Doctoral Dissertation

The Multidimensional Impacts of Multi-service Transport Platform (MSTP) on Activity-travel Behavior and Urban Form: A Case of Jakarta, Indonesia

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ABSTRACT

Background and motivations

Information and communication technology (ICT) is the critical enabler of innovation. Recently, there has been a rapid escalation in the number of Internet users worldwide. In 2020, there were 4.54 billion Internet users, the equivalent of 59% of the world's population. This number increased by 7% in January 2019 (Global Digital Reports, 2020). Some benefits may be obtained from ICT, such as better information and access to goods and amenities, increased connection anywhere and anytime, and the convenience of the sharing economy and delivery services. On the other hand, the evolution of ICT has consequences that cannot be ignored, such as the possibility of job losses and bankruptcy in the economic sector, lack of data privacy, reduced personal interactions, and reduced physical activity.

The interaction between information and communication technologies (ICT) and human activity-travel behavior has become an important theme in transportation research in recent years. Researchers have recognized that an increase in the use of ICT may lead to changes in the location, timing, and duration of people's activities, and the widespread use of ICT will likely be associated with new patterns of activity and travel in space-time (Kwan, 2020; Dijst, 2004). Analyses of these patterns could provide part of the empirical basis and/or behavioral foundation for enhancing our understanding of the interaction between ICT, activity-travel behavior and urban form.

Recently, several issues concerning the interaction between transportation and urban form in the era of ICT have arisen. Changes in the concentration of urban activities, transportation systems, and individual mobility are expected. ICT may improve people's access to goods, services, and even jobs through virtual connectivity, which can allow activities to take place almost anytime and anywhere. Several studies have investigated how urban space and ICT covary. Nevertheless, it is possible that ICT only affects activity spaces and schedules (and not the converse). There is growing interest in questions related to the bidirectional relationships between urban form and ICT.

One significant ICT innovation is multiservice transport platforms (MSTP). MSTP are innovative platforms that integrate transportation systems and daily service provision. In Indonesia, some MSTP companies (e.g., GoFood by Gojek, Grab-Food, and Uber Eats) have expanded their services, including their online food delivery (FD) services. They utilize fleet drivers to provide transportation and offer other daily services such as delivering food from merchant partners to the consumer. However, to maintain the quality of the food, they set maximum service areas. The service area determines the number of food merchants that users can access from their location. Maximum distances were set to maintain the quality and freshness of food delivered to the consumer. Thus, the accessibility of local food merchants and the extent of delivery service areas are critical factors in the delivery system and consumer choice.

As one ICT innovation, MSTP also change people's daily activity-travel behavior in the short run and possibly city development in the long run. Because users do not need to allow time for travel when they use online food delivery services, they may order foods from far afield. These changes could increase the spatial mismatch between the customer location (i.e., home or office) and that of restaurants/food merchants, resulting in urban sprawl and loss of vitality in cities. Thus, if people can access the same quality of goods and services without commuting, they may be willing to live in far suburbs where more affordable land can provide good living conditions. For this reason, the presence of MSTP may cause changes that cannot be ignored in travel behavior, activity patterns, and commercial location decisions. Further analysis of the impacts of MSTP is needed to provide a comprehensive understanding of the potential benefits or risks to be considered by policymakers and researchers.

Research questions and aims

This thesis aims to provide a comprehensive understanding of the impacts of MSTP and examine them empirically based on a case study in Jakarta, Indonesia. The specific objective is to assess the impact of MSTP in Indonesia on urban form and activity-travel behavior. In this study, three research questions regarding the impact of MSTPs are included:

(1.1) How to quantify the concentration of facility distribution?
(1.2) How is the association between facility distribution and city-level characteristics?
(2.1) What distribution changes do MSTP bring about on the facility distribution?
(2.2) How do these induced changes in urban form?
(3.1) How to capture the virtual activities on daily activity-travel behavior?
(3.2) How MSTP change the distribution of activities?
(3.3) What factors that influence people to choose online activities?
(4.1) How the presence of MSTP's online food delivery service will affect people's eating behavior?
(4.2) What factors that affects MSTP's service level?
(5.1) How to extend the current dynamic discrete choice model for activity-travel analysis to incorporate the impact of MSTP use on activity-travel pattern?

Methodology

In this study, to analyze the impact of MSTPs on the urban form, we analyze facilities' spatial distribution through agglomeration index analysis and its correlation with the city-level characteristics. We employ the agglomeration analysis across the different scales of the area and different types of facilities. Regarding analyzing the impact of MSTP on activity-travel behavior, both revealed preference (RP) and the probe-person (PP) data are collected to capture the current activity-travel behaviors and preference of using MSTPs. A travel-activity diary survey was conducted in Jakarta within 14 days (from January 28th to February 10th, 2020), along with two additional questionnaires about the individual characteristics and their preference of MSTPs usage, mainly, the online-based food delivery service. To achieve this research aim, we extend the dynamic discrete choice model by adding the component of MSTPs to assess the impact of MSTPs on activity-travel behavior.

Main Findings

In recent years, the presence of MSTP as one of the innovations of ICT in transportation and daily service provision has rapidly expanded and had a significant impact on our daily activity. Daily activities and travel are inseparable since travel results from an individual's desire or need to engage in an activity. While the location to perform activities is spatially distributed over a wide range of areas. Hence, these activities cannot be carried out at the same location. Then, the result is the desire to conduct some trip or travel to another location. With this realization in mind, this thesis had presented the result of an analysis that examined the multi-dimensional impact of MSTP on urban form and activity-travel behavior.

This research aimed to examine the impact of Multi-Service Transport Platform

(MSTP) on the urban form and activity-travel behavior. Based on the analysis of the impact of MSTP on the urban form and activity-travel behavior, it can be concluded that MSTP changes the behavior of individuals toward online activities and change the decision location of food merchants. The results indicate that MSTP brings the new agglomeration forces that induce the new distribution pattern of facilities (i.e., food merchants), where the distribution of facilities itself will affect the MSTP's services level and affect the individual's preferences toward online activities and services as well as their activity-travel behavior (i.e., eating behavior).

In this study, to analyze the impact of MSTP on the urban form, this study develops a new approach in quantifying the distribution of facilities through the agglomeration index analysis. The presence of MSTP brings a new agglomeration force for a certain type of facility (i.e., online food merchants) through the flexibility in the location decision. Since the online food merchants can provide the food through online delivery services and the central area is not a prime location for the merchants since the MSTP services available. In our analysis, we also found that the agglomeration index is highly correlated with the city-transportation characteristics, such as the share of public and private transport mode, the area size of the city, population density, and the average travel time.

To analyze the impact of the MSTP on the activity-travel behavior, several approaches have been utilized, including the improvement of activity-travel diary survey that can incorporate with the MSTP and online activities component, analyzing the changes in activity and travel composition, and we also propose the new framework in activity-travel behavior analysis by improving the current dynamic discrete choice model with the MSTP components.

Adding the online activities and MSTP component on the Future Mobility Sensing (FMS) activity-travel diary survey application can enrich the activity-travel diary survey. We observed that the presence of MSTP influences the decision of people for conduct activity and choosing mode. Under the influence of the MSTP services, for eating and shopping, more than 50% of activity was conducted online. People are preferred to use MSTP's transport service (i.e., online ojek and ride-hailing) rather than public transit for the daily transport mode.

The presence of MSTP also affects the individual's eating behavior through online food delivery services. This research clearly illustrates that the improvement of MSTP's online food delivery service can increase the changes in an individual's eating behavior, which the improvement of the service level is associated with the distribution of online food merchants itself. People will gain more benefits from MSTP in the area with a greater number of online food merchants.

This study also simulates the impact of MSTP on activity-travel behavior by adding the MSTP component in the dynamic discrete choice model for activity-travel behavior analysis. Through the simulation, we found that MSTP changes the activity scheduling and the choice of conducting activities. However, the further application of this framework with the actual data is needed to see how the models are interacting.

While the existing studies do not consider the presence of MSTP, this study attempt to provide a comprehensive understanding of the impact of MSTP on urban form and activity-travel behavior through the agglomeration analysis of facilities and the eating behavior analysis. The results are well explained the impact of MSTP and answering all of the research questions. However, there are some insights that arose in the process that will be addressed as the recommendation for future study.

Significant Contributions

Academic Contributions

The concept of Multi-service Transport Platforms (MSTP), a part of ICT innovation, is expanded in the field of activity-travel behavior research. In particular, this study could successfully:

1) It is the first study in the literature to explore the impact of MSTP on urban form and travel behavior in Indonesia comprehensively.
2) Establish the comprehensive survey framework to capture the individuals' activity-travel behavior simultaneously with the usage of online activities and their preferences towards the online services (MSTP).
3) Propose the new approach in quantifying the distribution of facilities through the agglomeration index analysis and shows the importance of the selection of counterfactuals and distance metrics.
4) Propose the new framework of activity-travel behavior modeling by expanding the dynamic discrete choice model component with the addition of the MSTP component.

Practical Contributions

1) This study brings new insight for the online food merchant's location decision, where the fringe area can be an alternative location as long as they keep agglomerated with other online food merchants to keep a certain number of drivers around their area. Since the number of drivers is associated with the additional waiting time that affecting MSTP's service level.
2) MSTP could be an alternative in the unusual condition like nowadays COVID-19 pandemic, where people can access to many services while staying at the same location (e.g., home). The practitioner may consider improving the quality of MSTP's services, in terms of delivery time and delivery cost may increase the potential demand of the services.

Contributions to Policy Implications

Given the strong interrelationship between urban form and transport, along with the presence of MSTP as the ICT-based innovation in transport, the integration of land-use and transportation planning represents a unique policy opportunity. When MSTP brings the new agglomeration forces for online food merchants by giving some flexibility to decide their location while still keep a certain number of consumers through online food delivery services, the new neighborhood-scale center may develop. The type of service that MSTP provides is the service that relies on the spatial interaction among food merchants as the supply side, among the users as the demand side, and the spatial interaction among the user and the food merchants. By having the flexibility to be located, the presence of MSTP has the potential to change the structure of cities. In the long run, this kind of service may lead to a less structured city—the further regulation and policy regarding the location of an online-based food merchant. When the online food merchants are scattered agglomerated across the city, the practitioner should consider putting some regulation in the location of online food merchants. To avoid the new trip attraction increased in the neighborhood-scale, the practitioner could allocate the new center at the bigger scale (e.g., district-scale), assumes that a bigger area scale can accommodate a bigger activity scale and bigger traffic volume.

Since the provision of strategic infrastructure is one of the most critical public policy instruments informing the long-term shape and characters of a city at any stages in

developments, MSTP as a part of transport infrastructure and services play a key role in determining urban mobility patterns within urban planning, including modal choice and delivery services. Regulatory policy instruments also play a key role in shaping urban transport performance, including the limitation of MSTP's fleet in one area to avoid overcrowding traffic.

Content of Chapters

The dissertation consists of nine chapters. The first chapter provides an introduction, including the research background, research objective and questions, research framework, and significance and contribution of this study. The remainder of the dissertation is organized as follows.

Chapter Two broadly reviews the literature regarding MSTP, which has seldom been examined in existing research. The general explanation of the interaction between activity, urban form, and transportation will be explored at the beginning of this chapter, following by the exploration of the impact of ICT on activity, urban form, and transportation system. This chapter will also explain the general definition and working system of the Multi-Service Transport Platform (MSTP).

Chapter Three descript the research design and methodology of this study. Including the theoretical and conceptual framework, research aims and objectives, general design of this study, survey design, and the context-awareness of stated preference survey and the broad analysis methodology that will be used. The characteristics of two different locations of the case study (i.e., Jakarta, Indonesia, and Japan) will also be explained in this chapter.

Chapter Four analyzes the association between the agglomeration index and the city-level characteristics in 69 cities in Japan. By utilizing the agglomeration index approach, we analyze the concentration of facilities in the city and its association with the city-level characteristics, including the transportation and socio-geographic characteristics.

Chapter Five empirically assesses the impact of MSTP on the urban form in Jakarta through the analysis of the agglomeration index of facilities. Adopting the agglomeration index calculation approach, we explored the spatial distribution of food merchants under the MSTP's influences.

Chapter Six broadly explore the changes in the activity and travel distribution under the presence of MSTP. This chapter explores the data from the improved activity-travel diary survey that includes online activities such as online food delivery, online shopping, online working, online study, online social activity, and online leisure/entertainment, with the case study in Jakarta, Indonesia.

Chapter Seven examines the impact of online-based food delivery services on individual meal choice behavior, i.e., eating out or using a delivery service. This chapter attempts to identify empirical factors affecting people's preferences for online-based food delivery services using adaptive stated preference (SP) survey data.

Chapter Eight aims to extend the existing dynamic discrete choice activity-travel model to incorporate ICT use into activity-travel patterns. We argue that the presence of MSTP increases the utility of activity links by allowing people to access services virtually in local areas without travel, i.e., MSTP drivers bring services to the clients' homes.

Chapter Nine summarizes the findings and draws conclusions concerning the multidimensional impacts of MSTP on urban form and activity-travel behavior from a case study of Jakarta, Indonesia.

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Chapter 1: INTRODUCTION

This chapter provides an introduction, including the research background, research objective and questions, research framework, and significance and contribution of this study.

1.1. RESEARCH BACKGROUND

Information and communication technology (ICT) is the critical enabler of innovation. Recently, there has been a rapid escalation in the number of Internet users worldwide. In 2020, there were 4.54 billion Internet users, the equivalent of 59% of the world's population. This number increased by 7% in January 2019 (Global Digital Reports, 2020). Some benefits may be obtained from ICT, such as better information and access to goods and amenities, increased connection anywhere and anytime, and the convenience of the sharing economy and delivery services. On the other hand, the evolution of ICT has consequences that cannot be ignored, such as the possibility of job losses and bankruptcy in the economic sector, lack of data privacy, reduced personal interactions, and reduced physical activity.

The interaction between information and communication technologies (ICT) and human activity-travel behavior has become an important theme in transportation research in recent years. Researchers have recognized that an increase in the use of ICT may lead to changes in the location, timing, and duration of people's activities, and the widespread use of ICT will likely be associated with new patterns of activity and travel in space-time (Kwan, 2020; Dijst, 2004). Analyses of these patterns could provide part of the empirical basis and/or behavioral foundation for enhancing our understanding of the interaction between ICT, activity-travel behavior, and urban form.

Recently, several issues concerning the interaction between transportation and urban form in the era of ICT have arisen. Changes in the concentration of urban activities, transportation systems, and individual mobility are expected. ICT may improve people's access to goods, services, and even jobs through virtual connectivity, allowing activities to take place almost anytime and anywhere. Several studies have investigated how urban space and ICT covary. Nevertheless, it is possible that ICT only affects activity spaces and schedules (and not the converse). There is growing interest in questions related to the bidirectional relationships between urban form and ICT.

One significant ICT innovation is multiservice transport platforms (MSTP). MSTP is an innovative platform that integrates transportation systems and daily service provision. In Indonesia, some MSTP companies (e.g., GoFood by Gojek, Grab-Food, and Uber Eats) have expanded their services, including their online food delivery (FD) services. They utilize fleet drivers to provide transportation and offer other daily services such as delivering food from merchant partners to the consumer. However, to maintain the quality of the food, they set maximum service areas. The service area determines the number of food merchants that users can access from their location. Maximum distances were set to maintain the quality and freshness of food delivered to the consumer. Thus, the accessibility of local food merchants and the extent of delivery service areas are critical factors in the delivery system and consumer choice.

As one ICT innovation, MSTP also changes people's daily activity-travel behavior in the short run and possibly city development in the long run. Because users do not need to allow time for travel when they use online food delivery services, they may order foods from far afield. These changes could increase the spatial mismatch between the customer location (i.e., home or office) and restaurants/food merchants, resulting in urban sprawl and loss of vitality in cities. Thus, if people can access the same quality of goods and services without commuting, they may be willing to live in far suburbs where more affordable land can provide good living conditions. For this reason, the presence of MSTP may cause changes that cannot be ignored in travel behavior, activity patterns, and commercial location decisions. Further analysis of the impacts of MSTP is needed to provide a comprehensive understanding of the potential benefits or risks to be considered by policymakers and researchers.

1.2. RESEARCH OBJECTIVE AND QUESTIONS

This research aims to provide a comprehensive understanding of the impacts of MSTP and examine them empirically based on a case study in Jakarta, Indonesia. The specific objective is to assess the impact of MSTP in Indonesia on urban form and activity-travel behavior. Follows are the detail of research objectives, research topics, and questions for this study.

Table 1.1. Research objectives, research topics, and research questions

Research Objective	Research Topic	Research Question
To analyze the impact of MSTP on the urban form	(1) The impact of MSTP on facility distribution and city characteristics	(1.1) How to quantify the concentration of facility distribution? (1.2) How is the association between facility distribution and city-level characteristics?
	(2) The impact of MSTP on the facility distribution	(2.1) What distribution changes do MSTP bring about on the facility distribution? (2.2) How do these induced changes in urban form?
To analyze the impact of MSTP on the activity-travel behavior	(3) Changes in Activity-Travel Distribution under MSTP	(3.1) How to capture the virtual activities on daily activity-travel behavior? (3.2) How does MSTP change the distribution of activities? (3.3) What factors influence people to choose online activities?
	(4) Impact of MSTP on the Individual's Eating Behavior	(4.1) How the presence of MSTP's online food delivery service will affect people's eating behavior? (4.2) What factors affect MSTP's service level?
	(5) Impact of MSTP on the Activity-Travel Behavior	(5.1) How to extend the current dynamic discrete choice model for activity-travel analysis to incorporate the impact of MSTP use on the activity-travel patterns?

1.3. RESEARCH FRAMEWORK

Recently, MSTP has become one of the important aspects of an individual's daily activity. On a daily basis, to fulfill their needs and desire, an individual may need to conduct some activities (e.g., shopping, eating, working, and so on). However, as we know, some activities may need to be conducted at a certain place scattered across space (e.g., shopping at the market, working at the office, study at school, and so on), and the facility distribution reflects it. In the activity-travel behavior study, we know that travel is a "derived demand" from individuals to fulfill their needs at a certain location. To access the location of a certain facility, an individual will be traveling or conduct a trip from their original location to their desire destination. Therefore, the association between activity, facility distribution, and transportation system need to be comprehensively understood to develop a better public policy and management.

Recently, there are many innovations invented in the field of transportation to make travel faster, cheaper, and more convenient. The integration of the transportation field and the use of information and communication technologies (ICTs) has become an important research topic in transportation. As one of the ICT-based innovations in transportation, MSTP provides many kinds of online and transportation services to connect the service suppliers and the consumers. It has also become one of the most used transportation modes in the city. The presence of MSTP may significantly impact an individual's behavior and the distribution of facilities.

In this study, we aim to provide a comprehensive study exploring the impact of MSTP on both activity-travel behavior and the urban form. There are some hypotheses that we want to test in this study. Those hypotheses including:

(1) MSTP will change the facility location distribution through the provision of online food delivery services. The food merchants may gain some incentives to be located away from the central area. At the same time, they still maintain the same number of customers as demand through MSTP's online food delivery services.
(2) MSTP will change an individual's activity and travel decisions through MSTP's online delivery services and MSTP's online transportation services.
(3) MSTP will change an individual's eating behavior by providing a better online food delivery service.
(4) MSTP will change an individual's daily activity-travel behavior.

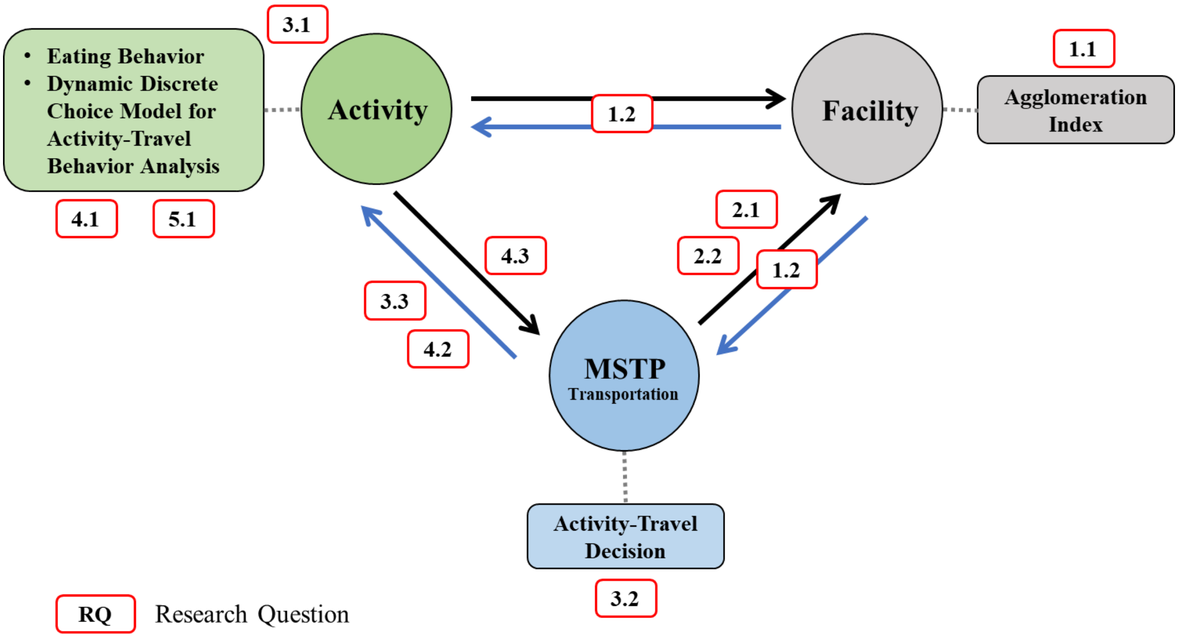


Figure 1.1. Conceptual framework

1.4. OVERVIEW OF FINDINGS

The innovation of information and communication technology has influenced many aspects of our daily lives, such as economic activities, study, medical, and others. In Indonesia, one of the innovations of ICT that very popular and widely used by many people since 2010 is the Multi-Services Transport Platform (MSTP). There are more than 21.7 million users of MSTP in Indonesia, where most of them are concentrated in the metropolitan and big cities such as Jakarta, Bandung, and Surabaya. With a high demand for the MSTP, it indicates that MSTP becomes an essential aspect in people's daily life, and it may affect their activity and travel behavior and change how the cities work.

This study included four parts of analysis: (1) the analysis of facilities distribution through agglomeration index analysis, (2) the descriptive analysis of the online and physical activity and transportation behavior, (3) the analysis of the impact of MSTP on the individual eating behavior, and we also attempt to develop the (4) dynamic discrete choice model for activity-travel behavior that includes the component of MSTP to see whether the MSTP components will affect the decision of our daily activity and travel. Some findings and discussion of the studies are showed to empirically explain the impact of MSTP on the urban form and activity-travel behavior.

First, MSTP changes the distribution of online food merchants by introducing the new agglomeration forces or the mechanism to be agglomerated from attracting more MSTP drivers into their area. Using the agglomeration index approach, we analyze the distribution and concentration of facilities in Jakarta, Indonesia. Due to the presence of MSTP, we found that a high agglomeration of online food merchants happened around the central area and 12-14 km away from the central area (e.g., fringe area) of Jakarta city. This may happen due to the mechanism of MSTP that relies on the fast service and high accessibility level to serve the consumers, so they set a particular distance as their maximum area coverage to keep their food quality for the consumers. By considering the cities' geographical and traffic characteristics, MSTP set their maximum coverage area within 6 kilometers away from the consumer's location. In other words, the online food merchants tend to be agglomerated within the MSTP's area coverage (i.e., 6 km) in order to attract more drivers into their area. This has contributed to exploring the behavior of the facilities under the influence of MSTP.

Second, the descriptive analysis of activity-travel behavior showed that the MSTP services have been more favorable toward eating and shopping activities. This has contributed to the reduction of the physical trip of the users. Based on a two-week activity-travel diary survey, we found that more than 55% of eating and shopping activities have been preferable to conduct by using MSTP. Those percentage indicates a high demand for MSTP services. If our samples represented the actual characteristics of all Jakarta's population, then this might be some significant changes in the daily behavior. The shift in people's behavior of conducting physical trips to online activity can have significant implications for transportation planning and urban development. If many people were shifting to conduct online activities and less conduct the physical trips, fewer people will use the road, and less congestion may happen. Less congestion may lead to some sustainable development of the cities.

Third**,** based on the activity-travel diary survey, we found that using MSTP's transport services is more favorable than public transport in Jakarta. Despite their role as an online delivery service, there are a significant number of MSTP transport service usage in Jakarta. Having a high number of demands does not make MSTP can replace the usage of a private vehicle and reduce traffic congestion. The basic idea of MTSP to optimize the fleets by allowing them to provide many kinds of services was a good initiative. However, as we mentioned above, it is uncertain that MSTP can reduce traffic congestion due to the unknown driver's behavior.

Forth, the delivery time and delivery cost that MSTP proposed is the significant variable that affects people using online food delivery services rather than conducting a physical trip. The findings suggested that utilitarian orientation is an important determinant of users' behavior toward MSTP online food delivery services. People find that using online food delivery services is relatively cheaper in the term of value of time than conducting a round trip of the trip for eating purposes. The improvement of delivery time and delivery cost may increase people's tendency to use MSTP online food delivery services. In the delivery time of MSTP online food delivery services, there are three main components: the time for food preparation by the merchants, the travel time by online ojek, and the additional time to find nearby drivers to take the orders. Where the time for food preparation is given by the condition of the cross-side network effect of demand and supply, the additional time is influenced by the same-side network effect. The number of drivers in the nearby area will affect the additional time. The additional time will decrease in the area with the increase in the density of online food merchants. In general, drivers would standby around the area with higher demand. Having more drivers in the area may reduce the additional time for searching for the driver and reduce the delivery time.

Fifth, the exploration of MSTP impact on individual activity-travel behavior through the simulation on the dynamic discrete choice model showed that the MSTP components (i.e., online transportation services, the availability of online food delivery services, and the number of food merchants as the attraction of each area) show that MSTP may change the timing decision, destination choice, and the activity purpose of individuals in their daily activity-travel pattern. As mentioned above, some studies can address some limitations by using the improved DDCM framework.

1.5. RESEARCH SIGNIFICANCE AND CONTRIBUTION

Theoretical contribution:

This study constructs a research framework for MSTP of both supply and demand, based on the relationship of the travel and spatial context of urban form with activity-travel behavior. In particular, it supplements previous studies of MSTP, which is an ICT innovation that affects the urban form and activity-travel behavior. To date, to the author’s knowledge, this study will be the first comprehensive analysis of the impact of MSTP on activity-travel behavior and urban form, particularly in a developing country. There is no published academic research on this topic, and a decade after the rise of MSTP in Indonesia, their impact on activity-travel behavior and urban form remains unexamined. Chapter Two explores the concept, systems, and mechanisms of MSTP to understand how they work and what components are vital.

Methodological contribution:

This study will explore a new method of using a smartphone-based diary app to capture travel activity and consider context-dependent factors affecting ICT use and activity-travel behavior. By this method, users can voluntarily report their activities in real-time. Several new methods and approaches are explored in this study, including the new approach to capturing online activity data by modifying the activity-travel diary survey explained in Chapter Three. Chapter Four proposes a new approach to calculating the agglomeration index by developing a new counterfactual for agglomeration analysis. Chapter seven expands the current dynamic discrete choice model by adding online activity (i.e., MSTP) components to the models and assessing their impact on activity-travel behavior.

Practical contribution:

This research is an empirical assessment of the impact of MSTP on urban form and travel behavior, particularly in Indonesia. The findings may indicate ways for policy to maximize the presence of MSTP while maintaining a balance of urban economy activities and city structure. In terms of policy relevance, the results of this study will provide a framework to improve the provision of MSTP that incorporates activity-travel behavior and distribution of commercial facilities. In Chapters Four and Five, we empirically applied the agglomeration analysis to examine the distribution of online food merchants across the area and its impact on the urban form. Then, in Chapter Seven, we empirically analyze the impact of MSTP on individuals' eating behavior through their preferences for using MSTP.

1.6. OUTLINE OF THE DISSERTATION

The dissertation consists of nine chapters. This chapter provides an introduction, including the research background, research objective and questions, research framework, and significance and contribution of this study. The remainder of the dissertation is organized as follows.

Chapter Two broadly reviews the literature regarding MSTP, which has seldom been examined in existing research. The general explanation of the interaction between activity, urban form, and transportation will be explored at the beginning of this chapter, following by the exploration of the impact of ICT on activity, urban form, and transportation system. This chapter will also explain the general definition and working system of the Multi-Service Transport Platform (MSTP). Some current trends and analytical challenges are also explained in this chapter.

Chapter Three descript the research design and methodology of this study. Including the theoretical and conceptual framework, research aims and objectives, general design of this study, survey design for activity-travel diary survey, and the context-awareness of stated preference survey and the broad analysis methodology that will be used. The characteristics of two different locations of the case study (i.e., Jakarta, Indonesia, and Japan) will also be explained in this chapter.

Chapter Four analyzes the association between the agglomeration index and the city-level characteristics in 69 cities in Japan. By utilizing the agglomeration index approach, we analyze the concentration of facilities in the city and its association with the city-level characteristics, including the transportation and socio-geographic characteristics. We develop the agglomeration index by considering three types of distance metrics, and we are carefully select the counterfactual facilities in the analysis.

Chapter Five empirically assesses the impact of MSTP on the urban form in Jakarta through the analysis of the agglomeration index of facilities. Adopting the agglomeration index calculation approach, we explored the spatial distribution of food merchants under the MSTP's influences. This chapter explains how the distribution of online food merchants is different from other facilities, and we also showed the importance of spatial boundary setting in agglomeration analysis.

Chapter Six broadly explore the changes in the activity and travel distribution under the presence of MSTP. This chapter explores the data from the improved activity-travel diary survey that includes online activities such as online food delivery, online shopping, online working, online study, online social activity, and online leisure/entertainment, with the case study in Jakarta, Indonesia.

Chapter Seven examines the impact of online-based food delivery services on individual meal choice behavior, i.e., eating out or using a delivery service. This chapter attempts to identify empirical factors affecting people's preferences for online-based food delivery services using adaptive stated preference (SP) survey data.

Chapter Eight aims to extend the existing dynamic discrete choice activity-travel model to incorporate ICT use into activity-travel patterns. We argue that the presence of MSTP increases the utility of activity links by allowing people to access services virtually in local areas without travel, i.e., MSTP drivers bring services to the clients' homes.

Chapter Nine summarizes the findings and draws conclusions concerning the multidimensional impacts of MSTP on urban form and activity-travel behavior from a case study of Jakarta, Indonesia.

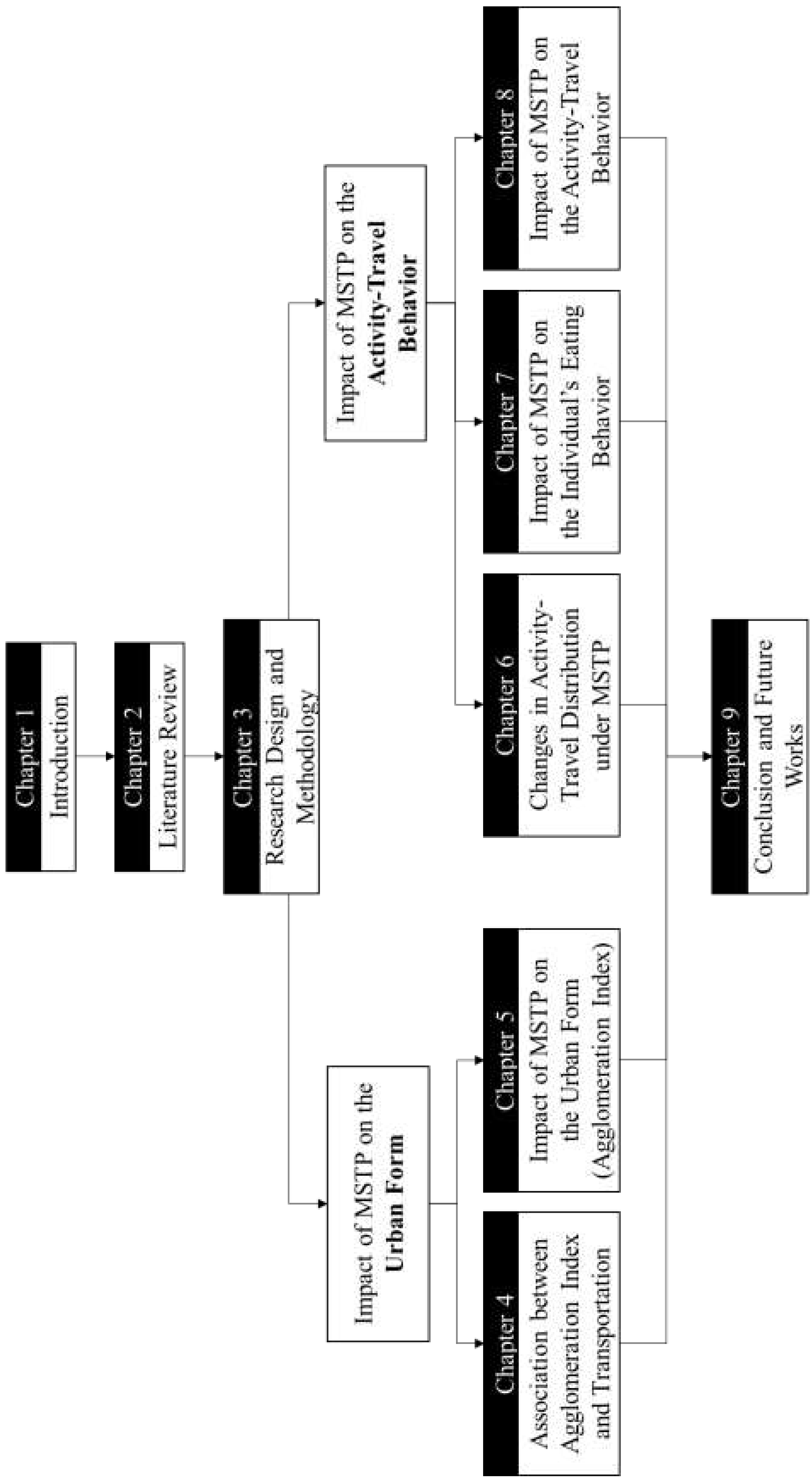


Figure 1.2. Structure of the dissertation

Chapter 2: LITERATURE REVIEW

This chapter broadly reviews the literature regarding MSTP, which has seldom been examined in existing research. The general explanation of the interaction between activity, urban form, and transportation will be explored at the beginning of this chapter, following by the exploration of the impact of ICT on activity, urban form, and transportation system. This chapter will also explain the general definition and working system of the Multi-Service Transport Platform (MSTP). Some current trends and analytical challenges are also explained in this chapter.

2.1. ACTIVITY, URBAN FORM, AND TRANSPORTATION

It is widely known that the relationship between urban form and transport systems is complicated, given that land use and transportation are part of a retroactive feedback system, with one influencing the other (Giuliano, 2004). Transportation has a strong influence on the urban form through its spatial structure at the local, regional and global levels. A historical perspective on the evolution of transport systems underlines the impacts of technological innovations and how transportation improvements were interdependent with economic, social, and spatial changes. Thus, the current transport systems are the outcome of a long evolution marked by periods of rapid changes where new transport technologies were adopted. Transportation systems are composed of a complex set of relationships between the demand, the locations they service, and the networks that support movements. Such conditions are closely related to the development of transportation networks, both in capacity and in spatial extent. The same forces will likely shape future transportation systems as in the past, but it remains to be seen which technologies will prevail and their impacts on the structure. The unique purpose of transportation is to overcome space, which is shaped by various human and physical constraints such as distance, time, administrative divisions, and topography. The specific purpose of transportation is to fulfill a demand for mobility since transportation can only exist if it moves people, freight, and information around. Otherwise, it has no purpose. This is because transportation is dominantly the outcome of derived demand.

Transport represents one of the most important human activities worldwide. It is an indispensable component of the economy and plays a major role in spatial relations between locations. Transport creates valuable links between regions and economic activities, between people and the rest of the world. The development of activities reflects the cumulative relationships between transport infrastructure, economic activities, and the built-environment. The important factors that shaped the spatial structure are included:

- Costs. The spatial distribution of activities is related to distance factors, and the locational decisions are taken to minimize costs of transportation and production.
- Accessibility. All locations have a level of accessibility, but some are more accessible than others because of transportation. Some locations are perceived as more valuable than others.
- Agglomeration. There is a tendency for activities to agglomerate to take advantage of the value of specific locations. The more valuable a location, the more likely agglomeration will take place. The organization of activities is essentially hierarchical, resulting from the relationships between agglomeration and accessibility at the local, regional, and global levels.

One of the most basic transportation relationships involves how much space can be overcome within a given amount of time. The faster the mode, the larger the distance can be overcome within the same amount of time. Transportation, notable improvements in transport systems, changes the relationship between time and space. When this relationship involves easier, faster, and cheaper access between places, this result is defined as space/ time convergence because the amount of space that can be overcome for a similar amount of time increases significantly. It is, however, a spatially and socially uneven process since it will impact the accessibility of locations differently. The outcome has been significant differences in space/time relationships, mainly between developed and developing countries, reflecting differences in the efficiency of transport systems. Five major factors are related to the relationship between transportation and space, including speed, economic scale, expansion of transport infrastructures, and the evolution of information technologies.

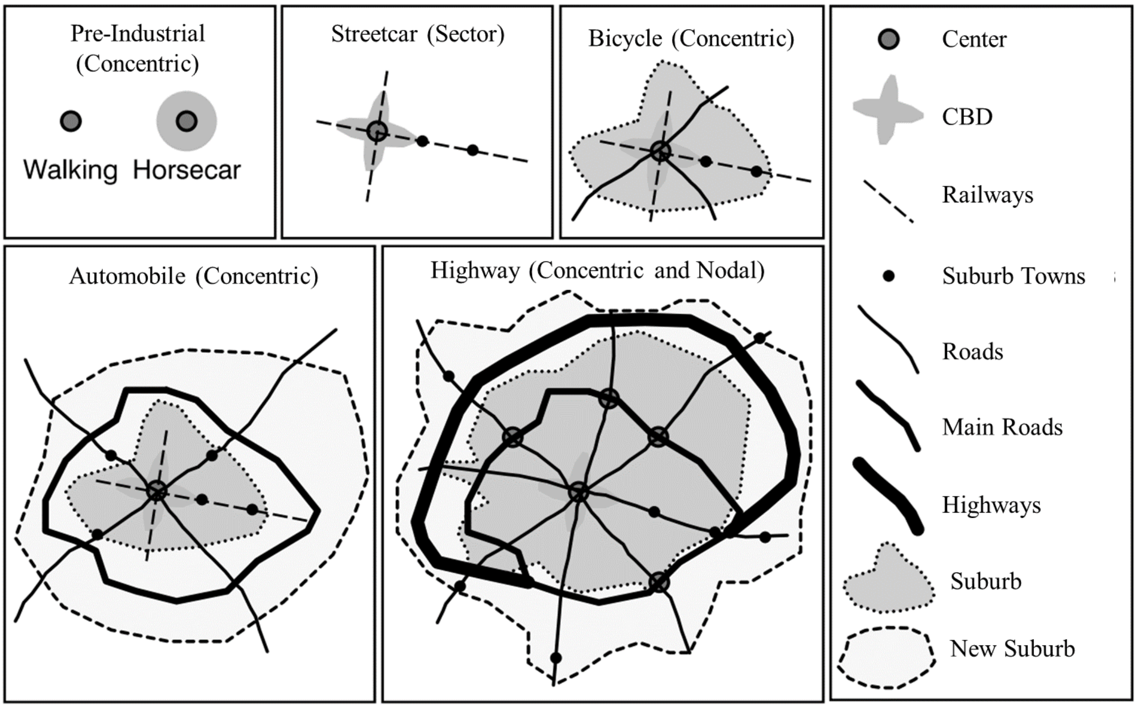


Figure 2.1. The land use formation of urban landscapes and transportation
Source: Adapted from Taaffe E. J. et al. (1996)

In the past decades, the innovation of the transportation system has been impacting the urban form, as we know that the urban form is an outcome of spatial differentiation and spatial interaction. The spatial differentiation itself is the outcome of a cumulative process as several elements of the spatial structure, such as urban areas, are the outcome of a long accumulation process, which tends to change slowly. The spatial interactions where attributes such as origins, destinations, and flows are also illustrative of inequalities. Transportation not only favors economic development but also has an impact on spatial organization.

On the other side, the urban form is one of the more essential outputs of those location decisions and transportation developments. In a free-market economy, the urban form is the outcome of location choices made by thousands of households, private firms, and public agencies. An urban agglomeration is one of the important outputs of those location decisions, shaping urban form together with transportation developments. The literature identifies three sources of agglomeration of commercial facilities: *matching*, *sharing,* and *trip chaining*

(Takahashi, 2013; Koster et al., 2019). Takahashi (2013) considers that consumers seek a better *matching* between their preferred varieties and the varieties sold in each commercial area and confirms that agglomeration would occur when consumers exhibit taste heterogeneity while the available information is imperfect. Alternatively, agglomeration may also occur when there are positive externalities through *sharing*. Shopping malls are typical, i.e., shops in a mall share fixed costs such as facility maintenance and customer acquisition costs (Pashigian and Gould, 1998).

In the past decades, many researchers in urban and regional science have tried to show that the agglomeration economies may be one source of the uneven distribution of economic activities and economic growth across cities and regions (see Strange, 2004). A number of theoretical studies indicate that transportation cost plays a significant role in determining agglomeration and dispersion forces (Krugman, 1991). For example, Tabuchi (1998) shows that agglomeration would reduce transport costs, and then re-dispersion would come in when transportation costs monotonically decrease. The effect of agglomeration economies on localized firms' behavior can be expected to differ, however, across sectors, space, and time (McCann and Folta, 2008; (Groot et al., 2009). At the same time, little is known about the importance of agglomeration economies for individual firms' location decisions (Acs and Armington 2004; Martin et al. 2008).

Although a number of empirical studies have been conducted (see Combes and Gobillon, 2015, for example), providing empirical evidence on these theoretical works is generally difficult, essentially because of the difficulties in establishing appropriate counterfactuals. Another major problem is that, since theoretical models simplify the real world, it is often difficult to establish an appropriate mixture of deductive and inductive techniques to derive empirical evidence. For example, most theoretical models do not explicitly deal with multiple transport modes, making it challenging to execute the appropriate empirical analysis.

Given that, scholars have argued that the death of distance through digital evolution is still premature. However, many innovations in the field of ICT have significantly impacted our daily lives. As one ICT innovation, MSTP also brings changes to the transportation system. How urban space and ICT co-vary remains as elusive as ever. While it is still possible that ICT only affects activity spaces and schedules (and not the converse), there is growing interest in questions related to the bi-directional relationships between urban form and ICT. Having virtual connectivity can allow activities to take place almost anytime and anywhere. Thus, if people are allowed to telecommute, they might be willing to live far out in the suburbs, where larger land plots at affordable prices can provide high-quality living conditions. Even if travel to the workplace needs to be done, ICTs become more and more immersed in various transportation modes (especially for public transport and ridesharing services today and presumptively for autonomous vehicles in the future). When ICT (MSTP) presence leads to unignorable changes in people's travel behavior and activity patterns, it may also affect the facilities' location decisions. It is possible that, in this case, ICT would contribute to the concentration of urban space. Since the users do not need to allocate time for travel when they use online-based food delivery services, there is a possibility that people tend to order foods provided in a distant place. These changes could increase the spatial mismatch between the location people stay (i.e., home and office) and restaurants/food merchants' locations, resulting in urban sprawl and the city's loss of vitality.

In this study, an activity-travel pattern is defined as a sequence of performed activities and trips that start and end at home located in a whole day. Each day's uniqueness of individuals' activity-travel pattern is not only based on a single dimension, but also the interaction between multiple dimensions, such as the combination of travel mode, travel purpose, activity location, and arrival time (Koppelman and Pas, 1985; Schlich and Axhausen, 2003; Susilo and Axhausen, 2014). Individuals with different daily constraints in economic, social-cultural, temporal, and geographical perspectives would have different day-to-day activities configuration and scheduling. They had different time-space constraints that can also associate with how an individual has more varied/more predictable activity-travel behaviors on a different day.

Theories on the relationship between urban form and travel patterns are mainly based on the concept that travel results from an individual's desire or need to engage in an activity. The location to perform activities is spatially distributed over a wide range of areas. Hence, these activities cannot be carried out at the same location. Then, the result is the desire to conduct some trip or travel. Theoretical reflections on the potential effects of urban form typically concern the spatial distribution of essential activity locations such as residences, jobs, and shops. Shortening distance between these types of locations is often represented as a means to decrease mobility growth. The nearest facilities and service from the home may be the best alternative as destinations for activity participation for some individuals.

2.2. ICT ON ACTIVITY, URBAN FORM, AND TRANSPORTATION

Back in the past, the ability of an individual to access people, goods, and information are restricted by several constraints such as capability constraints, coupling constraints, and authority constraints. The capability constraints are related to the limited ability to perform certain tasks within a given transportation technology and the fact that we can be in only one place at a time. Coupling constraints that related to the need to undertake certain activities at certain places with other people. Then, the authority constraints related to the social, political, and legal restrictions on access. Other constraints that widely discussed in the late 1960s and 1970s is the time-space constraints.

The time-space constraint concept that experts in human geography have discussed since. It emphasizes that time and space delimit an individual's opportunities to participate in activities and travel, imposing restrictions on people's access and mobility (Hägerstrand, 1970; Burns, 1979; Schwanen, 2008). A number of activity-based models (e.g., Kitamura and Fujii, 1998; Pendyala et al., 2002; Liao et al., 2013) have been developed based on this time-space concept, together with the assumption that travel is a derived demand of activity engagement at destination (i.e., people are traveling for extrinsic motivations rather than intrinsic motivations).

With the presence of ICT and its innovation in our daily life, many aspects have been influenced by it can reduce the constraints that we faced. Some advantages and disadvantages of using ICT in our daily life have been discussed by researchers in many research filed, including the transportation and urban planning field. One of the advantages of ICT in the transportation and urban planning field is that ICT can improve people's accessibility to their needs and preferences through virtual spaces. People can gain more information about their needs and even get their needs without traveling by using online shopping or online delivery services. On the other hand, in the current situation, when the source of information is still limited, not all real-world conditions can be represented in the virtual space. For example, for those who did not have access to the internet (e.g., conventional shops at the traditional market), their shops' information will not be accessed by other people unless they or other people share their shop's information internet or people make a physical trip to the market and found the shops. In this sub-chapter, we explore the discussion related to the presence of ICT in many aspects of our daily life, including ICT on activity-travel behavior, ICT on Urban Form, and ICT on transportation.

The impacts of information and communication technologies (ICTs) infuse the society, spanning from the reorganization of cities and large businesses to modifications in an individual's daily activities. ICTs contribute to reshaping the way we work, live, and interact with each other, the way we participate in social and leisure activities, and the way we travel. Definitively identifying the impacts of ICT in each of these areas may be impossible because of the many overlapping relationships between (1) the development and adoption of ICT and (2) the headlong rate of development of modern technologies, which continuously modifies the available applications and services.

2.2.1. ICT on Activity-Travel Behavior

In this 21st century, several issues about the interaction between transportation and urban form in the era of information technologies have been brought forward. In the era of information and communication technology (ICT), changes in urban activities concentration, the transportation system, and individual mobility are expected. For example, based on Kakujo et al. (2019), the introduction of fully autonomous vehicles (AVs) may allow users to do a multitasking behavior while traveling, and it is generating a positive utility. The AVs may potentially lead to more extended travel. In the long run, AVs may also induce residential relocation since the users get more benefits from traveling, along with conducting some multitasking may reduce the value of time. Shaw and Yu (2009) also claimed that virtual activity engagement via ICT cannot be represented and explained by the classical time-space constraint framework. Also, such virtual activity engagement would reduce travel if travel were a purely derived demand of activity engagement, but this may not be entirely true since people would travel not only for extrinsic but also intrinsic motivations (Mokhtarian et al., 2015). These arguments call for further investigations on observing and modeling interdependencies between ICT use and travel.

The interaction between ICT use and human activity-travel behavior is highly complex. It cannot be simply described in terms of substitution and/or generation. As Mokhtarian (1990, p. 240) suggested, the most important impact of ICT use is that "it permits much more flexibility in whether, when, where, and how to travel, and thus loosening the constraint of having to be at a certain place at a certain time." She made the important point that including considerations of the decision, location, timing, and duration of activities and travel in the analysis will likely be more fruitful than focusing only on one particular aspect of such interaction. We hope the articles in this special issue will help stimulate further research on the complex interaction between ICT and individual behavior, especially the fragmentations and regrouping of daily activities and trips.

Based on the time-space constraint concept, several activity-based models have been developed together to assume that travel is a derived demand of activity engagement at the destination. On the other hand, several researchers have discussed how ICT usage affects travel behavior from various angles, such as how ICT affects the mode choice, route choice, and scheduling (e.g., Lenz, B. & Novis, C., 2007, Aguiléra, A. et al., 2012, Fiore, F. D., et al., 2014, Ben-Elia, E., 2018). However, most studies focus on the overall impact of ICT on activity-travel behavior. At the same time, they do not take into account context-dependent factors affecting ICT use and activity-travel behavior. For example, the use of an online food delivery service for lunch may depend on the time pressure the person is under at that time.

Dynamic discrete choice models have received widespread acceptance in transport research and are used in travel demand modeling and behavioral analysis. In the context of travel behavior analysis, dynamic discrete choice models have been used for modeling route choice behavior (Fosgerau et al., 2013; Oyama and Hato, 2019) and recently used for modeling whole activity-travel patterns in a given period of time (Västberg, O. B., Karlström, A., Jonsson, D., & Sundberg, M., 2019), i.e., a sequence of activity-travel decisions is considered as a path choice in a time-space prism (Chikaraishi et al., 2018). While the model strictly reflects time-space constraints, the current version does not represent virtual activity engagement through MSTP that would virtually nullify time-space constraints. This study attempts to fill in this gap.

Figure 2.2. shows how a person's activity-travel behavior, the utility that they get from the "real" experience, may be different from the utility they get from the "virtual" access; there may be some reduction in the amount of utility. However, their benefits are still higher than the cost they are made for the trips/movements. From the user's perspective, they have more alternatives or options to access the service or the other location's needs by having virtual access. This relates to how virtual access utility maximization can be achieved by staying at one location. This is similar to the concept of route choice in choosing the best route, which is considered to maximize its utility. The utility function used is a utility obtained through the "real" access and a utility obtained through "virtual" access.

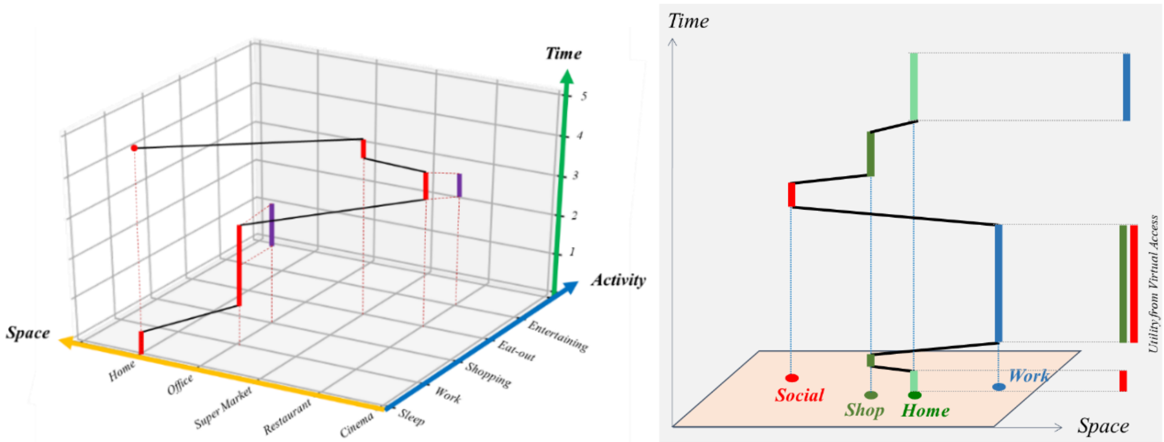


Figure 2.2. The daily travel-activity behavior embedded with ICT usage

By looking at the ICT usage of people within a particular time slot, we can know that someone can improve the utility by having virtual access to their needs through the Multi-service Transport Platform (MSTP). By having that virtual access would relax users' time and space constraints to reach the services or their needs. In this case, ICT will increase the cumulative utility obtained by someone. ICTs as a trip replacement strategy have been seen as a solution to many societal problems, including urban congestion, dependence on non-renewable energy sources, air pollution, and greenhouse gas emission, as well as rural underdevelopment, reduced economic opportunity for the mobility-limited, and the struggle to balance job and family responsibilities (Mokhtarian, Salomon, & Choo, 2005; Salomon, 1998). ICTs certainly do replace “a lot” of travel, but at the same time, they can generate additional travel as well. ICTs can influence an individual’s space-time constraints and the resulting activity participation and travel behavior in many ways, including imposing new constraints and relaxing some old ones. As with e-shopping, the interaction between ICT and travel behavior can include several possibilities, including ICTs can have no relevant effect on travel (neutrality), generate new travel (complementarity, or stimulation), alter travel that would have occurred anyway (modification), or reduce travel (substitution) (Salomon, 1986; Salomon & Mokhtarian, 2008).

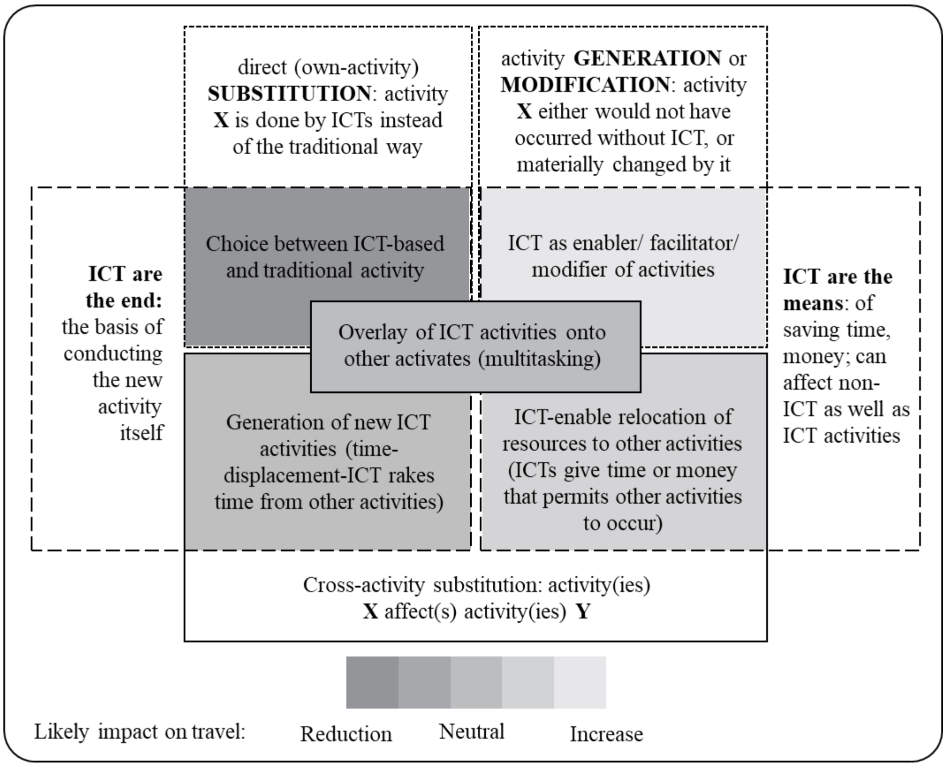


Figure 2.3. Association of ICT activities and other activities
Source: Adaptation from Rodrigue, J. P., Comtois, C., & Slack, B.2016.

Mokhtarian (2009a) discusses a number of reasons that favor complementarity as the dominant impact. She first notes that not all ICT based activities reduce travel because:

(1) Not all activities have an ICT counterpart.
(2) Even when an ICT alternative exists in theory, it may not be practically feasible.
(3) Even when feasible, ICT is not always a desirable substitute.
(4) In particular, travel carries a positive utility in its own right, not just as a means of accessing specific locations.
(5) Not all uses of ICT constitute a replacement for travel. She then presents several reasons why ICT actively increases travel.

In the short run, ICT may save time and/or money for other activities, some of which may involve travel. Specifically, it permits travel to be sold more cheaply (e.g., through last minute airline deals, or airfare and hotel bundles) through Intelligent Transportation Systems (ITS) and other technologies it increases the efficiency (and thus the effective capacity) of the transportation system, making travel less costly and therefore more attractive and personal ICT use can increase the productivity and/or enjoyment of travel time, thereby also increasing the attractiveness and/or decreasing the disutility of travel. Importantly, ICT directly stimulates additional travel through its ability to inspire and facilitate transactions (among other ways). In the long run, ICT is an engine driving the increasing globalization of commerce, facilitating shifts to more decentralized and lower-density land patterns.

On the other hand, ICT may also reduce travel in the following ways:

(1) It may directly substitute for making a trip.
(2) It consumes time (and/or money) that might otherwise be spent traveling.
(3) When travel becomes more costly, difficult, or dangerous, ICT substitution increases.
(4) It can be deployed to make shared means of transportation more attractive (reducing drive-alone trips).

(5) It can reduce unnecessary travel (such as when "letting your fingers do the walking" prevents driving to several stores to look for an item) (see Mokhtarian, 2009; Mokhtarian & Tal, 2013).

2.2.2. ICT on Urban Form

The current form of urban areas results from complex interactions among the numerous needs that influence the location of economic activities and residences. Living in cities allows individuals to save on transportation costs and provides diversity in offering goods and services (e.g., access to theaters, sports centers, restaurants, libraries, stores), facilitating communication and social relations. Similarly, it allows the firm to benefit from agglomeration economies, minimize the cost of transporting people and goods, and ensure proper access to information and connection with commercial partners, consumers, and suppliers (O' Sullivan, 2011). The organization of cities is not always efficient in all dimensions (e.g., as attested by the congestion level in many urban areas). However, nonetheless, cities continue to maintain a strong attractive power because of the benefits they provide.

Technology has gradually modified the distance constraints that limit the mobility of goods and people in two ways. First, it has allowed for an increase in travel speed by developing new modes of transportation and/or the improvement of road and rail infrastructure. This has led to a contraction of the average travel time needed to reach the specific destination (a process known as time-space convergence) (Janelle & Gillespie, 2004) or alternatively to an expansion of the set of destinations that can be reached in a specific unit of time (relaxing time-space constraints). Second, new technologies have helped make travel cheaper, reducing the cost of moving goods and people over long distances and making it practical to shop goods farther (or to travel longer distances, for passenger trips) than in the past. Over the years, these factors have allowed cities to expand beyond previous limits. The relationships between technological development and urban form and urban form have been studied in terms of technology-land substitution (Kim, Claus, Rank, & Xiao, 2009). Technological innovations can facilitate greater efficiency in the use of land, as happened in the process of urbanization in the first half of the 20th century, or they can improve accessibility, reducing the friction of distance and favoring low-density urban expansion, as happened in the second half of the last century.

Despite a consensus that ICTs can further lift space-time constraints, disagreements exist about the extent of that relaxation (Janelle, 2012; Nijkamp & Salomon, 1989). The most extreme position holds that ICTs portend the "end of geography" (O'Brien, 1992) and the "death of distance" (Cairncross, 2001). Physical proximity is a less binding constraint in the decision of where to locate economic activities and/or residence at a time "when dominant forces such as globalization and telecommunication seem to signal that place and the details of the local no longer matter" (Sassen, 2000, p. 144).

Modern ICTs are changing the urban geography of commercial and retail activity. The internet has given birth to new ways of buying and selling (including consumer-to-consumer, business-to-consumer, and business-to-business) that were simply not possible before. Furthermore, technologies can support the recent trend, at least among some segments of society, toward purchasing used items rather than new, toward bartering rather than paying money, and in general toward the reduced level of materialism (a phenomenon referred to as the "sharing economy" or "collaborative consumption"; Belk, 2014)

On the other side, ICT helps relax time and space constraints, which affects the organization of individuals' schedules and consequently the spatial distribution of economic activities and residences. But does it also help overcome physical marginality and reduce accessibility? Traditionally, cities have facilitated agglomeration of activities that help overcome time constraints by minimizing distance constraints: the large concentration of activities in the most central areas increases their cumulative attraction. It allows retailers to increase their sales volumes, and it allows consumers to satisfy more needs while minimizing travel distances.

2.2.3. ICT on Transportation

ICT innovations have profoundly modified individuals' personal decisions and travel behavior. For example, ICTs allow teleworkers to accept jobs far from home without residential relocation or have more freedom to choose a residential location by reducing constraints on commuting trips. Modern ICTs are also modifying users' relationships with the adoption and use of private vehicles. ICT-enabled carsharing, on-demand ride services, and bike-sharing services are a familiar presence in many urban areas: they substitute for the ownership and use of a private vehicle, allow users to enjoy automobility when needed while avoiding the fixed costs of owning a vehicle, and extend the area of coverage of public transportation.

A clear dominant effect of ICT on either reducing or stimulating travel cannot be confirmed in many cases. The specific impacts vary depending on local contexts and other concurrent causes. ICTs have contributed to reshaping work organization through increased opportunities for distributed teamwork and the devolution of important functions to remote locations. They have contributed to reshaping the demand for space in urban areas. While many residents are moving back into livelier and more central parts of American cities, firms require reduced space for front offices in these areas. They are reorganizing their production activities closer to important transportation hubs, in particular airports and freeway corridors. Similar changes affect the organization of retail stores, which are increasingly integrated into mixed forms with their virtual counterparts ("bricks and clicks"). In contrast, the physical organization of traditional stores has often evolved toward the model of entertainment centers, which are less subject to competition with e-shopping.

For a long time, policymakers have hoped ICT would be a valid substitute for physical trips as a way to reduce traffic congestion and increase transportation sustainability in urban areas. We have shown, however, that ICT can increase travel demand through both its direct and indirect effects on individuals' behaviors. For instance, ICT can (1) generate additional business travel via the increased number of ICT-based businesses; (2) reduce transportation costs and allow reinvesting some of the money and time savings in additional travel; and (3), in the longer term, promote economic growth and stimulate new activities that generate additional travel. ICT also provides alternatives to travel, and it increases people's freedom to eventually choose not to travel. It increases the efficiency of transportation so that more travel can be accommodated within the existing infrastructure. ICT has a central role in all these strategies: The way public policies will be implemented in future years will greatly affect its capability to reduce environmental externalities of transportation and ensure safe and reliable transportation options that satisfy travelers' mobility needs. To date, only limited aspects of the relationships between ICT and transportation have been uncovered: research has mainly focused on specific impacts of ICT on urban form and the organization of some activities, and on specific components of individuals' decisions and travel behavior—primarily commuting trips and to a lesser extent business, leisure, and shopping trips.

Many other impacts of ICT remain to be explored, including effects on congestion, fuel consumption, and greenhouse gas emissions. Future technologies have the potential to further induce dramatic changes in lifestyles and travel behavior, for example, through technologies for driverless vehicles that will automate the use of roads or technologies that will make point-to-point air travel feasible and affordable to a mass market. Important shifts are also associated with the type of technologies that will be used, with a larger prevalence of two-way communication solutions: not only will ICT provide services to users (e.g., information about travel time), but it will also be used increasingly for interactions between users and providers of services, and among users, for example, through an increased automatic collection of personal data and the introduction of additional location-aware services.

However, potential threats associated with the adoption of ICT relate to privacy issues, as in the case of the automatic collection of personal data through mobile communication devices, and equity, due to the increased technological gap suffered by non-ICT users. The latter topic, in particular, deserves renewed attention: new technologies are contributing to reshaping the world in unprecedented ways, but this has come at the expense of those individuals who, owing to economic conditions, physical disabilities, or other reasons, do not have access (permanently or even temporarily) to many of these technological solutions. In an increasingly globalized and connected world, policymakers should pay increased attention to how technological innovations affect these populations. Technological development will continue to evolve and will further reshape transportation in the 21st century. In this continuous transition, it will be the responsibility of future generations of transportation planners and policymakers to ensure that nobody is left behind in the modern digital society.

2.3. THE MULTI-SERVICE TRANSPORT PLATFORM (MSTP)

In recent years, one of the significant innovations of ICT is multi-service transport platforms (MSTP). By definition, MSTP is an online-based multi-service platform that relies on drivers providing access to a wide range of services, including ride-hailing transport, food delivery service, courier service, and daily need services (e.g., cleaning service, massage, hair salon, and other services). MSTP is an innovative platform that integrates transportation systems and daily service provision by managing the demand from consumers and the available fleet as the supply provides many services to the consumer. MSTP integrates several methodologies, including assortment optimization, vehicle routing, scheduling, and pricing, to design travel options and daily service provision in real-time. MSTP's system is included many components, including the consumer, the availability of the vehicle, the number and variance of merchants that can provide many services and goods, and the traffic condition.

Figure 2.5. shows the overall system of MSTP and how the interaction among components has happened. First, a consumer requests a ride or chooses the service/goods using a smartphone. MSTP handles the demand and supply by optimizing the source or fleet they have to accommodate consumer requests. They allow consumers to request the service and choose the best options by offering several service options. After the reservation is confirmed, one vehicle in the fleet will be notified of the schedule through their smartphone application. Since each driver is also attached to the GPS through their smartphone, they will continuously upload GPS data that the platform and the consumer can track. It can give the consumer information to estimate their driver's location and when they will arrive. Then, after using the service or getting the goods from the driver, the consumer can give real-time feedback to the driver and the platform regarding their experience directly on their apps. In

this sense, the consumer, MSTP, and the driver's fleet are in a triangular relationship interconnected and provided mutual feedback.

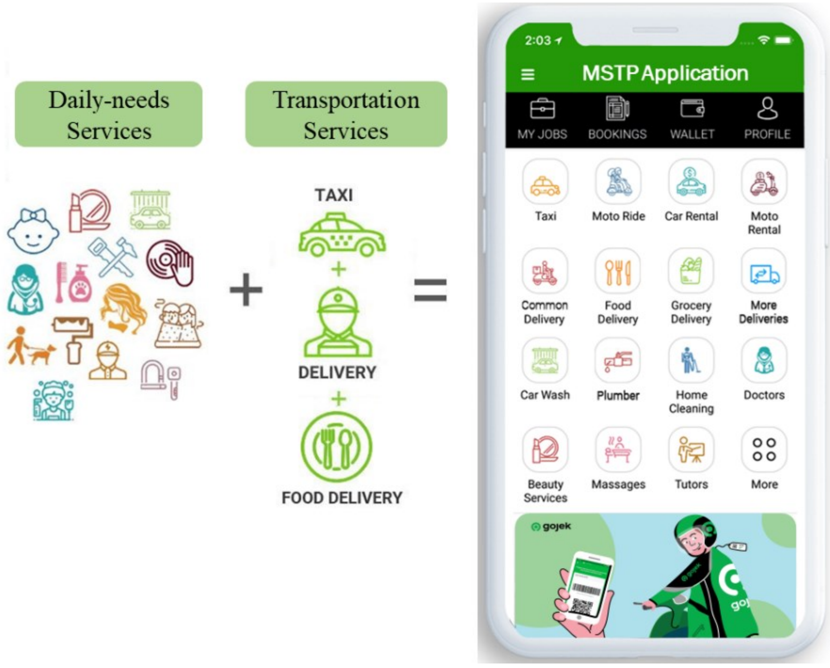


Figure 2.4. MSTP's components and application interface

One area of MSTP that is rapidly expanding is their online food delivery (online food delivery) service. Online food delivery refers to the systematic process whereby the food ordered through an online application or website is prepared and delivered to the consumer. In Indonesia, some of the MSTP company (e.g., GO-FOOD by GOJEK, Grab-Food, and Uber eats) has been expanding their services, including the online food delivery services. They utilize their fleet drivers to provide the transportation service and provide daily service, such as delivering the food from partnered food merchants to the consumer. By utilizing the existence MSTP system, the online food delivery service from MSTP serves a variety of functions, including providing the consumer with a wide variety of food choices, the monitoring of payment, the provision of tracking facilities, real-time feedback to the application platform, sometimes the MSTP also provide some monetary incentives to increase the consumers' tendency to order more food (Figure 2.6).

The platform (MSTP) has a different business model in online-based food service provision compared to other services. For the online-based food delivery service (online food delivery), the MSTP has set some maximum service range within 6 km from the destination location. The maximum boundary size for the services was placed to keep the quality of the food. By setting the maximum range, they can keep the maximum delivery time to keep their quality. In this sense, the accessibility and the range of service areas are the critical factors of online food delivery services. The user's locations are the crucial factors determining the wide range of food that user can get nearby their area. The users may gain more choices if they are located in an area with many food merchants available, such as the central area. On the other side, to provide some online food delivery service in certain areas, the platforms need some sufficient demand (users) and supply (food merchants partner) within the area, which implies that within a specific location, there is a minimum number of merchants that join the platform system that needed to attract the driver to come and get around those areas to provide some delivery.

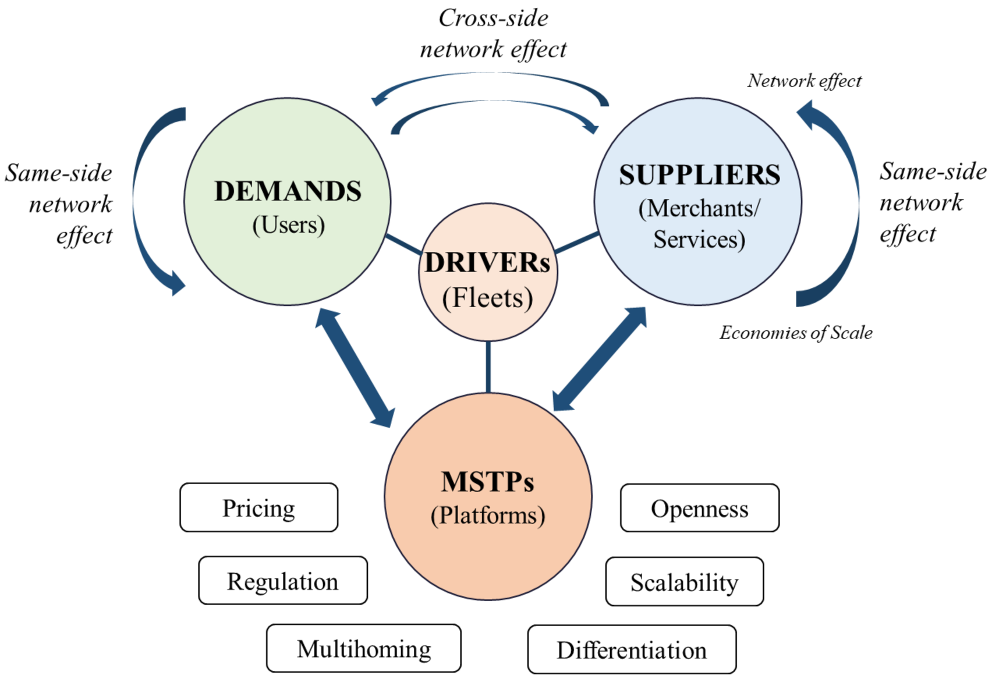


Figure 2.5. Components of MSTP

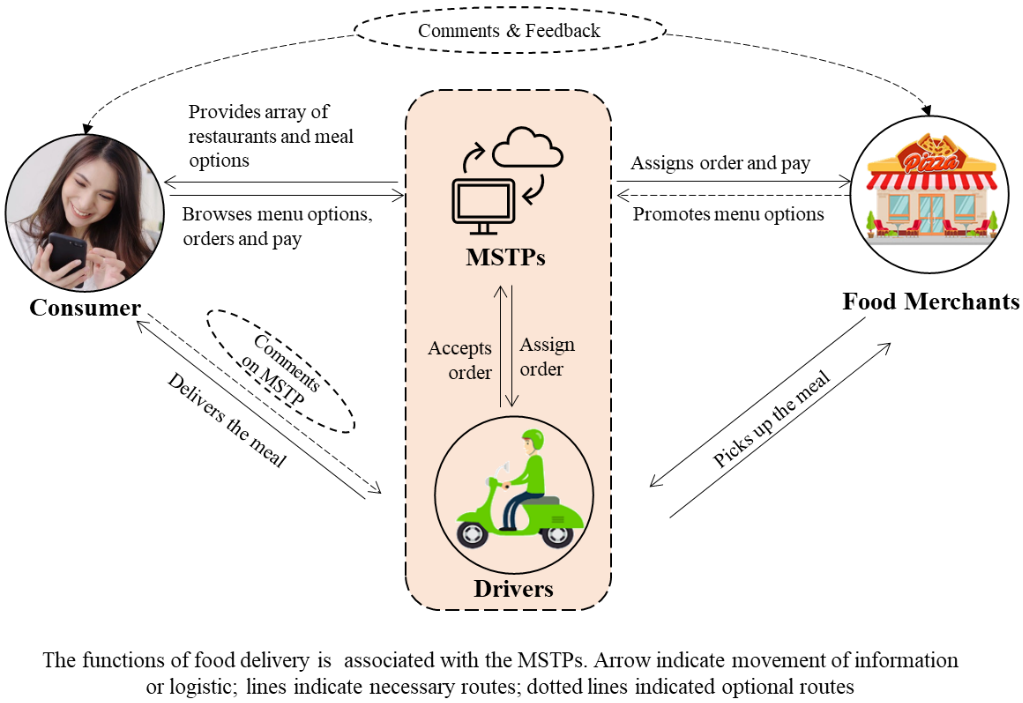


Figure 2.6. The function of online food delivery provided by MSTP

In Indonesia, 58% of MSTP users have used food delivery daily (Global Digital Reports, 2020). Based on Azzuhri, A. A. et al. (2018), some of the reasons why online food delivery is very popular are (1) save time/effort to queue and wait, (2) save time/energy in traveling to buy food, (3) there are many promotions / attractive offers, (4) there are practical payment options, and (5) attractive cash discounts, many choices (food outlets) to choose from, practical to order food whenever they want, make it easier to determine the type of food to be ordered through a favorite or bestseller list, and also it saves money from travel costs to buy food from food merchant.

Due to their popularity, the rise of MSTP has given some benefits to society, such as provided job opportunities for many people across various employment types, including delivery people (drivers), programmers behind the apps/online platforms, or chefs and administrative staff in restaurants. For example, GOJEK in 2018, GOJEK, employs around 2 million people to work as a driver, 600 thousand as food partners, and more than 5,000 people as office workers. Likewise, Grab in Indonesia has more than 2.5 million people works as a driver and 400 thousand food partners, and 6,000 office employees. Meantime, there is no doubt that the MSTP has provided many jobs, especially in the transportation and delivery sector.

MSTP also directly impacts traditional restaurant or food merchants. Recently, many food merchants have had to change the way they operate to stay in business. The conventional food merchants with a physical storefront noticed the decreased in-store dining and the increased food delivery. The decreasing number of people who did in-store dining may have happened because more of their consumers began ordering online food and eating it away from the restaurant, more likely at home or in the workplace. As online food delivery started to gain a foothold in the market, many conventional food merchants need to react quickly to consumer demand change by embracing online food delivery services to suffered from a declined profit.

With MSTP services, many food businesses have realized that they can reduce their dining area by utilizing the online food delivery service, thus saving some costs associated with space provision for in-dining locations. Regarding the study of Li, C., Mirosa, M., & Bremer, P. (2020), many cities in the UK, US, and India has been started to develop some trend called ghost kitchen (also known as cloud kitchens or dark kitchens) due to the increasing online food delivery service. These food merchants are shifting from owning the physical store to the food delivery businesses where they do not have any physical store for their daily operations. It may give some advantages for those food merchants in reducing the operational cost by eliminating the store rent, reducing the number of staff, and virtually and limitlessly increasing the diversity of their menu, concepts, or even their brands only one kitchen. In the context of daily activity, MSTP has changed the interaction between consumers and their food. One example is by modifying the way foods are obtained, processed, and consumed by consumers. Online food delivery services can save time otherwise spent on grocery shopping, cooking, or cleaning up afterward. According to Liu, C. and Chen, J. (2019), by shifting to use online food delivery, at least two hours a day could be "saved," and these customers liked to order online after their commute so that they could rest and enjoy the food when they arrive home.

These days, especially during the 2020 COVID-19 pandemic for the many people quarantined at home, another influence from the online food delivery and other MSTP application distribution and delivery individuals are given a vital lifeline. Online food delivery provided meals and employment for the people who prepared or delivered the food. Most online food delivery platforms adapted their food distribution software during this era, so delivery individuals and customers did not have to come into face-to-face contact. In comparison, many people's meal preferences changed from dining out or venturing out to buying groceries and preparing at home to online ordering frozen food under the lockdown conditions imposed in certain countries due to the pandemic. For instance, to devote more time to their jobs, many employees began or increased their online food delivery use. Globally, the rise of online food delivery services has changed how consumers and food merchants/suppliers interact.

Chapter 3: RESEARCH DESIGN

This chapter describes the research design, including the research framework, research aims and objectives, survey design, study location, target respondents, and a brief introduction to the analysis methods used in this study. In this chapter, we attempt to answers one of our research questions, "How to capture the virtual activities on daily activity-travel behavior?" (RQ 3.1.). The research question will be answered through the survey design that will be explained in this chapter.

3.1. RESEARCH FRAMEWORK

To the best of our knowledge, existing studies into the relationship between urban form and mobility have typically looked at specific trip purposes instead of a comprehensive activity-travel pattern. In the activity-based models, we assume that new (and existing) urban areas constitute an environment for individuals and households to live in. The urban environment forms a stage for people to act their lives. In doing so, individuals and households try to meet their basic needs and personal preferences, while the environment they live in offers them opportunities and constraints to doing so. Since activities cannot all be conducted at the same location, individuals have to travel between activity locations. This means that activity participation leads to activity-travel patterns, which show what kind of activities are executed and where at what times, and which transport modes are used.

The Figure 3.1. shows the conceptual framework underlying this study. It is important to know that individuals and households are assumed to organize their daily activity-travel patterns. Personal and household characteristics primarily influence such patterns. For example, the presence of children in a household will induce particular activities and hence travel. Children need to go to school, maybe be involved in sports, etcetera. Likewise, a double-earner household's activity-travel pattern is likely very different from an unemployed individual's activity-travel pattern. Personal and household characteristics lead to particular needs and preferences, hence inducing particular activities that need to be conducted at particular locations.

While the urban environment and transportation system offers opportunities to execute the activities, different transport modes' availabilities give options people can choose from; likewise, the spatial distribution of workplaces, shops, and other facilities directly determines how far people minimally have to travel to conduct their activities. Similarly, these facilities' attractiveness will influence whether they choose the nearest location or whether they will trade-off distance (or travel time) and attractiveness. The urban environment and transportation system, however, do not only provide opportunities but also constrain behavior. The role of urban form in this complex conceptualization is that particular forms, characterized in terms of variables such as urban shape, density, land use configuration, and network types. The way urban or city is formed may influence the spatial distribution of residences, jobs and facilities, and the relative accessibility of activity locations. As such, it potentially influences the opportunities and constraints offered by the urban environment.

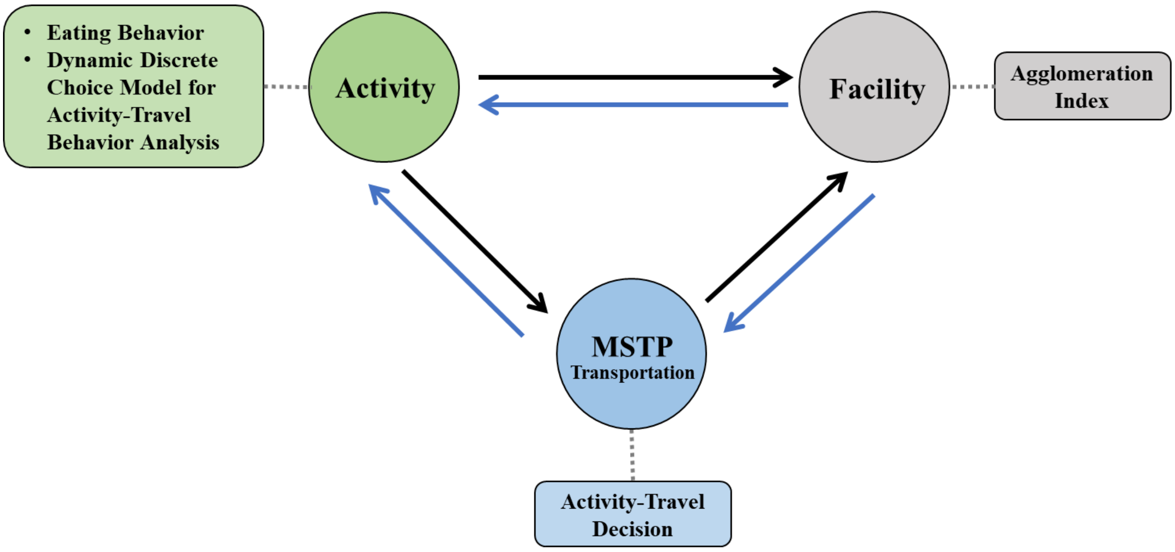


Figure 3.1. The general conceptual framework

In this research, we tried to provide a comprehensive understanding regarding the impact of MSTP through two components, including (1) the impact of MSTP on the facility distribution and (2) the impact of MSTP on activity-travel behavior. There are some hypotheses that we want to test in this study. Those hypotheses including:

(1) MSTP will change the facility location distribution through the provision of online food delivery services. The food merchants may gain some incentives to be located away from the central area. At the same time, they still maintain the same number of customers as demand through MSTP's online food delivery services.
(2) MSTP will change an individual's activity and travel decisions through MSTP's online delivery services and MSTP's online transportation services.
(3) MSTP will change an individual's eating behavior by providing a better online food delivery service.
(4) MSTP will change an individual's daily activity-travel behavior.

3.1.1. Conceptual Framework for Analyzing the Impact of MSTP on The Urban Form

To analyze the impact of MSTP on the urban form, the exploration on facility distribution analysis was done. By developing an agglomeration index, this study tries to quantify the distribution of the facility, and it is changed due to the presence of MSTP. The agglomeration index was developed by the ratio of the average pairwise distance of the targeted facility and counterfactual facility. The specific type of facilities that we want to analyze their distribution is denoted by the term "targeted facility" and we also use the term "counterfactual facility" to represent the type of facilities that we assume will be equally distributed across the area or there will be no agglomeration forces happened in distribution the counterfactual facilities. In this study, there are several types of targeted facilities that we will be analyzed, including the commercial facilities, combination food merchants, online food merchants, and dine-in food merchants, where the detailed explanation of each facility's characteristics later will be explained in chapter 4 and chapter 5.

In the development of the agglomeration index, three major components will be carefully selected. Those components including (1) distance metrics, (2) counterfactual facilities type, and (3) spatial boundary. To select distance metrics, we calculate the average pairwise distance of each facility by using three types of distance metrics, including the Euclidean distance, the network distance, and travel time using a car as the transport mode. In Chapter 4, we develop the agglomeration index that will be used in Chapter 5. By developing an agglomeration index, this study tries to quantify the facility's distribution, and it is changed due to the presence of MSTP. Using the agglomeration index, we can quantify the distribution of facilities, analyzing the distribution pattern, and comparing with other locations or other facility types. Some considerations in developing agglomeration are also discussed in Chapter 4, including selecting counterfactual facilities type and selecting distance metrics. Later in Chapter 5, we show that the selection of spatial boundary as the scale of analysis will significantly impact the agglomeration index result. The spatial boundary included in this study includes the metropolitan scale, the city scale, the district scale, and the neighborhood scale as the smallest area. By developing the agglomeration index for the targeted facilities, we explore the result in each scale through the agglomeration pattern analysis. As the next steps, several statistical analyses will be used to explore the association of the agglomeration index and the city's characteristics, including correlation analysis and decision tree analysis.

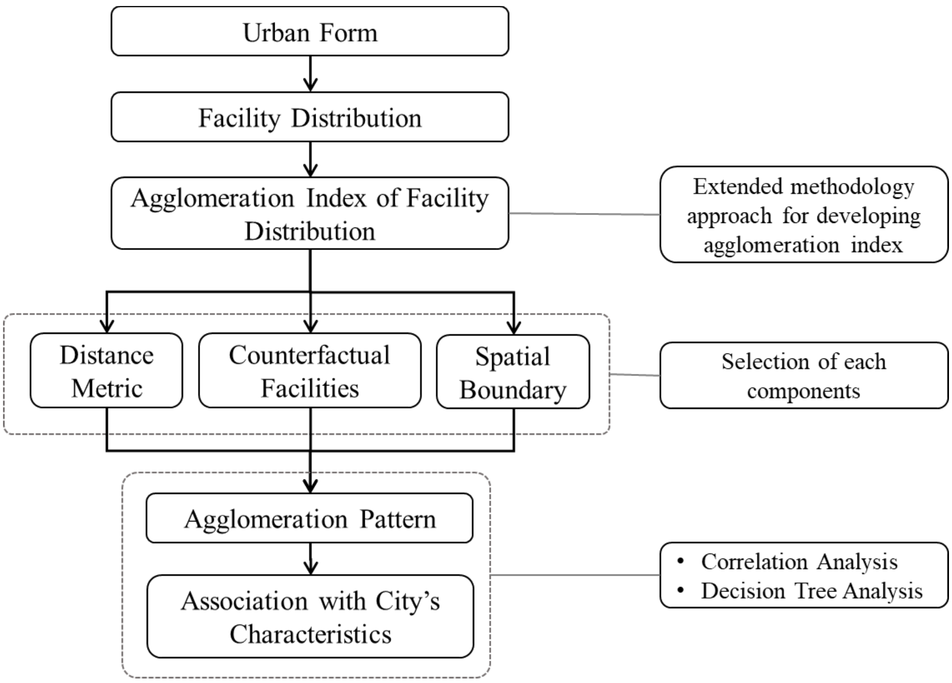


Figure.3.2. Workflow for analyzing the impact of MSTP on the urban form

3.1.2. Conceptual Framework for Analyzing the Impact of MSTP on the Changes in Activity-Travel Behavior

The presence of MSTP as one of the ICT-based innovations in transportation has become one of the important researches focuses that needs to be explored in the future. In this study, we attempt to explore the new survey method to capture the daily online activities together with the activity-travel diary and the context-awareness stated preference survey. Using the future mobility survey (FMS) application called X-ING, we improve the current activity-travel diary survey by adding the ICT (i.e., MSTP) components. On the other side, by utilizing the actual data or revealed preference data that we obtained from the activity-travel diary survey, we construct a context-awareness stated preference survey towards online activities. This study analyzes the distribution of physical and online activity-travel patterns and the individual's eating behavior by using the panel binary mixed logit model. Later in Chapter 6, we will explain the changes in activity-travel distribution under MSTP influences. In Chapter 7, we will explain our findings regarding the changes in individuals' activity and eating behavior by exploring the factors that influence people to conduct an online activity, the value of using online services, and the factors that affect MSTP's service level.

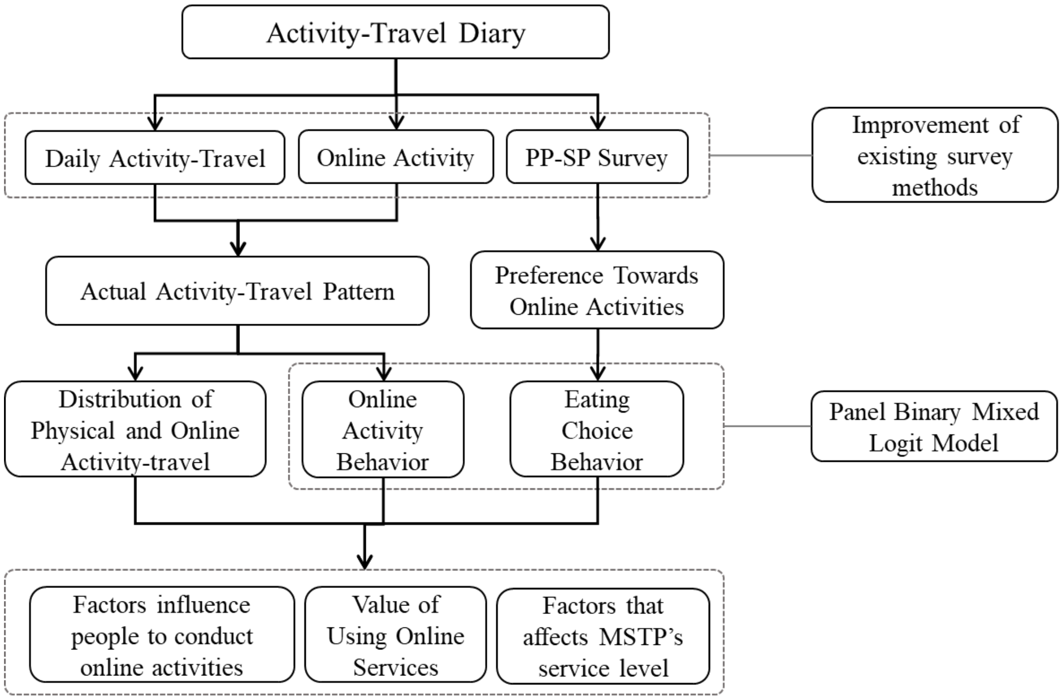


Figure.3.3. Workflow for analyzing the impact of MSTP on the urban form

3.1.3. Conceptual Framework for Analyzing the Impact of MSTP on The Activity-Travel Behavior

This study aims to extend an existing dynamic discrete choice activity-travel model to incorporate the impacts of ICT use on activity-travel patterns. This study focuses on a situation in Indonesia where multi-service transport platforms (MSTP), particularly GOJEK and Grab, have been widely used and have now become a vital part of people's daily lives, leading to unignorable changes in people's travel behavior and activity patterns. With the presence of the MSTP, the way of interacting between the supply-side (merchants) and demand-side (users) might change, essentially because the platform would relax users' time and space constraints to reach the services. We have attempted to develop a survey and modeling framework to comprehensively understand the impacts of MSTP on the urban form and activity-travel behavior. We believe that it is worth sharing the proposed framework together with empirical findings with other travel behavior scholars since the MSTP has been showing both unignorably positive and negative impacts on the society in Indonesia and putting the MSTP in a proper position of entire transport systems is one of the significant challenges we face.

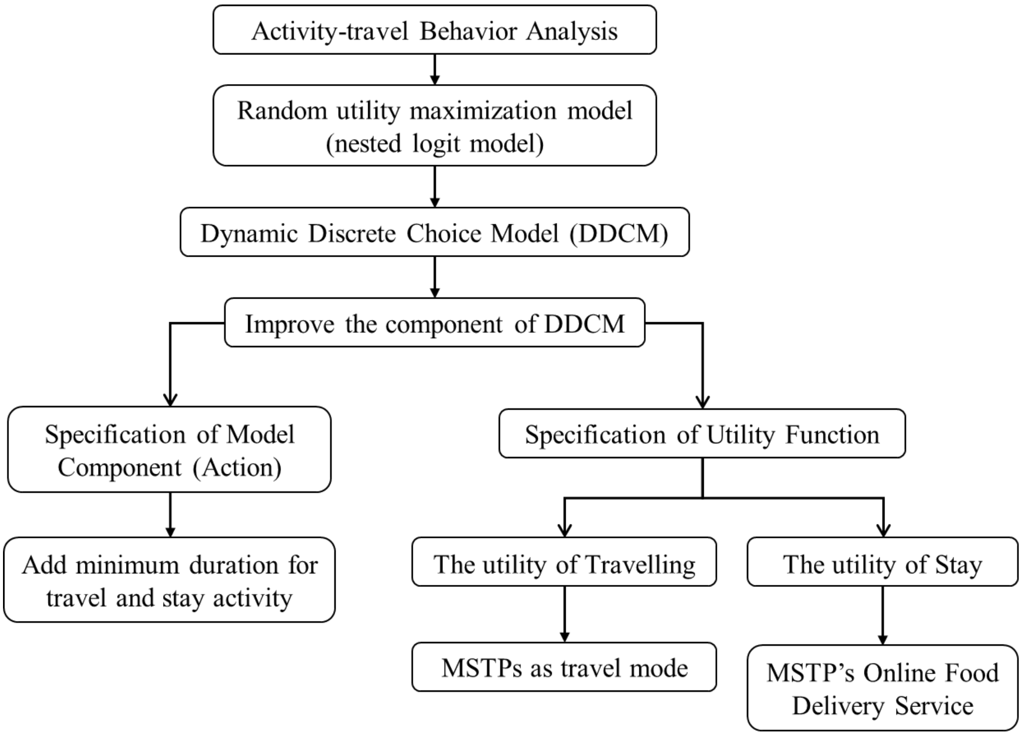


Figure.3.4. Workflow for analyzing the impact of MSTP on the activity-travel behavior

3.2. RESEARCH AIMS AND OBJECTIVES

This thesis aims to provide a comprehensive understanding of the impacts of MSTP and examine them empirically based on a case study in Jakarta, Indonesia. The specific objective is to assess the impact of MSTP in Indonesia on urban form and activity-travel behavior. Follows are the detail of research objectives, research topics, and questions for this study.

Table 3.1. Research objectives, research topics, and research questions

Research Objective	Research Topic	Research Question
To analyze the impact of MSTP on the urban form	(1) The impact of MSTP on facility distribution and city characteristics	(1.1) How to quantify the concentration of facility distribution? (1.2) How is the association between facility distribution and city-level characteristics?
	(2) The impact of MSTP on the facility distribution	(2.1) What distribution changes do MSTP bring about on the facility distribution? (2.2) How do these induced changes in urban form?
To analyze the impact of MSTP on the activity-travel behavior	(3) Changes in Activity-Travel Distribution under MSTP	(3.1) How to capture the virtual activities on daily activity-travel behavior? (3.2) How does MSTP change the distribution of activities? (3.3) What factors influence people to choose online activities?
	(4) Impact of MSTP on the Individual's Eating Behavior	(4.1) How the presence of MSTP's online food delivery service will affect people's eating behavior? (4.2) What factors affect MSTP's service level?
	(5) Impact of MSTP on the Activity-Travel Behavior	(5.1) How to extend the current dynamic discrete choice model for activity-travel analysis to incorporate the impact of MSTP use on the activity-travel patterns?

3.3. SURVEY DESIGN

To empirically examine the impact of MSTP comprehensively, the exploration of data and methodology is necessary. In this study, we attempt to collect the data regarding the impact of MSTP on the activity-travel behavior and facility distribution by conducting an activity-travel diary survey, online activity diary survey, socio-demographic survey, and context-awareness stated preference survey.

3.3.1. Activity-Travel Diary Survey

Recently, innovation in information and communication technologies (ICTs) have rapidly changed the daily activities, work organization, and social habits of everyone across the world. Many studies have been done to identifying the interaction between ICT and travel in many different fields. Some studies (Mokhtarian, 2013; Helling and Mokhtarian, 2001; Salomon and Mokhtarian, 2007) have attempted to identify the substitution and complementary effect of ICT on travel and found that ICT has a potential to substitute travel. Based on Hanson, S. & Giuliano, G. (2004), the effect of ICT on transportation can be divided into three categories, i.e., long-term, medium-term, and short-term. In the long-term impact, we discuss how ICT may affect the location, e.g., where to live, in the medium-term decision, e.g., buying a car. ICT revolutionizes many aspects of travel behavior in the short-term impact, such as activity participation and other trip-making aspects. ICTs have forever changed our society in ways that were barely imaginable only a few years ago. However, quantifying the impacts of these changes on urban transportation and activity-travel behavior is not easy. The challenges of identifying the impact of ICT rely on data availability. Recently, the smartphone-based travel activity survey has become one of the solutions to this challenge.

Smartphone-based travel activity surveys are gaining popularity as they provide solutions to the various limitations of traditional face-to-face and/or paper-based surveys. Unlike traditional paper-based questionnaires, smartphone-based surveys can easily integrate visual effects and provide more accurate descriptions of attributes for the respondents. In addition, most smartphones nowadays are equipped with multiple sensors, including GPS, Wi-Fi, GSM, and accelerometer, to provide a better data resolution and additional information on the user's activity and travel behavior. Also, the smartphone has become a vital component of a user's daily life which almost always will be carried and charged by the user. Moreover, using smartphone-based survey tools may reduce the cost of conducting the survey because the survey's device itself belongs to the users, making smartphones ideal "life-loggers" (Zhao et al., 2015).

One of the survey platforms used in existing studies is called Future Mobility Sensing (FMS), developed by MIT and commercialized by Mobile Market Monitor (MMM) and was first applied in Singapore, where both revealed preferences of travel and activity patterns of individuals were observed. The same application has been modified and used in different countries. Nahmias-Biran et al. (2018) used FMS in Israel and collected information over two days. Meanwhile, Zegras et al. (2018) used the same application to collect data from Tanzania and presented the challenges of collecting data from a developing country as most application applications had been in the developed world. Similarly, Qudratullah and Maruyama (2019) presented the challenges to conducting a smartphone-based travel survey in the cities of Afghanistan. However, they did not utilize the FMS application. Other applications were also developed to collect either travel or travel and activity participation information with pilot studies from different countries, mainly from the global north. Table

3.2. presents a summary of the different studies which have used smartphone-based applications for surveys.

The table lists out the primary focus of these surveys, the method, the country of application, the number of days participants were surveyed, and whether information on online virtual activities or MSTP was captured in those surveys or not. Most studies were observed to capture revealed preference (RP) data over multiple days (see Table 1). RP data are generated by a choice process in the real world (Ben-Akiva et al., 1994), and it is also known to have a high reliability and face validity. However, RP data are relatively inflexible and often inappropriate if we wish to forecast a real-world situation in the future. Stated preference (SP) choice data can be used to model the hypothetical world, which can be the input of the practitioner to make some policy for the future. The SP survey's main limitation is that they only record choices made in hypothetical scenarios (Fifer et al., 2014), resulting in different biases such as inattentiveness, attribute non-attendance, and inconsistency with actual behavior (revealed preferences). For example, Murphy et al. (2005) show that respondents' willingness to pay tends to be higher in SP surveys than in RP.

To address these biases, some researchers suggest a "pivoting" method, where the levels of attributes in the SP survey could be created based on the chosen RP alternatives, and an "SP-off-RP" method, where the choice experiment is conducted simply by hypothetically changing RP attributes while maintaining the RP context (Train and Wilson, 2008). Smartphone-based travel activity surveys have developed 'context-aware' SP surveys, which suggest attribute levels based on the RP information observed from the survey application. Cox (2015) and Danaf et al. (2019) used FMS to develop SP attributes and mode choice levels in Singapore and Boston, respectively. In the process, they also collected attribute-level information on certain MSTP, such as ride-sharing service applications.

The literature review highlights specific pertinent gaps in the literature that the survey methodology developed in this study will address. First, only a few studies have tried to develop context-aware smartphone-based SP surveys. Studies that have done that too have mainly focused on traditional mode choice. Many other aspects of activity participation, such as the decision to "eat out" or "order online," have not received much attention. Second, these smartphone-based survey applications rarely focus on capturing information on online activities performed during travel or during other activities. Capturing this information is important in order to fully understand the impacts of MSTP applications such as Uber and Go-Jek. Finally, only a few studies have implemented the use of smartphone-based applications in the countries of the global South. The developing economies pose unique challenges with respect to the acceptance of such methods and comprehensively understand the impact of MSTP on travel and activity participation behavior. There have been instances of extensive long-term activity-travel data collection in developing economies (such as by Dharmowijoyo et al., 2015) in Indonesia). However, the focus on identifying the impacts of ICT and the use of smartphone-based survey frameworks has been rare. As a part of this study, MMM's FMS was modified to incorporate features that addressed the literature gaps and were implemented in Jakarta, Indonesia. The survey methodology and framework are explained in the next section.

Table 3.2. Smartphone-based travel activity surveys: A review

Sl no	Study	Focus	Method	Online Activities	MSTP	Days	Country
1.	Cottrill et al. (2013)	A; T	RP	No	No	14	Singapore
2.	Safi et al. (2015)	T	RP	No	No	3	New Zealand
3.	Cox (2015)[+]	A; T	RP-SP	No	Yes	Multiple	Singapore
4.	Berger and Platzer (2015)	T	RP	No	No	3	Austria

Sl no	Study	Focus	Method	Online Activities	MSTP	Days	Country
5.	Maruyama et al., (2015)	T	RP	No	No	1	Japan
6.	Xiao et al. (2016)	T	RP	No	No	7-12	China
7.	Allström et al. (2017)	T	RP	No	No	7	Sweden
8.	Zegras et al. (2018)+	A; T	RP	No	No	24	Tanzania
9.	Nahmias-Biran et al. (2018) +	A; T	RP	No	No	2	Israel
10.	Thomas et al. (2019)	T	RP	No	No	28	Netherlands
11.	Danaf et al. (2019) +	A; T	RP-SP	No	Yes	Multiple	USA
12.	Qudratullah and Maruyama (2019)	T	RP	No	No	14	Afghanistan
##	**Our survey (this study)**	**A-T**	**RP-SP**	**Yes**	**Yes**	**14**	**Indonesia**

Notes: Primary focus: on Activity (A) or Travel (T) or both A; T; Survey method: Revealed preference (RP) or pivoted RP- stated preference (SP) (RP-SP); Online activities refer to capturing information on online or virtual activities conducted during the trip or primary activity; MSTP refers to capturing information on multi-service transport platforms such as Uber, etc. + refers that these surveys used the basic Future Mobility Survey (FMS) architecture developed by MMM, same as Cottrill et al. (2013).

A number of researchers have discussed how the usage of ICT affects travel behavior from various angles, such as how ICT affects the mode choice, route choice, and scheduling (e.g., Lenz, B. & Novis, C., 2007; Aguiléra, A. et al., 2012, Fiore, F. D., et al., 2014, Ben-Elia, E., 2018). However, most studies focus on the overall impact of ICT on activity-travel behavior. At the same time, they do not take into account context-dependent factors affecting ICT use and activity-travel behavior. For example, an online food delivery service for lunch may depend on the individuals' time and space constraints. This calls for an improved travel survey scheme, while there has been relatively little attempt to explore new data collection schemes unique to the problem. This activity-travel diary survey is a survey of the MSTP user's activity-travel pattern, including the destination choice, mode choice, activity choice, and virtual activities.

Travel diaries are widely accepted as one of the proxies for getting insights into individuals' and groups' travel behavior. On the other side, the amount of useful information extracted from travel diaries is matched by the difficulty of obtaining travel diaries. One of the main challenges in collecting travel diaries in this modern area is where the response rate to traditional travel diary collection methods has decreased in most countries (Prelipceana A.C. et al., 2018).

The survey's core part is an app called X-ING (by Mobile Market Monitor (MMM)). The X-ING app is an application that is installed on the smartphone that required an internet and GPS connection. This application records and infers a wide range of travel attributes, including location (origin and destination), travel time, travel purpose (activity), route choice (by GPS tracking), and mode choice, and provides a user-friendly interface for users to verify the auto-generated timeline and answer additional questions. Using this application, we are not only handling the obstacles of the previous travel diary methods, but we also collect much higher resolution data in real-time. We use the combination of revealed preference of trips and the uses of GPS mobile phones or other mobile communication tools and web diary on the internet to record trip information of person and vehicle. The variables to be recorded include (For the detailed explanation of variables, the choices, and some other notes for the filling, see appendices 3):

Table 3.3. Variable of activity-travel diary

No	Definition	No	Definition
1	Household ID	27	Type of parking area
2	Household person ID	28	Money spends on parking fee
3	Participant referral code	29	Bus type

No	Definition	No	Definition
4	Household member name	30	Car type
5	Unique ID for each segment	31	Identification of other types of car ride
6	Indicates if segment is stop or trip	32	the fare of car ride service
7	Start time of the segment	33	identification of driving the motorbike
8	End time of the segment	34	Motorbike ride hailing service
9	Final trip mode	35	Other motorbike ride hailing service
10	Source of interval	36	Motorbike ride hailing service fare
11	Source of stop	37	All types activities in the segment
12	Source of mode information	38	Other types of activities
13	Original algorithm for mode of the trip	39	Main activities
14	Original algorithm for latitude of the stop	40	Type of escort
15	Original algorithm for longitude of the stop	41	Passenger activities
16	Unique ID for each user	42	Type of shopping
17	Professional driver ability	43	Type of groceries
18	Original algorithm for start time	44	Other type of groceries
19	Original algorithm for end time	45	Type of non-groceries
20	Latitude of the stop	46	Other type of non-groceries
21	Longitude of the stop	47	Shopping expenses
22	Text value of mode_id	48	Food Type
23	Specification of other modes	49	Other type of food
24	Number of other people in the traveling party	50	Food expenses
25	Relationship with the accompanied	51	Online activity
26	Identification of driving activities	52	Other type of online activities

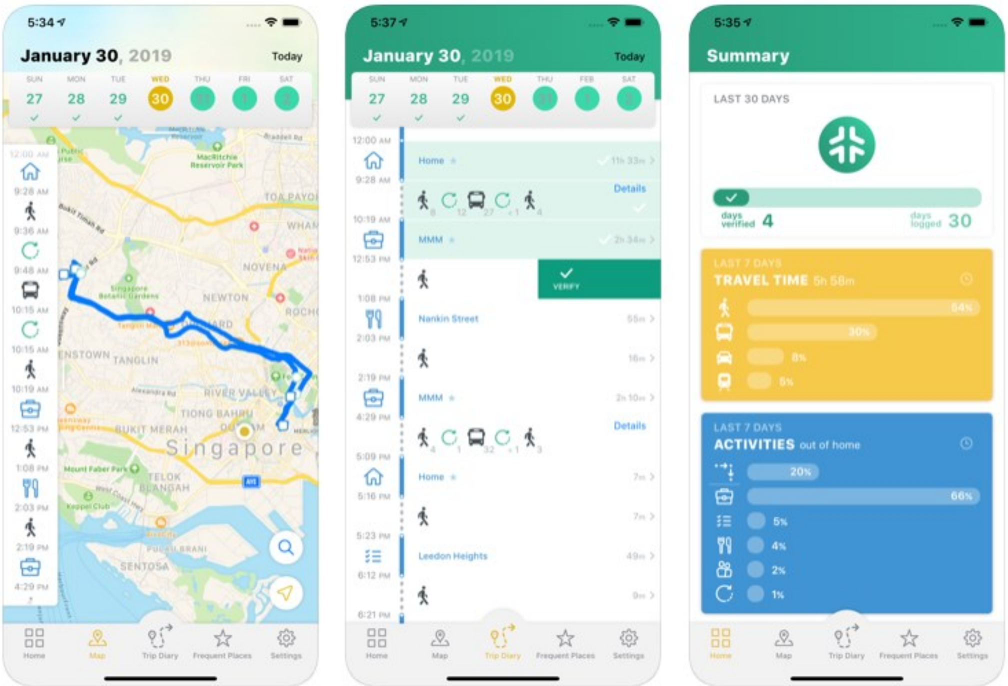


Figure 3.5. The interface of X-ING application
Source: Adaptation from X-ING, 2020

The smartphone-based survey framework utilizes a modified version of MMM’s FMS using the X-ING application to capture participants’ travel-activity patterns. The FMS platform consists of four interconnected technology components:

(1) a mobile app that unobtrusively collects raw sensor data, such as GPS, GSM, Wi-Fi, accelerometer, from iOS and Android smartphones.

(2) A machine-learning back-end that houses intelligent algorithms to detect stops and infer modes and activities using a) mobile sensor data, b) local contextual data such as transit network files, and c) user data, including household and personal characteristics collected in a recruiting survey and user-verified travel and activity history.
(3) An interface accessible via the smartphone apps through which users view and verify a daily travel and activity timeline and provide supplementary trip details.
(4) A data management system for monitoring and management of data collection activity.

The back-end inference algorithms, as well as the user-friendly interfaces, help reducing user burden when multiple days of travel data are collected. This platform was selected for our study as it had been applied in large-scale travel surveys in several cities and proven to collect high-quality data. In addition, the system can be customized to incorporate study-specific questions, which is required in our study. More details on the FMS platform can be found in Zhao et al. (2015). The data-collection framework for this study can be broadly divided into four parts (see Figure 1), described in detail in this section. The four different parts of the survey were the following:

1. Socio-demographic questionnaire.
2. An activity-travel survey using X-ING application: (2a) Travel diary and (2b) Information of activities.
3. Online activities survey using X-ING application.
4. Context-aware stated preference surveys:
    a. SP for eating out activities.
    b. SP for online activities.

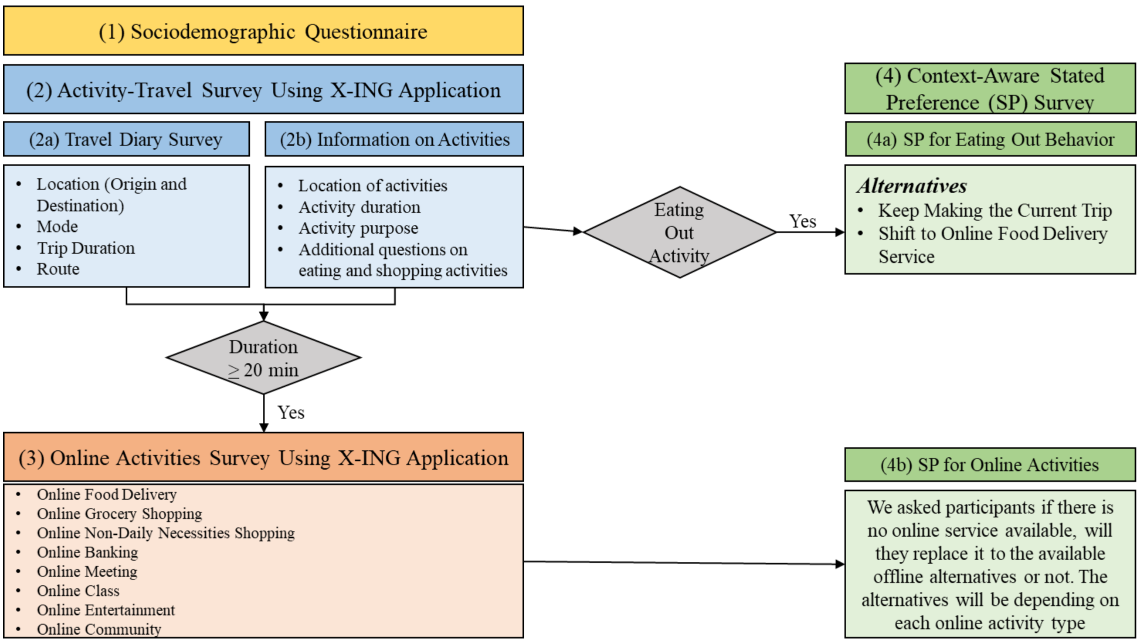


Figure 3.6. The smartphone-based activity-travel survey framework

The application records and infers a wide range of travel attributes, including location (origin and destination), travel time, travel purpose (activity), route choice (by GPS tracking), and mode choice, and provides a user-friendly interface for users to verify the auto-generated timeline and answer additional questions. Using this application, we are not only overcoming some of the obstacles of the traditional travel diary methods, but we also collect much higher resolution data in real-time. The application uses a combination of revealed preference of users, GPS tracking, machine learning back-end for activity diary inference, and user verifications in order to record the complete trip information.

The use of the application makes this survey one of the first smartphone-based activity-travel diary surveys that have been conducted in Indonesia. Participants were then requested to install the application, log their activity, and travel for 14 days (from January 28th to February 10th, 2020). The participants were awarded a 300,000 IDR (21 USD) cash prize for finishing the two weeks' survey.

For every trip made, the travel diary will record:

1. The location of origin and destination of the travel.
2. The duration of trips.
3. The route taken in the trips.
4. After the respondents made their trips, there will be a follow-up or confirmation question that asked some details about their trips, including (i) Mode of transport that they used; (ii) Travel cost; (iii) The number of people in the vehicle (if applicable); and (iv) The parking fee (if applicable).
5. Modification for MSTP:
   This part of the survey tried to capture the use of MSTP in their travel by adding additional alternatives in the mode choice for on-demand mobility services. Such an exclusive provision has been rarely tested in previous smartphone-based surveys. In addition, other transportation mode options specific to the study area, Jakarta, which includes the MSTP-based two-wheeler taxi (e.g., Online Ojek) and ride-hailing services, were also included in the list of alternatives.

The application (X-ING) can automatically detect if the users are moving, i.e., making a trip or 'staying,' i.e., participating in an activity. It uses a similar approach to the travel diary to capture a participant's activity behavior. Figure 3.7. illustrates a typical log entry for the travel and activities on the application.

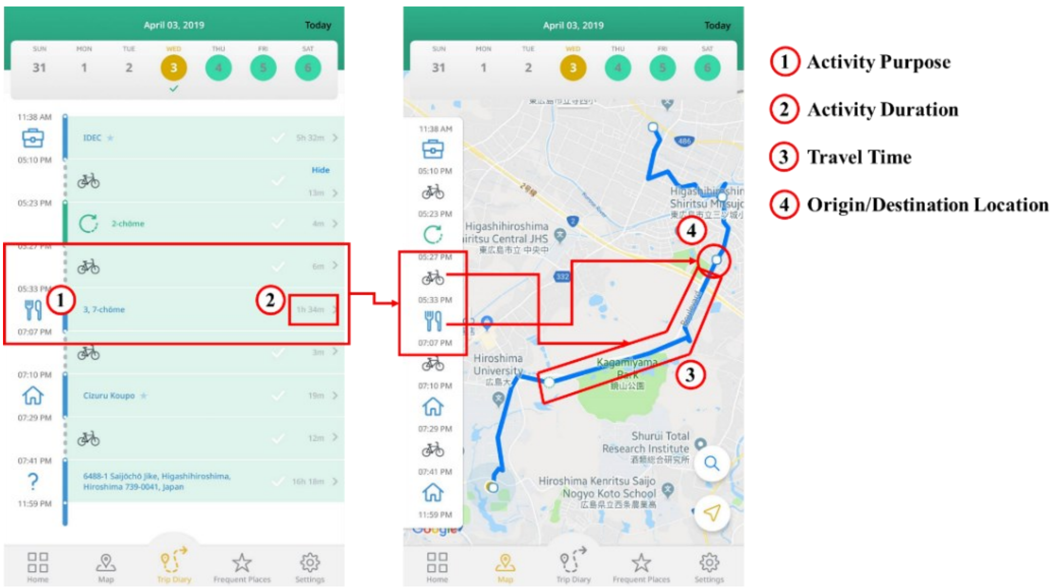


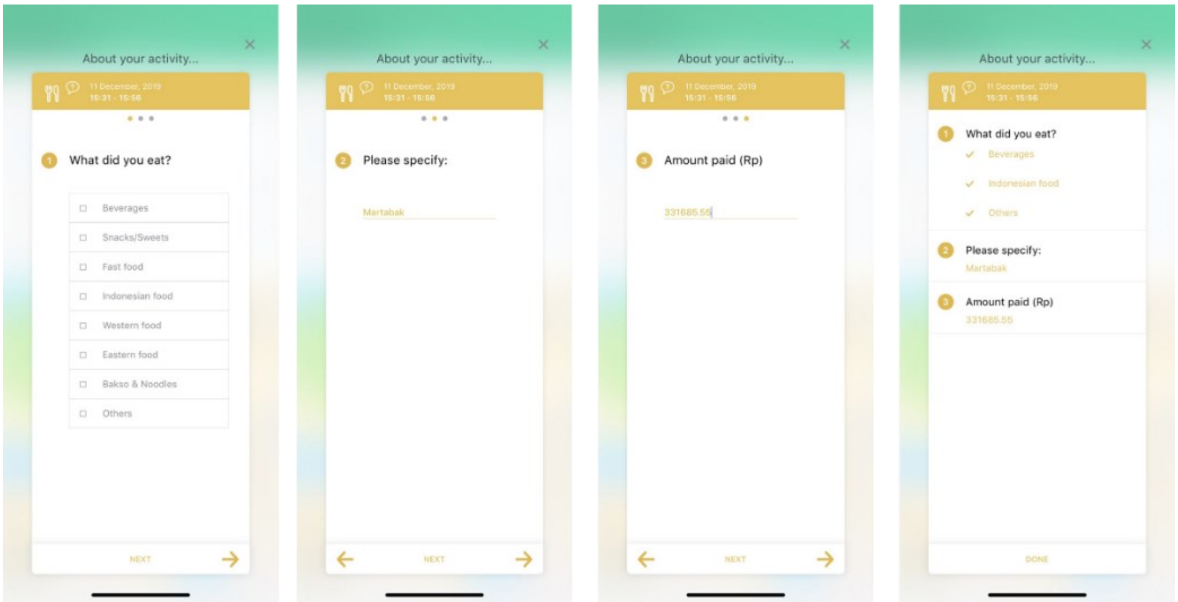
Figure 3.7. A typical activity and travel log in X-ING application

For every stay made, the application will record:

1. The location they stayed at.
2. The duration (starting and ending time) when they stayed at a place.

3. Activities performed at the location.
4. Modification for certain activity types.

We modified the questionnaire to capture additional information for specific activity purposes; if the participant performed one of the following activities, eat-out, grocery shopping, or non-grocery shopping, the respondents were asked additional details of their activity. These questions include what items the user purchased and how much money they spent on shopping or eating. Figure 3.8. shows the screenshots for the follow-up questions for eating out activities. The responses from these questions were later utilized to develop the context-aware SP questionnaire.



(1) Type of Food (2) Other Food Type (3) Food Price (4) Verification

Figure 3.8. Follow-up questions (prompt pop-up on the application) for eating out activities

3.3.2. Online Activities Diary Survey

The third major component of the survey framework involved collecting information on additional online or virtual activities performed during the primary activity (both during the stay and while moving, i.e., during traveling). This aspect of capturing secondary online activities using a smartphone-based survey has not received much attention in the literature and is a necessary component in understanding the impact of ICT on activity-travel behavior comprehensively. This survey was conducted for each activity or trip with a minimum duration of 20 minutes. Twenty minutes is chosen as the cut-off because many studies recently have observed that people frequently check their mobile phones (Ofcom, 2018), and the division between physical and virtual activities is blurring (Deloitte, 2018). In addition, 20 minutes provides a sizeable time limit to perform additional online activities along with the primary activity. For every such activity (i.e., duration greater than or equal to 20 minutes), an additional prompt question was presented to users, asking them about the types of additional online activities they performed during the time duration of the primary activity. The list of online activity categories are included (1) online food delivery (FD), (2) online grocery shopping, (3) online non-grocery shopping, (4) online banking or payment, (5) online meeting, (6) online class, (7) online entertainment (e.g., playing games, watching films, etc.), (8) other online activities, and (9) no online activity.

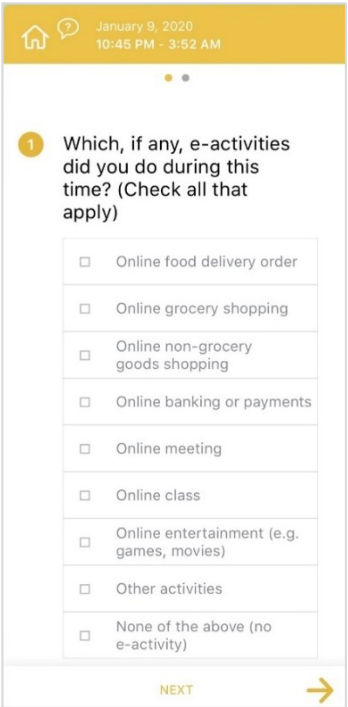


Figure 3.9. Follow up question for online activities

3.3.3. Socio-Demographic Questionnaire

The first part of the activity-travel diary survey captured personal socioeconomic and demographic characteristics from users. It included questions on gender, age, income, family size, vehicle ownership, education level, and occupation type, among other variables. Each person who participated in the survey responded to these questions before filling out travel diaries, constituting the second part of the survey. The component of the questionnaire is as follows (See the appendix 4 for the detail):

1. Gender.
2. Marital status.
3. Phone number.
4. Email address.
5. Home address.
6. Office address.
7. Education level.
8. Job type.
9. Driving license ownership.
10. Household vehicle(s) ownership.
11. Household member data.
12. Average household monthly income (including all of household member’s income).
13. Average household monthly expenses.
14. Average respondent’s monthly travel expenses.
15. Average respondent’s monthly meal expenses.
16. Average respondent’s monthly grocery expenses.
17. Average respondent’s monthly non-grocery expenses.
18. Credit card ownership.
19. E-money ownership.
20. Smartphone(s) ownership.

21. Wi-Fi ownership.
22. Average time spent in an activity.
23. Working schedule.
24. Lunch behavior.
25. Provision of lunch from the office.
26. The daily schedule of working and arriving at home.

3.3.4. Context-aware Stated Preference Surveys

Stated preferences surveys are most commonly used to provide behavioral insights on hypothetical travel scenarios such as new transportation services or attribute ranges beyond those observed in existing conditions. When designing SP surveys, considerable care is needed to balance the statistical objectives with the realism of the experiment (Ben-Akiva et al., 2019). The realism of experiments involves accounting for the market, personal, or contextual constraints and presenting alternatives in the same way as their market framing. These objectives can be met by designing context-aware SP surveys, which pertain to a specific context already faced by the respondent. For example, a transportation mode SP survey would refer to a trip performed by the respondent but present different alternatives and attributes from those originally experienced by this respondent. In this study, we conduct two context-awareness stated preference surveys, including the context-aware stated preference survey for eating behavior and the context-aware stated preference survey for online activities.

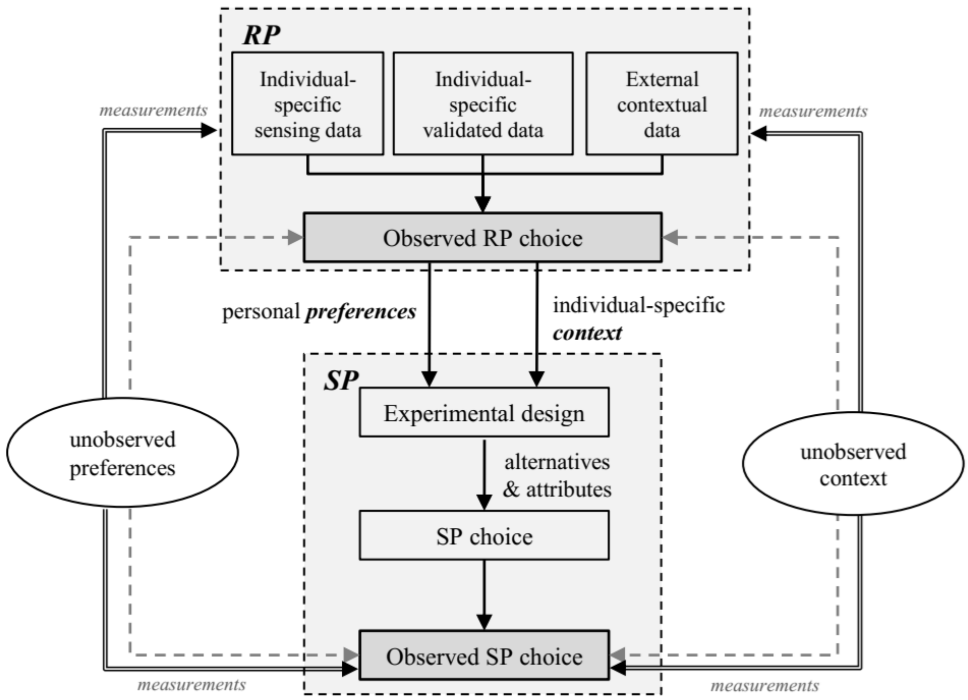


Figure 3.10. Context-aware SP methodology
Source: Adaptation from Atasoy B. et al., 2018

3.3.4.1. Context-aware stated preference survey for eating behavior

This survey was designed particularly to capture changes in eating out behavior. Hypothetical scenarios denoting online food delivery options were provided to users, and their choice of whether they will shift to online food delivery or continue to conduct the eating-out activity was observed. This is an important aspect with respect to understanding the effects of ICT on travel behavior. It will aid in analyzing if ICT will substitute physical travel in case of eating out trips. Four different stated preference (SP) attributes were selected viz. a) delivery time for online food delivery, b) delivery cost for online food delivery, c) combination of ordered food types, and d) food cost for online food delivery.

Each attribute's levels were decided based on revealed preference information collected from other parts of the survey. For each user, one of their eating out activities was selected at random from the first week of their travel, and then based on their revealed preference (RP), attribute levels were decided. Each user was then provided with five choice scenarios to choose between the online food delivery option and their present eating-out trip. This context-aware stated preference survey is deemed better than when all choice contexts in an SP survey are purely hypothetical. It is because such a design accounts for context-dependent factors such as motivation and constraints they had at that time. In addition, this kind of context-aware survey design could capture the complex interdependencies between ICT use and travel since their travel decisions may come from extrinsic motivations (e.g., getting a lunch meal) and intrinsic motivations (e.g., interacting with friends traveling, and having lunch).

The attribute levels for the context-aware stated preference survey were generated using the following RP information. For a), i.e., delivery time for online food delivery, the travel time information captured from travel before eating out the activity (for one randomly selected context) was utilized to create five different levels (see Table 2). Meanwhile, for b), i.e., delivery cost, travel distance information for the previous trip before eating out activity captured automatically through GPS sensors was utilized and multiplied with an assumed per km cost for delivery of 6,000 IDR (0.43 USD) across five different levels. For c), i.e., a combination of ordered food types, the same categories offered to users for their eat-out trips were utilized to create four different levels, denoting the combination and the number of food items ordered. Finally, for d), i.e., food cost for online food delivery and information from RP on the user's actual expenditure on the eating out activity was utilized to create five different levels. The variations in the food cost are an important factor as often it is seen that MSTP collaborate with food merchants to provide services at discounted rates. The attributes and their corresponding levels are shown in Table 3.4.

Table 3.4. Attributes and levels for context-aware SP survey for eating out activities

Attributes	Level
a) Delivery time for online food delivery. *(Based on the actual travel time from the travel diary data; revealed-preference-based question)*	1. 0.4* actual travel time 2. 0.7*actual travel time 3. 1.0*actual travel time 4. 1.3*actual travel time 5. 1.6*actual travel time
b) Delivery cost for online food delivery. *(Based on the actual travel distance from the travel diary data; revealed-preference-based question)*	1. 0.4*6,000 IDR*actual travel distance 2. 0.7*6,000 IDR*actual travel distance 3. 1.0*6,000 IDR*actual travel distance 4. 1.3*6,000 IDR*actual travel distance 5. 1.6*6,000 IDR*actual travel distance
c) Combinations of Online food delivery's Food Types (1. Beverages, 2. Snacks/Sweets, 3. Fast food, 4. Indonesian food, 5. Western food, 6. Eastern food, 7. Bakso/Noodles)	1. One food type 2. Three food types 3. Five food types 4. Seven food types
d) Food cost for online food delivery. (Based on the actual food cost from the	1. 0.8*actual food cost 2. 0.9*actual food cost

Attributes	Level
activity information data; *revealed-preference-based question*)	3. 1.0*actual food cost 4. 1.1*actual food cost 5. 1.2*actual food cost

The five scenarios were presented to participants with two choices in each, with the actual eating-out trip information on the left side and the attribute levels for the online food delivery option on the right (see Figure 4). The questions show context-aware SP scenarios for an online food delivery service introduced in Jakarta. As the context-aware SP survey was conducted at a later time, we strived to make respondents remember the actual conditions they felt at the time of participating in that activity. By showing the date when they took the eating-out trip, it is hoped that the respondents will be able to remember the conditions and constraints they had at that time. The question was then posed to the respondents as part of the SP survey, "*by considering all the activities and constraints you have at that time if the following online food delivery service is available, will you be shifting from eating out to ordering an online food delivery service?*"

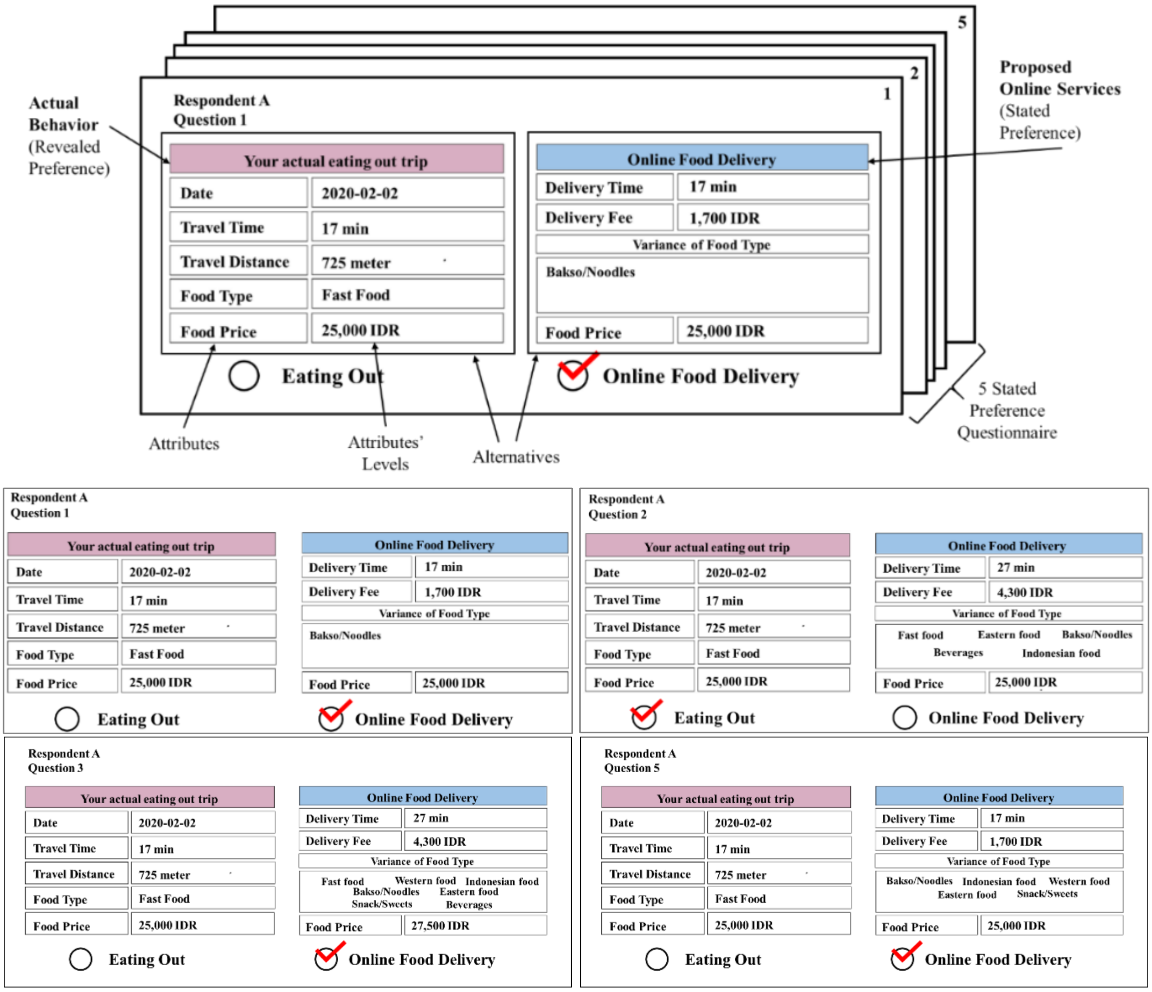


Figure 3.11. Example of questionnaire

We asked users if they would replace the eating-out with an online-based food delivery service if the service is available with specified price and service quality parameters by pivoting the revealed preferences (e.g., Hensher and Greene, 2003). In those five questions, the respondent will be provided with their actual eat-out data, shown by the pink table on the left side and the purposed online-based food delivery service showed by the blue table on the right side. In each questionnaire, the respondents are required to choose the alternatives. This context-aware SP survey will be using the actual eat-out activity from the first-week data of the activity-travel diary survey respondents' data. This allows us to confirm whether ICT use substituted a trip or not. Importantly, this pivoted stated preference design allows respondents to represent their preferences given all context-dependent factors such as motivation and constraints they had at that time. This feature is of particular importance to capture the complex interdependencies between ICT use and travel since their travel decisions may come from extrinsic motivations (e.g., getting a lunch meal) and intrinsic motivations (e.g., interacting with friends while traveling and having lunch). The respondent would not choose an online-based food delivery service, even when the service level is very high if they made a trip for intrinsic motivations.

3.3.4.2. Context-aware stated preference survey for online activities

Additional context-aware SP surveys were conducted to understand ICT's impact on activity-travel behavior better. Users' RP information from the first week of the survey was obtained from part 3 of the survey framework, i.e., the survey for online activities, where users were prompted to record the online activities that they performed along with a primary activity (when its duration was more than 20 minutes) was utilized for this SP survey. Whenever the users reported having conducted online food delivery orders and online shopping (both grocery and non-grocery), an additional SP survey was conducted with a hypothetical scenario where that particular online activity which they performed ceased to exist.

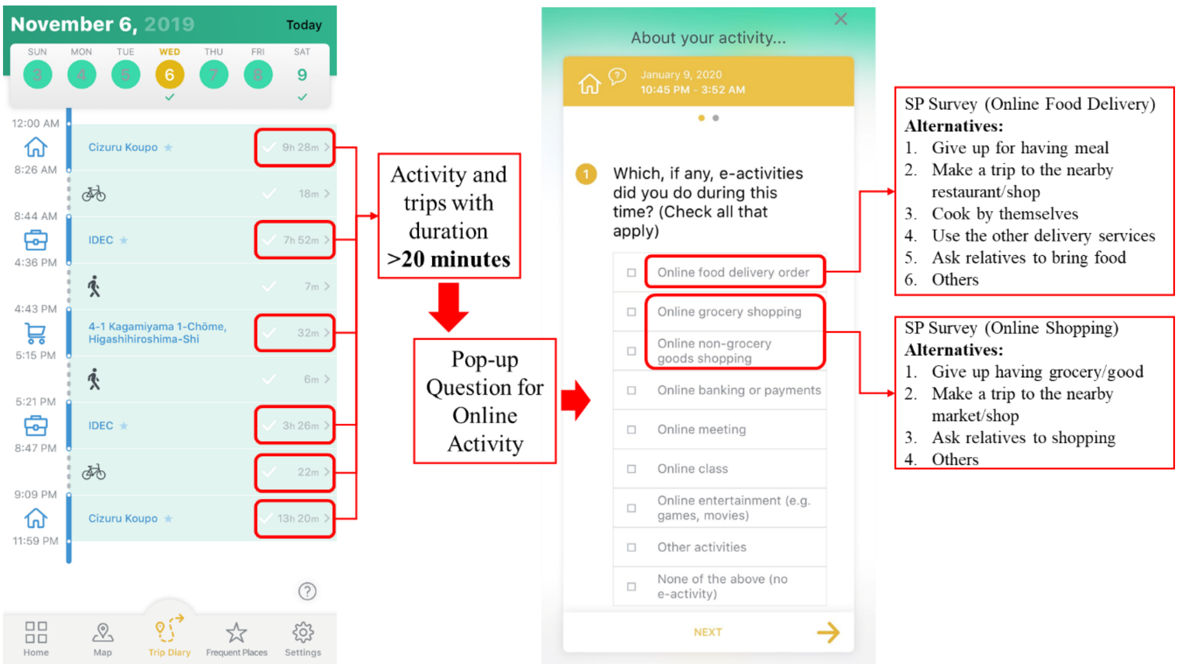


Figure 3.12. RP and SP surveys for online activities

In the case of online food delivery order, the users were provided with six alternatives to choose from, including 1) give up having a meal, 2) make a trip to the nearby restaurant, 3) cook by themselves, 4) use traditional food delivery services (such as calling the restaurants), 5) ask other people to bring them food, and 6) others. Meanwhile, in the case of online shopping (both grocery and non-grocery), the users were provided with four alternatives, including 1) give up the online shopping activity, 2) make a trip to the nearby shop or market, 3) ask other people to bring them or buy them the goods, and 4) others. The following question was then posed to the respondents as part of these SP surveys *"if there are no MSTP services available at that time, which of the following alternatives will you choose?"*. All of X-ING feature was shown in English, while the SP questionnaire was shown in Bahasa Indonesia.

3.4. STUDY LOCATIONS

In this study, we employ research in Jakarta, Indonesia, and 69 cities in Japan. In analyzing MSTP's impact on the urban form, we employ an agglomeration analysis in Japan and Jakarta. While analyzing MSTP's impact on the activity-travel behavior, we altogether employ the data that we collected in Jakarta, Indonesia, where the MSTP is available and popularly used.

3.4.1. Study in Jakarta, Indonesia

Jakarta (the Special Capital Region of Jakarta or Daerah Khusus Ibukota (DKI) Jakarta) is the capital and the largest city of Indonesia. With an area size of 664.13 Km^2 and 10,770,487 population, enact DKI Jakarta is the world's second-most populous urban area after Tokyo, with a population density of 21,974 people/Km^2. Based on UN indicators (UNDP, 2020), Jakarta is the largest metropolitan area in Southeast Asia, acknowledged for a tremendous rate of population growth.

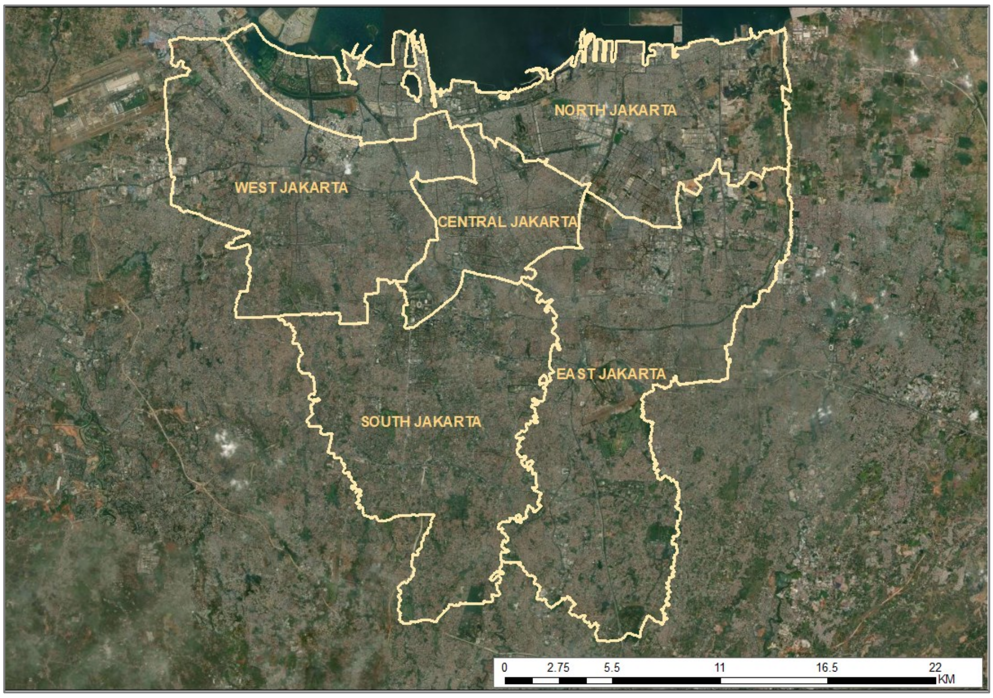


Figure 3.13. Map of study area in Jakarta, Indonesia

In this study, we analyze at the aggregate level of the metropolitan area of Jakarta and analyze within a disaggregated level, including five administrate cities, 42 districts, and 262 neighborhoods. Table 3.5. shows the general characteristics of the case studies following with Figure 3.14 and Figure 3.15, which will show the land use and city's structure of Jakarta.

Table 3.5. The characteristics of the study area

City Name	Area Size (Km^2)	Population (People)	Population Density (people/Km^2)	Number of Districts	Number of Neighborhood
Central Jakarta	52.38	1,138,346	21,732	8	44
South Jakarta	154.32	2,188,457	14,181	10	65
West Jakarta	124.44	2,324,121	18,676	8	56
East Jakarta	182.70	2,944,493	16,116	10	66
North Jakarta	139.99	1,711,386	12,225	6	31

Source: Badan Pusat Statistik Provisi DKI Jakarta, 2021

Based on PTSP Jakarta (2019), the allocation of land for housing occupies the largest proportion, namely 48.41% of the mainland area of DKI Jakarta. Meanwhile, the area for industrial, office, and commercial buildings only reached 15.68%. As part of their spatial structure, Jakarta has two activity center systems, including the primary activity center and the secondary activity center shown in Figure 3.15. The location of Jakarta's main activity will be determined by the central area or central business district (CBD) area that will be used in the following analysis (see Chapter Five). We will only use the primary activity center location for the analysis, including an 11-point location throughout Jakarta.

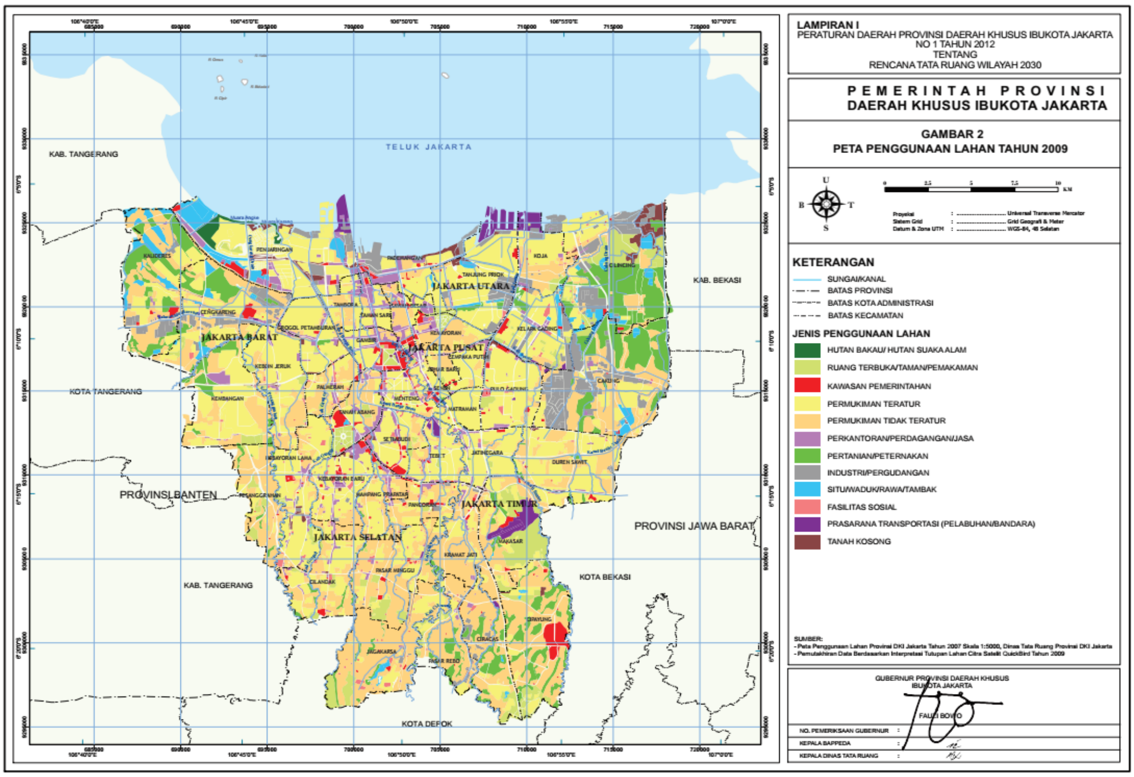


Figure 3.14. Land use map of Jakarta 2009
Source: Province Government of DKI Jakarta

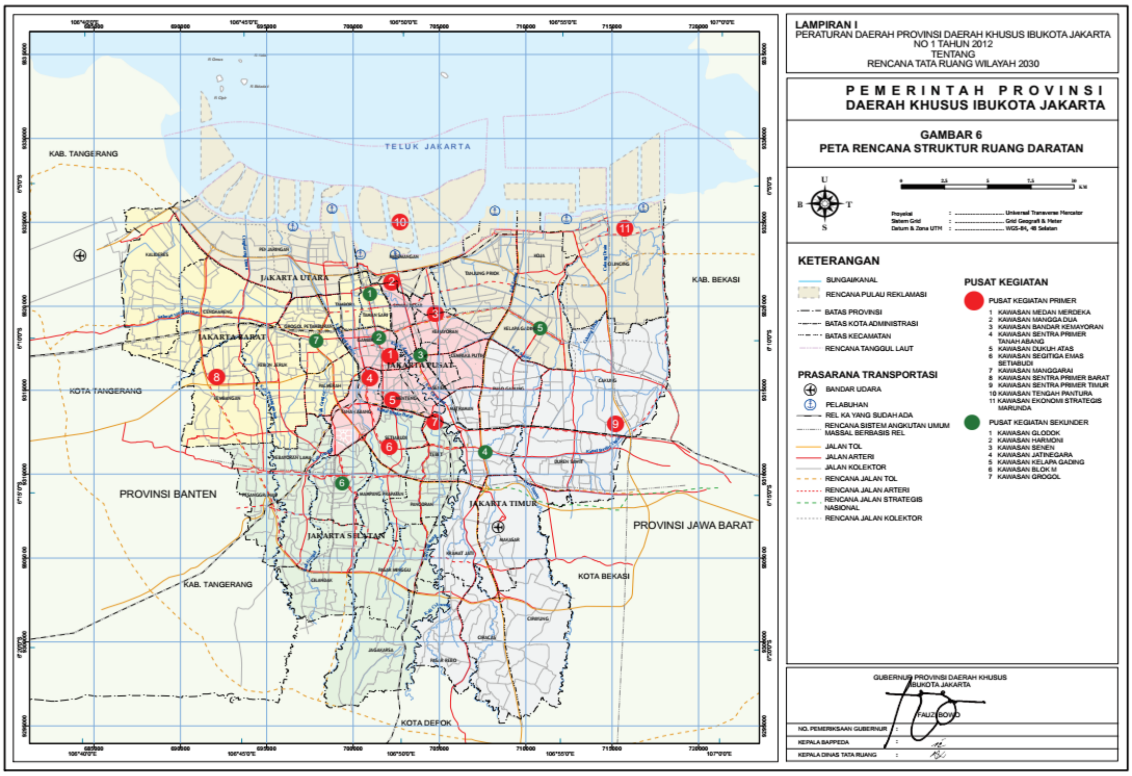


Figure 3.15. Map of Jakarta city's structure
Source: Province Government of DKI Jakarta

3.4.2. Study in 69 Cities of Japan

Japan is an island country located west of the Pacific Ocean in the Northern Hemisphere. Japan comprises 6,852 islands covering 377,974.17 square kilometers (145,936.64 square miles) (Geospatial Information Authority of Japan, 2019). Japan is divided into 47 administrative prefectures and eight traditional regions, with Tokyo as its capital city. With a total number of populations around 125,929,817 (Statistics Bureau, Ministry of Internal Affairs and Communications, 2020), Japan is the most densely populated country globally and the eleventh most populous country in the world. We select the 69 Japanese cities according to the availability of other city-level information, particularly from the nationwide person trip survey conducted by the Ministry of Land, Infrastructure, Transport, and Tourism (2008). Therefore, we select 69 cities in Japan as our case study with regards to the availability data.

Concerning the availability of MSTP, there is no MSTP kind of services available yet. In several big cities such as Tokyo, Osaka, and Kyoto, uber eats food delivery services, but they are not integrated with the transportation system as befits in Indonesia. Regulatory issues related to transportation modes related to safety, legality, and market competition with existing transport fleets make it difficult for ride-hailing services to be established in Japan. Until now, based on the knowledge of the author, there is no MSTP service in Japan.

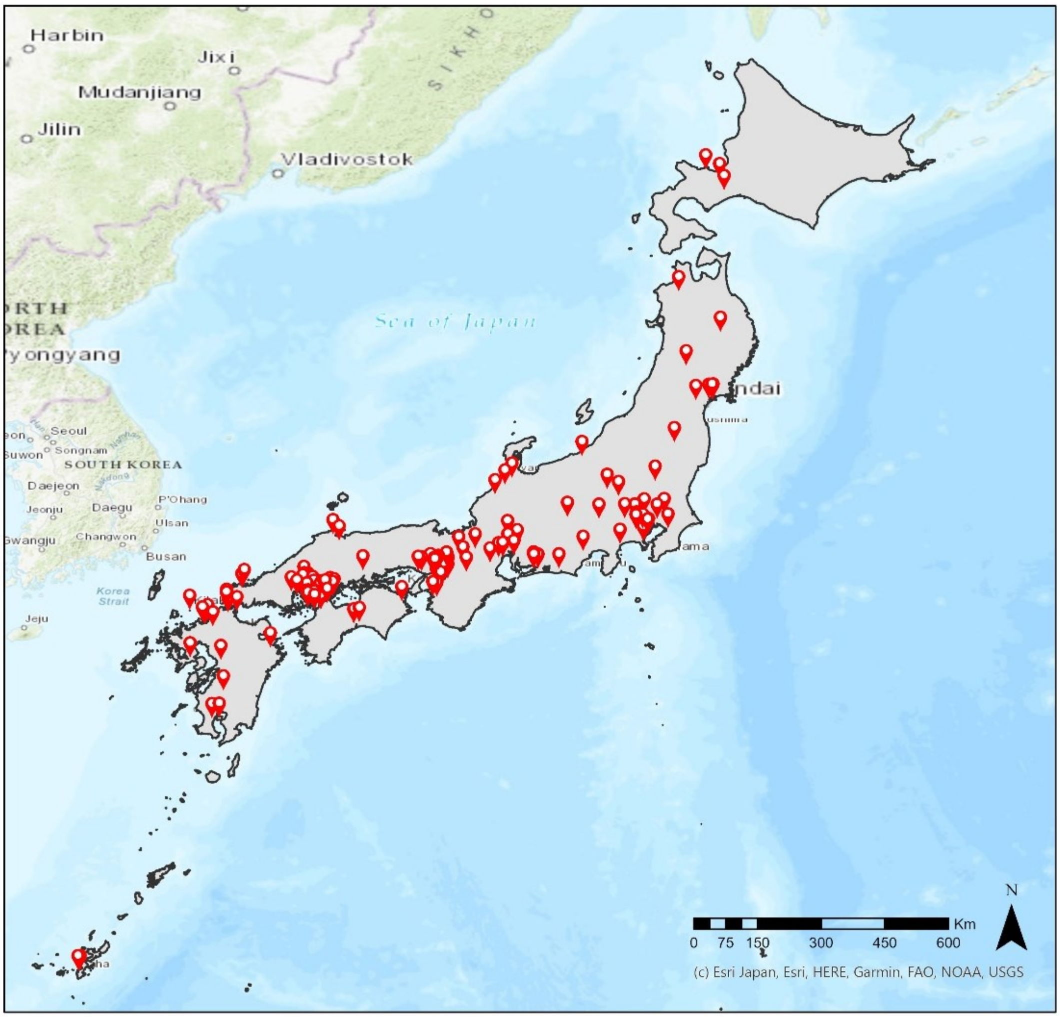


Figure 3.16. Map of study area in Japan

3.5. TARGET RESPONDENTS

This study will be collecting data from 300 individuals who will complete the 14 days (2 weeks) application-based travel-activity diary survey from Jan January 28th to February 10th, 2020. The respondent is a user of an online-based multi-service platform who lives and works (home-work place-based sampling) in South Jakarta City, Indonesia. Respondents were randomly chosen based on their home and workplace location. Respondents will be asked to complete three types of surveys, including the travel-activity diary and ICT usage, online-based questionnaire, and stated preference. All surveys will be done within the travel-activity dairy survey period. The criteria of target respondents of this study are:

(1) People with age 18 years old and above.
(2) Having a smartphone that can support relatively accurate GPS detection.
(3) An active user of MSTP's online services (i.e., online food delivery service).
(4) Lives or works (home-work place-based sampling) nearby South Jakarta City.

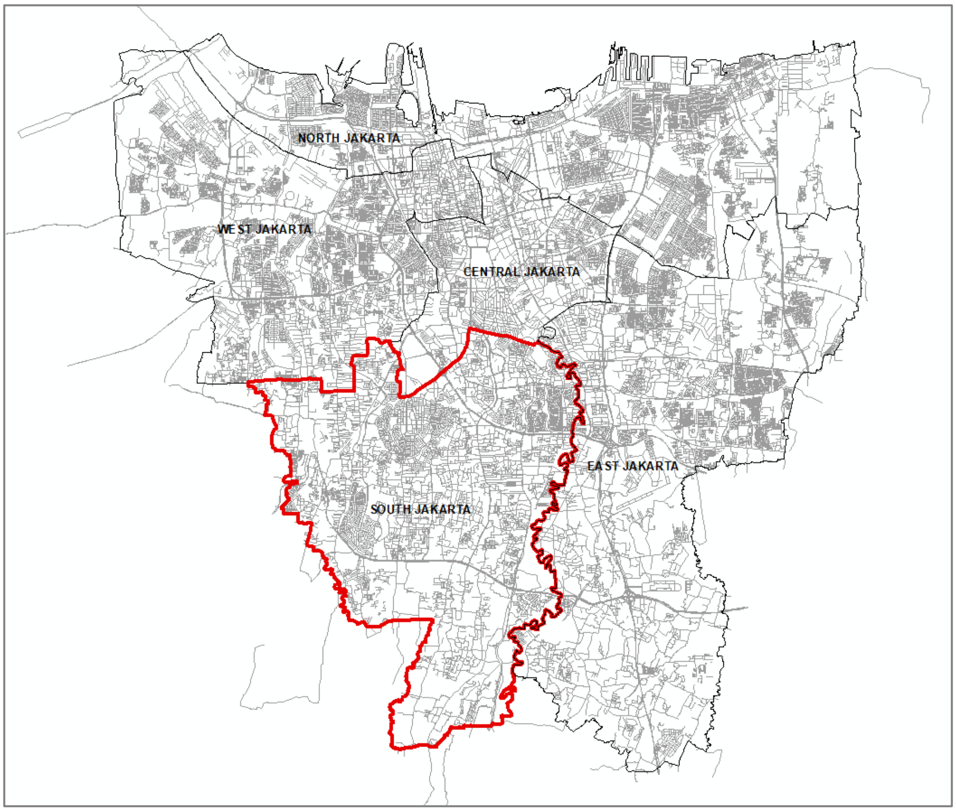


Figure 3.17. Location of sampling selection

3.6. ANALYSIS METHODOLOGY

In this section, we briefly explain the analysis methodology that will be used in this study, including (1) agglomeration index, (2) correlation analysis, (3) decision tree analysis, (4) propensity score analysis, and (6) the dynamic discrete choice model for activity-travel analysis. The detail of each methodology will be explained in Chapters 4 to Chapter 8.

3.6.1. Agglomeration Index

Agglomeration index is an index that is used to represent the distribution of facilities across space. To calculate the agglomeration index, the analytical procedure will be divided into four steps analysis: (1) calculating the average pairwise distance of each targeted facility (i.e., combination food merchants, online food merchants, and dine-in food merchants); (2) constructing the counterfactuals, i.e., calculating the average pairwise distance of public facilities; (3) developing the agglomeration index; and (4) comparing the agglomeration index result across different spatial boundaries and different facility types.

1) Calculating the average pairwise network distance of targeted facilities
   Following Safira and Chikaraishi (2019), to calculate the average pairwise distance among facilities, we adopt the Euclidean-based distance, the network distance, and the travel time to reflect the actual distance between facilities The pairwise network distance for targeted facilities $\bar{d}^{TF}$ is define as:

$$\sum_{i}\sum_{j(\neq i)} d_{ij}^{TF} / (n_{TF}(n_{TF}-1)) \tag{3.1}$$

   where n_{TF} is the total number of targeted facilities, and d_{ij}^{TF} is the pairwise distance between facility i and j.

2) Constructing the counterfactuals
Counterfactuals need to control for the overall tendency of the facility to agglomerate. The locations of public facilities serve as counterfactuals. The selection of the public facilities as counterfactuals assumes that the provision of public facilities in urban areas is based on the principle of equitable distribution or need-based on the location of the community residence. It would be reasonable to assume that the spatial distribution of these facilities is free from agglomeration forces. Similar to commercial facilities, the pairwise network distance of public facilities $\bar{d}^{CF}$ is defined as:

$$\sum_i \sum_{j(\neq i)} d_{ij}^{CF} / (n_{CF}(n_{CF} - 1)) \tag{3.2}$$

where n_{CF} is the total number of public facilities, and d_{ij}^{CF} is the pairwise distance between facility i and facility j.

3) Developing the agglomeration index
We define the agglomeration index as the ratio of the average pairwise network distance of commercial facilities divided by the average pairwise network distance between public facilities as:

$$AI = \frac{\bar{d}^{CF}}{\bar{d}^{TF}} \tag{3.3}$$

where AI is the agglomeration index of a city, with a higher value indicating the more significant agglomeration of commercial facilities.

3.6.2. Correlation Analysis

Correlation analysis is used to test the relationship between each variable to measure how things are related. Correlations are useful because if you can find out what relationship variables have, you can make predictions about future behavior. Knowing what the future holds is very important in the social sciences like government and healthcare. Businesses also use these statistics for budgets and business plans. In this study, we explore the correlation among variables using the correlogram matrix. A correlogram is a graph of the correlation matrix. Useful to highlight the most correlated variables in a data table. In this plot, correlation coefficients are colored according to the value. The correlation matrix can also be reordered according to the degree of association between variables.

3.6.3. Decision Tree Analysis

The decision tree is a supervised learning model used for both classification and regression. Answer sequential questions that send us down a certain route of the tree the model behaves with if this than those conditions leading us to a final prediction. A Decision Tree Analysis is a graphic representation of various alternative solutions available to solve a problem. The manner of illustrating often proves to be decisive when making a choice. A Decision Tree Analysis is created by answering several questions that are continued after each affirmative or negative answer until a final choice can be made. A Decision Tree Analysis is a scientific model and is often used in the decision-making process of organizations. When making a decision, the management already envisages alternative ideas and solutions. By using a decision tree, the alternative solutions and possible choices are illustrated graphically, as a result of which it becomes easier to make a well-informed choice. This graphic representation is characterized by a tree-like structure in which the problems in decision-making can be seen in the form of a flowchart, each with branches for alternative choices.

The Decision Tree Analysis makes good use of the 'what if' thought. Several alternatives consider both the possible risks and benefits that are brought about by certain choices. The possible alternatives are also made clearly visible, and therefore the decision tree provides clarity with respect to the consequences of any decisions that will be made. There are several ways in which a decision tree can be represented. Lines, squares, and circles commonly represent this analysis. The squares represent decisions, the lines represent consequences, and the circles represent uncertain outcomes. By keeping the lines as far apart as possible, there will be plenty of space to add new considerations and ideas. The representation of the decision tree can be created in four steps:

(1) Describe the decision that needs to be made in the square.
(2) Draw various lines from the square and write possible solutions on each of the lines.
(3) Put the outcome of the solution at the end of the line. Uncertain or unclear decisions are put in a circle. When a solution leads to a new decision, the latter can be put in a new square.
(4) Each of the squares and circles is reviewed critically so that a final choice can be made.

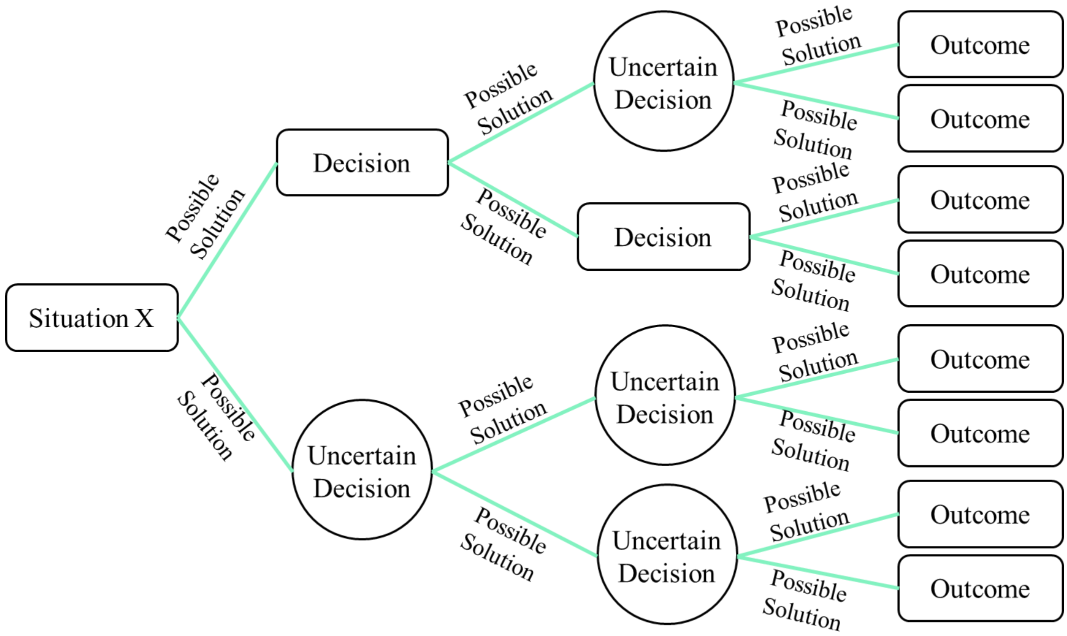


Figure 3.18. Example of decision tree analysis

The advantages to using decision trees:

1. Easy to interpret and make for straightforward visualizations.
2. The internal workings are capable of being observed and thus make it possible to reproduce work.
3. Can handle both numerical and categorical data.
4. Perform well on large datasets.
5. Are extremely fast.

The disadvantages of decision trees:

1. Building decision trees require algorithms capable of determining an optimal choice at each node. However, choosing the best result at a given step does not

ensure you will be headed down the route that will lead to the optimal decision when you make it to the final node of the tree, called the leaf node.

2. Decision trees are prone to overfitting, especially when a tree is particularly deep. This is due to the amount of specificity we look at, leading to a smaller sample of events that meet the previous assumptions. This small sample could lead to unsound conclusions.

Ideally, we would like to minimize both errors due to bias and errors due to variance. Enter random forests. Random forests mitigate this problem well. A random forest is simply a collection of decision trees whose results are aggregated into one final result. Their ability to limit overfitting without substantially increasing error due to bias is why they are powerful models.

3.6.4. Propensity Score

The propensity score is the probability of treatment assignment conditional on observed baseline characteristics. The propensity score allows one to design and analyze an observational (nonrandomized) study to mimic some of the particular characteristics of a randomized controlled trial. In particular, the propensity score is a balancing score: conditional on the propensity score, the distribution of observed baseline covariates will be similar between treated and untreated subjects. Propensity score analysis (PSA) arose as a way to achieve exchangeability between exposed and unexposed groups in observational studies without relying on traditional model building. Exchangeability is critical to our causal inference. In experimental studies (e.g., randomized control trials), the probability of being exposed is 0.5. Thus, the probability of being unexposed is also 0.5. The probability of being exposed or unexposed is the same. Therefore, a subject's actual exposure status is random. This equal probability of exposure makes us feel more comfortable asserting that the exposed and unexposed groups are alike on all factors except their exposure. Therefore, we say that we have exchangeability between groups.

3.6.5. Dynamic Discrete Choice Model

In this study, the fundamental modeling approach is a dynamic discrete choice model based on random utility-maximizing principles. Following Västberg, O. B. et al. (2020), we briefly introduce the Dynamic Discrete Choice Model (DDCM) and its use for estimations. Dynamic discrete choice models have received widespread acceptance in transport research and are used in travel demand modeling and behavioral analysis. Following the random utility maximization model, specifically the standard nested logit model, in DDCM, the path choice problem is formulated as a link choice sequence. At each state, the decision-maker or agent chooses the utility-maximizing outgoing link with link utilities given by the instantaneous cost, the expected maximum utility to the destination (value function), and i.i.d. extreme value (with zero means) (M Fosgerau, 2013).

The DDCM was constructed based on the Markov Decision Process (MDP) to model the choice of daily activity-travel pattern. The activity-travel pattern can be defined by the sequences of states $\mathbf{s}$ and actions $\mathbf{a}$ transverse during a day. Giving that the individuals' preference for taking a decision a_k in a specific state s_k and reaching the state s_{k+1} is represented by a one-stage utility function. It is assumed that an agent makes an action that can maximize his or her total utility in a given period of time. Observed an individual who has made sequences of actions $\mathbf{a}_n = \{a_{0,n}, a_{1,n}, \dots, a_{K_n,n}\}$ and reached states $\mathbf{x}_n = \{x_{0,n}, x_{1,n}, \dots, x_{K_n+1,n}\}$, The total utility $U(\mathbf{s}, \mathbf{a})$ is defined as the sum of utilities obtained from reaching a specific state and from conducting some actions as follows:

$$U(\mathbf{s}, \mathbf{a}) = \sum_{k=0}^{K} u\,(s_k, a_k, s_{k+1}) \tag{3.4}$$

Where the k is an index to denote the order of the state s_k in the sequence of the state that is transverse during the day. By assuming that individuals behaved as if they choose the utility-maximizing travel pattern, a rational agent that starts in a state s would behave according to policy π, determining the action $a_k = \pi(s_k)$ that maximize the expected future utility of a day. Then, the one-stage utility $u(a_k, x_k)$ of taking an action a_k in the state s_k is:

$$u(s_k, a_k) = u(a_k, x_k) + \epsilon_k(a_k) \tag{3.5}$$

Where $u(a_k, x_k)$ is the utility function of the observed variable at state s_k and $\epsilon_k(a_k)$ is the random terms that will be assumed as i.i.d Gumbel distribute. Finding the optimal policy and then calculating the choice probabilities requires computing the expected value function in each state x_k. The expected future utility conditional on a state is the value function in the state:

$$V(s) = \max_{\pi} E_s \left\{ \sum_{k=0}^{K} u\,(s_k, a_k, s_{k+1}) | s_k = s, a_k = \pi(s_k) \right\} \tag{3.6}$$

Where E_s is respected to the stochasticity of s_k given the decision rule $a_k = \pi(s_k)$. With the assumption that q (transition probability), u (one-stage utility function), and $C(s_k)$ (choice set) is under Markovian condition, so they are independent of the history. The Markovian assumption is not a problem in theory because it could include all previous history in a finite horizon model. Following Rust (1987), we have assumed that the random state variable ϵ_k is conditionally independent of the previous state and action and enters the one-stage utility additively. Observe that value function $V(s)$ can be defined recursively through Bellman's equation as (Bellman 1957, Rust 1987).

$$V(x_k, \epsilon_k) = \max_{a_k}\{u(x_k, a_k) + \epsilon_k(a_k) + EV(x_k, a_k)\} \tag{3.7}$$

Where the $EV(x_k, a_k)$ is the expected value of the value function of the state reached when taking action a_k in state (x_k, ϵ_k). If $EV(x_k, a_k)$ is known for each state-action pair, the principle of optimality states that the optimal policy π is obtained by, conditionally on a state s_k, choosing the action a_k that maximizes the utility function, then $EV(x_k, a_k)$ is given by:

$$\begin{aligned} EV(x_k, a_k) &= E_{t^{(k+1)}, h^{(k+1)}, \epsilon_{k+1}}[V(x_{k+1}, \epsilon_{k+1}) | x_k, a_k] \\ &= \int_{t'} \left(\sum_{j=1}^{N_h} q_h(h_j | t', t, h, \tilde{p}) \cdot \bar{V}(x_{k+1}) \right) dq_t\big(t' | t, l, \tilde{m}, \tilde{d}\big) \end{aligned} \tag{3.8}$$

Where in turn $\bar{V}(x_k) = E_{\epsilon_k}[V(x_k, \epsilon_k)]$. When $\epsilon_k(a_k)$ is independent and identically distributed (i.i.d.) with Gumbel distributed (with zero means), $\bar{V}$ is given by the following log-sum:

$$\bar{V}(x_k) = \log\left(\sum_{a_k \in C(x_k)} e^{u(x_k, a_k) + EV(x_k, a_k)} \right) \tag{3.9}$$

With i.i.d. Gumbel distributed k, the probability that an action a_k will be the utility-maximizing alternative in a state $x_k$when k is unobserved is simply given by the MNL model:

$$P(a_k|x_k) = \frac{e^{u(x_k,a_k)+EV(x_k,a_k)}}{\sum_{a_k \in C(x_k)} e^{u(x_k,\tilde{a}_k)+EV(x_k,\tilde{a}_k)}} \tag{3.10}$$

After we suppressed the parameters θ from the utility functions' specification and the individual's dependence in that the model describes, the likelihood for the observation of an individual is then given by:

$$L_n(\mathbf{a}_n, \mathbf{x}_n|x_0, \theta) = \prod_{k=0}^{K_n} P_n\big(a_{k,n}\big|x_{k,n}, \theta_u\big) \cdot q\big(x_{k+1}\big|a_{k,n}, x_{k,n}, \theta_q\big) \tag{3.11}$$

Let *N* observations construct the set of observations ∂_N ON. The log-likelihood function for ∂_Nbased on the conditional likelihoods becomes:

$$\bar{L}L(\partial_N; \theta) = \sum_{n=1}^{N} \log(L_n(\mathbf{a}_n, \mathbf{x}_n|x_0, \theta)) \tag{3.12}$$

Chapter 4: THE ASSOCIATION BETWEEN AGGLOMERATION INDEX AND CITY-LEVEL CHARACTERISTICS

This chapter explores the association between agglomeration index and city-level characteristics with a case study in 69 cities of Japan. This study attempt to answer the research questions regarding "How to quantify the concentration of facility distribution?" (RQ 1.1) and "How is the association between facility distribution and city-level characteristics?" (RQ 1.2) through the development of the agglomeration index and the association analysis. This chapter also contains the introduction of the study, methodology approach, study area, data used, result and discussion, and conclusion.

4.1. INTRODUCTION

It is widely known that the relationship between urban form and transport systems is complex, given land use and transportation are part of a retroactive feedback system, with one influencing the other (Giuliano, 2004). This suggests a lack of independence in the evolution of transportation and urban form, i.e., changes in transportation systems influence location decisions and vice versa (Anderson et al., 1997). In a free-market economy, the urban form is the outcome of location choices made by thousands of households, private firms, and public agencies. An urban agglomeration is one of the important outputs of those location decisions, shaping urban form together with transportation developments. While there is no unique definition of urban agglomeration (Fang and Yu, 2017), we use the term urban agglomeration to simply indicate the concentration of socio-economic and human development, following Combes and Gobillon (2015), Fang and Yu (2017), and Uchida and Nelson (2009).

In the past few decades, the urban agglomeration has been the subject of intensive analysis in the field of urban economics and geography studies (e.g., Anas, et al., 1998; Combes et al., 2008), particularly with the emergence of the new economic geography (Krugman, 1991; Fujita et al., 1999). Problematically, as observed, an urban agglomeration is the outcome of various agglomeration, and dispersion forces operating at various scales, establishing a solid link between empirical work and theoretical models remains a challenging task (Combes and Gobillon, 2015; Akamatsu et al., 2017). In this study, we focus on the agglomeration of commercial facilities within a city with special attention to the role of transport systems. Although a number of empirical studies have been conducted on interregional agglomeration (e.g., Malmberg et al., 2000; Malmberg and Maskell, 2002), few have addressed agglomeration within a city (Koster et al., 2019).

The literature identifies three sources of agglomeration of commercial facilities: *matching, sharing,* and *trip chaining* (Takahashi, 2013; Koster et al., 2019). Takahashi (2013) considers that consumers seek a better *matching* between their preferred varieties and the varieties sold in each commercial area and confirms that agglomeration would occur when consumers exhibit taste heterogeneity while the available information is imperfect. Alternatively, agglomeration may also occur when there are positive externalities through *sharing*, shopping malls being a typical example, i.e., shops in a mall share fixed costs such as facility maintenance and customer acquisition costs (Pashigian and Gould, 1998). Lastly, Koster et al. (2019) explain the agglomeration of commercial facilities in shopping streets from the viewpoint of consumer *trip chaining* behavior, whereby consumers can reduce transport and search costs owing to the spatial proximity of shops, while shops receive more customers due to the increase in the number of pedestrians passing by.

In this study, we conduct an exploratory analysis to argue that transportation systems moderate these agglomeration forces. Although a number of studies have repeatedly shown that transportation systems account for both agglomeration and dispersion forces such as congestion (e.g., Tabuchi, 1998; Glaeser and Kahn, 2004), a few concerns with how transportation systems moderate agglomeration forces. Through an empirical analysis, we argue that it may be better to pose the question "*In what conditions would agglomeration force play a more significant role?*" instead of repeatedly asking, *"Which agglomeration force is the most relevant determinant?"* While recent analyses explore the presence of complex agglomeration forces in interregional industry agglomeration (Faggio et al., 2017), there is no existing investigation on the agglomeration of commercial facilities within a city.

Intuitively, the moderation effects of transportation systems are as follows. As pointed out by Koster et al. (2019), European cities maintain active shopping streets better than cities in other developed countries mainly because consumer trip-chaining behavior contributes to the reduction of transport and search costs and thereby increases the number of customers in shopping streets. However, this is only valid when cities rely on public transit or non-motorized transport. When cities become car-dependent (as in the US), the costs of accessing shopping streets become prohibitively expensive owing to high parking costs and traffic congestion, thereby reducing the effectiveness of the agglomeration force derived from trip chaining. For these car-dependent cities, rather than maintaining shopping streets, agglomeration through sharing may be more feasible, for example, by establishing a large-scale shopping mall in a suburban area where congestion and parking costs are sufficiently low. These extreme cases of European and US cities imply that transportation systems moderate the effectiveness of each agglomeration force.

Although not directly mentioning transportation systems as a moderator, narratives similar to the aforementioned are available in the literature (e.g., Glaeser and Kahn, 2004). However, to the authors' knowledge, there is little empirical confirmation of the moderation effects of transportation systems on agglomeration forces. As appropriate urban and transport policies depend on the type of the dominant agglomeration/dispersion forces, it is essential for policymakers to have a proper understanding of the role of transport systems in shaping them. Particularly in Japan, there are various types of cities, ranging from the very car-dependent to the very public transport dependent, and thus the suitable urban and transport policy decisions vary by city.

Given these considerations, this study empirically examines the association between the agglomeration of commercial facilities and city-level characteristics (including transportation, socio-economic and geographical characteristics) in 69 Japanese cities. We particularly discuss how transportation systems moderate agglomeration forces influencing the spatial distribution of commercial facilities. In the empirical analysis, we employ a simple agglomeration index. We first calculate the pairwise network distance between commercial facilities and among public facilities in a city, where the pairwise distance among public facilities serves as a counterfactual to calculate the agglomeration index, given the assumption that agglomeration phenomena do not exist for public facilities. We then identify the association between the agglomeration indexes, including city-level characteristics, using a decision tree analysis to discuss the moderation effects of transport systems in shaping agglomeration forces. Note that the present work is an exploratory analysis with a particular focus on the association between an agglomeration index and transport systems, not one directly identifying actual agglomeration forces in Japanese cities. Despite this, we believe that our study makes a significant contribution to the existing literature: one of the most critical arguments derived from our empirical analysis is that agglomeration mechanisms seem to be far more complicated than most theoretical models on agglomeration forces suggest. Of course, theoretical models need not necessarily be realistic. Nonetheless, it does matter when we derive policy implications from the theoretical models: if what the theoretical models indicate is quite different from our empirical observations, policymakers should carefully consider the implications arising from these theoretical models.

4.2. METHODOLOGY

There are two important ideas in our empirical analysis. First, to explore the association between the agglomeration of commercial facilities and transportation systems, we conduct a nationwide comparison analysis (of 69 Japanese cities), including cities varying from car-dependent to public transport dependent. Given other possible confounding factors such as population and area size could affect this association, we conduct exploratory analysis using a decision tree model including a number of other city-level characteristics. Second, inspired by the work of Duranton and Overman (2005), we use a travel time-based or distance-based agglomeration index where space is treated as continuous instead of other popular indices such as the Isard Herfindahl and Theil indices, which require arbitrary geographical units. Specifically, we define the agglomeration index based on the difference between (1) the actual spatial distribution of commercial facilities where various agglomeration forces would work and (2) the counterfactual spatial distribution where facilities are randomly distributed, i.e., none of the agglomeration forces are effective.

Unlike other indices involving aggregation at a specific spatial level, the continuous index possesses the following two properties: (1) the values are comparable across spatial scales, and (2) the values are unbiased with respect to arbitrary changes to spatial classification (Combes et al., 2008). These properties are particularly important for the current study where we compare the index values across cities: other zone-based agglomeration indices would invoke bias as the spatial scales of administrative boundaries differ by city (for example, zone size tends to be typically larger in less populated areas). Notably, we compare the pairwise distance result from three different distance metrics, including Euclidean distance, network distance, and travel time (by car). By comparing three different distance metrics, we attempt to explore the importance of using travel time and network-based distance measures that can reflect the actual distance between facilities accurately considering the geographic conditions restricting the developable area. In the remainder of this section, we first introduce the data used, followed by details of the analytical procedure.

The analytical procedure applied in this study can be divided into four steps: 1) calculating the pairwise network distance of commercial facilities, 2) constructing the counterfactuals, 3) establishing the agglomeration index, and 4) analyzing the association between the agglomeration index and city-level variables through correlation and decision tree analyses.

1) Calculating the pairwise network distance of commercial facilities

   We first calculate the pairwise distance of commercial facilities. While most previous studies (e.g., Duranton and Overman, 2005) employ Euclidean distance, we adopt the network distance and travel time to reflect the actual distance between facilities accurately considering the geographic conditions restricting the developable area. More specifically, the pairwise network distance $\bar{d}^c$ is defined as:

$$\sum_i \sum_{j(\neq i)} d_{ij}^c / n_c(n_c - 1) \tag{4.1}$$

where n_c is the total number of commercial facilities, and d_{ij}^c is the pairwise distance between facility i and facility j.

2) Constructing counterfactuals
The locations of public facilities (i.e., school, medical, community center, park, and the combination among them) serve as counterfactuals. It would be reasonable to assume that these facilities' spatial distribution is free from agglomeration forces and that the pairwise network distance between schools and medical facilities within a city can then serve as a counterfactual. Similar to commercial facilities, the pairwise network distance of public facilities $\bar{d}^p$ is defined as:

$$\sum_i \sum_{j(\neq i)} d_{ij}^p / n_p(n_p - 1) \tag{4.2}$$

where n_p is the total number of public facilities, and d_{ij}^p is the pairwise distance between facility i and facility j.

3) Calculating the agglomeration index
We define the agglomeration index as the ratio of the average pairwise network distance of commercial facilities divided by the average pairwise network distance between public facilities as:

$$AI = \frac{\bar{d}^p}{\bar{d}^c}, \tag{4.3}$$

where *AI* is the agglomeration index of a city, with a higher value indicating the greater agglomeration of commercial facilities.

4) Analysis of association with city-level variables
To explore the association between the agglomeration index and city-level characteristics, we perform two analyses. First, we calculate the Pearson correlation coefficients between the agglomeration index and city-level characteristics. Second, we develop a decision tree model using the significant variables identified from the correlation analysis. There are two reasons to use decision tree analysis. First, many city-level characteristic variables are highly correlated, as shown in the manuscript, and thus using standard multivariate statistics would be problematic. Second, we can classify cities into several groups based on their characteristics. This allows us to take the further analysis of the association between agglomeration index and its transportation characteristic and its share of commercial facilities in agglomerated areas. Note that Safira and Chikaraishi (2019) made the first attempt to obtain an agglomeration index using Euclidian distance and revealed no significant association with car dependence. The second group comprises city-level characteristics, including the city population, the city's total area size in a square kilometer, the city's population density, the number of commercial facilities, and the number of public facilities.

4.3. STUDY AREA

We select the 69 Japanese cities according to the availability of other city-level information, particularly from the nationwide person trip survey conducted by the Ministry of Land, Infrastructure, Transport, and Tourism (2008). Therefore, we select 69 cities in Japan as our case study with regards to the availability data. The cities are included:

Table 4.1. The 69 cities in Japan

No	City Name	No	City Name	No	City Name	No	City Name
1	Nara	19	Tokorozawa	37	Tokushima	55	Tokai
2	Otake	20	Yamanashi	38	Kanazawa	56	Soja
3	Fukuoka	21	Oyabe	39	Yasugi	57	Hitoyoshi
4	Yokohama	22	Shizuoka	40	Morioka	58	Toyohashi
5	Kawasaki	23	Yokkaichi	41	Omihachiman	59	Toyonaka
6	Kitakyushu	24	Kyoto	42	Uji	60	Yuzawa
7	Matsuyama	25	Matsudo	43	Usuki	61	Imabari
8	Saitama	26	Akashi	44	Iwata	62	Ina
9	Kobe	27	Kochi	45	Shiogama	63	Otaru
10	Sendai	28	Takasaki	46	Inagi	64	Kameyama
11	Nagoya	29	Ome	47	Toride	65	Urasoe
12	Sapporo	30	Joetsu	48	Kasugai	66	Kure
13	Hiroshima	31	Komatsu	49	Dazaifu	67	Nagato
14	Koriyama	32	Matsue	50	Isahaya	68	Chitose
15	Kumamoto	33	Gifu	51	Kagoshima	69	Kainan
16	Utsunomiya	34	Tsushima	52	Hirosaki		
17	Chiba	35	Sakai	53	Izumisano		
18	Osaka	36	Odawara	54	Nankoku		

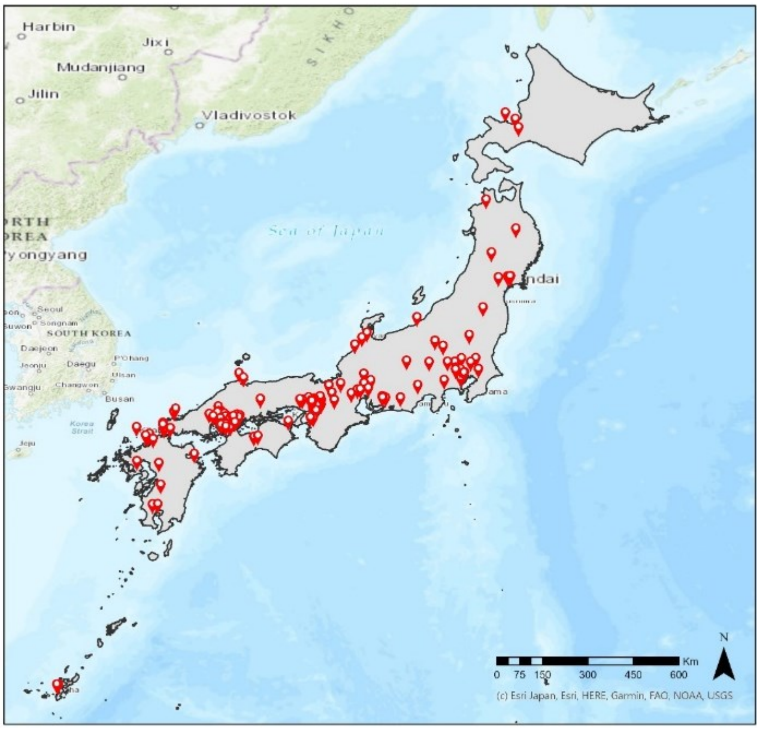


Figure 4.1. Map of 69 Japanese cities as the study area

4.4. DATA

To conduct the analysis, we used commercial facility location data from the Census of Commerce conducted by the Ministry of Economy, Trade, and Industry in Japan in 2014. This data includes the street address of the commercial facility and the name and type of facility. The commercial facilities in this study comprise department stores, textile, clothing, fashion, personal items, food and beverage, building materials, mineral/metal materials, machine tools (i.e., automobile, bicycle, equipment, etc.), general supermarkets and others (e.g., furniture, fuel, book stationery, sporting goods, office for mail order/online shop, vending machines, etc.). Although making a distinction in service type is an important research topic, particularly when identifying co-agglomeration phenomena (e.g., Kolko, 2007), it lies outside the scope of the present analysis.

One unique characteristic of the Census of Commerce data is that it contains information on whether commercial facilities are located in agglomerated areas with the following five categories: (1) station, (2) central business district (CBD), (3) residence, (4) roadside and (5) others (i.e., tourism site, religious site, etc.). We can expect that higher transit dependency would increase the number of commercial facilities falling into the category of “station” while shops in the shopping streets of European cities would typically be included in “CBD”. Conversely, we may observe that additional commercial facilities fall into the category of “roadside” when cities are more car-dependent.

In the empirical analysis, in addition to the geographical coordinates of commercial facilities, we use the public facility location data to obtain the counterfactual distribution. The candidate public facilities include schools (i.e., elementary school, junior high school, senior high school), medical facilities (i.e., hospital and clinic), community centers, and parks in 2015. The public facilities data was obtained from the website of the Ministry of Land, Infrastructure, and Transport (available from http://nlftp.mlit.go.jp/ksj/).

After obtaining the agglomeration index, we analyze the association between the agglomeration index and the city-level characteristics, including transportation, socio-economic and geographical characteristics. For transportation characteristics, we used the data from the nationwide person trip survey conducted by the Ministry of Land, Infrastructure, Transport, and Tourism in 2008 that including the average of trip distance, an average of travel time, and the share of transport mode usage (i.e., car, motorbike, walk, train, bike, and bicycle). For socio-economic and geographical characteristics, population size, population density, and area size data that obtained from the population census data from the Ministry of Internal affairs and Communication in 2015. Using data from the person-trip survey enables us to analyze the association between the agglomeration index and city-level travel-related variables. Note that transport infrastructure and consequent travel behavior do not have a one-to-one correspondence. In this study, we use variables on the revealed travel behavior as proxy indices of the service level of transportation systems, which are the outcomes of the combination of transport infrastructure and service operations. The selection of 69 Japanese cities is corresponding to the availability of other city-level data, particularly the nationwide person trip survey.

Table 4.2. General transportation (modal share) characteristics of the case study

Components	Average Value
Transportation Variable	
% of Walk Share	15.39
% of Bicycle Share	9.54
% of Motorbike Share	2.00
% of Car Share	61.72
% of Bus Share	1.83
% of Train Share	9.50
Area Size	342.11
Number of Population	503,527.28

Source: MILT, 2020

4.5. RESULT AND DISCUSSION

In this section, we first introduce the selection results of public facility types for counterfactuals and distance metrics. We then explore the association between the agglomeration level and city-level characteristics through correlation analysis and decision tree analysis.

4.5.1. Selection of Counterfactuals and Distance Metrics

Ideally, the use of residential distribution at the disaggregate level would be the best to obtain counterfactuals. However, we could not obtain the data for this analysis, and thus we decided to use the distribution of public facilities to obtain the counterfactuals. The choice of public facility type needs to be carefully done since the agglomeration would occur for some type of public facility. To empirically identify a suitable counterfactual, we empirically compare the average pairwise distances for different public facilities (including schools, medicals, community centers, parks, the combination of schools and community centers, and combination of schools, community centers, and parks) and select the facility type that gives the largest average pairwise distance, assuming that the longer pairwise distance implies that less agglomeration occurs. Table 4.3. shows the results. We confirm that the combination of school and community center (SC) has the largest average pairwise distance and thus use it to obtain counterfactuals with the assumption that there is no agglomeration for the school and community centers.

For distance metrics, we compare three different distance metrics, including the Euclidean-based distance, the network-based distance, and car travel time in the calculation of average pairwise distance and its agglomeration index. In this study, car travel time was chosen for the subsequent analysis since both shopping destination choice (by the consumer) and commercial facility location choice (by supplier) would be made based on travel time rather than distance. However, for some cities or countries, the availability of travel distance data was difficult to obtain. Our results shown in Table 4.3 confirm that the results with network distance would be quite similar to those with car travel time, while the results with Euclidean distance are considerably different. The dataset of all cities' average pairwise distance and the agglomeration index by public facility type and distance metric is provided in Appendices.

Table 4.3. Average pairwise distance and agglomeration index

Facility Type	Average pairwise distance			Agglomeration index		
	Euclidean distance	Network distance	Travel time	Euclidean distance	Network distance	Travel time
Commercial	5.07	6.09	14.42	-	-	-
School (S)	7.42	8.07	18.16	1.49	1.35	1.29
Medical (M)	5.37	5.90	14.27	1.04	0.96	0.97
Community center (C)	7.69	8.37	18.05	1.51	1.36	1.26
Park (P)	6.04	6.67	16.06	1.16	1.08	1.08
School & medical (SM)	6.45	6.42	15.21	1.29	1.05	1.05
School & community center (SC)	7.75	8.49	20.06	1.59	1.41	1.36
School, community center, and park (SCP)	7.56	7.78	17.88	1.51	1.28	1.25

Using the travel time-based distance metric with school and community centers as counterfactuals, we calculate the average pairwise distance and agglomeration index for all

69 Japanese cities. Table 4.4. summarizes cities with the longest and shortest average pairwise distance for both public facilities and commercial facilities, and Table 4.5. summarizes the most and the least agglomerated cities. We found that Yokohama has the longest average pairwise distance for commercial and public facilities, while Shiogama has the shortest average pairwise for public facilities, and Hitoyoshi has the shortest average pairwise for commercial facilities. We also found that there are significant differences between the average pairwise distance of commercial facilities and that of public facilities (Welch's t-test result: 4.09, statistically significant at the one percent significance level).

Table 4.4. Average pairwise distance of facilities
(Distance metric: car travel time; public facility type: school & community center)

Travel time (min)	Commercial facility	Public facility
Longest (City)	32.80 (Yokohama)	49.79 (Yokohama)
Shortest (City)	4.97 (Hitoyoshi)	4.94 (Shiogama)
Mean	14.42	20.06
Std. dev.	5.90	9.79
Observations	69	

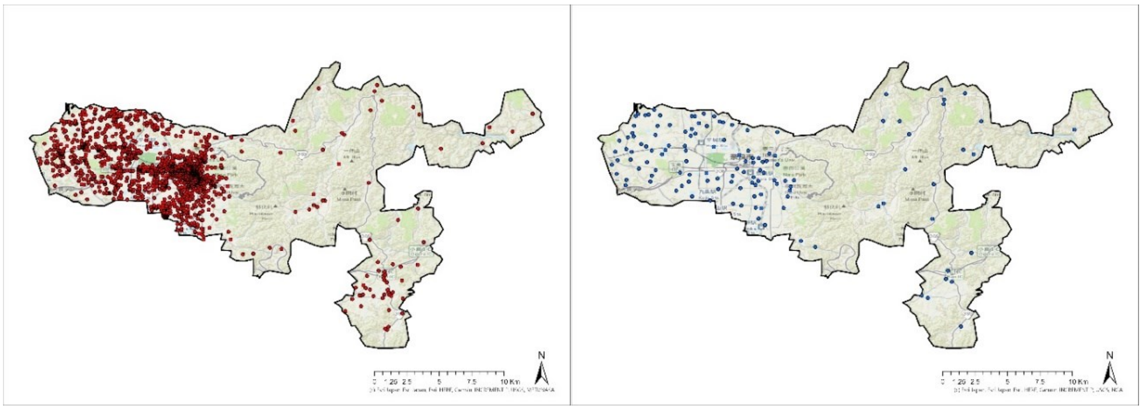
As mentioned above, we took the ratio between the average pairwise distance of public facilities and commercial facilities to obtain the agglomeration index. As shown in Table 4, Nara City is the most agglomerated city with an agglomeration index of 1.82, and Imabari City is the least agglomerated city among 69 Japanese cities with an agglomeration index is 0.77.

Table 4.5. Summary of agglomeration index of 69 Japanese cities

Variable	Agglomeration Index
Highest Agglomeration Index (City)	1.82 (Nara)
Lowest Agglomeration Index (City)	0.77 (Imabari)
Mean	1.36
Std Dev	0.21
Observations	69

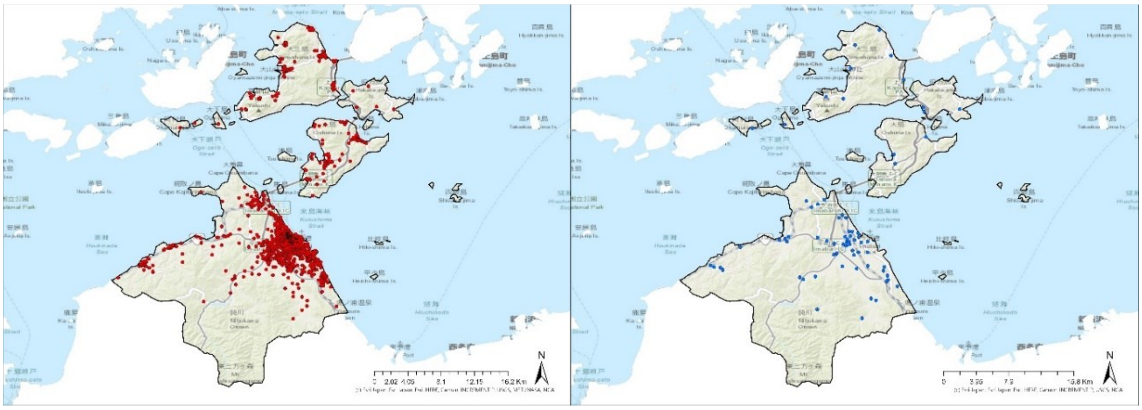
Nara, the most agglomerated city, is a famous historical tourist destination in Japan. From Figure 4.2., we can confirm that commercial facilities agglomerate in an area connecting Nara Station and the Todaiji Temple. In contrast, there appears to be less agglomeration in the public facilities, largely because the distribution of public facilities follows the distribution of the residents. The least agglomerated city is Imabari, a typical local city in Japan, where population decline has accelerated (down about 20% from its peak). We also found that, out of 11 cities with one million or more inhabitants, the agglomeration index exceeds 1.5 for 9 cities, implying that the larger cities tend to be agglomerated.

In contrast, the five least-agglomerated cities (Imabari, Shiogama, Urasoe, Tokai, and Dazaifu) are less populated (populations of these five cities are from 56,256 to 167,872). This indicates that the city scale could be one of the important factors affecting the agglomeration level. Given that population typically influences the development of transport systems as well, we should carefully discuss the impacts of transport systems on the agglomeration level. As revealing the actual causal structure may not be possible with cross-sectional data, in the following sections, we conduct an exploratory analysis (correlation and decision tree analyses) to discuss the possible associations between the agglomeration index and city-level characteristics, including scale-related variables such as population and area size, and transportation variables such as modal share.



(a) Commercial facility distribution (b) Public facility distribution

Figure 4.2. Facility distributions of Nara, the most agglomerated city



(a) Commercial facility distribution (b) Public facility distribution

Figure 4.3. Facility distributions of Imabari, the least agglomerated city

4.5.2. Association with City-Level Characteristics: Correlation Analysis

To identify city-level characteristics that are highly correlated with the agglomeration index, the Pearson correlation is first confirmed. Table 4.7. and Figure 4.4. show the results. We found that the area size, population density, average travel time, the share of car usage, and the share of train usage are significantly correlated with the agglomeration index. The major findings from the identified correlation coefficients are as follows.

1. Population density and area size have positive associations with the agglomeration index.
2. The average travel time (trip duration) has a negative association with the agglomeration level, implying that the greater agglomeration would emerge together with the shorter travel time.
3. Regarding the association between the agglomeration level and modal share, more car-dependent and transit-dependent cities are less agglomerated. In contrast, a greater share of walk and bicycle increases the agglomeration level, though these are not statistically significant. Note that the impacts of train share are non-linear, and thus we could not simply conclude that transit-dependent cities are always less agglomerated.

Overall, the correlation results indicate that there is a significant association between transport systems and the agglomeration level. Simultaneously, there are high correlations among the city-level characteristics, implying that it may be difficult to establish a one-to-one relationship between the agglomeration level and the state of the transportation system.

Table 4.6. List of correlation and decision tree analysis variables

Variable	Description
Agglomeration index	
AI_TT_SC	Agglomeration index of city based on travel distance calculation with school and community center as the counterfactual
City-level attributes	
Population	The logarithm of the total city population
Area	The total area of the city in km^2
PopDensity	The city population density
N_Com	The total number of commercial facilities in the city
N_SCH	The total number of schools in the city
N_CC	The total number of community centers in the city
Dist_Com	The average pairwise network distance of commercial facilities
Dist_SC	The average pairwise network distance of public facilities (schools and community centers)
Transportation variables	
Travel Time	The average travel time per trip within the city
Distance	The average distance per trip within the city
Car	Percentage of modal share, car
Motorbike	Percentage of modal share, motorcycle
Bicycle	Percentage of modal share, bicycle
Walk	Percentage of modal share, walking
Train	Percentage of modal share, train
Bus	Percentage of modal share, bus

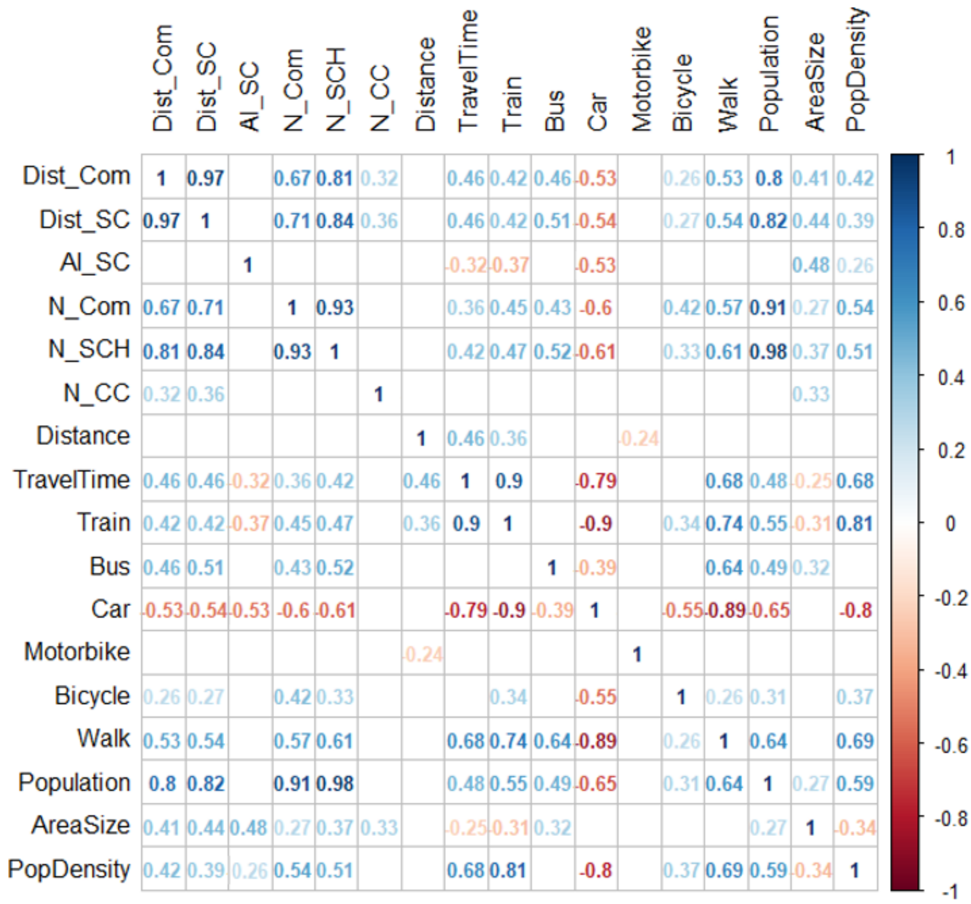


Figure 4.4. Correlation matrix of variables

Table 4.7. Correlation coefficients

Variables	Estimates Value	t-Value	Sig. Sign
Population	4.35E-07	1.58	
Area Size	4.82E-03	3.08	**
PopDensity	2.61E-02	3.21	**
N_Com	-8.36E-07	-0.08	
N_SCH	-2.16E-05	-1.28	
N_CC	2.27E-04	0.22	
Dist_Com	-5.46E-04	-1.42	
Dist_SC	4.64E-04	1.38	
Travel Time	-3.22E-02	-3.11	**
Distance	4.74E-01	0.35	
Car	-5.37E-02	3.49	**
Motorbike	2.65E-01	0.03	
Bicycle	2.27E-01	0.34	
Walk	3.47E-01	0.31	
Train	-3.71E-02	3.02	**
Bus	3.19E-01	0.03	

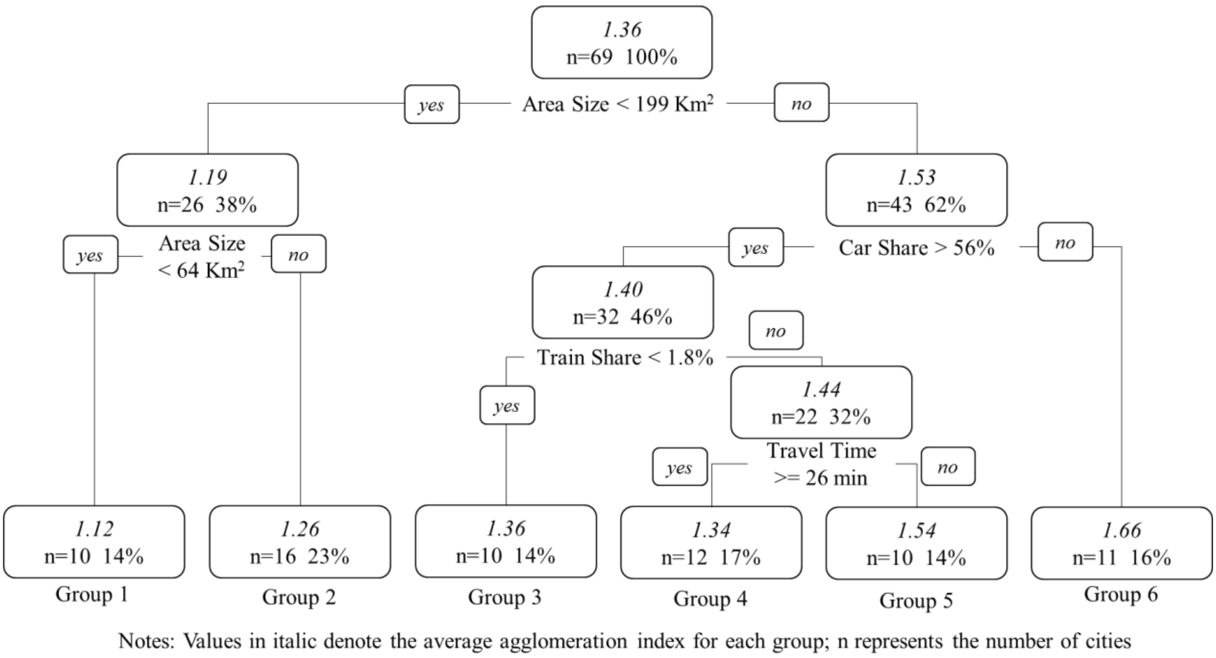
** Significant at 0.01 level.

4.5.3. Association with City-Level Characteristics: Decision Tree Analysis

Based on the correlation analysis in the previous section, we include five significant variables in the decision tree analysis, including area size, population density, average travel time, car share, and train share. We apply a Classification and Regression Trees (CART) algorithm (Breiman et al., 1984), which is one of the most widely used algorithms for decision tree analysis, in order to classify cities into several groups based on their characteristics. For the analysis, we used the R package "rpart" (Therneau et al., 2019), where the "ANOVA" method was chosen to produce a group of cities based on the degree of similarity in their characteristics. We set the minimum split and minimum bucket as 10, ensuring that final nodes (called groups in this study) contain at least ten cities.

Figure 4.5. illustrates the results of the decision tree analysis. The analysis divides the 69 cities into six groups. The first split is done based on area size (whether it is smaller than 199 km^2 or not), confirming that cities with larger area sizes tend to be agglomerated. One of the possible reasons is the cities with larger area sizes would obtain larger benefits from agglomeration: benefits from *matching* and *trip chaining* would be getting larger with the increase in area size.

In the second split, cities with smaller area sizes are further divided into two groups by area size (whether it is smaller than 64 km^2 or not), confirming that smaller cities tend to be less agglomerated (group 1). For cities with larger area sizes they are further divided into two groups based on car share (whether it is larger than 56% or not): we confirm that cities with larger area sizes and lower car share tend to be agglomerated (group 6). Actually, most of the cities in group 6 are metropolitan cities, such as Kyoto, Osaka, Sapporo, Fukuoka, and Hiroshima. For cities with larger area sizes and higher car share are further divided into two groups by train share (whether it is smaller than 1.8% or not). It is confirmed that cities with a lower train share tend to be less agglomerated (group 3) compared to cities with a higher train share. Most of the cities in group 3 are local cities, such as Hirosaki, Hitoyoshi, Imabari, etc. Cities with higher train share are further divided into two groups by travel time (whether it is smaller than 26 minutes or not). It is found that cities with longer travel times tend to be less agglomerated (group 4), and cities with shorter travel times tend to be more agglomerated (group 5). In order to further understand the characteristics of each group, in the remaining part of this section, we conduct an additional aggregation analysis.



Group 1	Akashi, Dazaifu, Inagi, Izumisano, Matsudo, Shiogama, Tokai, Toyonaka, Tsushima, Urasoe
Group 2	Iwata, Kainan, Kameyama, Kasugai, Kawasaki, Nankoku, Odawara, Ome, Omihachiman, Otake, Oyabe, Sakai, Tokorozawa, Tokushima, Toride, Uji
Group 3	Hirosaki, Hitoyoshi, Imabari, Ina, Kochi, Komatsu, Matsue, Nagato, Yasugi, Yuzawa
Group 4	Kagoshima, Kitakyushu, Koriyama, Kumamoto, Kure, Morioka, Sendai, Soja, Takasaki, Toyohashi, Utsunomiya, Yokkaichi
Group 5	Chitose, Gifu, Isahaya, Joetsu, Kanazawa, Matsuyama, Otaru, Shizuoka, Usuki, Yamanashi
Group 6	Chiba, Fukuoka, Hiroshima, Kobe, Kyoto, Nagoya, Nara, Osaka, Saitama, Sapporo, Yokohama

Figure 4.5. The results of decision tree analysis

Table 4.8. presents the share of commercial facilities by the type of agglomerated areas for each group, and Table 4.9. presents the average city-level characteristics for each group. From Table 4.8., we confirm that cities in group 1 and group 2 have more commercial facilities around stations. It is common for the smaller cities in Japan to have more commercial facilities near stations since the station is often designed or dedicated as a central area of the city. This finding is also supported by the share of the train in group 1 and group 2 that is 15.53% and 11.59%, respectively. Although their train shares are relatively high compared to other groups, their agglomeration levels are the lowest across groups. This would be because their area sizes are small: as discussed above, *sharing* and *trip chaining* would be less beneficial for a city with a smaller area size.

In contrast, cities in group 3 have larger area sizes, resulting in more agglomeration compared to cities in groups 1 and 2. On the other hand, the agglomeration index of group 3 is lower compared to groups 4, 5, and 6. This would be because of the characteristics of the transportation systems in group 3: Group 3 has the highest car share (77.27%), leading to the highest agglomeration level on roadside areas (19.16%). This indicates that agglomeration forces that occurred in group 3 are different from those in groups 1 and 2: Residents in cities belonging to group 3 may access commercial facilities in CBD and roadside areas by car.

Groups 4 and 5 have similar characteristics in terms of the type of agglomeration areas and modal share. They have a higher car share, while agglomeration occurs in residential areas. These imply that these cities may have a polycentric urban form, but further analysis is needed to make a general conclusion.

In cities belonging to group 6, commercial facilities are agglomerated in station and CBD areas, while they have the highest train share among the six groups. Their average travel distance and travel time are the largest, indicating that agglomeration benefits are obtained with the higher travel cost in these cities.

Table 4.8. Share of commercial facilities by the type of agglomerated areas

Group	*Type of agglomerated areas*				
	(1) Station	*(2) CBD*	*(3) Residence*	*(4) Roadside*	*(5) Others*
Group 1	56.74%	9.69%	19.29%	11.25%	3.02%
Group 2	56.87%	11.30%	26.04%	5.00%	0.79%
Group 3	12.08%	35.96%	28.19%	19.16%	4.61%
Group 4	22.81%	31.78%	34.02%	11.23%	0.16%
Group 5	24.01%	28.37%	33.08%	9.68%	4.87%
Group 6	41.83%	35.10%	15.23%	6.32%	1.52%
All Group	35.72%	24.54%	26.81%	10.44%	2.49%

Note: Shaded cells indicate the highest share in each group.

Table 4.9. City-transport characteristics

Group	Average Travel Distance	Average Travel Time	Average Percentage of Transport Mode Usage (%)						Average Population Size (people)	Average Area Size (Km^2)	Average Density (population /km^2)
			Train	Bus	Car	Motor bike	Bicycle	Walk			
1	11.89	29.26	15.53	1.18	54.43	2.28	9.20	17.39	179,010	35.92	4,806
2	12.09	27.77	11.59	0.87	61.10	2.24	10.13	14.07	268,511	123.87	2,241
3	12.17	22.78	1.27	0.84	77.27	1.68	8.48	10.46	123,615	467.56	300
4	11.76	26.91	4.56	2.61	67.79	1.73	8.60	14.72	490,789	483.60	1,083
5	11.77	24.57	3.50	2.16	69.35	2.07	8.38	14.54	274,971	524.87	628
6	12.80	30.59	19.31	3.57	41.61	1.94	12.07	21.51	1,707,435	503.36	4,502
Average	12.08	27.10	9.50	1.83	61.73	2.00	9.55	15.39	503,527	342.11	2,257

Taking the types of agglomeration forces into account, we found that (1) cities with larger area sizes and higher train shares enjoy agglomeration presumably through *matching* and/or *trip chaining*, while cities with smaller area sizes less enjoy agglomeration even their train share is high, (2) car-dependent cities enjoy agglomerations presumably through *sharing,* particularly by agglomerating in their residential and roadside areas. These results indicate that transportation systems may moderate agglomeration forces, i.e., the dominant agglomeration forces vary across cities depending on the transportation systems. These also imply the importance of handling how transportation systems moderate the agglomeration economy in the development of theoretical and empirical models, rather than simply identifying to what degree the level of accessibility or density (which can be seen as simplified transportation system performance measures) lead to the agglomeration economy.

The above-mentioned findings are crucial in shaping relevant policies, particularly in transport investment appraisals. Recently, evaluating the broader economic impact of transport infrastructure investment in an agglomeration economy has gained popularity (Graham, 2007; Chatman and Noland 2011, 2014; Kidokoro, 2015; Graham and Gibbons, 2019). Graham (2007) estimates the additional benefits from the agglomeration would be around 25%, while Horcher et al. (2020) show that agglomeration benefits strongly affect optimal public transport policies, indicating that optimizing transportation services without considering agglomeration effects would not be optimal in the long run.

Thus, existing studies clearly indicate the importance of considering agglomeration effects in decision-making on transport investment and management strategies. However, there are a number of important limitations in the existing literature. Chatman and Noland (2011) state that "… the challenges are numerous in conducting research to determine whether and when public transport improvements increase agglomeration economies. The possible agglomeration mechanisms at work imply a dizzying array of possible measures and methods. Tracing the links between public transport and agglomeration is an important step that has not been explored yet”. Our study contributed to addressing this research gap as we empirically show that the significant association between agglomeration and city characteristics, including transport characteristics.

4.6. CONCLUSION

In this study, we conducted an exploratory analysis on the association between the urban agglomeration of commercial facilities and the city-level characteristics of 69 Japanese cities with a particular focus on transportation systems. We develop a simple agglomeration index inspired by Duranton and Overman (2005) that we can compare across cities. Major findings from our empirical analysis are (1) cities with larger area sizes, and higher train shares enjoy agglomeration presumably through *matching* and/or *trip chaining* (Takahashi, 2013; Koster et al., 2019), while cities with smaller area sizes less enjoy agglomeration even their train share is high, (2) car-dependent cities enjoy agglomerations presumably through *sharing* (Pashigian and Gould, 1998), particularly by agglomerating in their residential and roadside areas. These findings also lead to two academic implications. First, our results highlight the importance of handling how transportation systems moderate the agglomeration economy in the development of theoretical and empirical models, rather than simply identifying to what degree the level of accessibility or density leads to an agglomeration economy. Second, in empirical analysis, it is crucial to use travel time or network distance rather than Euclidian distance, as the results could differ substantially between them.

We should also note that this study involves a number of limitations. First, while we simply use a city’s administrative boundary to define the unit of analysis, this could be inappropriate. One simple solution would be to deal with the whole of Japan as a unit and compute the pairwise distance between all facilities. Unfortunately, this would be computationally expensive. For example, there are 52,394 commercial facilities in Osaka, and thus around 2.7 billion pairs (52,394 × 52,393) exist in just one city. As the number of pairs exponentially increases, there is a need for an alternative way to solve this issue. Second, the approach we took in this paper was more statistical than economic, and thus it is not possible to connect our analysis directly with the discussion on transport investment appraisal. To do this would require a solid microeconomic foundation that could differ depending on the agglomeration forces. Third, in the analysis, we did not distinguish agglomeration in a building (like a shopping mall) from agglomeration on the street, but the difference between these two would be important for urban planners. Related to this, the design of streets, including size, speed, and width, and zoning constraints, would also affect the emergence of agglomeration. Extending the method that can consider these aspects is an important remaining challenge. Lastly, Safira and Chikaraishi (2021) argue that on-demand transport services change the type of the dominant agglomeration forces. More empirical studies on how these emerging mobilities change agglomeration forces would also be needed to discuss their wider impacts.

Chapter 5: THE IMPACT OF MSTP ON THE URBAN FORM: A CASE OF JAKARTA, INDONESIA

This chapter explores the impact of MSTP on facility distribution (i.e., combination food merchant, online food merchant, and dine-in food merchant) through the agglomeration index analysis in Jakarta, Indonesia. This study attempt to answer two research questions regarding the impact of MSTP on the urban form, including "What distribution changes do MSTP bring about on the facility distribution?" (RQ 2.1) and "How these induced changes in urban form?" (RQ 2.2). This chapter also contains the introduction, methodology, study area, data used, result and discussion, and conclusion of the study.

5.1. INTRODUCTION

Recently, exploring the role of information and communication technologies (ICT) in human activity-travel decisions has become a significant theme in transportation research due to the rapid development of ICT tools. Researchers have recognized that an increase in the use of ICT may lead to changes in the location, timing, and duration of people's activities, and the widespread use of ICT will induce new patterns of activity and travel in space and time (Kwan, 2020; Dijst, 2004).

Multi-service transport platforms (MSTPs) are one of the ICT innovations in the field of transportation, which has been used by many people recently. In Indonesia, there are two major MSTPs companies called GOJEK and GRAB. The core of their operating system is the presence of motorbike drivers. MSTPs companies utilize motorbike drivers as their fleets to provide not only transportation services called ojek online (motorbike ride-hailing), but also other life services, including online food delivery (FD) service, grocery, and non-grocery shopping agency service, cleaning service, massage services, and so forth. Among others, the popularity of online FD services is growing rapidly. GoFood by GOJEK and Grab Food by GRAB, started in 2015, are the most popular online FD services in Indonesia. Increases in the number of online food merchants and hence food options and provision of monetary incentives (e.g., discount and voucher) have further led to the increasing number of service users. The presence of online FD services from MSTPs allows people to access many food merchants nearby without traveling.

Replacement of physical access with virtual access through MSTPs would lead to changes in facility distribution in a city. Numerous literatures has emerged in the field of regional science and urban economies that examines the questions of whether spatial circumstances give rise to agglomeration economies where firms can benefit through co-location (Glaeser et al. 1992; Rosenthal and Strange, 2003). However, the benefits from the agglomeration could become lower under the presence of MSTPs due to the reduced need for physical proximity. For example, Rodrigue (2020) pointed out that ICT innovation in the transportation field has broadly led to changes in urban form. The more extreme the changes in transportation technology have been, the more changes in the urban form could happen. Some researchers predict the dissolution of the city due to the increasing ease of transportation and communication (e.g., Webber, 1968; Fathy, 1991), where the ease of transportation and communication may be able to break the spatial barriers resulting in spatial dispersion in community. A similar phenomenon with the increasing ease of transportation and communication might happen due to the presence of MSTPs, increasing the spatial mismatch between the place people stay (i.e., home and office) and food merchant locations, potentially resulting in urban sprawl and the loss of vitality of the cities in the long term.

Given the above background, this study aims to empirically explore the impact of MSTPs on the distribution of food merchants by exploring differences in the density and agglomeration of the facilities between dine-in and online food merchants. Our main hypotheses to be tested are:

(1) dine-in food merchants may tend to be agglomerated in the center of the metropolitan (agglomeration at the metropolitan level) to increase their area's attraction for the consumer to come, and

(2) online food merchants may tend to be agglomerated at the neighborhood level to attract a certain amount of motorbike drivers to keep the delivery service level.

Confirming these hypotheses is crucial since, if the above hypotheses are true, the diffusion of online food merchants could lead to the degradation of the city's vitality, and in the long run, it may also change the structure and form of the city.

In order to test the above hypotheses, we utilize the method to calculate the agglomeration index of facilities used in Safira and Chikaraishi (2019), where the index is defined as the ratio of the average pairwise distance of target facilities and that of public facilities. In addition, we also pay attention to the areal unit or boundary of the analysis. The selection of the areal boundary has long been discussed in spatial and geographical analysis, which is well known as the Modifiable Areal Unit Problem (MAUP). Based on Arbia and Petrarca (2011), the MAUP refers to the representation of data whose value is affected, often signed by the spatial unit employed. More specifically, to explore the agglomeration at the city level, we may have to employ the larger spatial boundary. In comparison, the smaller spatial boundary would be more appropriate to explore the agglomeration at the neighborhood level. To handle this, we apply the method to different spatial units (i.e., cities, districts, and neighborhoods).

5.2. METHODOLOGY

This study explores the density and agglomeration index of facilities to explore the impact of MSTP on the distribution of facilities. Following Safira and Chikaraishi (2019), we calculate the agglomeration index of each type of facility by taking the average pairwise distance of each food facility and divided by the average pairwise distance of public facilities. Unlike other indices involving aggregation at a specific spatial level, the continuous index used has the following two advantages: (1) the values are comparable across spatial scales, and (2) the values are unbiased with respect to arbitrary changes to spatial classification. Although these properties partially avoid the MAUP mentioned in the introduction yet, the index values would still depend on the spatial boundary employed. Thus we calculate the agglomeration indices with four different spatial boundaries, including metropolitan, city, district, and neighborhood.

The analytical procedure will be divided into four steps analysis: (1) calculating the average pairwise distance of each targeted facility (i.e., combination food merchants, online food merchants, and dine-in food merchants); (2) constructing the counterfactuals, i.e., calculating the average pairwise distance of public facilities; (3) developing the agglomeration index; and (4) comparing the agglomeration index result across different spatial boundaries and different facility types.

1) Calculating the average pairwise network distance of targeted facilities

In this study, there will be three types of target facilities that will be used, including

(i) the combination of food merchants, (ii) online food merchants, and (iii) dine-in food merchants. Following Safira and Chikaraishi (2019), to calculate the average pairwise distance among facilities, we adopt the network-based distance and travel time (by car) to reflect the actual distance between facilities, considering the geographical condition that restricts the developable area. The pairwise network distance for targeted facilities $\bar{d}^{TF}$ is define as:

$$\sum_{i}\sum_{j(\neq i)} d_{ij}^{TF} /(n_{TF}(n_{TF}-1)) \tag{5.1}$$

where n_{TF} is the total number of targeted facilities, and d_{ij}^{TF} is the pairwise distance between facility i and j.

2) Constructing the counterfactuals
The locations of public facilities (i.e., park, school, mosque, church, fire station, library, and post office) serve as counterfactuals. The selection of the public facilities as counterfactuals assumes that the provision of public facilities in urban areas is based on the principle of equitable distribution or need-based on the location of the community residence. It would be reasonable to assume that the spatial distribution of these facilities is free from agglomeration forces. Similar to commercial facilities, the pairwise network distance of public facilities $\bar{d}^{CF}$ is defined as:

$$\sum_{i}\sum_{j(\neq i)} d_{ij}^{CF} /(n_{CF}(n_{CF}-1)) \tag{5.2}$$

where n_{CF} is the total number of public facilities, and d_{ij}^{CF} is the pairwise distance between facility i and facility j.

3) Developing the agglomeration index
We define the agglomeration index as the ratio of the average pairwise network distance of commercial facilities divided by the average pairwise network distance between public facilities as:

$$AI = \frac{\bar{d}^{CF}}{\bar{d}^{TF}} \tag{5.3}$$

where AI is the agglomeration index of a city, with a higher value indicating the more significant agglomeration of commercial facilities.

4) Association of Agglomeration Index and City Characteristics
The agglomeration indices are obtained for each facility type with different spatial units. The facility type includes commercial facilities, food merchants (combination), online food merchants, and dine-in food merchants. The spatial unit employed in this study includes metropolitan area, city-scale, district-scale, and neighborhood-scale.

5.3. STUDY AREA

As mentioned in the previous section, we analyze the agglomeration index within a different scale in this study. Our study's area is the metropolitan DKI Jakarta. Its sub-metropolitan area included five administrative cities (i.e., Central Jakarta, South Jakarta, West Jakarta, East Jakarta, and North Jakarta), 42 districts under those five administrative cities, and 262 neighborhoods under those 42 districts. Figure 5.1. shows the map of our case study and Table 5.1. shows the general characteristics of the area.

Table 5.1. The characteristics of the study area

City Name	Area Size (Km^2)	Population (People)	Population Density (people/Km^2)	Number of Districts	Number of Neighborhood
Central Jakarta	52.38	1,138,346	21,732	8	44
South Jakarta	154.32	2,188,457	14,181	10	65
West Jakarta	124.44	2,324,121	18,676	8	56
East Jakarta	182.70	2,944,493	16,116	10	66
North Jakarta	139.99	1,711,386	12,225	6	31

Source: BPS, 2020

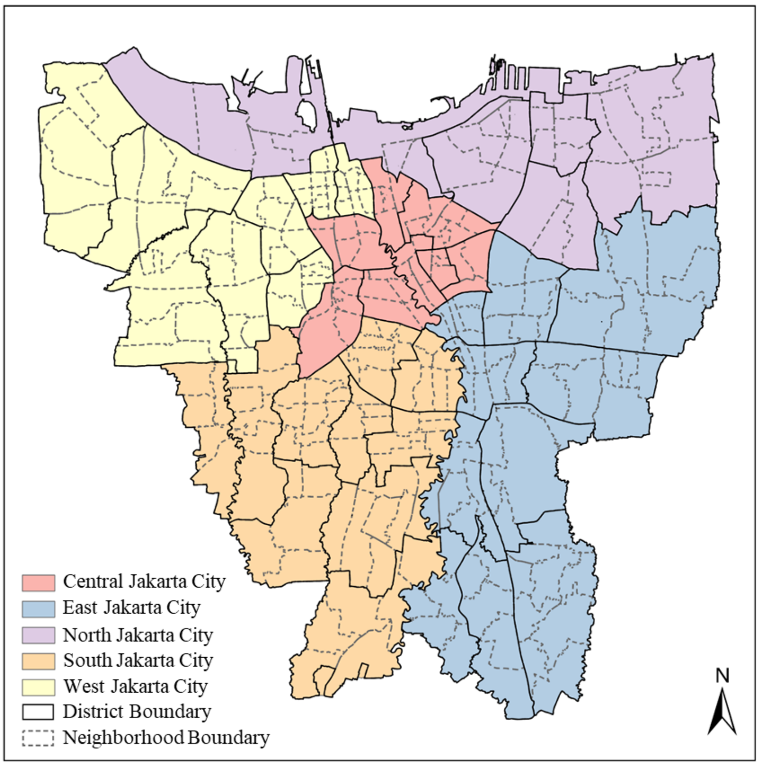


Figure 5.1. Map of study area in Jakarta, Indonesia

5.4. DATA

This study obtains the commercial and public facilities data from Google maps by using web crawler methods. Mapping data is becoming increasingly relevant in the Internet age, creating market value and supporting decision-making. Such data are commonly used in sectors; for example, catering firms may determine where to open a new restaurant by evaluating map data and competitors in the vicinity. Nowadays, web scraping and web crawling are the most used methods to extract data from websites, including the data from interactive maps (e.g., Google Maps). Web crawlers are computer programs that automatically collected several web documents from one or more web pages. A web crawler processes the obtained data and prepares the data to be eventually analyzed by other systems.

The data includes the name of the facilities, type of facilities, street address, coordinate location, opening hours, and other variables. Table 5.2. shows all categories and detail of the facilities that we use in this analysis. Although making a distinction in service type is an important research topic, particularly when identifying co-agglomeration phenomena (e.g., Kolko, 2007), it lies outside the present analysis scope.

Table 5.2. Facility type

Category	Detail
Food Facilities	(1) Restaurant; (2) Café; (3) Coffee shop; (4) Bakery; and (5) Street food vendor
Commercial Facilities	(1) Automobile shop; (2) Groceries shop; (3) Market; (4) Bank; (5) Pharmacy; (6) Hair and beauty salon; (7) Appearance store; (8) Home appliance store; (9) Electronic store; and (10) Movie theater
Public Facilities	(1) Park; (2) School; (3) Mosque; (4) Church; (5) Fire station; (6) Library; and (7) Post office

This study classifies food merchants into three groups, as shown in Table 5.3. The first type is called "combination" food merchants, which provide both dine-in and online food delivery services. The second type is online food merchants, which only provide online delivery services without any dine-in facility. It is also called ghost kitchens in cities in the UK, US, and India. These food merchants are shifting from owning the physical store to the businesses where they do not have any physical store. It may give some advantages for those food merchants in reducing the operational cost by eliminating the store rent and reducing the number of staff. The last type is dine-in food merchants, which is the food merchants only providing dine-in services without any delivery services. Using the web-crawler methods, we successfully obtained 7,408 public facilities' locations; 6,810 commercial facilities' locations; 4,458 combination food merchants' locations; 3,718 online food merchants' locations; and 586 dine-in food merchants' locations.

Table 5.3. The service of food merchants

Type of Food Merchant	Dine-in Facility	Online Delivery Facility
Food Merchant (Combination)	Available	Available
Online Food Merchant	Not Available	Available
Dine-in Food Merchant	Available	Not Available

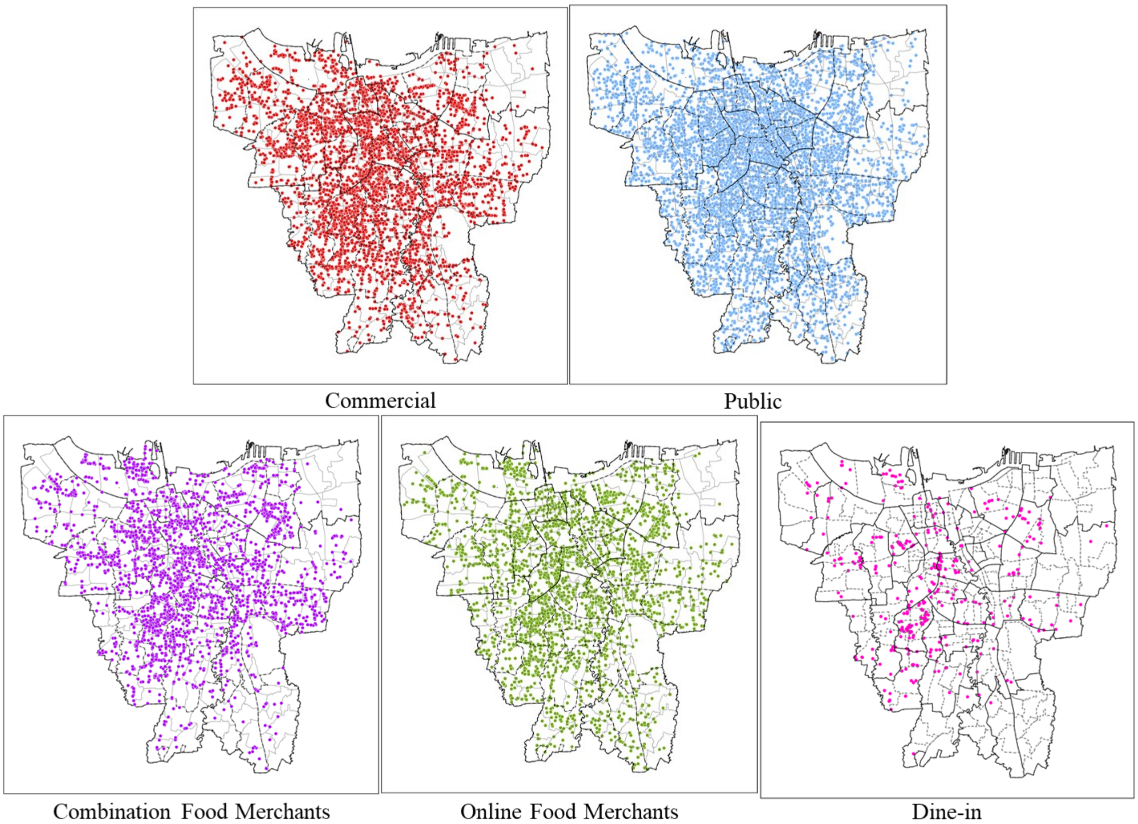


Figure 5.2. Distribution of facilities

5.5. RESULT AND DISCUSSION

5.5.1. Identified Agglomeration Indices

Table 5.4 summarizes the calculated agglomeration indices (AI) for different facility types with different spatial boundaries. Also, Figures 5.3., 5.4., 5.5. show the spatial distributions of agglomeration indices by merchant type and by the spatial scale. The details of calculated agglomeration indices are shown in appendix. The main findings can be summarized as follows:

1. Although AI values are similar across merchant types at the metropolitan scale, online food merchants (AI: 0.99) are less agglomerated than the combination and dine-in food merchants (1.06 and 1.09, respectively). This indicates that, while dine-in food merchants tend to be agglomerated, for example, in CBD (Central Business District) area at the metropolitan scale, online food merchants do not, implying that little agglomeration forces exist for online food merchants.
2. The AI values tend to be more significant when we employ a finer spatial scale. In particular, the results show that, while the agglomeration level of dine-in food merchants is not so high at the neighborhood level (1.40), that of online food merchants reaches 2.21. The higher agglomeration level was observed for online food merchants presumably because of the necessity for attracting motorbike drivers under MSTPs to keep the service level of delivery.
3. The higher agglomeration level of online food merchants at the neighborhood level was observed in the urban core and urban fringe (Figure 5.4).

The above first and second findings support the first and second hypotheses mentioned in the introduction of chapter 5, indicating that the spatial distribution of food merchants would be affected by MSTPs. The 3rd point is not expected, but it is an interesting finding to be further explored. Since higher agglomeration levels in the urban core were observed for combination and dine-in food merchants as well, the unique characteristic of online food merchants would be in the agglomeration of facilities within a neighborhood in the urban fringe. The following subsection is dedicated further to explore this unique nature of online food merchants.

Table 5.4. Average agglomeration indices with different spatial scales

Scale	Agglomeration Index								
	Combination Food Merchants			Online Food Merchants			Dine-in Food Merchants		
	Mean	Min	Max	Mean	Min	Max	Mean	Min	Max
Metropolitan	1.06	-	-	0.99	-	-	1.09	-	-
City	1.08	0.94	1.25	1.01	0.94	1.06	1.12	0.90	1.47
District	1.09	0.70	1.53	1.13	0.84	2.45	1.06	0.30	2.51
Neighborhood	1.84	0.24	6.24	2.21	0.31	7.12	1.40	0.37	4.41

Based on Figure 5.3, we found that South Jakarta has a higher agglomeration index for combination food merchants than other areas. However, on the district scale, the area with a higher agglomeration index was located in South Jakarta but scattered across districts. On the other side, the agglomeration index in the neighborhood scale shows some spatial patterns. The area with a higher agglomeration index for combination food merchants tends to be located in the central area or near the central area and some in the fringe area.

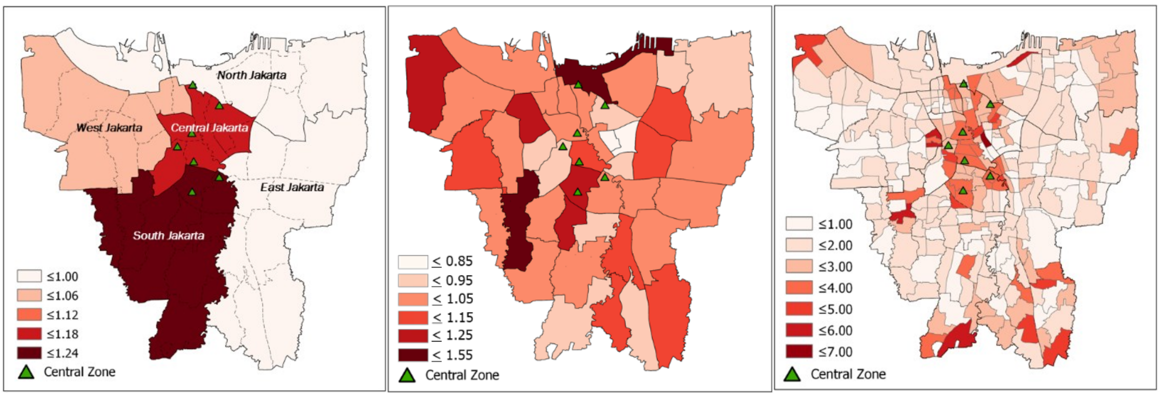


Figure 5.3. Agglomeration index of food merchants (combination)

On the other side, Figure 5.4. shows the spatial distribution of the agglomeration index for online food merchants. On the city scale, we can identify that West Jakarta has the highest agglomeration index for online-food merchants (with 2.11) than the other area, followed by Central Jakarta and South Jakarta with 2.05 and 2.04, respectively. Similar to the agglomeration index for combination food merchants, the spatial distribution of the agglomeration index for online food merchants also changed in the district scale. The spatial distribution was changed, but the agglomeration index's range also changed on the district scale. However, the result of the agglomeration index in neighborhood-scale shows some tendency in spatial distribution. The area which has a higher agglomeration index was located in the central area and the fringe area. In this sense, online food delivery may lead to developing the new service core in the central and fringe areas, which will be discussed in the next sub-section.

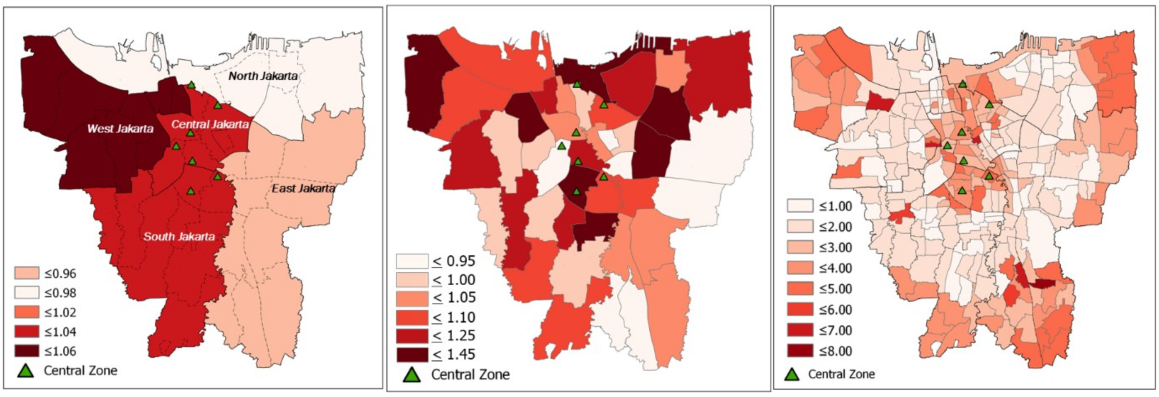


Figure 5.4. Agglomeration index of online food merchants

Figure 5.5. also shows the changes in the area that has a higher agglomeration index across space. On the city scale, most dine-in food merchants are located in Central Jakarta. This led to Central Jakarta has a higher agglomeration index of dine-in food merchants compare to other cities. However, on the district scale, many districts located in Central Jakarta are in the middle to low range of agglomeration index value. The district with the higher agglomeration index is located in the West and South Jakarta. On the other side, the dine-in food merchant's spatial tendency is to be located, as shown in the neighborhood scale agglomeration index. We can see that the dine-in food merchant tends to be agglomerated nearby the central area and less agglomerated in the fringe area.

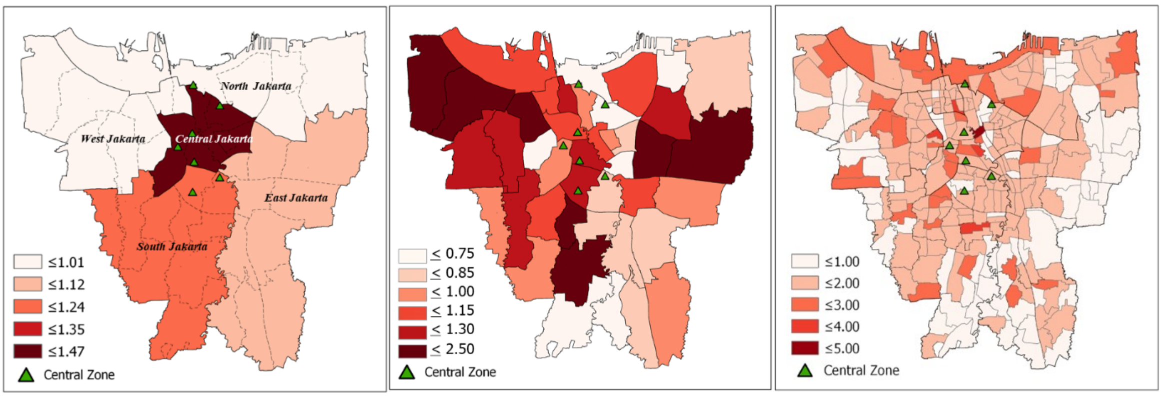


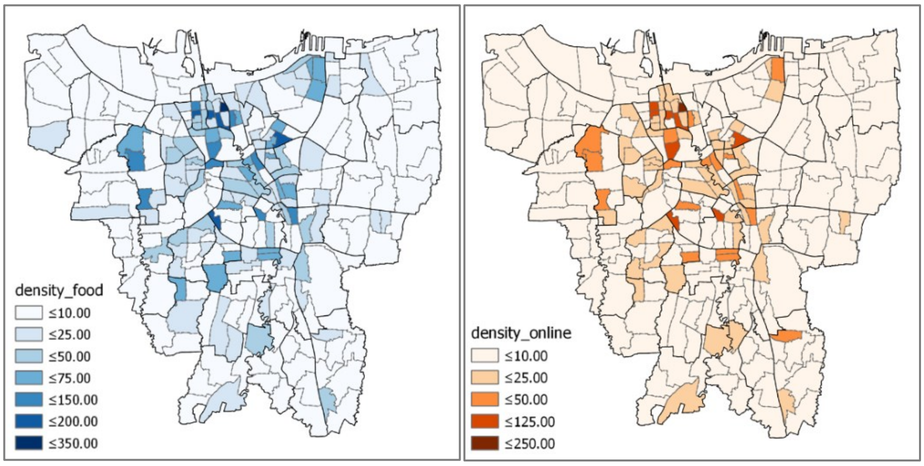
Figure 5.5. Agglomeration index of dine-in food merchants

5.5.2. Association of Agglomeration Index and City Characteristics

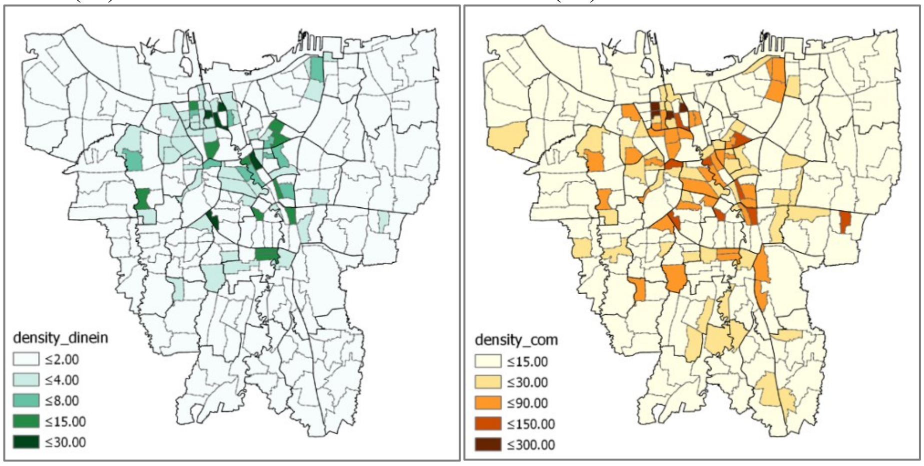
To further understand the characteristics of the distribution of online food merchants, we first explore the densities of combination, dine-in, and online food merchants. Then, we also do the same for commercial facilities for comparison purposes. We also compare how densities and agglomerations are different depending on the distance from the central area of Jakarta for each facility type. Finally, we examine how densities and agglomerations are associated with the share of commercial land use.

Figures 5.6. and 5.7. show the density and agglomeration indices for each facility type at the neighborhood level. We also aggregate densities and agglomerations by the distance from the central area of Jakarta. Figure 5.8. shows the distance information[1], and Figures 5.9. and 5.10. show the average density and agglomeration indices with respect to distance from the central area. Thus, we can confirm that dine-in food merchants are more concentrated in the urban core than calculated facility densities. In contrast, another facility type is more dispersed over the area, including commercial facilities. This indicates that dine-in food merchants are more agglomerated at the metropolitan scale, while others are not. On the other hand, if we look at agglomeration indices at the neighborhood level (Figure 5.7.), dine-in food merchants and commercial facilities are agglomerated only in the central area of the cities. In contrast, combination and food merchants are agglomerated in the urban fringe as well. Figures 5.9. and 5.10. also support the above findings, i.e., more online food merchants exist in the urban core and urban fringe, and they tend to be agglomerated in the urban core and urban fringe.

[1] We use 7 locations of central primer as our central area of the Central Business District (CBD) area. Four location of central primer was omitted due to the under-planning status of these areas.

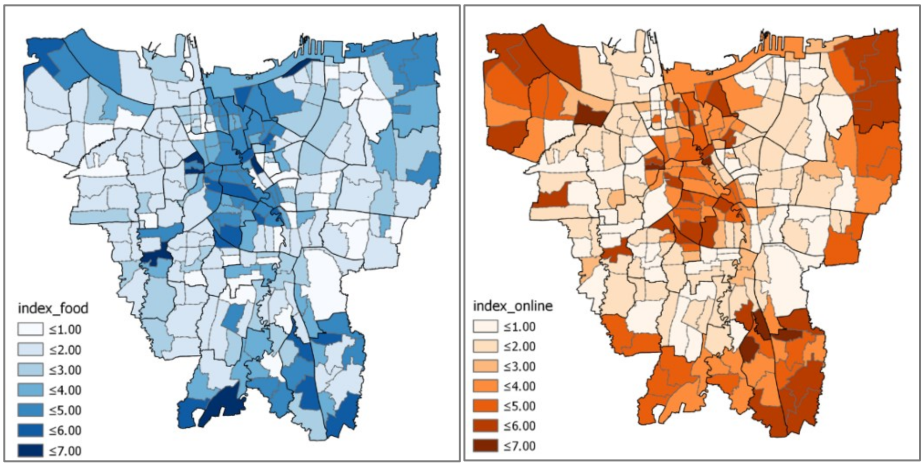


(6a) Combination food merchant (6b) Online food merchant

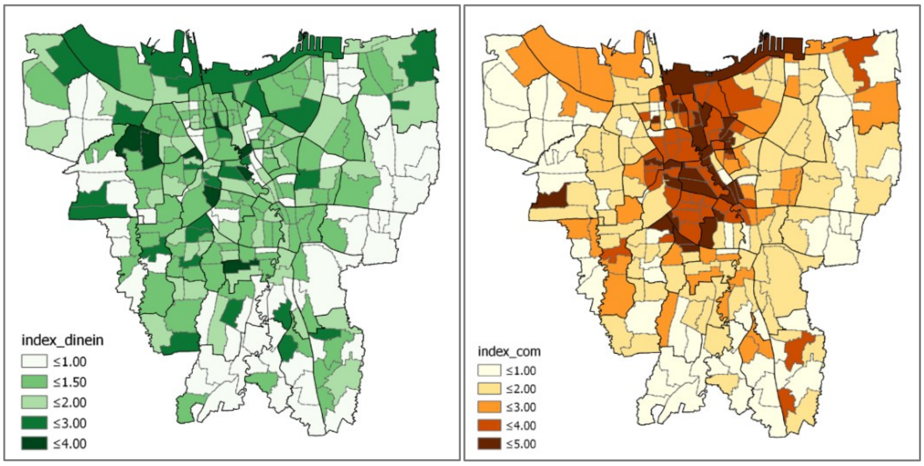


(6c) Dine-in food merchant (6d) Commercial facility

Figure 5.6. Facility densities at the neighborhood level



(7a) Combination food (7b) Online food



(7c) Dine-in food (7d) Commercial

Figure 5.7. Comparison of agglomeration indices at the neighborhood level

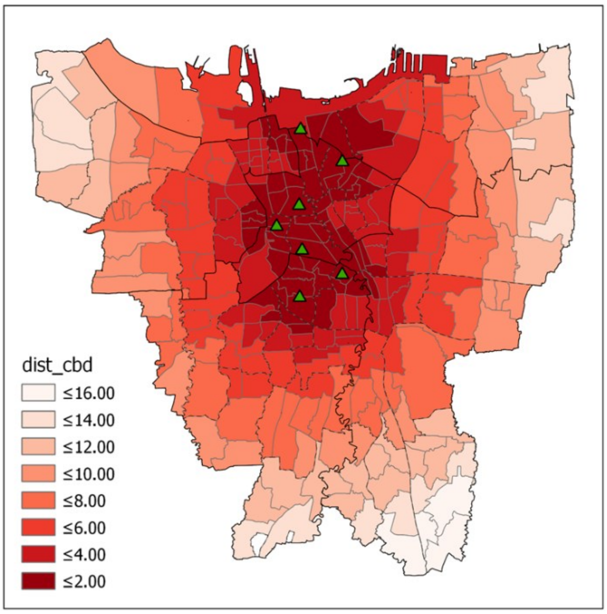
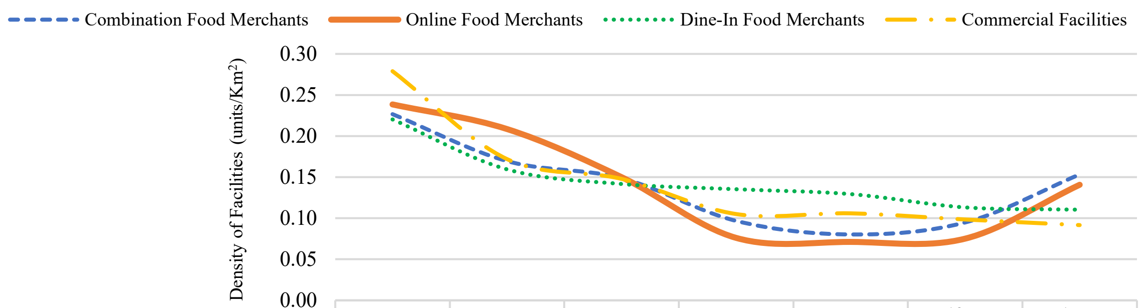


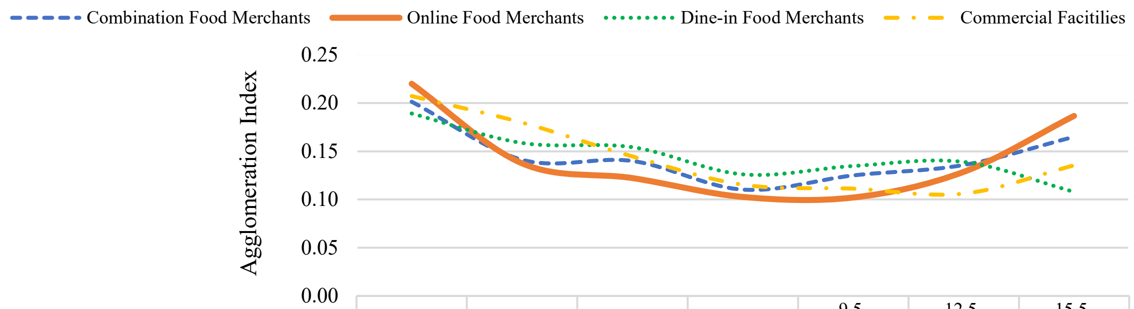
Figure 5.8. Distance from central area



	<0.5	0.5-3.5	3.5-6.5	6.5-9.5	9.5-12.5	12.5-15.5	15.5-18.5
Combination Food Merchants	0.23	0.17	0.15	0.10	0.08	0.09	0.15
Online Food Merchants	0.24	0.21	0.15	0.08	0.07	0.08	0.14
Dine-In Food Merchants	0.22	0.16	0.14	0.14	0.13	0.11	0.11
Commercial Facilities	0.28	0.17	0.15	0.11	0.11	0.10	0.09

Distance to The Central Area (Km)

Figure 5.9. Average densities with respect to distance to the central area



	<0.5	0.5-3.5	3.5-6.5	6.5-9.5	9.5-12.5	12.5-15.5	15.5-18.5
Combination Food Merchants	0.20	0.14	0.14	0.11	0.13	0.14	0.17
Online Food Merchants	0.22	0.14	0.12	0.10	0.10	0.13	0.19
Dine-in Food Merchants	0.19	0.16	0.15	0.13	0.13	0.14	0.11
Commercial Facitilies	0.21	0.18	0.14	0.12	0.11	0.11	0.14

Distance to The Central Area (Km)

Figure 5.10. Average agglomeration indices with respect to distance to the central area

A remarkable difference between combination and online food merchants from dine-in food merchants and commercial facilities is that they do not require users to travel. In the literature, the benefits of agglomeration are considered to be rooted in (1) *matching*: the cost of walking around to find preferable shops and restaurants would be lower in an agglomerated state (Takahashi, 2013), and (2) *trip chaining*: consumers can reduce transport and search costs owing to the spatial proximity of shops and restaurants (Koster *et al.*, 2019). Thus, one logical explanation we could make on the above observation is that the distribution of online food merchants would not be affected by these agglomeration forces, resulting in the different spatial distribution from dine-in food merchants. Also, it is important to mention that a new agglomeration force would exist for online food merchants as mentioned above: online food merchants need a certain amount of MSTP drivers to keep their service level, and thus a certain level of agglomeration would be crucial. This could be a reason why higher agglomeration in the urban fringe was observed for online food merchants. Although this study could not further investigate the mechanism of the above-mentioned agglomeration forces, it would be worth further investigating changes in agglomeration forces due to the presence of MSTPs from both theoretical and empirical perspectives.

In the daily operations, the MSTPs' driver can travel and standby everywhere within the city without any distance restriction. However, when it comes to the online food delivery services, the driver who got an order to deliver the food will have some distance restriction or maximum area coverage that the drivers can cover. The online food delivery service provided by MSTPs, and other food delivery services have a similar rule in considering the distance between food merchants and the customer's location. Specifically, the distance between the origin (i.e., the location of food merchants) and destination (i.e., the customer's location) will undoubtedly have an impact on the quality of services. In Indonesia, the online food delivery service provided by MSTP has an average maximum coverage area or maximum delivery distance up to 6 km from the location of food merchants to the location of their customers in principle. Therefore, the distribution of food merchants will significantly impact the online delivery service's quality.

Another phenomenon that we should discuss is that the reason why neighborhoods between urban core and fringe areas tend to have lower densities and agglomeration indices for online food merchants. One of the possible reasons is that the middle area gets access to both central and fringe areas, and thus facilities may not need to be located in those neighborhoods. However, it requires further analysis to identify whether this notation is likely to be true or not.

Finally, we explore how densities and agglomerations are associated with the share of commercial land use. According to the Jakarta provincial government's city planning document, 15.68% of the total land is allocated for commercial use. We calculate the percentage of commercial land use in each neighborhood (Figure 5.11.) and then calculate the average densities and agglomeration indices by the share of commercial land use shown in Figures 5.12. and 5.13. The main finding is that, while densities and agglomeration indices of combination and dine-in food merchants and commercial facilities are getting larger with the increase in the share of commercial land use, online food merchants are less affected by the share. This implies that the distribution of online food merchants is less consistent with the intended land use that the government specifies compared to other merchant types. This may require city planners to pay special attention to the spatial distribution of online food merchants and further discuss how properly embed them into their city planning.

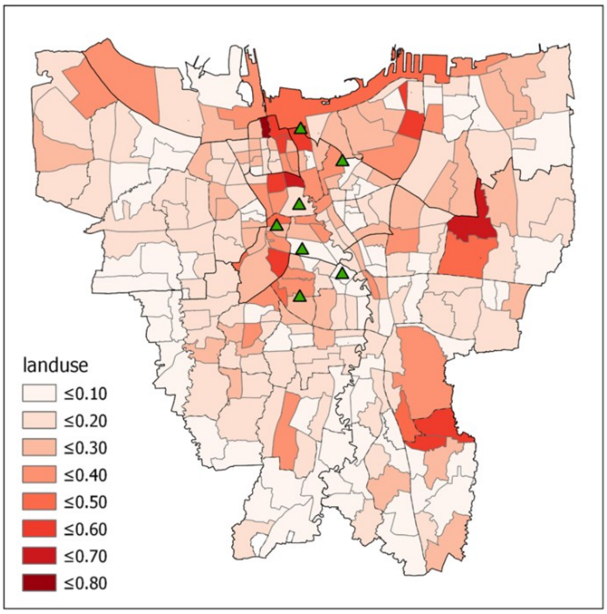
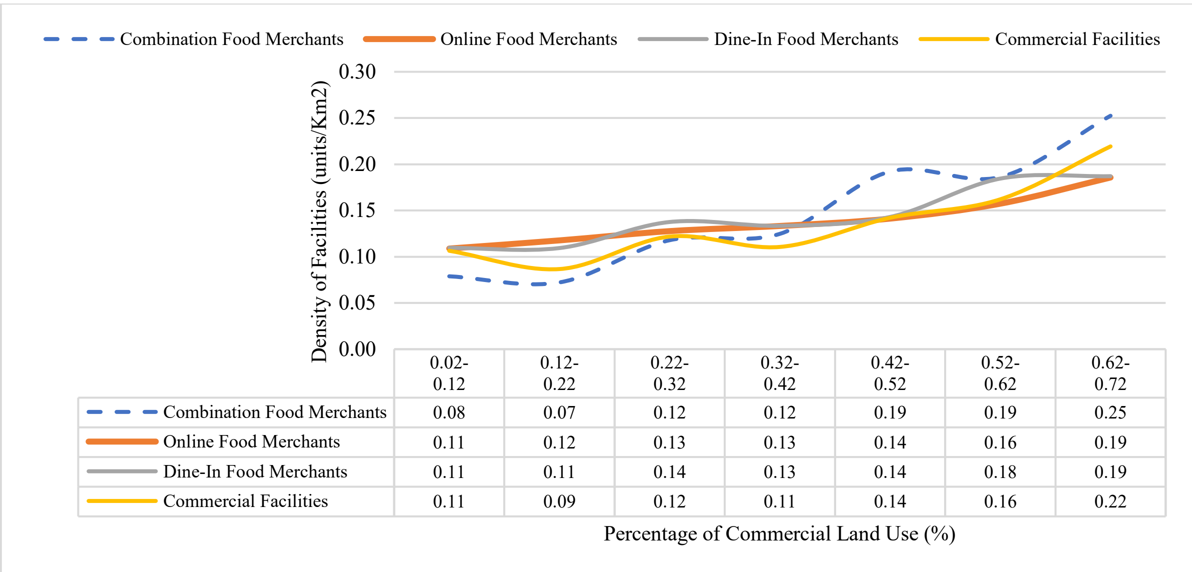
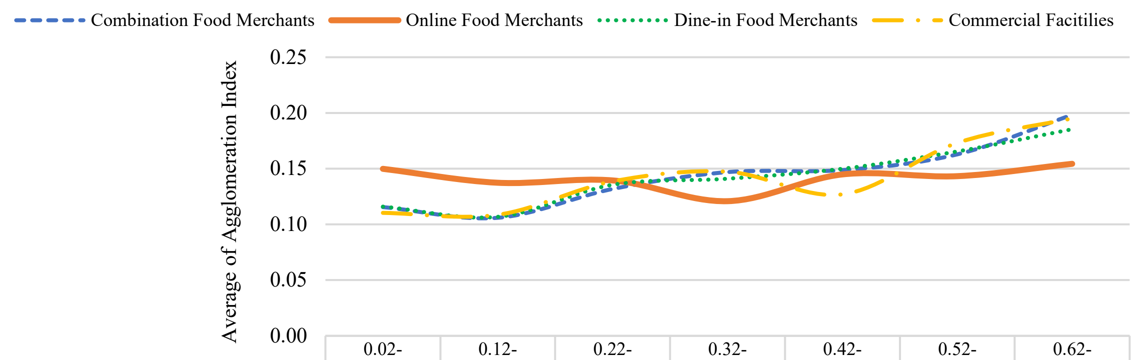


Figure 5.11. The percentage of commercial land use in Jakarta



	0.02-0.12	0.12-0.22	0.22-0.32	0.32-0.42	0.42-0.52	0.52-0.62	0.62-0.72
Combination Food Merchants	0.08	0.07	0.12	0.12	0.19	0.19	0.25
Online Food Merchants	0.11	0.12	0.13	0.13	0.14	0.16	0.19
Dine-In Food Merchants	0.11	0.11	0.14	0.13	0.14	0.18	0.19
Commercial Facilities	0.11	0.09	0.12	0.11	0.14	0.16	0.22

Figure 5.12. Average facilities densities and the share of commercial land use



	0.02-0.12	0.12-0.22	0.22-0.32	0.32-0.42	0.42-0.52	0.52-0.62	0.62-0.72
Combination Food Merchants	0.12	0.11	0.13	0.15	0.15	0.16	0.20
Online Food Merchants	0.15	0.14	0.14	0.12	0.14	0.14	0.15
Dine-in Food Merchants	0.12	0.11	0.14	0.14	0.15	0.17	0.19
Commercial Facitilies	0.11	0.11	0.14	0.15	0.13	0.17	0.20

Percentage of Commercial Land Use (%)

Figure 5.13. Average agglomeration indices and the share of commercial land use

5.6. CONCLUSION

Multi-service transport platforms (MSTPs) such as GOJEK and GRAB may lead to changes in activity and travel decisions, in turn leading to changes in the distribution of facilities, evidenced by a rapid increase in the number of online food merchants that only provide online food delivery services. This study has investigated to empirically confirm whether or not these rapidly emerging online food merchants have different spatial patterns compared to the conventional dine-in food merchants with a particular focus on the agglomeration and density of the facilities. Our empirical results showed that, while dine-in food merchants are more agglomerated at the metropolitan scale, online food merchants are more agglomerated at the neighborhood scale, presumably due to the necessity to attract MSTP drivers to keep the delivery service level. We also found that online food merchants tend to be agglomerated in the center and fringe area of the city. We discuss possible mechanisms on it, particularly from the perspective of changes in agglomeration forces by the MSTPs.

There are a number of limitations of this study. First, although this study took an empirical approach, theoretical investigations would also be needed to understand the impacts of MSTPs on urban form fully. The possible changes mentioned in this paper, i.e., weakening existing agglomeration forces (i.e., *matching* and *trip-chaining*) and emerging new agglomeration forces (i.e., attracting MSTP drivers to keep the delivery service level), would provide a valuable tip to conduct theoretical works. Second, it is clearly better to take into account the demand side, for example, by using daytime and nighttime population information, but this study could not do it due to the lack of access to the data. This would be one of the major future tasks. Third, the impact of the current pandemic situation in the distribution of the potential demand needs to be considered. As we know, in a pandemic situation like nowadays where many people tend to conduct work-from-home activities may change the distribution of potential demand (i.e., customer) of online food delivery services, especially in the daytime. In this situation, the number of online food delivery service orders from home-based locations may increase compared to the "normal" condition where the increased work-from-home activities may change the distribution of potential demand (i.e., customer) of online food delivery services, especially in the daytime. The number of online food delivery service orders from home-based locations may increase compared to office-based locations. However, the further analysis of the changes in the demand distribution due to the pandemic situation will be considered as our future task. Fourth, street food vendors play an important role in the food industry in Indonesia, but we could not really take them into account due to the lack of data. Maybe a field observation would be needed to properly reflect it in the future. Fifth, the results would also be different depending on the choice of distance metrics and facility type for constructing counterfactuals. In the future, we should test the robustness of the results by changing the metrics. Sixth, we only explore the differences between dine-in and online food merchants in Jakarta. However, the impacts would be pretty different depending on city size, development stage, and so forth. Further empirical analysis should undoubtedly be needed to understand the impacts of MSTPs on urban form comprehensively.

Chapter 6: CHANGES IN ACTIVITY-TRAVEL DECISION UNDER THE INFLUENCE OF MSTP

This chapter describes the changes in activity-travel decision and distribution under MSTP influence. In this chapter, we attempt to answer two research questions, including "How MSTP changes the distribution of activities?" (RQ 3.2) and "What factors influence people to choose online activities?" (RQ 3.3). This chapter also contains the introduction of the study, methodology approach, study area, data used, result and discussion, and conclusion of the study.

6.1. INTRODUCTION

Information and communication technologies (ICT) may improve people's access to goods, services, and even jobs through virtual connectivity, allowing them to participate in activities across space and time. The ICT systems are evolving fast and have the potential to cause changes in people's activity and travel patterns. In the short term, ICT has been observed to substitute, complement, and modify physical travel (Andreev et al., 2010) while improving access to activity opportunities (Novo-Corti et al., 2014). Meanwhile, in the long-term, it has the potential to affect congestion, emission levels, and urban form. With such important policy-level impacts, it is evident that analyzing the complex interrelationships between ICT and activity-travel behavior has become an essential theme in transportation research in recent years.

ICT systems have seeped into the lives of people and are continually evolving. One of the latest ICT innovations is the multi-service transport platform (MSTP). MSTP can be defined as an online-based platform that provides access to a wide range of services, including ride-hailing transportation, food delivery service, courier service, and daily need services (such as cleaning service, massage, hair salon, etc.). Besides playing the role of a mediator between the demand from the consumer's side and the supply from the provider's side, MSTP also gets involved in the direct distribution of goods and services by relying on their drivers and fleets. MSTP allows people to virtually access the services, relaxing their time and space constraints. Therefore, they have the potential to severely impact the activity and travel behavior patterns of people.

The speed of the evolution of analytical and survey methods capturing the interrelationships between ICT and activity-travel behavior has not kept up with the evolution of ICT systems. To comprehensively understand the full extent of these relationships, good quality data is required, and the recent advancements in smartphone-based surveys provide the scope to capture that adequately. Studies recently have highlighted the advantages of smartphone-based activity and travel surveys (Cottrill et al., 2013; Zhao et al., 2015), which collect the activity and travel diaries in an inexpensive and non-intrusive manner (Prelipcean et al., 2015). However, there are many opportunities to improve such survey frameworks to improve the data quality and, subsequently, the analysis. This study is an attempt towards that. Most of the current smartphone-based surveys still focus on collecting conventional travel and activity diary survey data.

Further expansion of this method is needed to allow researchers and practitioners to observe virtual or online activities and analyze their impacts on activity-travel behavior. Hence, this calls for improving the survey scheme, while there has been relatively little attempt to explore new data collection schemes concerning online or virtual activities. In addition, most of these surveys have been conducted in the developed world, while very little is known about the effect of ICTs on activity-travel behavior in the fast-changing cities of the developing world (Lila and Anjaneyulu, 2017; Varghese and Jana, 2019).

This study presents the framework for a smartphone-based activity-travel survey conducted in Jakarta, Indonesia. The paper explains and discusses the approaches undertaken to modify and improve existing smartphone-based activity-travel behavior surveys. It describes the data collection effort that can be used to comprehensively understand the interrelationships between ICT use and activity-travel behavior with a special focus on capturing the impact of newly popularized MSTP. Also, it presents the preliminary findings from the survey with a particular focus on the choice between physical and virtual activity engagements.

6.2. METHODOLOGY

In this study, we explore the activity-travel diary data that we obtain from our travel-diary survey and describe changes that happened in the individual's activity and travel decision under the influence of MSTP. This study also tests the effect of the variables mentioned above on the binary choice between virtual and physical activities using a mixed logit model with random error components accounting for inter-individual heterogeneity of unobserved variables. In addition, we calculate the influence of these variables and compare them with the influence of unobserved variables. This was done by decomposing the total variance of utility differences as a sum of variations in observed and unobserved variables (Chikaraishi et al., 2011a, 2011b). The total variance of utility difference between virtual and physical activities could be denoted by:

The total variance of utility differences between virtual and physical activities

$$Var(U_{2it} - U_{1it}) = Var(\hat{\beta}_2 X_{2it} - \hat{\beta}_1 X_{1it}) + \sigma_i^2 + {\pi^2}/{3} \tag{6.1}$$

Where,

U_{1it} = Utility for physical activity engagement for individual i for t-th activity

U_{2it} = Utility for virtual activity engagement for individual i for t-th activity

$\hat{\beta}_1$, = A vector of estimated coefficients for physical activity engagement

$\hat{\beta}_2$, = A vector of estimated coefficients for virtual activity engagement

X_{1it} = A vector of observed variables for physical activity engagement for individual i's t-th activity

X_{2it} = A vector of observed variables for virtual activity engagement for individual i's t-th activity

σ_i^2 = Variance of a random term representing unobserved inter-individual variations

${\pi^2}/{3}$ = White noise, i.e., variance due to other unobserved variables

Using the above formulation, the contribution of observed and unobserved variables towards the total variance of utility differences could be calculated by using the following formulations:

Contribution of observed variables (%)

$$= (Var(\hat{\beta}_2 X_{2it} - \hat{\beta}_1 X_{1it}) / Var(U_{2it} - U_{1it})) \times 100 \tag{6.2}$$

Contribution of unobserved inter-individual variables (%)

$$= (\sigma_i^2 / Var(U_{2it} - U_{1it})) \times 100 \tag{6.3}$$

Contribution of other unobserved variables including intra-individual variations (%)
$$= (3^{-1}\pi^2/Var(U_{2it} - U_{1it})) \times 100 \quad (6.4)$$

Four separate binary choice models were developed modeling the effect of variables on the choices of four activity types 1) online food delivery (base alternative: eating out), 2) online shopping (base alternative: physical shopping), 3) online leisure (base alternative: physical leisure), and 4) online social (base alternative: physical social). Work and education activities were not modeled as the choice of virtual activities for these activity types could be constrained based on the workplace requirements and the school. However, the users were free to choose between the physical and the virtual alternatives for the other four activity types.

6.3. DATA AND STUDY AREA

A total of 225 users participated in the survey conducted in and around Jakarta, Indonesia, for 14 days between January 28th to February 10th, 2020. The study location was in Jakarta, Indonesia. Jakarta (the Special Capital Region of Jakarta or Daerah Khusus Ibukota (DKI) Jakarta) is Indonesia's capital and the largest city. The city has an area size of 664.13 sq. km and a population of 10.77 million, with a population density of 21,974 people per sq. km (Central Bureau of Statistics, 2020). Figure 6.1 shows the distribution of the home locations of these participants. The spatial distribution shows a relatively higher concentration of participants from the South Jakarta region, where Jakarta's central business district is located. The participants were recruited based on a workplace-based sampling done in the South Jakarta region of the city, which meant that all the users who participated worked in the South Jakarta region. An additional recruitment questionnaire explaining the research project's scope and objectives was developed and shared on social media websites. Initially, 312 participants were shortlisted to participate in the survey based on the online recruitment questionnaire's responses. However, only 225 participants managed to complete the entire 14 days of the survey.

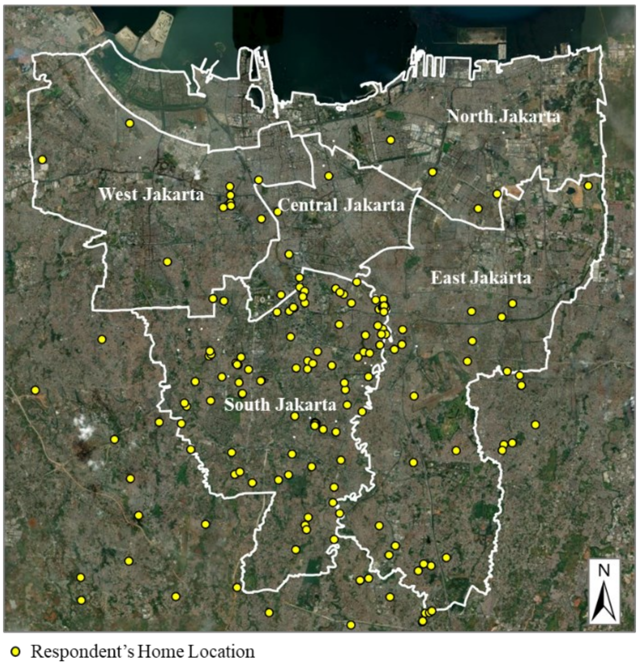


Figure 6.1. Spatial distribution of home locations of the survey participants

6.4. RESULT AND DISCUSSION

6.4.1. Socio-Demographic Characteristics

The socio-demographic information of participants shows that 55.56% of participants were female. Meanwhile, the highest percentage of respondents belonged to the age group 23-27 years (56.89%), indicating that the survey sample distribution was slightly biased towards a younger population. A possible reason behind this could be that as the survey only recruited people with a smartphone and an active internet connection, this might have resulted in the biased recruitment of young people who have a relatively higher propensity to use ICT-based services. Expectedly, 67.56% of the respondents were single. Meanwhile, 59.55% of the respondents had at least one college degree. In addition, it was observed that people who have a fixed work schedule and need to go to the office, i.e., the *office workers* constituted 91.11% of the total respondents.

Table 6.1. Data description of socio-demographic variables

Variable	Category	Total	Percentage
Total number of respondents		225	100.00%
Gender	Male	100	44.44%
	Female	125	55.56%
Age	18-22	21	9.33%
	23-27	128	56.89%
	28-32	43	19.11%
	33-37	29	12.89%
	38-42	4	1.78%
Marital	Single	152	67.56%
	Married	73	32.44%
Education	Junior High School	1	0.44%
	Senior High School	90	40.00%
	Diploma	14	6.22%
	Bachelor	110	48.89%
	Master and Doctor	10	4.44%
Job	Office Worker	205	91.11%
	Non-office Worker	20	8.89%
Provision Lunch by Workplace	Provided	42	18.67%
	Not Provided	183	81.33%
Car Ownership	Yes	158	70.22%
	No	67	29.78%
Motorbike Ownership	Yes	71	31.56%
	No	154	68.44%
Family Size	1	105	46.67%
	2	29	12.89%
	3	58	25.78%
	4	33	14.67%
	>5	10	4.44%
Average Income (in Mil. IDR per month)	Less than 1	8	3.56%
	1-3.99	58	25.78%
	4-7.99	118	52.44%
	8-9.99	31	13.78%
	More than 10	9	4.00%

In contrast, the group of people who do not have fixed work schedules or do not need to go to the office, i.e., the *non-office workers*, constitutes the remaining 8.89%. There are 42 respondents that have their lunch provided by their workplace. 70.22% of respondents owned a car for vehicle ownership, whereas 31.56% of them owned a two-wheeled motor vehicle. A high percentage of 46.67% of the respondents lived alone with a family size equal to 1, whereas only 14.67% of the respondents had a family size of 4 or more people (see Table 3). Finally, the distribution of income showed that the majority of respondents belonged to the mid-income ranges of 1 to 3.99 million IDR (25.78%), 4 to 7.99 million IDR (52.44%), 8 to 9.99 million IDR (13.78%), with 4.00% of the respondents with an income of 10 million or more.

6.4.2. Activity and Travel Behavior Characteristics

In the empirical analysis, we collected data from 272 individuals who complete 14 days (2 weeks) smartphone app-based travel-activity diary survey, from January 28th to February 10th, 2020, in Jakarta, Indonesia. We use office-based sampling. The respondents are users of the online-based food delivery service provided by MSTP (e.g., Go-Food and GrabFood) who work in South Jakarta City, Indonesia. The data include individual activity and travel behavior on a given 14 days survey period and their online activity behavior. Before addressing the analyses of the travel performance indicator derived from the activity-diaries, this section discusses the activity-travel pattern in these diaries in a more general way.

We used the term "travel activities" is referring to the number of observed linked trips and the "stay activities" as the number of observed stops with a purpose. Within the 14 days of observation, 225 respondents total 7,112 travel activities (trips) and 7,154 stay activities. It was observed that of all the stay activities, 38.51% were stay-at-home activities, whereas 32.07% were work activities. Other activity types such as eating out, shopping, education, leisure, social, and other activities witnessed a share of .56%, 5.10%, 1.10%, 1.80%, 8.05%, and 5.80% of all activities, respectively (see Table 4). It should be noted that these stay activities denote the primary physical activities in which the users participated.

The duration of these activities also varied, e.g., most activities were either done for a duration between 0-60 minutes (26.98%) or greater than 300 minutes (50.87%) (see Table 4 for the complete distribution). In addition, the distribution across activity types also varied with the time duration. Activities such as eating out, social activities, and shopping activities were mainly done for a shorter time period between 0-60 minutes. Meanwhile, work and stay-at-home activities were highly conducted for short and long durations (0 to 60 minutes and greater than 300 minutes, respectively).

Table 6.2. Distribution of activity participation and time allocation in primary activities

Activity Types	Duration (in minutes)							
	0-60	61-120	121-180	181-240	241-300	>300	Total (1)	% (1)
Eating out	324	96	40	24	16	41	541	7.56%
Shopping	236	51	29	10	9	30	365	5.10%
Working	366	154	135	119	122	1398	2294	32.07%
Education	35	5	8	6	6	19	79	1.10%
Leisure	38	24	33	13	2	19	129	1.80%
Social	288	91	50	37	20	90	576	8.05%
Home	376	140	101	85	65	1988	2755	38.51%
Others	267	51	25	10	8	54	415	5.80%
Total (2)	1930	612	421	304	248	3639	7154	100.00%
% (2)	26.98%	8.55%	5.88%	4.25%	3.47%	50.87%	100.00%	

On the other side, for travel activities (trips), every movement that the users made was identified and associated with a travel mode. It was observed that 17.83% of the travel activities were conducted on foot. Meanwhile, 29.96% and 19.76% of all the travel activities were conducted using private cars and motorbikes, respectively. Public transport modes, including *angkutan kota (angkot)/*minibus, bus, and trains, were used for 10.46% of the trips, whereas Ojek online, an MSTP-based taxi motorbike, was used in 16.65% of the total travel activities. Four-wheeler ride-hailing and taxi services were used in 2.35% of the trips, whereas other modes (such as bicycles, airplanes) were used in 2.99% of the trips.

Table 6.3. Distribution of mode choice for travel activities

Travel mode	Average Travel Time (min)	Average Distance (km)	Percentage of trips (%)
Walk	95.82	2.65	17.83%
Car	47.18	19.24	29.96%
Motorbike	70.92	12.42	19.76%
Public Transit	77.59	15.16	10.46%
Ojek Online	51.40	5.31	16.65%
Ride-Hailing/Taxi	36.83	15.34	2.35%
Others	230.31	25.39	2.99%
Total (7112 trips)	319.59	19.18	100.00%

6.4.3. Online Virtual Activities

The third part of the survey captured information on the online activities performed by respondents during primary activities, which had a duration of greater than or equal to 20 minutes. A basic descriptive analysis of the data showed that users participated the most in online leisure activities (34.69%), followed by online social (25.56%), online food delivery services (17.32%), shopping (8.31%), work (9.21%), and education activities (4.91%). The survey also captured the primary activities during which these online activities were performed, and it was observed that the most significant number of online activities were performed during stay at home (39.36%) and travel activities (26.18%), followed by work activities, which accounted for 21.46% of the total online activities. This trend is reasonably expected as these activity types were also observed to be the most performed "stay" activities in the activity and travel diaries.

Table 6.4. Distribution of online activities

Physical Activities	Virtual/Online Activities						Total (1)	% of total (1)
	Eat	Shopping	Working	Education	Leisure	Social		
Eating out	35	9	2	0	72	30	148	2.71
Shopping	14	18	3	2	23	10	70	1.28
Working	230	128	180	57	318	259	1172	21.46
Education	5	2	1	16	23	5	52	0.95
Leisure	2	3	0	1	26	4	36	0.66
Social	26	2	8	12	57	73	178	3.26
Home	371	152	202	109	868	448	2150	39.36
Others	12	7	3	4	62	138	226	4.14
Travel	251	133	104	67	446	429	1430	26.18
Total (2)	946	454	503	268	1895	1396	5462	
% of total (2)	17.32	8.31	9.21	4.91	34.69	25.56		

6.4.4. Physical vs. Virtual Activities: Influence of Variables

Finally, an analysis of the effect and influence of variables on the choice of virtual online activities was performed. A direct comparison was made between the primary physical activity types and their virtual online counterparts. Figure 6.2. shows this comparison between the shares of physical and virtual activities across six different activity types. It could be seen that social, educational, leisure, shopping, and eating activities, the share of virtual activities is higher than physical activities. Only in the case of work activities was it observed that people participated in many physical activities (more than 90% of the total work activities).

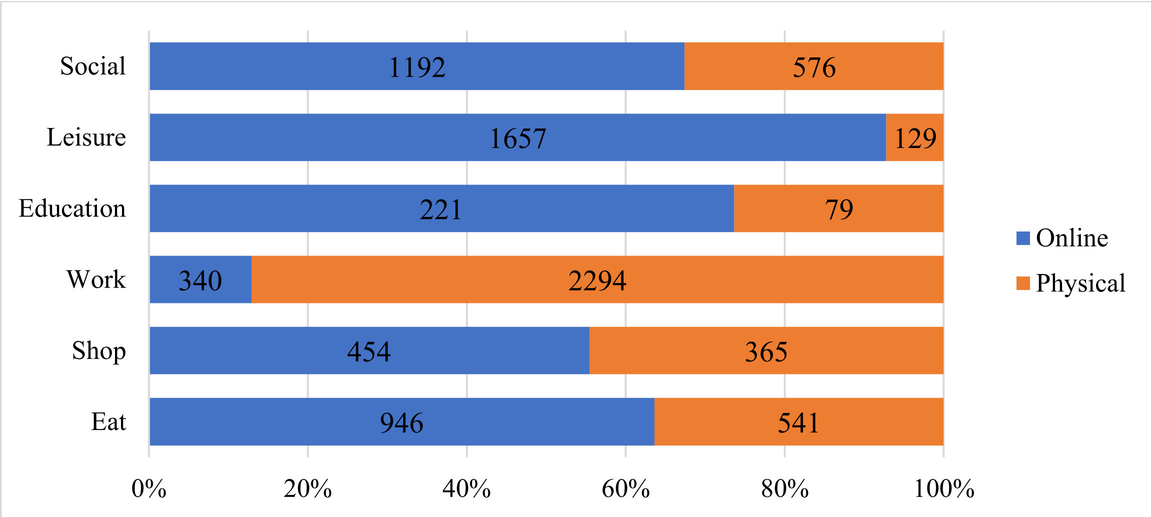


Figure 6.2. Physical vs. virtual activities: The share of activity participation

It is expected that these shares, i.e., the choice of whether to participate in an activity type, would depend on several variables. Figure 8 shows the variations in activity participation across the six activity types based on the time of day. Certain activities such as work are constrained in time and space, with most people having non-flexible choice options (start time is mostly during morning hours). Meanwhile, other activity types provide a higher level of flexibility for users to choose from. In addition, virtual activities may relax these strict space and time constraints. In almost all activity types, the influence of time of the day is evident, with varying peaks throughout the day. Apart from the time of the day, other socio-demographic variables such as gender, age, marital status, education level, job type, car ownership, motorbike ownership, family size, and average monthly income could influence the choice between virtual and physical activities.

The binary logit models' results show that most socio-demographic observed variables included in the model did not have a statistically significant relationship with the choice of virtual activities relative to their respective physical activities. For an online food delivery (eating behavior), we found that the average monthly income and family sizes have a significant negative value. The result may indicate people with a lower income, and a smaller number of family member tend to have a meal by him/herself through online food delivery services. People with a higher income and bigger family size tend to eat out, which may indicate some tendency to have some social interaction through eating together. For online shopping activities, people with higher education tend to conduct online shopping. The result may indicate that with a higher education level, the ability to access the information of the goods online and operate the application led them to conduct some online shopping where they found it more convenient than conducting shopping physically. For social activities, age and marital status are the significant variables affecting people's decision to conduct online social activities. Younger people tend to conduct social activities online rather than physically, but married people tend to conduct social activities. This may be the initial indicator of the social interaction changes of the younger people in urban areas that tend to communicate and interact online socially. It is noted that the result is produced with the majority of the respondents in the age range 23-27 years old, which may describe some similarities in the daily behavior or lifestyle, especially their eating behavior. Based on Demografi L. (2017), 77% of the MSTP users are in the range age of 20-39 years old, with 70.4% of them are using online food delivery services for their daily consumption. People find it is more convenient and cheaper to order food by using MSTP rather than cooking by themselves.

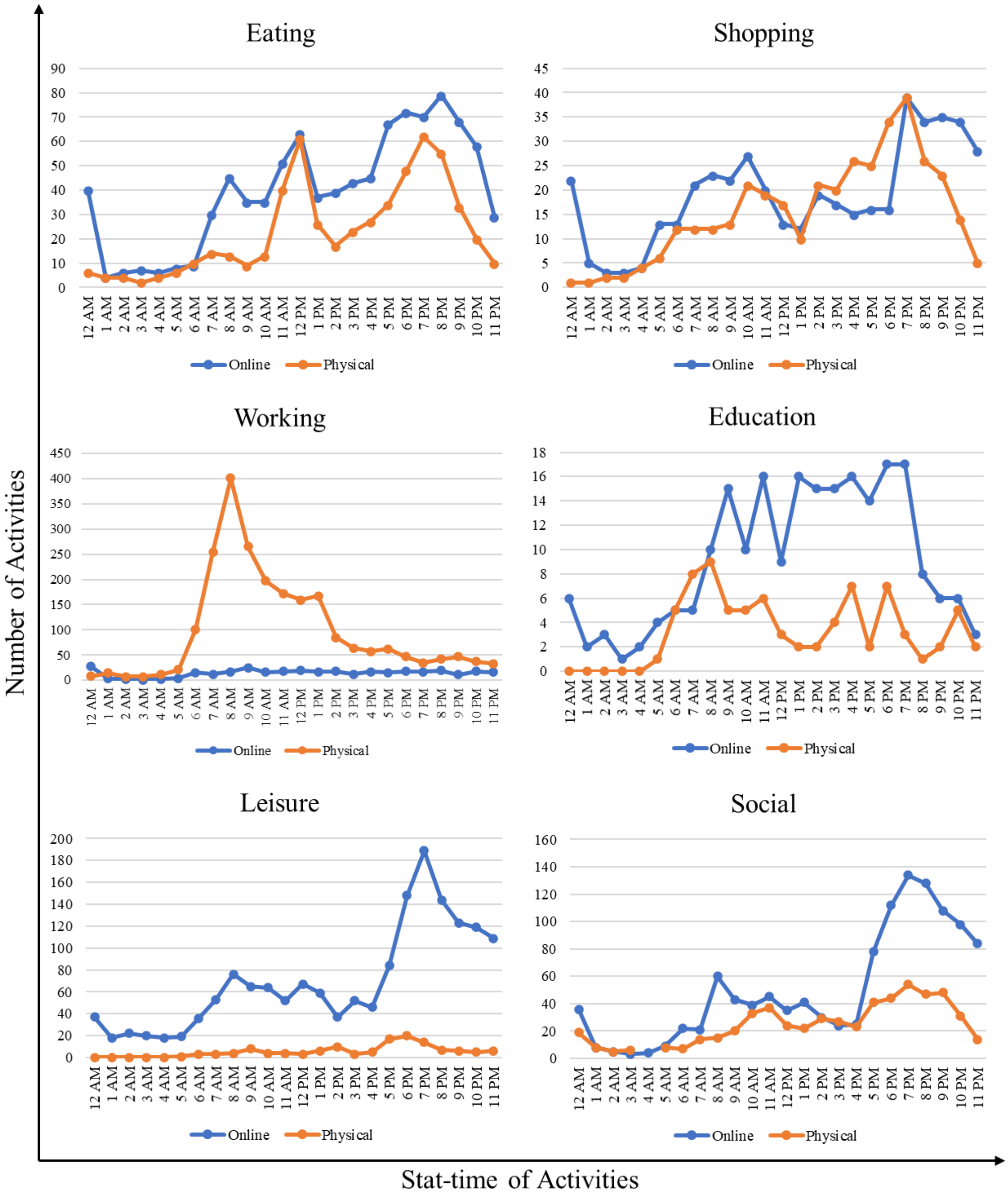


Figure 6.3. Variations in activity participation based on time of day

On the other hand, the time of the day seemed to have a stronger relationship with the activity choices. Twenty-four hours were divided into six time zones, and a dummy variable for each was tested in the model (with the time between 00:00:00 to 03:59:59 as the reference category, time 1). It was observed that for eating activities, users were less likely to order food online (relative to going out for eating) from 12 PM to 12 AM as compared to after 12 AM till 4 AM in the morning, as three dummy variables for time zones 4, 5, and 6 showed significant negative relationships (see Table 6.5). Similarly, for shopping activities, it was observed that people were more likely to shop online between time one, i.e., between 00:00:00 and 03:59:59 as compared to between 08:00:00 and 23:59:59. Meanwhile, for leisure, time 2 (04:00:00-07:59:59), time 4 (12:00:00-15:59:59), time 5 (16:00:00-19:59:59) showed a negative relationship. Indicating that people are more likely to perform online leisure between 12 AM and 4 AM. For online social activities, similar negative relationships were observed for time 5 (16:00:00-19:59:59) and time 6 (20:00:00-23:59:59). It is interesting to note that the time period after midnight and before the early morning was the most conducive time to participate in online virtual activities across different activity types.

Table 6.5. Effect of variables on the choice of physical vs. virtual activities

Explanatory Variables	**Eating (Online food delivery)**		**Shopping (online)**		**Leisure (online)**		**Social (online)**	
	Est.	t-stat	Est.	t-stat	Est.	t-stat	Est.	t-stat
Constant	-1.90	-0.99	-2.26	-0.81	8.22	1.98 [b]	6.58	2.80 [a]
Gender (0=Male; 1=Female)	0.54	1.16	0.4	0.55	0.91	0.65	-0.57	-0.97
Age	0.12	1.53	0.11	0.83	-0.03	-0.17	-0.25	-2.33 [b]
Marital (0=Single; 1=Married)	0.25	0.35	-0.6	-0.55	0.51	0.35	1.5	1.66 [c]
Education (0= Not graduate; 1= Bachelor's degree or above)	0.2	0.37	-1.31	-1.77 [c]	-1.5	-1.17	-0.62	-1.01
Job (0=Non-office worker; 1=Office worker)	0.75	0.81	0.76	0.63	2.17	0.8	-0.71	-0.66
Car ownership (0= No; 1=Yes)	-0.22	-0.45	0.82	1.19	-0.39	-0.38	0.02	0.03
Motorbike ownership (0= No; 1=Yes)	0.65	1.18	-0.16	-0.25	-1.86	-1.33	-0.76	-0.95
Family size	-0.28	-1.73 [c]	-0.18	-0.78	-0.11	-0.33	0.12	0.79
Avg. income (in mil. IDR)	-0.13	-1.66 [c]	0.1	0.88	-0.19	-1.16	-0.07	-0.77
Time 2 (04:00:00-07:59:59)	0.07	0.18	-0.08	-0.13	-2.05	-2.51 [b]	-0.53	-1.46
Time 3 (08:00:00-11:59:59)	-0.002	-0.004	-1.14	-2.10 [b]	-1.09	-1.32	0.05	0.14
Time 4 (12:00:00-15:59:59)	-1.32	-3.93 [a]	-0.98	-1.74 [c]	-1.6	-2.27 [b]	-0.31	-1.00
Time 5 (16:00:00-19:59:59)	-1.15	-3.68 [a]	-1.33	-2.52 [b]	-2.11	-3.42 [a]	-0.72	-2.15 [b]
Time 6 (20:00:00-23:59:59)	-1.22	-3.69 [a]	-1.32	-2.48 [b]	-0.29	-0.37	-0.73	-2.11 [b]
Sigma (random parameter)	-2.31	-9.00 [a]	2.95	7.80 [a]	-3.95	-5.56 [a]	3.55	9.04 [a]
Number of individuals	177		137		121		163	
Sample size	1592		840		1864		2030	
LL (0)	-1103.49		-582.24		-1292.03		-1407.09	
LL (Final)	-714.88		-338.28		-358.92		-738.02	
AIC	1461.75		708.57		749.83		1508.04	
Variance Explained by (%)								
Observed Variables	24.10		7.85		24.18		22.68	
Unobserved inter-individual variables	46.91		66.87		62.59		61.30	
Other unobserved variables including intra-individual variations.	28.99		25.28		13.23		16.02	

Notes: Est. Represents parameter estimates; variables Age, Family size, and Avg. income was introduced in the model as continuous variables. ([a]) significant at the 1% level, ([b]) significant at the 5% level, ([c]) significant at the 10% level

The analysis of the contribution of variables towards the total variance of utility differences shows that for all activity types, the contribution of observed variables is far less than that of unobserved variables. For eating activities, observed variables only explain 24.10% of the variance in the total utility difference. Meanwhile, unobserved inter-individual variables explain 46.91%, and other unobserved variables, including intra-individual variations, explain 28.99% of the total variance. A similar trend was observed for other activity types as well, although the unobserved inter-individual variables explain a relatively higher 66.87%, 62.59%, and 61.30% of the total utility differences in shopping, leisure, and social activities, respectively (differences calculated relative to their respective physical activities) . The unobserved variables include all individual-specific unobserved variables, including the attitudinal and personality-based variables, making specific individuals more prone to perform virtual activities than others. Although a detailed, comprehensive analysis on those variables is needed in the future to fully understand the effect of MSTP on travel and activity behavior, it is worth emphasizing that, while travel decisions rely more on contextual factors (Chikaraishi et al., 2010, 2009), decisions on virtual activity engagement seem to be dependent more on individual specific attributes. Collecting more attitudinal variables could be one way to explore further the factors affecting virtual activity engagement.

6.5. CONCLUSION

This study presented the framework for and preliminary findings from a smartphone-based activity-travel survey conducted in Jakarta, Indonesia. In the first part, we showed the framework of the activity-travel survey using FMS. Then we showed the preliminary result from our data analysis regarding the impact of ICT (MSTP) on activity and travel behavior on the individual scale. The framework of the survey consisted of four distinct but interconnected parts, which collected information regarding the effect of MSTP on activity-travel behavior. The four parts of the survey included, 1) socio-demographic questionnaire, 2) activity-travel survey using X-ING mobile phone application (with separate diaries for capturing information on travel and activities), 3) online activities survey using X-ING application, and 4) context-aware SP surveys (with separate surveys for eating out behavior and online activities). This study addressed certain pertinent literature gaps using and applying the survey method in a developing country scenario. First, by developing context-aware SP surveys for “eating out” or “ordering online” activities based on the RP information from users, the study collected important and relevant information to directly analyze the effect and importance of MSTP. Second, it captured rich information regarding additional online or virtual activities conducted by users along with their primary activities using a smartphone-based survey. This provided the scope to directly compare the two activity alternatives, i.e., physical vs. virtual. Finally, the application of the method to Indonesia helped accumulate new information about the changing trends in the use of MSTP and activity-travel behavior in developing countries.

This study also describes the information collected from the survey and performs basic analysis on the factors that influence activity participation behavior. The key findings could be summarized as follows: 1) out of all the stay activities, a high proportion of them was either stay-at-home activity (38.51%) and work (32.07%) activities. 2) The use of private cars (29.96%) and motorbike (19.76%) were the most popular modes of transport, representing how the respondents are more relying on a private vehicle. 3) Among the online activities, leisure (36.96%), social (25.56%), and ordering food online (17.31%) were the most commonly conducted virtual activities. 4) For the SP surveys, it was observed that in 53% of the scenarios, users chose to shift to order food online than making a trip to eat out. Meanwhile, in the case when MSTP ceased to exist, i.e., a case with no online alternatives, in 58% and 74% of the scenarios, the users chose to make a physical trip to the nearest restaurant and shop to participate in eating and shopping activities, respectively. These clearly reflect the importance of MSTP in the current context and how they could play an important role in modifying activity-travel patterns. Finally, 5) an analysis of the effect of variables on the choice of performing virtual activities relative to physical activities showed that unobserved variables, especially inter-individual unobserved variables, explained the majority of the variations in the difference of utilities between virtual and physical activities. This indicates the importance of individual unobserved variables such as attitudes and personalities of individuals towards ICT use. They might be pivotal in understanding the full extent of interrelationships between ICT and activity-travel behavior.

The study's findings clearly highlight the importance of MSTP and how seamlessly it has integrated with our lives. These could have major implications on transportation and land-use policies. MSTP could reduce user trips in the short run but could add additional trips from the supplier's end. Meanwhile, in the long run, these services could change the land use structure of the cities. In the past, especially in Indonesia, the function of smartphones has been limited to that of a daily communication tool (e.g., sending the message, chatting, and video calls) (See Gifary, S., 2015). With the presence of MSTP, our empirical results show that people are now significantly utilizing their smartphones not only for communication purposes but also for using online services. On the other side, the availability and use of a flexible smartphone-based survey tool like FMS have become one of the solutions in fulfilling the challenges of collecting the activity-travel behavior data. The flexibility of such tools provides the opportunity to keep up with the rapidly evolving MSTP systems. In our case, we modified the tool to capture virtual activities.

The smartphone-based survey conducted in Jakarta, Indonesia, addressed important research gaps and provided relevant information to comprehensively analyze the impact of MSTP on activity-travel behavior. However, the study has several limitations that should be addressed in the future. First, while capturing the online activities (i.e., 3rd part of the survey), the actual duration of online activities was not captured since it is attached with the physical activities and trips' duration. The actual duration is an important factor that helps in calculating the time allocation to activities. Studies in the future can ensure developing applications which capture that without increasing the burden on respondents. Second, the smartphone data might have some measurement error related to the sensors such as GPS (e.g., travel times and route trajectories). Third, as the survey was limited to people who owned a smartphone and had internet access, the recruitment process might have led to biases in sampling people who have a higher propensity to use ICT services, such as younger people. Future studies must put considerable attention in ensuring the representativeness of the study sample; one way to do this is to provide smartphones on loan during the survey period. Another important future research agenda is the utilization of such unique data. This study only showed preliminary results and did not conduct a deeper analysis of the relationship between virtual and physical activities. We are now developing an activity-based model that can simultaneously handle both virtual and physical activities to capture the impacts of MSTP on activity-travel behavior comprehensively. We believe that such research has great importance in handling the impacts of MSTP on society properly.

Chapter 7: THE IMPACT OF ONLINE FOOD DELIVERY SERVICE ON EATING-OUT BEHAVIOR

This chapter explores the impact of MSTP's online food delivery service on eating out behavior through the analysis of context-aware stated preference data. In this study, we attempt to answer two research questions regarding the impact of MSTP on the individual's eating behavior, including "How the presence of MSTP's online food delivery service will affect people's eating behavior?" (RQ 4.1) and "What factors that affects MSTP's service level?" (RQ 4.2). This chapter also contains the introduction of the study, methodology approach, study area, data used, result and discussion, and conclusion of the study.

7.1. INTRODUCTION

Information and communication technologies (ICTs) are the critical enablers of innovation in transport systems and daily lives. ICTs improve people's access to goods, services, and even jobs through virtual connectivity, allowing them to participate in activities across space and time. The ICT systems are evolving quickly and have the potential to influence people's activity and travel patterns. In the short term, ICTs have been observed to substitute, complement, and modify physical travel (Andreev et al., 2010) while improving access to activity opportunities (Novo-Corti et al., 2014). Meanwhile, in the long term, they have the potential to affect congestion, emission levels, and urban form. With such important policy-level impacts, analyzing the complex interrelationships between ICT and activity-travel behavior has become an essential theme in transportation research in recent years.

One of the latest ICT innovations is multi-service transport platforms (MSTPs). By utilizing the innovation of technology to improve people's daily lives, MSTPs can be defined as an online-based platform that provides access to a wide range of services, including ride-hailing transportation, food delivery service, courier service, and daily need services (such as cleaning services, massages, and hair salons). The main components of the MSTPs are (1) the efficient provision of transport services through real-time data processing and (2) the integration of transportation services and other daily life support services. MSTPs play the role of a mediator between the demand from the consumer's side and the supply from the provider's side and get involved in the direct distribution of goods and services by relying on their drivers and fleets. In daily life, the presence of MSTPs can change how people virtually access the services to fulfill their daily needs. MSTP allows people to fulfill their needs, including goods (e.g., meals and groceries) and services (e.g., massage service and car repair) without traveling.

In Indonesia, MSTPs (e.g., Gojek and Grab) have become an important part of people's daily life. One of the most used MSTP services is the online food delivery service, where people can order foods from food merchant partners across Indonesia. MSTPs allow people to virtually access the services, relaxing their time and space constraints. Because they do not need to allocate time to travel to get their meal, they can use the time to perform other activities. Pigatto et al. (2017) found that online food delivery services allow consumers to have a more comprehensive range of options to optimize their time usage, resulting in the rapid growth of online delivery services. From the behavior study perspective, several studies found a positive relationship between attitude toward technology adoption and behavioral intention (Ingham et al., 2015; Chang et al., 2012; Wagner et al., 2016). The rise of such online food delivery services may change eating-out behavior (demand side) and merchant behavior (supply side), as well as the interactions between consumers and food merchants (Atasoy et al., 2019). While the impacts of online food delivery services have been explored, as mentioned, more empirical works are certainly needed particularly to improve our understanding of the indirect impacts of food delivery services.

Given the presented background, this study empirically identifies the impacts of the contextual factors (i.e., time-space constraints and having a meal with friends/colleagues) as well as the service level factors (including delivery cost, delivery time, food cost, and available food types) on the use of online food delivery services using a stated preference (SP) survey data collected together with a multi-day smartphone-based travel diary survey in Jakarta, Indonesia. We believe that controlling contextual factors is key to not mislead the impacts, which have not been well addressed in existing studies. More specifically, a longer waiting time for food would prevent people from using online food delivery services, partially because of time-space constraints they have. For example, in the case of lunchtime, people must go back to their office after getting lunch; thus, people may not be able to use the food delivery service if the waiting time is too long. In other words, ordering foods from a distant place would be possible only when time-space constraints are satisfied, but this aspect has not really been explored in the literature. Another critical point that needs to be considered is that people often eat out to interact with friends and colleagues. With the consideration of this social interaction function of the meal, it seems evident that not all eating-out trips would be replaced with an online food delivery service. If the online food delivery service reduced the number of merchants in the central area of the city, as discussed previously, the social interaction function that merchants and transport systems have jointly provided (Urry, 2007) would be decreased. Understanding such social impacts of online food delivery services is crucial in forming a better public policy, yet the relevant works are still very limited.

Two efforts have been made in the empirical analysis to avoid potential biases in the estimated impacts. First, contextual factors vary across trips; thus, it is not easy to set the context in the standard SP technique where all information is hypothetical (Hensher D.A., Reyes A.J., 2000). To give a realistic context, we use a context-aware SP survey scheme: people first join an app-based activity-travel diary survey, and they are asked about the possibility of shifting to the use of online food delivery service for a particular eating-out trip. This allows for reflecting on the actual context the person had. However, it inevitably leads to another challenge, i.e., a self-selection issue: the population in the data set becomes not all individuals in the society, but all individuals who made eating-out trips, potentially leading to bias in the model estimation results. To control this potential bias, we employ one of the propensity score methods, the inverse probability weighting (IPW) method: we first estimate the propensity of eating out then use it to generate the weight used in the final model estimation to identify the preferences on online food delivery service use. Another important point to note is that although the presented survey method would let people consider contextual factors they had, the analyst typically cannot observe all contextual factors. We employ the mixed logit model to control these unobserved contextual factors where the random term varies across eating-out trips.

7.2. METHODOLOGY

Given the above background, this study attempts to empirically identify the impacts of the contextual factors (i.e., time-space constraints and having a meal with friends/colleagues) as well as the service level factors on the use of online food delivery service, including delivery cost, delivery time, food cost, and available food types. In the empirical analysis, we use a stated preference (SP) survey data collected together with a one-week smartphone-based travel diary survey in Jakarta, Indonesia. In the empirical analysis, there are a couple of methodological challenges. First, contextual factors vary across trips, and thus it is not easy to set the context in the standard stated preference technique, where all information is hypothetical (Hensher D.A., Reyes A.J., 2000).

To give a realistic context, we use an adaptive SP survey scheme: people first join an app-based activity-travel diary survey. They are asked about the possibility of shifting to the use of an online food delivery service for a particular eating-out trip. This allows for reflecting on the real context the person had. However, it inevitably leads to another challenge: the population in the data set becomes not all individuals in the society, but all individuals who made eating-out trips, potentially leading to bias in the model estimation results. To control this potential bias, we employ the inverse probability weighting (IPW) method, which is one of the propensity score methods: we first estimate the propensity of eating-out then use it to generate the weight used in the final model estimation to identify the preferences on online food delivery service use. In this study, we found that the use of IPW is critical to remove the bias.

Another important thing is that, although the above survey method would let people consider contextual factors they had, the analyst may not fully observe all contextual factors. We employ the mixed logit model to control these unobserved contextual factors where the random term varies across eating-out trips. Our empirical results also show that introducing the random term at the trip level is critical to control biases from omitted variables.

7.2.1. Survey Methodology and Data Preparation

This study focuses on Indonesia's, particularly in Jakarta’s situation where the multi-service transport platforms (MSTP), particularly GOJEK and Grab, have been operated since 2010. These platforms provide ride-hailing services and various services supporting their daily-life activities, including food delivery service, medicine delivery service, grocery shopping service, daily need services such as house cleaning service, online payment, and many more. They allow people to access various services without travel at a relatively affordable cost and relatively real-time service. They now have become one of the best alternatives that many people choose. With the presence of the MSTP, the way of interacting between the supply-side (merchants) and demand-side (users) might change, mostly because the platform would relax users' time and space constraints to reach the services.

In Indonesia, there were more than 500,000 food merchants in 2020 that partnered up with MSTPs for food distribution and more than 22 million active users every week. MSTPs’ online food delivery service has been dominating 70–75% of Indonesia’s online food delivery order market (Gojek News, 2019). Our study area is Jakarta, the capital city of Indonesia (Figure 1). Jakarta has a very high population density of 14,464 people per square kilometer (37,460/sq mi), while the metro area has a density of 4,383 people per square kilometer (11,353/sq mi). Jakarta also has the highest number of MSTP users among other cities in Indonesia, where around 8.8 million people (30–40% of the population) are active MSTP users. With regards to the online food delivery service activities, as of the year 2018, the Central Bureau of Statistics Indonesia confirms that 8.59% of food and beverages were ordered using online services.

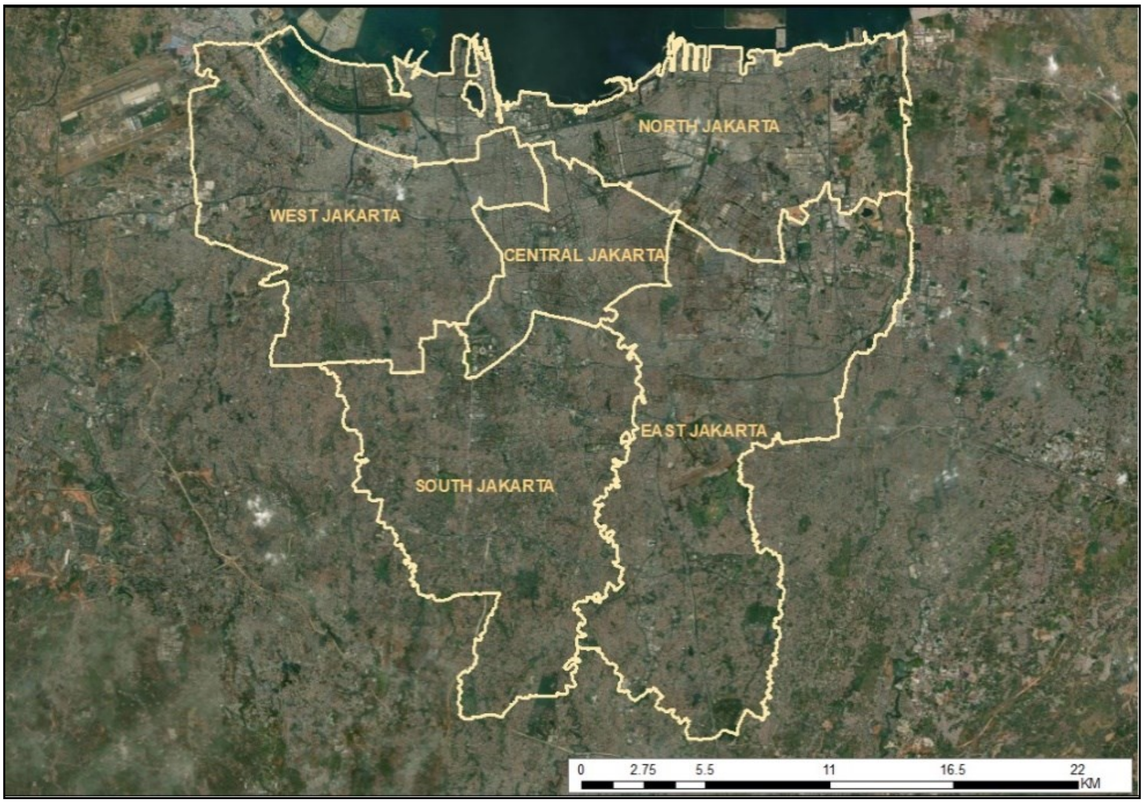


Figure 7.1. Map of study area in Jakarta, Indonesia

To analyze the impact of MTSPs on an individual's eating behavior, we conducted a context-aware SP survey together with the multi-day smartphone app-based travel diary (revealed preference (RP)) survey from January 28th to February 3rd, 2020, in Jakarta, Indonesia (see Safira et al. (2021) for details). We used office-based sampling, and thus all respondents were workers in South Jakarta, Indonesia, who have used online food delivery services (i.e., Go-Food by Gojek and GrabFood by Grab). In the survey, we used a smartphone-based app called X-ING (by Mobile Market Monitor (MMM), www.mobilemarketmonitor.com). The application provided a wide range of travel attributes, including location (origin and destination), travel time, travel purpose (activity), route choice (by GPS tracking), and mode choice.

For respondents who made eating-out trips, we further asked them to answer SP questions. The SP survey was designed and implemented to observe preferences on the respondents' eating behavior when the online food delivery service was improved. This is one type of context-aware SP question (Danaf et al., 2019), which combines a pivoting technique (Hess and Rose, 2009) and an SP-off-RP approach (Train and Wilson, 2008). By doing this, the real RP context, including the time-space constraints the respondents had, was reflected when answering the question. Note that there is also another similar SP survey design called an adaptive SP survey design (Fowkes and Shinghal, 2002) in which the attribute levels are dynamically modified depending on the previous choice results, but we did not employ this scheme.

This survey was designed particularly to capture changes in eating out behavior. Hypothetical scenarios with regard to online food delivery options were provided to users, and their choice of whether they will shift to online food delivery or continue to conduct the eating-out activity was observed. This is an important aspect with respect to understanding the effects of ICT on travel behavior as it will aid in analyzing if ICT will substitute physical travel in the case of eating-out trips. For each user, one of their eating-out activities was selected at random from the first week of their travel, and then based on their RP, attribute levels in SP were decided. Each user was then provided with five choice scenarios to choose between the online food delivery option and their present eating-out trip. This context-aware SP survey is deemed better than when all choice contexts in an SP survey are purely hypothetical. It is because such a design accounts for context-dependent factors such as motivation and constraints they had at that time. In addition, this kind of context-aware survey design could capture the complex interdependencies between ICT use and travel because their travel decisions may come from extrinsic motivations (e.g., getting a lunch meal) or intrinsic motivations (e.g., interacting with friends, traveling, and having lunch).

The attribute levels for the SP survey were generated using the RP information, as shown in Table 7.1. For a) delivery time for online food delivery, the travel time information captured from travel before the eating-out activity (for one randomly selected context) was utilized to create five different levels. Meanwhile, for b) delivery cost, travel distance information for the previous trip before the eating-out activity captured automatically through GPS sensors was utilized and multiplied with an assumed per km cost for delivery of 6,000 IDR (0.43 USD) across five different levels. For c) a combination of ordered food types, the same categories offered to users for their eating-out trips were utilized to create four different levels, denoting the combination and the number of food items ordered. Finally, d) food cost for online food delivery and information from RP on the user's actual expenditure on the eating-out activity was utilized to create five different levels. The variations in the food cost are an important factor, as often it is seen that MSTPs collaborate with food merchants to provide services at discounted rates.

Table 7.1. Attributes and levels for context-aware SP survey for eating out activities

Attributes	Level
a) Delivery time for online food delivery. *(based on the actual travel time from the travel diary data; revealed-preference-based question)*	6. 0.4* actual travel time 7. 0.7*actual travel time 8. 1.0*actual travel time 9. 1.3*actual travel time 10. 1.6*actual travel time
b) Delivery cost for online food delivery. *(based on the actual travel distance from the travel diary data; revealed-preference-based question)*	6. 0.4*6,000 IDR*actual travel distance 7. 0.7*6,000 IDR*actual travel distance 8. 1.0*6,000 IDR*actual travel distance 9. 1.3*6,000 IDR*actual travel distance 10. 1.6*6,000 IDR*actual travel distance
c) Combinations of Online food delivery's Food Types (1. Beverages, 2. Snacks/Sweets, 3. Fast food, 4. Indonesian food, 5. Western food, 6. Eastern food, 7. Bakso/Noodles)	5. One food type 6. Three food types 7. Five food types 8. Seven food types
d) Food cost for online food delivery. (based on the actual food cost from the activity information data; *revealed-preference-based question*)	6. 0.8*actual food cost 7. 0.9*actual food cost 8. 1.0*actual food cost 9. 1.1*actual food cost 10. 1.2*actual food cost

The five scenarios were presented to participants with two choices in each, with the actual eating-out trip information on the left side and the attribute levels for the online food delivery option on the right (Figure 7.2.), where alternatives are (1) continuing to conduct the eating-out trip, and (2) shifting to the online food delivery services. As the SP survey was conducted at a later time, we strived to make respondents remember the actual conditions they felt at the time of participating in that activity. By showing the date when they took the eating-out trip, it is hoped that the respondents will be able to remember the conditions and constraints they had at that time. The question was then posed to the respondents as part of the SP survey, "*by considering all the activities and constraints you have at that time if the following online food delivery service is available, will you be shifting from eating out to ordering an online food delivery service?*"

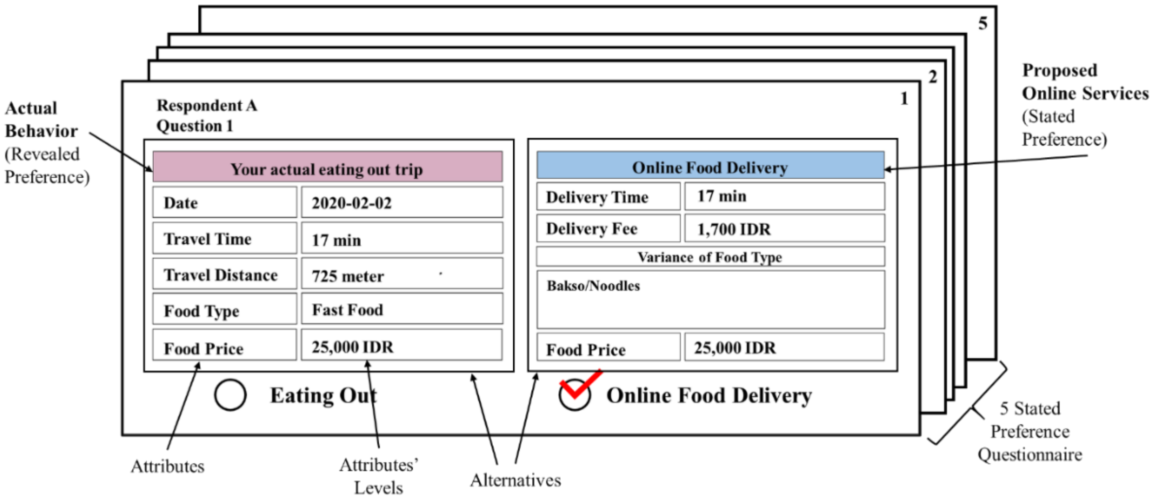


Figure 7.2. Context-aware SP questionnaire for eating out behavior

7.2.2. Modeling Framework

This section introduces a modeling framework to empirically identify the impacts of the level of service factors and contextual factors on the use of online food delivery services. As we briefly discussed in Section 1, it is not easy to introduce all contextual factors in a standard SP survey where all choice contexts are purely hypothetical. A feasible way to introduce realistic contexts is to ask respondents to answer SP questions in a real RP context (Huynh et al., 2017). We employed this context-aware SP survey approach. Specifically, we randomly picked up observed eating-out trips and asked respondents to answer whether they would like to shift to online food delivery services given the RP context. However, this process would lead to a self-selection issue by excluding respondents who did not have eating-out trips. To alleviate this self-selection issue, we used an inverse PWT (IPWT) method. In the method, we first estimated the propensity of having an eating-out trip for each eating behavior where the alternatives of eating behavior include eating-out and online food delivery service. Using the weights constructed from the estimated propensities, we developed an SP model on the use of online food delivery services. This process could remove the biases caused by the fact that the sample (i.e., people who made eating-out trips) used for the model estimation is systematically different from the population (i.e., people who made eating-out trips and who had a meal using an online food delivery service).

Note that because online food delivery services are already available in the market, it apparently seems that the RP data are good enough to explore preferences on the use of online food delivery services but taking the proposed SP approach is crucial to properly reflect contextual factors. It is well known that contextual factors are dominant in decision making; however, many of them are typically unobserved (Chikaraishi et al., 2009 & 2011). To control these unobserved contextual factors, it would be straightforward to show different online food delivery services to respondents repeatedly under the same RP context and observe how respondents change their decisions. Such repeated observations allow for introducing additional random terms representing unobserved trip-specific contextual factors analogous to random effects in panel data analysis. In the empirical analysis of this study, we employed a panel mixed logit model to control such unobserved trip-specific contextual factors. It should also be noted that a popular SP–RP combined model (Ben-Akiva and Morikawa, 1990) typically allows us to obtain statistically accurate estimation based on actual and hypothetical behavior (Sanko, 2001), but a straightforward application of this approach is not appropriate for our case study because, different from Ben-Akiva and Morikawa (1990), the SP data were not obtained from the population.

7.2.2.1. Estimation of the propensity score

We assume that whenever people want to use food services, they have two options: going to restaurants (i.e., making eating-out trips) and using online food delivery services. Given this assumption, we obtain the propensity of having an eat-out trip by estimating the following logit model:

$$p_{it} = \frac{\exp(v_{it})}{\exp(v_{it}) + 1} \tag{7.1}$$

where, p_{it} is the probability of choosing eating-out in the t-th eating behavior of individual i (called propensity score), $t \in T = \{T_e, T_{fd}\}$, where T is a set of all observed eating behavior, T_e is a set of observed eating-out trips, and T_{fd} is a set of observed online food delivery service uses, v_{it} is the systematic utility for making an eating-out trip, and $v_{it} = \beta \mathrm{x}_{\mathrm{it}}$ where x_{it} is a vector of explanatory variables, and β is a vector of parameters to be estimated. After obtaining the estimated propensity score $\hat{p}_{it}$, we take the inverse of propensity score as a weight, i.e.,

$$\widehat{w}_{it} = 1/\hat{p}_{it}. \tag{7.2}$$

7.2.2.2. Model specification for eating choice behavior

We then develop a panel binary mixed logit on the use of online food delivery service using SP data, where the utility is defined as follows:

$$u_{sit} = \alpha \mathrm{z}_{\mathrm{sit}} + \eta_{it} + \varepsilon_{sit} \tag{7.3}$$

where α is a vector of parameters to be estimated, $\mathrm{z}_{\mathrm{sit}}$ is a vector of explanatory variables for the s-th SP question for individual i's t-th trip ($t \in T_e$), and ε_{sit} is the error term following a standard Gumbel distribution. η_{it} is another random term following a normal distribution. This would capture the impacts of unobserved trip-specific attributes on the choice. The probability of choosing an online food delivery is defined as follows:

$$p_{sit} = \frac{\exp\left(\alpha \mathrm{z}_{\mathrm{sit}} + \eta_{it}\right)}{\exp(\alpha \mathrm{z}_{\mathrm{sit}} + \eta_{it}) + 1} \tag{7.4}$$

The following weighted likelihood function LL is used in the model estimation to control possible biases caused by the self-selection issue mentioned above.

$$LL = \int \sum_i \sum_{t \in t_e} \widehat{w}_{it} \ln(p_{sit}) \varphi(\eta_{it}) d\eta_{it} \tag{7.5}$$

For the model estimation, we use the *glmer* function of R-package lme4 (Bates et al., 2012).

7.3. DATA

In this study, we collected data from the respondents who completed the multi-day activity-travel diary survey. We found that 114 respondents were conducting eating activities that included both eating-out trips and ordering foods through online delivery services. Out of 557 eating activities, 272 were eating-out trips, and the remaining 285 were the use of online food delivery services. We also captured personal socioeconomic and demographic characteristics from users. It included questions on gender, age, income, family size, vehicle ownership, education level, and occupation type. Table 7.2. summarizes the number of individuals, samples of SP questionnaire, number of eating activities, and the explanatory variables used for the model estimation and their basic statistics.

Table 7.2. Data Description of Variables

Variable	Category	Total	Percentage
Eating behavior (RP)		557	100.00%
	Eating-out activities	272	48.83%
	Online food delivery services	285	51.17%
Eating behavior (SP)		570	100.00%
	Keep making an eat-out trip	271	47.54%
	Shifting to order online food delivery service	299	52.46%
Explanatory Variables			
Gender	Male	49	42.98%
	Female	65	57.02%
Age	18-22	12	10.53%
	23-27	44	38.60%
	28-32	28	24.56%
	33-37	18	15.79%
	38-42	12	10.53%
Marital Status	Single	72	63.16%
	Married	42	36.84%
Job	Office Worker	107	93.86%
	Non-office Worker	7	6.14%
Average Income per Month (in Mil. IDR)	Less than 1	3	2.63%
	1-1.99	7	6.14%
	2-3.99	21	18.42%
	4-5.99	42	36.84%
	6-7.99	15	13.16%
	8-9.99	10	8.77%
	More than 10	16	14.04%
Average Income per Month (in Mil. IDR)	Less than 1	4	3.51%
	1-1.99	7	6.14%
	2-3.99	24	21.05%
	4-5.99	42	36.84%
	6-7.99	13	11.40%
	8-9.99	8	7.02%
	More than 10	16	14.04%
Location Attributes of Activities			
Home Before	Location of Previous Activity is Home	55	9.65%
	Otherwise	515	90.35%
Home After	Location of Next Activity is Home	65	11.40%
	Otherwise	505	88.60%
Work Before	Location of Previous Activity is Workplace	150	26.32%
	Otherwise	420	73.68%
Work After	Location of Next Activity is Workplace	110	19.30%
	Otherwise	460	80.70%

Variable	Category	Total	Percentage
Social Interaction	Having a Desire to Interact with Others	390	68.42%
	Otherwise	180	31.58%

For the individual and household attributes, we used gender, age, marital status, respondents' occupation type, average monthly income of respondents, average monthly household expenses, dummy variables indicating the location before and after eating behavior, and the desire of having social interaction. The last attitudinal variable on social interaction was constructed from a 1–6 Likert scale attitudinal question, that is, "If I have someone to eat out with, I prefer to eat in a real restaurant rather than using online-based food delivery services," where negative answers (strongly disagree, disagree, and slightly disagree) are set as zero, while positive answers (slightly agree, agree, and strongly agree) are set as one.

For the eating choice behavior model estimation, we also use the variable from the SP questionnaire as our explanatory variables. Table 7.3 describes the variables from the SP questionnaire that represented the online food delivery services, including the variety of food, delivery time (in minutes), delivery cost (in IDR), and food cost (in IDR).

Table 7.3. Context-aware SP survey variable

Variable	Category	Total	Percentage
Sample Size		570	100.00%
Variety of Foods	1	145	25.44%
	3	133	23.33%
	5	142	24.91%
	7	150	26.32%
Delivery Time (in Minutes)	< 10	248	43.51%
	10-19	165	28.95%
	20-29	57	10.00%
	30-39	31	5.44%
	40-49	17	2.98%
	50-59	20	3.51%
	≥ 60	32	5.61%
Delivery Cost (in IDR; 10,000 IDR = 0.69 USD)	< 10,000	242	42.46%
	10,000-29,999	158	27.72%
	30,000-49,999	68	11.93%
	50,000-69,999	40	7.02%
	70,000-89,999	14	2.46%
	≥ 90,000	48	8.42%
Food Cost (in IDR; 25,000 IDR = 1.74 USD)	< 25,000	148	25.96%
	25,000-74,999	240	42.11%
	75,000-124,999	75	13.16%
	125,000-174,99	28	4.91%
	≥ 175,000	79	13.86%

7.4. RESULT AND DISCUSSION

To handle the self-selection issue, we first estimate the propensity score model. Table 7.4. shows the estimation results; it is confirmed that people who are young, male, or married or have high-income tend to choose eating out rather than online food delivery services. Regarding the scheduling-related factors, it is confirmed that those who have a job with a fixed schedule tend to choose eating out, and people who were staying at the workplace tend to choose eating out as well. We also found that those who have a desire to interact with others while eating tend to choose eating out rather than online food delivery services.

Table 7.4. The estimation results of the propensity score model

Explanatory Variables	Estimate	t-Values	Sig. Sign
Constant	-0.71	-1.08	
Age	-0.07	-5.14	***
Gender (0: Male; 1: Female)	-0.21	-2.21	*
Marital Status (0: Single; 1: Married)	0.54	3.03	***
Average Individual Monthly Income (mil IDR)	0.05	2.25	**
Average Household Monthly Expenses (mil. IDR)	0.03	2.11	*
Dummy for Occupation (0: occupation without a fixed schedule; 1: occupation with a fixed schedule)	2.04	5.03	***
Dummy for Home Before (1: location of the previous activity is home; 0: otherwise)	0.21	1.06	
Dummy for Home After (1: location of next activity is home; 0: otherwise)	0.04	0.21	
Dummy for Workplace Before (1: location of the previous activity is workplace; 0: otherwise)	0.61	3.08	**
Dummy for Workplace After (1: location of next activity is a workplace; 0: otherwise)	-0.01	-0.06	
Social interaction (1: having a desire to interact with others; 0: otherwise)	0.32	3.87	***
AIC		284.10	
Initial log-likelihood		-386.08	
Final log-likelihood		-294.95	
Sample size		557	

(***) significant at 0.1% level; (**) significant at 1% level; (*) significant at 5% level

Based on the estimation results shown in Table 7.4, we calculate the weights used in the following model estimations. Table 7.5 shows the estimation results of the models for eating choice behavior. We estimated how the presence of MSTP's online food delivery service would affect people's eating behavior by including the variables such as the social interaction, delivery time (in an hour), delivery cost (in 100,000 IDR), variety of food, food cost (in 100,000 IDR), the actual travel time for an eating-out trip, and the actual travel cost for the eating-out trip (in 100,000 IDR). In total, we estimated four models to identify the impacts of adding a random term representing unobserved trip-specific contextual factors and the impacts of the weights introduced. The results confirm the significant impacts of both the random term and weights on the estimated parameters. More specifically, the introduction of the random term changes the sign of parameter on delivery time, while taking weights into account changes the statistical significance of delivery time. The latter indicates that the population would be more sensitive to delivery time than the sample (i.e., eating-out trips). This can be logically understood because making eating-out trips implies that people have fewer time constraints compared with those who used online food delivery services. The estimated parameter values of the model with weights and random effects indicate that the delivery time, delivery cost, the actual travel time, and the actual travel cost are significant, while the variety of foods, food cost, and attitudes toward social interaction are not significant.

Based on our findings, we calculated the value of travel time for an eating-out trip and the value of waiting time for an online food delivery service. Note that the absolute values of parameters for SP variables are higher than those for RP variables as indicated by Ben-Akiva and Morikawa (1990), and thus the absolute values between RP and SP should not be directly compared. To make the comparison possible, we calculated the value of travel time for an eating-out trip and the value of waiting time for online food delivery services, where the former is 54,837 IDR/hour while the latter is 62,148 IDR/hour. This is apparently counterintuitive because people can conduct other activities while waiting for online food delivery services, and thus the value of waiting time should be lower than the value of travel time. However, several potential reasons make the value of waiting time greater than the value of travel time. First, using an online food delivery service is less flexible in terms of schedule modifications. For example, when travel time/food delivery time is increasing because of traffic congestions against their expectations, those who choose to eat out can change their destination to obtain their meal within the time constraint, but those who choose food delivery service may not be able to do that. Another possible reason is that a longer delivery time implies that people may not be able to have a fresh-cooked dish. Although we should further confirm whether these reasons are true in the future, our empirical results indicate that the impacts of online food delivery services on the spatial distribution of online food merchant's world could be modest because most people may use online food delivery services nearby, and thus merchants moving out to suburbs may have fewer online food delivery services' customers. However, it should be noted that in eating-out trips, they must make an additional trip to return to the original location, and thus the benefits of using online food delivery service would still be high even when the value of waiting time is higher than the value of travel time.

As confirmed, delivery time is one of the main factors affecting the use of online food delivery services. It may be natural to consider that delivery time will be decreased with the increased number of merchants nearby since it makes it easier to find MSTP drivers. To confirm this hypothesis empirically, we further explored the association between delivery time and the density of online food merchants. We first prepared travel time and delivery time data of online motorbike ride-hailing service (online ojek) using Google MAPs route search service for OD pairs of 262 zones in Jakarta (Figure 7.3). More specifically, we collected travel time and travel cost data of online ojek on Monday, November 2nd, 2020, at 10.00 a.m. In Indonesia's Google MAPs route search service, there is information on the online ride-hailing service's approximation cost for motorbike and car ride-hailing services. We took the average cost of the services as the travel cost of online motorbike ride-hailing (online ojek). It is noted that to order the services, people cannot use the Google MAPs directly; they must use the MSTP's application to order the services, and thus actual cost could be different from the one shown in Google MAPs. We also obtained information on delivery time and delivery cost of MSTP's online food delivery services. We used the Gojek application to obtain the information of GoFood (online food delivery services) delivery time and delivery cost from one zone to the other zones. It is noted that if we order the food using MSTP's online food delivery services, they might have some monetary incentives (e.g., coupons, price discounts, and other promotions) that may result in a different price at the time of ordering the food. However, we only included the regular average price of MSTP's online food delivery cost.

Table 7.5. The model estimation results of eating choice behavior

	Without $\boldsymbol{\eta_{it}}$						**With $\boldsymbol{\eta_{it}}$**					
	Without Weight			**With Weight**			**Without Weight**			**With Weight**		
	Estimate	**t-values**		**Estimate**	**t-values**		**Estimate**	**t-values**		**Estimate**	**t-values**	
Constant	-2.34	-13.12	**	-2.37	-14.00	**	-0.53	-0.41		-0.21	-0.15	
Social interaction	-0.21	-1.35		-0.28	-1.40		-0.14	-0.69		-0.37	-1.51	
Delivery time (hour)	-0.33	-2.45	*	0.76	1.68	.	-1.14	-2.13	*	-1.15	-2.14	*
Delivery cost (100,000 IDR)	-0.03	-3.51	**	-1.81	-2.92	**	-0.81	-1.36		-0.63	-3.97	**
Variety of foods	0.41	12.63	**	0.46	11.40	**	-0.003	-0.08		-0.01	0.13	
Food cost (100,000 IDR)	0.52	4.76	**	0.49	3.25	**	-0.12	-0.74		-0.15	-1.00	
Travel time (hour)	-0.14	-2.29	*	-0.84	-1.0438		-0.146	-1.93	.	-0.25	-1.74	.
Travel cost (100,000 IDR)	-0.07	-1.35		-0.43	-0.82		-0.062	-0.07		-0.15	-1.88	.
Random effect: σ_η^2							9.737			9.915		
AIC	422.54			437.88			361.43			246.74		
Initial log-likelihood	-395.09			-395.09			-395.09			-395.09		
Final log-likelihood	-252.98			-240.48			-221.40			-215.54		
Sample size	570											

(1) ** significant at 1% level; * significant at 5% level; (.) significant at 10% level
(2) At the time of the survey was conducted 1 USD = 14,602.75 IDR

(a) Map of 262 zones (b) Map of Jakarta's Road Networks

Figure 7.3. Maps of 262 zones and the road networks of Jakarta

We collect the data of several transportation modes on Monday, November 2nd, 2020, at 10.00 a.m. The data that we collected includes:

1. Travel time and travel cost of a private vehicle.

As we know that in Google MAPs route search services, there is no information of approximation cost for private vehicle usage available on the website. Therefore, to obtain the travel cost of private vehicle usage, we use travel distance information to calculate the average fuel cost of the distance. In this study, we simplified the formula of the consumption rate of fuel by Ipatov (1982) by ignoring all of the model coefficients and the vehicle capacity and ended up with:

$$tc_{ij}^{c} = (td_{ij} * fc_c)/1000 \tag{7.6}$$

Where,

tc_{ij}^{c} = travel cost of the car from zone i to zone j

td_{ij} = travel distance of from zone i to zone j

fc_c = the average price fuel consumption of 1 liter for the car (543.24 IDR)

2. Travel time and travel cost of private motorbike.

Similarly, with the travel cost of a private vehicle, there is no information of the approximation cost for private motorbike usage available on the website. Therefore, to obtain the travel cost of the private motorbike usage, we use travel distance information to calculate the average fuel cost for the motorbike for the certain travel distance among the zones, with the assumption that the average travel price of fuel consumption of 1 liter for a motorbike is cheaper than the car.

$$tc_{ij}^{m} = (td_{ij} * fc_m)/1000 \tag{7.7}$$

Where,

tc_{ij}^{m} = travel cost of a motorbike from zone i to zone j

td_{ij} = travel distance of from zone i to zone j

fc_m = the average price fuel consumption of 1 liter for a motorbike (443.24 IDR)

3. Travel time and travel cost of public transit.

To obtain the travel time and travel cost of public transit, we calculate the average travel time and travel cost from all public transit modes that individuals may use from one zone to the other by neglecting the types of mode, transit time, and walking time.

4. Travel time and travel distance of walking.

Since we cannot quantify the cost of walking in the transportation research yet, we only obtain the travel time and travel distance of walking for our transport service dataset.

5. Travel time and travel cost of online motorbike ride-hailing service (online *ojek*).

In Indonesia's Google MAPs route service, there is information on the online ride-hailing service's approximation cost for motorbike and car ride-hailing services. Then we took the average cost of the services as the travel cost of online motorbike ride-hailing (online *ojek*). It is noted that to order the services, people cannot use the Google MAPs directly; they must use the MSTP's application to order the services.

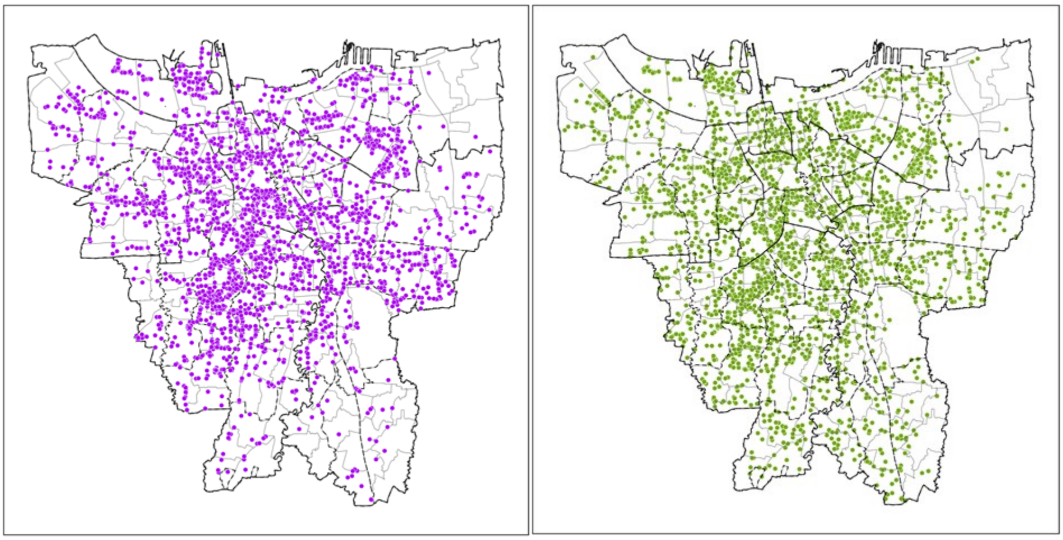
6. Travel time and travel cost of online car ride-hailing service.

In line with the data gathering for online *ojek*, we use the average cost of the online car ride-hailing services as the travel cost.

7. Delivery time and delivery cost of MSTP's online food delivery services.

To obtain the data of delivery time and delivery cost of MSTP's online food delivery, we only can access the information through their platform's application. Therefore, in this study, we use the GOJEK application to get the information of their GOFOOD (online food delivery services) delivery time and delivery cost from one zone to the others zone. It is noted that if we order the food by using MSTP's online food delivery services, they might have some monetary incentives (e.g., coupons, price discounts, and other promotions) that may be resulting in a different price at the time you order the food. However, we only include the regular average price of MSTP's online food delivery cost.

We also obtained the location information of online food merchants from Google MAPs using web crawler tools. We extracted the location information on December 3rd, 2020. The extracted data include the name of facilities/stores, type of facilities, street address, coordinate location, opening hours, and other variables. In this study, we categorized the food merchants into two groups: (1) the "combination" food merchants who provide both dine-in and online food delivery services and (2) the online food merchants who only provide an online food delivery service (no dine-in service available at their store). Regardless of the type of food merchants, we only considered the food merchants with the fixed location of stores. The mobile food merchants such as mobile street food vendors were omitted. Using the web crawler data collection method, we successfully obtained 4,458 combination food merchants and 3,718 online food merchants across the area in Jakarta.



Combination Food Merchants Online Food Merchants

Figure 7.4. Distribution of food merchants

The delivery time includes both travel time by online ojek and the additional time such as time for searching a driver. Because this additional time makes online food delivery service less efficient, we employed the ratio of delivery time and travel time by online ojek as a service efficiency index for online food delivery service. Figure 7.5. shows the indicator values by the density of food merchants. The figure indicates that the additional time decreases with an increased density of online food merchants. In other words, people have more time-saving benefits if they order foods from an area that has a high density of online food merchants.

In general, drivers standby around areas that have higher demand. If the drivers standby in areas that have more online food merchants, the chance for them to obtain some orders is higher than in areas with a smaller number of online food merchants. Having more drivers in the area may reduce the additional time for searching for a driver and hence reduce the delivery time. This new kind of agglomeration must be considered when we explore the long-term impacts of online food delivery services on the distribution of food merchants. From the modeling perspective, in the future, delivery time should be dealt with as an endogenous variable because delivery time depends on the demand in the area.

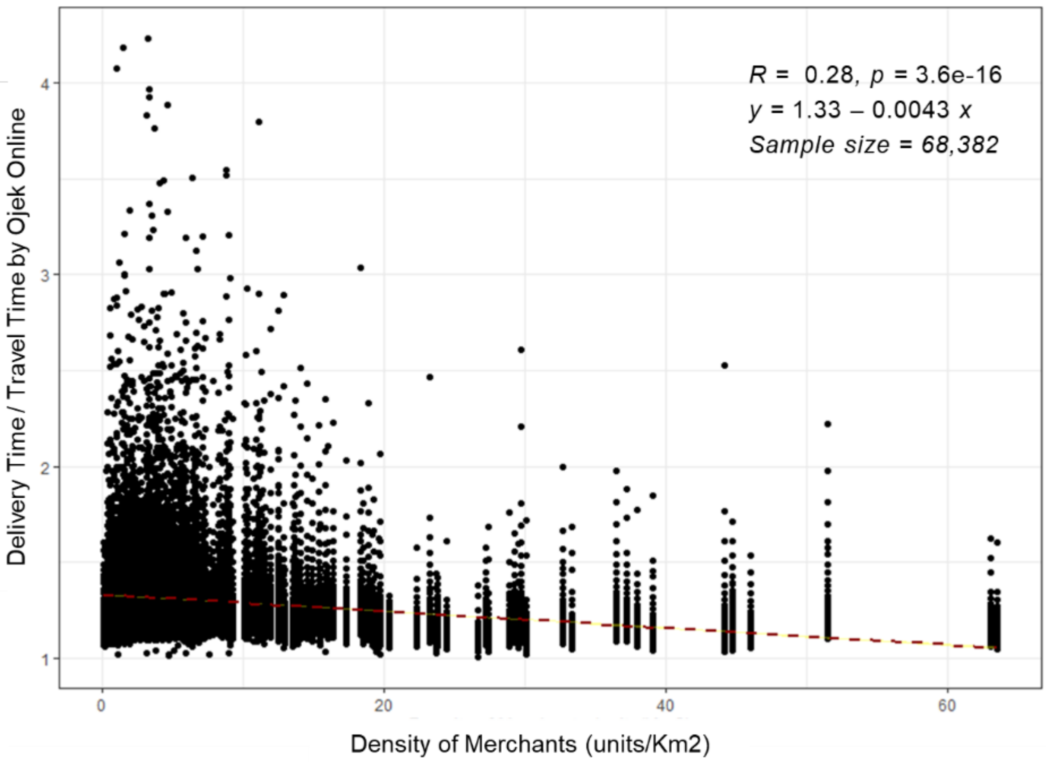


Figure 7.5. Correlation between service efficiency index and the density of combination and online food merchants

7.5. CONCLUSIONS

This study examined the impact of online food delivery services on individuals' eating activity behavior. The empirical analysis was conducted using context-aware SP survey data collected in Jakarta, Indonesia, together with multi-day smartphone-based travel diary survey data. Although this context-aware SP survey leads to a self-selection issue in the sense that all the respondents were persons who made eating-out trips, it allows us to elicit respondents' preference on the use of online food delivery services under the real-time–

space constraints they had. In our empirical model estimation, we used the IPWT method to control biases caused by the self-selection and introduced a random term to control unobserved trip-specific contextual factors. The empirical results indicate the importance of using both IPWT and random-effect models to alleviate the biases in the estimates.

Empirical results showed that delivery time and delivery cost, along with the other unobserved random variables, are key factors affecting people's preferences on the use of MSTPs' online food delivery services. Our empirical results also confirmed that the value of waiting time for online food delivery services (62,148 IDR/hour) is larger than the value of travel time for an eating-out trip (54,837 IDR/hour), potentially because (1) using online food delivery service is less flexible in terms of schedule modifications, and/or (2) longer delivery time implies that people may not be able to have a fresh-cooked dish, though further analysis is needed to reach a general conclusion.

The delivery time of MSTPs' online food delivery service includes both travel time by the online ojek and the additional time of searching for a driver who can pick up the order. We empirically confirmed that the additional time could be substantially shorter with the increase in the number of online food merchants nearby because drivers would standby around the area that has higher demand. This may become a new agglomeration force for online food merchants that may need to be considered when evaluating the long-term impacts of online food delivery services on urban form.

There are several major remaining tasks. First, we need to evaluate how merchants (as the supply side of MSTPs) react to the changes in users' behavior. Second, the use of online food delivery services should properly be embedded into an activity-based model. Although the impacts on land use may be marginal, as indicated by our empirical results, travel patterns are affected by the shift from eating out to the use of online food delivery services. Another major challenge is the comprehensive evaluation of ICT tools on activity-travel behavior. Now ICT tools have tremendous impacts on our activity-travel behavior in multiple ways, including online shopping and teleworking, and having a better understanding of the negative/positive and direct/indirect impacts of shifting to these virtual activities need to be further explored for better policy decisions.

Chapter 8: THE IMPACT OF MSTP ON ACTIVITY-TRAVEL BEHAVIOR (THE IMPROVEMENT OF DYNAMIC DISCRETE CHOICE MODEL FOR ACTIVITY-TRAVEL BEHAVIOR ANALYSIS UNDER THE PRESENCE OF MSTP)

In this chapter, we proposed the improvement of the current dynamic discrete choice model for activity-based analysis that incorporates the presence of MSTP. In this study, we attempt to answer one of our research questions that "How to extend the current dynamic discrete choice model for activity-travel analysis to incorporate the impact of MSTP use on the activity-travel pattern?" (RQ 5.1). This chapter is containing the introduction of the study, methodology, proposed model, simulation results, conclusion, and the way forward of the proposed methodology.

8.1. INTRODUCTION

Theories on the relationship between urban form and travel patterns are mainly based on the concept that travel results from an individual's desire or need to engage in an activity. The location to perform activities is spatially distributed over a wide range of areas. Hence, these activities cannot be carried out at the same location. Then, the result is the desire to conduct some trip or travel. Theoretical reflections on the potential effects of urban form typically concern the spatial distribution of essential activity locations such as residences, jobs, and shops. Shortening distance between these types of locations is often represented as a means to decrease mobility growth. The nearest facilities and service from the home may be the best alternative as destinations for activity participation for some individuals.

According to the activity-based approach, it is assumed that individuals and households will try to meet their basic needs and personal preferences by participating in activities. At the same time, the environment they live in offers them opportunities and constraints to doing so. Then, travel is the result of the locations for conducting activities where it is also spatially distributed. Activity-based is a comprehensive approach, including all travel motives that use a disaggregate scale by focusing on individuals and households. An activity-based approach's advantage is that it recognizes that travel patterns are the outcome of a highly complex interplay between personal and household characteristics, features of the urban environment, the transportation system, and the institutional context. The activity-based model will be appropriate for evaluating how people will behave or organize their activities in time and space.

In the activity-based approach, several activity-based models have been developed together to assume that travel is a derived demand of activity engagement at the destination based on the time-space constraint concept. This concept emphasizes that time and space delimit an individual's opportunities to participate in activities and travel, imposing restrictions on people's access and mobility (Hägerstrand, 1970; Burns, 1979; Schwanen, 2008). For example, Kitamura and Fujii (1998), Pendyala et al. (2002), and Liao et al. (2013) have been developed based on this time-space concept, together with the assumption that travel is a derived demand of activity engagement at destination (i.e., people are traveling for extrinsic motivations rather than intrinsic motivations). Based on the time-space constraint concept, the critical question here is how individuals (households) organize their daily activity-travel pattern within the opportunities and constraints set by their immediate and larger urban environment. Moreover, ICTs, particularly MSTP, may also give some dynamic changes in each individual and household opportunities and constraints to conduct some activities.

The recent studies, together with the rapid progress of ICT, have questioned these two foundations of the model. Shaw and Yu (2009) claim that virtual activity engagement via ICT cannot be represented and explained by the classical time-space constraint framework. Also, such virtual activity engagement would reduce travel if travel is a purely derived demand of activity engagement, but this may not be entirely true since people would travel not only for extrinsic but also for intrinsic motivations (Mokhtarian et al., 2015). These arguments call for further investigations on observing and modeling interdependencies between ICT use and travel.

On the other hand, several researchers have discussed how ICT usage affects travel behavior from various angles, such as how ICT affects mode choice, route choice, and scheduling. However, most studies focus on the overall impact of ICT on activity-travel behavior, while they do not consider the context-dependent factors affecting ICT use and activity-travel behavior. A number of researchers have discussed how the usage of ICT affects travel behavior from various angles, such as how ICT affects the mode choice, route choice, and scheduling (e.g., Lenz, B. & Novis, C., 2007, Aguiléra, A. et al., 2012, Fiore, F. D., et al., 2014, Ben-Elia, E., 2018). However, most studies focus on the overall impact of ICT on activity-travel behavior. At the same time, they do not take into account context-dependent factors affecting ICT use and activity-travel behavior. For example, the use of an online food delivery service for lunch may depend on the time pressure the person is under at that time.

In this study, we aim to extend an existing dynamic discrete choice activity-travel model to incorporate the impacts of ICT use on activity-travel patterns. This study focuses on a situation in Indonesia where multi-service transport platforms (MSTP), particularly GOJEK and Grab, have been widely used and have now become a vital part of people's daily lives, leading to unignorable changes in people's travel behavior and activity patterns. With the presence of the MSTP, the way of interacting between the supply-side (merchants) and demand-side (users) might change, essentially because the platform would relax users' time and space constraints to reach the services. We have attempted to develop a survey and modeling framework to comprehensively understand the impacts of MSTP on the urban form and activity-travel behavior. We believe that it is worth sharing the proposed framework together with empirical findings with other travel behavior scholars since the MSTP has been showing both unignorably positive and negative impacts on the society in Indonesia and putting the MSTP in a proper position of entire transport systems is one of the significant challenges we face.

8.2. METHODOLOGY

8.2.1. Modeling Approach

Based on Rasouli, S., & Timmermans, H. (2014), three different modeling approaches can be distinguished in developing activity-based models of travel demand shown in Figure 8.1. includes:

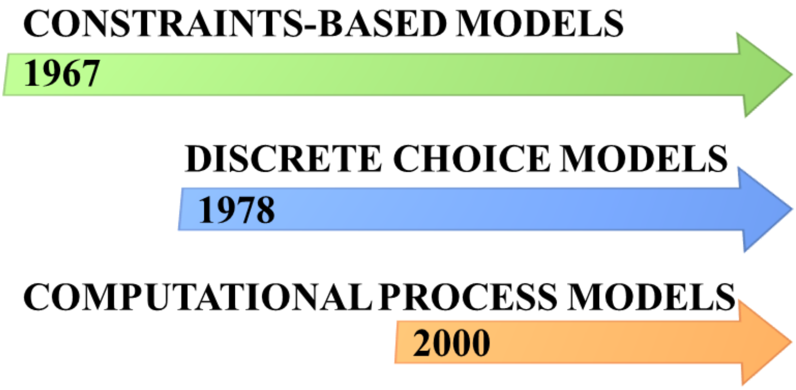


Figure 8.1. History of the development of the activity-based model

(a) Constraints-Based Models

This model attempts to check whether any given activity agenda is feasible to be performed in a specific space-time context instead of predicting individual or household activity-travel patterns. The inputs of this model are activity programs that describe a set of activities with a specific duration that can be performed at a particular time. In this model, the space context is defined as the location where the activities can be performed, including the available transportation mode and approximation of travel time between locations by different transportation modes. One of the exciting attributes included in this model is the opening and closing hours of the facilities at the locations. Thus, these constraints-based models' strength is their ability to identify infeasible activity schedules in a changing time-space context. However, there are several limitations to this model. First, most models consider individual accessibility, not household accessibility. Second, most models and applications have been based on deterministic representations of the urban and travel environment: travel times are fixed, opening hours are fixed, space-time prisms tend to be derived from the maximum speed, etc. Finally, individual and household choice behavior's conceptualization does not include any mechanisms related to choosing behavior under uncertainty.

(b) Utility-Maximizing Models

In the activity-based model, there is an assumption that individuals will maximize their utility throughout a day by choosing between activity-travel pattern alternatives or individuals a utility maximizer of their daily activity and travel. According to the utility maximization assumption, the activity-based model was extended the complexity of discrete choice models (in particular, the nested logit model) developed earlier to model, for example, destination–transport mode decisions to include more nests and choice options. Early applications were straightforward extensions in the sense that logit models were used to predict the probability of an individual choosing a multifaceted activity-travel profile (e.g., Adler & Ben-Akiva, 1979; Recker, McNally, & Root, 1986a, 1986b). This nested logit model is consisting of five nests: (i) activity pattern, representing a choice of a pattern with and one without travel, (ii) primary tour time of day, (iii) primary destination and mode, (iv) secondary tour time of day and (v) secondary tour destination and mode. A nested logit model is used to predict activity-type choice. The upper nest represents the choice of an in-home activity, activity at or near the fixed activity location, and general out-of-home activity.

(c) Computational Process Models
Some researchers proposed the formulation of rule-based models to explain decision heuristics in order to relax the rigid and behaviorally irrational assumption of utility-maximizing behavior. These models were often formulated in the context of computational process models, which mimic the underlying decision-making process. In line with earlier theoretical notions of time geography, individuals and households are assumed to conduct activities to attain specific goals. These activities need to be scheduled interactively with other individuals to decide who will participate in the activities, when, where, how long, and how to travel between locations where the activities can be performed. The model system that bears some resemblance with computational process modeling is AMOS, a dynamic micro-simulator of household activities and travel over time and space (Pendyala, Kitamura, Chen, & Pas, 1997; Pendyala, Kitamura, & Reddy, 1998). Choice sets delineated based on space-time prisms, and other constraints are *updated dynamically* during the scheduling process.

8.2.2. Dynamic Discrete Choice Model (DDCM)

In this study, the fundamental modeling approach is a dynamic discrete choice model based on random utility-maximizing principles. Following Västberg, O. B. et al. (2020), we briefly introduce the Dynamic Discrete Choice Model (DDCM) and its use for estimations. Dynamic discrete choice models have received widespread acceptance in transport research and are used in travel demand modeling and behavioral analysis. Following the random utility maximization model, specifically the standard nested logit model, in DDCM, the path choice problem is formulated as a link choice sequence. At each state, the decision-maker or agent chooses the utility-maximizing outgoing link with link utilities given by the instantaneous cost, the expected maximum utility to the destination (value function), and i.i.d. extreme value (with zero means) (M Fosgerau, 2013).

The DDCM was constructed based on the Markov Decision Process (MDP) to model the choice of daily activity-travel pattern. Markov decision-making can be formally represented with four components (see Figure 7.1), including (1) a set of states (S), which is the outcome of the decision or actions that the decision-maker took, (2) a set of actions (A), (3) the transition probabilities (q) that can describe the dynamic of the environment, and (4) there is a real-valued reward or utility function (u) on states which is an instantaneous utility function as a reward from the action that agent took.

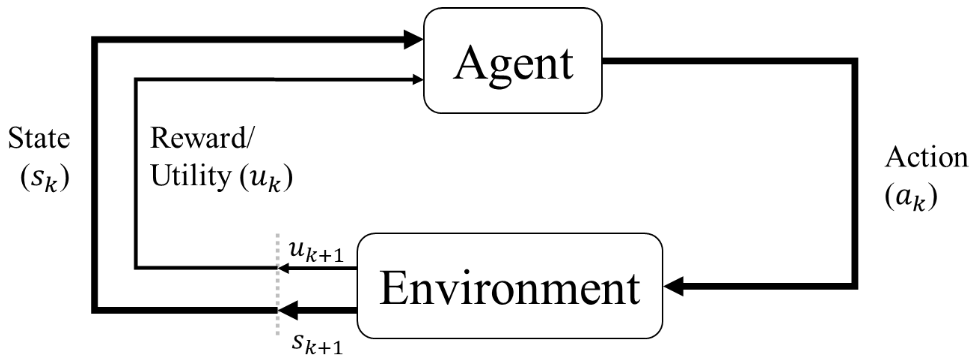


Figure 8.2. Markov Decision Process (MDP)
Source: Adaptation from https://towardsdatascience.com, 2020

A sequence of actions forming a path between states where a state s_k may define the location l and time of day t, among other things represents the daily activity-travel pattern. While S

denote the set of all states and the set of states available at a specific point in time *t* by s_t. In this model, the time *t* is a continuous state variable, but we assume that decisions are taken at discrete points in time. The index k is used to denote the order of the state s_k in the sequence of states that are traversed during the day.

In each state, an individual can choose an action $a_k \in C(s_k)$, where $C(s_k) \subset \mathrm{C}$ defines the subset of discrete actions that are feasible in the specific state s_k. An action may define, e.g., the type and duration of an activity or destination and mode of transport of a trip. When the environment is stochastic, the state s_{k+1} reached when choosing a_k in state s_k may be uncertain and given by some probability density function $q(s_{k+1}|a_k, s_k)$. Daily variations in travel times may cause such uncertainty. One could have a state that represents the need to perform an activity on a specific day and allow the stochastic process q to model how this need evolves over a day, resembling how need-based models (e.g., Arentze, Ettema, and Timmermans, 2011) to capture how the need to perform activities evolves between days over a week. We assume that individuals are aware of the stochasticity introduced by q and take it into account when making decisions.

The activity-travel pattern can be defined by the sequences of states $\mathbf{s}$ and actions $\mathbf{a}$ transverse during a day. Giving that the individuals' preference for taking a decision a_k in a specific state s_k and reaching the state s_{k+1} is represented by a one-stage utility function. It is assumed that an agent makes an action that can maximize his or her total utility in a given period of time. Observed an individual who has made sequences of actions $\mathbf{a}_n = \{a_{0,n}, a_{1,n}, \dots, a_{K_n,n}\}$ and reached states $\mathbf{x}_n = \{x_{0,n}, x_{1,n}, \dots, x_{K_n+1,n}\}$, The total utility $U(\mathbf{s}, \mathbf{a})$ is defined as the sum of utilities obtained from reaching a specific state and from conducting some actions as follows:

$$U(\mathbf{s}, \mathbf{a}) = \sum_{k=0}^{K} u\,(s_k, a_k, s_{k+1}) \tag{8.1}$$

Where the k is an index to denote the order of the state s_k in the sequence of the state that is transverse during the day. By assuming that individuals behaved as if they choose the utility-maximizing travel pattern, a rational agent that starts in a state s would behave according to policy π, determining the action $a_k = \pi(s_k)$ that maximize the expected future utility of a day. Then, the one-stage utility $u(a_k, x_k)$ of taking an action a_k in the state s_k is:

$$u(s_k, a_k) = u(a_k, x_k) + \epsilon_k(a_k) \tag{8.2}$$

Where $u(a_k, x_k)$ is the utility function of the observed variable at state s_k and $\epsilon_k(a_k)$ is the random terms that will be assumed as i.i.d Gumbel distribute. Finding the optimal policy and then calculating the choice probabilities requires computing the expected value function in each state x_k. The expected future utility conditional on a state is the value function in the state:

$$V(s) = \max_{\pi} E_s \left\{ \sum_{k=0}^{K} u\,(s_k, a_k, s_{k+1}) | s_k = s, a_k = \pi(s_k) \right\} \tag{8.3}$$

Where E_s is respected to the stochasticity of s_k given the decision rule $a_k = \pi(s_k)$. With the assumption that q (transition probability), u (one-stage utility function), and $C(s_k)$ (choice set) is under Markovian condition, so they are independent of the history. The Markovian assumption is not a problem in theory because it could include all previous history in a finite horizon model. Following Rust (1987), we have assumed that the random state variable ϵ_k is conditionally independent of the previous state and action and enters the one-stage utility additively. Observe that value function $V(s)$ can be defined recursively through Bellman's equation as (Bellman 1957, Rust 1987).

$$V(x_k, \epsilon_k) = \max_{a_k}\{u(x_k, a_k) + \epsilon_k(a_k) + EV(x_k, a_k)\} \tag{8.4}$$

Where the $EV(x_k, a_k)$ is the expected value of the value function of the state reached when taking action a_k in state (x_k, ϵ_k). If $EV(x_k, a_k)$ is known for each state-action pair, the principle of optimality states that the optimal policy π is obtained by, conditionally on a state s_k, choosing the action a_k that maximizes the utility function, then $EV(x_k, a_k)$ is given by:

$$\begin{aligned} EV(x_k, a_k) &= E_{t^{(k+1)}, h^{(k+1)}, \epsilon_{k+1}}[V(x_{k+1}, \epsilon_{k+1}) | x_k, a_k] \\ &= \int_{t'} \left(\sum_{j=1}^{N_h} q_h(h_j | t', t, h, \tilde{p}) \cdot \bar{V}(x_{k+1}) \right) dq_t(t' | t, l, \tilde{m}, \tilde{d}) \end{aligned} \tag{8.5}$$

Where in turn $\bar{V}(x_k) = E_{\epsilon_k}[V(x_k, \epsilon_k)]$. When $\epsilon_k(a_k)$ is independent and identically distributed (i.i.d.) with Gumbel distributed (with zero means), $\bar{V}$ is given by the following log-sum:

$$\bar{V}(x_k) = \log\left(\sum_{a_k \in C(x_k)} e^{u(x_k, a_k) + EV(x_k, a_k)} \right) \tag{8.6}$$

With i.i.d. Gumbel distributed k, the probability that an action a_k will be the utility-maximizing alternative in a state $x_k$when k is unobserved is simply given by the MNL model:

$$P(a_k | x_k) = \frac{e^{u(x_k, a_k) + EV(x_k, a_k)}}{\sum_{a_k \in C(x_k)} e^{u(x_k, \tilde{a}_k) + EV(x_k, \tilde{a}_k)}} \tag{8.7}$$

After we suppressed the parameters θ from the utility functions' specification and the individual's dependence in that the model describes, the likelihood for the observation of an individual is then given by:

$$L_n(\mathbf{a}_n, \mathbf{x}_n | x_0, \theta) = \prod_{k=0}^{K_n} P_n(a_{k,n} | x_{k,n}, \theta_u) \cdot q(x_{k+1} | a_{k,n}, x_{k,n}, \theta_q) \tag{8.8}$$

Let N observations construct the set of observations ∂_N ON. The log-likelihood function for ∂_Nbased on the conditional likelihoods becomes:

$$\overline{L}L(\partial_N; \theta) = \sum_{n=1}^{N} \log(L_n(\mathbf{a}_n, \mathbf{x}_n | x_0, \theta)) \tag{8.9}$$

8.3. PROPOSED MODEL

In the context of travel behavior analysis, dynamic discrete choice models have been used for modeling route choice behavior (Fosgerau et al., 2013; Oyama and Hato, 2019) and recently used for modeling whole activity-travel patterns in a given period of time (Västberg, O. B., Karlström, A., Jonsson, D., & Sundberg, M., 2019), i.e., a sequence of activity-travel decisions is considered as a path choice in a time-space prism (Chikaraishi et al., 2018). While the model strictly reflects time-space constraints, the current version does not represent virtual activity engagement through MSTP that would virtually nullify time-space constraints.

Figure 8.3. shows how a person's activity-travel behavior, the utility that they get from the "real" experience, may be different from the utility they get from the "virtual" access; there may be some reduction in the amount of utility. However, the benefits they get are still higher than the cost they are made for the trips/movements. From the user's perspective, they have more alternatives or options to access the service or the other location's needs by having virtual access. This relates to how virtual access utility maximization can be achieved by staying at one location. This is similar to the concept of route choice in choosing the best route, which is considered to maximize its utility. The utility function used is a utility obtained through the "real" access and a utility obtained through "virtual" access.

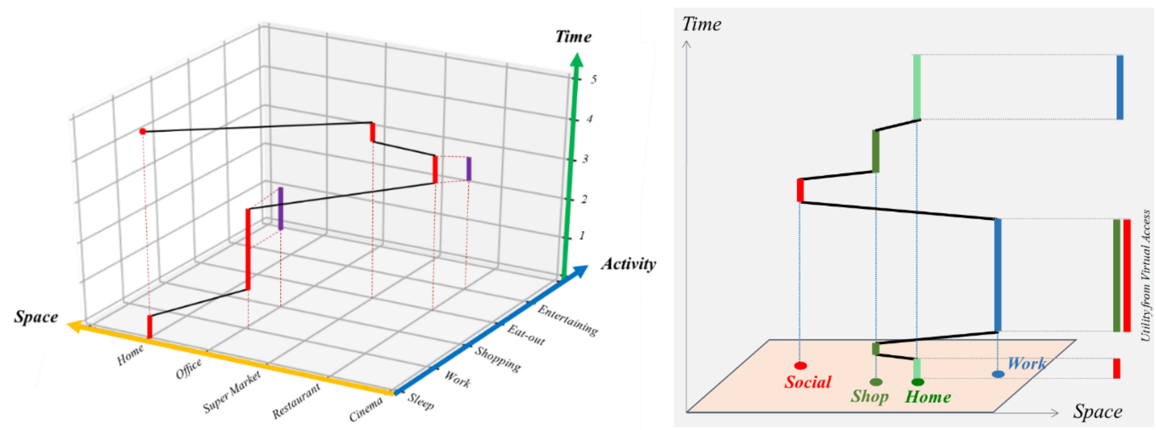


Figure 8.3. The daily travel-activity behavior embedded with ICT usage

By looking at the ICT usage of people within a particular time slot, we can know that someone can improve the utility by having virtual access to their needs through the Multi-service Transport Platform (MSTP). By having that virtual access, it would relax users' time and space constraints to reach the services or their needs. In this case, ICT will increase the cumulative utility obtained by someone. To handle the disadvantage, we are adding a log sum term representing the expected maximum utility obtained from ICT use into the instantaneous utility of the recursive logit model would allow us to represent the impacts of ICT use on travel behavior.

In this study, we attempted to analyze the impact of MSTP on the whole daily activity-travel behavior. However, due to the limitation in time and data preparation, we will conduct some simulations by using small-scale data instead of using a whole daily activity-travel behavior data. The challenge that we faced is the size of the data or model's problem. The actual problem size that we need to handle if we want to analyze the whole daily activity-travel behavior is.

- Time period : 05:00 a.m. to 11:00 p.m. (18 hours)
- Number of zones : 262 zones
- Number of respondents : 272 persons
- Purposes : 6 purposes (working, eating out, shopping, recreation,

home, and others)

- Transportation mode : 8 modes (stay, walk, car, motorbike, public transport, ojek online, ride-hailing, and others)

Later, we will show why this size of whole daily activity-travel behavior is challenging to handle in the activity-behavior analysis. This study aims to extend the existing dynamic discrete choice model for activity-travel behavior analysis by taking into account the presence of MSTP. To test the behavior of the proposed model, we used the small-scale data for the simulation of lunch behavior with the specification as follows:

- Time period : 11:00 a.m. to 14:00 p.m. (3 hours)
- Number of zones : 4 zones
- Purposes : 4 purposes (work, eating out, MSTP, others)
- Transportation mode : 4 modes (stay, walk, car, public transport)

To be able to perform the dynamic discrete choice model, several things need to be specified in the network data, including:

1. **Specification of actions *(a_k)***

   In the dynamic discrete choice model, we assumed that an individual will makes an action that can maximize his or her total utility in a given period of time. The decision variable that defines actions a_k are destination $\tilde{d} \in L$; mode of transport $\widetilde{m} \in M$; and purpose $\tilde{p} \in P$. Here $L, M,$ and P define the set of locations, modes, and purposes, respectively.

$$a_k = \begin{pmatrix} \tilde{d} \\ \widetilde{m} \\ \tilde{p} \\ \tau \end{pmatrix} = \begin{pmatrix} destination \\ mode - of - transport \\ purpose \\ min.\ duration\ for\ \{\tilde{d}, \widetilde{m}, \tilde{p}\} \end{pmatrix} \in \begin{Bmatrix} 1,2,\dots,N_L \\ m_{stay}, m_1, \dots, m_{N_M} \\ p_1, p_2, \dots, p_{N_P} \\ [0,T] \end{Bmatrix} = \begin{Bmatrix} L \\ M \\ P \\ \tau \end{Bmatrix} \tag{8.10}$$

   In this simulation, we define the action a_k as follows.

$$a_k = \begin{Bmatrix} 1,2,3,4 \\ m_{stay}, m_{walk}, m_{car}, m_{pt} \\ p_{work}, p_{eat}, p_{mstp}, p_{others} \\ [0,T] \end{Bmatrix} \tag{8.11}$$

2. **Specification of state *(s_k)***

   In the DDCM, the state is the position of the agents in a specific environment where it should include all information necessary to formulate the choice set and one-stage utility function. As state s_k consist of (1) the time-of-day t, which are modeled as a continuous variable between 0 and T ($t \in [0, T]$); (2) the current location $l \in L$; (3) the purpose of a previous action $p \in P$; (4) the previous mode of transport $m \in M$ was used to allow for interdependence among the mode choice between subsequent trips; (5) activity history h that stores the relevant history related to previously performed activities in the form of an index; it stores the number of times each activity has been performed during the day; and (6) the non-modeled random attributes of the available actions $\epsilon_k \in \mathbb{R}^{N_C}$. While $x_k = (t, l, p, m, h)$ is denote the observable part of the state space, so that $s_k = (x_k, \epsilon_k)$.

$$s_k = \begin{pmatrix} t \\ l \\ p \\ m \\ h \\ \epsilon \end{pmatrix} = \begin{pmatrix} time-of-day \\ location \\ purpose\ of\ previous\ act \\ previous\ mode\ of\ transport \\ activity\ history \\ random\ state\ vector \end{pmatrix} \in \begin{Bmatrix} [0,T] \\ 1,2,\ldots,N_L \\ p_1, p_2,\ldots,p_{N_P} \\ m_{stay}, m_1,\ldots,m_{N_M} \\ 1,2,\ldots,N_h \\ \mathbb{R}^{N_C} \end{Bmatrix} \tag{8.12}$$

In this simulation, we define the state s_k as follows.

$$s_k = \begin{pmatrix} t \\ l \\ p \\ m \\ h \\ \epsilon \end{pmatrix} = \begin{Bmatrix} 0,1,2,\ldots,18 \\ 1,2,3,4 \\ p_{work}, p_{eating-out}, p_{mstp}, p_{others} \\ m_{stay}, m_{walk}, m_{car}, m_{pt} \\ 1,2 \\ \mathbb{R}^{N_C} \end{Bmatrix} \tag{8.13}$$

With the assumption that every decision is made every 10-minute interval (Δt).

3. **Specification of the conditional choice set ($C(x_k)$)**
   Defining the conditional choice set on the state s_k involves defining the set of purposes, destinations, and modes that are available in a specific state s_k. We assume that the conditional choice set is independent of ϵ. With a few limitations, an individual can in each time step decide to either stay ($m = m_{stay}$) at the same location l and perform the previous activity p for a while longer; or travel with a mode $\tilde{m} \in M(m)$ to a new destination $\tilde{d} \in L$ and start a new activity $\tilde{p} \in P$. In this simulation, the choice set is restricted in the following ways:

$$M^n(m) = \begin{cases} m_{walk}, m_{pt}, m_{oj}, m_{rh} & if\ \delta^n_{car} = 0 \\ m_{car}, m_{walk}, m_{pt}, m_{oj}, m_{rh} & if\ \delta^n_{car} = 1,\ m = m_{stay} \end{cases}$$
$$L^n_{act.}(\tilde{p}) = \begin{cases} L & if\ \tilde{p} = p_{eat}, p_{other} \\ l^n_{work} & if\ \tilde{p} = p_{work}, p_{mstp} \end{cases} \tag{8.14}$$

4. **State Transition (q)**
   The unspecified state transition is q_t and q_h. In this simulation, we define the minimum time *t* that individuals need to take some actions; it is defined as:

$$min\left(t^{(k)}\right) = \begin{cases} 1 & if\ p = work \\ 3 & if\ p = eating-out \\ 2 & if\ p = MSTP \\ 1 & if\ p = other \\ 0 & if\ p = travel \end{cases} \tag{8.15}$$

   h denotes the number of finished eating our MSTP activities; it is increased by one whenever the activities are performed. It is defining as:

$$h^{(k+1)} = \begin{cases} h^{(k)} + 1 & if\ \tilde{p} = p_{eat}, p_{mstp} \\ h^{(k)} & else \end{cases} \tag{8.16}$$

5. **One-stage Utility Function (u)**
   We divide the one-stage into the utility of traveling $u_{travel}(t, l, \tilde{d}, \tilde{m})$ and the utility of staying $u_{stay}(t, l, p, \tilde{p})$. Where the utility of staying is consisting of the utility of eating out $u_{eat,size}(l)$, the utility of using an online food delivery service

$u_{mstp,size}(l)$, utility to perform other activities $u_{other,size}(l)$, the utility obtained from working $u_{work,stay}(t)$And the utility of staying at home $u_{home,stay}(t)$. Below is the specification of the utility functions used in this study.

1. The utility of Travelling ($\boldsymbol{u_{travel}}$)

$$u_{travel}(\mathrm{t}, l, \tilde{d}, \tilde{m}) = \theta_{\tilde{m}} + \theta_{tt} \cdot TT_{\tilde{m}}(t, l, \tilde{d}) + \theta_{cost} \cdot C_{\tilde{m}}(t, l, \tilde{d}) \tag{8.17}$$

The utility of traveling depends on the time of day when deciding to travel, the current location, the destination, and the chosen mode of transportation. The utility function of travel is constructed by the parameter of each mode $\theta_{\tilde{m}}$, the travel time of the chosen mode of transportation $TT_{\tilde{m}}$ from the current location to the destination, and the travel cost of the chosen mode of transportation $C_{\tilde{m}}$ from the current location to the destination.

2. The utility of Stay ($\boldsymbol{u_{stay}}$)
The utility of stay was constructed with the utility of eating out, the utility of ordering online food delivery service (MSTP), and the utility of working.

a) Eating out

$$u_{eat}(l) = \theta_{C,eat} + \theta_{food} \cdot x_{food}(l) + \theta_{I,food} \cdot I_{food}(l) \tag{8.18}$$

The utility function of eating will depend on the current location where the individual n is located. Where the variable of eating-out utility including the number of food merchants at the location (x_{food}) and agglomeration index of food merchants at the location (I_{food}).

b) MSTP (Online food delivery service)

$$u_{mstp}(l) = \theta_{C,mstp} + \theta_{C,logsummstp} \cdot u_{logsummstp}(l)$$

The log-sum variable of MSTP defines as follows.

$$\begin{aligned} u_{logsummstp}(l) \\ &= \ln\Big[\sum \exp\big(\theta_{mstp} \cdot x_{mstp}(l) + \theta_{I,mstp} \cdot I_{mstp}(l) \\ &\quad - \theta_{del,c} \cdot C_{del}(l) - \theta_{del,t} \cdot DT_{del}(l)\big)\Big] \end{aligned} \tag{8.19}$$

The utility of using an online-based food delivery service (MSTP) will be reflected by the log-sum function and the size variable of MTSP, including:

1) Number of online food merchants at the location (x_{mstp})
2) Agglomeration index of online food merchants at the location (I_{mstp})
3) Delivery cost to the current location ($C_{del}(l)$)
4) Delivery time to the current location ($DT_{del}(l)$)

c) Utility from working

$$u_{work}(t) = \theta_{work} \tag{8.20}$$

We conduct the simulation of our model by using a small amount of data to see how the model will behave. The observation of the simulation's result cannot be used to examine how the MSTP affects the activity-travel behavior directly. However, in the activity-travel behavior analysis, we need to handle 9 or more dimensions in the model, including the dimension for actions (a_k) that consist of 4 dimensions (destination ($\tilde{d}$), mode ($\tilde{m}$), purpose ($\tilde{p}$), and duration (τ)) and the dimension for states (s_k) that consist of at least 5 dimensions (time-of-day (t), previous location (l), previous purpose (p), previous mode (m), history of activities (h)). With this number of dimensions, the conventional sparse matrix that has been used in the recursive logit model for value function calculation will not be able to handle it due to the huge amount of combination and high computational burden.

In this simulation, we introduce the new approach to calculate the value function by using a tensor matrix. Conceptually, the tensor is similar to the sparse matrix, but it can handle a multidimensional space. By using the tensor, we can handle the multidimensional space of variables from the combination of action and state that will be used in the calculation of the value function. Following the framework of the recursive logit model, in this dynamic-discrete choice model, the value function is also defined recursively through Bellman's equation.

In the analysis, we want to handle the tensor problem as a matrix form to be able to do the calculation, make a product, and sum up different tensors. Then, to do that, we change the tensor into matrix form (see Figure 7.6.). The combination of location, mode, and purpose both in state and action can produce several combinations of action-state pair, including (1) change activity purpose, (2) activity soon after travel, (3) continue the same purpose, and (4) traveling.

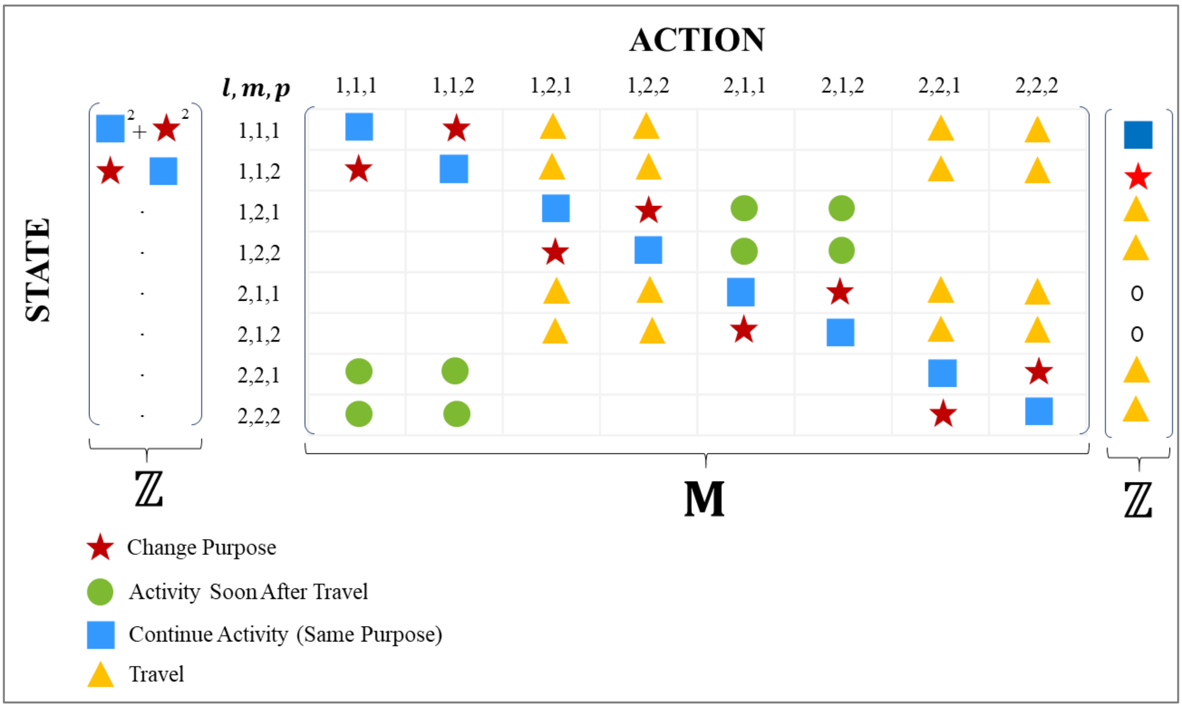


Figure 8.4. Tensor for action-state pair

In this study, we attempt to introduce the time (t) dimension into the activity-travel behavior model. By adding the time component, it is means adding an additional dimension into our matrix (see Figure 8.5). The diagonal block is the central part of the model where the action-state is changing over time. Even though most of the values will be empty or zero due to the limitation of the choice set, but not all of them will be zero because some combination of action can be taken during the time period.

The expected value function is approximated in a number of discrete time steps. In this simulation, we define the time steps Δt is in every 10 minutes interval, then the difference between T-1 and T is 10 minutes. When the value is needed between these time steps, some approximating function is used. When travel time is 16 min and the time step (T) = 10 min, the agent is assumed to move to t+1 with 40% probability and to t+2 with 60% probability. The same proximation also will be used as the weight in the calculation of travel time. By using these weights, we can simulate such a condition where the travel time is placed between the time steps. For example, if the travel time is 47 minutes, then the utility value will be placed in the time steps 4.7. Then the time step before travel was taken is 4 and after travel was taken is 5. By adding the weight into the utility calculation, we found that a 30% probability of the utility will be at T+4, and a 70% probability of the utility will be at T+5. If we allocate 10 persons in that state, then by following the calculation, we found 3 persons will stay at the same state where 7 persons will go to T+5. However, they will go through the same procedure in the next state and their decision may be changed over time.

In the same manner, we can set up a minimum time duration for activity. For example, the previous one is travel, and you travel to the new places and start the new activity and at that point, we can add the minimum time required. We forced them to spend time conducting an activity, but it may not reflect the reality because some people may skip their activities at the first destination due to several reasons, such as queuing, closed facilities, and other reasons. However, this minimum duration for taking some activities is the part of actions or decision variables that need to be considered from the decision maker's point of view.

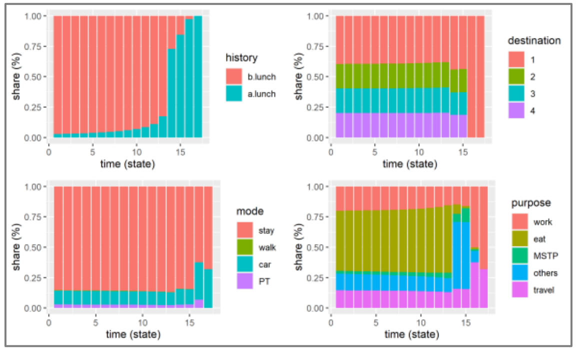
8.4. CONCLUSION AND WAY FORWARD

Based on our simulation, we found that our proposed model is well-behaving as expected. This proposed model is one of the major contributions of this study to construct the methodological framework for activity behavior analysis based on the dynamic discrete choice model that taking account the presence of MSTP. In this simulation, all the parameter is given, while in the actual calculation, we will estimate all parameters for each action and states. In this study, we also found that the use of tensor can handle the multidimensional component of activity-travel behavior. We are also introducing the way to taking account the time (t) component into our model. Also, we introduce how we handle the travel time uncertainty by using the weight in the calculation of the expected utility proportion that can reduce the computational burden. Another dimension that we will add to our model is the history component of activities which is a part of states, and the individual characteristics that can restrict the decision makers' choice set.

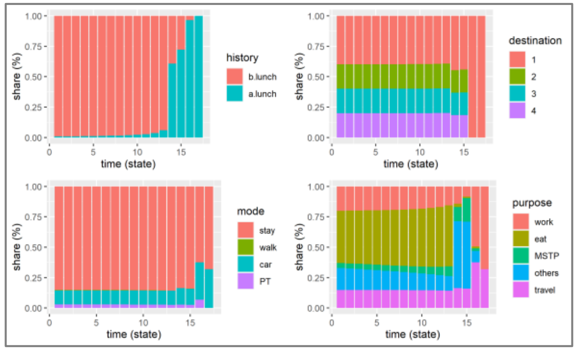
Although this is still ongoing research, we have attempted to develop a modeling framework to comprehensively understand the impacts of multi-service transport platform (MSTP) on travel behavior with a focus on Indonesia, where MSTP services have been widely used and have now become a vital part of people's daily lives. We believe that it is worth sharing the proposed framework together with empirical findings with other travel behavior scholars since the MSTP has been showing both unignorable positive and negative impacts on the society in Indonesia, and putting the MSTP in a proper position of entire transport systems is one of the significant challenges we faced.

Figure 8.5. Tensor for action-state pair including time dimension

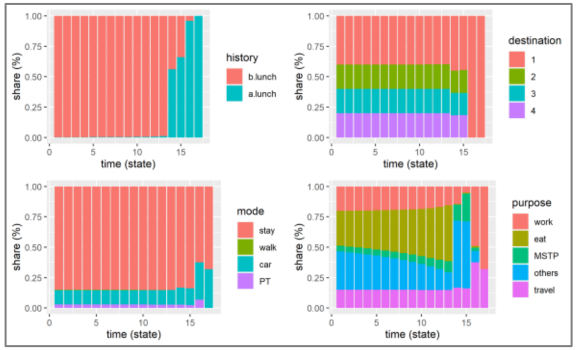
8.5. SIMULATION RESULTS



Log sum parameter = 0.1

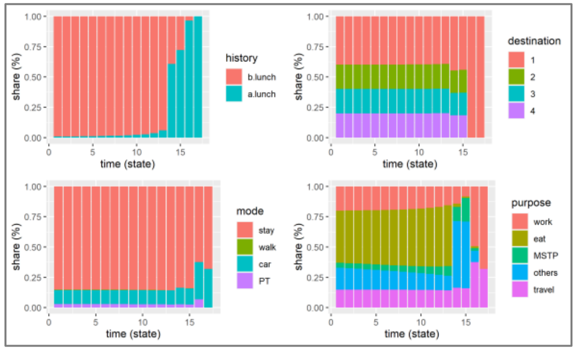


Log sum parameter = 0.5

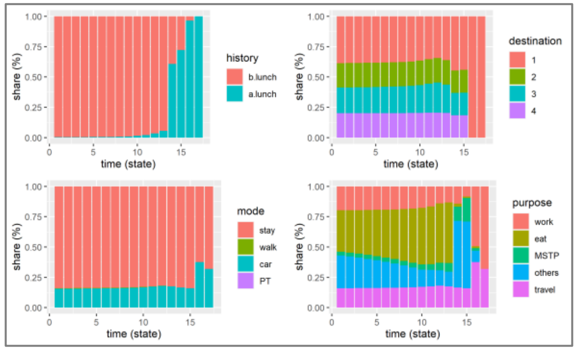


Log sum parameter = 0.9

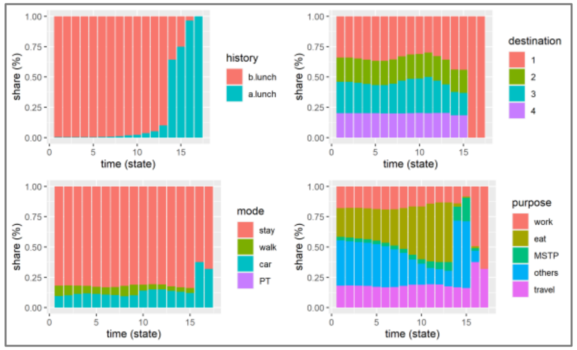
Figure 8.6. Simulation results 1 (the impact of MSTP service level)



Car const = 0; walk const = 0

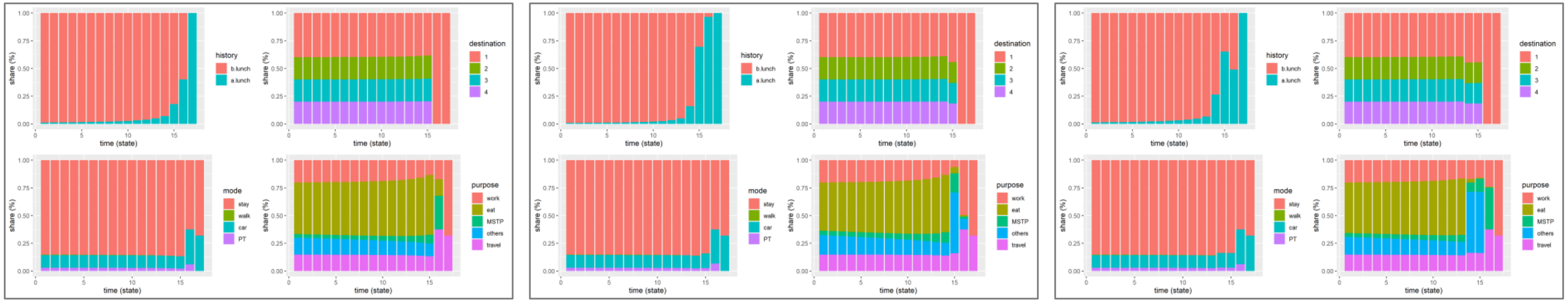


Car const = 5; walk const = 5.



Car const = 5; walk const = 10.

Figure 8.7. Simulation results 2 (impacts of travel impedance)



Eat = 10, MSTP = 10 Eat = 20, MSTP = 20 Eat = 30, MSTP = 10

Figure 8.8. Simulation results 3 (the impacts of minimum duration of activities)

Chapter 9: CONCLUSIONS AND RECOMMENDATION

In recent years, the presence of MSTP as one of the innovations of ICT in transportation and daily service provision has rapidly expanded and had a significant impact on our daily activity. Daily activities and travel are inseparable since travel results from an individual's desire or need to engage in an activity. While the location to perform activities is spatially distributed over a wide range of areas. Hence, these activities cannot be carried out at the same location. Then, the result is the desire to conduct some trip or travel to another location. With this realization in mind, this thesis had presented the result of an analysis that examined the multi-dimensional impact of MSTP on urban form and activity-travel behavior.

This research aimed to examine the impact of Multi-Service Transport Platform (MSTP) on the urban form and activity-travel behavior. Based on the analysis of the impact of MSTP on the urban form and activity-travel behavior, it can be concluded that MSTP changes the behavior of individuals toward online activities and change the decision location of food merchants. The results indicate that MSTP induces the new distribution of facilities (i.e., food merchants, where the distribution of facilities itself will affect the MSTP's services level and affect the individual's behavior (i.e., eating behavior).

While the existing studies do not consider the presence of MSTP, this study attempts to provide a comprehensive understanding of the impact of MSTP on urban form and activity-travel behavior through the agglomeration analysis of facilities and the eating behavior analysis. The results are well explained the impact of MSTP and answering all of the research questions. However, there are some insights that arose in the process that will be addressed as the recommendation for future study.

The contribution of this study to international literature include:

1) examining the impact of MSTP on facility distribution through the agglomeration index analysis.
2) capturing the online activities and MSTP services together with the improvement on the activity-travel diary survey.
3) proposing the theoretical framework for activity-travel behavior analysis that considering the presence of MSTP.

9.1. CONCLUSION

The innovation of information and communication technology has influenced many aspects of our daily lives, such as economic activities, study, medical, and others. In Indonesia, one of the innovations of ICT that very popular and widely used by many people since 2010 is the Multi-Services Transport Platform (MSTP). MSTP is an online-based multi-service platform that relies on drivers/fleets providing access to a wide range of services, including daily-needs services (e.g., online food delivery services, common delivery, grocery delivery, car wash, and others) and transportation services (e.g., online car ride-hailing and online motorbike ride-hailing/ojek online). MSTP is allowing people to virtually access services in other areas nearby without travel. In other words, MSTP may improve the accessibility and minimizing the cost (i.e., travel cost, travel time, energy). There are more than 21.7 million users of MSTP in Indonesia, where most of them are concentrated in the metropolitan and big cities such as Jakarta, Bandung, and Surabaya. With a high demand for the MSTP, it indicates that MSTP becomes an essential aspect in people's daily life, and it may affect their activity and travel behavior and change how the cities work.

This dissertation explores the impact of the MSTP on the activity-travel behavior and urban form in Jakarta, Indonesia. The purposes were to understand better how MSTP affects the urban form and individual's activity-travel behavior. A dynamic change of daily activity-travel behavior and urban form through MSTP can induce more sustainable cities and convenient lives. Those can only be achieved if the urban and transportation policies, spatial development patterns, individual decisions, private sector decisions, and interdependencies are understood and properly implemented. Therefore, this study included four parts of analysis: (1) the analysis of facilities distribution through agglomeration index analysis, (2) the descriptive analysis of the online and physical activity and transportation behavior, (3) the analysis of the impact of MSTP on the individual eating behavior, and we also attempt to develop the (4) dynamic discrete choice model for activity-travel behavior that includes the component of MSTP to see whether the MSTP components will affect the decision of our daily activity and travel.

Some findings and discussion of the studies are showed to empirically explain the impact of MSTP on the urban form and activity-travel behavior. **First**, MSTP changes the distribution of online food merchants by introducing the new agglomeration forces or the mechanism to be agglomerated from attracting more MSTP drivers into their area. Using the agglomeration index approach, we analyze the distribution and concentration of facilities in Jakarta, Indonesia. Due to the presence of MSTP, we found that a high agglomeration of online food merchants happened around the central area and 12-14 km away from the central area (e.g., fringe area) of Jakarta city. This may happen due to the mechanism of MSTP that relies on the fast service and high accessibility level to serve the consumers, so they set a particular distance as their maximum area coverage to keep their food quality for the consumers. By considering the cities' geographical and traffic characteristics, MSTP set their maximum coverage area within 6 kilometers away from the consumer's location. In other words, the online food merchants tend to be agglomerated within the MSTP's area coverage (i.e., 6 km) in order to attract more drivers into their area. This has contributed to exploring the behavior of the facilities under the influence of MSTP.

Some studies (e.g., Akamatsu et al., 2017), Combes, P. P., & Gobillon, L. (2015), and Fang, C., & Yu, D. (2017)) mentioned that the agglomeration might increase the productivity of firms and the economic development. It also happened to the online food merchants, where they tend to be agglomerated on a neighborhood scale. Suppose all of the urban facilities have behaved like the online food merchants that rely on online delivery services, where the physical movement of the customers is less required to access the services. In that case, there might be some flexibility in the location of facilities that may change the spatial equilibrium of the cities. However, an extensive exploration of the behavior of the facilities and their interdependencies is needed to see how the MSTP can affect facilities behavior, moreover whether MSTP can increase the productivity of the facilities and city economic development. We need to explore how online-based facilities interact with other types of facilities. Whether they will compete, support, or eliminate each other's will be our remaining tasks.

Second, the descriptive analysis of activity-travel behavior showed that the MSTP services have been more favorable toward eating and shopping activities. This has contributed to the reduction of the physical trip of the users. Based on a two-week activity-travel diary survey, we found that more than 55% of eating and shopping activities have been preferable to conduct by using MSTP. Those percentage indicates a high demand for MSTP services. If our samples represented the actual characteristics of all Jakarta's population, then this might be some significant changes in the daily behavior. The shift in people's behavior of conducting physical trips to online activity can have significant implications for transportation planning and urban development. If many people were shifting to conduct online activities and less conduct the physical trips, fewer people will use the road, and less congestion may happen. Less congestion may lead to some sustainable development of the cities.

It is uncertain that the high demand for MSTP may reduce traffic congestion. Even the consumers conduct fewer physical trips due to relying on MSTP online delivery services. However, a certain number of MSTP drivers (fleets) are still conducting some physical trips with their vehicles. Existing studies (see Suhartanto, D. et al. (2018)) show that MSTP drivers induce some traffic at a specific time nearby the center of activities, such as university, office, and shopping mall. To avoid some side-effects from an oversupply of drivers, we may need to explore how the MSTP's drivers behave. Some drivers may only serve in one area, while others serve in many areas. Some concentration of drivers may also relate to the agglomerated facilities that bring some potential demand or order for the drivers.

Another critical issue that arises is a way to decide the sufficient number of drivers to serve an area without having an under or oversupply of drivers. To the best of the author's knowledge, the number of drivers is decided by the natural market mechanism. We found that the market mechanism of MSTP is a complicated multi-sided market with a network effect where the number of users, merchants, and drivers is affected will affect each other decisions. Without any regulation that can control and estimate how many drivers that needed to serve an area, an insufficient number of drivers may happen. If the number of drivers exceeds the number of orders, many drivers are standby on the road without any orders, which may lead to traffic problems such as congestion and illegal parking. In this sense, the government must take action to regulate the optimal number of drivers to avoid some negative impacts on the transportation system and urban development.

Third, based on the activity-travel diary survey, we found that using MSTP's transport services is more favorable than public transport in Jakarta. Despite their role as an online delivery service, there are a significant number of MSTP transport service usage in Jakarta. Having a high number of demands does not make MSTP can replace the usage of a private vehicle and reduce traffic congestion. The basic idea of MTSP to optimize the fleets by allowing them to provide many kinds of services was a good initiative. However, as we mentioned above, it is uncertain that MSTP can reduce traffic congestion due to the unknown driver's behavior.

Based on the greater Jakarta commuter data in 2019, the usage of MSTP transport service (i.e., online motorbike ride-hailing (online ojek) and online car ride-hailing) cannot be used as the primary transportation mode for the whole trip due to their expensive fees compare to the public transportation such as private car, private motorbike, MRT, and bus. In Jakarta, people prefer to use their private motorbike for the first-mile trip, then some transport hub (e.g., MRT, KRL, Bus), and using some online-based transportation for the last mile. However, there is a similar percentage of MSTP transport service and private cars for the first mile and last mile. This indicates that people feel MSTP transport service is relatively cheap to be used as the first and last mile of transport mode, and it can provide high flexibility compared to the other modes. It is implicated that if the MSTP transport service quality is improved, the use of the car and other private vehicles for the first and last mile of the trip may be reduced. It also may reduce the traffic congestion caused by private vehicle usage. However, it may happen if there is a good integration between MSTP and public transport hub to reduce the use of private vehicles.

Forth, the delivery time and delivery cost that MSTP proposed is the significant variable that affects people using online food delivery services rather than conducting a physical trip. The findings suggested that utilitarian orientation is an important determinant of users' behavior toward MSTP online food delivery services. People find that using online food delivery services is relatively cheaper in the term of value of time than conducting a round trip of the trip for eating purposes. The improvement of delivery time and delivery cost may increase people's tendency to use MSTP online food delivery services. In the delivery time of MSTP online food delivery services, there are three main components: the time for food preparation by the merchants, the travel time by online ojek, and the additional time to find nearby drivers to take the orders. Where the time for food preparation is given by the condition of the cross-side network effect of demand and supply, the additional time is influenced by the same-side network effect. The number of drivers in the nearby area will affect the additional time. The additional time will decrease in the area with the increase in the density of online food merchants. In general, drivers would standby around the area with higher demand. Having more drivers in the area may reduce the additional time for searching for the driver and reduce the delivery time. However, it is unsure that having MSTP can improve the productivity of each individual in their daily activities by substitute all the essential tips into online delivery services. Future research by academics should focus on the impact of MSTP on individual activity-travel behavior, especially on the timing decision to see whether MSTP people can allocate more time for productive activities (e.g., working and studying).

Fifth, the exploration of MSTP impact on individual activity-travel behavior through the simulation on the dynamic discrete choice model showed that the MSTP components (i.e., online transportation services, the availability of online food delivery services, and the number of food merchants as the attraction of each area) show that MSTP may change the timing decision, destination choice, and the activity purpose of individuals in their daily activity-travel pattern. As mentioned above, some studies can address some limitations by using the improved DDCM framework. To decide whether MSTP can support the development of a sustainable city, another exploration needs to be done, such as analyzing individual activity-travel behavior and their preference towards MSTP and other online activities. By analyzing an individual's activity-travel behavior through some activity-based analysis (i.e., dynamic discrete choice model (DDCM) for activity-based analysis), we can explore the impact of MSTP on their activity decision (e.g., timing decision, mode decision choice, destination choice, activity choice, and so on). The future improvement of DDCM is needed to taking account the new component, including MSTP's transportation service, MSTP's online food delivery service, the new attraction of the zones, and congestion. This contributes to a comprehensive understanding of MSTP's impact on activity-travel behavior on an individual scale and its implication to urban development.

9.2. IMPLICATION FOR POLICY AND PLANNING

Given the strong interrelationship between urban form and transport, along with the presence of MSTP as the ICT-based innovation in transport, the integration of land-use and transportation planning represents a unique policy opportunity. When MSTP brings the new agglomeration forces for online food merchants by giving some flexibility to decide their location while still keep a certain number of consumers through online food delivery services, the new neighborhood-scale center may develop. By having the flexibility to be located, the presence of MSTP has the potential to change the structure of cities. In the long run, this kind of service may lead to a less structured city—the further regulation and policy regarding the location of an online-based food merchant. When the online food merchants are agglomerated across the city, the practitioner should consider putting some regulations in the location of online food merchants. In some cases, when that agglomerated online food merchants will induce some new trip attraction, at least for the online drivers that need to pick up the consumer's orders. In some cities in Indonesia, where the food merchants have to gain more popularity or maybe have some promotional programs, the number of orders will be increased and the number of drivers that were going to the merchant's location also increased. If many online food merchants in the agglomerated area are gain more orders, the significant number of trips to the agglomerated area will happen and it may cause some changes in the city's traffic and mobility flows where the particular area has more trip assignments compare to how they allocation.

To avoid the new trip attraction increased in the neighborhood-scale, the practitioner could allocate the new center at the bigger scale (e.g., district-scale), assumes that a bigger area scale can accommodate a bigger activity scale. Since the provision of strategic infrastructure is one of the most critical public policy instruments informing the long-term shape and characters of a city at any stages in development, MSTP as a part of transport infrastructure and services play a crucial role in determining urban mobility patterns within urban planning, including modal choice and delivery services. Regulatory policy instruments also play a crucial role in shaping urban transport performance, including the limitation of MSTP's fleet in one area to avoid overcrowding traffic.

Based on the analysis that we have done, to achieve a more sustainable urban development by optimizing the potential that MSTP has, this study recommends a higher facility density and higher agglomeration of economic activities in multiple locations, including the policies that are promoting more mixed-use and denser development around residential areas encourage changes in activity behavior, such as switching from making an eating behavior to using MSTP online food delivery service. Some researchers (see Ewing R. et al., 2018) already mentioned that compact development that is diverse, dense, well-designed, etc., produces fewer vehicle miles traveled than sprawling development. In this case, MSTP induces the concentration of activities based on their origin and destination that gain a benefit from a compact design city. On the other side, the distribution of facilities has become an attraction for people to choose MSTP online food delivery services. Closer distance and more variance of online food merchants may interact more users of MSTP online food delivery service. It can be applied for others MSTP delivery services that rely on accessibilities and delivery time. This study suggests that, in Jakarta, policies adapted toward increasing facility density and the mix of land use to maximize the potential of MSTP, and it is related to the multi-core urban development.

9.3. LIMITATION OF THE STUDY AND RECOMMENDATION

In this study, there are some limitations that can be encountered in the future to enrich the study. This section provides some direction for further research based on the limitations and findings reported in this study. **First,** this study research clearly illustrates the impact of MSTP on the urban form through the changes in the facility distribution. However, a systematic review of the literature was not possible given the limited academic work available. As this is a burgeoning academic field, we encourage future researchers to adopt a systemic approach to understand the sustainability impacts of the MSTP. **Second**, as we mentioned above, the exploration of the behavior of the facilities and its interdependencies is needed to see how the MSTP can affect facilities behavior, moreover whether MSTP can increase the productivity of the facilities and city economic development. An extensive exploration of the behavior of the facilities and their interdependencies is needed to see how the MSTP can affect facilities behavior, moreover whether MSTP can increase the productivity of the facilities and city economic development. We need to explore how online-based facilities interact with other facilities; whether they will compete, support, or eliminate each other's will be our remaining tasks. **Third**, to avoid some side-effects from an oversupply of drivers, we may need to explore how the MSTP's drivers behave. Some drivers may only serve in one area, while others serve in many areas. Some concentration of drivers may also relate to the agglomerated facilities that bring some potential demand or order for the drivers. **Forth**, the development of the dynamic discrete choice model to incorporate the presence of MSTP is needed to provide a more comprehensive analysis.

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LIST OF PUBLICATIONS

Journal Papers and International Proceeding

(1) Chapter 4
   a. Title: Association between Facility Location Agglomeration and Car Dependency: A Case of Japanese Cities.
   b. Status: Published.
   c. Journal name: Journal of the Eastern Asia Society for Transportation Studies
   d. Vol, Pages: 13, 1087-1098
   e. Publication date: 2019/12/31

(2) Chapter 5
   a. Title: Exploring the Impacts of Online Food Delivery Service on Facility Distribution: A Case of Jakarta, Indonesia.
   b. Status: Accepted.
   c. Journal name: Conference Proceeding of the 14th International Conference of Eastern Asia Society for Transportations Studies (EASTS) and nominated for Journal of Asian Transport Studies (ATS).
   d. Publication date: 2021.

(3) Chapter 6
   a. Title: Toward a Comprehensive Understanding of ICT Impacts on Activity-Travel Behavior: Preliminary Results from a Two-week Smartphone-based Survey in Jakarta, Indonesia.
   b. Status: Accepted
   c. Journal name: Conference Proceeding of the 14th International Conference of Eastern Asia Society for Transportations Studies (EASTS) and nominated for Journal of Eastern Asia Society for Transportations Studies (EASTS).
   d. Publication date: 2021.

(4) Chapter 5
   a. Title: On the empirical association between spatial agglomeration of commercial facilities and transportation systems: A nationwide analysis of Japan.
   b. Status: 2nd round peer-review
   c. Journal name: Journal of Transport and Land Use.

(5) Chapter 7
   a. Title: Exploring the Impacts of Online Food Delivery Service on Facility Distribution: A Case of Jakarta, Indonesia.
   b. Status: Submitted.
   c. Journal name: Journal of Transportation.
   d. Date of submission: 2021/07/06.

International Conference

- Safira Maya, Chikaraishi Makoto. (2021). Toward a Comprehensive Understanding of ICT Impacts on Activity-Travel Behavior: Preliminary Results from a Two-week Smartphone-based Survey in Jakarta, Indonesia. The 14th International Conference of Eastern Asia Society for Transportations Studies (EASTS). Hiroshima, Japan. September 12-15, 2021.

- Safira Maya, Chikaraishi Makoto. (2021). Exploring the Impacts of Online Food Delivery Service on Facility Distribution: A Case of Jakarta, Indonesia. The 14th International Conference of Eastern Asia Society for Transportations Studies (EASTS). Hiroshima, Japan. September 12-15, 2021.
- Safira Maya, Chikaraishi Makoto. (2020). The Impact of Online-based Food Delivery Service on Individuals' Eating Behavior: A Case Study on the Multi-service Transport Platforms (MSTPs) in Indonesia. The 5th PlanoCosmo International Conference, Institut Teknologi Bandung, Indonesia. October 20-21, 2020.
- Safira Maya, Chikaraishi Makoto (2020). Observing and modeling Interdependencies between ICT use and travel in the presence of multi-service transport platform: A case from Jakarta, Indonesia. hEART 2020: 9th Symposium of the European Association for Research in Transportation, ENTEPE, Lyon, France. April 7-9, 2021.
- Safira Maya, Chikaraishi Makoto (2020). The Impact of Online-based Food Delivery Service on Individuals' Eating Behavior: A Case Study on the Multi-service Transport Platforms (MSTPs) in Indonesia. The 5th PlanoCosmo International Conference, Institut Teknologi Bandung, Indonesia. October 20-21, 2020.
- Safira Maya, Chikaraishi Makoto (2019). Association Between Facility Location Agglomeration and Car Dependency: A Case of Japanese Cities. The 13th International Conference of Eastern Asia Society for Transportations Studies (EASTS), Sri Lanka. September 9-11, 2019
- Safira Maya, Chikaraishi Makoto (2019). Association Between Facility Location Agglomeration and Car Dependency: A Case of Japanese Cities. 2019 International Conference on Climate Change, Disaster Management, and Environmental Sustainability, Kumamoto University, Japan. September 19-21, 2019.
- Safira Maya, Chikaraishi Makoto (2018). Agglomeration of Commercial Facilities and Modal Share Case Study: 16 Cities in Japan. 58th ERSA Congress, Cork, Ireland. August 28- 31, 2018.

CURRICULUM VITAE

I. Personal Information

Name	**Maya Safira, ST., MT., Dr. Eng.**
Place, Birth Date	Bandung, 14 December 1993
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II. Education Background

Program	**Bachelor (S-1)**	**Master (S-2)**	**Doctor (S-3)**
University	Institut Teknologi Bandung	Institut Teknologi Bandung	Hiroshima University
Major	Urban and Regional Planning	Urban and Regional Planning	Urban and Transportation Engineering
Entrance Year	2011	2015	2018
Graduate Year	2015	2016	2021
GPA	3.24 / 4.00 (Very Satisfied)	3.86 / 4.00 (Cum Laude)	4.00 / 4.00 (Cum Laude)
Thesis Title	Study of Land Price Changes in Public Apartment in Cimahi, Indonesia	System Development of Municipality Asset Management. Case Study: Kecamatan Coblong, Kota Bandung	The Multidimensional Impact of Multi-Service Transport Platform (MSTP) on Activity-travel Behavior and Urban Form: A Case of Jakarta, Indonesia
Supervisor(s)	Sugiyantoro, Ir., MIP	Dr. Ir.Denny Zulkaidi, MUP	1. Makoto Chikaraishi, Dr. Eng. 2. Prof. Akimasa Fujiwara 3. Prof. Junyi Zhang

III. Publication and Research Participation

3.1. International Journal

No	Title	Role	Journal Details
1	On the empirical association between spatial agglomeration of commercial facilities and transportation systems: A nationwide analysis of Japan.	First Author	Submitted to Journal of Transport and Land Use. (2021)
2	Exploring the Impacts of Online Food Delivery Service on Facility Distribution: A Case of Jakarta, Indonesia.	First Author	Submitted Journal of Asian Transport Studies (ATS). (2021)
3	Toward a Comprehensive Understanding of ICT Impacts on Activity-Travel Behavior: Preliminary Results from a Two-week Smartphone-based Survey in Jakarta, Indonesia.	First Author	Submitted Journal of the Eastern Asia Society for Transportation Studies.

No	Title	Role	Journal Details
			(2021)
4	Road Network Vulnerability and City-level Characteristics: A Nationwide Comparative Analysis of Japanese Cities	Co-Author	Environment and Planning B: Urban Analytics and City Science. (2020)
5	Association between Facility Location Agglomeration and Car Dependency: A Case of Japanese Cities.	First Author	Journal of the Eastern Asia Society for Transportation Studies. (2019)

3.2. International Conference Proceeding

No	Title	Role	Proceeding Detail
1	Toward a Comprehensive Understanding of ICT Impacts on Activity-Travel Behavior: Preliminary Results from a Two-week Smartphone-based Survey in Jakarta, Indonesia.	First Author	Proceeding of the 14th International Conference of Eastern Asia Society for Transportations Studies (EASTS). 2021.
2	Exploring the Impacts of Online Food Delivery Service on Facility Distribution: A Case of Jakarta, Indonesia.	First Author	Proceeding of the 14th International Conference of Eastern Asia Society for Transportations Studies (EASTS). 2021.
3	Observing and modeling Interdependencies between ICT use and travel in the presence of a multi-service transport platform: A case from Jakarta, Indonesia.	First Author	Proceeding of hEART 2020: 9th Symposium of the European Association for Research in Transportation. 2020.
4	The Impact of Online-based Food Delivery Service on Individuals' Eating Behavior: A Case Study on the Multi-service Transport Platforms (MSTPs) in Indonesia.	First Author	Proceeding of the 5th PlanoCosmo International Conference, Institut Teknologi Bandung, Indonesia. 2020.
5	Association Between Facility Location Agglomeration and Car Dependency: A Case of 69 Japanese Cities.	First Author	Proceeding of 2019 International Conference on Climate Change, Disaster Management, and Environmental Sustainability, Kumamoto University, Japan. 2019
6	Road Network Vulnerability: A Nationwide Analysis of 69 Cities from Japan	Co-Author	Proceeding of 2019 International Conference on Climate Change, Disaster Management, and Environmental Sustainability. 2019.
7	Association Between Facility Location Agglomeration and Car Dependency: A Case of Japanese Cities.	First Author	Proceeding of the 13th International Conference of Eastern Asia Society for Transportations Studies (EASTS). 2019
8	Agglomeration of Commercial Facilities and Modal Share Case Study: 16 Cities in Japan	First Author	Proceeding of the 58th ERSA Congress. 2018.

3.3. Participation in International Conferences

No	Conference	Date	Role as	
			Presenter	Participant
1	The 14th International Conference of Eastern Asia Society for Transportations Studies (EASTS)	12-15 Sept 2021	√	
2	hEART 2020: 9th Symposium of the European Association for Research in Transportation	7-9 April 2021	√	
3	The 5th PlanoCosmo International Conference	20-21 Oct	√	

No	Conference	Date	Role as	
			Presenter	Participant
		2020		
4	2019 Transportation Research Board (TRB) Annual Meeting	13-17 Jan 2019		√
5	2019 International Conference on Climate Change, Disaster Management, and Environmental Sustainability	19-21 Sept 2019	√	
6	The 13th International Conference of Eastern Asia Society for Transportations Studies (EASTS)	9-12 Sept 2019	√	
7	2018 Transportation Research Board (TRB) Annual Meeting	7-11 Jan 2018		√
8	The 58th ERSA Congress	28-31 Aug 2018	√	

IV. WORK EXPERIENCE

No	Institution	Position	Years
1	Graduate School for International Development and Cooperation, Hiroshima University, Japan	1. Teaching Assistant for Development Technology Department 2. Research Assistant for Risk and Infrastructure Laboratory	March 2018 – March 2021
2	Urban and Regional Planning Departement; School of Architecture, Planning, and Policy Development; Institut Teknologi Bandung, Indonesia	1. Academic Assistant for the School of Architecture, Planning, and Policy Development 2. Teaching Assistant for Urban and Regional Planning Department 3. Research Assistant for City Planning and Design Research Group 3. Facilitator of Functional Training for National Government Officer (Diklat JFP Pertama and Muda) Collaboration of BAPPENAS and ITB	August 2015 – September 2017
3	Center of Urban Design Study, Bandung, Indonesia	Urban analysist	August 2014 – December 2014

V. TEACHING EXPERIENCE

No	Institution	Subject	Year	Position
1	Hiroshima University	Seminar on risk management technology for graduate program of development technology department	2018-2021	Teaching Assistant
2	Hiroshima University	Special seminar for linkage program II for the graduate program of development technology department	2020	Teaching Assistant
3	Bandung Institute of Technology	Urban planning studio for urban planning concentration of the graduate program of urban and regional planning department	2017	Teaching Assistant and Studio Assistant
4	Bandung Institute of Technology	Land management for the graduate program of urban and regional planning department	2017	Teaching Assistant
5	Bandung	Urban facility planning for the graduate	2017	Teaching Assistant

No	Institution	Subject	Year	Position
	Institute of Technology	program of urban and regional planning department		
6	Bandung Institute of Technology	Site planning studio for the undergraduate program of urban and regional planning department	2016	Teaching Assistant
7	Bandung Institute of Technology	Urban planning studio	2016	Teaching Assistant and Studio Assistant
8	Bandung Institute of Technology	Planning process studio	2016	Teaching Assistant and Studio Assistant
9	Bandung Institute of Technology	Introduction of spatial data (Geographic Information System)	2015	Teaching Assistant and Lab Session Instructor

VI. RESEARCH EXPERIENCE

No	Research Title	Year	Position	Institution
1	Evaluation of sediment-related disaster evacuation facility plan due to heavy rain under COVID-19 situation (COVID-19 状況下での豪雨による土砂災害避難施設計画の評価)	2020	Research Assistant	Hiroshima University and Ministry of Transportation of Japan
2	Study on Interdependencies Between ICT and Travel Behavior	2020	Research Assistant	Hiroshima University and Ministry of Transportation of Japan
3	Short-term Prediction for Travel Demand Management in Disaster Situation	2019	Research Assistant	Hiroshima University and Ministry of Transportation of Japan
4	Interaction Between Urban Form and Travel Behavior in a Smart City Environment	2018	Research Assistant	Hiroshima University and Ministry of Transportation of Japan
5	Study of The Development of Communicative City Towards Smart Cities	2017	Research Assistant	Lembaga Penelitian dan Pengabdian kepada Masyarakat (LPPM) ITB
6	Urban-Village Asset Management	2017	Research Assistant	Lembaga Penelitian dan Pengabdian kepada Masyarakat (LPPM) ITB
7	Formulating A Smart Region Concept in The Context of Tropical Islands Cities System	2017	Research Assistant	Lembaga Penelitian dan Pengabdian kepada Masyarakat (LPPM) ITB

APPENDICES LIST

APPENDIX 1. AGGLOMERATION INDEX FOR 69 CITIES

Average Pairwise Distance

No	City	Average Pairwise Euclidean Distance								Average Pairwise Network Distance								Average Pairwise Travel Distance							
		Com	S	M	C	P	SM	SC	SCP	Com	S	M	C	P	SM	SC	SCP	Com	S	M	C	P	SM	SC	SCP
1	Nara	5.8	9.19	5.33	10.89	5.07	9.07	9.38	7.64	6.83	10.54	5.71	12.67	6.28	9.83	11.38	8.22	18.86	27.52	16.82	31.67	18.7	26.01	29.26	22.92
2	Otake	1.78	4.8	1.76	5.15	2.92	3.38	5.28	3.79	2.9	7.15	2.75	6.78	3.87	3.98	7.05	5.1	6.92	13.48	6.42	12.81	8.9	8.51	13.42	10.66
3	Fukuoka	5.67	9.73	7.26	9.3	10.47	8.46	9.1	10.84	6.65	10.41	7.95	10.12	11.32	8.27	10.32	10.84	19.67	29.41	23.25	28.58	32.18	24.17	29.19	30.91
4	Yokohama	9.34	11.68	12.28	10.78	12.45	12.76	12.62	13.58	12.11	13.71	12.84	14.24	13.56	12.73	13.79	13.74	32.8	37.99	35.29	38.49	37.47	34.96	38.08	37.88
5	Kawasaki	9.68	10.64	9.78	10.52	10.84	10.55	10.23	11.15	10.07	10.56	9.9	10.54	10.58	9.88	10.7	10.66	29.96	31.51	29.48	31.41	31.3	29.43	31.88	31.58
6	Kitakyushu	9.93	11.75	10.96	10.96	12.11	11.78	11.13	12.85	10.93	12.47	11.66	11.41	13.32	11.7	12.3	13.27	27.69	30.77	29.1	28.04	32.01	29.29	30.4	31.95
7	Matsuyama	5.26	8.07	5.83	13.58	8.65	6.97	9.66	9.46	6.35	8.72	6.56	13.54	9.69	6.86	11.49	9.61	15.76	20.04	16.24	25.11	22.66	16.81	24.69	22.24
8	Saitama	6.12	4.77	6.64	6.97	7.44	7.57	8.52	8.44	7.48	4.97	6.97	7.25	8.12	7.26	8.43	8.22	25.9	9.19	24.3	25.25	28.19	25.28	29.07	28.51
9	Kobe	10.09	12.8	11.96	11.49	14.46	12.74	12.48	14.62	11.26	13.96	12.44	11.53	15.59	12.69	14.09	15.3	23.6	28.77	26.43	23.13	30.84	26.9	28.94	30.66
10	Sendai	6.46	9.89	7.36	10.85	10.57	8.14	9.57	10.8	7.4	10.41	7.8	11.13	10.63	7.92	10.55	10.76	18.11	24.34	19.06	25.16	25.57	19.19	24.52	25.52
11	Nagoya	6.94	9.71	8.41	8.81	10.89	9.38	9.28	11.14	8.23	9.83	8.83	10.36	10.85	8.95	9.88	10.65	22.88	27.28	24.58	27.78	29.89	24.95	27.42	29.33
12	Sapporo	7.79	12.96	8	12.06	14.18	10.9	12.45	14.2	8.2	11.63	9.22	12.16	12.52	9.21	11.62	12.22	20.08	27.42	22.56	27.92	29.63	22.44	27.39	28.93
13	Hiroshima	6.81	11.86	8.24	12.97	10.47	9.52	11.65	11.75	8.43	13.35	9.12	14.31	12.22	9.56	13.6	12.57	19.39	29.66	21.34	31.14	28.23	22.17	30.08	28.57
14	Koriyama	5.26	10.68	5.22	13.67	5.84	7.36	10.56	10.34	6.28	10.72	5.88	13.58	5.82	6.96	12.04	9.88	13.81	21.14	13.18	25.28	13.52	14.99	23.09	19.85
15	Kumamoto	5.63	8.32	7.13	8.29	8.13	7.51	8.9	7.47	7.04	9.12	7.22	8.73	8.79	7.47	9.17	8.88	18.01	22.41	18.47	21.08	22.18	19	22.48	22.33
16	Utsunomiya	5.44	8.14	6.61	11.35	8.13	7.58	8.96	7.99	6.71	9.17	6.72	11.04	8.29	7.11	9.45	8.55	15	19.35	15.21	21.96	18.69	15.9	19.77	19
17	Chiba	7.2	9.54	8.47	9.18	8.91	5.37	8.98	7.89	8.14	9.81	8.8	9.35	9.45	9	9.73	9.59	22.77	26.37	24.33	24.92	25.46	24.82	26.13	25.81
18	Osaka	4.93	8.35	7.78	2.08	8.4	7.96	8.85	7.97	6.71	8.78	7.77	2.36	9.05	7.87	8.78	8.94	21.34	28.06	24.81	7.97	28.64	25.15	28.07	28.42
19	Tokorozawa	4.16	4.62	3.37	4.47	4.26	4.04	5.05	4.82	4.44	5.16	3.82	4.45	4.72	4.01	5.17	4.88	13.02	14.69	11.76	12.79	14.33	12.19	14.66	14.51
20	Yamanashi	3.29	6.51	3.85	5.99	1.84	5.28	6.78	6.3	4.41	7.44	4.11	6.64	2.13	5.25	7.1	6.59	9.82	15.4	9.63	13.04	5.82	11.64	14.43	13.7
21	Oyabe	3	3.75	2.87	5.29	0.51	4.23	5.61	5.42	3.64	4.43	3.43	5.46	0.55	4	5.29	5.09	6.93	11.73	6.38	9.94	1.6	7.4	9.65	9.34
22	Shizuoka	7.4	12.12	7.88	15.81	9.77	9.26	12.37	11.46	8.5	13.85	8.35	20.4	10.23	9.26	15.03	12.12	22.23	31.74	22.04	43.6	26.04	23.76	33.99	29.24
23	Yokkaichi	4.86	6.62	5.85	8.13	6.99	6.73	8.08	7.71	5.96	7.82	6.27	8.5	7.64	6.57	8.06	7.77	16.06	19.2	16.54	20.29	19.36	17.09	19.66	19.47
24	Kyoto	5.17	9.46	6.99	9.75	9.34	8.18	9.06	9.98	6.95	10.34	7.8	9.69	9.65	8.23	10.42	10.04	21.7	30.57	24.52	26.77	29.91	25.52	30.7	30.5
25	Matsudo	3.95	4.66	0.5	4.36	4.42	4.85	9.82	4.99	4.79	5.18	4.71	4.23	4.93	4.77	11.36	5.03	14.73	15.74	14.52	12.64	15.14	14.67	21.94	15.4
26	Akashi	5.32	5.93	6.28	6.06	5.48	6.35	6.49	6.5	5.57	6.27	5.96	6.51	6.14	6.01	6.36	6.28	14.38	16.07	15.28	16.87	15.76	15.41	16.36	16.15
27	Kochi	4.25	6.15	4.02	9.46	6.45	5.11	8.01	6.88	5.22	7.22	4.91	10.93	7.08	5.29	8.74	7.45	12.29	16.35	11.66	22.73	16.46	12.45	19.15	17.06
28	Takasaki	6.08	9.97	6.9	8.19	6.86	8.24	9.04	8.63	7.05	10.1	7.28	8.2	7.16	7.75	9.64	8.37	16.58	21.89	16.92	18.56	17.17	17.79	21.11	19.13
29	Ome	3.82	3.75	3.94	5.07	3.11	4.05	4.36	3.86	4.12	4.43	4.26	5.29	3.38	4.3	4.71	3.98	11.06	11.73	11.23	13.2	9.85	11.33	12.24	10.99
30	Joetsu	9.04	14.3	10.48	17.87	5.97	12.44	16.06	12.86	10.67	14.38	10.65	18.54	5.82	11.84	16.93	14.54	18.84	24.87	18.97	31.28	10.89	20.91	28.92	25.12
31	Komatsu	3.7	6.58	4.09	5.88	6.26	5.47	6.88	6.88	4.7	6.85	4.54	6.05	6.59	5.24	6.66	6.75	8.67	12.02	8.68	11.21	10.91	9.74	11.88	11.6
32	Matsue	6.16	9.93	6.45	11.04	8.51	7.99	5.09	9	7.42	10.98	7.43	12.01	9.14	8.17	5.22	10.71	15.17	21.34	15.49	22.95	17.67	16.72	15.84	20.68
33	Gifu	4.58	7.48	5.9	7.3	7.37	6.68	7.97	7.99	5.63	7.97	6.28	7.76	8.03	6.52	7.95	8.01	15.23	20.42	16.68	19.64	20.1	17.23	20.26	20.2
34	Tsushima	2.89	3.24	2.18	2.79	1.22	3.03	3.49	3.27	3.14	3.44	2.92	3.08	1.54	3.01	3.48	3.25	7.29	8.07	6.89	7.1	3.96	7.09	8.12	7.68
35	Sakai	4.92	8.2	5.52	4.9	5.94	6.5	6.9	6.71	6.42	8.57	6.5	5.38	6.7	6.51	7.05	6.76	18.09	29.55	18.4	15.16	18.86	18.41	19.85	19.04
36	Odawara	3.34	4.68	3.42	2.66	5.29	4.25	5.06	5.39	4.17	5.39	4.11	2.99	5.75	4.31	5.56	5.77	11.47	14.18	11.46	7.6	14.28	11.9	14.28	14.47
37	Tokushima	4.12	6.17	3.79	6.74	6.25	4.99	6.86	6.94	5.23	7.01	4.89	7.83	7.57	5.21	7.34	7.5	12.26	15.98	11.53	17.63	17.09	12.22	16.6	16.95
38	Kanazawa	4.14	7.06	5.5	7.05	6.88	6.21	7.65	7.52	5	7.47	5.58	7.33	7.07	5.92	7.51	7.27	11.66	16.47	13.05	16.07	16.18	13.68	16.55	16.42
39	Yasugi	6.59	8.7	5.97	11.89	10.32	8.25	10.48	11.49	8.31	10.1	6.49	13.17	11.97	8.17	11.97	11.98	13.89	16.52	11.59	21.77	20.57	14	19.64	19.63
40	Morioka	4.52	9.65	5.72	14.52	7.1	6.7	9.7	8.72	5.89	9.74	5.46	14.98	7.68	6.24	10.27	8.34	13.26	19.35	12.56	21.26	17.58	13.85	20.13	18.28
41	Omihachiman	3.3	4.58	3.35	5.19	1.86	3.84	5.2	4.42	3.91	4.84	3.45	5.58	2.37	3.79	5.11	4.34	8.56	10.16	7.77	11.37	5.65	8.42	10.58	9.38
42	Uji	2.49	3.81	3.2	2.96	2.88	3.86	4.06	3.66	3.52	4.52	3.95	3.21	3.8	4.04	4.45	3.99	9.97	11.81	10.71	9.04	11.31	10.94	11.76	11.48
43	Usuki	5.14	8.4	5.06	9.7	0.54	6.57	9.31	9.03	6.46	9.31	5.55	10.47	0.64	6.9	9.68	9.36	11.08	15.73	9.51	17.59	1.68	11.77	16.29	15.81
44	Iwata	4.58	6.65	5.31	6.84	3.9	6.45	7.25	6.04	5.98	6.89	6	7.01	4.66	6.18	6.98	5.88	12.79	14.42	12.88	14.54	10.36	13.19	14.57	12.61
45	Shiogama	2.03	1.58	0.87	0.46	2.42	1.74	1.61	2.36	2.35	2.18	1.79	0.77	2.68	1.87	1.88	2.58	6.08	5.84	4.78	2.01	7	4.97	4.94	6.76

No	City	Average Pairwise Euclidean Distance								Average Pairwise Network Distance								Average Pairwise Travel Distance							
		Com	S	M	C	P	SM	SC	SCP	Com	S	M	C	P	SM	SC	SCP	Com	S	M	C	P	SM	SC	SCP
46	Inagi	2.26	2.36	2.67	2.29	1.96	2.77	2.7	2.69	2.97	2.93	3.02	2.67	3.03	3.03	3.1	3.04	8.46	8.08	8.47	7.75	8.69	8.48	8.68	8.65
47	Toride	4.69	4.88	4.4	4.91	3.42	4.91	5.44	4.81	4.95	5.33	4.62	5.21	4.47	4.8	5.4	4.88	10.49	11.2	9.88	10.81	9.69	10.22	11.25	10.39
48	Kasugai	4.96	6.14	4.88	5.15	5.88	6.03	6.57	6.19	5.36	6.37	5.55	5.92	5.66	5.72	6.38	5.94	13.31	15.46	13.66	13.99	14.16	14.05	15.46	14.72
49	Dazaifu	2.44	2.42	2.15	2.37	2.18	5.72	2.58	3.05	2.98	2.97	2.47	3.27	3.35	2.67	2.93	3.3	8.26	8.46	7.07	8.96	9.74	7.65	8.31	9.55
50	Isahaya	6.23	9.63	5.6	10.49	4.01	7.33	9.45	8.63	7.44	10.94	6.7	11.77	4.44	7.63	11.25	9.2	13.9	19.53	12.76	20.31	9.17	14.26	19.94	16.83
51	Kagoshima	4.98	10.27	6.96	13.11	7.99	7.91	10.06	8.91	8.04	11.62	7.62	14.44	9.32	8.28	11.96	9.93	19.7	25.43	18.71	29.72	22.23	19.97	25.93	23.1
52	Hirosaki	3.94	9.38	3.41	9.09	3.26	5.72	9.15	6.52	4.45	8.95	3.94	9.87	4.17	5.19	9.16	6.07	9.69	16.71	8.81	17.75	10.12	10.84	17.02	12.83
53	Izumisano	2.44	3.35	2.87	1.84	3.46	3.08	3.47	3.53	3.38	3.54	3.5	2.03	3.54	3.54	3.48	3.54	9.59	9.82	9.23	5.89	9.97	9.39	9.71	9.94
54	Nankoku	3.19	4.74	3.36	4.97	1.64	4.2	5.31	5.46	4.6	5.61	3.73	5.79	3.37	4.45	5.75	5.99	9.06	10.92	7.6	11.03	6.95	8.89	11.07	11.56
55	Tokai	2.83	3.49	3.84	2.6	3.18	3.87	3.62	3.69	3.95	3.73	3.75	2.93	3.62	3.76	3.64	3.67	9.7	9.13	9.19	7.51	9.05	9.22	9	9.13
56	Soja	3.79	6.53	3.33	5.82	2.62	4.7	6.89	5.06	4.48	7.49	3.92	6.77	3.68	4.84	7.4	5.39	8.99	13.72	8.09	12.16	7.97	9.58	13.46	10.55
57	Hitoyoshi	2.03	6.37	1.69	5.08	1.33	2.98	6.73	5.32	2.59	8.5	2.12	5.73	1.75	3.22	7.95	6.18	4.98	14.2	4.24	9.96	3.78	5.98	13.44	10.63
58	Toyohashi	4.47	7.03	5.17	7.44	6.01	5.84	7.71	6.95	5.26	7.37	5.3	7.78	6.44	5.65	7.54	6.83	13.06	17.54	13.19	18.45	15.64	13.94	17.92	16.45
59	Toyonaka	3.74	3.87	3.61	4.86	3.9	3.96	4.32	4.23	4.03	4.27	3.88	4.72	4.36	3.92	4.4	4.36	12.72	13.54	12.28	14.57	13.74	12.44	13.89	13.76
60	Yuzawa	6.81	10.55	7.88	9.53	4.19	9.57	9.51	10.28	8.48	11.08	7.8	11.69	4.53	9.18	11.41	9.7	13.69	17.83	12.56	18.48	7.79	14.78	18.22	15.67
61	Imabari	6.89	6.56	4.59	7.75	4.23	5.49	11.7	6.7	10.41	7.07	5.07	8.36	4.9	5.48	14.16	6.66	17.68	14.38	10.81	16.59	11.41	11.57	22.6	14.06
62	Ina	4.98	8.25	4.32	7.46	5.67	5.48	8.59	8.38	5.61	8.8	4.21	7.93	5.92	5.28	8.62	8.42	11.13	16.73	8.52	14.97	11.75	10.46	16.37	16.02
63	Otaru	4.86	8.27	4.43	7.78	8.07	6.26	7.03	10.48	4.96	8.01	4.69	8.09	9.96	5.51	8.21	9.48	8.53	13.02	8.12	12.48	15.64	9.35	13.28	15.04
64	Kameyama	4.5	5.78	3.09	5.43	3.66	4.35	5.95	4.47	5.04	6.26	4.05	6.56	3.88	4.61	6.06	4.64	10.22	12.19	8.49	12.54	7.59	9.5	11.82	9.09
65	Urasoe	2.12	1.83	1.51	1.25	2.33	2.16	2.01	2.27	2.9	2.46	2.47	1.83	2.83	2.48	2.57	2.76	7.19	6.11	6.22	4.35	7.11	6.23	6.4	6.94
66	Kure	8.1	7.92	6.53	10.13	8.75	7.12	9.34	8.85	7.45	9.53	7.3	11.71	10.37	7.68	11.95	10.21	16.24	20.04	15.89	23.33	21.8	16.62	23.74	21.44
67	Nagato	7.81	9.89	7.84	8.99	8.15	9.04	11.2	11.96	9.12	10.26	8.22	10.61	10.84	8.92	12.37	11.86	13.38	14.38	11.88	14.88	14.68	12.73	17.67	16.74
68	Chitose	4.05	8.63	4.01	7.73	4	2.56	8.94	5.62	4.75	8.19	3.82	8.49	4.66	4.82	8	5.26	7.92	12.83	6.82	13.33	8.55	8.2	12.57	9.3
69	Kainan	4.9	6.73	4.41	5.18	5.08	5.46	6.98	7.1	5.66	8.08	4.85	5.69	5.93	5.68	7.64	7.63	11.2	15.01	9.59	11.21	11.23	11.03	14.38	14.33

Agglomeration Index

No	City	Agglomeration Index (Euclidean Distance)							Agglomeration Index (Network Distance)							Agglomeration Index (Travel Distance)						
		S	M	C	P	SM	SC	SCP	S	M	C	P	SM	SC	SCP	S	M	C	P	SM	SC	SCP
1	Nara	1.58	0.92	1.88	0.87	1.56	1.62	1.32	1.54	0.84	1.86	0.92	1.44	1.67	1.20	1.46	0.89	1.68	0.99	1.38	1.55	1.22
2	Otake	2.70	0.99	2.90	1.64	1.90	2.97	2.13	2.46	0.95	2.34	1.33	1.37	2.43	1.75	1.95	0.93	1.85	1.29	1.23	1.94	1.54
3	Fukuoka	1.71	1.28	1.64	1.85	1.49	1.60	1.91	1.57	1.20	1.52	1.70	1.24	1.55	1.63	1.49	1.18	1.45	1.64	1.23	1.48	1.57
4	Yokohama	1.25	1.31	1.15	1.33	1.37	1.35	1.45	1.13	1.06	1.18	1.12	1.05	1.14	1.13	1.16	1.08	1.17	1.14	1.07	1.16	1.15
5	Kawasaki	1.10	1.01	1.09	1.12	1.09	1.06	1.15	1.05	0.98	1.05	1.05	0.98	1.06	1.06	1.05	0.98	1.05	1.04	0.98	1.06	1.05
6	Kitakyushu	1.18	1.10	1.10	1.22	1.19	1.12	1.29	1.14	1.07	1.04	1.22	1.07	1.13	1.21	1.11	1.05	1.01	1.16	1.06	1.10	1.15
7	Matsuyama	1.54	1.11	2.58	1.65	1.33	1.84	1.80	1.37	1.03	2.13	1.52	1.08	1.81	1.51	1.27	1.03	1.59	1.44	1.07	1.57	1.41
8	Saitama	0.78	1.08	1.14	1.21	1.24	1.39	1.38	0.66	0.93	0.97	1.09	0.97	1.13	1.10	0.35	0.94	0.98	1.09	0.98	1.12	1.10
9	Kobe	1.27	1.19	1.14	1.43	1.26	1.24	1.45	1.24	1.11	1.02	1.39	1.13	1.25	1.36	1.22	1.12	0.98	1.31	1.14	1.23	1.30
10	Sendai	1.53	1.14	1.68	1.64	1.26	1.48	1.67	1.41	1.06	1.50	1.44	1.07	1.43	1.45	1.34	1.05	1.39	1.41	1.06	1.35	1.41
11	Nagoya	1.40	1.21	1.27	1.57	1.35	1.34	1.60	1.19	1.07	1.26	1.32	1.09	1.20	1.29	1.19	1.07	1.21	1.31	1.09	1.20	1.28
12	Sapporo	1.66	1.03	1.55	1.82	1.40	1.60	1.82	1.42	1.12	1.48	1.53	1.12	1.42	1.49	1.37	1.12	1.39	1.48	1.12	1.36	1.44
13	Hiroshima	1.74	1.21	1.90	1.54	1.40	1.71	1.73	1.58	1.08	1.70	1.45	1.13	1.61	1.49	1.53	1.10	1.61	1.46	1.14	1.55	1.47
14	Koriyama	2.03	0.99	2.60	1.11	1.40	2.01	1.97	1.71	0.94	2.16	0.93	1.11	1.92	1.57	1.53	0.95	1.83	0.98	1.09	1.67	1.44
15	Kumamoto	1.48	1.27	1.47	1.44	1.33	1.58	1.33	1.29	1.02	1.24	1.25	1.06	1.30	1.26	1.24	1.03	1.17	1.23	1.05	1.25	1.24
16	Utsunomiya	1.50	1.22	2.09	1.49	1.39	1.65	1.47	1.37	1.00	1.64	1.23	1.06	1.41	1.27	1.29	1.01	1.46	1.25	1.06	1.32	1.27
17	Chiba	1.32	1.18	1.27	1.24	0.75	1.25	1.10	1.20	1.08	1.15	1.16	1.11	1.19	1.18	1.16	1.07	1.09	1.12	1.09	1.15	1.13
18	Osaka	1.69	1.58	0.42	1.70	1.62	1.80	1.62	1.31	1.16	0.35	1.35	1.17	1.31	1.33	1.32	1.16	0.37	1.34	1.18	1.32	1.33
19	Tokorozawa	1.11	0.81	1.07	1.02	0.97	1.21	1.16	1.16	0.86	1.00	1.06	0.90	1.16	1.10	1.13	0.90	0.98	1.10	0.94	1.13	1.11
20	Yamanashi	1.98	1.17	1.82	0.56	1.60	2.06	1.91	1.69	0.93	1.51	0.48	1.19	1.61	1.50	1.57	0.98	1.33	0.59	1.19	1.47	1.40
21	Oyabe	1.25	0.96	1.76	0.17	1.41	1.87	1.80	1.22	0.94	1.50	0.15	1.10	1.46	1.40	1.69	0.92	1.43	0.23	1.07	1.39	1.35
22	Shizuoka	1.64	1.07	2.14	1.32	1.25	1.67	1.55	1.63	0.98	2.40	1.20	1.09	1.77	1.43	1.43	0.99	1.96	1.17	1.07	1.53	1.32

No	City	Agglomeration Index (Euclidean Distance)							Agglomeration Index (Network Distance)							Agglomeration Index (Travel Distance)						
		S	M	C	P	SM	SC	SCP	S	M	C	P	SM	SC	SCP	S	M	C	P	SM	SC	SCP
23	Yokkaichi	1.36	1.20	1.67	1.44	1.39	1.66	1.59	1.31	1.05	1.43	1.28	1.10	1.35	1.30	1.20	1.03	1.26	1.21	1.06	1.22	1.21
24	Kyoto	1.83	1.35	1.89	1.81	1.58	1.75	1.93	1.49	1.12	1.39	1.39	1.18	1.50	1.44	1.41	1.13	1.23	1.38	1.18	1.41	1.41
25	Matsudo	1.18	0.13	1.10	1.12	1.23	2.49	1.26	1.08	0.98	0.88	1.03	1.00	2.37	1.05	1.07	0.99	0.86	1.03	1.00	1.49	1.05
26	Akashi	1.11	1.18	1.14	1.03	1.19	1.22	1.22	1.13	1.07	1.17	1.10	1.08	1.14	1.13	1.12	1.06	1.17	1.10	1.07	1.14	1.12
27	Kochi	1.45	0.95	2.22	1.52	1.20	1.88	1.62	1.38	0.94	2.09	1.36	1.01	1.67	1.43	1.33	0.95	1.85	1.34	1.01	1.56	1.39
28	Takasaki	1.64	1.13	1.35	1.13	1.36	1.49	1.42	1.43	1.03	1.16	1.02	1.10	1.37	1.19	1.32	1.02	1.12	1.04	1.07	1.27	1.15
29	Ome	0.98	1.03	1.33	0.82	1.06	1.14	1.01	1.08	1.03	1.28	0.82	1.04	1.14	0.96	1.06	1.01	1.19	0.89	1.02	1.11	0.99
30	Joetsu	1.58	1.16	1.98	0.66	1.38	1.78	1.42	1.35	1.00	1.74	0.54	1.11	1.59	1.36	1.32	1.01	1.66	0.58	1.11	1.54	1.33
31	Komatsu	1.78	1.10	1.59	1.69	1.48	1.86	1.86	1.46	0.97	1.29	1.40	1.11	1.42	1.43	1.39	1.00	1.29	1.26	1.12	1.37	1.34
32	Matsue	1.61	1.05	1.79	1.38	1.30	0.83	1.46	1.48	1.00	1.62	1.23	1.10	0.70	1.44	1.41	1.02	1.51	1.16	1.10	1.04	1.36
33	Gifu	1.63	1.29	1.59	1.61	1.46	1.74	1.75	1.42	1.12	1.38	1.43	1.16	1.41	1.42	1.34	1.10	1.29	1.32	1.13	1.33	1.33
34	Tsushima	1.12	0.75	0.97	0.42	1.05	1.21	1.13	1.10	0.93	0.98	0.49	0.96	1.11	1.04	1.11	0.95	0.97	0.54	0.97	1.11	1.05
35	Sakai	1.66	1.12	1.00	1.21	1.32	1.40	1.36	1.34	1.01	0.84	1.04	1.01	1.10	1.05	1.63	1.02	0.84	1.04	1.02	1.10	1.05
36	Odawara	1.40	1.02	0.80	1.58	1.28	1.52	1.62	1.29	0.99	0.72	1.38	1.04	1.33	1.38	1.24	1.00	0.66	1.25	1.04	1.24	1.26
37	Tokushima	1.50	0.92	1.64	1.52	1.21	1.66	1.68	1.34	0.93	1.50	1.45	0.99	1.40	1.43	1.30	0.94	1.44	1.39	1.00	1.35	1.38
38	Kanazawa	1.70	1.33	1.70	1.66	1.50	1.85	1.82	1.50	1.12	1.47	1.41	1.18	1.50	1.45	1.41	1.12	1.38	1.39	1.17	1.42	1.41
39	Yasugi	1.32	0.91	1.80	1.57	1.25	1.59	1.74	1.21	0.78	1.58	1.44	0.98	1.44	1.44	1.19	0.83	1.57	1.48	1.01	1.41	1.41
40	Morioka	2.14	1.27	3.22	1.57	1.48	2.15	1.93	1.65	0.93	2.54	1.30	1.06	1.74	1.42	1.46	0.95	1.60	1.33	1.04	1.52	1.38
41	Omihachiman	1.39	1.02	1.57	0.56	1.16	1.58	1.34	1.24	0.88	1.43	0.61	0.97	1.31	1.11	1.19	0.91	1.33	0.66	0.98	1.24	1.10
42	Uji	1.53	1.29	1.19	1.16	1.55	1.63	1.47	1.28	1.12	0.91	1.08	1.15	1.26	1.13	1.18	1.07	0.91	1.13	1.10	1.18	1.15
43	Usuki	1.63	0.98	1.89	0.10	1.28	1.81	1.76	1.44	0.86	1.62	0.10	1.07	1.50	1.45	1.42	0.86	1.59	0.15	1.06	1.47	1.43
44	Iwata	1.45	1.16	1.49	0.85	1.41	1.58	1.32	1.15	1.00	1.17	0.78	1.03	1.17	0.98	1.13	1.01	1.14	0.81	1.03	1.14	0.99
45	Shiogama	0.78	0.43	0.23	1.19	0.86	0.79	1.17	0.93	0.76	0.33	1.14	0.80	0.80	1.10	0.96	0.79	0.33	1.15	0.82	0.81	1.11
46	Inagi	1.04	1.18	1.01	0.87	1.23	1.20	1.19	0.99	1.02	0.90	1.02	1.02	1.04	1.02	0.96	1.00	0.92	1.03	1.00	1.03	1.02
47	Toride	1.04	0.94	1.05	0.73	1.05	1.16	1.03	1.08	0.93	1.05	0.90	0.97	1.09	0.99	1.07	0.94	1.03	0.92	0.97	1.07	0.99
48	Kasugai	1.24	0.98	1.04	1.19	1.22	1.33	1.25	1.19	1.03	1.10	1.06	1.07	1.19	1.11	1.16	1.03	1.05	1.06	1.06	1.16	1.11
49	Dazaifu	0.99	0.88	0.97	0.89	2.34	1.06	1.25	1.00	0.83	1.10	1.13	0.90	0.99	1.11	1.02	0.86	1.08	1.18	0.93	1.01	1.16
50	Isahaya	1.55	0.90	1.68	0.64	1.18	1.52	1.39	1.47	0.90	1.58	0.60	1.02	1.51	1.24	1.40	0.92	1.46	0.66	1.03	1.43	1.21
51	Kagoshima	2.06	1.40	2.63	1.60	1.59	2.02	1.79	1.44	0.95	1.80	1.16	1.03	1.49	1.23	1.29	0.95	1.51	1.13	1.01	1.32	1.17
52	Hirosaki	2.38	0.87	2.31	0.83	1.45	2.33	1.66	2.01	0.89	2.22	0.94	1.17	2.06	1.36	1.73	0.91	1.83	1.05	1.12	1.76	1.32
53	Izumisano	1.37	1.17	0.75	1.41	1.26	1.42	1.45	1.05	1.04	0.60	1.05	1.05	1.03	1.05	1.02	0.96	0.61	1.04	0.98	1.01	1.04
54	Nankoku	1.48	1.05	1.56	0.51	1.31	1.66	1.71	1.22	0.81	1.26	0.73	0.97	1.25	1.30	1.21	0.84	1.22	0.77	0.98	1.22	1.28
55	Tokai	1.23	1.36	0.92	1.12	1.37	1.28	1.31	0.94	0.95	0.74	0.92	0.95	0.92	0.93	0.94	0.95	0.77	0.93	0.95	0.93	0.94
56	Soja	1.72	0.88	1.54	0.69	1.24	1.82	1.33	1.67	0.87	1.51	0.82	1.08	1.65	1.20	1.53	0.90	1.35	0.89	1.07	1.50	1.17
57	Hitoyoshi	3.13	0.83	2.50	0.65	1.47	3.31	2.62	3.29	0.82	2.22	0.68	1.24	3.07	2.39	2.85	0.85	2.00	0.76	1.20	2.70	2.14
58	Toyohashi	1.58	1.16	1.67	1.35	1.31	1.73	1.56	1.40	1.01	1.48	1.22	1.07	1.43	1.30	1.34	1.01	1.41	1.20	1.07	1.37	1.26
59	Toyonaka	1.04	0.96	1.30	1.04	1.06	1.16	1.13	1.06	0.96	1.17	1.08	0.97	1.09	1.08	1.06	0.97	1.15	1.08	0.98	1.09	1.08
60	Yuzawa	1.55	1.16	1.40	0.62	1.41	1.40	1.51	1.31	0.92	1.38	0.53	1.08	1.35	1.14	1.30	0.92	1.35	0.57	1.08	1.33	1.14
61	Imabari	0.95	0.67	1.13	0.61	0.80	1.70	0.97	0.68	0.49	0.80	0.47	0.53	1.36	0.64	0.81	0.61	0.94	0.65	0.65	1.28	0.80
62	Ina	1.66	0.87	1.50	1.14	1.10	1.72	1.68	1.57	0.75	1.41	1.05	0.94	1.54	1.50	1.50	0.77	1.35	1.06	0.94	1.47	1.44
63	Otaru	1.70	0.91	1.60	1.66	1.29	1.45	2.16	1.62	0.95	1.63	2.01	1.11	1.66	1.91	1.53	0.95	1.46	1.83	1.10	1.56	1.76
64	Kameyama	1.28	0.69	1.20	0.81	0.97	1.32	0.99	1.24	0.80	1.30	0.77	0.92	1.20	0.92	1.19	0.83	1.23	0.74	0.93	1.16	0.89
65	Urasoe	0.86	0.71	0.59	1.10	1.02	0.95	1.07	0.85	0.85	0.63	0.98	0.85	0.89	0.95	0.85	0.87	0.61	0.99	0.87	0.89	0.97
66	Kure	0.98	0.81	1.25	1.08	0.88	1.15	1.09	1.28	0.98	1.57	1.39	1.03	1.61	1.37	1.23	0.98	1.44	1.34	1.02	1.46	1.32
67	Nagato	1.27	1.00	1.15	1.04	1.16	1.43	1.53	1.13	0.90	1.16	1.19	0.98	1.36	1.30	1.07	0.89	1.11	1.10	0.95	1.32	1.25
68	Chitose	2.13	0.99	1.91	0.99	0.63	2.21	1.39	1.72	0.80	1.79	0.98	1.01	1.69	1.11	1.62	0.86	1.68	1.08	1.04	1.59	1.17
69	Kainan	1.37	0.90	1.06	1.04	1.11	1.42	1.45	1.43	0.86	1.01	1.05	1.00	1.35	1.35	1.34	0.86	1.00	1.00	0.98	1.28	1.28

Transportation-City Characteristics

No	City	Distance	Travel Time	Modal Share (%)						Population	Area Size	Population Density	Number of Facilities					GROUP
				Train	Bus	Car	Motorbike	Bicycle	Walk				Com	M	S	C	P	
1	Nara	11.9	31.56	17.69	3.16	50.24	3.25	9.14	16.53	364,969	277.95	1313	2327	422	57	44	281	4
2	Otake	14.37	27.64	8.41	0.49	60.74	2.14	12.59	15.63	28,430	77.53	367	7659	1280	231	48	881	7
3	Fukuoka	10.87	28.05	10.8	6.64	44.79	1.46	13.84	22.45	1,474,326	351.62	4193	858	107	29	21	156	27
4	Yokohama	12.42	33.41	29.41	5.19	31.65	1.12	5.71	26.92	3,714,200	436.88	8502	629	78	27	3	111	4
5	Kawasaki	12.83	34.38	32.01	3.11	28.76	1.03	10.56	24.52	1,433,765	143.05	10023	21627	2570	300	150	1476	7
6	Kitakyushu	13.03	28.37	6.39	5.4	63.11	1.36	5.5	18.25	981,891	503.61	1950	5820	695	112	51	328	27
7	Matsuyama	11.18	24.45	2.51	1.3	57.19	7.45	16.03	15.52	518,050	435.91	1188	2254	291	80	15	207	12
8	Saitama	12.34	32.14	24.02	1.41	37.04	0.64	15.1	21.8	1,253,582	217.26	5770	14376	1987	295	71	983	7
9	Kobe	17.93	33.15	23.15	3.98	37.04	3.89	6.43	25.51	1,553,789	560.51	2772	570	80	14	7	13	12
10	Sendai	11.86	29.2	7.66	3.57	60.66	2.33	7.54	18.24	1,049,578	785.67	1336	2254	210	46	43	95	12
11	Nagoya	10.7	29.61	18.31	1.86	48.82	1.59	11.82	17.6	2,254,891	327.29	6890	849	104	26	9	13	12
12	Sapporo	10.58	26.9	12.93	4.81	51.89	0.04	9.78	20.56	1,930,496	1120.42	1723	419	85	22	5	67	4
13	Hiroshima	14.41	29.21	7.8	3.97	56.31	3.13	10.8	17.99	1,186,928	915.56	1296	1654	227	58	18	65	27
14	Koriyama	11.17	27.26	2.04	1.53	74.73	0.62	7.92	13.17	326,075	756.17	431	1584	195	42	16	79	5
15	Kumamoto	9.82	25.82	1.79	3.57	63.31	3.65	12.88	14.8	734,287	397.18	1849	1304	149	22	3	28	4
16	Utsunomiya	12.43	26.52	3.38	1.29	75.66	1.13	9.73	8.81	518,878	416.57	1246	2489	248	97	79	151	27
17	Chiba	15.49	33.28	21.28	1.25	47.35	0.55	9.09	20.48	960,051	272.25	3526	7837	996	159	13	575	26
18	Osaka	14.71	31.37	30.73	2.17	16.53	1.69	22.42	26.45	2,667,830	225.48	11832	791	99	26	11	15	5
19	Tokorozawa	12.68	32.38	23.19	0.85	39.31	1.11	13.28	22.26	342,925	71.94	4767	427	59	16	11	49	5
20	Yamanashi	10.58	23.85	3.93	0.18	80.81	1.9	4.3	8.88	37,116	290.22	128	7090	682	129	55	422	27
21	Oyabe	13.22	23.86	3.35	0.43	83.39	0.64	5.42	6.77	31,669	134.34	236	2461	353	66	5	215	5
22	Shizuoka	10.27	25.01	4.71	1.56	57.82	3.51	16.76	15.64	718,774	1414.13	508	9122	1748	229	13	800	5
23	Yokkaichi	11.81	26.83	6.79	0.74	71.97	1.22	7.33	11.95	313,203	207.45	1510	11774	1721	274	58	1469	26
24	Kyoto	9.41	27.86	16.25	4.78	36.06	3.96	18.68	20.27	1,420,719	831.77	1708	18184	2587	359	11	1259	7
25	Matsudo	14.22	35.8	25.82	0.99	42.79	1.42	9.94	19.04	485,962	61.22	7939	4633	538	102	38	514	12
26	Akashi	14.06	30.01	15.81	0.72	51.32	2.63	11.91	17.61	297,057	49.52	5998	1391	134	46	18	71	12
27	Kochi	8.39	21.73	0.9	0.77	64.4	4.35	16.67	12.91	338,909	312.01	1086	4304	437	116	89	215	26
28	Takasaki	11.58	26.3	3.96	0.5	74.1	0.42	9.88	11.14	375,229	459.9	816	8493	1103	192	10	800	26
29	Ome	11.5	28.8	14.15	1.11	57.17	0.81	9.61	17.15	137,833	103.25	1335	2707	373	73	22	284	26
30	Joetsu	12.59	24.03	1.95	0.67	76.8	0.64	7.84	12.11	201,794	973.25	207	19813	2614	395	5	689	7
31	Komatsu	11.42	22.37	1.63	0.07	80.62	0.53	7.12	10.02	108,980	372.91	292	3174	569	82	4	196	4
32	Matsue	12.32	22.59	1.5	2.03	77.1	1.29	6.03	12.05	206,404	579.04	356	2715	318	77	36	100	12
33	Gifu	10.56	25.68	2.98	2.06	70.4	0.75	10.87	12.95	416,625	204.31	2039	5572	763	117	47	260	27
34	Tsushima	11.25	27.51	8.76	0.45	66.13	0.97	11.94	11.75	65,114	25.35	2568	4105	500	102	14	384	26
35	Sakai	12.07	29.5	18.79	0.9	45.83	2.95	16.28	15.26	849,107	150.63	5637	548	49	20	9	9	12
36	Odawara	14.11	30	15.48	1.36	50.7	1.76	12	18.71	196,493	113.85	1726	32872	3643	499	2	1254	7
37	Tokushima	9.04	22.24	0.56	1.37	68.66	2.59	17.12	9.7	257,718	193.54	1332	554	59	32	19	24	5
38	Kanazawa	10.59	23.38	2.36	3.2	65.54	0.84	9.42	18.64	452,144	469.54	963	3092	23	113	52	401	7
39	Yasugi	11.43	22.63	1.71	0.61	79.76	1.48	7.01	9.44	41,213	425.89	97	2222	281	50	2	106	5
40	Morioka	12.16	25.83	2.51	3.76	62.18	0.85	12	18.71	295,680	885.7	334	1074	174	32	11	76	5
41	Omihachiman	12.55	26.65	9.17	0.31	68.92	1.27	11.18	9.15	82,429	180.18	457	921	85	22	11	28	5
42	Uji	11.9	28.82	19.82	0.35	47.82	6.34	9.05	16.62	191,802	67.72	2832	52394	5934	583	10	900	7
43	Usuki	15.4	25.53	3.53	0.29	77.11	2.24	6.45	10.39	41,486	296.3	140	333	43	11	10	45	5
44	Iwata	10.88	26.17	2.74	0.77	76.4	2.63	7.04	10.41	170,960	162.52	1052	1782	179	52	3	86	27
45	Shiogama	10.63	27.79	8.78	1	67.48	1.08	4.55	17.12	56,256	17.17	3276	393	34	12	16	19	5
46	Inagi	14.39	33.84	29.77	1.77	35.33	1.11	8.88	23.14	86,169	17.74	4858	10438	1577	229	59	714	7
47	Toride	13.62	30.63	16.3	0.93	60.61	0.46	7.18	14.51	109,595	69.78	1570	6982	1250	183	7	907	5
48	Kasugai	10.18	27.64	10.41	1.05	65.05	1.23	8.84	13.41	309,854	92.67	3344	18589	2768	419	10	2478	7
49	Dazaifu	12.97	28.95	12.61	1.6	60.96	2.98	6.78	15.07	71,245	30.05	2371	14226	1525	268	62	1474	26
50	Isahaya	11.6	25.6	3.36	1.26	75.45	2.46	2.79	14.68	141,011	327.09	431	822	71	10	3	36	4

No	City	Distance	Travel Time	Modal Share (%)						Population	Area Size	Population Density	Number of Facilities					GROUP
				Train	Bus	Car	Motorbike	Bicycle	Walk				Com	M	S	C	P	
51	Kagoshima	10.31	26.26	2.23	6.03	63.25	3.99	5.07	19.44	609,250	558.86	1090	10178	928	193	36	414	27
52	Hirosaki	10.48	21.37	1.43	1.67	73.9	0.89	11.38	10.73	180,370	523.47	345	548	78	22	6	47	26
53	Izumisano	13.22	29.41	16.72	0.25	52.5	3.74	13.86	12.92	101,685	56.92	1787	4665	586	112	45	233	26
54	Nankoku	10.49	22.96	2.09	0.32	74.95	3.75	8.16	10.73	48,688	127.13	383	856	116	22	11	45	4
55	Tokai	10.26	25.67	9.5	0.17	69.23	0.94	5.76	14.4	112,310	45.14	2488	2359	389	59	12	152	5
56	Soja	13.41	27.62	5.31	0.19	77.81	0.83	7.05	8.8	67,765	214.23	316	3766	494	79	42	98	5
57	Hitoyoshi	12.87	21.07	1.03	0.31	76.68	2.09	8.9	10.99	34,911	215.6	162	840	123	34	14	110	5
58	Toyohashi	12.04	26.48	6.59	0.42	68.47	1.29	9.82	13.41	379,582	261.39	1452	4138	482	93	73	400	26
59	Toyonaka	11.17	31.11	26.73	2.34	26.98	2.01	16.36	25.58	400,086	36.58	10938	3006	678	80	6	368	4
60	Yuzawa	15.09	25.04	1.22	0.4	82.34	0.31	6.98	8.74	49,851	790.1	63	772	91	16	3	9	4
61	Imabari	11.74	22.47	1.13	0.5	71.25	3.91	12.51	10.7	167,872	423.44	396	1279	236	42	5	128	5
62	Ina	12.72	23.88	1.26	0.7	84.38	0.63	2.9	10.12	70,258	668.1	105	1211	156	26	4	78	4
63	Otaru	10.46	24.4	4.51	9.7	59.84	0.51	2.07	23.36	127,224	243.34	523	493	56	25	9	11	27
64	Kameyama	11.94	25.87	3.34	0.18	80.32	1.97	4.07	10.11	50,073	191.56	261	6101	758	132	20	669	26
65	Urasoe	6.76	22.48	0.8	2.5	71.53	5.88	2.05	17.24	114,217	19.53	5847	357	43	17	13	19	27
66	Kure	11.44	26.38	6.05	4.26	58.17	3.12	8.47	19.93	238,046	356.41	668	486	42	25	25	26	12
67	Nagato	15.28	24.69	0.89	1.36	82.22	1.36	5.28	8.89	37,384	365.08	102	3424	427	84	26	308	26
68	Chitose	14.45	23.77	5.19	1.39	72.56	0.39	7.26	13.2	95,481	594.6	161	27980	5137	697	5	2236	7
69	Kainan	12.02	26.77	5.69	0.31	68.91	5.14	9.77	10.17	54,838	102.29	536	705	59	26	14	44	12

APPENDIX 2. AGGLOMERATION INDEX OF JAKARTA (MSTPs)

No	Area Name			Zone ID	% Commercial Land use	Distance to Central	Ratio Online/ Dine	Index				Density			
	Neighborhood	District	City					Food	Online	Dine-in	Com	Food	Online	Dine-in	Com
1	Cengkareng Barat	Cengkareng	West Jakarta	226	0.18	11.49	0.69	1.14	3.31	0.84	1.06	1.01	2.53	0.25	5.32
2	Cengkareng Timur	Cengkareng	West Jakarta	225	0.19	10.21	0.79	1.42	3.39	0.86	1.08	2.41	4.16	0.22	8.32
3	Duri Kosambi	Cengkareng	West Jakarta	221	0.17	10.81	0.49	0.94	3.04	0.51	1.05	3.8	3.42	1.14	5.50
4	Kapuk	Cengkareng	West Jakarta	224	0.09	7.98	0.88	1.95	1.92	1.68	1.84	1.57	2.54	0.39	10.57
5	Kedaung Kali Angke	Cengkareng	West Jakarta	223	0.09	7.38	0.4	0.55	6.16	2.45	1.22	1.34	2	0.33	2.00
6	Rawa Buaya	Cengkareng	West Jakarta	222	0.1	9.17	0.94	0.73	0.57	0.54	1.23	0.8	0.27	0.27	0.27
7	Grogol	Grogol Petamburan	West Jakarta	198	0.2	3.66	0.92	1.16	1.09	1.5	1.65	4.93	10.85	1.97	20.71
8	Jelambar	Grogol Petamburan	West Jakarta	199	0.12	4.58	0.6	0.96	1.43	1.35	1.08	1.17	1.17	0.58	2.33
9	Jelambar Baru	Grogol Petamburan	West Jakarta	201	0.15	4.79	0.67	1.14	1.22	1.12	1.42	14.1	14.8	2.11	35.95
10	Tanjung Duren Selatan	Grogol Petamburan	West Jakarta	196	0.24	3.12	1.19	0.98	0.73	1.37	1.32	20.04	20.04	2.97	43.80
11	Tanjung Duren Utara	Grogol Petamburan	West Jakarta	195	0.22	3.92	1.03	1.17	1.09	1.62	1.47	10.48	10.48	2.99	26.19
12	Tomang	Grogol Petamburan	West Jakarta	197	0.16	2.72	1.39	1.12	1.01	2	1.41	18.89	8.34	3.89	7.78
13	Wijaya Kesuma	Grogol Petamburan	West Jakarta	200	0.21	5.79	0.71	1.26	1.3	1.53	1.46	4.75	7.6	0.47	12.34
14	Kalideres	Kalideres	West Jakarta	228	0.21	13.6	0.87	0.97	2.63	0.81	1	3.21	1.96	0.36	2.50
15	Kamal	Kalideres	West Jakarta	231	0.19	14.67	0.8	4.08	4	1.68	0.53	0.54	0.36	0.18	0.54
16	Pegadungan	Kalideres	West Jakarta	229	0.11	13.9	0.95	1.13	3.52	1.16	1.09	1.33	2.39	0.13	2.39
17	Semanan	Kalideres	West Jakarta	227	0.14	12.73	0.75	0.79	4.56	2	0.51	10.05	7.67	1.28	17.54
18	Tegal Alur	Kalideres	West Jakarta	230	0.36	12.61	0.96	2.68	4.2	2.3	1.76	0.54	0.54	0.18	1.44
19	Duri Kepa	Kebon Jeruk	West Jakarta	186	0.15	4.79	1.96	1.15	1.19	2.93	1.55	1.36	0.27	0.27	5.18
20	Kebon Jeruk	Kebon Jeruk	West Jakarta	185	0.17	4.89	0.97	0.9	1.06	1.33	1.3	1.86	1.59	0.27	1.33
21	Kedoya Selatan	Kebon Jeruk	West Jakarta	187	0.2	5.91	0.73	0.95	0.92	1.27	1.51	77.1	36.47	5.73	60.95
22	Kedoya Utara	Kebon Jeruk	West Jakarta	188	0.17	6.42	2.47	1.25	1.19	2.95	1.47	32.16	31.58	2.34	20.76
23	Kelapa Dua	Kebon Jeruk	West Jakarta	184	0.08	5.76	0.72	1.3	1.32	1.26	1.17	86.86	49.73	11.21	75.65
24	Sukabumi Selatan	Kebon Jeruk	West Jakarta	182	0.15	6.08	0.81	0.84	0.98	0.8	1.34	12.62	17.52	2.8	25.93
25	Sukabumi Utara	Kebon Jeruk	West Jakarta	183	0.13	4.86	0.63	0.97	1.81	1.65	1.47	6.7	4.69	0.67	2.68
26	Joglo	Kembangan	West Jakarta	176	0.09	9.24	4.13	1.46	1.33	2.53	1.4	11.35	7.94	1.36	9.08
27	Kembangan Selatan	Kembangan	West Jakarta	180	0.16	7.57	0.89	0.78	0.79	0.7	1.19	3.37	1.78	0.2	5.54
28	Kembangan Utara	Kembangan	West Jakarta	181	0.08	8.17	0.92	1.14	1.48	1.37	1.19	1.53	0.51	0.25	1.53
29	Meruya Selatan	Kembangan	West Jakarta	178	0.07	9.35	0.52	0.89	4.33	2.25	3.48	5.59	6.58	0.66	4.28
30	Meruya Utara	Kembangan	West Jakarta	179	0.15	9.23	0.66	0.99	1.51	1	0.93	2.15	1.91	0.24	5.26
31	Srengseng	Kembangan	West Jakarta	177	0.09	6.83	0.85	1.09	1	0.84	1.46	1.85	2.47	0.41	6.57
32	Jati Pulo	Palmerah	West Jakarta	194	0.09	1.75	0.96	5.66	2.52	3.22	3.23	10.77	14.36	2.39	25.14
33	Kemanggisan	Palmerah	West Jakarta	191	0.13	2.72	0.84	0.92	0.93	1.09	1.74	10.8	5.4	0.98	15.21
34	Kota Bambu Selatan	Palmerah	West Jakarta	193	0.24	1.36	0.38	5.67	6.74	2.11	2.83	6.81	10.21	1.7	23.83
35	Kota Bambu Utara	Palmerah	West Jakarta	192	0.03	1.42	0.55	3.42	4.43	1.74	4.52	16.52	13.52	1.5	67.58
36	Palmerah	Palmerah	West Jakarta	189	0.12	3.27	0.73	1.14	1.43	1.64	1.52	13.72	9.74	0.89	14.17
37	Slipi	Palmerah	West Jakarta	190	0.25	1.76	0.72	1.82	2.93	1.24	2.76	13.19	8.12	1.01	6.09
38	Glodok	Taman Sari	West Jakarta	219	0.24	1.95	0.61	2.51	2.76	1.25	3.16	16.34	21.78	2.72	27.23
39	Keagungan	Taman Sari	West Jakarta	218	0.18	2.3	0.81	1.11	0.89	1.02	2.06	174.1	75.82	19.66	165.68
40	Krukut	Taman Sari	West Jakarta	213	0.17	2.52	0.54	0.83	1.76	1.25	1.14	7.14	8.92	1.78	17.85
41	Mangga Besar	Taman Sari	West Jakarta	217	0.51	1.48	0.4	3.26	4.25	1.21	3.75	9.02	19.85	1.8	12.63
42	Maphar	Taman Sari	West Jakarta	214	0.34	2.28	1.9	2.04	2.14	3.42	1.84	145.45	87.91	19.18	102.29
43	Pinangsia	Taman Sari	West Jakarta	220	0.58	1.6	0.81	3.5	2.13	1.51	2.9	9.92	13.88	0.99	16.86
44	Taman Sari	Taman Sari	West Jakarta	215	0.33	2.01	0.97	2.77	3.58	1.26	2.68	12.04	12.04	1.51	12.04
45	Tangki	Taman Sari	West Jakarta	216	0.26	1.28	0.92	3.3	3.11	1.43	3.47	367.3	238.74	26.24	291.21
46	Angke	Tambora	West Jakarta	208	0.14	3.78	0.76	1.68	1.6	1.71	1.28	7.36	2.45	1.23	4.91
47	Duri Selatan	Tambora	West Jakarta	203	0.09	3.12	0.99	1.46	1.2	1.8	2.09	15.46	25.76	2.58	41.22

No	Area Name			Zone ID	% Commercial Land use	Distance to Central	Ratio Online/ Dine	Index				Density			
	Neighborhood	District	City					Food	Online	Dine-in	Com	Food	Online	Dine-in	Com
48	Duri Utara	Tambora	West Jakarta	205	0.21	3.29	0.41	0.98	3.44	1.9	4.72	21.68	16.26	2.71	27.09
49	Jembatan Besi	Tambora	West Jakarta	207	0.21	3.82	0.76	1.72	0.97	1.04	2.96	3.74	7.48	1.87	11.23
50	Jembatan Lima	Tambora	West Jakarta	209	0.27	2.89	0.78	1.23	0.58	0.75	1.11	117.64	124.06	12.83	205.34
51	Kalianyar	Tambora	West Jakarta	202	0.12	3.74	0.57	0.77	0.96	0.84	1.5	6.61	3.31	3.31	9.92
52	Kredang	Tambora	West Jakarta	206	0.29	3.06	0.55	1.34	1.31	1.22	1.19	127.62	88.12	6.08	188.40
53	Pekojan	Tambora	West Jakarta	212	0.24	2.68	0.84	1.02	0.81	1.18	1.84	2.49	8.7	1.24	6.21
54	Roa Malaka	Tambora	West Jakarta	211	0.72	2.08	0.44	1.24	1.67	1.34	3.42	26.83	16.1	3.58	17.89
55	Tambora	Tambora	West Jakarta	210	0.19	2.35	0.66	1.09	0.81	1.13	1.2	14.14	14.14	3.54	17.68
56	Tanah Sereal	Tambora	West Jakarta	204	0.12	2.87	0.61	0.8	1.02	1.13	1.5	21.01	17.78	3.23	35.56
57	Cempaka Putih Barat	Cempaka Putih	Central Jakarta	156	0.14	3.34	0.7	2.39	1.51	1.56	1.86	15.11	18.29	5.57	21.47
58	Cempaka Putih Timur	Cempaka Putih	Central Jakarta	155	0.2	3.48	0.71	0.89	1.12	1.4	1.57	2.73	1.36	0.45	3.64
59	Rawasari	Cempaka Putih	Central Jakarta	154	0.21	3.07	0.81	0.78	0.87	1.01	1.47	25.48	18.53	2.32	24.71
60	Cideng	Gambir	Central Jakarta	170	0.31	1.75	0.44	2.06	3.17	0.72	3.09	1.56	2.35	0.78	2.35
61	Duri Pulo	Gambir	Central Jakarta	175	0.16	2.84	0.95	0.51	0.54	0.81	1.24	20.45	13.15	2.92	45.29
62	Gambir	Gambir	Central Jakarta	172	0.13	0.11	0.9	3.24	3.83	1.25	2.93	2.81	2.81	1.21	4.82
63	Kebon Kelapa	Gambir	Central Jakarta	173	0.62	1.35	1.71	2.91	2.93	2.05	2.83	21.42	12.6	1.26	54.18
64	Petojo Selatan	Gambir	Central Jakarta	171	0.36	1.23	0.68	2.26	2.48	1.13	2.49	95.7	85.86	9.84	67.08
65	Petojo Utara	Gambir	Central Jakarta	174	0.52	1.79	0.74	1.99	2.04	1.37	2.88	32.85	32.85	3.55	51.50
66	Galur	Johar Baru	Central Jakarta	153	0.16	2.64	0.68	1.05	1.02	1.19	4.02	10.77	17.95	3.59	21.54
67	Johar Baru	Johar Baru	Central Jakarta	150	0.08	3.05	0.76	0.77	1.04	1.38	1.91	9.35	3.4	0.85	26.36
68	Kampung Rawa	Johar Baru	Central Jakarta	151	0.1	3.05	0.6	1.4	2.12	1.57	3.15	33.3	59.93	6.66	83.24
69	Tanah Tinggi	Johar Baru	Central Jakarta	152	0.07	2.42	0.76	0.69	0.89	0.97	1.74	12.7	17.47	3.18	44.46
70	Cempaka Baru	Kemayoran	Central Jakarta	158	0.1	2.17	0.89	1.28	1.11	1.13	1.46	139.04	104.02	10.61	148.60
71	Gunung Sahari Selatan	Kemayoran	Central Jakarta	164	0.38	0.79	0.78	2.83	2.86	0.97	2.86	5.58	2.79	0.46	6.97
72	Harapan Mulya	Kemayoran	Central Jakarta	157	0.07	2.05	0.46	3.02	4.38	1.66	3.72	43.3	21.65	5.9	47.24
73	Kebon Kosong	Kemayoran	Central Jakarta	162	0.05	0.69	0.84	3.17	2.91	1.24	3.55	3.95	3.95	0.99	5.92
74	Kemayoran	Kemayoran	Central Jakarta	163	0.3	1.43	0.71	2.5	2.52	0.81	3.11	10.12	11.81	1.69	13.50
75	Serdang	Kemayoran	Central Jakarta	160	0.11	1.37	0.77	2.97	2.89	1.41	2.44	45.22	23.22	9.78	28.11
76	Sumur Batu	Kemayoran	Central Jakarta	159	0.29	2.56	0.8	0.95	1.27	1.61	1.95	1.78	0.89	0.89	2.67
77	Utan Panjang	Kemayoran	Central Jakarta	161	0.13	1.46	0.45	4.17	4.4	1.54	3.46	7.46	7.46	1.86	27.97
78	Cikini	Menteng	Central Jakarta	141	0.33	1.45	2.78	3.1	2.83	3.18	2.91	35.24	17.62	5.03	61.68
79	Gondangdia	Menteng	Central Jakarta	142	0.25	0.92	1.35	3.39	3.24	2.72	3.62	9.52	7.62	1.9	23.49
80	Kebon Sirih	Menteng	Central Jakarta	143	0.35	1.13	0.8	3.03	2.92	1.34	2.74	18.8	10.12	1.45	13.02
81	Menteng	Menteng	Central Jakarta	139	0.09	0.54	0.68	3.71	2.93	1.7	3.77	15.17	14.35	1.64	31.16
82	Pegangsaan	Menteng	Central Jakarta	140	0.1	1.19	0.78	2.93	2.67	1.03	3.04	16.23	16.23	2.03	28.40
83	Gunung Sahari Utara	Sawah Besar	Central Jakarta	166	0.23	1.38	0.96	3.14	3.03	1.19	3.59	10.58	4.07	0.81	13.84
84	Karang Anyar	Sawah Besar	Central Jakarta	168	0.22	2.01	0.41	2.23	4.1	1.38	3.1	63.84	48.82	7.51	71.35
85	Kartini	Sawah Besar	Central Jakarta	167	0.1	1.9	0.78	1.89	1.68	1.03	3.33	36.48	21.12	3.84	49.92
86	Mangga Dua Selatan	Sawah Besar	Central Jakarta	169	0.52	0.7	0.64	2.82	3.31	1.51	2.9	14.44	9.12	3.04	8.36
87	Pasar Baru	Sawah Besar	Central Jakarta	165	0.32	1.33	0.68	3.18	3.66	1.59	3.53	3.29	3.84	0.55	11.52
88	Bungur	Senen	Central Jakarta	149	0.11	2.09	0.54	1.67	1.9	1.53	2.47	9.47	15.79	1.58	15.79
89	Kenari	Senen	Central Jakarta	144	0.16	2.05	0.93	0.76	1.7	0.95	3.42	24.6	19.01	5.59	34.66
90	Kramat	Senen	Central Jakarta	146	0.25	2.23	0.93	6.24	1.16	0.91	1.41	66.36	38.71	17.97	67.74
91	Kwitang	Senen	Central Jakarta	147	0.19	1.62	0.33	2.12	6.82	2.24	3.3	32.62	44.27	13.98	93.20
92	Paseban	Senen	Central Jakarta	145	0.15	2.12	0.66	0.89	1.54	1.61	1.1	4.83	7.25	1.21	12.08
93	Senen	Senen	Central Jakarta	148	0.32	1.34	1.47	4.33	4.46	4.41	4.05	2.37	8.31	1.19	15.43
94	Bendungan Hilir	Tanah Abang	Central Jakarta	133	0.27	2.86	0.8	0.97	0.94	1.34	1.58	3.52	2.69	0.83	4.14
95	Gelora	Tanah Abang	Central Jakarta	132	0.46	3.47	0.56	1.71	1.15	0.95	1.24	22.51	11.26	2.81	30.96
96	Kampung Bali	Tanah Abang	Central Jakarta	138	0.49	0.31	0.76	2.77	2.87	1.57	3.5	84.54	53.68	5.37	99.31
97	Karet Tengsin	Tanah Abang	Central Jakarta	134	0.54	1.62	1.54	3.34	2.35	2.84	2.91	1.31	0.65	0.65	1.31
98	Kebon Kacang	Tanah Abang	Central Jakarta	137	0.21	0.39	1	2.81	2.8	1.6	2.78	5.46	2.73	1.37	19.11

No	Area Name			Zone ID	% Commercial Land use	Distance to Central	Ratio Online/ Dine	Index				Density			
	Neighborhood	District	City					Food	Online	Dine-in	Com	Food	Online	Dine-in	Com
99	Kebon Melati	Tanah Abang	Central Jakarta	135	0.31	1.11	0.92	4.1	4.16	2.57	3.47	5.53	4.61	0.92	7.37
100	Petamburan	Tanah Abang	Central Jakarta	136	0.26	1.77	0.97	1.89	2.45	1.61	3.01	19.17	12.4	2.26	28.19
101	Cilandak Barat	Cilandak	South Jakarta	16	0.14	8.05	1.08	0.89	1.05	1.13	0.92	8.05	6.51	1.2	7.19
102	Cipete Selatan	Cilandak	South Jakarta	18	0.15	5.89	1.11	1.04	1.26	1.7	1.5	1.26	4.61	0.42	2.51
103	Gandaria Selatan	Cilandak	South Jakarta	17	0.29	6.37	1.44	1.24	1.11	1.6	1.3	36.8	19.33	3.12	62.99
104	Lebak Bulus	Cilandak	South Jakarta	14	0.09	10.05	1.43	1.6	3.37	1.81	1.51	0.68	1.59	0.23	4.32
105	Pondok Labu	Cilandak	South Jakarta	15	0.1	10.01	1.49	1.04	3.29	2.37	1.7	1.91	2.18	0.27	1.36
106	Ciganjur	Jagakarsa	South Jakarta	3	0.04	12.53	0.89	2.2	3.25	0.93	0.72	1.41	3.39	0.28	1.13
107	Cipedak	Jagakarsa	South Jakarta	1	0.18	14.74	0.85	3.86	3.68	1.35	0.8	3.36	1.22	0.92	6.11
108	Jagakarsa	Jagakarsa	South Jakarta	4	0.08	11.4	0.82	0.89	3.25	0.86	0.94	3.75	2.25	0.56	3.38
109	Lenteng Agung	Jagakarsa	South Jakarta	5	0.04	11.19	0.74	2.09	2.85	0.93	0.94	1.59	1.59	0.32	1.59
110	Srengseng Sawah	Jagakarsa	South Jakarta	2	0.03	13.19	0.88	6	3.02	0.9	1.13	12.79	16.13	1.3	10.57
111	Tanjung Barat	Jagakarsa	South Jakarta	6	0.1	9.27	0.81	1.88	1.12	0.91	1.25	22.14	14.41	1.54	23.68
112	Cipete Utara	Kebayoran Baru	South Jakarta	31	0.12	4.85	0.8	0.81	0.8	1.24	1.2	1.17	1.75	0.58	5.25
113	Gandaria Utara	Kebayoran Baru	South Jakarta	30	0.14	5.49	0.54	1.25	1.49	1.11	1.53	7.68	16.63	0.64	8.32
114	Gunung	Kebayoran Baru	South Jakarta	36	0.15	4.1	1.02	1.11	1.18	1.71	1.6	18.95	10.53	0.7	14.74
115	Kramat Pela	Kebayoran Baru	South Jakarta	35	0.21	4.52	1.18	1.07	0.87	1.33	1.47	7.14	6.34	0.79	11.89
116	Melawai	Kebayoran Baru	South Jakarta	34	0.34	3.67	1.46	1.1	0.9	1.61	1.49	6.29	5.51	1.57	5.51
117	Petogogan	Kebayoran Baru	South Jakarta	33	0.19	2.77	1.03	1.36	1.31	1.95	1.44	9.39	16.42	1.17	18.77
118	Pulo	Kebayoran Baru	South Jakarta	32	0.21	4.34	2.23	1.46	0.94	2.4	1.23	4.54	9.98	0.91	13.62
119	Rawa Barat	Kebayoran Baru	South Jakarta	38	0.16	2.09	1.27	0.95	2.86	1.4	2.82	6.18	9.27	1.54	3.09
120	Selong	Kebayoran Baru	South Jakarta	37	0.09	2.8	1.09	1.25	1.47	2.1	1.2	11.97	2.82	0.7	9.85
121	Senayan	Kebayoran Baru	South Jakarta	39	0.31	1.95	0.91	1.09	4.3	2.51	3.58	23.1	14	3.5	35.70
122	Cipulir	Kebayoran Lama	South Jakarta	27	0.12	6.25	1.31	0.95	1.01	1.33	1.34	2.93	1.17	0.59	4.10
123	Grogol Selatan	Kebayoran Lama	South Jakarta	28	0.17	5.19	0.78	3.28	1.05	1.12	1.61	3.45	4.48	0.34	9.65
124	Grogol Utara	Kebayoran Lama	South Jakarta	29	0.17	4.6	0.78	1.06	1.29	1.31	1.72	4.06	8.43	0.62	7.80
125	Kebayoran Lama Selatan	Kebayoran Lama	South Jakarta	25	0.24	6.66	0.75	2.49	1.34	1	2.12	3.06	4.37	0.44	10.06
126	Kebayoran Lama Utara	Kebayoran Lama	South Jakarta	26	0.18	6	0.27	5.95	5.34	2.5	2.5	15.81	8.62	0.48	21.56
127	Pondok Pinang	Kebayoran Lama	South Jakarta	24	0.18	7.86	0.86	1.81	1.44	1.24	1.99	4.97	7.01	1.02	11.10
128	Bangka	Mampang Prapatan	South Jakarta	40	0.17	4.39	0.64	1.15	1.4	1.4	1.64	41.07	17.79	3.23	37.51
129	Kuningan Barat	Mampang Prapatan	South Jakarta	44	0.28	1.41	0.64	4.05	4.18	1.8	3.49	9.19	5.11	1.02	6.13
130	Mampang Prapatan	Mampang Prapatan	South Jakarta	43	0.19	1.99	0.83	1.04	3.59	1.37	3.27	5.06	3.8	1.27	8.86
131	Pela Mampang	Mampang Prapatan	South Jakarta	41	0.09	2.9	0.7	1.23	1.22	1.35	2.26	3.05	3.05	0.51	8.63
132	Tegal Parang	Mampang Prapatan	South Jakarta	42	0.07	2.67	0.71	0.69	1.63	1.77	1.34	33.44	32.48	2.87	27.70
133	Cikoko	Pancoran	South Jakarta	50	0.19	3.61	0.84	1.58	0.31	0.86	0.88	41.74	31.66	8.64	51.81
134	Duren Tiga	Pancoran	South Jakarta	47	0.18	3.54	3.25	2.17	0.88	3.15	1.67	12.42	5.46	1.99	12.42
135	Kalibata	Pancoran	South Jakarta	45	0.19	4.35	0.83	0.85	1.22	1.61	1.82	1.69	0.84	0.42	10.55
136	Pancoran	Pancoran	South Jakarta	48	0.25	2.89	0.72	1.23	0.86	1.22	2.08	10.06	5.75	0.72	23.00
137	Pengadegan	Pancoran	South Jakarta	49	0.06	4.07	0.81	0.83	0.93	1.35	1.79	45.47	35.13	9.3	34.10
138	Rawajati	Pancoran	South Jakarta	46	0.18	4.73	0.74	1.91	1.46	1.38	1.67	3.38	5.4	0.68	8.10
139	Cilandak Timur	Pasar Minggu	South Jakarta	7	0.15	7.55	0.78	1.09	1.3	1	1.74	3.64	3.12	0.52	10.67
140	Jati Padang	Pasar Minggu	South Jakarta	11	0.09	7.02	1.63	3.2	1.3	2.12	1.53	1.72	0.43	0.43	3.00
141	Kebagusan	Pasar Minggu	South Jakarta	9	0.2	9.4	0.92	1.8	0.73	0.67	1.04	11.21	8.68	1.45	15.91
142	Pasar Minggu	Pasar Minggu	South Jakarta	10	0.12	7.32	0.69	1.19	1.4	0.96	1.67	6.08	5.57	1.01	20.26
143	Pejaten Barat	Pasar Minggu	South Jakarta	12	0.11	5.4	0.82	0.76	0.89	1.24	1.3	4.34	3.67	0.33	10.01
144	Pejaten Timur	Pasar Minggu	South Jakarta	13	0.07	7.41	0.79	1.42	1.18	0.93	1.56	1.7	2.72	0.34	3.06
145	Ragunan	Pasar Minggu	South Jakarta	8	0.37	8.19	1.64	0.93	0.98	1.61	1.05	7.96	4.3	0.86	4.95
146	Bintaro	Pesanggrahan	South Jakarta	19	0.1	8.73	0.77	0.92	1.05	0.8	1	2.63	1.97	0.22	10.95
147	Pesanggrahan	Pesanggrahan	South Jakarta	20	0.06	8.45	0.66	1.74	1.85	1.22	1.1	3.54	6.07	1.52	14.15
148	Petukangan Selatan	Pesanggrahan	South Jakarta	22	0.06	8.48	0.95	1.14	0.71	0.67	0.9	5.74	7.18	1.44	15.80
149	Petukangan Utara	Pesanggrahan	South Jakarta	23	0.07	8.54	0.77	0.94	1.29	1	2.1	0.71	1.41	0.35	1.06

No	Area Name			Zone ID	% Commercial Land use	Distance to Central	Ratio Online/ Dine	Index				Density			
	Neighborhood	District	City					Food	Online	Dine-in	Com	Food	Online	Dine-in	Com
150	Ulujami	Pesanggrahan	South Jakarta	21	0.1	7.3	0.76	1.28	1.34	1.03	1.78	4.4	3.91	0.49	3.42
151	Guntur	Setia Budi	South Jakarta	64	0.1	1.02	0.58	2.84	3.31	1.47	2.83	9.23	6.15	1.54	12.31
152	Karet	Setia Budi	South Jakarta	61	0.31	1.2	0.44	2.54	3.52	1.15	2.43	35.14	37.15	1	66.26
153	Karet Kuningan	Setia Budi	South Jakarta	60	0.35	0.5	0.59	3.28	3.28	0.99	3.18	2.67	3.74	1.07	4.27
154	Karet Semanggi	Setia Budi	South Jakarta	58	0.45	1.13	0.72	3.35	2.98	0.93	3.74	224.33	134.01	27.68	120.90
155	Kuningan Timur	Setia Budi	South Jakarta	59	0.3	0.76	0.68	3.54	3.93	1.74	3.08	3.2	4.57	0.46	0.91
156	Menteng Atas	Setia Budi	South Jakarta	62	0.2	1.37	0.92	2.49	2.37	1.31	2.58	2.9	4.83	0.97	2.90
157	Pasar Manggis	Setia Budi	South Jakarta	63	0.13	1.02	0.58	2.65	3.5	1.05	3.07	9.06	7.76	2.59	55.63
158	Setia Budi	Setia Budi	South Jakarta	65	0.26	0.94	0.51	2.51	4.22	1.6	2.43	13.33	8.89	1.48	29.63
159	Bukit Duri	Tebet	South Jakarta	55	0.05	1.3	1.89	3.14	3.12	1.85	3.11	5.51	10.1	0.92	6.43
160	Kebon Baru	Tebet	South Jakarta	54	0.06	2.65	0.65	0.86	1.34	1.18	1.64	5.53	11.84	0.79	10.26
161	Manggarai	Tebet	South Jakarta	57	0.09	0.14	0.47	3.09	4.32	1.38	2.96	1.88	0.94	0.94	2.82
162	Manggarai Selatan	Tebet	South Jakarta	56	0.09	0.86	0.85	3.8	2.53	1.05	3.31	98.02	71.29	14.26	114.06
163	Menteng Dalam	Tebet	South Jakarta	51	0.28	1.65	0.31	2.52	4.61	1.38	3.36	2.04	4.89	0.41	4.08
164	Tebet Barat	Tebet	South Jakarta	52	0.2	2.48	0.78	1.16	1.7	1.84	1.65	2.49	4.35	0.62	3.11
165	Tebet Timur	Tebet	South Jakarta	53	0.15	2.42	0.73	1.15	1.35	1.49	1.12	16	4.57	0.76	4.57
166	Cakung Barat	Cakung	East Jakarta	117	0.22	9.71	0.99	1.89	2.64	0.64	1.17	3.39	4.29	0.36	12.33
167	Cakung Timur	Cakung	East Jakarta	116	0.11	11.84	0.28	1.32	3.61	0.46	1.53	1.78	2.66	0.11	1.89
168	Jatinegara	Cakung	East Jakarta	112	0.48	7.32	0.86	1.2	1.43	1.23	1.38	5.51	2.83	0.31	5.51
169	Penggilingan	Cakung	East Jakarta	113	0.13	9.39	0.82	1.33	0.94	0.77	0.93	2.42	2.64	0.22	7.69
170	Pulo Gebang	Cakung	East Jakarta	114	0.05	11.4	0.84	0.96	2.75	0.8	1.42	0.45	0.3	0.15	0.30
171	Rawa Terate	Cakung	East Jakarta	118	0.61	8.07	0.83	0.9	2.07	1.71	1.34	3.43	3.89	0.69	8.70
172	Ujung Menteng	Cakung	East Jakarta	115	0.17	12.91	0.7	3.13	3.16	0.74	0.98	1.16	1.16	0.47	0.47
173	Bambu Apus	Cipayung	East Jakarta	82	0.28	12.48	0.91	0.97	3.76	1.5	2.59	1.17	1.17	0.29	1.76
174	Ceger	Cipayung	East Jakarta	83	0.09	11.94	0.79	1.89	2.57	0.77	1.13	4.28	2.44	0.61	4.28
175	Cilangkap	Cipayung	East Jakarta	78	0.02	14.89	0.64	1.25	4.54	1.63	0.65	1.57	1.92	0.17	1.05
176	Cipayung	Cipayung	East Jakarta	80	0.04	13.61	0.9	0.99	3.47	1.23	0.86	5.24	4.03	0.81	5.65
177	Lubang Buaya	Cipayung	East Jakarta	84	0.56	10.75	0.69	3.11	4.53	1.67	1.09	2.22	1.67	0.28	2.22
178	Munjul	Cipayung	East Jakarta	79	0.19	15.63	0.59	2.38	4.08	1.22	2.7	25.06	15.42	0.48	19.28
179	Pondok Ranggon	Cipayung	East Jakarta	77	0.22	16.95	0.75	4.11	4.42	0.92	1.6	0.82	0.62	0.21	1.03
180	Setu	Cipayung	East Jakarta	81	0.02	13.24	0.84	2.93	2.58	0.83	1.62	3.26	2.18	0.36	3.26
181	Tmii	Cipayung	East Jakarta	66	0.59	11.18	0.41	4.73	7.12	2.09	1.38	14.33	29.28	1.25	20.56
182	Cibubur	Ciracas	East Jakarta	72	0.1	15.98	0.8	1.4	4.62	0.81	1.1	3.2	3.01	0.38	3.95
183	Ciracas	Ciracas	East Jakarta	74	0.22	12.37	0.96	2.64	2.72	0.98	1.22	6.08	4.82	0.25	3.55
184	Kelapa Dua Wetan	Ciracas	East Jakarta	73	0.06	14.23	0.74	4.1	2.89	0.81	0.9	6.22	5.62	0.89	15.39
185	Rambutan	Ciracas	East Jakarta	76	0.05	11.37	0.79	3.57	3.6	1.02	2.16	3.1	0.44	0.44	2.66
186	Susukan	Ciracas	East Jakarta	75	0.2	10.72	0.39	1.4	5.66	2.26	1.86	1.41	0.47	0.47	1.89
187	Duren Sawit	Duren Sawit	East Jakarta	106	0.11	7.59	0.93	0.77	0.75	0.7	1.09	2.33	2.97	0.42	11.04
188	Klender	Duren Sawit	East Jakarta	111	0.11	6.42	0.45	0.84	0.82	0.37	1.37	2.68	2.01	0.67	25.78
189	Malaka Jaya	Duren Sawit	East Jakarta	109	0.09	9.44	0.56	2.18	1.49	0.84	0.78	10.34	12.21	1.88	92.08
190	Malaka Sari	Duren Sawit	East Jakarta	110	0.09	8.73	0.9	0.94	1.09	0.97	1.01	12.28	1.53	0.77	10.74
191	Pondok Bambu	Duren Sawit	East Jakarta	105	0.14	6.07	1.16	1.17	1.22	1.42	1.51	2.26	1.26	0.25	2.76
192	Pondok Kelapa	Duren Sawit	East Jakarta	107	0.12	9.65	0.57	1.12	3.11	0.63	1.19	0.86	1.03	0.17	3.62
193	Pondok Kopi	Duren Sawit	East Jakarta	108	0.24	10.33	0.75	0.7	3.14	0.7	0.93	1.34	1.79	0.45	1.34
194	Bali Mester	Jatinegara	East Jakarta	103	0.37	1.92	0.93	2.52	2.67	1.29	2.77	16.34	11.88	1.49	47.53
195	Bidara Cina	Jatinegara	East Jakarta	97	0.16	3.26	0.63	1.16	2.07	1.6	1.15	1.6	2.41	0.8	4.81
196	Cipinang Besar Selatan	Jatinegara	East Jakarta	99	0.17	3.85	0.89	1.08	0.98	1.47	1.61	24.54	14.37	1.8	11.97
197	Cipinang Besar Utara	Jatinegara	East Jakarta	101	0.09	3.3	0.5	2.49	2.28	1.44	1.71	6.38	4.56	0.91	3.65
198	Cipinang Cempedak	Jatinegara	East Jakarta	98	0.09	3.71	0.89	0.92	0.87	1.27	1.41	1.83	0.61	0.61	3.65
199	Cipinang Muara	Jatinegara	East Jakarta	100	0.06	4.55	0.74	1.07	1.06	1.09	1.51	7.48	6.36	1.12	17.20
200	Kampung Melayu	Jatinegara	East Jakarta	104	0.12	0.95	0.67	4.36	3.46	1.51	3.11	8.73	8.73	2.18	19.64

No	Area Name			Zone ID	% Commercial Land use	Distance to Central	Ratio Online/ Dine	Index				Density			
	Neighborhood	District	City					Food	Online	Dine-in	Com	Food	Online	Dine-in	Com
201	Rawa Bunga	Jatinegara	East Jakarta	102	0.24	2.45	0.68	0.67	0.86	1.18	1.74	84.28	53.41	13.06	103.27
202	Bale Kambang	Kramat Jati	East Jakarta	90	0.05	6.86	0.88	0.92	1.13	0.99	1.74	6.56	4.77	1.19	15.50
203	Batu Ampar	Kramat Jati	East Jakarta	91	0.09	7.04	0.72	0.99	1.19	0.86	1.44	5.12	7.48	0.79	13.78
204	Cawang	Kramat Jati	East Jakarta	96	0.15	4.61	0.69	1.6	1.77	1.83	1.54	8.8	4.95	1.65	25.84
205	Cililitan	Kramat Jati	East Jakarta	95	0.08	5.72	0.67	1.43	1.63	1.6	2.28	1.69	2.82	0.56	3.95
206	Dukuh	Kramat Jati	East Jakarta	93	0.05	9.63	0.21	1.18	6.48	1.79	0.74	1.17	5.84	0.58	14.03
207	Kampung Tengah	Kramat Jati	East Jakarta	92	0.12	8.36	0.52	0.43	4.07	2.1	0.87	5.42	2.47	0.99	9.37
208	Kramat Jati	Kramat Jati	East Jakarta	94	0.15	7.17	0.68	1.19	1.32	0.9	1.46	4.7	2.68	1.34	3.35
209	Cipinang Melayu	Makasar	East Jakarta	89	0.06	7.94	0.8	0.98	1.03	0.82	1.35	3.81	4.96	1.14	10.68
210	Halim Perdana Kusuma	Makasar	East Jakarta	88	0.31	7.57	0.88	0.78	0.8	0.7	1.42	0.46	0.23	0.08	0.31
211	Kebon Pala	Makasar	East Jakarta	87	0.13	5.66	0.8	1.36	1.08	1.46	1.32	16.85	12.1	1.3	37.60
212	Makasar	Makasar	East Jakarta	86	0.11	8	0.62	2.3	1.17	0.72	1.44	13.76	7.57	1.38	45.42
213	Pinang Ranti	Makasar	East Jakarta	85	0.44	9.5	0.55	2.5	2.36	1.31	1.63	3.65	1.83	0.91	3.65
214	Kayu Manis	Matraman	East Jakarta	129	0.09	1.69	0.65	2.82	2.41	1.23	4.26	54.16	29.88	9.34	91.52
215	Kebon Manggis	Matraman	East Jakarta	126	0.13	0.65	0.72	3.05	3.76	1.62	3.32	7.68	5.12	1.28	5.12
216	Pal Meriem	Matraman	East Jakarta	127	0.21	1.35	0.92	3.2	3.42	1.81	3.49	7.79	10.91	1.56	21.82
217	Pisangan Baru	Matraman	East Jakarta	128	0.07	2.05	0.8	0.73	2.55	0.94	2.51	13.69	9.58	1.37	47.91
218	Utan Kayu Selatan	Matraman	East Jakarta	130	0.07	2.27	0.73	1.44	1.32	1.35	2.14	34.48	17.24	5.17	57.75
219	Utan Kayu Utara	Matraman	East Jakarta	131	0.26	2.72	0.83	0.66	0.76	0.93	1.22	7.19	6.16	1.03	5.14
220	Baru	Pasar Rebo	East Jakarta	69	0.03	11.21	0.77	2.16	2.8	0.54	1.06	1.56	3.12	0.52	8.31
221	Cijantung	Pasar Rebo	East Jakarta	70	0.03	11.2	0.71	0.76	2.86	0.82	0.84	1.93	2.7	0.77	1.93
222	Gedong	Pasar Rebo	East Jakarta	71	0.09	9.29	0.79	1.38	0.95	0.75	1.15	3.69	9.68	1.38	20.73
223	Kalisari	Pasar Rebo	East Jakarta	68	0.02	12.53	0.86	2.77	3.69	1.19	1.57	1.16	0.77	0.39	3.09
224	Pekayon	Pasar Rebo	East Jakarta	67	0.18	13.94	0.8	2.94	3	0.64	0.76	4.71	2.83	1.26	10.36
225	Cipinang	Pulo Gadung	East Jakarta	120	0.05	4.54	0.94	0.73	0.76	1.22	1.72	7.32	4.66	2	15.98
226	Jati	Pulo Gadung	East Jakarta	122	0.13	5.52	0.71	0.81	1.58	1.72	1.89	3.33	5.71	0.48	8.56
227	Jatinegara Kaum	Pulo Gadung	East Jakarta	121	0.19	5.65	0.82	1.66	1.13	1.23	1.9	1.56	7.78	0.78	16.35
228	Kayu Putih	Pulo Gadung	East Jakarta	124	0.21	4.71	0.75	1.4	1.12	1.34	1.52	7.01	3.12	0.26	2.86
229	Pisangan Timur	Pulo Gadung	East Jakarta	119	0.14	3.31	0.92	1.35	1.38	1.88	1.46	5.97	3.8	1.09	13.02
230	Pulo Gadung	Pulo Gadung	East Jakarta	125	0.13	6.27	0.84	1.23	0.93	0.78	1.53	2.29	6.28	0.57	16.00
231	Rawamangun	Pulo Gadung	East Jakarta	123	0.32	3.99	1.56	1.07	1.23	2.21	1.45	5.78	5.78	0.77	6.17
232	Cilincing	Cilincing	North Jakarta	259	0.28	11.41	0.74	2.69	4.15	1.67	2.78	2.81	1.32	0.17	2.98
233	Kali Baru	Cilincing	North Jakarta	262	0.33	8.95	0.82	2.71	2.22	1.83	2.36	1.61	0.4	0.4	6.05
234	Marunda	Cilincing	North Jakarta	258	0.11	13.03	0.82	2.72	4.5	2.05	0.74	4.84	3.41	0.77	6.05
235	Rorotan	Cilincing	North Jakarta	257	0.05	11.85	0.62	2.19	4.91	1.81	2.13	0.7	0.3	0.1	0.20
236	Semper Barat	Cilincing	North Jakarta	261	0.1	8.8	0.84	0.49	1.39	1.17	1.09	6.52	5.9	0.31	8.70
237	Semper Timur	Cilincing	North Jakarta	260	0.3	9.9	0.59	1.5	3.47	1.1	1.29	1.04	3.12	0.21	2.29
238	Suka Pura	Cilincing	North Jakarta	256	0.19	8.59	0.75	0.24	0.73	0.55	0.67	0.63	0.63	0.32	1.42
239	Kelapa Gading Barat	Kelapa Gading	North Jakarta	253	0.2	4.99	0.98	1.49	1.38	1.85	1.67	0.69	0.69	0.14	0.14
240	Kelapa Gading Timur	Kelapa Gading	North Jakarta	254	0.23	6.14	0.98	1.13	1.09	1.08	1.38	3.83	5.42	1.28	6.38
241	Pegangsaan Dua	Kelapa Gading	North Jakarta	255	0.25	7.23	1.49	1.04	0.89	1.32	1.38	0.36	0.9	0.18	1.44
242	Koja	Koja	North Jakarta	252	0.14	6.91	0.91	1.53	1.62	1.48	1.95	11.89	5.1	1.7	5.10
243	Lagoa	Koja	North Jakarta	250	0.13	7.94	0.97	0.43	0.58	0.57	1.26	1.29	5.16	0.65	11.61
244	Rawabadak Selatan	Koja	North Jakarta	247	0.35	5.89	0.76	1.53	0.63	0.98	2.19	11.78	3.53	0.59	18.85
245	Rawabadak Utara	Koja	North Jakarta	251	0.08	6.41	0.85	0.59	0.59	0.5	0.99	3.94	2.36	0.79	2.36
246	Tugu Selatan	Koja	North Jakarta	248	0.1	6.9	0.72	0.56	1.37	0.99	1.56	3.18	4.24	0.53	7.42
247	Tugu Utara	Koja	North Jakarta	249	0.1	7.54	0.94	1.07	0.98	0.93	1.38	3.38	2.11	0.42	3.80
248	Ancol	Pademangan	North Jakarta	239	0.44	3.69	0.92	1.88	2.32	2.72	3.48	2.3	1.33	0.15	3.41
249	Pademangan Barat	Pademangan	North Jakarta	237	0.2	0.96	0.74	3.67	3.26	1.21	3.13	6.77	3.38	1.35	7.45
250	Pademangan Timur	Pademangan	North Jakarta	238	0.27	1.36	0.55	2.92	4.97	2.13	2.94	7.61	6.57	0.35	12.45
251	Kamal Muara	Penjaringan	North Jakarta	232	0.34	10.61	0.78	2.66	4.88	2.4	2.09	1.39	0.74	0.19	5.18

No	Area Name			Zone ID	% Commercial Land use	Distance to Central	Ratio Online/ Dine	Index				Density			
	Neighborhood	District	City					Food	Online	Dine-in	Com	Food	Online	Dine-in	Com
252	Kapuk Muara	Penjaringan	North Jakarta	233	0.17	7.33	0.93	1.18	1.53	1.43	1.77	2.44	1.71	0.12	3.90
253	Pejagalan	Penjaringan	North Jakarta	234	0.29	4.79	0.86	1.11	1.24	1.57	1.42	3.76	2.42	0.54	1.34
254	Penjaringan	Penjaringan	North Jakarta	235	0.33	3.48	2.74	1.08	0.65	2.27	1.32	1.13	1.36	0.45	1.58
255	Pluit	Penjaringan	North Jakarta	236	0.09	5.26	1.17	1.32	1.34	2.16	1.79	2.07	2.66	0.44	7.68
256	Kebon Bawang	Tanjung Priok	North Jakarta	245	0.14	5.65	0.93	1.05	0.86	1.3	1.38	39.96	28.37	4.63	31.85
257	Papango	Tanjung Priok	North Jakarta	242	0.26	3.76	0.9	0.97	0.93	1.44	1.42	8.69	8.35	1	6.68
258	Sungai Bambu	Tanjung Priok	North Jakarta	244	0.55	4.52	0.73	1.56	1.55	1.74	1.66	30.67	25.02	2.02	55.29
259	Sunter Agung	Tanjung Priok	North Jakarta	240	0.21	2.02	1.01	2.81	2.91	1.32	2.91	2.46	1.32	0.19	2.84
260	Sunter Jaya	Tanjung Priok	North Jakarta	241	0.32	2.72	1.63	1.64	1.36	2.72	2.05	1.14	1.14	0.19	0.57
261	Tanjung Priuk	Tanjung Priok	North Jakarta	246	0.12	4.96	0.99	5.5	0.66	1.25	2.4	19.53	6.51	0.93	15.81
262	Warakas	Tanjung Priok	North Jakarta	243	0.06	4.57	0.72	1.08	0.99	1.31	1.69	11.09	5.54	0.92	9.24

APPENDIX 3. ATTRIBUTE OF ACTIVITY-TRAVEL DIARY SURVEY

No	Variable	Definition	Questions	Options	Note
1	hhid	Household ID			Automatic filled
2	individ	Household person ID			Automatic filled
3	access_code	Participant referral code			Automatic filled
4	hhmember_name	Household member name			Automatic filled
5	interval_id	Unique ID for each segment			Automatic filled
6	interval_type	Indicates if segment is stop, trip or data gap			Automatic filled
7	start_time	Start time of the segment			Automatic filled
8	end_time	End time of the segment			Automatic filled
9	mode_id	Final trip mode			Automatic filled
10	sid_interval	Source of interval		3 (automatic generated; user generated; user changed)	Flexible
11	sid_stop	Source of stop		3 (automatic generated; user generated; user changed)	Flexible
12	mode_source	Source of mode information		3 (automatic generated; user generated; user changed)	Flexible
13	original_mode_id	Original algorithm generated mode of the trip before this stop			Automatic filled
14	replaced_lat	Original algorithm generated latitude of the stop			Automatic filled
15	replaced_lon	Original algorithm generated longitude of the stop			Automatic filled
16	user_id	Unique ID for each user in MMM			Automatic filled
17	pro_driver	If participant indicated that they were a professional driver	Are you a professional driver?	2 (Yes; No)	Respondent choose
18	orginal_start_time	Original algorithm generated start time of the segment			Only when the user changes the start/stop times of the segment during validation.
19	original_end_time	Original algorithm generated end time of the segment			If the segment is validated and these fields are empty, it means the system detected times are correct.
20	lat	Latitude of the stop			Automatic filled using GPS
21	lon	Longitude of the stop			Automatic filled using GPS
22	how_travelled	Text value of mode_id	How did you travel?	7 (walk; car; motorbike; public transport; ojek online; ride hailing; and others)	Respondent choose
23	other_mode	Specification of other modes		Please specify (If Travel Mode = Other)	Respondent fill
24	num_accomp	Number of other people in your traveling party			Respondent fill
25	accomp_type	Relationship with the accompanied	Who was with you?	3 (Household member only; non-household member only, both household and non-household member)	Respondent choose
26	is_driver	Identification of driving activities	Were you the driver?	2 (Yes; No)	Respondent choose
27	park_type	Type of parking area	Where did you park at the end of this trip?	4 (street; residential garage/driveaway; commercial or public parking lot/garage; other)	Respondent choose
28	park_fee	Money spend for parking fee	Paid amount (IDR)	How much did you pay for the parking fee?	Respondent fill
29	bus_type	Bus type	What type of bus did you use?	4 (public bus; school bus, company bus; shuttle bus)	Respondent choose
30	car_type	Car type	Which of the following services did you use?	4 (GO-CAR; GREB-CAR; Taxi; Other)	Respondent choose
31	car_type_other	Identification of other type of car ride	Please specify (If Car Mode = Other)		Respondent fill
32	fare_paid	the fare of car ride service	Paid amount (IDR)		Respondent fill
33	is_motor_driver	identification of driving the motorbike	Were you the driver?	2 (Yes; No)	Respondent choose
34	moto_type	Motorbike ride hailing service	Which of the following services did you use?	6 (GO-RIDE; GRAB-BIKE; Oke Jack; Ladyjek; Ojek Pangkalan; Other)	Respondent choose
35	moto_type_other	Other motorbike ride hailing service	Please specify (If Motor Type = Other)		Respondent fill
36	moto_fare	Motorbike ride hailing service fare	Paid amount (IDR)		Respondent fill
37	activities	All type activities in the segment	Please select the type(s) of activity that best describes what you did here	6 (Home; Work; Eat-out; Shopping; Recreation; Other)	Respondent choose

No	Variable	Definition	Questions	Options	Note
38	activities_other	Other types of activities	Please select the type(s) of activity that best describes what you did here		Respondent fill
39	activities_main	Main activities	Which was your main activity? (If more than one chosen)	6 (Home; Work; Eat-out; Shopping; Recreation; Other)	Respondent choose
40	escort_type	Type of escort	Which of the following activities did you do at this stop?	3 (Dropped off passenger(s); Picked up passenger(s); Accompanied passenger(s) to his/her activity)	Respondent choose
41	psgr_activ	Passenger activities	Please indicate one or more activities that the passenger(s) you were transporting engaged in at this stop.	6 (Home; Work; Eat-out; Shopping; Recreation; Other)	Respondent choose
42	shop_type	Type of shopping	Please select the type(s) of shop that best describes what you did here	3 (Groceries; Non-groceries; Both (groceries and non-groceries))	Respondent choose
43	groc_type	Type of groceries	Please select the type(s) of grocery that best describes what you did here	7 (Fresh produce (fruit or vegetables); Meat, Chicken, Seafood; Dairy, Eggs, Cheese, Tofu, Tempe; Dried or Canned food; Frozen food; Bakery products; Other)	
44	groc_type_other	Other type of groceries	Please specify (if groc_type=other)		Respondent fill
45	nongroc_type	Type of non-groceries	Please select the type(s) of grocery that best describes what you did here	5 (Books/ Magazines; Electronics/ Home appliances; Fashion goods; Household products; Other)	Respondent choose
46	nongroc_type_other	Other type of non-groceries	Please specify (if non-groc_type = other)		Respondent fill
47	grocnongroc_amount	Shopping expenses	Paid amount (IDR)		Respondent fill
48	food_type	Food Type	Food type	8 (Beverages; Snacks/Sweets; Fast food; Indonesian food; Western food; Eastern food; Bakso & Noodles; Other)	Respondent choose
49	food_type_other	Other type of food	Please specify (if food type = other)		Respondent fill
50	food_amount	Food expenses	Paid amount (IDR)		Respondent fill
51	e_activities	Online activity	Type of online activities	9 (Online food delivery order; Online grocery shopping; Online non-grocery goods shopping; Online banking or payments; Online meeting; Online class; Online entertainment (e.g. games, movies); Other activities; None of the above (no e-activity))	Respondent choose
52	e_activities_other	Other type of online activities	Please specify (if e-activity = other)		Respondent fill

APPENDIX 4. ATTRACTION EACH ZONE IN JAKARTA

No	Zone Name	District Name	City Name	Population	Area Size (Km^2)	Density	Number of Facilities				
							C_Food	O_Food	D_Food	Comm	Public
1	Ancol	Pademangan	Jakarta Utara	29570	5.77	4981	32	21	4	48	68
2	Angke	Tambora	Jakarta Barat	35807	0.8	43826	7	5	3	6	12
3	Balekambang	Kramat Jati	Jakarta Timur	35466	1.67	18012	12	11	4	28	11
4	Bali Mester	Jatinegara	Jakarta Timur	11405	0.67	17304	12	11	3	34	35
5	Bambu Apus	Cipayung	Jakarta Timur	31585	3.17	8400	5	7	3	8	14
6	Bangka	Mampang Prapatan	Jakarta Selatan	25999	3.3	7351	128	58	12	118	43
7	Baru	Pasar Rebo	Jakarta Timur	29403	1.89	14133	4	9	3	18	5
8	Batu Ampar	Kramat Jati	Jakarta Timur	58613	2.55	19983	14	22	4	37	21
9	Bendungan Hilir	Tanah Abang	Jakarta Pusat	26314	1.58	16018	132	101	12	142	129
10	Bidara Cina	Jatinegara	Jakarta Timur	44378	1.26	35493	18	16	6	22	29
11	Bintaro	Pesanggrahan	Jakarta Selatan	63416	4.56	11808	20	26	9	29	25
12	Bukit Duri	Tebet	Jakarta Selatan	41644	1.08	38906	8	10	5	14	8
13	Bungur	Senen	Jakarta Pusat	22626	0.64	34463	3	6	3	8	14
14	Cakung Barat	Cakung	Jakarta Timur	72509	6.19	10030	7	6	3	10	15
15	Cakung Timur	Cakung	Jakarta Timur	73107	9.81	6464	23	14	5	26	22
16	Cawang	Kramat Jati	Jakarta Timur	40201	1.79	21827	13	12	3	52	43
17	Ceger	Cipayung	Jakarta Timur	23012	3.63	5492	5	7	3	8	15
18	Cempaka Baru	Kemayoran	Jakarta Pusat	41523	0.99	38088	7	14	3	9	20
19	Cempaka Putih Barat	Cempaka Putih	Jakarta Pusat	43913	1.22	32561	7	13	3	12	30
20	Cempaka Putih Timur	Cempaka Putih	Jakarta Pusat	28804	2.22	12326	20	27	4	71	63
21	Cengkareng Barat	Cengkareng	Jakarta Barat	80056	4.26	16409	29	17	6	51	48
22	Cengkareng Timur	Cengkareng	Jakarta Barat	99960	4.18	20735	21	24	5	53	50
23	Cibubur	Ciracas	Jakarta Timur	79698	4.5	15686	17	27	3	19	24
24	Cideng	Gambir	Jakarta Pusat	18466	1.26	14584	17	12	5	49	49
25	Ciganjur	Jagakarsa	Jakarta Selatan	46319	3.61	10334	8	7	3	9	19
26	Cijantung	Pasar Rebo	Jakarta Timur	50406	2.37	18589	5	13	3	23	21
27	Cikini	Menteng	Jakarta Pusat	10199	0.82	11711	30	25	8	38	52
28	Cikoko	Pancoran	Jakarta Selatan	12944	0.72	17661	3	7	3	8	15
29	Cilandak Barat	Cilandak	Jakarta Selatan	61331	6.05	9546	56	61	8	98	92
30	Cilandak Timur	Pasar Minggu	Jakarta Selatan	31342	3.53	8075	12	22	3	40	44
31	Cilangkap	Cipayung	Jakarta Timur	33247	6.03	4396	5	9	3	12	9
32	Cililitan	Kramat Jati	Jakarta Timur	49254	1.8	26094	18	19	4	23	34
33	Cilincing	Cilincing	Jakarta Utara	54779	8.31	6326	3	6	3	5	6
34	Cipayung	Cipayung	Jakarta Timur	31928	3.08	8441	6	15	3	6	14
35	Cipedak	Jagakarsa	Jakarta Selatan	45954	4.24	8473	6	10	4	7	17
36	Cipete Selatan	Cilandak	Jakarta Selatan	31942	2.37	12751	48	41	9	44	43
37	Cipete Utara	Kebayoran Baru	Jakarta Selatan	41311	1.83	20664	15	15	4	43	34
38	Cipinang	Pulo Gadung	Jakarta Timur	47860	1.54	29756	10	14	3	8	21
39	Cipinang Besar Selatan	Jatinegara	Jakarta Timur	43128	1.63	23417	23	20	7	33	22
40	Cipinang Besar Utara	Jatinegara	Jakarta Timur	58392	1.15	48850	4	8	3	9	11
41	Cipinang Cempedak	Jatinegara	Jakarta Timur	39036	1.67	22917	18	11	3	20	31
42	Cipinang Melayu	Makasar	Jakarta Timur	51540	2.53	18551	14	13	4	16	37
43	Cipinang Muara	Jatinegara	Jakarta Timur	67193	2.9	21525	21	17	3	34	35
44	Cipulir	Kebayoran Lama	Jakarta Selatan	48491	1.94	22494	12	7	5	22	19
45	Ciracas	Ciracas	Jakarta Timur	78854	3.93	17648	4	14	3	8	32
46	Dukuh	Kramat Jati	Jakarta Timur	30380	1.98	13402	3	6	3	11	12
47	Duren Sawit	Duren Sawit	Jakarta Timur	73679	4.58	14100	35	29	6	40	44
48	Duren Tiga	Pancoran	Jakarta Selatan	33743	2.45	12987	12	10	5	26	30

No	Zone Name	District Name	City Name	Population	Area Size (Km^2)	Density	Number of Facilities				
							C_Food	O_Food	D_Food	Comm	Public
49	Duri Kepa	Kebon Jeruk	Jakarta Barat	71926	3.86	17148	60	34	7	103	51
50	Duri Kosambi	Cengkareng	Jakarta Barat	95004	5.03	15866	42	27	5	22	43
51	Duri Pulo	Gambir	Jakarta Pusat	24997	0.72	35628	7	11	3	12	20
52	Duri Selatan	Tambora	Jakarta Barat	17106	0.42	41460	3	4	3	5	5
53	Duri Utara	Tambora	Jakarta Barat	24143	0.4	60175	8	8	3	6	5
54	Galur	Johar Baru	Jakarta Pusat	23056	0.27	79022	4	4	3	8	11
55	Gambir	Gambir	Jakarta Pusat	3066	2.58	1350	16	15	5	39	125
56	Gandaria Selatan	Cilandak	Jakarta Selatan	26488	1.76	13816	11	16	5	30	22
57	Gandaria Utara	Kebayoran Baru	Jakarta Selatan	47546	1.52	29247	21	20	5	48	16
58	Gedong	Pasar Rebo	Jakarta Timur	43716	2.65	14684	6	14	4	23	30
59	Gelora	Tanah Abang	Jakarta Pusat	3883	2.59	1450	6	5	3	9	13
60	Glodok	Taman Sari	Jakarta Barat	8665	0.38	24153	26	14	6	27	6
61	Gondangdia	Menteng	Jakarta Pusat	4666	1.46	3194	155	95	21	85	90
62	Grogol	Grogol Petamburan	Jakarta Barat	20320	1.22	16960	25	22	3	16	22
63	Grogol Selatan	Kebayoran Lama	Jakarta Selatan	53392	2.85	17009	3	13	3	26	22
64	Grogol Utara	Kebayoran Lama	Jakarta Selatan	52051	3.33	14342	12	17	4	54	27
65	Guntur	Setia Budi	Jakarta Selatan	4445	0.65	7174	6	4	3	21	20
66	Gunung	Kebayoran Baru	Jakarta Selatan	10921	1.32	8043	21	21	8	31	33
67	Gunung Sahari Selatan	Kemayoran	Jakarta Pusat	23768	0.53	43858	15	12	4	33	51
68	Gunung Sahari Utara	Sawah Besar	Jakarta Pusat	19980	1.98	9933	7	13	3	18	21
69	Halim Perdana Kusuma	Makasar	Jakarta Timur	34989	13.07	2546	9	9	3	12	50
70	Harapan Mulya	Kemayoran	Jakarta Pusat	28877	0.91	29205	4	8	3	8	14
71	Jagakarsa	Jagakarsa	Jakarta Selatan	74998	4.85	12940	13	29	3	15	38
72	Jati	Pulo Gadung	Jakarta Timur	38743	2.15	17270	14	30	4	27	47
73	Jati Padang	Pasar Minggu	Jakarta Selatan	45448	2.5	16524	9	24	5	47	32
74	Jati Pulo	Palmerah	Jakarta Barat	35251	0.87	38834	9	7	3	13	26
75	Jatinegara	Cakung	Jakarta Timur	104837	6.6	14709	11	16	3	30	25
76	Jatinegara Kaum	Pulo Gadung	Jakarta Timur	30619	1.23	21792	7	7	3	10	17
77	Jelambar	Grogol Petamburan	Jakarta Barat	35928	1.44	24624	28	18	3	23	31
78	Jelambar Baru	Grogol Petamburan	Jakarta Barat	46049	1.44	30778	13	9	3	17	15
79	Jembatan Besi	Tambora	Jakarta Barat	37228	0.55	66447	14	8	3	19	17
80	Jembatan Lima	Tambora	Jakarta Barat	25590	0.46	54543	4	6	3	6	7
81	Joglo	Kembangan	Jakarta Barat	49365	4.86	8812	21	15	5	20	43
82	Johar Baru	Johar Baru	Jakarta Pusat	45833	1.19	35270	8	15	3	20	41
83	Kali Baru	Cilincing	Jakarta Utara	85725	2.47	34278	3	4	3	4	7
84	Kalianyar	Tambora	Jakarta Barat	30115	0.32	94166	5	4	3	9	8
85	Kalibata	Pancoran	Jakarta Selatan	51167	2.2	21353	10	15	4	23	34
86	Kalideres	Kalideres	Jakarta Barat	88518	5.72	13726	36	21	4	37	42
87	Kalisari	Pasar Rebo	Jakarta Timur	52193	2.89	15517	3	13	3	23	7
88	Kamal	Kalideres	Jakarta Barat	65722	4.49	12257	3	5	3	6	11
89	Kamal Muara	Penjaringan	Jakarta Utara	15170	10.53	1144	51	38	8	42	26
90	Kampung Bali	Tanah Abang	Jakarta Pusat	14451	0.73	19941	12	7	3	33	33
91	Kampung Melayu	Jatinegara	Jakarta Timur	31479	0.48	63973	5	4	3	17	12
92	Kampung Rawa	Johar Baru	Jakarta Pusat	27181	0.3	86123	3	4	3	5	10
93	Kampung Tengah	Kramat Jati	Jakarta Timur	54252	2.03	24281	5	5	3	27	25
94	Kapuk	Cengkareng	Jakarta Barat	167088	7.18	20919	19	14	4	16	18
95	Kapuk Muara	Penjaringan	Jakarta Utara	42848	10.56	3243	20	14	4	28	30
96	Karang Anyar	Sawah Besar	Jakarta Pusat	32573	0.51	63122	4	5	3	10	14
97	Karet	Setia Budi	Jakarta Selatan	11581	0.94	12948	30	19	7	51	37
98	Karet Kuningan	Setia Budi	Jakarta Selatan	19346	1.79	10414	77	65	7	139	75
99	Karet Semanggi	Setia Budi	Jakarta Selatan	3214	0.9	3202	16	11	4	58	32
100	Karet Tengsin	Tanah Abang	Jakarta Pusat	23994	1.53	13912	64	43	6	76	57

No	Zone Name	District Name	City Name	Population	Area Size (Km^2)	Density	Number of Facilities				
							C_Food	O_Food	D_Food	Comm	Public
101	Kartini	Sawah Besar	Jakarta Pusat	27385	0.55	49862	7	7	3	6	10
102	Kayu Manis	Matraman	Jakarta Timur	30764	0.57	52740	5	7	3	11	9
103	Kayu Putih	Pulo Gadung	Jakarta Timur	48382	4.37	11179	11	21	4	27	51
104	Keagungan	Taman Sari	Jakarta Barat	21068	0.32	65800	7	8	3	10	5
105	Kebagusan	Pasar Minggu	Jakarta Selatan	54289	2.26	20705	12	8	4	21	17
106	Kebayoran Lama Selatan	Kebayoran Lama	Jakarta Selatan	49670	2.57	17598	9	16	4	56	29
107	Kebayoran Lama Utara	Kebayoran Lama	Jakarta Selatan	52141	1.78	27853	36	40	3	68	34
108	Kebon Baru	Tebet	Jakarta Selatan	42930	1.3	31580	6	10	4	10	16
109	Kebon Bawang	Tanjung Priok	Jakarta Utara	63919	1.73	35952	28	15	3	13	21
110	Kebon Jeruk	Kebon Jeruk	Jakarta Barat	65382	2.69	20957	63	30	9	61	81
111	Kebon Kacang	Tanah Abang	Jakarta Pusat	26794	0.71	35545	13	20	6	22	25
112	Kebon Kelapa	Gambir	Jakarta Pusat	12486	0.78	15890	32	27	6	46	18
113	Kebon Kosong	Kemayoran	Jakarta Pusat	37289	1.13	28014	8	18	3	15	17
114	Kebon Manggis	Matraman	Jakarta Timur	19822	0.78	25601	8	13	3	25	13
115	Kebon Melati	Tanah Abang	Jakarta Pusat	40678	1.26	30563	70	52	10	57	49
116	Kebon Pala	Makasar	Jakarta Timur	57560	2.3	22647	8	9	3	7	23
117	Kebon Sirih	Menteng	Jakarta Pusat	15407	0.83	18577	34	21	3	47	34
118	Kedaung Kali Angke	Cengkareng	Jakarta Barat	40507	2.61	14438	5	5	3	16	17
119	Kedoya Selatan	Kebon Jeruk	Jakarta Barat	38985	2.28	15519	18	13	3	45	28
120	Kedoya Utara	Kebon Jeruk	Jakarta Barat	54802	3.14	15976	40	31	5	89	48
121	Kelapa Dua	Kebon Jeruk	Jakarta Barat	28560	1.5	17297	14	10	3	11	23
122	Kelapa Dua Wetan	Ciracas	Jakarta Timur	56286	3.37	14203	5	9	3	8	17
123	Kelapa Gading Barat	Kelapa Gading	Jakarta Utara	41741	4.53	8515	149	73	13	119	80
124	Kelapa Gading Timur	Kelapa Gading	Jakarta Utara	39073	5.31	7089	111	111	10	73	49
125	Kemanggisan	Palmerah	Jakarta Barat	38642	2.33	16328	23	14	4	33	43
126	Kemayoran	Kemayoran	Jakarta Pusat	25623	0.55	44202	7	10	3	10	11
127	Kembangan Selatan	Kembangan	Jakarta Barat	32223	3.6	7866	125	74	18	110	80
128	Kembangan Utara	Kembangan	Jakarta Barat	66417	3.65	15703	18	12	3	30	20
129	Kenari	Senen	Jakarta Pusat	11431	0.91	11757	9	9	4	79	82
130	Klender	Duren Sawit	Jakarta Timur	86157	3.08	25456	22	22	5	54	37
131	Koja	Koja	Jakarta Utara	35550	3.27	10838	6	8	3	3	5
132	Kota Bambu Selatan	Palmerah	Jakarta Barat	26522	0.61	41082	7	5	3	8	26
133	Kota Bambu Utara	Palmerah	Jakarta Barat	31177	0.63	46608	8	6	3	5	26
134	Kramat	Senen	Jakarta Pusat	35760	0.71	47630	5	9	3	16	31
135	Kramat Jati	Kramat Jati	Jakarta Timur	41707	1.52	25801	12	12	3	47	45
136	Kramat Pela	Kebayoran Baru	Jakarta Selatan	17366	1.23	12872	49	31	15	51	47
137	Kredang	Tambora	Jakarta Barat	24904	0.32	74109	8	7	4	7	7
138	Krukut	Taman Sari	Jakarta Barat	23375	0.55	42111	10	8	3	8	11
139	Kuningan Barat	Mampang Prapatan	Jakarta Selatan	15734	0.98	15120	10	11	3	17	23
140	Kuningan Timur	Setia Budi	Jakarta Selatan	7155	2.15	3335	43	32	4	64	79
141	Kwitang	Senen	Jakarta Pusat	19078	0.45	40724	5	8	3	12	16
142	Lagoa	Koja	Jakarta Utara	74371	1.58	44105	8	13	3	4	12
143	Lebak Bulus	Cilandak	Jakarta Selatan	44061	4.41	8840	15	22	8	42	39
144	Lenteng Agung	Jagakarsa	Jakarta Selatan	65486	2.28	24703	3	11	3	20	29
145	Lubang Buaya	Cipayung	Jakarta Timur	77230	3.72	18055	4	10	3	21	27
146	Makasar	Makasar	Jakarta Timur	42454	1.85	20695	6	8	3	7	15
147	Malaka Jaya	Duren Sawit	Jakarta Timur	37270	0.99	36535	9	9	3	10	15
148	Malaka Sari	Duren Sawit	Jakarta Timur	32994	1.38	23592	17	5	3	16	8
149	Mampang Prapatan	Mampang Prapatan	Jakarta Selatan	22566	0.78	27765	11	10	3	37	20
150	Mangga Besar	Taman Sari	Jakarta Barat	8875	0.51	17882	21	14	4	68	14
151	Mangga Dua Selatan	Sawah Besar	Jakarta Pusat	34983	1.29	26203	12	16	4	100	42
152	Manggarai	Tebet	Jakarta Selatan	35007	0.95	36246	5	6	3	9	17

No	Zone Name	District Name	City Name	Population	Area Size (Km^2)	Density	Number of Facilities				
							C_Food	O_Food	D_Food	Comm	Public
153	Manggarai Selatan	Tebet	Jakarta Selatan	28023	0.51	52659	6	14	3	9	12
154	Maphar	Taman Sari	Jakarta Barat	19419	0.59	34693	20	15	6	13	11
155	Marunda	Cilincing	Jakarta Utara	35644	7.92	3105	3	4	3	5	9
156	Melawai	Kebayoran Baru	Jakarta Selatan	3067	1.26	2528	56	43	10	66	58
157	Menteng	Menteng	Jakarta Pusat	31108	2.44	11968	92	58	14	66	102
158	Menteng Atas	Setia Budi	Jakarta Selatan	33725	0.9	35511	9	10	4	9	24
159	Menteng Dalam	Tebet	Jakarta Selatan	44336	2.58	16355	38	38	6	78	37
160	Meruya Selatan	Kembangan	Jakarta Barat	39069	2.85	11142	12	10	4	26	22
161	Meruya Utara	Kembangan	Jakarta Barat	52740	4.76	9608	45	34	9	57	48
162	Munjul	Cipayung	Jakarta Timur	28765	1.9	12734	4	8	3	5	6
163	Pademangan Barat	Pademangan	Jakarta Utara	92393	3.53	24947	6	15	3	12	21
164	Pademangan Timur	Pademangan	Jakarta Utara	44736	2.61	16245	18	23	4	15	39
165	Pal Meriem	Matraman	Jakarta Timur	24060	0.65	36818	10	11	3	24	15
166	Palmerah	Palmerah	Jakarta Barat	76683	2.11	33544	53	35	3	42	57
167	Pancoran	Pancoran	Jakarta Selatan	23693	1.24	17127	7	10	3	23	25
168	Papango	Tanjung Priok	Jakarta Utara	48692	2.8	16353	11	8	4	13	17
169	Pasar Baru	Sawah Besar	Jakarta Pusat	15236	1.89	8041	23	22	3	38	88
170	Pasar Manggis	Setia Budi	Jakarta Selatan	32684	0.78	40395	6	10	3	16	27
171	Pasar Minggu	Pasar Minggu	Jakarta Selatan	29594	2.79	9965	8	9	4	45	39
172	Paseban	Senen	Jakarta Pusat	29333	0.71	38400	13	14	4	42	31
173	Pegadungan	Kalideres	Jakarta Barat	89902	8.89	8364	32	25	4	34	47
174	Pegangsaan	Menteng	Jakarta Pusat	28771	0.98	27151	15	11	3	34	32
175	Pegangsaan Dua	Kelapa Gading	Jakarta Utara	59011	6.28	8216	27	28	5	22	49
176	Pejagalan	Penjaringan	Jakarta Utara	88877	3.23	27856	11	21	3	20	25
177	Pejaten Barat	Pasar Minggu	Jakarta Selatan	44922	2.9	14338	17	19	4	30	33
178	Pejaten Timur	Pasar Minggu	Jakarta Selatan	70771	2.88	22624	6	14	3	17	29
179	Pekayon	Pasar Rebo	Jakarta Timur	53257	3.14	14600	3	8	3	10	12
180	Pekojan	Tambora	Jakarta Barat	27692	0.78	35333	15	12	4	7	19
181	Pela Mampang	Mampang Prapatan	Jakarta Selatan	52827	1.62	30940	14	14	3	32	21
182	Pengadegan	Pancoran	Jakarta Selatan	25553	0.95	24076	6	11	3	11	10
183	Penggilingan	Cakung	Jakarta Timur	120095	4.48	22483	14	10	3	17	22
184	Penjaringan	Penjaringan	Jakarta Utara	108579	3.95	28071	16	12	6	35	34
185	Pesanggrahan	Pesanggrahan	Jakarta Selatan	33294	2.1	13859	3	10	3	7	14
186	Petamburan	Tanah Abang	Jakarta Pusat	42817	0.9	43262	7	9	3	19	29
187	Petogogan	Kebayoran Baru	Jakarta Selatan	13717	0.86	15895	45	37	11	35	27
188	Petojo Selatan	Gambir	Jakarta Pusat	17969	1.14	14465	12	15	3	37	49
189	Petojo Utara	Gambir	Jakarta Pusat	21379	1.12	18987	28	30	6	61	39
190	Petukangan Selatan	Pesanggrahan	Jakarta Selatan	44882	2.11	18260	6	9	4	9	19
191	Petukangan Utara	Pesanggrahan	Jakarta Selatan	65329	2.99	19001	5	14	3	30	17
192	Pinang Ranti	Makasar	Jakarta Timur	33297	1.89	14793	8	15	5	30	22
193	Pinangsia	Taman Sari	Jakarta Barat	12890	0.96	13791	18	14	4	27	35
194	Pisangan Baru	Matraman	Jakarta Timur	38531	0.68	54913	6	6	3	5	5
195	Pisangan Timur	Pulo Gadung	Jakarta Timur	49766	1.8	26931	9	17	3	18	32
196	Pluit	Penjaringan	Jakarta Utara	54858	7.71	6344	108	99	13	77	56
197	Pondok Bambu	Duren Sawit	Jakarta Timur	74591	5	13285	38	40	6	60	45
198	Pondok Kelapa	Duren Sawit	Jakarta Timur	86150	5.72	12673	34	27	5	34	37
199	Pondok Kopi	Duren Sawit	Jakarta Timur	43152	2.06	18136	16	12	4	12	19
200	Pondok Labu	Cilandak	Jakarta Selatan	55099	3.61	13349	13	18	5	35	35
201	Pondok Pinang	Kebayoran Lama	Jakarta Selatan	66946	6.84	8897	56	45	9	98	68
202	Pondok Ranggon	Cipayung	Jakarta Timur	30535	3.66	6772	3	7	3	5	6
203	Pulo	Kebayoran Baru	Jakarta Selatan	6630	1.27	5408	34	23	7	53	34
204	Pulo Gadung	Pulo Gadung	Jakarta Timur	41862	1.29	30260	9	7	4	10	21

No	Zone Name	District Name	City Name	Population	Area Size (Km^2)	Density	Number of Facilities				
							C_Food	O_Food	D_Food	Comm	Public
205	Pulo Gebang	Cakung	Jakarta Timur	116962	6.86	13716	11	17	3	19	27
206	Ragunan	Pasar Minggu	Jakarta Selatan	47768	5.05	8681	15	21	5	54	56
207	Rambutan	Ciracas	Jakarta Timur	45264	2.09	19324	3	10	3	15	23
208	Rawa Barat	Kebayoran Baru	Jakarta Selatan	6506	0.69	9778	38	22	10	25	20
209	Rawa Buaya	Cengkareng	Jakarta Barat	77907	4.67	14886	10	8	3	13	16
210	Rawa Bunga	Jatinegara	Jakarta Timur	26241	0.88	28478	10	9	3	22	21
211	Rawa Terate	Cakung	Jakarta Timur	31452	4.1	7387	6	9	3	23	8
212	Rawabadak Selatan	Koja	Jakarta Utara	53387	1.33	35441	4	7	3	5	12
213	Rawabadak Utara	Koja	Jakarta Utara	43182	1.33	31357	8	11	3	7	23
214	Rawajati	Pancoran	Jakarta Selatan	24745	0.67	29915	15	17	6	37	22
215	Rawamangun	Pulo Gadung	Jakarta Timur	44958	2.6	16963	35	51	9	78	64
216	Rawasari	Cempaka Putih	Jakarta Pusat	26730	1.25	19945	22	10	3	19	35
217	Roa Malaka	Tambora	Jakarta Barat	3857	0.53	8275	5	6	3	7	8
218	Rorotan	Cilincing	Jakarta Utara	50715	10.64	3859	4	5	3	4	9
219	Selong	Kebayoran Baru	Jakarta Selatan	3222	1.4	3014	38	23	6	25	56
220	Semanan	Kalideres	Jakarta Barat	88410	5.98	13037	8	4	3	8	17
221	Semper Barat	Cilincing	Jakarta Utara	85887	4.44	18003	5	9	3	4	12
222	Semper Timur	Cilincing	Jakarta Utara	44793	3.17	12725	4	4	3	3	6
223	Senayan	Kebayoran Baru	Jakarta Selatan	3332	1.53	2856	72	48	13	89	60
224	Senen	Senen	Jakarta Pusat	8515	0.81	10158	16	20	5	40	47
225	Serdang	Kemayoran	Jakarta Pusat	37395	0.82	41837	6	11	3	14	26
226	Setia Budi	Setia Budi	Jakarta Selatan	3603	0.94	3852	16	18	4	18	20
227	Setu	Cipayung	Jakarta Timur	24673	3.25	6028	4	6	3	4	11
228	Slipi	Palmerah	Jakarta Barat	20244	0.97	19980	18	7	3	16	39
229	Srengseng	Kembangan	Jakarta Barat	54847	4.92	9446	22	22	3	30	48
230	Srengseng Sawah	Jagakarsa	Jakarta Selatan	70267	6.75	8912	6	18	3	13	27
231	Suka Pura	Cilincing	Jakarta Utara	69410	5.61	11602	5	10	3	7	19
232	Sukabumi Selatan	Kebon Jeruk	Jakarta Barat	46192	1.57	26532	10	9	3	11	25
233	Sukabumi Utara	Kebon Jeruk	Jakarta Barat	47231	1.6	26438	14	11	3	8	11
234	Sumur Batu	Kemayoran	Jakarta Pusat	28508	1.15	23271	10	15	4	34	26
235	Sungai Bambu	Tanjung Priok	Jakarta Utara	37393	2.36	15221	22	9	3	8	16
236	Sunter Agung	Tanjung Priok	Jakarta Utara	86152	6.65	12234	70	90	9	59	72
237	Sunter Jaya	Tanjung Priok	Jakarta Utara	77091	4.68	14791	19	28	6	39	28
238	Susukan	Ciracas	Jakarta Timur	46367	2.19	19019	5	7	4	11	13
239	Taman Sari	Taman Sari	Jakarta Barat	16815	0.68	26441	11	10	3	6	9
240	Tambora	Tambora	Jakarta Barat	12499	0.28	45375	4	4	3	6	6
241	Tanah Sereal	Tambora	Jakarta Barat	31653	0.62	49860	9	11	3	10	16
242	Tanah Tinggi	Johar Baru	Jakarta Pusat	47611	0.62	71177	5	7	3	7	24
243	Tangki	Taman Sari	Jakarta Barat	15512	0.37	43827	14	14	4	24	2
244	Tanjung Barat	Jagakarsa	Jakarta Selatan	48015	3.65	11460	9	14	4	30	27
245	Tanjung Duren Selatan	Grogol Petamburan	Jakarta Barat	30115	1.76	15915	141	94	12	113	66
246	Tanjung Duren Utara	Grogol Petamburan	Jakarta Barat	20192	1.11	18227	87	59	8	94	46
247	Tanjung Priuk	Tanjung Priok	Jakarta Utara	43407	5.59	7794	4	6	3	10	18
248	Tebet Barat	Tebet	Jakarta Selatan	25015	1.72	14080	36	37	5	31	52
249	Tebet Timur	Tebet	Jakarta Selatan	21170	1.39	14544	24	50	4	35	31
250	Tegal Alur	Kalideres	Jakarta Barat	102989	4	23429	35	18	9	16	16
251	Tegal Parang	Mampang Prapatan	Jakarta Selatan	39681	1.06	34830	7	11	3	16	18
252	Tmii	Cipayung	Jakarta Timur	23012	3.93	#N/A	9	8	3	11	22
253	Tomang	Grogol Petamburan	Jakarta Barat	35399	1.88	18103	41	23	8	69	57
254	Tugu Selatan	Koja	Jakarta Utara	49245	1.86	22869	6	8	4	4	15
255	Tugu Utara	Koja	Jakarta Utara	85545	2.37	34123	10	11	3	9	33
256	Ujung Menteng	Cakung	Jakarta Timur	36549	4.43	6972	8	9	3	7	8

No	Zone Name	District Name	City Name	Population	Area Size (Km^2)	Density	Number of Facilities				
							C_Food	O_Food	D_Food	Comm	Public
257	Ulujami	Pesanggrahan	Jakarta Selatan	49789	1.71	26161	5	7	3	17	12
258	Utan Kayu Selatan	Matraman	Jakarta Timur	40218	1.12	34434	13	9	3	12	20
259	Utan Kayu Utara	Matraman	Jakarta Timur	34252	1.05	31694	11	19	3	28	30
260	Utan Panjang	Kemayoran	Jakarta Pusat	37137	1.05	31889	4	5	3	5	10
261	Warakas	Tanjung Priok	Jakarta Utara	56128	1.09	49384	7	9	3	5	8
262	Wijaya Kesuma	Grogol Petamburan	Jakarta Barat	47778	2.61	17092	21	9	3	34	29

APPENDIX 5. USER'S QUESTIONNAIRE

SECTION 1. SOCIO-DEMOGRAPHIC

In this section, the respondent is asked to fill in some data related to self and family identity. The purpose of this section is to see whether individual attributes can influence habits and decisions in traveling and daily activities.

1. ID of respondent (filled by surveyor)
2. Gender:
   01. Male
   02. Female
3. Marital Status:
   01. Married
   02. Single
   03. Divorce
   04. Others (please specify), _____________
4. Phone Number:
5. Email Address:
6. Home Address:
   01. Street name and number
   02. RT/RW (block number)
   03. District
   04. Postal Code
7. Office Address:
   01. Street name and number
   02. RT/RW (block number)
   03. District
   04. Postal Code
8. Education Level:
   01. Elementary School
   02. Junior High School
   03. Senior High School
   04. Diploma
   05. Bachelor
   06. Master or Doctorate
   07. Others (please specify), _____________
9. Occupancy:
   01. Working (Full time, Gov't Employee)
   02. Working (Part time, Gov't Employee)
   03. Working (Full time, Private Employee)
   04. Working (Part time, Private Employee)
   05. Teacher or Lecturer
   06. Entrepreneur
   07. University Student
   08. Others (please specify), _____________
10. Driving License Ownership: (multiple answer is allowed)
    01. SIM A
    02. SIM B
    03. SIM C
    04. Do Not Have Any
    05. Others (please specify), _____________
11. Household Vehicle(s) Ownership:
    01. Car : _______ unit(s)
    02. Motorbike : _______ unit(s)
    03. Bicycle : _______ unit(s)
    04. Others (please specify): _______ unit(s)
12. Household Member Data (Including Respondents, please give a circle mark on yourself section)

No	Age (Y.O)	Gender 1. Male 2. Female	Position in Family	Social Activity
01.				
02.				
03.				
04.				
05.				
06.				
07.				
08.				
09.				
10.				

Position in Family:

01. Head of Household
02. Wife/Spouse
03. Child
04. Daughter/Son in Law
05. Parents
06. Brother
07. Sister
08. Grandchild
09. Housekeeper
10. Others

Social Activity:

01. Working (Full time, Gov't Employee)
02. Working (Part time, Gov't Employee)
03. Working (Full time, Private Employee)
04. Working (Part time, Private Employee)
05. Teacher or Lecturer
06. Entrepreneur
07. University Student
08. Students
09. Housewife
10. Retired
11. Do not work/Jobless
12. Others

13. Average Household Monthly Income (Including all of Household member's income)
14. Average Household Monthly Expenses
15. Average Respondent's Monthly Travel Expenses
16. Average Respondent's Monthly Meal Expenses
17. Average Respondent's Monthly Grocery Expenses
18. Average Respondent's Monthly Non-Grocery Expenses

The options for question number 13-18:

01. Under Rp. 1.000.000
02. Rp. 1.000.000-Rp. 1.499.999
03. Rp. 1.500.000-Rp. 1.999.999
04. Rp. 2.000.000-Rp. 2.999.999
05. Rp. 3.000.000-Rp. 3.999.999
06. Rp. 4.000.000-Rp. 4.999.999
07. Rp. 5.000.000-Rp. 5.999.999
08. Rp. 6.000.000-Rp. 7.999.999
09. Rp. 8.000.000-Rp. 9.999.999
10. Rp.10.000.000-Rp.12.499.999
11. Rp.12.500.000-Rp.14.999.999
12. Rp.15.000.000-Rp.17.499.999

13. Rp.17.500.000-Rp.19.999.999
14. Rp.20.000.000-Rp.22.499.999
15. Rp.22.500.000-Rp.24.999.999
16. More than Rp.25.000.000

19. How many smartphone(s) did you have?
    01. One
    02. Two
    03. Three
    04. More than Three
20. What type is your monthly plan?
    01. Prabayar
    02. Pascabayar
21. How many giga byte your monthly plan for internet on smartphone(s)?
    01. Under 500 MB
    02. 1 GB
    03. 3 GB
    04. 5 GB
    05. 7 GB
    06. 10 GB
    07. More than 10 GB
    08. Unlimited
22. Did you have Wi-Fi in your home?
    01. Yes
    02. No
23. Is your home's Wi-Fi unlimited?
    01. Yes
    02. No
24. Did you have access to Wi-Fi at your office?
    01. Yes
    02. No
25. Is your office's Wi-Fi unlimited?
    01. Yes
    02. No
26. Do you have any requirement on the day that you need to be at the office?
    01. Yes
    02. No (Go to question 28)
27. Do you go to the office every day? (Please select all that apply)

Monday ☐ Never Go ☐ Mostly Not Go ☐ Mostly Go ☐ Always Go	Tuesday ☐ Never Go ☐ Mostly Not Go ☐ Mostly Go ☐ Always Go
Wednesday ☐ Never Go ☐ Mostly Not Go ☐ Mostly Go ☐ Always Go	Thursday ☐ Never Go ☐ Mostly Not Go ☐ Mostly Go ☐ Always Go
Friday ☐ Never Go ☐ Mostly Not Go ☐ Mostly Go ☐ Always Go	Saturday ☐ Never Go ☐ Mostly Not Go ☐ Mostly Go ☐ Always Go
Sunday ☐ Never Go ☐ Mostly Not Go ☐ Mostly Go ☐ Always Go	

28. Do you have any assigned working schedule?
    01. Yes
    02. No (Go to question 30)
29. When is the starting and ending time of your work schedule? (Exact time)

Starting Time		
HH (hours)	MM (minutes)	a.m. / p.m.

Ending Time		
HH (hours)	MM (minutes)	a.m. / p.m.

※ Put dash (-) mark if no requirement

30. Do you have any minimum requirement of working hour?
    01. Yes
    02. No (Go to question 32)
31. How many hours is the lunch break time in a day?

HH (hours)	MM (minutes)

32. Do you have any assigned lunch schedule?
    01. Yes
    02. No (Go to question 32)
33. When is the starting and ending time of your lunch break? (Exact time)

34. Starting Time		
HH (hours)	MM (minutes)	a.m. / p.m.

Ending Time		
HH (hours)	MM (minutes)	a.m. / p.m.

※ Put dash (-) mark if no requirement

35. How many hours is the lunch break time in a day?

HH (hours)	MM (minutes)

※ Put dash (-) mark if no requirement

36. Do you have any assigned schedule of the arriving time at home?
01. Yes
02. No
37. How many hours is the lunch break time in a day?

HH (hours)	MM (minutes)

※ Put dash (-) mark if no requirement

38. Does your workplace have designated place for lunch (e.g., Canteen or Café) inside the office?
    01. Yes
    02. No
39. Does your workplace provide some free lunch for the employee?
    01. Yes
    02. No
40. How far is the distance of the nearby shops from your workplace?
    01. ≤500 meter
    02. 501 m – 1 Km
    03. 1 – 2 Km
    04. 2 – 3 Km
    05. 3 – 4 Km
    06. More than 4 Km
41. By which mode usually you went there?
    01. Never went there
    02. Walking
    03. Your own Bicycle
    04. Your own motorbike
    05. Online Ojek

06. Taxi
07. Busway
08. Others (please specify), _____________

SECTION 2. TRAVEL DIARY AND ICT USAGE

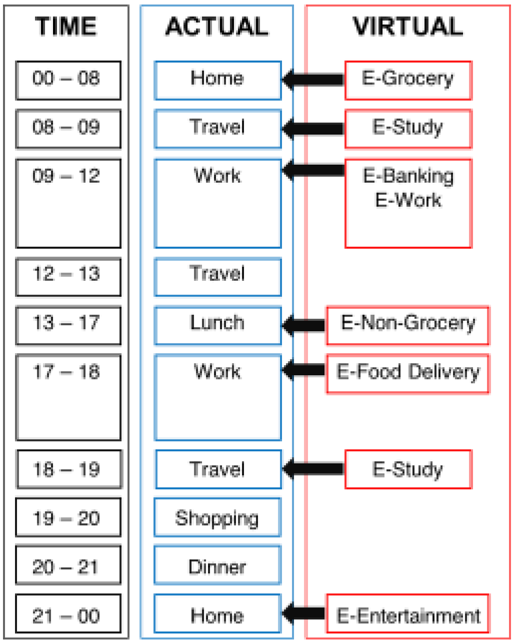


Figure 1 - Trip-Activity Path

By using the travel diary survey application (provided by MMM @Singapore) we are trying to capture the real (actual) travel-activity behavior and the virtual activity behavior that happened within 24 hours. In the detail we will colleting respondent's:

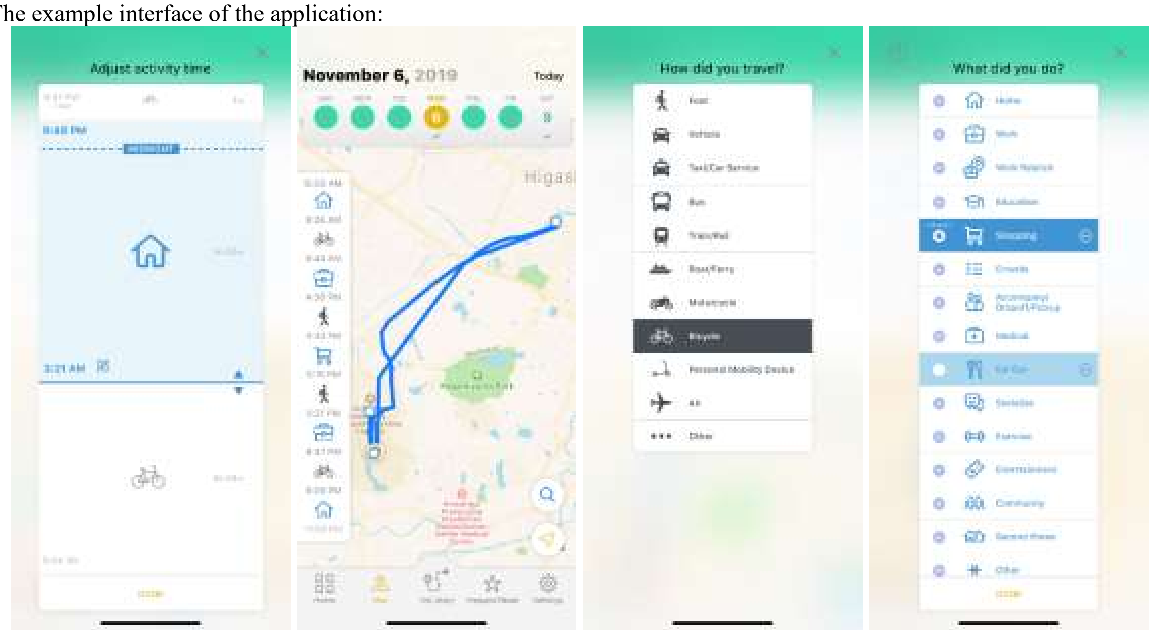
1. Origin
2. Destination
3. Travel time
4. Travel purpose
5. Activity time (duration of activity)
6. Route choice
7. Mode choice
8. **ICT usage** on every activity
9. **Follow-up questions**:

(1) Frequent place
(2) Reason if did not make any trips on that day

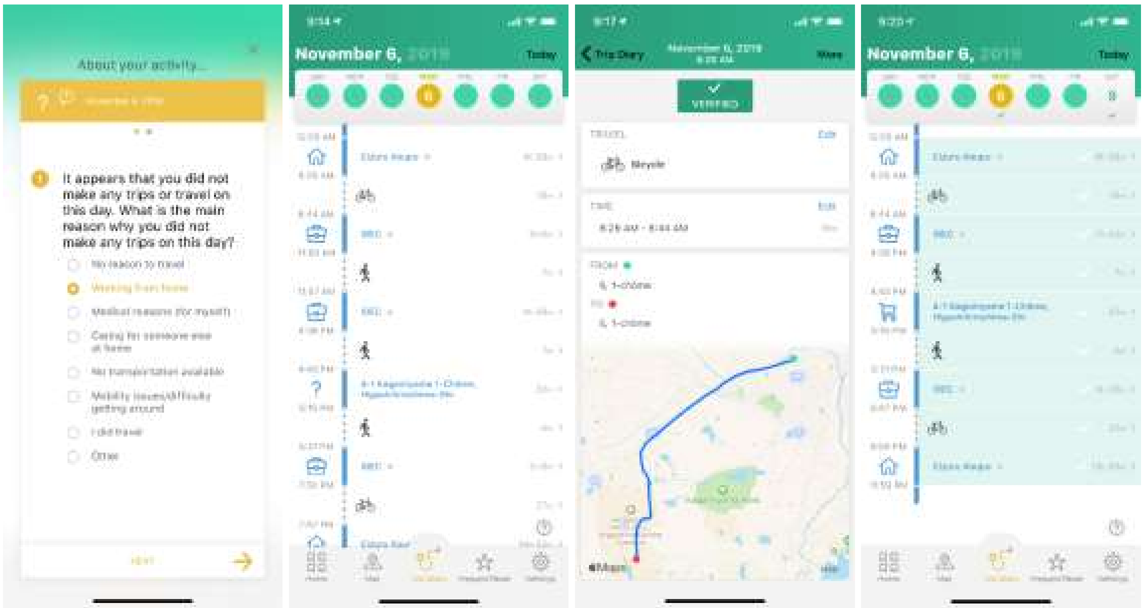
How does the application work?

1. In the beginning of the survey, the respondents will be asked to fill the username and the password that will provided by MMM Company.
2. Make sure to turn on the GPS.
3. Every day in 2-weeks (14 days) the respondent will be asked to open the MMM Application to make sure the application is running.
4. Let the application running in your background.
5. Verify the trips/activities in the end of trips/activities or in the end of the dat.
6. Answer the follow up question.
7. Finish.

The example interface of the application:



Travel time | Route Choice | Mode Choice | Trip Purpose



Follow up questions | Trip Diary | Detail of Trips | Verification

ICT Usage Questionnaire

The ICT usage question will be asked in the end of every trips/activities. By asking what kind of e-activities that they have done along with the actual trips/activities, we tried to capture the virtual activities pattern that happened in the same time.

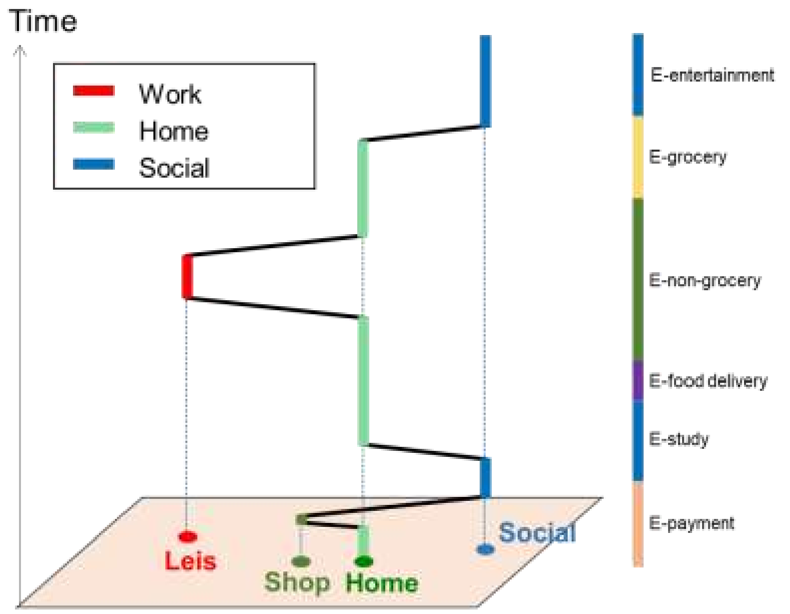


Figure 2. Time-space path for Actual and Virtual Travel-Activity

The questions are follows:

"Did you do some e-activity within this activity? (multiply answer allowed)"

The options are follows:
1. No
2. Order food from online food delivery services
3. Buying a grocery by online
4. Buying non-grocery goods by online
5. Online banking/online payment
6. Joining some online meeting
7. Joining some online class
8. Watch an online movie or playing an online game (e-entertainment)
9. Other e-activities

Follow-up Questionnaire (attached to the application)

Standard travel diary questions:

- **Shopping trip** purpose
  - Keep the shopping purpose
  - Insert the follow up question, asking:
    - Whether it was for:

1. **Grocery**,
2. **Non-grocery**,
3. **Both (grocery and non-grocery)**.

- After choosing the category, there will be a detail category for each:
  1. **Grocery** (multiple answer is allowed)
     01. Fresh product (vegetable or fruit)
     02. Meat, Chicken, Seafood
     03. Diary, Eggs, Cheese, Tofu, Tempe
     04. Dry and Canned Goods
     05. Frozen Food
     06. Bakery
     07. Others (fill manually)
  2. **Non-grocery** (multiple answer is allowed)
     01. Books/Magazine
     02. Electronics & Home Appliance
     03. Make Up & Skin Care
     04. Fashion
     05. Household Products
     06. Others (fill manually)
  3. If they choose **both** the above options will be **shown again**
     - Price paid in **total** for the whole transaction.
       1. No need to distinguish or separate the bills for every category of shopping.
       2. The cost in here is total amount that they paid in one-time activity.

- **Eat-out** trip purpose
  - Insert the follow up question, asking:
    - The **type** of food they ate or buy. The category of type food is:
      1. Beverages
      2. Snack/Sweets
      3. Fast Food
      4. Indonesian Food
      5. Western Food
      6. Eastern Food
      7. Noodles & Meatballs
      8. Others (fill manually)
    - How much they paid for the food they ordered?
- **Mode Choice**
  - Online car trips would be included in the taxi/ride hailing. With the follow-up questions:
    - Which service was used?
      1. GO-CAR
      2. GRAB-CAR
      3. Bluebird Taxi
      4. Others (fill manually)
    - How much is the fare that they paid?
  - Online motorcycle included in the Motorcycle mode category. With the follow-up questions:
    - Asking if the user was the driver or passenger. If Passenger, there will be another follow up questions:
    - If any of the following services were used?"
      1. GO-RIDE by GOJEK
      2. GRAB-BIKE by GRAB
      3. Oke Jack
      4. LADYJEK
      5. Ojek Pangkalan
      6. Others (fill manually)
    - The fare paid if a service was used (that it's possible to be a passenger riding on the motorcycle of a friend or family member without using a service).

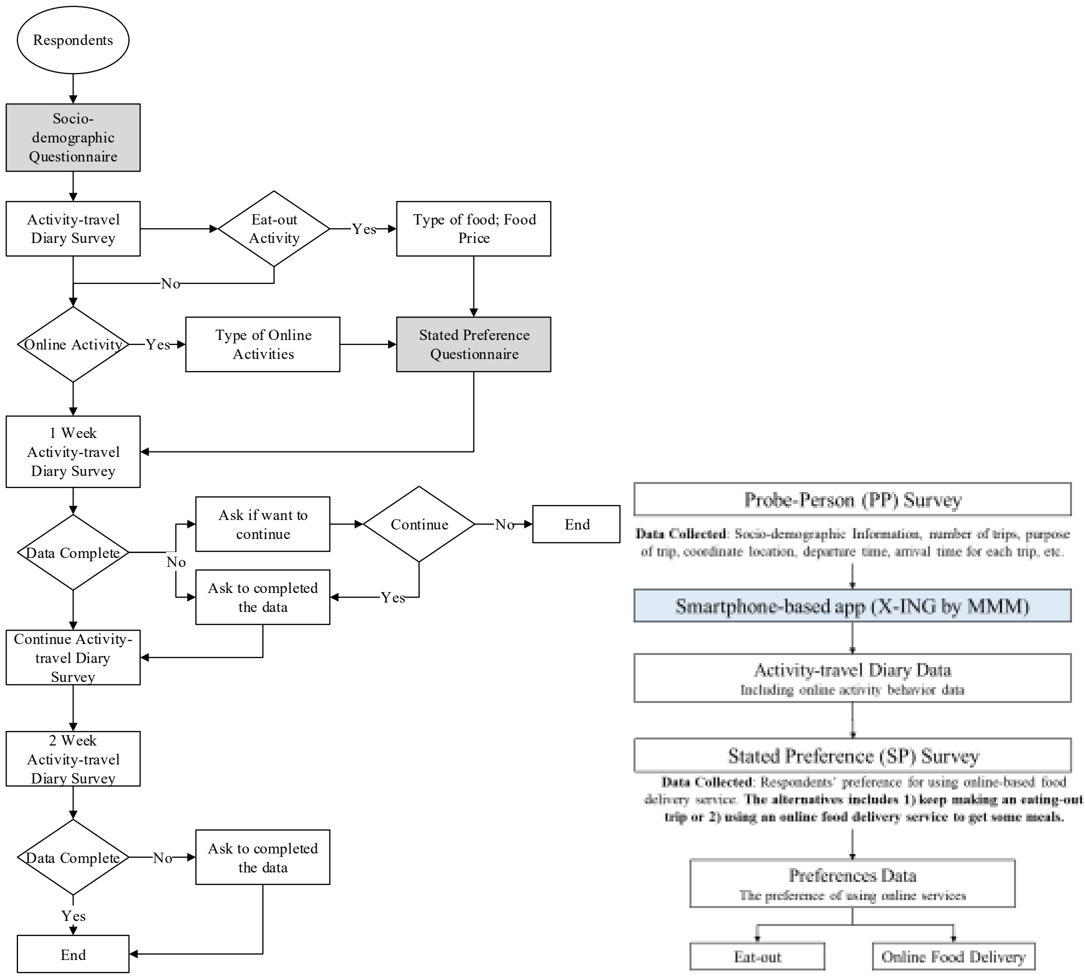
For the follow up questions, it will be better to put the Indonesian language. This following table is the complete questions including the Indonesian translation.

Section	English	Indonesian
Shopping Trip Purpose		
Question 1	What did you buy?	Apakah yang anda beli?
Category for shopping	**Grocery** 1. Fresh product (vegetable or fruit) 2. Meat, Chicken, Seafood 3. Diary, Eggs, Cheese, Tofu, Tempe 4. Dry and Canned Goods 5. Frozen Food 6. Bakery 7. Others (fill manually)	**Bahan makanan** 1. Produk segar (sayuran atau buah) 2. Daging, ayam, ikan 3. Telur, susu, keju, tempe, tahu 4. Makanan kering dan kalengan 5. Makanan beku 6. Roti dan kue **7.** Lainnya (fill manually)
	Non-Grocery 1. Books/Magazine 2. Electronics & Home Appliance 3. Make Up & Skin Care 4. Fashion 5. Household Products 6. Others (fill manually)	**Bukan bahan makanan** 1. Buku / Majalah 2. Elektronik & Perlengkapan Rumah Tangga 3. Make Up & Skin Care 4. Fashion & Hijab 5. Produk Rumah Tangga 6. Lainnya (fill manually)
Question 2	How much did you pay in this activity?	Berapakah total harga barang yang anda beli pada aktifitas ini?
Eat-out Purpose		
Question 1	What type of food did you eat?	Apakah jenis makanan yang anda pesan?
Category for food	1. Beverages 2. Snack/Sweets 3. Fast Food 4. Indonesian Food 5. Western Food 6. Eastern Food 7. Noodles & Meatballs 8. Others (fill manually)	1. Minuman 2. Snack/Sweets 3. Fast Food 4. Indonesian Food 5. Western Food 6. Eastern Food 7. Mie & Bakso 8. Lainnya (fill manually)
Question 2	How much did you pay for the food?	Berapakah harga makanan yang anda pesan?

Section	English	Indonesian
Mode Choice (the option for taxi/ride hailing)		
Question 1	Which service you used?	Apa layanan yang anda gunakan?
Category for taxi/ride hailing	1. GO-CAR 2. GRAB-CAR 3. Bluebird Taxi 4. Others (fill manually)	1. GO-CAR 2. GRAB-CAR 3. Bluebird Taxi 4. Others (fill manually)
Question 2	How much is the fare paid if a service was used in this travel activity?	Berapa biaya yang anda keluarkan dalam menggunakan jasa transportasi tersebut?
Mode Choice (Online motorcycle)		
Question 1	Which service you used?	Apa layanan yang anda gunakan?
Category for online motorcycle	1. GO-RIDE by GOJEK 2. GRAB-BIKE by GRAB 3. Oke Jack 4. LADYJEK 5. Ojek Pangkalan 6. Others	1. GO-RIDE by GOJEK 2. GRAB-BIKE by GRAB 3. Oke Jack 4. LADYJEK 5. Ojek Pangkalan 6. Others
Question 2	How much is the fare paid if a service was used in this travel activity?	Berapa biaya yang anda keluarkan dalam menggunakan jasa transportasi tersebut?

SECTION 3. STATED PREFERENCE

To capture the effects of such context-dependent factors, we designed a data collection process that is summarized in Figure 3.10. Upon successful recruitment, a respondent will first answer a web-based survey on her social-demographic information. Following that, she will download an app onto her phone that will track her daily mobility activities automatically. The user's daily timeline will be displayed in the app to verify the activity and trips they made and answer additional questions about trip and activity details and ICT usage. The tracking and verification process goes on for 14 days, during which a customized stated-preference questionnaire will also be delivered to the user for selected eating-out or shopping activities. Finally, at the end of the two weeks, participants will be required to take a short survey on their attitude towards ICT.



Survey Flowchart

The attribute in question will be based on data obtained from travel-activity dairy. We strive to make respondents remember the actual conditions they felt at that time by indicating the date they were traveling. By showing the date when they took the eat-out trip, it is hoped that the respondents will be able to remember all the activities and constraints they had at that time. Next, we convert the respondent's actual travel time into delivery time from online FD. Next, we calculate the travel distance by calculating the travel route's distance from origin and destination for the respondent's eat-out trip. This travel distance will then be multiplied by the based fare from online FD delivery in Jakarta, 6,000 IDR per Km, which is then used as an attribute delivery fee. We also generated the food variance that we developed from the database of all food categories in the MSTPs apps, with seven types of food variance. We showed a random combination of seven variants with several different combinations for each question on each questionnaire. The last attribute we added was the food cost for online FD. With the collaboration between MSTPs and the merchant, there might be differences in food prices between the respondent eating directly on the spot and food price if ordering via FD online. We made a possible food price scenario based on food prices that the respondent reported on to the activity-travel diary survey application.

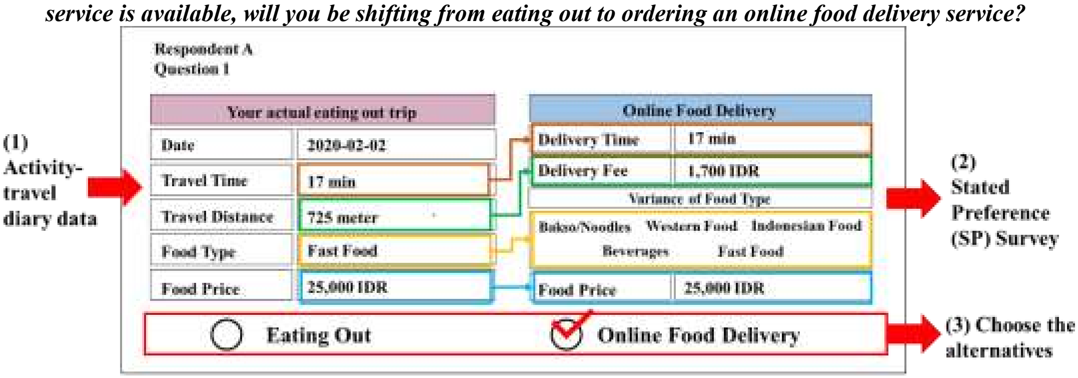
Attributes and Level of SP Survey

Attributes	Level
Delivery time for online FD	1. 0.4*actual travel time 2. 0.7*actual travel time 3. 1.0*actual travel time 4. 1.3*actual travel time 5. 1.6*actual travel time
Delivery cost for online FD	1. 0.4*6,000 IDR*actual travel distance 2. 0.7*6,000 IDR*actual travel distance 3. 1.0*6,000 IDR*actual travel distance 4. 1.3*6,000 IDR*actual travel distance 5. 1.6*6,000 IDR*actual travel distance
Combinations of Food Types 1. Beverages 2. Snacks/Sweets 3. Fast food 4. Indonesian food 5. Western food 6. Eastern food 7. Bakso/Noodles	1. One food type 2. Three food types 3. Five food types 4. Seven food types
Food cost for online FD	1. 0.8*actual food cost 2. 0.9*actual food cost 3. 1.0*actual food cost 4. 1.1*actual food cost 5. 1.2*actual food cost

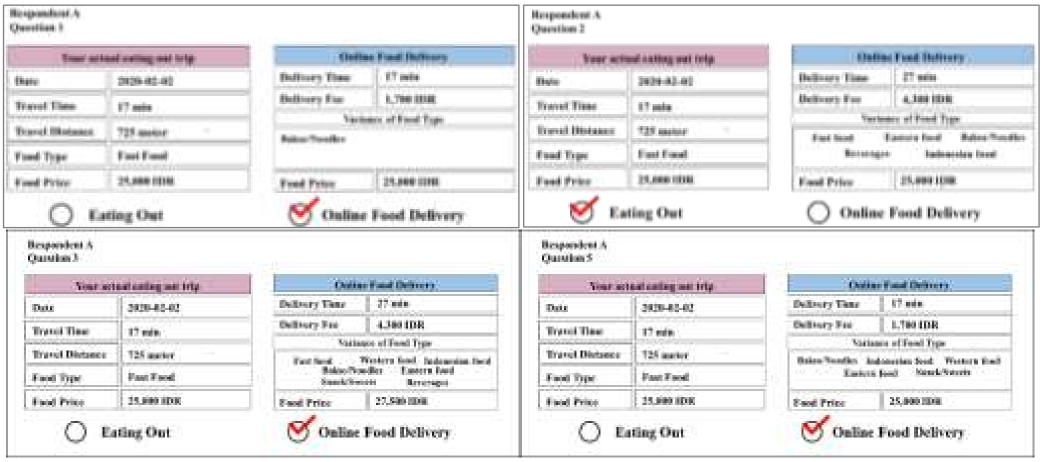
Source: Author, 2020

Respondents will be asked about five different scenarios of online-based food delivery services. The respondents' options are (1) continuing to conduct the eat-out trip or (2) shifting to the online-based food delivery services. The following questions show hypothetical scenarios of an online food delivery service introduced in Jakarta and how residents would use it.

By considering all the activities and constraints you have at that time if the following online food delivery service is available, will you be shifting from eating out to ordering an online food delivery service?



Questionnaire Construction Flow



Example of Questionnaire

We asked users if they would replace the eating-out with an online-based food delivery service if the service is available with specified price and service quality parameters by pivoting the revealed preferences (e.g., Hensher and Greene, 2003). In those five questions, the respondent will be provided by their actual eat-out data, shown by the pink table on the left side and the purposed online-based food delivery service showed by the blue table on the right side. In each questionnaire, the respondents are required to choose the alternatives. This SP-pivoted RP survey will be using the actual eat-out activity from the first-week data of the activity-travel diary survey respondents' data. This allows us to confirm whether ICT use substituted a trip or not. Importantly, this pivoted stated preference design allows respondents to represent their preferences given all context-dependent factors such as motivation and constraints they actually had at that time. This feature is of particular importance to capture the complex interdependencies between ICT use and travel, since their travel decisions may come from not only extrinsic motivations (e.g., getting lunch meal), but also intrinsic motivations (e.g., interacting with friends while traveling and having lunch). The respondent would not choose an online-based food delivery service, even when the service level is very high if they made a trip for intrinsic motivations.

SECTION 4. ATTITUDE TOWARDS ICT QUESTIONNAIRE

A. Food Delivery Services

1. Have you ever ordered food from restaurant's delivery services (Restaurant-to-Consumer (R2C) Delivery)?
   01. Yes
   02. No
2. Which Restaurant-to-Consumer (R-C) food delivery service that has you tried? (Please select all that apply)
   - Restaurant Sederhana
   - KFC
   - McDonald's
   - Pizza Hut (PHD)
   - Domino's Pizza
   - Hoka-hoka Bento
   - Bakmi GM
   - Others (please specify), _____________
3. On the average, how often you use Restaurant-to-Consumer (R2C) food delivery service within a month?
   - 1-3 times
   - 4-6 times
   - 7-9 times
   - 10-12 times
   - 13-15 times
   - More than 15 times
4. For what purpose(s) do you usually use the Restaurant-to-Consumer (R-C) food delivery service? (please select all that apply)
   - Breakfast
   - Lunch
   - Dinner
   - Snack/Sweets
   - Family Gathering
   - Company's meeting
   - Party
   - Others (please specify), _____________
5. What kind of food that you have ordered from R-C Food Delivery Service? (please select all that apply)
   - Beverages
   - Snacks/Sweets
   - Fast Food
   - Indonesian Food
   - Western Food
   - Eastern Food
   - Noodles & Meatballs
   - Others (please specify), _____________
6. On the average, how much are your weekly expenses for food Restaurant-to-Consumer (R2C) food delivery service?
   - < Rp. 50.000
   - Rp. 50.000 – Rp. 150.000
   - Rp. 150.001 – Rp. 200.000
   - More than Rp. 200.000
7. Do weather conditions motivate you to use (R-C) online-based food delivery services?
   - Yes
   - No
8. What weather conditions that the most motivate you to use R2C food delivery services?
   - Moderate Hot

- Extreme Hot
- Extreme Cold
- Moderate Rain
- Heavy Rain
- Others (please specify), _____________

9. Have you ever ordered food from Online-based Food (Platform-to-Consumer (P-C) Food Delivery Services)?
   - Yes
   - No
10. Which Platform-to-Consumer (P2C) food delivery service that has you tried? (please select all that apply)
    - Go-Food
    - Grab Food
    - Uber Food
    - Click-Eat
    - Deliveroo
    - Others (please specify), _____________
11. On the average, how often you use Platform-to-Consumer (P2C) food delivery service within a month?
    - 1-3 times
    - 4-6 times
    - 7-9 times
    - 10-12 times
    - 13-15 times
    - More than 15 times
12. For what purpose(s) do you usually use the Platform-to-Consumer (P-C) food delivery service? (please select all that apply)
    - Breakfast
    - Lunch
    - Dinner
    - Snack/Sweets
    - Family Gathering
    - Company's meeting
    - Party
    - Others (please specify), _____________
13. What kind of food that you have ordered from P-C Food Delivery Service? (please select all that apply)
    - Beverages
    - Snacks/Sweets
    - Fast Food
    - Indonesian Food
    - Western Food
    - Eastern Food
    - Noodles & Meatballs
    - Others (please specify), _____________
14. On the average, how much are your weekly expenses for food Platform-to-Consumer (P-C) food delivery service?
    - < Rp. 50.000
    - Rp. 50.000 – Rp. 150.000
    - Rp. 150.001 – Rp. 200.000
    - More than Rp. 200.000
15. Do you know there are many promotions/monetary incentives on online-based food delivery services?
    - Yes
    - No
16. Where did you usually get information about the promotion of online-based food delivery services? (please select all that apply)
    - Informed by friends/family
    - Advertisement
    - News
    - LINE
    - Recommendation from the apps
    - Instagram
    - Twitter
    - Platform application's timeline
    - Facebook
    - YouTube
    - WhatsApp
    - Others (please specify), _____________
17. Have you ever ordered food from a restaurant that provides a delivery service (R-C) but using online-based (P-C) food delivery services? (e.g., Ordering the KFC by using GO-FOOD)
    - Yes
    - No
18. Have you ever had an unpleasant experience while using online-based food delivery services? (please select all that apply)
    - I do not have any
    - Delivery time is too long
    - The food is not fresh
    - Incorrect order
    - Food is damage
    - Others (please specify), _____________
19. Will you use the online-food delivery services (either R-C or P-C) in the future?
    - Yes
    - No
20. Do weather conditions motivate you to use (P-C) online-based food delivery services?
    - Yes
    - No
21. What weather conditions that the most motivate you to use R2C food delivery services?
    - Moderate Hot
    - Extreme Hot
    - Extreme Cold
    - Moderate Rain
    - Heavy Rain
    - Others (please specify), _____________

B. Online Non-Grocery Shop

22. Have you ever ordered a goods from online delivery services?
    - Yes
    - No
23. How often you do an online shop for non-groceries online-based food delivery services within a month?
    - 1-3 times
    - 4-6 times
    - 7-9 times
    - 10-12 times
    - 13-15 times
    - >15 times
24. How much do you typically spend on online shopping per month for non-groceries?
    - < Rp. 100.000
    - Rp. 100.000 – Rp. 250.000
    - Rp. 250.001 – Rp. 500.000

- Rp. 500.001 – Rp. 750.000
- Rp. 750.001 – Rp. 1.000.000
- Rp. 1.000.001 – Rp. 1.500.000
- Rp. 1.500.001 – Rp. 2.000.000
- More than Rp. 2.000.000

25. Which platforms that have you tried? (Please select that all apply)
    - Go-Mart
    - Sdsd
    - Dsd
    - Sdsd
26. What types of products do you usually buy online? (please select that all apply)
    - Books/Magazine
    - Electronics & Home Appliance
    - Make Up & Skin Care
    - Fashion
    - Household Products
    - Others (fill manually)
27. Please indicate which factors that affect your satisfaction most during your previous shop online experience?
    - Goods price
    - The speed of delivery
    - Quality of the goods
    - Delivery fee
    - Hospitality of merchants
    - Others

C. Online Grocery Shop

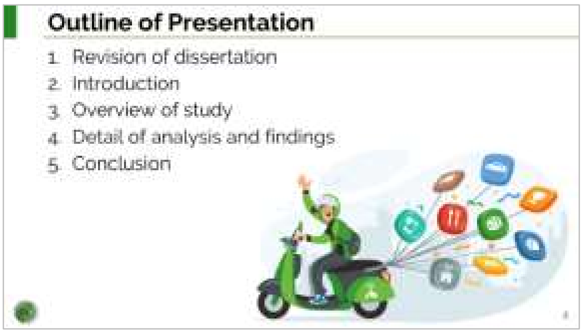
28. Have you ever ordered groceries from online delivery services?
    - Yes
    - No
29. How often do you shop online for the groceries within a month?
    - 1-3 times
    - 4-6 times
    - 7-9 times
    - 10-12 times
    - 13-15 times
    - >15 times
30. How much do you typically spend on online shopping per month for groceries?
    - < Rp. 100.000
    - Rp. 100.000 – Rp. 250.000
    - Rp. 250.001 – Rp. 500.000
    - Rp. 500.001 – Rp. 750.000
    - Rp. 750.001 – Rp. 1.000.000
    - Rp. 1.000.001 – Rp. 1.500.000
    - Rp. 1.500.001 – Rp. 2.000.000
    - More than Rp. 2.000.000
31. Which platforms that have you tried? (please select that all apply)
    - Go-Mart
    - SayurBox
    - Fresh Box
    - TukangSayur
32. What types of products do you usually buy online? (please select that all apply)
    - Fresh product (vegetable or fruit)
    - Meat, Chicken, Seafood
    - Diary, Eggs, Cheese, Tofu, Tempe
    - Dry and Canned Goods
    - Frozen Food
    - Bakery
    - Others (fill manually)
33. Please indicate which factors that affect your satisfaction most during your previous shop online experience?
    - Goods price
    - The speed of delivery
    - Quality of the goods
    - Delivery fee
    - Hospitality of merchants
    - Others

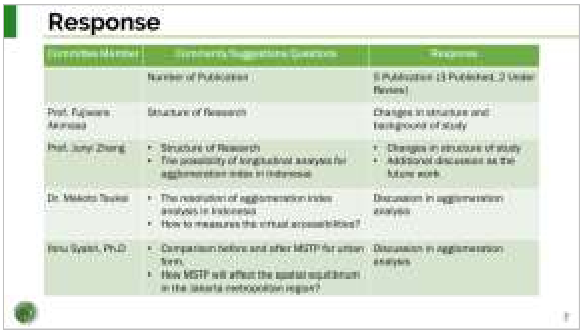
APPENDIX 6. LIST OF VARIABLES

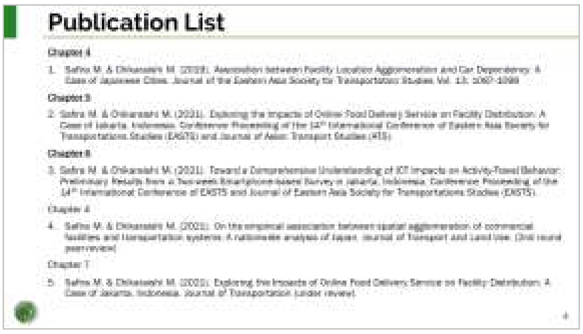
No	Notation	Definition
1	A	Set of all actions
2	$\boldsymbol{a}$	Sequence of actions
3	a_k	Action
4	$\mathbb{C}_n$	Choice set
5	$C^n(x_k)$	Conditional choice ser for an individual n in specific states x_k
6	C	Variable cost
7	$C_{\widetilde{m}}(t, l, \tilde{d})$	Travel Cost variable for the specific transportation mode
8	$C_{del}(l)$	Delivery cost for online food delivery service (MSTP)
9	$\tilde{d}$	Destination (zones)
10	del	Delivery component
11	DT	Variable delivery time
12	$DT_{del}(l)$	Delivery time for online food delivery service (MSTP)
13	δ^n_{mode}	Dummy variable for mode ownership
14	$\Delta_p t$	Total time to performing an activity
15	ϵ	Random state vector
16	ϵ_k	Random state vector at the specific k
17	$\epsilon_k(a_k)$	Random state vector at the specific k taken in an action a_k
18	E_s	Respected to the stochasticity of s_k given the decision rule $a_k = \pi(s_k)$
19	$EV(x_k, a_k)$	Expected value
20	h	Activity history
21	I	Agglomeration index
22	$I_{food}(l)$	Agglomeration index for food merchants
23	$I_{mstp}(l)$	Agglomeration index for online food merchants
24	$I_{com}(l)$	Agglomeration index for commercial facilities
25	J_n	alternatives
26	k	Index (order of sequence states and actions
27	k_{nj}	The number of times alternative j appears in the choice set
28	K	Total number of stages (actions and states) during the time period
29	L	The set of locations
30	l	Current location
31	$L^n_{act.}(\tilde{p})$	A set of location for an individual to performing specific purposes (actions)
32	l^n_{work}	Location for an individual to performing work activity
33	l^k	Location in specific k
34	$\widetilde{m}$	The chosen mode of transport (when taking action a_k)
35	M	The set of modes of transportation
36	$M^n(m)$	A set of modes for an individual
37	m	Previous mode of transport
38	n	Individual variable
39	N_h	Total number of activity history
40	$\tilde{p}$	Chosen activity purpose (the next activity when taking action a_k)
41	P	The set of activity purposes
42	p	Activity purpose of the previous act
43	$Pr(a_k\|x_k)$	Probability of path choice
44	π	Policy
45	$\pi(s_k)$	Policy at state s_k)
46	$q_n(i)$	The probability that alternative $j \in \mathbb{C}_n$
47	q_t	The transition of the state variables for time (t), part of stochasticity
48	q_h	The transition of the state variables for activity history (h), part of stochasticity
49	$\boldsymbol{s}$	Sequence of states
50	s_k	The current state
51	s_{k+1}	The state that reached when taking action a_k in the state s_k
52	S	Set of all states
53	S_p	The number of size variables for activity p
54	t	Time of the day (time-steps, depends on the interval ($t = time\ period/interval$)
55	t^k	The current time steps
56	$t^{(k+1)}$	The next time steps
57	$TT_{\widetilde{m}}(t^{(k)}, l^{(k)}, \tilde{d})$	Travel time for a specific mode
58	$\theta_{\widetilde{m}}$	Parameter for modes

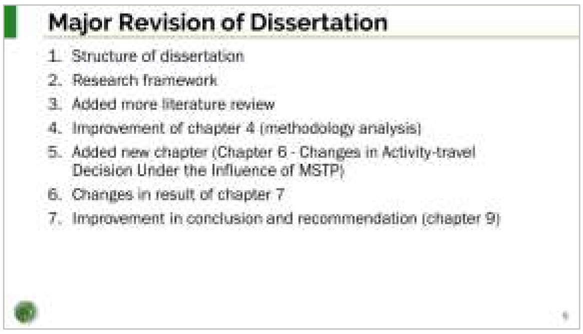
No	Notation	Definition
59	θ_{tt}	Parameter for travel time
60	θ_{cost}	Parameter for travel cost
61	$\theta_{C,eat}$	Parameter for eating activity
62	$\theta_{eat,size}$	Parameter for opportunity size to conduct eat activity
63	θ_{food}	Parameter for food merchants
64	$\theta_{I,food}$	Parameter for agglomeration index of food merchants
65	$\theta_{C,mstp}$	Parameter for order online food delivery service activity
66	$\theta_{mstp,size}$	Parameter for opportunity size to order online food delivery service activity
67	θ_{mstp}	Parameter for online food merchants
68	$\theta_{I,mstp}$	Parameter for agglomeration index of food merchants
69	$\theta_{del,c}$	Parameter for delivery cost for online food delivery service
70	$\theta_{del,t}$	Parameter for delivery time for online food delivery service
71	$\theta_{C,other}$	Parameter for other activities
72	$\theta_{other,size}$	Parameter for opportunity size to conduct other activities
73	θ_{com}	Parameter for commercial facilities
74	$\theta_{I,com}$	Parameter for agglomeration of commercial facilities
75	$\theta_{work,j}$	Parameter for starting work activity
76	$\theta_{work,j+1}$	Parameter for ending work activity
77	$U(\mathbf{s},\mathbf{a})$	Utility function
78	u	One-stage utility function
79	$u_{travel}(t,\ l,\ \tilde{d},\tilde{m})$	The utility of travel
80	$u_{act.}(t,l,p,\tilde{p})$	The utility of performing some actions
81	$u_{p,size}(l,p)$	The utility of opportunity size to performing some activity
82	$u_{work}(t)$	The utility of working
83	$u_{eat,size}(l)$	The utility of opportunity size to performing eat activities
84	$u_{mstp,size}(l)$	The utility of opportunity size to performing order online food delivery service
85	$u_{other,size}(l)$	The utility of opportunity size to performing other activities
86	$u(s_k,a_k,s_{k+1})$	The utility function for activity-travel pattern
87	$u(x_k,a_k)$	The utility of observed variables
88	V	Value function
89	$\bar{V}$	Expected value function before the state variable ϵ_k have been observed
90	$V(s)$	Value function at states
91	$V(x_k,\epsilon_k)$	Value function in recursive form
92	$\bar{V}(x_k)$	the expected value of the value function before the state variables ϵ_k have been observed
93	x_k	The observable part of the state space ($s_k = (x_k,\epsilon_k)$)
94	$x_{p,l,s}e^{\theta_{p,s}}$	The size variables
95	$x_{food}(l)$	The number of food merchants at specific locations
96	$x_{mstp}(l)$	The number of online food merchants at specific locations
97	$x_{com}(l)$	The number of commercial facilities at specific locations
98	ξ	The need to perform activities

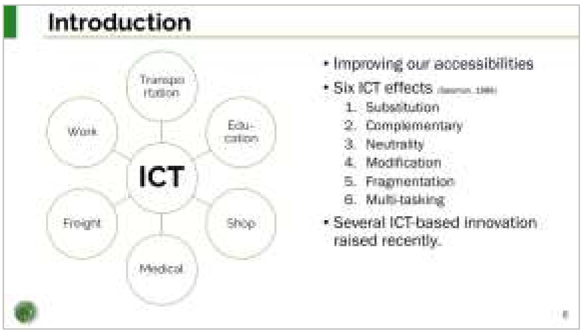
APPENDIX 7. PUBLIC HEARING PRESENTATION HANDOUT

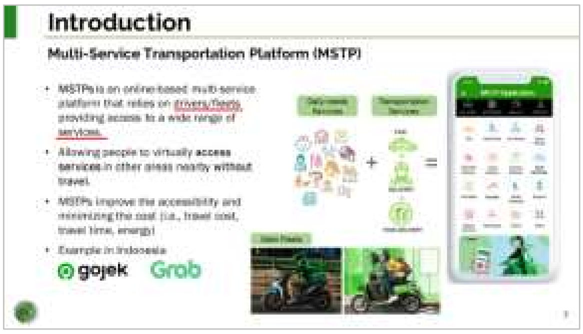


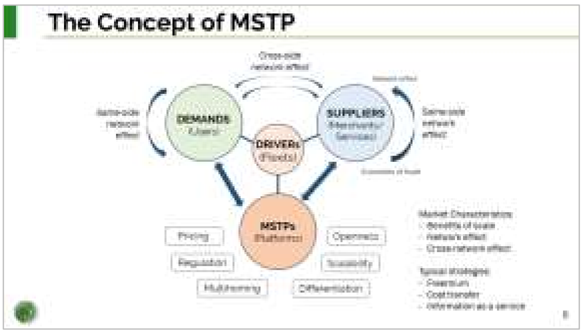


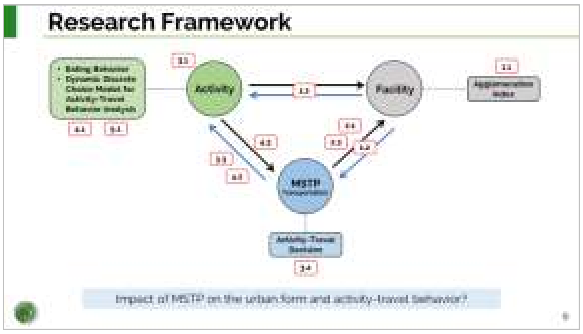


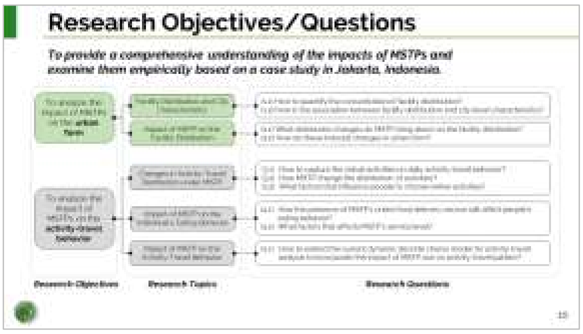


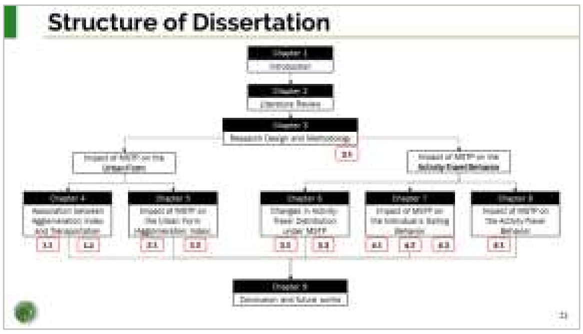


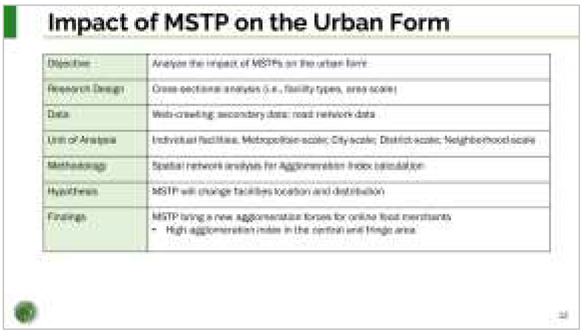


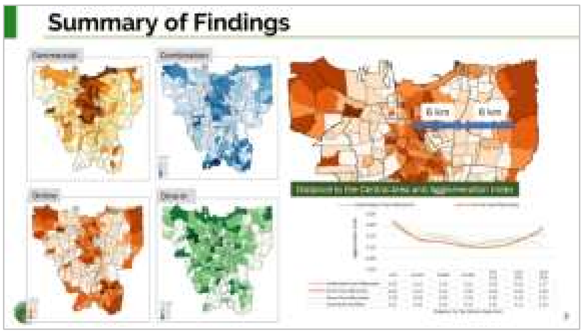


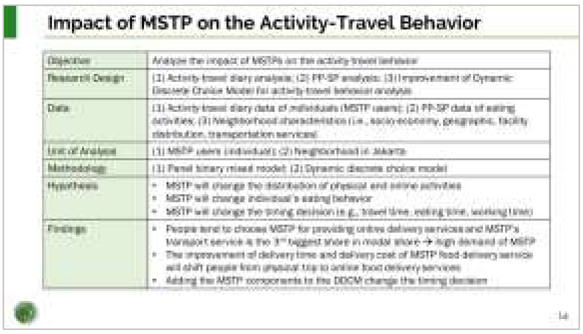


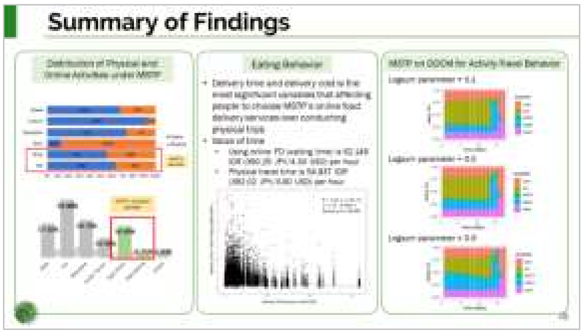


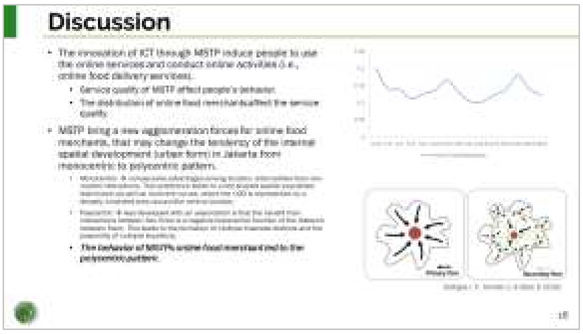

Structure of Dissertation
Chapter 1
Introduction
Chapter 2
Literature Review
Chapter 3
Research Design and Methodology
Impact of MSTP on the Urban Form
Impact of MSTP on the Activity-Travel Behavior
Chapter 4
Chapter 5
Chapter 6
Chapter 7
Chapter 8
Chapter 9
Conclusion and future works

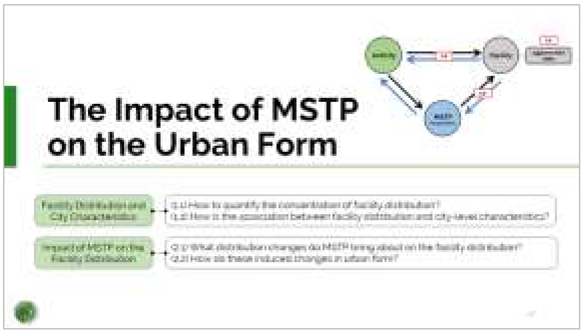

Impact of MSTP on the Urban Form
Objective
Analyze the impact of MSTPs on the urban form
Research Design
Cross-sectional analysis (i.e., facility types, area scale)
Data
Web-crawling; secondary data; road network data
Unit of Analysis
Individual facilities; Metropolitan scale; City scale; District scale; Neighborhood scale
Methodology
Spatial network analysis for Agglomeration Index calculation
Hypothesis
MSTP will change facilities location and distribution
Findings
MSTP bring a new agglomeration forces for online food merchants
High agglomeration index in the central and fringe area

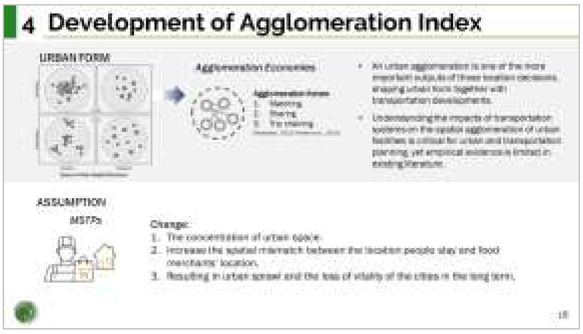

Summary of Findings
6 km
6 km

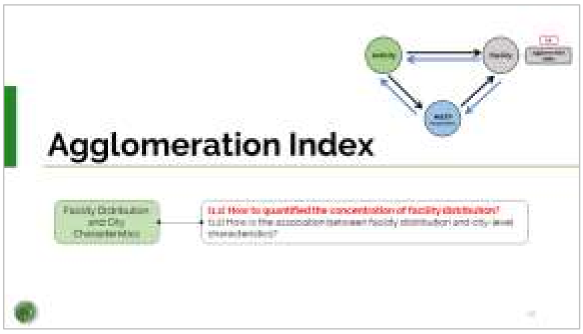

Impact of MSTP on the Activity-Travel Behavior
Objective
Analyze the impact of MSTPs on the activity-travel behavior
Research Design
(1) Activity-travel diary analysis; (2) PP-SP analysis; (3) Improvement of Dynamic Discrete Choice Model for activity-travel behavior analysis
Data
(1) Activity-travel diary data of individuals (MSTP users); (2) PP-SP data of eating activities; (3) Neighborhood characteristics (i.e., socio-economy, geographic, facility distribution, transportation services)
Unit of Analysis
(1) MSTP users (individual); (2) Neighborhood in Jakarta
Methodology
(1) Panel binary mixed model; (2) Dynamic discrete choice model
Hypothesis
MSTP will change the distribution of physical and online activities
MSTP will change individual's eating behavior
MSTP will change the timing decision (e.g., travel time, eating time, working time)
Findings
People tend to choose MSTP for providing online delivery services and MSTP's transport service is the 3rd biggest share in modal share → high demand of MSTP
The improvement of delivery time and delivery cost of MSTP food delivery service will shift people from physical trip to online food delivery services
Adding the MSTP components to the DDCM change the timing decision

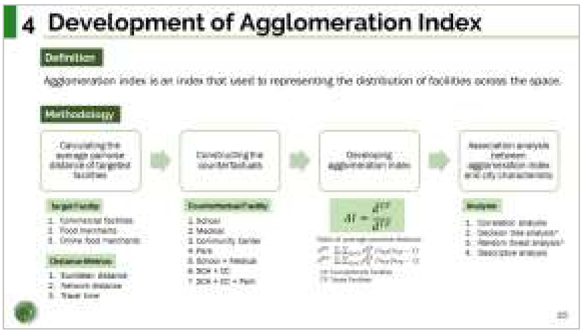

Summary of Findings
Eating Behavior
MSTP on DDCM for Activity-Travel Behavior

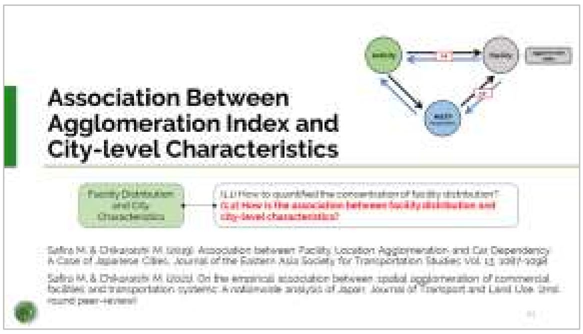

Discussion
The innovation of ICT through MSTP induce people to use the online services and conduct online activities (i.e., online food delivery services).
Service quality of MSTP affect people's behavior.
MSTP bring a new agglomeration forces for online food merchants, that may change the tendency of the internal spatial development (urban form) in Jakarta from monocentric to polycentric pattern.

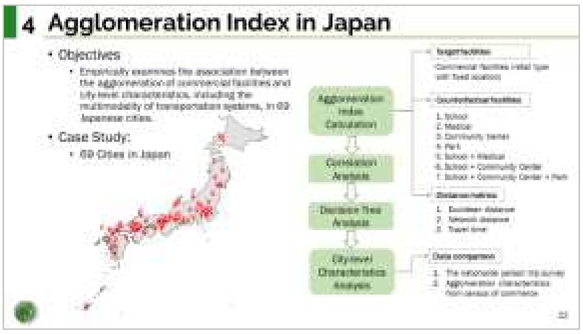

The Impact of MSTP on the Urban Form
Activity
Facility
MSTP
Facility Distribution and City Characteristics
Impact of MSTP on the Facility Distribution

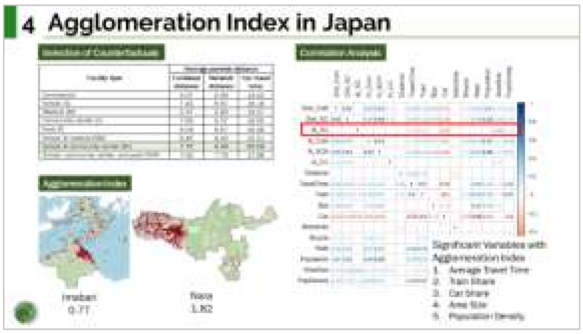

4 Development of Agglomeration Index
URBAN FORM
Agglomeration Economies
ASSUMPTION
MSTPs
Change:
1. The concentration of urban space.
2. Increase the spatial mismatch between the location people stay and food merchants' location.
3. Resulting in urban sprawl and the loss of vitality of the cities in the long term.

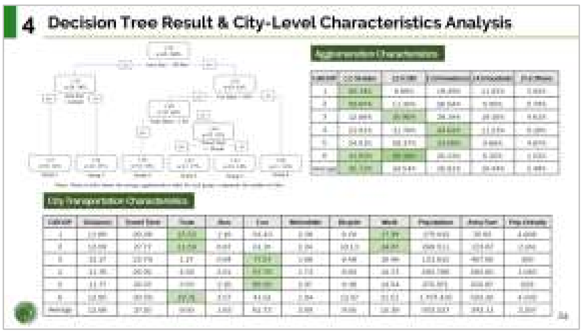

Agglomeration Index
Activity
Facility
MSTP
Facility Distribution and City Characteristics

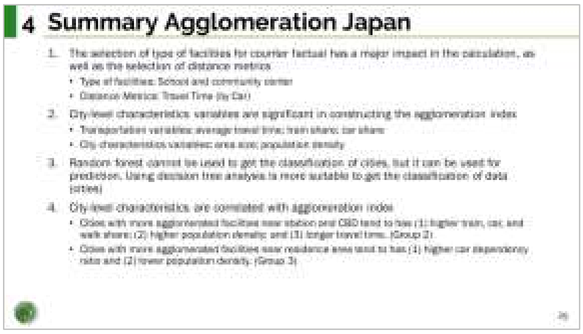

4 Development of Agglomeration Index
Definition
Agglomeration index is an index that used to representing the distribution of facilities across the space.
Methodology
Constructing the counterfactuals
Developing agglomeration index
Target Facility
Analysis


Association Between Agglomeration Index and City-level Characteristics
Facility Distribution and City Characteristics

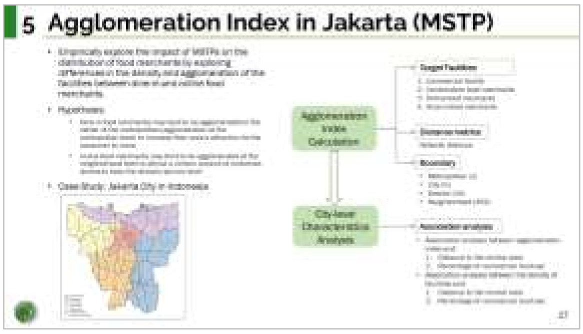

4 Agglomeration Index in Japan
Objectives
Case Study:
69 Cities in Japan
Agglomeration Index Calculation
Correlation Analysis
Decision Tree Analysis
City-level Characteristics Analysis

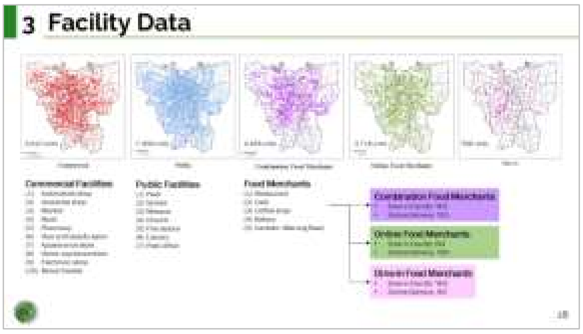

4 Agglomeration Index in Japan
Significant Variables with Agglomeration Index
1. Average Travel Time
2. Train Share
3. Car Share
4. Area Size
5. Population Density

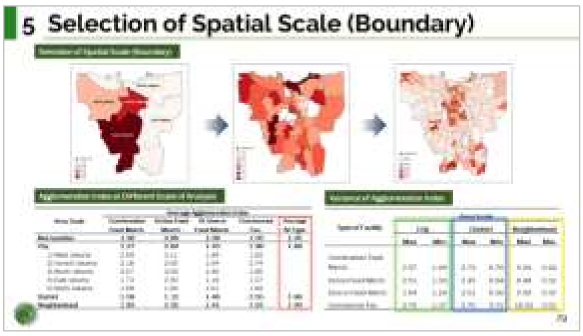

4 Decision Tree Result & City-Level Characteristics Analysis

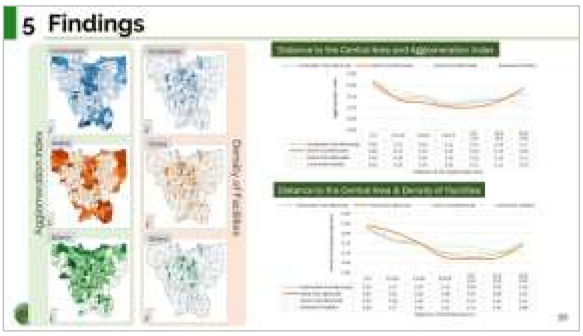

4 Summary Agglomeration Japan


The Impact of MSTP on the Facility Distribution (Urban Form) in Jakarta

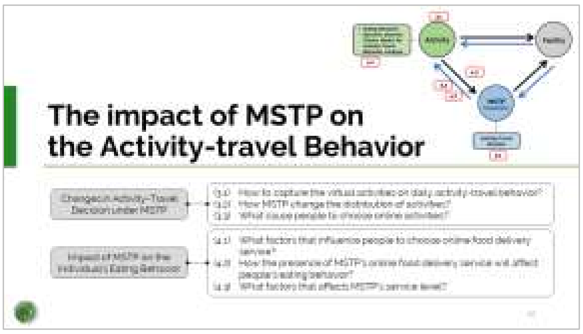

5 Agglomeration Index in Jakarta (MSTP)
Agglomeration Index Calculation
City-level Characteristics Analysis

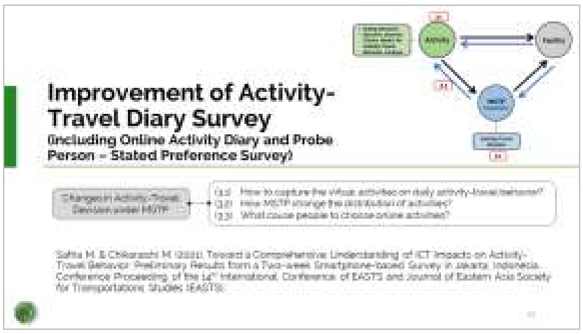

3 Facility Data

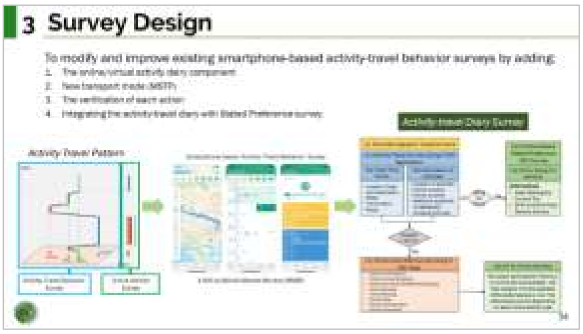

5 Selection of Spatial Scale (Boundary)

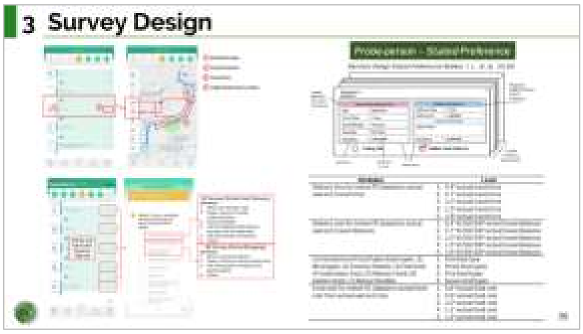

5 Findings

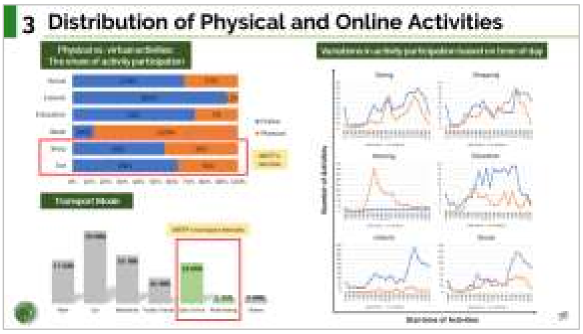

5 Summary Agglomeration Jakarta
1. Methodological Contribution
The selection of spatial boundary (analysis scale) is crucial in the calculation of agglomeration index.
Working in smaller scale of area boundary give a better and more vibrant result of agglomeration index.
2. The Impact of MSTPs on Urban Form
A new agglomeration force would exist for online food merchants because online food merchants need a certain amount of MSTP drivers to keep their service level. (The average maximum coverage area up to 6 km from the customer's location in principle).
While dine in food merchants are more agglomerated at the metropolitan scale, online food merchants are more agglomerated at the neighborhood scale presumably due to the necessity to attract MSTP drivers to keep the delivery-service level. The online food merchants tend to be agglomerated in the center and fringe area of the city.
The intermediate neighborhoods (located between urban core and fringe areas) tend to have lower densities and agglomeration indices for online food merchants because the middle area gets access to both central and fringe areas, and thus facilities may not need to be located in those neighborhoods.

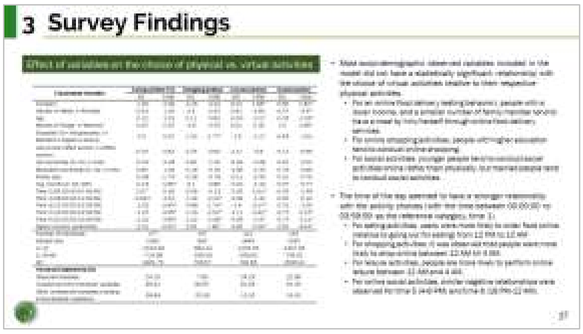

The impact of MSTP on the Activity-travel Behavior
Changes in Activity-Travel Decision under MSTP
How to capture the virtual activities on daily activity-travel behavior?
How MSTP change the distribution of activities?
What cause people to choose online activities?
Impact of MSTP on the Individual's Eating Behavior
What factors that influence people to choose online food delivery service?
How the presence of MSTP's online food delivery service will affect people's eating behavior?
What factors that affects MSTP's service level?

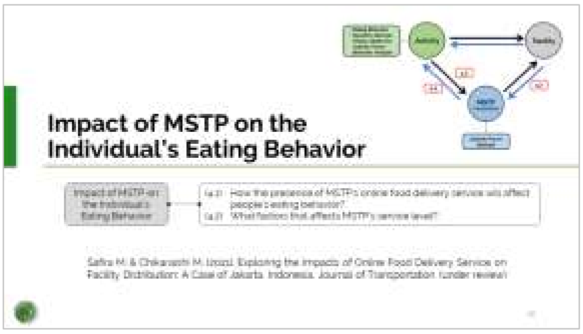

Improvement of Activity-Travel Diary Survey
(Including Online Activity Diary and Probe Person – Stated Preference Survey)
Changes in Activity-Travel Decision under MSTP
How to capture the virtual activities on daily activity-travel behavior?
How MSTP change the distribution of activities?
What cause people to choose online activities?
Safira M. & Chikaraishi M. (2021). Toward a Comprehensive Understanding of ICT Impacts on Activity-Travel Behavior: Preliminary Results from a Two-week Smartphone-based Survey in Jakarta, Indonesia. Conference Proceeding of the 14th International Conference of EASTS and Journal of Eastern Asia Society for Transportation Studies (EASTS).

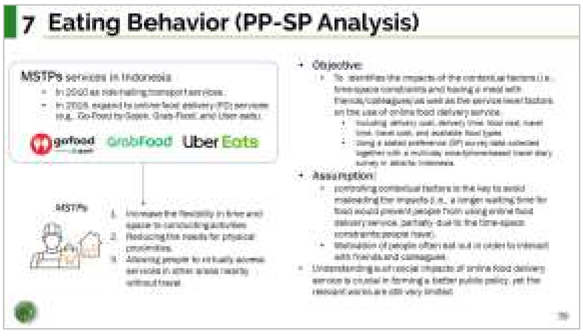

3 Survey Design
To modify and improve existing smartphone-based activity-travel behavior surveys by adding:
1. The online/virtual activity diary component
2. New transport mode (MSTP)
3. The verification of each action
4. Integrating the activity-travel diary with Stated Preference survey
Activity-travel Diary Survey
Activity-Travel Pattern

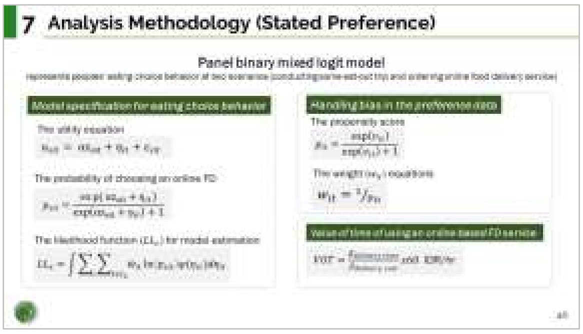

3 Survey Design
Probe person – Stated Preference

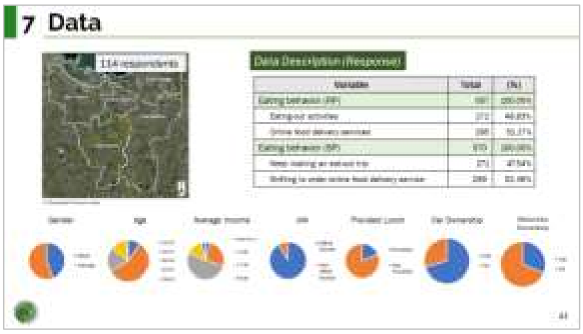

3 Distribution of Physical and Online Activities
Physical vs. virtual activities: The share of activity participation
Variations in activity participation based on time of day
Transport Mode
MSTP's transport features

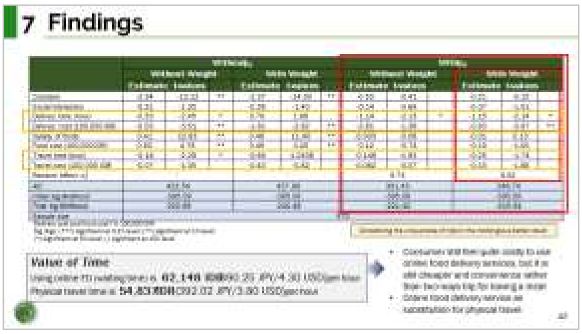

3 Survey Findings
Effect of variables on the choice of physical vs. virtual activities

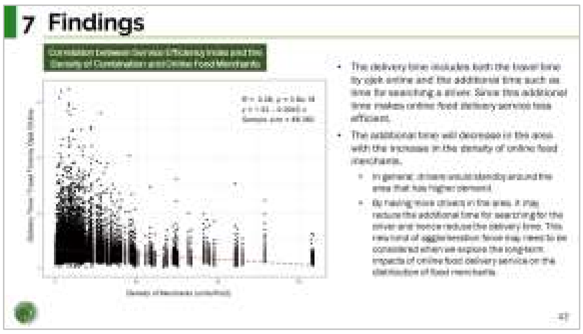

Impact of MSTP on the Individual's Eating Behavior
Impact of MSTP on the Individual's Eating Behavior
How the presence of MSTP's online food delivery service will affect people's eating behavior?
What factors that affects MSTP's service level?
Safira M. & Chikaraishi M. (2022). Exploring the Impacts of Online Food Delivery Service on Facility Distribution: A Case of Jakarta, Indonesia. Journal of Transportation (under review)

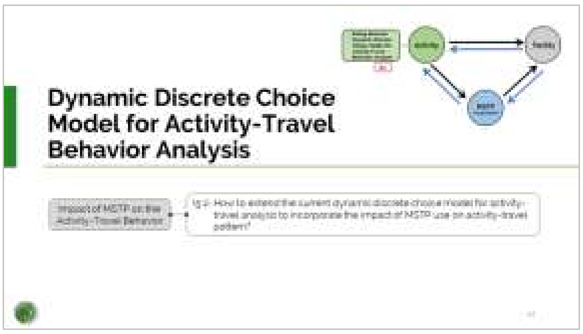

7 Eating Behavior (PP-SP Analysis)
MSTPs services in Indonesia
gofood
GrabFood
Uber Eats
MSTPs
Objective:
Assumption:

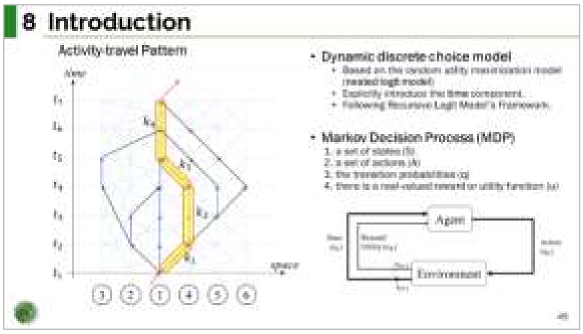

7 Analysis Methodology (Stated Preference)
Panel binary mixed logit model
Model specification for eating choice behavior
Handling bias in the preference data
Value of time of using an online-based FD service

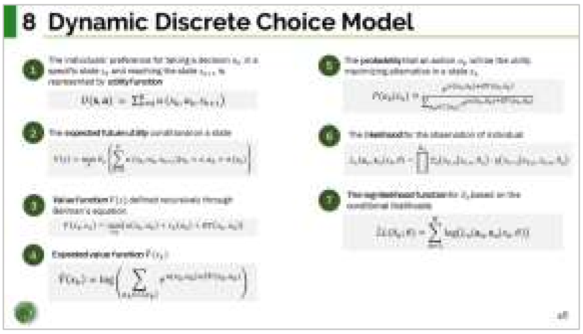

7 Data
134 respondents
Data Description (Response)

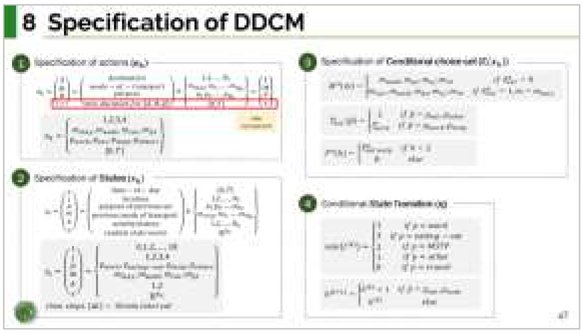

7 Findings
Value of Time

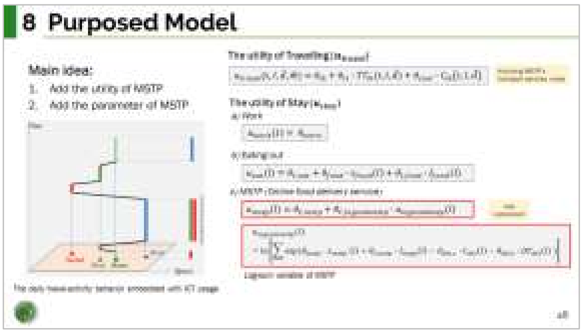

7 Findings

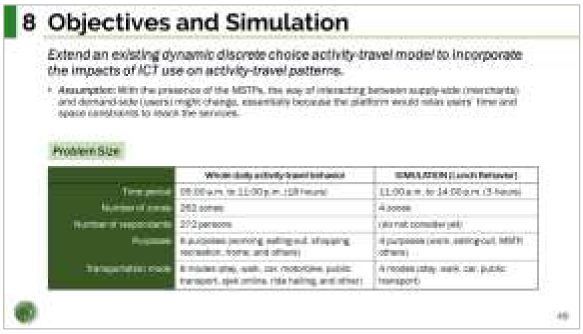

Dynamic Discrete Choice
Model for Activity-Travel
Behavior Analysis

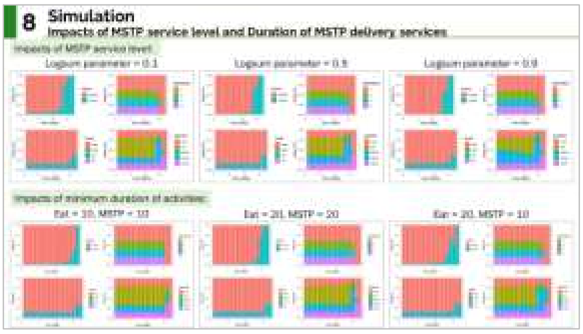

8 Introduction
Activity-travel Pattern
Dynamic discrete choice model
Markov Decision Process (MDP)
Agent
Environment


8 Dynamic Discrete Choice Model


8 Specification of DDCM


8 Purposed Model
Main idea:
1. Add the utility of MSTP
2. Add the parameter of MSTP


8 Objectives and Simulation
Extend an existing dynamic discrete choice activity-travel model to incorporate the impacts of ICT use on activity-travel patterns.
Problem Size


8 Simulation
Impacts of MSTP service level and Duration of MSTP delivery services

Conclusion

1. Summaries
2. Conclusions
3. Contributions
4. Limitation & Future Directions

Summary (Impact of MSTPs on the Urban Form) (1)

(1.1) How to quantified the concentration of facility distribution?
(1.2) How is the association between facility distribution and city-level characteristics?

(1.1) Agglomeration index can be used to analyze the concentration of facilities by considering the selection of counterfactuals, distance metrics, and spatial boundary.

(1.2) City-level characteristics variables are significant in constructing the agglomeration index
- Transportation variables: average travel time; train share; car share
- City characteristics variables: area size; population density

City-level characteristics are correlated with agglomeration index
- Cities with more agglomerated facilities near station and CBD tend to has (1) higher train, car, and walk share; (2) higher population density; and (3) longer travel time.
- Cities with more agglomerated facilities near residence area tend to has (1) higher car dependency ratio and (2) lower population density.

Summary (Impact of MSTPs on the Urban Form) (2)

(2.1) What distribution changes do MSTP bring about on the facility distribution?
(2.2) How do these induced changes in urban form?

(2.1) MSTP bring a new agglomeration force for online food merchants due to the effort to maintained the number of MSTP driver to keep their service level. MSTP encouraging the online food merchants to be agglomerated anywhere and generate new service center zones.

(2.2) MSTP affect tendency of the online food merchants to be agglomerated in the neighborhood scale in attract MSTP drivers to keep the delivery service level and mostly they are located in the central and fringe area of the city.

Due to the flexibility location that MSTP brings, the online food merchants and other MSTP's merchants partner may be located everywhere and induce the new urban form/urban pattern in the future.

Summary (Online Activity-travel Diary Survey)

(3.1) How to capture the virtual activities on daily activity-travel behavior?
(3.2) How MSTP change the distribution of activities?
(3.3) What factors that influence people to choose online activities?

(3.1) The modification of the Future Mobility Sensing (FMS) activity-travel diary survey application by adding the online activity diary and MSTP component may be one of the solutions to capture the virtual activities data on a daily activity-travel behavior. By integrating the actual activity-travel diary data with the stated preference data we can produce the context-aware stated preference survey that can improve the quality of survey.

(3.2) The presence of MSTP influence the decision of people for conduct activity and choosing mode. Under the influence of the MSTP services, for eating and shopping, more than 50% of activity was conducted by online.

People are preferred to use MSTP's transport service (i.e., online ojek and ride-hailing) rather than public transit for the daily transport mode.

(3.3) Some socio-demographic variables are significant for a certainty activities. For eating activity, income and family size are significant. For shopping activity, education level are significant. For social activities, age and marital status are significant.

The time of the day also influence people's decision to conduct activities.

Summary (The Impact of MSTP on eating Behavior)

(4.1) How the presence of MSTP's online food delivery service will affect people's eating behavior?
(4.2) What factors that affects MSTP's service level?

(4.1) MTSP influence people's eating behavior through the comparison between the value of using online food delivery (waiting) time (4.30 USD) and the value of travel time for eating out (7.60 USD for round trip). The improvement of MSTP's delivery service quality will affect people's decision/behavior.

(4.2) The additional time for searching the nearest available driver affect the total delivery time of online food delivery service. The additional time will decrease in the area with higher density of online food merchants and distribution of online food delivery service will affect the MSTP's service level, which it also will affect people's decision of using online food delivery services.

The shorter additional time for searching the nearest available driver due to the high number of driver and online food merchants may increase the tendency people to choose online food delivery service.

Summary (DDCM for Activity-Travel Analysis under MSTP)

(5.1) How to extend the current dynamic discrete choice model for activity-travel analysis to incorporate the impact of MSTP use on activity-travel pattern?

1. Methodological Contribution
   - The development of activity-based analysis using DDCM that taking account MSTPs aspect
   - The introduction of tensor in calculating expected value function.
   - The introduction the weight of travel time to treat the travel time as continuous variable and handling the travel time uncertainty.
   - Improving the calculation of value function that located in between time steps by using proportional calculation of value function
2. The proposed model is well behave as expected and can be use for the larger data set such as a whole daily activity-travel behavior data.
3. Another dimension that can be added into the model is the history component of activities which is a part of states and the individual characteristics that can restrict the decision makers' choice set.

Conclusion

- MSTP is one of the major innovation of ICT in transportation field that give a significant impact to many dimension.
- Impact of MSTP on the Urban Form:
  1. MSTP bring the new agglomeration forces for the online food merchants.
  2. The flexibility of food merchants to be located anywhere as long they can maintain their demand level resulting the new agglomeration/central service area in neighborhood scale.
- Impact of MSTP on the Activity-Travel Behavior:
  1. MSTP influence people's decision on conducting online activities and the selection of transport mode.
  2. Service quality (delivery time and delivery cost) of MSTP affect people's eating behavior.
  3. The distribution of online food merchants affect the number of driver and the service quality.
  4. MSTP may change the timing decision of daily activity and travel.
- Policy implication

  The current one strong CBD in Jakarta do not fit to the online food merchant's pattern, if we need want to maintain one CBD, the regulation regarding urban land use, building permit, transportation management, and traffic control is needed.

Contributions

1. It is the first study in literature to explore the impact of MSTP on urban form and travel behavior in Indonesia.
2. It is the first attempt to capture the presence of online activities through FMS Activity-travel Diary Application Survey and its application in Jakarta.
3. Developing agglomeration index that can be used for analyzing the concentration of facilities together with its association with city-level characteristics.
4. Calculation of value of waiting time for using online food delivery services.
5. It is first attempt to conceptually extend the DDCM for activity-travel behavior analysis under the presence of MSTP.

Limitations and Future Direction

Limitation
- The missing data of city-level transport characteristics of Jakarta.
- The missing time activity duration of online activities.
- The missing data of potential demand of MSTP (daytime and nighttime population in Jakarta) in micro-scale/neighborhood scale.
- Consideration of pandemic situation in Jakarta for the changes in MSTP demand and services.
- Spelling and writing.

Future Works
- Further analyses of existing data and obtaining the missing data.
- The impact of MSTP on the Urban Form
  - Discussion about the other interaction (e.g., competition, agglomeration, dispersion among facilities
  - Discussion of the demand distribution of MSTP's services.
  - Enlargement of city scale for agglomeration analysis (Prospect to develop MSTP in the middle-sized city and rural area (market expansion))
- The impact of MSTD on the Activity-travel Behavior
  - Application of extended DDCM for the actual activity-travel diary data
- Understand the behavior of MSTP market which is very complex, because it interacted with many different component. It is very different from normal transportation market.

Thank you!

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safira.msa@gmail.com