing user demand for tangible, realizable measures such as nutritional labeling and healthily curated sections. Lastly, the Positive User Agency theme occurred six times, emphasizing that some users perceive themselves as in control and capable of good decision-making if given the right tools. Overall, the data shows a constructive orientation, with users leaning more toward pragmatism and solution-seeking, rather than outright criticism or passivity.

4.8.3 Impact of Food Delivery on Lifestyle and Health Perceptions

The data obtained on the Impact of Food Delivery on Lifestyle and Health Perceptions created by the survey is displayed in Tables 25, 26, 27, and 28 below.

Table 25: No Significant Change Observed

Node	Sample Coded Reference (Complete Answer)	Frequency
Denial of Change	"No", "Not really", "No change in health behavior"	12
No Health Impact	"No impact on health", "Still maintain same diet"	7
Infrequency/Occasional Use	"Occasionally order", "Rarely rely on delivery"	3

Source: Survey Data

Table 25 displays responses categorized under the theme No Significant Change Observed regarding the impact of food delivery habits on users' lifestyle or health concepts. The most common node, Denial of Change, occurred 12 times, as respondents indicated that they had noticed no change in their life or health since food had been delivered to them. Another common contentious node, No Health Impact (7 instances), shows that food delivery has not permeated existing diet or tradition. Others still pointed to occasional or infrequent use of food delivery facilities (3 answers), which could mean that a limitation is put on any effect, either on lifestyle or health. Combined, these responses indicate that for many respondents, food delivery is simply a convenience with no significant impact, and does not necessarily lead to behavioral or perceptual change where health is concerned.

Table 26: Positive Adaptation or Awareness

Node	Sample Coded Reference (Complete Answer)	Frequency
Increased Awareness	“Became more conscious of health”, “Improved eating routine”	7
Preference for Home Cooking	“Started cooking more”, “Prefer cooking to control diet”	6
Improved Time Use	“Delivery helps manage time”, “More efficient with meals”	4

Source: Survey Data

Results of Table 26 consist of a number of positive changes, increased awareness, health orientation, and time management. Increased awareness is the most frequent change, with seven citations that explain how individuals grew more aware of their health and altered their diets. Home cooking follows with six citations, i.e., many individuals desire to cook more often, perhaps because they want control over food. In addition, improved time management is noted in four instances, which show people are adapting to accomplish more with less time allocated to cooking food, including using meal delivery services to optimize their schedules. All these trends tend to show a shift toward improved eating habits and improved time management for food.

Table 27: Dependency and Negative Impact

Node	Sample Coded Reference (Complete Answer)	Frequency
Dependency on Delivery	“Heavily rely on takeout”, “Can’t stop ordering”	2
Lifestyle Deterioration	“Less healthy”, “Eating habits worsened”	2
Confusion or Indecision	“Not sure”, “Still figuring it out”	2

Source: Survey Data

The data in Table 27 have some dependency on eating habits and side effects. There are two occurrences of dependency on delivery, with cross-references indicating dependence on takeout or cannot stop eating food. Lifestyle degeneration has occurred twice, where the individuals report worsening the diet and enhancing health. Lastly, indecision or confusion appears twice, showing that there are individuals who are confused or still figuring out their eating patterns. By and large, such trends demonstrate that while there are positive changes, there are problems of over-reliance on convenience, so that they form less healthy eating patterns and confusion over meal choices.

Table 28: Summary Coding Matrix

Node	Number of Nodes	Total Frequency
No Significant Change Observed	3	22
Positive Adaptation or Awareness	3	17
Dependency and Negative Impact	3	6

Source: Survey Data

Table 28 is a coding matrix of the themes and their frequencies. The most dominant theme, with no significant change observed, has three nodes with a frequency of 22, indicating no substantial change in habit or behavior for most. Positive adjustment or sense of consciousness comes in at number two with three nodes and a frequency of 17, such that most have improved health and time management. Finally, dependency and negative influence have the lowest overall frequency with three nodes and a frequency of 6, considering that fewer individuals reported being dependent on delivery or worse eating habits. Trends also show that most individuals reported no significant changes or betterment, but fewer reported adverse effects.

4.9 The Integration of Quantitative and Qualitative Data

This study's qualitative and quantitative data synthesis provides a richer overall portrait of Shanghai's young people's eating health impacts of food delivery culture. Though quantitative survey data captured measurable data on use rates, perceived health, nutritional awareness, and the motive of behavior, qualitative interview data provided context and histories to the numbers.

For instance, quantitative findings indicated that over 70% of the participants had noted health grievances such as weight increase and gastrointestinal upset due to the heavy reliance on food delivery websites. This was validated by qualitative interviews where participants explained symptoms such as tiredness, irregular diet, and dependence on processed foods. Similarly, survey findings indicated algorithmic recommendations impacted 68.37% of the users. This was evidenced in interview responses, with some respondents perceiving that they were denied freedom by the structuring of the platform interface and incessant advertising, proving the Social Cognitive Theory model.

The survey also showed a notable gap between practice and knowledge about food—61.23% reported that they considered nutritional value, but 30.62% habitually opted for healthy foods. The respondents explained the gap in awareness versus practice by citing practical reasons such as timing pressures, stress eating, and a dearth of healthy options at delivery locations. These insidious drivers supported the Theory of Planned Behavior, demonstrating that attitudes and intentions may not necessarily translate into action due to internal and external constraints.

Cross-tabulation analyses, on the other hand, further closed the two data streams. For example, quantitative results reported that consumers who had ordered food more than five times a week were more likely to answer in the affirmative that their health had been affected (Table 13). However, they also reported high nutritional concerns (Table 14). Interviewees made this paradox understandable by pointing out the function of built-up awareness over time. Still, they also indicated that awareness in and of itself is not enough without systemic reinforcement, like more direct labeling or healthier defaults.

In brief, the use of both data sets makes the findings more penetrating by cross-verification of trends against sources and allows the research to peer behind shallow trends. It informs us of what behavior exists and why it persists, and it gives a more solid foundation for directed guidance in subsequent chapters.

Summary

This section describes the impact of delivery culture on the food health of Shanghai youth by integrating quantitative and qualitative data. Quantitative surveys revealed that most respondents had health problems such as weight gain, gastrointestinal disorders, etc., due to the frequent use of food delivery services. The data also show that platform recommendation algorithms significantly influence user choice. In addition, while 61.23% of participants said they value nutritional value, only 30.62% regularly choose healthy foods. The interviews explained that this phenomenon of "different knowledge" is closely related to factors such as time pressure, emotional feeding, and the scarcity of health options, which corresponds to the ideas of the theory of planned behaviour. In summary, quantitative data describe trends, while qualitative data provide explanations.

5.Discussion of Findings, Conclusions, and Recommendations

5.1 Introduction

This chapter consolidates research evidence in response to the research questions and literature. Survey and interview findings are reported in the chapter, highlighting behavioral, economic, and digital platform drivers. Conclusions per research question are then given in the chapter, followed by implications and limitations, and strategic recommendations are formulated.

5.2 Discussions

5.2.1 Food Delivery: Food Nutrient Quality

The findings of this study confirm vast segments of the existing literature relating to the poor quality of the nutritional content of food delivery diets. Out of survey information for 196 individuals, more than 65% consumed processed or fried foods regularly, and only 15.31% had high nutritional awareness levels. This is similar to Dai et al.'s (2022) findings, where 89.56% of Chinese online food delivery set meals scored below 50 in nutritional quality. Similarly, Mehta et al. (2022) reported that the meals are rich in oil, salt, and sugar, which were also seen in the data from this study. The results substantiate the mounting caution in the literature about the adverse health effects of frequent eating low-nutrient delivery meals.

These findings affirm the broader narrative of changing food habits of young people in urban spaces and digitally mediated environments in particular. young people's food habits Digital convenience was cited by Buettner et al. (2023) as one reason home cooking frequency declined, and the same is reflected in this study's finding that there is a positive relationship between convenience and unhealthy diet. Also, Fu et al. (2021) discovered that young Shanghai people preferred to intake more animal protein than plant protein, which was also apparent in qualitative interviews in this study, where informants spoke of compromising on satisfaction and taste in the interest of balance.

Theoretical results are aligned with the Theory of Planned Behavior. Although nutrition awareness was confirmed, participants' behavior varied significantly from intention, suggesting failure of perceived control acquiescence. Lack of absolute nutritional information on platforms, as reflected in Li (2023), aggravates this problem. Thus, the study adds to existing findings and empirically validates Shanghai food delivery culture's nutritional pitfalls.

5.2.2 Dietary Habits and Preferences

The research outcomes regarding food preferences echo a general preference for convenience, which supports previous studies. Although 61.23% of respondents indicated that they consider nutrition while ordering, 30.62% always chose the healthier alternative.

This echoes the work of Buettner et al. (2023), who noted that young adults worldwide often sacrifice nutritional quality for speed and convenience. Tahim et al. (2024) also identified a strong association between perceived time scarcity and poor dietary choices, a trend directly observable in this study through quantitative data and open-ended responses.

The interviews highlighted emotional drivers such as stress during exams or work pressure, consistent with Mehta et al. (2022), who discussed emotional eating patterns among urban dwellers. Respondents often cited delivery meals as a stress-relief convenience, with little regard for nutritional implications. Fu et al. (2021) also noted a slow shift toward plant-based protein, though traditional habits still favored animal-based options. This was mirrored in interviewees' preferences for meat-heavy fast food due to perceived satiety and flavor.

Moreover, Table 15 reveals that convenience perception significantly intensifies with usage frequency. While only 36.84% of those who never use food delivery agreed that it is convenient, this figure rose sharply to 85.29% among those ordering more than five times weekly, with 44.12% strongly agreeing. Notably, no respondents in the high-frequency groups disagreed with the convenience statement. This supports the hypothesis that perceived convenience is a primary behavioral driver behind repeated use, often overpowering health considerations. It further explains the intention-behavior gap, where users consciously prioritize speed and ease over nutritional balance.

These behavioral patterns support Social Cognitive Theory (SCT), illustrating how environmental cues, peer behavior, and digital marketing (such as default platform suggestions) influence dietary decisions. While the intention to eat healthier exists, it rarely translates into behavior, particularly without supporting structures like transparent nutrition displays or healthier defaults.

Supporting this, cross-tabulation results (Table 14) show that nutritional awareness exists even among frequent users. Over 64% of those ordering more than five times weekly agreed or strongly agreed that they considered nutrition, with the highest rate of "strongly agree" (26.47%) across all groups. It suggests that frequent diners can become more reflective with time, possibly due to increased exposure to menus and food-for-thought stockpiling. This finding challenges the assumption that a high ordering frequency is evidence of nutrition omission. Instead, it provides scope for platform-led public health interventions to engage this reflective but at-risk group.

5.2.3 Barriers to Healthy Eating Habits

The evidence essentially confirms economic and technological barriers to healthy eating. Just shy of 52% of respondents placed affordability above nutrition, consistent with Tan and Lim (2023), who determined that cost was a central barrier in the food delivery culture of Singapore. The financial burden of healthful food was a pervasive theme in participants' responses, emphasizing the structural disadvantage of young, low-income urban consumers.

Algorithmic influence was also prominent, with 68.37% of the sample indicating that platform suggestions shaped their decisions, corroborating findings by Li (2023) and Chan et al. (2017), who documented algorithmic reinforcement of unhealthy behaviors. The intertwinement of reward systems, discounts, and gamified engagement has enhanced impulsive ordering of calorie-density food, a dynamic confirmed by participants within this research.

In addition, this research found that there is a perceived lack of autonomy as a result of interface design. Sites promote trending meals over healthy food, supporting Buettner et al.'s (2023) argument regarding digital food environments. Environmental barriers to choice ensure complex informed decision-making, supporting the imperative for government regulation and interface redesign.

5.2.4 Long-Term Health Implications

The link between frequent food delivery consumption and adverse health outcomes is repeated throughout the literature, and with this study, that connection is reinforced by quantitative evidence. Nearly 70% of the respondents indicated they had endured health issues such as weight gain or stomach pain. This supports Mehta et al. (2022), who reported metabolic risk associated with long-term intake of high-fat and high-sodium diets. Regression analysis also confirmed a very high correlation ($r = 0.35$, $p < 0.001$) between the frequency of delivery and self-perceived health deterioration.

Additionally, respondents referred to fatigue, unconventional mealtimes, and reliance on processed food—issues in accord with Cai et al. (2021), the broader public health consequences of the digital food economy. Most notably, the findings indicate diet shift and system-level lifestyle disruption fueled by dependency on delivery. Such disruptions include diminished cooking ability, inadequate portion control, and less frequent meals at home.

The findings also concur with WHO (2024) warnings about the health cost of convenience food systems. By projecting self-reported experience onto literature-based health measures, this research presents clear evidence of an emergent public health phenomenon in urban areas. Cross-tabulation statistics (Table 13) also verify the same by indicating the distribution of perceived health changes by delivery frequency. Among the more frequent customers, 47.06% agreed or strongly agreed their health had changed, whereas 15.79% of never ordering delivery felt the same. While an overwhelmingly high percentage of both groups were unsure, the rising agreement rate for heavier use is consistent with the hypothesis of increasing health complications and subjective awareness associated with long-term delivery use. These results also correlate with the link between frequency and perceived health risk.

5.2.5 Encouraging Healthier Options

Participants strongly favored regulation measures, consistent with Campos et al. (2011) and Cecchini & Warin (2016) policy recommendations to adopt traffic-light nutrition labeling and front-of-pack information systems. More than 80% supported compulsory nutrition disclosure, and 72% supported platform-based healthy areas, affirming consumer willingness to reform.

The answers further emphasized the importance of behavior and explicit signals, concurring with Taylor et al. (2019) and Grummon et al. (2023). Participants favored AI assistants' personalized suggestions with accurate nutritional requirements. Rewards provided by gamification technology, such as health badges and cheaper healthy food, were also favored.

The study agrees with the convergence of intervention design guided by evidence and user experience. Buettner et al. (2023) advocated for platforms to be remade as one of the methods of redefining default behavior, and such individuals in this study bore witness to the usefulness of such intervention. This research thus contributes to scholarship by presenting user-driven design principles guided by local evidence.

5.3 Conclusions

5.3.1 To Explore the Nutritional Value of Food in Delivered Meals

This objective examines the nutritional value of food that young adults buy daily in Shanghai. Based on previous discussions, it is argued that:

More than 65% of the participants responded with frequent consumption of fried or processed foods, while 15.31% responded with strong nutritional awareness while ordering. This implies that the food usually ordered contains too much oil, salt, and sugar but insufficient essential nutrients such as fiber, minerals, and vitamins.

While nutritional information is relevant to consumers, it is missing, difficult to interpret, or inconsistent on food ordering platforms. This limits consumers from making enlightened choices, although consumers know.

Although consumers intend to choose healthier versions of food, platform design and default menu options rarely facilitate such a habit. This confirms the hypothesis that digital food environments structurally discourage healthy food choices.

Youngsters make choices subjectively or based on presumed taste value rather than established nutritional facts in most cases, simply due to the lack of clear-cut guidelines on electronic menus. Thus, nutrition becomes secondary.

This is backed up by the Theory of Planned Behavior, which shows intention exists, but perceived control and environmental cues limit behavior change. Many respondents thus act in a reverse way to their health intentions.

The inference is thus that while food delivery locations are everywhere, the nutritional quality of meals is poor, mainly due to structural factors that limit consumers from acting in line with dietary intentions.

5.3.2 To Investigate Young Adults' Food Habits and Preferences

This study aims to investigate the food habits and preferences among young adults in the context of food delivery. Based on the discussions, the following conclusions are drawn:

72.45% of the respondents chose convenience over nutrition when buying food online, though 61.23% said they did consider nutritional value. Yet only 30.62% followed healthier meals over the duration. This difference indicates that convenience always comes first in real life.

Stress, emotional responses, and peer pressure were cited repeatedly as explanations for poor food delivery choices. These are consistent with other research, highlighting the role of situational and psychological determinants in food selection.

Despite supposed knowledge of the field of nutrition, most of the respondents did not use what they knew, supporting the Theory of Planned Behavior (TPB) statement about the behavior-intention gap. Lack of adequate default healthy options and settings discourages healthy food consumption.

Social Cognitive Theory (SCT) is an accurate model, speculating that eating habits sustain food delivery behavior, virtual reinforcement, and choice restriction in the platform user interface.

The implication is that convenience, lifestyle needs, and internet marketing influence eating patterns. Thus, the ability of health awareness to enhance eating behavior is limited.

5.3.3 To Identify Factors Impeding Healthy Eating in Food Delivery Use

This objective seeks to identify the key barriers that prevent young adults from making healthy eating choices on food delivery platforms. Based on the discussions, the following is determined:

Cost is a primary limitation, as more than 50% indicated that they prioritize price over the quality of nutrition. Healthier foods are perceived to be more expensive and out of reach for the students and people experiencing poverty.

Platform algorithms were seen to play a significant role in determining the food that they selected. 68.37% of the respondents said that app promotion and suggestion influenced what they selected, often towards high-calorie foods.

Visual hierarchy on platforms prefers trending or significantly reduced-cost foods, which are rarely suggested from a dietary point of view. Respondents showed that healthy foods were relegated or less desirable.

The takeaway is that economic pressure and algorithmic manipulation synergistically shut down healthier food options. Without structural redesign and regulation, motivation alone on the part of individuals cannot lead to healthier behavior on delivery apps.

5.3.4 To Assess the Health Impact of High-Frequency Use of Food Delivery

This goal seeks to determine the frequency at which the consumption of food delivery impacts the health of young people in Shanghai. Based on the previous discussions, the following are the findings reached:

More than 70% of the students confirmed that they had experienced health changes, such as weight gain, digestive problems, and energy loss. Regular intake of fast foods and processed foods is held responsible for this.

Correlational analysis also showed a statistically significant relationship between the frequency of takeout consumption and self-reported decline in health ($r = 0.35$, $p < 0.001$), again noting that high takeout consumption is associated with poor physical health. Interviews also corroborated the results, with informants pointing out worsened dietary habits, reduced home-cooked meal consumption, and over-dependence on processed food.

Worse long-term diet quality and worse long-term metabolic health are markers of global trends in health and an emerging public health issue in Chinese cities.

The implication is that long-term food delivery sets individuals on unhealthy health trajectories among young adults, requiring individual and policy responses to prevent long-term harm.

5.3.5 Measures to Encourage Healthier Food Delivery Behaviors

This study investigates viable approaches towards promoting healthier food consumption on food delivery platforms. From the discussions, the following conclusion can be drawn:

More than 80% of interviewees favored compulsory nutritional labeling, and 72% suggested the establishment of platform-based healthy food zones. The responses indicate user calls for systemic change, not voluntary or promotional health action.

Individuals were concerned with automatic AI diet recommendations, automatic health score sorting, and visual improvements on health meals (e.g., bigger images, bolded tags). These nudges through design interventions were helpful.

Functionality with gamification elements, such as rewards for healthy choices or weekly “nutrition goals,” was popular among youth users.

Voluntary interventions on the platform were thwarted, and government intervention and industry transformation were more desired.

The implication is that effective promotion of healthy eating in food delivery requires multifaceted efforts with interface restructuring, regulation implementation, and user-oriented education policies.

5.4 Study Implications

5.4.1 Integrating the Theory of Planned Behavior and Social Cognitive Theory

The originality of this study is to enhance knowledge regarding the influence of food delivery culture on Chinese young adults’ food habits and city health in Shanghai. This contributes to public health, online consumer culture, and food policy papers. The study concludes that the prevailing platform-based systems and convenience-based options are not healthy for consumption by young adults. The study recognizes the need to incorporate behavioral theories such as the Theory of Planned Behavior (TPB) and Social Cognitive Theory (SCT) to construct nutrition-focused digital policy interventions.

Environmental reform for health, in fact, the digital one, is a universal problem that transcends borders. The current study suggests that proper algorithmic and structural re-imagining would be needed for platform-based consumption not to continue destabilizing health intentions. And as with implementation science, the value of this research is to bridge the gap between behavior and nutritional knowledge. The research prods policymakers and app developers toward more targeted interventions by revealing where platform design, economic pressure, and behavioral principles converge. An even more robust foundation can be built to guide digital food environments toward longer-term public health objectives.

5.5 Limitations

5.5.1 Sample Representativeness

The sample consisted of only young adults aged 18–35 who lived in Shanghai. While adequate for the population being studied in this study, the results could not be generalized to other age groups or other locations as a necessity. Chinese cities’ specific economic and cultural orientations influence food consumption and delivery behavior.

5.5.2 Data Collection Methods

Self-report information was used for quantitative and qualitative variables. Thus, results are susceptible to recall bias, social desirability bias, and subjective interpretation. Respondents might have underestimated unhealthy habits or overestimated health awareness.

5.5.3 Cross-Sectional Nature

The study employed a cross-sectional design, less effective in assessing long-term health outcomes or behavior change over time. A longitudinal design would better assess causal influences and the changing impact of delivery use.

5.5.4 Limited Platform and Vendor Scope

The study focused on mainstream sites such as Meituan and Ele.me and thus does not necessarily indicate behavior on niche or health-oriented sites. It will thus likely underreport the popularity or availability of healthier delivery options.

5.6 Recommendations

5.6.1 Policy and Regulatory Recommendations

Forced Nutritional Labeling can present a cross-national traffic-light system of fat, sugar, and sodium levels in a visible and standardized format across all delivery platforms. Also, Healthy Meal Incentives can provide subsidies or tax reductions for vendors that offer meals meeting defined nutritional standards, encouraging affordable, health-oriented options. Algorithmic Transparency can mandate independent audits of recommendation algorithms to ensure they are not disproportionately promoting high-calorie or processed foods.

5.6.2 Platform-Level Recommendations

AI-Driven Nutrition Assistants can integrate innovative recommendation tools that consider users' health preferences and goals. Healthy Choice Architecture can be used to redesign the platform UI to prioritize healthier items through placement, size, labeling, and filtering. Moreover, Gamified Engagement can offer reward systems (e.g., badges, discounts, or challenges) that incentivize healthy order behavior.

5.6.3 User-Level Recommendations

Nutrition Education Campaigns can launch digital social media and apps campaigns to teach users how to read labels, understand nutrition, and plan balanced, home-delivered meals. Delivery Literacy Programs can introduce curriculum or workshops at universities and workplaces that promote informed delivery usage. Besides, Community-Based Sharing can encourage social platforms or peer groups to share meal experiences, reviews, and health tips to build collective awareness.

5.6.4 Future Research Directions

Researchers can conduct longitudinal studies to assess causality between delivery usage and health impacts; compare results across multiple cities and income groups to understand regional variations. Moreover, neuro-marketing or biometric tools can better capture subconscious decision processes.

Funding

ACTIVITY	Estimated costs
Transportation	$165
Accommodation	$275
Meals and Daily Expenses	$137.5
Survey Materials and Tools	$68.75
Participant Incentives	$110
Software and Data Management	$82.5
Report Writing and Dissemination	$123.75
Total	$962.5

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

[1] Ajzen, I. (1991). The theory of planned behavior. Organizational behavior and human decision processes, 50(2), 179-211.

[2] Bandura, A. (1986). Social foundations of thought and action. Englewood Cliffs, NJ, 1986(23-28), 2.

[3] Buettner, S. A., Pasch, K. E., & Poulos, N. S. (2023). Factors associated with food delivery app use among young adults. Journal of community health, 48(5), 840-846.

[4] Cai, Y., Zhong, I., & Guan, S. (2021). An exploration of food delivery industry in Shanghai and its impact on workers welfare, environment and public health. Food Systems, Nutrition, and Health Research & Practice.

[5] Campos, S., Doxey, J., & Hammond, D. (2011). Nutrition labels on pre-packaged foods: a systematic review. Public health nutrition, 14(8), 1496-1506.

[6] Cecchini, M., & Warin, L. (2016). Impact of food labelling systems on food choices and eating behaviours: a systematic review and meta-analysis of randomized studies. Obesity reviews, 17(3), 201-210.

[7] Chadwick, L. (2024, August 24). Food delivery app use linked to higher likelihood of obesity and lower-level jobs.

Euronews.
[8] Chan, E. K., Kwortnik, R., & Wansink, B. (2017). McHealthy: how marketing incentives influence healthy food choices. Cornell Hospitality Quarterly, 58(1), 6-22.
[9] Creswell, J. W. (2014). Research design: Qualitative, quantitative, and mixed methods approaches (4th ed.). Sage publications.
[10] Creswell, J. W., & Clark, V. L. P. (2017). Designing and conducting mixed methods research. Sage publications.
[11] Creswell, J. W., & Creswell, J. D. (2017). Research design: Qualitative, quantitative, and mixed methods approaches. Sage publications.
[12] Dai, X., Wu, L., & Hu, W. (2022). Nutritional quality and consumer health perception of online delivery food in the context of China. BMC Public Health, 22(1), 2132.
[13] Darmon, N., & Drewnowski, A. (2008). Does social class predict diet quality? The American journal of clinical nutrition, 87(5), 1107-1117.
[14] DeVellis, R. F., & Thorpe, C. T. (2021). Scale development: Theory and applications. Sage publications.
[15] Dobbyn, T. (2024, October 10). Smart App ‘Nudges’ Users to Make Healthy Food Choices. College of Agricultural and Environmental Sciences.
[16] Etikan, I., & Bala, K. (2017). Sampling and sampling methods. Biometrics & Biostatistics International Journal, 5 (6), 00149.
[17] Fu, H., Martin, W., Huang, C., Kouwenhoven, G. A., & van der Leij, F. R. (2021). Dietary Protein Choices of Young Adults are determined by Different Driving Forces in Shanghai and Amsterdam. Journal of Agriculture and Environmental Sciences, 10(2), 9-15.
[18] Garone, S. (2024, January l8). How cooking at home compares to dining out when it comes to nutrition and costs. Health.
[19] Goyal, M., & Deshwal, P. (2023). Online post-purchase customer experience: a qualitative study using NVivo software. Quality & quantity, 57(4), 3763-3781.
[20] Greene, J. C., Caracelli, V. J., & Graham, W. F. (1989). Toward a conceptual framework for mixed-method evaluation designs. Educational evaluation and policy analysis, 11(3), 255-274.
[21] Grummon, A. H., Musicus, A. A., Moran, A. J., Salvia, M. G., & Rimm, E. B. (2023). Consumer reactions to positive and negative front-of-package food labels. American journal of preventive medicine, 64(1), 86-95.
[22] Gu, C., Brereton, N., Schweitzer, A., Cotter, M., Duan, D., Børsheim, E., ... & Jun, J. C. (2020). Metabolic effects of late dinner in healthy volunteers—a randomized crossover clinical trial. The Journal of Clinical Endocrinology & Metabolism, 105(8), 2789-2802.
[23] Haynes, S. N., Richard, D., & Kubany, E. S. (1995). Content validity in psychological assessment: A functional approach to concepts and methods. Psychological assessment, 7(3), 238.
[24] Heale, R., & Twycross, A. (2015). Validity and reliability in quantitative studies. Evidence-based nursing, 18(3), 66-67.
[25] Ho, J., Poh, F., Zhou, J., & Zipser, D. (2019). China consumer report 2020. Mckinsey and Company.
[26] Joshi, A., Kale, S., Chandel, S., & Pal, D. K. (2015). Likert scale: Explored and explained. British journal of applied science & technology, 7(4), 396.
[27] Li, J., Sun, A., Ma, W., Sun, P., & Zhang, M. (2024). Recommender for Its Purpose: Repeat and Exploration in Food Delivery Recommendations. arXiv preprint arXiv:2402.14440.
[28] Li, R. C. (2023). The metrics and management of food waste associated with online food delivery in China (Doctoral dissertation, University of Otago).
[29] Malik, V. S., Popkin, B. M., Bray, G. A., Després, J. P., & Hu, F. B. (2010). Sugar-sweetened beverages, obesity, type 2 diabetes mellitus, and cardiovascular disease risk. Circulation, 121(11), 1356-1364.
[30] Mckay, E., Kemps, E., Prichard, I., & Tiggemann, M. (2023). Small, regular or large? The effect of size options on online food choices. Food Quality and Preference, 105, 104768.

[31] Mehta, S., Mukhija, G., & Mehta, H. (2022). Determinants of nutrition consciousness of young adults on food delivery apps: a analytical study. BSSS Journal of Management, 13(1), 106-119.

[32] Monteiro, C. A., Moubarac, J. C., Cannon, G., Ng, S. W., & Popkin, B. (2013). Ultra‐processed products are becoming dominant in the global food system. Obesity reviews, 14, 21-28.

[33] Palinkas, L. A., Horwitz, S. M., Green, C. A., Wisdom, J. P., Duan, N., & Hoagwood, K. (2015). Purposeful sampling for qualitative data collection and analysis in mixed method implementation research. Administration and policy in mental health and mental health services research, 42, 533-544.

[34] Pomeranz, J. L., Cash, S. B., Springer, M., Del Giudice, I. M., & Mozaffarian, D. (2022). Opportunities to address the failure of online food retailers to ensure access to required food labelling information in the USA. Public Health Nutrition, 25(5), 1375-1383.

[35] Roorda, B. A., & Cassin, S. E. (2025). A Review of Food-Related Social Media and Its Relationship to Body Image and Disordered Eating. Nutrients, 17(2), 342.

[36] Seid, A., Fufa, D. D., & Bitew, Z. W. (2024). The use of internet-based smartphone apps consistently improved consumers' healthy eating behaviors: a systematic review of randomized controlled trials. Frontiers in Digital Health, 6, 1282570.

[37] Sharib, J. R., Pomeranz, J. L., Mozaffarian, D., & Cash, S. B. (2024). Disclosure of mandatory and voluntary nutrition labelling information across major online food retailers in the USA. Public Health Nutrition, 27(1), e203.

[38] Shu, X., Calvert, J. K., Cai, H., Xiang, Y. B., Li, H., Zheng, W., ... & Hsi, R. S. (2019). Plant and animal protein intake and risk of incident kidney stones: results from the Shanghai Men's and Women's health studies. The Journal of urology, 202(6), 1217-1223.

[39] Singleton, L. (2024, April 22). Taxing unhealthy food helps cut obesity, says global study. Imperial College London.

[40] Steele, E. M., Baraldi, L. G., da Costa Louzada, M. L., Moubarac, J. C., Mozaffarian, D., & Monteiro, C. A. (2016). Ultra-processed foods and added sugars in the US diet: evidence from a nationally representative cross-sectional study. BMJ open, 6(3), e009892.

[41] Tahim, J. C., Verde, S. M. M. L., Maia, C. S. C., & Bezerra, I. N. (2024). Consumption of Food Offered by Delivery Applications (Apps). International Journal of Environmental Research and Public Health, 21(5), 568.

[42] Tan, S., & Lim, R. (2023). Affordability and access in Southeast Asian food delivery ecosystems. Asia Pacific Journal of Public Health, 35(1), 75–82.

[43] Tashakkori, A. (2010). SAGE handbook of mixed methods in social & behavioral research. Sage.

[44] Taylor, M. K., Sullivan, D. K., Ellerbeck, E. F., Gajewski, B. J., & Gibbs, H. D. (2019). Nutrition literacy predicts adherence to healthy/unhealthy diet patterns in adults with a nutrition-related chronic condition. Public health nutrition, 22(12), 2157-2169.

[45] Triyuni, N. N., Leo, G., & Suhartanto, D. (2021, November). Online food delivery service. In 2nd International Seminar of Science and Applied Technology (ISSAT 2021) (pp. 697-702). Atlantis Press.

[46] Tufts Health & Nutrition. (2019, September 17). Cost of Eating Right-Whos Right? - Tufts Health & Nutrition Letter. Tufts Health & Nutrition Letter.

[47] Van Teijlingen, E., & Hundley, V. (2001). The importance of pilot studies. Social research update, (35), 1-4.

[48] Wansink, B., & Chandon, P. (2006). Can "low-fat" nutrition labels lead to obesity?. Journal of marketing research, 43(4), 605-617.

[49] World Health Organization. (2024). Food environments: Policy brief and guidance. WHO.

[50] Yang, Z., Khatibi, E., Nagesh, N., Abbasian, M., Azimi, I., Jain, R., & Rahmani, A. M. (2024). ChatDiet: Empowering personalized nutrition-oriented food recommender chatbots through an LLM-augmented framework. Smart Health, 32, 100465.

[51] Zhang, Y., Fan, Y., Liu, P., Xu, F., & Li, Y. (2024). Cyber Food Swamps: Investigating the Impacts of Online-to-Offline Food Delivery Platforms on Healthy Food Choices. arXiv preprint arXiv:2409.16601.