A Study on Measurement, Modeling, and Evaluation for Urban Street Space Design Considering both Travel and Place Functions

Travel／Place 機能を考慮した街路空間設計のための観測，モデリング，評価に関する研究

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ABSTRACT

Urban street space in Japan is used for human activities and the movement of people and goods. At the same time, urban street space is a space that generates people's social communication. Specifically, children played, people did business, and people performed various activities in urban street space in the Edo period. However, the development of motorization eliminated people from the urban street space, and the urban street space was used to prioritize car use. In recent years, due to the increasing frequency of car accidents and growing environmental concerns, the use of urban street space is shifting from car use to people use. Moreover, the use of space for the introduction of new mobility devices such as AVs and kickboards is also becoming more important. To accommodate these needs, diverse uses of urban street space are important. Diverse uses of urban street space can create various benefits such as exercise, business and tourism, social inclusion, education, health promotion, culture and arts, and climate change mitigation.

In order to induce diverse uses of urban street space, the urban street space needs to fulfill two main functions: (1) *Travel function*, which supports the movement of people and goods, and (2) *Place function*, which provides space for people's activities. For urban street space design, it is necessary to evaluate the space based on user behavior and redistribute both functions according to this evaluation. However, each function has been targeted in different fields, leading to different evaluation approaches. It is therefore necessary to construct a framework that allows the evaluation of both functions in a consistent manner. In this dissertation, we develop an evaluation framework for urban street space considering *Travel function* and *Place function* using consumer surplus.

In this dissertation, we propose to access the urban street space according to three scale based on the different effects of interaction on pedestrian walking. These are: (1) the effect of psychological interactions of objects and behavioral phenomena close to the pedestrian at the moment (current location), (2) the local effect of physical interactions of other pedestrians/vehicle behaviors or objects surrounding the pedestrian (i.e., a few seconds/meters ahead), and (3) the global effect of the physical interactions of objects or behavioral phenomena (e.g., crowding, liveliness) going to the destination (i.e., several tens of seconds/meters ahead). Accordingly, the urban street space is divided into three parts as follows: (1) *personal space* (i.e., space less than about 1.5m), which focuses on the user perception of objects, vehicles, and pedestrians when the pedestrian approaches them at the present time (position), (2) *public space*, which is further divided into a *local*

domain and a *global domain*, based on the differences in pedestrian prediction of the behavior of vehicles and pedestrians and the location of objects. The *local domain* is the domain where the local effect of the physical interactions surrounding the pedestrian is considered, and the *global domain* is the domain where the global effect of the physical interactions going to the destination is considered.

When evaluating the use of this urban street space, there are some challenges in measurement, modeling, and evaluation. This dissertation addresses the following three issues: (a) in the location-specific preference survey that observes the user preference at a location-specific point, the difference between when to complete a behavior and when to answer a question affects the choice result; (b) a framework describing interactions with new modes (e.g., autonomous vehicles, kickboards) has not been established using real data; (c) there is no model that describes interactions between moving and staying using Random Utility Maximization (RUM) theory. Each research challenge is consistent with the definition of the urban street space. The first challenge focuses on the observation of user perception in *personal space*. The second challenge focuses on description of the micro interactions between autonomous vehicles (AVs) and pedestrians in *local domain* of *public space*. The third challenge focuses on developing a methodology for evaluating the use of urban street spaces that takes into account the interaction between moving and staying in *global domain* of *public space*.

To address the first research challenge, we analyze the difference between when to complete a behavior and when to answer a question on choice result. We call this time difference as *recall time*. The used data are from the location-specific preference survey conducted in Hiroshima and Kumamoto metropolitan areas in 2020, which observe the behavior change under congestion pricing scheme. The data is not related to pedestrian behavior in urban street space, but because it observes preferences at specific points (zones) in an urban area, it represents a similar implication to the observation of user perception of urban street space. Using this data, we analyze whether the *recall time* causes systematic bias in the choice result and whether the *recall time* strengthens (or weakens) the effect of behavioral attributes and preference attributes on the choice result. We estimate parameters using explanatory variables related to the *recall time* and explanatory variables that set the function of the *recall time* as a scale parameter for the preference attributes and behavioral attributes in discrete choice model. In addition, we employ variance decomposition to analyze how changes in *recall time* change the effect of several attributes such as preference attributes and behavioral attribute on the choice results. From these results, we find that a longer *recall time*, leads to users placing more emphasis on the preference attribute rather than considering the behavioral context, and introduces systematic biases in the results of their responses. For example, when the *recall time* is long, users often choose not to change their behavior even if they pay a congestion fee. Therefore, a long *recall time* leads to a systematic bias in the choice result and strengthens (or weakens) the effect of behavioral attributes and preference attributes.

To address the second research challenge, we extend the discrete choice pedestrian model to consider pedestrian-vehicle interaction and conduct an analysis of the difference in pedestrian behavior around AVs and other vehicles (i.e., cars, bicycles, and motorcycles). We use data obtained by video camera measurement of pedestrian and vehicle behavior at crossings in the Hiroshima University. For pedestrian-vehicle interaction, we create utility function considering four components: likelihood of collision, perception of vehicle behavior, risk at collision, and safety distance to collision. We set four behavioral hypotheses based on the components, but this Chapter only tests two hypotheses related to likelihood of collision and perception of vehicle behavior because of the instability of the model estimation. From the estimation result, we find that (1) when the car is not decelerating, the pedestrian avoids it, but when the car is decelerating, pedestrian does not avoid and (2) the pedestrian does not avoid it regardless of the AV's acceleration or deceleration. These results allow us to analyze the difference in pedestrian behavior toward vehicles using this utility function.

To address the third challenge, we develop a pedestrian model that describes the interaction between moving and staying with a dynamic discrete choice model, allowing the evaluation of the use of the urban street space using consumer surplus. In this chapter, using this proposed model, we conduct a numerical simulation in different spatial scenarios (i.e., difference in the number of sojourners/travelers entering the street and object location) in order to analyze the change in the consumer surplus and behavioral outcomes for different use in urban street space. From the simulation result, the consumer surplus is stationary despite the existence of multiple equilibria (i.e., different location with concentrations of sojourners who stay). Moreover, we also find that the change in the number of travelers unexpectedly causes a paradox of the consumer surplus for travelers between center case and top and bottom case, i.e., the number of travelers is reduced, which should have made it easier to walk, but instead it made it harder to walk in the top and bottom case.

In conclusion, we discuss the contribution of each chapter in the evaluation of the urban street space design from the perspectives of *Travel function* and *Place function*. First, through the model in Chapter 5, we find results consistent with existing research, such as increased travel time when the number of sojourners decreases. However, contradictory results were found, such as the expected decrease in travelers making it easier for them to walk, but more difficult in the top and bottom cases. Thus, this evaluation framework is the basic framework to evaluate the use of urban street space considering the trade-off between *Travel function* and *Place function* (i.e., the interaction between moving and staying).

Second, the contribution of Chapter 4 is related to *Travel function*. Specifically, by developing a model framework for pedestrian-vehicle interaction using a discrete choice pedestrian model, we were able to analyze the differences in pedestrian behavior toward different vehicles, indicating that the importance of pedestrian-vehicle coexistence when designing space.

Third, the contribution of Chapter 3 is related to both functions. Specifically, we found that the larger the recall time, the lower the accuracy of the observation, and thus the more biased the selection results and the greater tendency of users to ignore the influence of behavioral factors. Similarly, in the context of observing pedestrian behavior, the influence of location-specific policy interventions (e.g., installing benches or planting trees) on pedestrians may diminish with the time difference since their interaction at the specific location.

There are several research challenges remaining to be explored in the future. For example, in this research, we consider only trade-offs between both functions, i.e., when one function is prioritized, the other function will be reduced within the space. In the urban street network with multiple urban street spaces, however, there is a natural segregation of both functions, so that both functions are complementary. Therefore, it is necessary to evaluate the complementary and competitive (i.e., trade-offs) between the functions of moving and staying.

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Chapter 1: Introduction

1.1. The value of diversity in the use of urban street space

Urban street spaces in Japan have originally been used not only for the movement of people and goods, but also as places for human interaction. For example, during the Edo period, urban street spaces were used for business, performance, and children's playgrounds. However, with the rise of motorization in postwar Japan, urban street space has shifted to give priority to cars, and space has been allocated to vehicles, with car-only streets and parking lots occupying vast areas. At the same time that human interaction and communication were being eliminated from urban street space, social problems such as traffic congestion, traffic accidents, and environmental burdens arose. In response to these social problems, pedestrian zones and pedestrian-only streets were introduced in the 1970s, and in the 2000s, the development of urban street spaces accelerated in various areas. In recent years, the creation of systems such as the "*Pedestrian Convenience Enhancement Road System*" is expected to further accelerate the pace of urban street space development. In addition, with the advent of new mobility devices such as autonomous vehicles (AVs) and electric kickboards, the coexistence of people and vehicles is also an important issue today. Future urban street space will be a place that triggers diversified uses by people, while keeping "mobility" at its core.

As the use of urban street space diversifies, the value of urban street space continues to expand from various aspects such as transportation, economy and tourism, social inclusion, education, health promotion, and culture and art (Izumiyama et. al., 2023). Specifically, the value of urban street space is to reduce people's social isolation, promote physical, mental, and social health, provide a place for student education, improve people's safety and comfort, reduce carbon emissions, generate economic benefits such as job creation, higher land prices, and increased consumption, and create local festivals and events. Because of these value creations, the design of urban street spaces that brings about a variety of uses is considered to be important.

1.2. Urban street space design considering *Travel function* and *Place function*

The four requirements for urban diversity proposed by Jacobs (1961) are: mixed uses, short city blocks, buildings of different ages, and high-density clusters. Meanwhile, the five key elements of the urban "*Image*" proposed by Lynch (1963) are: paths, edges, districts, nodes, and landmarks. These urban philosophies have remained the basis of urban planning and urban design theory to this day. Montgomery (1998) proposes three components of "*Place*": "*Activity*", "*Image*" and "*Form*". "*Form*" refers to the physical characteristics of a space, "*Image*" refers to people's psychology toward a space and the historical and cultural characteristics of a space, and "*Activity*" refers to the voluntary or obligatory actions that people take within a space. There is a clear order in the formation of "*Form*", "*Image*", and "*Activity*": "*Form*" defines the quality and extent of the physical space, which induces "*Activity*", and "*Image*" arises from the sense of combined experience by both "*Activity*" and "*Form*" (Sonoda, 2019). Therefore, the value of urban street space design in response to "*Image*" and "*Activity*" is very high. In addition, Gehl (2013) emphasizes that "*activity attracts people*", this indicating that people's activities are what make urban street spaces attractive. Thus, activity-first spatial design is considered to be one of the effective means to achieve the various uses of urban street space described above.

In the urban street space design, it is important to structure the space in consideration of the *Travel function* and the *Place function* proposed by Jones and Boujenko (2009). Each function is defined as (1) *Travel function* that supports the movement of people and goods to their destinations by various means of transportation (e.g., public transportation, cars, bicycles, walking) and (2) *Place function* that provides sufficient space for people to stay (e.g., rest, shopping, performance). In urban street space design with two functions, it is important to consider the distribution of these functions while taking a comprehensive view of both functions. Specifically, as shown in **Figure 1.1**, in pedestrian-centered spaces, in addition to providing space for safe and comfort movement, it is necessary to design spaces where people can stay by installing benches and planting trees, etc. On the other hand, in pedestrian-vehicle coexistence space, spatial design is required to limit the speed and flow of vehicles and to ensure safe and comfortable spaces for people.

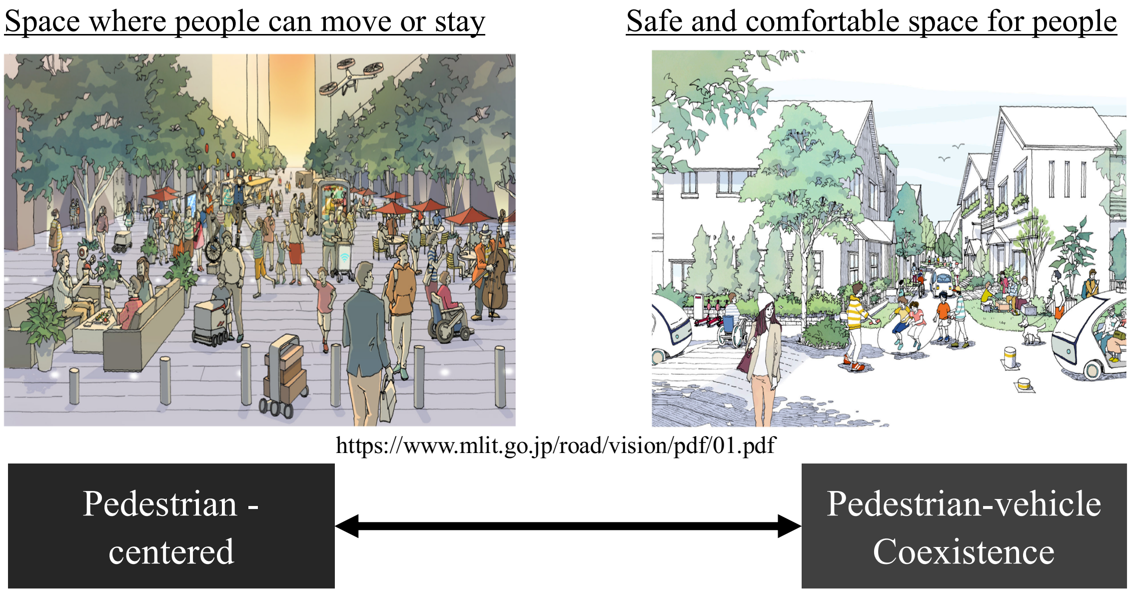

Figure 1. 1 The urban street space design considering *Travel function* and *Place function*

However, due to the limited space size, it is difficult to design a space that satisfies the two functions simultaneously, and it is necessary to redistribute both functions according to the evaluation of use of urban street space. In other words, we need to consider each function that has been targeted in different fields. Specifically, *Travel function* focuses on interactions associated with moving, such as improving of traffic safety (e.g., collision avoidance) and crowding mitigation, and there are many existing studies in the field of traffic engineering such as pedestrian interaction model, while *Place function* focuses on interactions associated with staying, such as creating liveliness and improving comfort, and there are many existing studies in the field of urban planning and design such as public life surveys and biological function observations. Therefore, it is necessary to construct a framework that allows the evaluation of both functions in a consistent manner, instead of the existing frameworks that evaluate each function separately. However, to consider two functions at the same time, it is also necessary to handle with a trade-off between both functions (e.g., expanding the space for people to stay reduces the convenience of movement), in other words, the interaction between moving and staying.

Although there are many evaluation indicators such as density, travel time for evaluating such urban street space, this dissertation focuses on consumer surplus because (1) it is a rational indicator based on microeconomics, and (2) it is often used in the field of transportation to evaluate policy interventions by changes in consumer surplus before and after a policy intervention (Ben-Akiva and Litman, 1985). In this dissertation, we develop an evaluation framework for urban street space considering *Travel function* and *Place function* using consumer surplus.

1.3. Target urban street space

In this study, we consider the urban street space to consist of three scales based on the temporal and spatial differences in the interactions that the pedestrian faces, namely (1) the effect of psychological interactions of objects and behavioral phenomena close to the pedestrian at the moment (current location), (2) the local effect of physical interactions of other pedestrians/vehicle behaviors or objects surrounding the pedestrian (i.e., a few seconds/meters ahead), and (3) the global effect of the physical interactions of objects or behavioral phenomena (e.g., crowding, liveliness) going to the destination (i.e., several tens of seconds/meters ahead). In terms of the effect of these interactions on the pedestrian, the urban street space is composed of the following three scales as shown **Figure 1.2**. First is *personal space* (i.e., space less than about 1.5m), which focuses on the user perception (e.g., safety or comfortable) of objects, vehicles, and pedestrians when the pedestrian approaches them at the present time (position). This *personal space* is similar to the definition by Hall (1966), and Zou and Yai (2022), which is the space that the pedestrian feels uncomfortable when invaded by others. Next is *public space*, which is divided into a *local domain* and a *global domain* according to the differences in pedestrian prediction of the behavior of vehicles and pedestrians and the location of objects. The *local domain* (i.e., space less than about 5m) is the domain where the local effect of the physical interactions surrounding the pedestrian are considered, and the *global domain* (i.e., space less than about 20m) is the domain where the global effect of the physical interactions going to the destination are considered. This division is similar to the one proposed by Oyama (2024), i.e., traveler route choice decisions are based on the experience and information they have about the destination at the time of pre-trip (i.e., global path preference) and the current network situation such as the streetscape or the road surface conditions they face while traveling (i.e., local response). In this dissertation, we aim to construct the evaluation framework for these three scales.

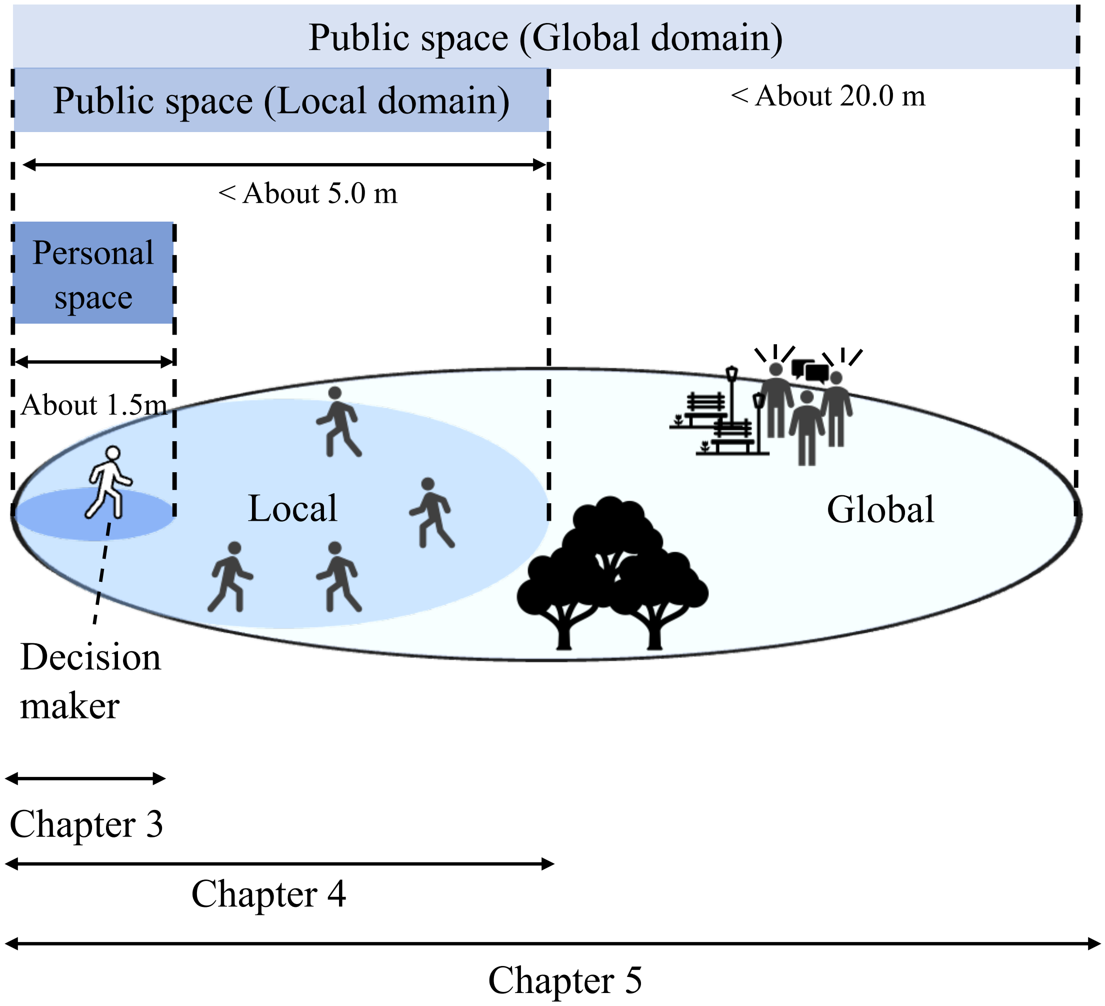

Figure 1. 2 Urban street space as conceptualized in this dissertation

1.4. Challenges of the urban street space evaluation

When evaluating the use of urban street space, as shown in **Figure 1.2**, there are some challenges related to observation and modeling in the evaluation framework requirements. First, in *personal space*, it is necessary to accurately observe user perception at a location-specific point (time). Specifically, for *Travel function*, it is necessary to observe differences in the perception of vehicles (e.g., whether the pedestrian feels trust or safety when a vehicle approaches) when pedestrians and multiple vehicles are present. For both functions, it is also necessary to observe the perception of objects (e.g., whether the pedestrian finds them as attractive or obstacles). These perceptions can be observed using a location-specific preference survey. In this survey, the preferences are observed immediately as users move through the policy intervention area, capturing the user preference for a specific location. However, a challenge in the location-specific preference survey is the time difference between completing a behavior and answering the survey question; the larger this time gap, the more likely the users are to forget the perception (preference) at that point in time (e.g., behavioral phenomena change over time, and perceptions of these phenomena also change), leading to biased choice results. In the context of preference surveys, many studies have focused on *response time* (Haaijer et al., 2000; Rose and Black, 2006) or *time intervals* between surveys (Kitamura, 2002). There are few studies on the time gap.

Second, for *public space*, we need to describe local effects surrounding the pedestrian such as pedestrian-pedestrian, and describe pedestrian-vehicle interactions and global effects such as liveliness and crowdedness on going to the destination based on the framework of Random Utility Maximization (RUM) theory. One model is the dynamic discrete choice model, where the local effect on the surroundings of the pedestrian can be described as the instantaneous utility, and the global effect going to the destination can be described as the expected maximum utility. Existing studies have focused on the instantaneous utility and proposed a framework to describe micro interactions (e.g., collision avoidance) between pedestrian-pedestrian or between pedestrian-vehicle (e.g., pedestrians, bicycles, or cars) has been proposed in the framework. However, interactions with new vehicles (e.g., AVs, kickboards) have not been established (i.e., whether the existing framework can be applied to interactions with new vehicles has not been tested). Furthermore, to the author's knowledge, there is no model that describes interactions such as the interaction between moving and staying (i.e., the interaction between *Place function* and *Travel function*) using the dynamic discrete choice model (i.e., not describing interactions in a framework that includes expected maximum utility).

1.5. The objectives of this dissertation

In this dissertation, we focus on three issues and formulate the following research objectives.

(a) Analyze the effect of the difference between the point in time when a behavior is completed and the point in time when the answer a question on the choice result.

(b) Develop a model framework for pedestrian-vehicle collision avoidance and analyze pedestrian behavior toward AVs.
(c) Develop a framework for evaluating space use based on dynamic discrete choice model, taking into account the interaction between moving and staying, among moving (or staying).

To achieve the above objectives, we first record the difference between when a behavior has been completed and when a question was answered, using a location specific preference survey to observe the preferences of users at the time of the policy intervention. We then analyze the occurrence of bias (e.g., increased percentage of specific alternatives) in the choice result in relation to change in this time difference increases.

Next, pedestrian behavior around AVs and conventional vehicles (CVs), including cars, bicycles, and motorcycles, is observed; a pedestrian model that describe collision avoidance with AVs and CVs is constructed using the observed data, and differences in pedestrian behavior toward vehicles are analyzed from the estimated results. Finally, we propose a pedestrian model that describes the interaction between moving and staying using the dynamic discrete choice model framework and then analyze the differences between scenarios regarding the use of urban street space with the interaction between moving and staying through scenario simulation analysis using the proposed model.

Each research objective draws on the definition of urban street space in **Figure 1.2** and focuses on the following points. Objective (a) is to observe user perceptions in *personal space*; Objective (b) is to describe the interaction between pedestrians and vehicles in the *local domain* of *public space*; and Objective (c) is to evaluate the use of space considering the global effect of going to the destination, that is, the *global domain* of *public space*.

1.6. Framework of this dissertation and overview of each chapter

The structure of this thesis and an overview of the chapters are shown in **Figure 1.3**.

Chapter 1 describes the value of diversity in the use of urban street space, urban street space design considering both functions, and broadly introduces the challenges and objectives of this dissertation in terms of the measurement, modeling, and evaluation of urban street space.

Chapter 2 systematically reviews existing approaches to measurement, modeling, and evaluation in urban street space design, and clarifies their problems and the position of the evaluation framework in this dissertation. Many approaches have been proposed from various fields such as urban planning, traffic engineering, and psychology. In this chapter, these existing approaches are discussed from the behavioral and psychological aspects as well as from the perspective of biological functions and the structure of urban street space.

Chapters 3 to 5 present the results of empirical and simulation analyses for each of the research objectives.

In Chapter 3, we analyze the direct and indirect effects of the time difference (referred to as "*recall time*"), between when to complete a behavior and when to answer a question using a location-specific preference survey, to observe the user's choice results. Specifically, we focus on whether *recall time* causes systematic bias in the choice results and whether it strengthens (or weakens) the effect of behavioral factors (or preference attributes). The data used are from the location-specific preference survey conducted in the Hiroshima and Kumamoto metropolitan areas in 2020, assuming zone-level congestion pricing. Although the spatial scale of this data is different from the spatial scale of the urban street space targeted in this dissertation, it is equivalent in terms of preferences in a specific area (i.e., zone) within a city and can be used as knowledge for observation of urban street space. As an analytical method, we estimate the scale parameters of the preference and behavioral attributes using an explanatory variable for the *recall time* and an explanatory variable for the function of that time. Furthermore, variance decomposition is used to analyze how changes in *recall time* affect the effects of preference attributes, behavioral attributes, individual attributes, and error terms (i.e., unobserved behavioral factors) on the choice results.

In Chapter 4, we analyze the differences in pedestrian behavior around AVs and CVs (i.e., cars, bicycles, and motorcycles). Specifically, pedestrian behavior at an intersection at Hiroshima University and the behavior of AVs and CVs are observed by video camera. We develop a pedestrian model that considers the collision avoidance with vehicles, which includes four components: likelihood of collision, perception of vehicle behavior, risk at collision, and safety distance to collision. Two types of collision likelihood situations are considered: first, a situation in which the pedestrian does not estimate the speed of the vehicle, but judges whether a collision will occur based on his/her direction of the pedestrian and the vehicle, and second, a situation in which the pedestrian estimates the speed of the vehicle and judges whether a collision will occur based on his (or her) prediction of the future location of the vehicle and the him/her. Based on the estimation results of the model for the different potential collision situations, we test the hypotheses about the four factors and analyze the difference in pedestrian behaviors in response to different vehicles.

In Chapter 5, we analyze the differences in space use patterns between travelers (who only move) and sojourners (who both move and stay), based on the differences in behavioral outcomes and consumer surplus between scenarios. As an analysis method, we propose a pedestrian model that describes interactions between moving and staying, among moving, and among staying by using a dynamic discrete choice model. Furthermore, using the proposed model, numerical simulations are conducted under different spatial designs with different numbers of pedestrians and different object arrangements, and the changes in consumer surplus and behavioral outcomes (e.g., travel time) are analyzed.

Finally, Chapter 6 summarizes the contribution of each chapter in this dissertation to the urban street space design considering *Travel function* and *Place function*, and discusses future tasks for research in the future.

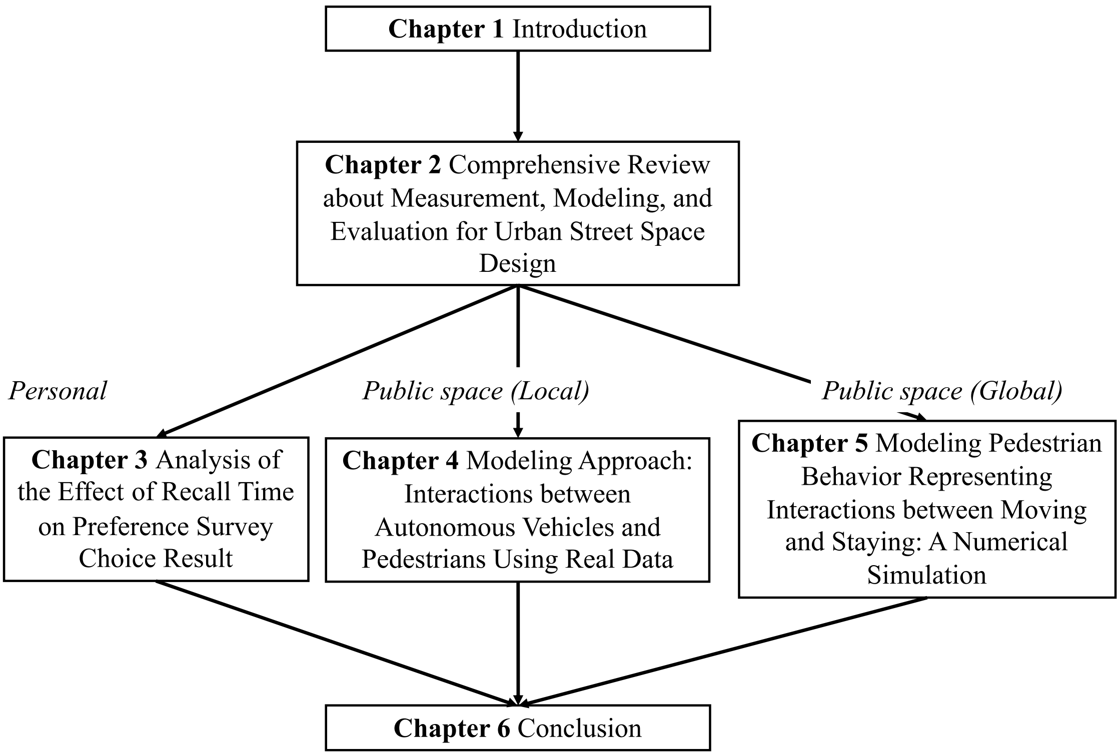

Figure 1. 3 The framework of this dissertation

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Chapter 2: Comprehensive Review about Measurement, Modeling, and Evaluation for Urban Street Space Design

2.1. Introduction

A variety of methods for measurement, modeling, and evaluation for urban street space design are used in diverse research fields, including urban planning, traffic engineering, and psychology, respectively. This chapter systematically reviews these diverse existing approaches. Section 2.2 describes measurement methods for (1) observing behaviors in real space, (2) observing preferences (i.e., one of the perceptions), and (3) observing biological functions (i.e., observing perception as an objective indicator). Section 2.3 describes models that consider (1) macro interactions (i.e., aggregated interactions) and (2) micro interactions (i.e., disaggregated interactions). Section 2.4 focuses on evaluation methods for spatial structure, behavioral aspects, and psychological aspects. Finally, section 2.5 clarifies the position of the evaluation framework developed for this study within these existing methods.

2.2. Measurement methods

Since there are a wide variety of existing measurement methods, this section focuses on (1) methods for observing user behavior in real space, (2) methods for observing user preference, and (3) methods for observing user biological function. A summary of each item is shown in **Table 2.1**.

Table 2. 1 Summary of measurement methods

2.2.1. Methods for observing user behavior in real space
Analog survey
Counting, Questionnaire, Interviewing, Mapping, Trajectory tracing, Daily observation
Public life survey (Gehl and Svarre, 2013)
Person-trip survey
Traffic count survey
Digital survey
Cross-sectional traffic volume survey using laser sensors
Motion trajectory survey by GPS device/AI camera
Traffic flow survey by Wi-Fi packet sensor
2.2.2. Methods for observing user preference
Preference survey
Preferences for different street spatial structures (Giergiczny and Kronenberg, 2014; Shao et al., 2020; Botes and Zanni, 2021)
Safety, acceptability, and trust for AVs (Deb et al., 2017; Hulse et al., 2018; Hafeez et al., 2022)
Preference surveys integrated with behavioral data for new services (Danaf et al., 2019; Safira and Chikaraishi, 2022)
Preference survey with virtual reality
Pedestrian behavior and preferences for AVs (Deb et al., 2017; Iryo-Asano et al., 2018; Jayaraman et al., 2019; Kani and Iryo, 2020; Camera et al., 2021)
User behavior and preferences for urban street structure (Ohashi et al., 2019; Hishikawa and Iryo, 2020; Ramírez et al., 2021; Kasraian et al., 2022; Argota et al., 2024)
2.2.3. Methods for observing user biological function
Biological functions (EEG, heartbeat, eye movement, etc.)
EEG and pedestrian behavior (Aspinall et al., 2015; Neale et al., 2020; Tang et al., 2023)
Heart rate and walking behavior (Suzuki et al., 2013; Suzuki et al., 2019)

2.2.1. Methods for observing user behavior in real space

As traditional survey methods, manual analog surveys such as questionnaires and count surveys are still widely used today. For example, in public life surveys (Gehl and Svarre, 2013), the actual use of urban street space, such as trajectories, number of pedestrians, types of activities, and duration of stay, is observed using counting, mapping, trajectory tracing, and observation diaries. In a person-trip survey, the average daily activities of subjects within a certain study area, such as travel time, purpose, mean of transportation, and destination, are observed through questionnaires. However, these analog surveys, on the other hand, have the following problems: (1) limited data types, (2) difficulty in long-term and continuous observation of behavior from starting point to destination, and (3) large human-caused observation errors.

To address these issues, efficient observation is now possible through digital surveys using video cameras, laser sensors, 3D LiDAR, GPS, Wi-Fi, etc. (https://www.mlit.go.jp/toshi/file/useful/ nigiwaisokutei_R5.5.pdf , viewed May 4, 2024). Specifically, laser sensors can automatically observe cross-sectional traffic in a certain area, GPS devices can observe behavior on the network over time and repeatedly, and video cameras can comprehensively observe detailed activity trajectories of pedestrians and vehicles in a certain area. Furthermore, AI cameras can use machine learning such as CNN to perform image recognition, object detection, and object tracking to automatically generate behavioral data. There are also applications such as Miles (https://www.getmiles.com/jp, viewed May 4, 2024) that can automatically identify means of transportation. On the other hand, digital surveys have the following issues: (1) accurate observation while respecting privacy, (2) possible loss of observation accuracy due to variations in the observation environment, and (3) ensuring sufficient storage space for a large amount of data.

2.2.2. Methods for observing user preference

One method for observing user preferences is a preference survey. It is characterized by (1) the ease of controlling external factors that affect preferences and (2) the ease of quantifying individual differences through repeated observations (Kitamura et al., 2002). Specifically, user preferences are studies in relation to street trees, sidewalks, and bicycle paths (Giergiczny and Kronenberg, 2014; Shao et al., 2020; Botes and Zanni, 2021), as well as safety and acceptability of AVs (Deb et al., 2017; Hulse et al., 2018; Hafeez et al., 2022), etc. To bridge the gap between the preference survey and reality, attribute levels and alternatives for the preference survey are adjusted based on the attribute levels of users obtained from the behavioral survey (Rose et al., 2008; Train and Wilson, 2008). For example, it has been used to observe preferences for new transportation services, such as demand observations for new on-demand transportation (Danaf et al., 2019) and the availability of online food delivery services (Safira and Chikaraishi, 2022). Furthermore, by integrating user preference and behavioral data, it can be extended to location-specific preference surveys that allow observing preferences at specific locations. This approach makes it possible to simultaneously consider user behavior and preference in urban street space design. Specifically, it is possible to observe the pedestrian's preference for objects, vehicles, etc. in the environment at the current time. However, there are some problems with this method, such as the difficulty of continuously observing changes in preferences, as is the case with continuous observation of behavior using video cameras and GPS devices, and the fact that the time elapsed between the completion of an action and the response of preferences can cause changes in user preferences.

On the other hand, Virtual Reality (VR) a method to observe behaviors and preferences in a virtual space. This observation method has various advantages, such as easy control of the experimental environment and increased immersion in the virtual scenario. Furthermore, VR is highly consistent with preference surveys and can be used to conduct preference surveys with enhanced realism, such as observing user behavior and preferences for AVs (Deb et al., 2018; Velasco et al., 2019; Kani and Iryo, 2020) and measuring user behavior and preferences for different road structures (Ohashi et al., 2019; Argota et al., 2024).

2.2.3. Methods for observing user biological function

The aforementioned preference survey is a method to subjectively and cross-sectionally observe users' preferences through questionnaires, but this method may cause biases (e.g., biases that justify inconsistencies) in choice results. To avoid such biases, there is a method to objectively (i.e., quantitatively) grasp the user perception through the observation of their biological functions. Using this observation method, it is possible, for example, to quantitatively analyze to what extent better urban street space design mitigates negative perception (e.g., safety) or causes positive perception (e.g., comfort) (Mavros et al., 2022).

Specifically, there are existing studies that measure biological functions such as facial expressions, heart rate, eye tracking, and electroencephalogram (EEG) while walking in an urban street space (Aspinall et al., 2015; Tang et al., 2023; Neale et al., 2020; Mavros et al., 2022; Suzuki et al., 2013; Suzuki et al., 2019). For example, some studies to analyze the factors of pedestrian avoidance behavior by observing EEG and eye tracking simultaneously with their behavior (Tang et al., 2021), while other studies to analyze the relationship between stress and the urban street space environment by observing heartbeats during walking (Suzuki et al., 2019).

However, to observe biological functions it is necessary to resolve various issues, such as the difficulty of collecting a sample number of subjects, the difficulty of continuing for a long period of time due to cost and mental (i.e., physical) burden, privacy (e.g., consent of subjects), and individual differences among subjects. On the other hand, the observation of the biological functions is easier to correlate with the behavioral data than the preference survey, because it allows for long-term and continuous observation. In addition, since user perception can be observed simultaneously with behavior, it is believed that changes in preferences over time, which occur in preference surveys, do not occur.

2.3. Modeling

The modeling approach focuses on models that describe macro interactions (e.g., congestion) as densities and traffic volumes on each link and models that describe micro interactions (e.g., collision avoidance and leader-follower) at the individual level. These models are summarized in **Table 2.2**.

Table 2. 2 Summary of modeling methods

2.3.1. Models that describe macro interactions
Vehicle flow
Route (or Link) choice approach
Explicit route enumeration:
Dijkstra approach
Logit model approach
PSL model (Ben-Akiva and Lerman,1985), PCL model (Chu,1989)
Implicit route enumeration:
Logit Assignment (Dial, 1971)
Markov Chain Assignment (Sasaki, 1965; Bell, 1995; Akamatsu, 1996)
Recursive logit (RL) model (Fosgerau et al., 2013)
Discounted RL model (Oyama and Hato, 2017)
Nested RL model (Mai et al., 2015), Mixed RL model (Mai et al., 2018)
Inverse reinforcement learning
(Ziebart et al., 2008; Liu et al., 2020; Zhao and Liang, 2023)
Link flow approach
Point-Queue model
Lighthill-Whitham-Richards model (Lighthill and Whitham, 1955; Richard, 1956)
Cellular transmission model (Dagazo, 1994)
Pedestrian flow
Route (or Link) choice approach
Markov Chain Assignment

Recursive logit model (van Oijen et al., 2020; Oyama, 2023; 2024)
Prism constrained RL model (Oyama and Hato, 2016;2017)
Inverse reinforcement learning (Hidaka et al., 2019)
Link flow approach
Continuum model (Hughes, 2002; Huang, 2009)
Dynamic programing on continuous space
(Hoogendoorn and Bovy, 2004; Hoogendoorn et al., 2015)
Mean field model (Lachapelle and Wolfram, 2011)

Multimodal flow
Route (or Link) choice approach
Markov Chain Assignment
RL model (de Freitas et al., 2019; Tabuchi and Fukuda, 2020)
MA-AIRL learning model (Ogawa and Hato, 2023)
Multi network equilibrium assignment model
(Wu et al., 2005; Scarinci et al., 2017; Murakami and Oyama, 2023)

2.3.2. Models that describe micro interactions

Interactions among pedestrians
Discrete choice pedestrian model (Robin et al., 2009; Asano et al., 2009)
Social force model (Helbing and Molnar, 1995)
Cellular automata model (Blue and Adler, 2001; Kirchner et al., 2003)
Interaction between vehicle and pedestrian
MA-AIRL learning model (lsaleh and Sayed, 2021)
Social force model (Anvari et al., 2015; Dias et al., 2018)

2.3.1. Models that describe macro interactions

In traffic engineering and transportation planning (i.e., the field in *Travel function*), there are many models that describe the flow and choice behavior of vehicles (or pedestrians) on a network or within each link. Often, these models describe macro interactions such as congestion using density, traffic volume, or travel time. In this dissertation, "macro interactions" are defined as aggregate quantities formed by the actions of individual vehicles and pedestrians on each link. We focus on two approaches (Akamatsu and Wada, 2014): (1) an approach that describes route (or link) choice behavior and (2) an approach that describes vehicle or pedestrian flow within a link based on physical conditions. These approaches are often used in static/dynamic user equilibrium allocations that allocate traffic volumes satisfying Wardrop's first principle.[1]

[1] The first principle of Wardrop assumes that in the route choice of vehicles on the transportation network, "among the available routes between the origin and destination points, the travel costs of the routes that are actually used are all equal and are smaller than or at most equal to the travel costs of the routes that are not used".

The former approach introduces link utilities (e.g., travel time, link length, travel cost, etc.) and link performance functions such as the Bureau of Public Roads (BPR) function and the Davison function that describe the increase in travel time associated with an increase in traffic and the impact of macro interactions on each link cost. This approach can be broadly classified into (1) *Explicit route enumeration* and (2) *Implicit route enumeration*. In the former method, the Dijkstra algorithm is widely used to calculate the shortest path (i.e., minimum cost) from the starting point to the destination in a forward direction. In addition, stochastic route choice models based on the framework of the logit model are also used, in which the decision maker is assumed to choose a route from a set of alternatives (set of observable routes) according to the probability of choice. For example, the Multinominal logit model, the Nested logit model, the Paired Combinatorial logit model (which considers correlations among all paths) (Chu, 1989), and the Pass sized logit model (which introduces a modification term to express the degree of link sharing) (Ben-Akiva and Lerman,1985). The *explicit route enumeration* method is difficult to apply to large transportation networks with numerous routes from origin to destination, in which case the latter method, the Implicit route enumeration method, is preferred. Implicit route enumeration method is effective. As a representative model, the Dial model (i.e., logit assignment), which focuses on "Efficient paths (i.e., paths that move away from the starting point and approach the destination)", has been proposed (Dial, 1971). This method implicitly limits the path and may generate unrealistic paths. Markov Chain Assignment (Sasaki, 1965; Bell, 1995; Akamatsu, 1996) has been proposed as a method that does not restrict routes. In this method, route choice is represented as transitions between links (or nodes), and the next state is determined from the current state according to transition probabilities. A similar dynamic discrete choice model has also been proposed.

The dynamic discrete choice model proposed by Rust (1987) uses dynamic programming (DP) to describe a decision-making process that makes sequential choices while considering future circumstances. Specifically, assuming a Markov decision process, individual n chooses the option $a_{n,t}$ that maximizes the expected utility (utility with respect to global effects) to the destination in the current state $s_{n,t}$ at time t. Then, according to the transition probability $q(s_{n,t+1}|s_{n,t}, a_{n,t})$, the next state is $s_{n,t+1}$. For brevity, the subscript n is omitted. Expected utility is described using the following equation:

$$E\left(\sum_{i=0}^{J-t} \beta^i u(s_{t+i}, a_{t+i})\right) \tag{2.1}$$

where T is the time range (i.e., maximum time to reach the destination), $\beta \in (0,1)$ is the discount rate (i.e., future uncertainty; the closer the value is to 1, the greater the weight of expected utility), and $u(s_t, a_t)$ is the utility at time t. The DP problem of maximizing $u(s_t, a_t)$ is followed the optimal Bellman principle and described by the following Bellman equation using the value function $V(s_t)$.

$$V(s_t) = \max_{a_t \in A(s_t)} \{u(s_t, a_t) + \beta EV(s_t, a_t)\} \tag{2.2}$$

where $u(s_t, a_t)$ is divided into instantaneous utility $v(s_t, a_t)$ and error term $\varepsilon(a_t)$, and when $\varepsilon(a_t)$ follows an independent and identical distribution (i.i.d), the expected value $\bar{V}(s_t)$ of the value function for $\varepsilon(a_t)$ is given as follows:

$$\bar{V}(s_t) = \ln\left(\sum_{a_t \in A(s_t)} e^{\frac{1}{\mu}(v(s_t,a_t)+\beta EV(s_t,a_t))}\right) \tag{2.3}$$

where $A(s_t)$ is the choice set of the current state s_t and μ is the scale parameter. The expected value of $\bar{V}(s_t)$, $EV(s_t, a_t)$, for transition probability q is defined by the following equation

$$EV(s_t, a_t) = \int_{\check{s}} \bar{V}(\check{s})\ dq(\check{s}|s_t, a_t) \tag{2.4}$$

The probability of choosing action a_t from the current state s_t is defined in the form of a logit model.

$$P(a_t|s_t) = \frac{e^{\frac{1}{\mu}(v(s_t,a_t)+\ \beta EV(s_t,a_t))}}{\sum_{a_t \in A(s_t)} e^{\frac{1}{\mu}(v(s_t,a_t)+\ \beta EV(s_t,a_t))}} \tag{2.5}$$

While the above model describes stochastic state transitions ($s_{t+1} \neq a_t$), Fosgerau et al.

(2013) proposed the Recursive logit (RL) model, which applies the above dynamic discrete choice model to route choice on a physical network consisting of links and nodes This RL model applies the above dynamic discrete choice model to route choice on a physical network consisting of links and nodes. In this RL model, an individual n at the current link k (current state s_t) deterministically transitions to the next state s_{t+1} ($= a$) by selecting the link set $a \in A(k)$ connected to link k that maximizes his expected utility. In this case, **Equation (2.3-5)** is transformed as follows

$$V(k) = \max_{a \in A(k)} \left(v(a|k) + V(a) + \mu\varepsilon(a) \right) \tag{2.6}$$

$$V(k) = \ln \left(\sum_{a \in A(k)} e^{v(a|k) + V(a)} \right) \tag{2.7}$$

$$P(a|k) = \frac{e^{\frac{1}{\mu}(v(a|k) + V(a))}}{\sum_{a \in A(k)} e^{\frac{1}{\mu}(v(a|k) + V(a))}} \tag{2.8}$$

Furthermore, Oyama and Hato (2017) introduce a spatial discount rate in the RL model to account for sequential and forward-looking dynamic decision making. In addition, the Nested RL model (Mai et al., 2015) and the Mixed RL model (Mai et al., 2016) have been proposed to solve the problem of path overlap (i.e., correlation among paths) in the RL model. In parallel with the RL model, Inverse Reinforcement Learning (IRL) models (Ziebart et al., 2008; Liu et al., 2020; Zhao and Liang, 2023) have also been proposed. These models are similar to the RL model in that they describe route choice as a sequence of link choices, but IRL can introduce a nonlinear function in the link utility.

The second approach is to describe vehicular or pedestrian flows using traffic volumes, speeds, and densities. This approach imposes constraints on traffic volume, speed, and density to account for macro interactions. For example, the Point-Queue model describes congestion in terms of queue delay and number of vehicles in queue, while the FIFO (first in first flow) principle holds for the Whitham-Richards model (LWR) (Lighthill and Whitham, 1955; Richard, 1956) which describes traffic flow as a one-dimensional wave (i.e., traffic volume is expressed as a concave function of density) under the assumptions of traffic volume conservation law and Fundamental Diagram (FD). The model calculates traffic volume and density in space and time by solving partial differential equations under boundary conditions derived from the two assumptions (Akamatsu and Wada, 2014). Furthermore, the Cellular transmission model (Dangazo, 1995) computes traffic volumes and densities in discrete time and space from the state equation under the assumption of a piecewise linear approximation of FD and a traffic volume conservation law.

The RL model has been used to describe pedestrian flow and route choice behavior (van Oijen et al., 2020; Oyama, 2023; 2024). However, the RL model, which was originally intended for drivers' shortest path problems, has the inherent difficulty of not being able to handle positive instantaneous utilities such as pedestrians stopping at green spaces (Oyama, 2023). To solve this problem, Oyama and Hato (2016; 2017) proposed the Prism-constrained RL (Prism-RL) model, which extends the RL model to a time-structured network. In this Prism-RL model, pedestrian behavior on a temporally structured network can be described as a sequence of moving and staying, which indicates that this model also consider the *Place function* related to staying. Hidaka et al. (2019) also proposed an IRL-based pedestrian model for pedestrian detouring behavior under time constraints. On the other hand, for approaches dealing with flow, two-dimensional LWR (Hughes, 2002; Huang, 2009), which describes pedestrian flow as a potential field, has been widely used. Similarly, Hoogendoorn and Bovy (2004) describe pedestrian flow in a potential field that takes into account the expected utility to the destination in the framework of DP, and Hoogendoorn et al. (2015) extend the model to consider local effects (i.e., micro interactions that occur during walking). The mean field model describes pedestrian flows in continuous space using partial differential equations based on density and value functions (Lachapelle and Wolfram, 2011).

When designing the urban street network, it is essential to consider the trade-offs between different means of transportation, such as the relationship between sidewalk width and roadway width, and between crowding and liveliness. Therefore, it is necessary to determine measures on a network where multiple modes of transportation exist simultaneously. Several conventional models consider the flow of multiple modes of transportation simultaneously. For example, Wu et al. (2005), Scarinci et al. (2017), and Murakami and Oyama (2022) use a user equilibrium assignment model that simultaneously allocates routes for all modes of transportation, taking into account the link costs of each transportation mode. They calculate the optimal sidewalk assignment on a multimodal network. Furthermore, with Markov assignment models on multimodal networks, de Freitas et al. (2020) use an RL model that considers route choice and transportation mode choice, and Ogawa and Hato (2023) use an adversarial inverse reinforcement learning model that simultaneously learns an agent's reward and strategy.

When considering multiple modes of transportation, the focus is on multiple networks, which creates issues such as huge computational cost (e.g., efficient computation of value functions in the RL model) and estimation stability (e.g., stability in the joint estimation of multiple value functions).

2.3.2. Models that describe micro interactions

In this section, we discuss a model that describes micro-interactions. The term "micro interactions" describes complex interactions (e.g., collision avoidance, leader-following) that occur between individuals. On the other hand, it is said that it is difficult to understand the properties of model systems in which complex interactions exist. There are two general approaches to understanding the properties of such model systems: (1) to interpret the properties of model systems theoretically, and (2) to explore the properties of model systems through simulations. The former approach mainly uses deterministic approximations (i.e., ordinary differential equations) of stochastic evolutionary processes in evolutionary game theory. For example, Iryo and Watling (2020) use this method to analyze the theoretical properties of equilibrium solutions of model systems with complex interactions. However, this deterministic approximation is not suitable for describing the behavior of pedestrians in the presence of complex interactions, since the environment is often unrealistic. Therefore, a simulation approach is used for the latter. This approach uses the cellular automata (CA) model (Blue and Adler, 2001; Kirchner et al., 2003), the social force model (Helbing and Molnar, 1995), and the discrete choice pedestrian model (Antonini et al., 2006; Robin et al., 2009), which describe sequential behaviors in terms of speed and angle at small time intervals. Specifically, in the CA model, behavior in discrete spatio-temporal space is changed by changing the state of the cell at each discrete time step according to a transition rule. In the social force model, behavior in continuous spatio-temporal space is described using repulsive and attractive forces in the framework of the equations of motion. The discrete choice pedestrian model describes behavior in discrete time and continuous space using the logit model framework to describe the speed and angle at each time interval. These models can describe detailed interactions between pedestrians (e.g., collision avoidance and leader-following) using the current speed and angle, which mainly focus on the *Travel function*. Some models focus on the interaction between pedestrian and attractions (Kwak et al., 2013;Wang et al., 2014). These model frameworks have also been proposed to describe the interaction between pedestrians and vehicles. Specifically, various models using the social force model have been proposed to describe interactions, including pedestrian-vehicle interactions (Anvari et al., 2015; Dias et al., 2018a and 2018b) and pedestrian-bicycle interactions using a multi-agent adversarial inverse reinforcement learning approach (Alsaleh and Sayed, 2021). With the increase in the number of agent types (e.g., sojourners, travelers, vehicles) in the urban street space, many interactions that have not been described previously have emerged (e.g., the cohesion of sojourners attracting other sojourners), highlighting the need to develop methodologies to describe these interactions. In addition, both the CA model and the discrete choice pedestrian model discretize continuous space, necessitating consideration of the unit of aggregation when describing behavior. The CA model has advantages such as the application of realistic velocity distributions and the description of anisotropy (Guo et al., 2014; Fu et al., 2018) due to finer discretization (i.e., making the cell size smaller than the pedestrian size). However, it can also result in unrealistic behaviors (e.g., pedestrian bias in spatial distribution and fundamental diagrams) that do not match real phenomena (Kirchner et al., 2004; Guo et al., 2014).

On the other hand, while these models describe causal relationships based on prior beliefs (i.e., the assumption that each driver acts to minimize his/her own travel time), there are many models that describe causal relationships based on evidence obtained from observational data. These models quantitatively analyze the relationships between variables related to user psychology. For example, covariance structure models analyze the relationship between subjects' psychological factors and urban street structure (Fujii and Sakai, 2002; Peng et al., 2021), as well as the relationship between pedestrians' psychological factors and AVs (Deb et al., 2017; Hafeez et al., 2022). In other cases, discrete choice models have been used to analyze the factors that influence preferences for different urban street structures (Giergiczny and Kronenberg, 2014; Shao et al., 2020; Hishikawa and Iryo, 2020; Botes and Zanni, 2021; Ramírez et al., 2021).

2.4. Evaluation

In this section, we focus on evaluation methods such as evaluation from the aspect of spatial structure, evaluation from the behavioral aspect, and evaluation from the psychological aspect. A summary of each item is shown in **Table 2.3**.

Table 2. 3 Summary of evaluation methods

2.4.1. Evaluation from the behavioral aspect

Indicators based on behavioral outcomes.

LOS indicators (Fruin, 1971)

Pedestrian density, speed, and pedestrian volume.
(Teknomo, 2006; Asano et al., 2009; Liu et al., 2014)

Sojourners' density, number of sojourners and the duration of actives.
(Ito and Hato, 2013; Oyama and Hato, 2017; Miura et al., 2023)

Cost-benefit evaluation

Reduction of travel time, reduction of travel expenses, reduction of traffic accidents.

Consumer surplus (consumer surplus)

Evaluation of improvements to the walking environment (Chikaraishi et al., 2019)
Evaluation of user satisfaction with Mass (Tabuchi and Fukuda, 2019)
Evaluation of accessibility of transportation networks (Safitri and Chikaraishi, 2021)

2.4.2. Evaluation from the psychological aspect

The magnitude and strength of the cause and effect

Importance of Psychological Factors for Street Space
(Fuji and Sakai, 2002; Peng et al., 2021)

Importance of pedestrian preference factors for autonomous vehicles
(Deb et al., 2017; Hafeez et al., 2022)

Marginal willingness to pay

Evaluate modification of urban street space.
(Giergiczny and Kronenberg, 2014; Shao et al., 2020; Botes and Zanni, 2021)

Safety analysis for urban street space.
(Svensson and Johansson, 2010; Antoniou, 2014)

2.4.3. Evaluation from the aspect of spatial structure

Int. V: Efficiency of movement on the network

Analysis of factors affecting pedestrian volume or flow
(Aratani et al., 2005; Ueno and Kishimoto, 2008; Ito et al., 2021; Yıldırım and Celik, 2023)

Walkability Index (Frank et al., 2005)

Influence of walking space (Kanai et al., 2019)
Factors affecting walking (Kimura and Kanai, 2022)

2.4.1. Evaluation from the behavioral aspect

For the evaluation of urban street space and policies, evaluation indices that can be directly calculated from behavioral results, such as density, travel time, and travel distance, are used because of their consistency with data and simplicity. Specifically, the evaluation of urban street space includes the evaluation of level of service (LOS) using pedestrian density as the evaluation index (Fruin, 1971) and the evaluation of the actual condition of urban street space using pedestrian density, speed, and traffic volume as indicators to evaluation of *Travel function* (Teknomo, 2006; Asano et al., 2009; Liu et al., 2014). In addition, regarding the *Place function*, the actual situation of urban street space is evaluated by density and the number of people who stay (Miura et al., 2023), the liveliness of urban street space is evaluated by the nigiwai index (Abdelwahab et al., 2021), and transportation network modifications are evaluated by duration of activity and traffic volume (Ito and Hato, 2013; Oyama and Hato, 2017).

In addition, cost-benefit evaluation, which is consistent with microeconomics, is used to evaluate transportation plans, such as pre- and post-implementation evaluations of road plans. Basically, as evaluation index for *Travel function*, three benefits (i.e., the monetary unit index) (1) reduced travel time, (2) reduced travel costs, and (3) reduced traffic accidents are used in actual transportation planning (https://www.mlit.go.jp/road/ir/ir-hyouka/ben-eki_2.pdf, viewed May 6, 2024). In addition, generalized costs among OD are used to evaluate cost benefits among OD, which can be evaluated in terms of consumer surplus (Ben-akiva and Litman, 1985) using the logit model. However, minimum cost or weighted average methods using deterministic utility instead of random utility may also be used. Consumer surplus is described by the following expected maximum utility of all individual choices:

$$E\left[\max_{i\in C_n} U_{in}\right] = \frac{1}{\mu}\ln\sum_{i\in C_n}\exp(\mu V_{in}) \tag{2.9}$$

where i is a certain choice in the choice set C_n of individual n, V_{in} the random utility U_{in} represents the deterministic utility, and μ is the scale parameter. The consumer surplus has the following characteristics

I. Consumer surplus always increases when a new alternative is added (**Equation (2.10)**).

$$E\left[\max_{i\in C_n} U_{in}\right] \leq E\left[\max_{i\in \acute{C}_n} U_{in}\right] \tag{2.10}$$

where the conventional choice set C_n is a subset of the new choice set $\acute{C}_n$.

II. Whenever the deterministic utility of an alternative rises, consumer surplus rises (**Equation (2.11)**).

$$\frac{\partial}{\partial V_{jn}} E\left[\max_{i\in C_n} U_{in}\right] = P_n(j) > 0, \forall j \in C_n \tag{2.11}$$

where $P_n(j)$ represents the probability of choosing alternative j. Furthermore, if we consider the discrete choice model as an individual demand function, and let vectors V_n^1 and V_n^2 be the deterministic utility values of each alternative before and after the policy intervention, the change in consumer surplus is as follows (**Equation (2.12)**).

$$\Delta CS_n = \sum_{i\in C_n} \int_{\mathbf{V}_n^1}^{\mathbf{V}_n^2} P(i|\mathbf{V})d\mathbf{V} = \frac{1}{\mu}\ln \sum_{i\in C_n^2} \exp(\mu V_{in}^2) - \frac{1}{\mu}\ln \sum_{i\in C_n^1} \exp(\mu V_{in}^1) \tag{2.12}$$

This value can be converted into monetary units by dividing by the value of the cost parameter of the utility function. Furthermore, the sum of the product of the value of all routes (**Equation (2.12)**) and the traffic between OD is used to calculate the user benefits between ODs.

In the RL model described in section 2.3.1, using **Equation (2.7)**, the expected maximum utility from origin to destination (i.e., consumer surplus) can be calculated, and behaviors from origin to destination such as driver accessibility can be evaluated in terms of consumer surplus. In addition, by including various factors (e.g., factors related to both moving and staying) in the deterministic part of the utility function, a composite evaluation can be performed. For example, Chikaraishi et al. (2019) evaluate the improvement of the walking environment, Tabuchi and Fukuda (2020) the user satisfaction of Mobility as a Service (MaaS), and Safitri and Chikaraishi (2022) the accessibility of transportation networks during disasters. Compared to direct indicators from behavioral outcomes, consumer surplus is a rational indicator (i.e., consistent with microeconomics). The consumer surplus should be used as an indicator of the urban street space design, as it does not take into account all aspects of the urban street space.

2.4.2. Evaluation from the psychological aspect

When describing causal relationships among variables in a covariance structure model, the magnitude of the coefficients (i.e., the magnitude or strength of the causal relationship) can be used, for example, to evaluate important factors that influence user perception of the structure of the urban street space (Peng et al., 2021). There are also methods to evaluate urban street spaces by quantifying the psychology of users based on their external characteristics. For example, Sato et al. (2014) quantitatively evaluated user perception when walking in an urban street space by calculating the degree of smiling of pedestrians using video camera data. Compared to observing biological functions, the use of video cameras has advantages, such as ensuring the number of samples and reducing the cost of observations, but there may be a discrepancy between the user perception and external characteristics, such as facial expressions.

Furthermore, when conducting a preference survey that includes financial attributes such as construction costs related to the structure of the urban street space, it is possible to calculate the marginal willingness to pay (WTP), which can be used to evaluate the users' preferences for the structure of the urban street space in monetary terms. For example, WTP can be used to evaluate the users' preferences for the restructuring and design of the urban street space (Giergiczny and Kronenberg, 2014; Shao et al., 2020; Botes and Zanni, 2021) and the safety of the urban street space (e.g., traffic accident risk) (Svensson and Johansson, 2010; Antoniou, 2014).

2.4.3. Evaluation from the aspect of spatial structure

There are existing methods to evaluate the relationship between the spatial structure of an urban street space and user behavior. First, Hiller et al. (1984) proposed the Space Syntax (SS) theory as a method for modeling the structure of urban street spaces. Based on graph theory, this SS theory describes spatial relationships of structures among urban street spaces (Yamu et al., 2021). As shown in **Figure 2.1**, urban street spaces are decomposed into elements such as convex spaces, axis lines, and isovistas, and are visually described by maps or graphs composed of these elements (Yamu et al., 2021). Specifically, when analyzing street trends, an axial line is drawn in the space, an axial map composed of axial lines is created, and the space is described as an axial map. The indicators of the spatial structure of the street space in this SS theory are calculated using indices such as connectivity, betweenness, and proximity (Int.V). For example, Global (or Local) Int.V, calculated from the topological distance (or depth) between axes, represents the efficiency of movement on the network and is used to analyze the relationship with pedestrian volume and pedestrian flow (Aratani et al., 2005; Ueno and Kishimoto, 2008; Ito et al., 2021; Yıldırım and Celik, 2023).

As another indicator, Frank et al. (2005) proposed the walkability index as an index to evaluate the *walkability*[2] of urban street space. Specifically, the walkability index is calculated using z-values of geographic environmental variables (e.g., land use composition, household density, intersection density) quantified by GIS. As an example of application, existing studies have applied this index to the analysis of the impact of walking space development (Kanai et al., 2019) and the analysis of factors affecting walking (Kimura and Kanai, 2022). These indicators for evaluating spatial structure provide evidence of the factors that cause behavior to occur.

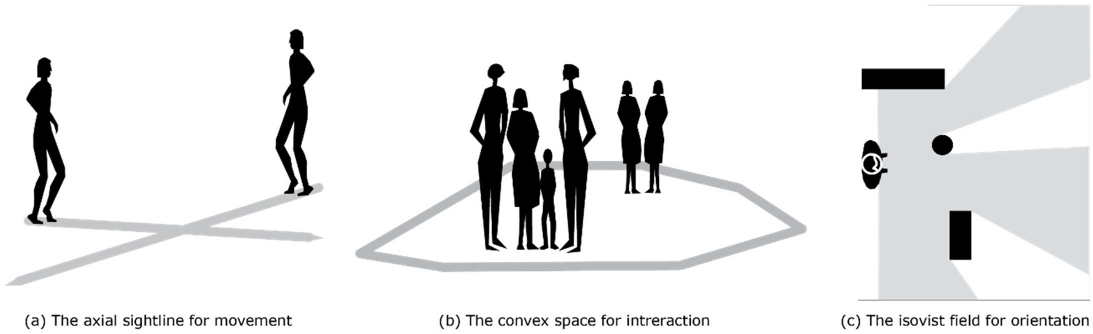

Figure 2. 1 The analysis unit of Space syntax (Yamu et al., 2021).

2.5. The position and challenges of the evaluation framework that we focus on in this dissertation

This chapter systematically organizes existing methods for measurement, modeling, and evaluation in urban street space design. In this dissertation, we focus on the consumer surplus in the evaluation of the use of urban street space, taking into account *Travel function* and *Place function*. Unlike other evaluation index, the consumer surplus is rational (i.e., consistent with microeconomic theory) and has been applied to the policy evaluation in the field of transportation (i.e., evaluation related to *Travel function*). Furthermore, it has the advantage of being able to be evaluated in a composite manner by incorporating various factors as explanatory variables in the model. One such evaluation framework using consumer surplus is the framework by proposed Chikaraishi et al. (2019), which is consistent with dynamic discrete choice model (in section 2.3.1). However, this model has limitations in that (1) it does not take into account the *Place*

[2] *Walkability* is a concept that encompasses all living environments that promote walking, and refers to the formation of good local communities, environmentally friendly lifestyles without the use of cars, and enabling a healthy lifestyle both physically and mentally (Kanai et al., 2019).

function (i.e., which only considers pedestrian crowding) and (2) it does not describe micro interactions (i.e., collision avoidance and leader follower) in detail. In this dissertation, we basically follow the framework of Chikaraishi et al. (2019), and we apply this framework to evaluate the use of urban street space shown in **Figure 2.2**.

However, there are some challenges in the requirements for measurement, modeling, and evaluation when considering this urban street space. In *public space,* we first have to model interactions between moving and staying, among staying (or moving) using dynamic discrete choice model in order to consider *Travel function* and *Place function*. In these interactions, *Place function* focuses only on the staying and *Travel function* focuses only on the moving. Although some models develop frameworks to describe the micro interactions between attractions and pedestrians (Kwak et al., 2013; Wang et al., 2014) (i.e., models focus on the instantaneous utility), few models also consider the expected maximum utility of these interactions.

Second, a framework for describing collision avoidance with new modes (e.g., AVs, kickboards) has not been established using real data. In addition, although many models use the social force model to describe collision avoidance between pedestrians and vehicles (e.g., cars and bicycles), their interactions have not been described within the framework of the discrete choice pedestrian model proposed by Robin et al. (2009). The use of such a discrete choice pedestrian model framework important to facilitate the extension to model frameworks using RUM theory, allowing the calculation of consumer surplus from origin to destination. In *personal space*, many studies have established methods for observing pedestrian preferences for vehicles and for the structure of the urban street space, but not many have observed preferences at specific locations (moment) using location-specific preference surveys. Furthermore, in location-specific preference surveys, we need to analyze the effect of the time difference between when to complete the action and when to answer the question on the choice result because the user forgets the effect of the policy intervention as time passes.

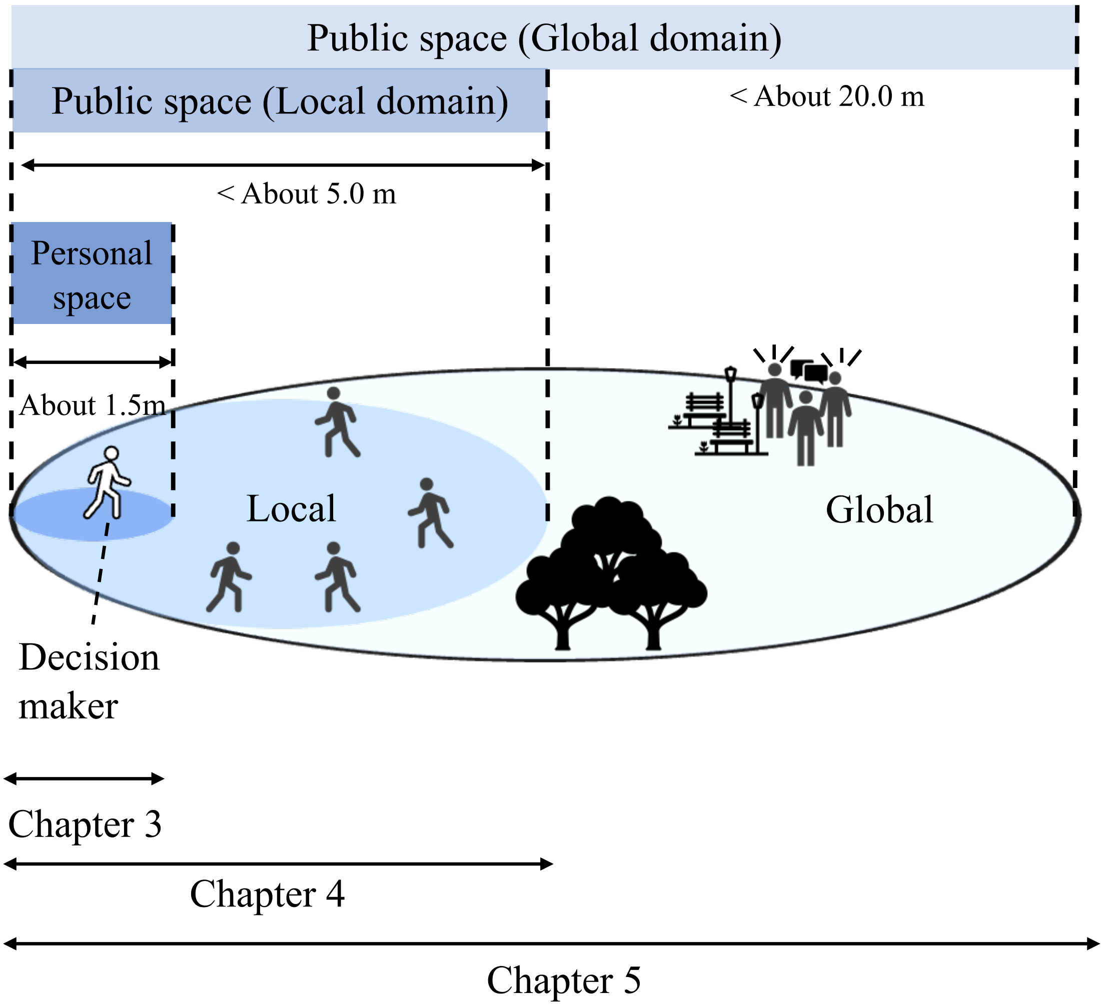

Figure 2. 2 Urban street space focused on this dissertation (same as Figure 1.2)

As discussed in detail in Chapter 1, Chapters 3 through 5 focus on the more detailed issues of the measurement, modeling, and evaluation methodologies. The following chapters describe the issues focused on in each chapter and the methodology used to analyze them.

In Chapter 3, we focus on the effect of memory on the observation of the user preference. In particular, we focus on the *personal space* shown in **Figure 2.2**. Specifically, we focus on the effect of the time difference between when to complete behaviors and when to answer a question (referred to *recall time*) on the choice results of the policy intervention. In this chapter, we use the location-specific preference survey integrated with the behavioral survey described in section 2.2.2 to observe user preferences for the congestion pricing scheme as a measure at the zone level of urban areas, although it is not a measure targeting urban street space. At the same time, we observe the *recall time* from the completion of the behavioral survey to the completion of the preference survey. The relationship between effect of the recall time on the choice results is analyzed.

In Chapter 4, we focus on empirical analysis of pedestrian behavior around AVs from a modeling perspective. In particular, we consider micro interactions around the pedestrian, i.e., the *local domain* of the *public space* shown in **Figure 2.2**. Specifically, we use video cameras and object detection and tracking (section 2.2.1) to generate pedestrian and vehicle behavior data. In this chapter, we use the discrete-choice pedestrian model described in section 2.3.2 to describe the decision-making process of pedestrians (e.g., factors that cause them to avoid collisions), and thus micro interactions between pedestrians and vehicles (AVs and CVs). However, compared to the model proposed in Chapter 5, this chapter applies the discrete choice pedestrian model because (1) it is superior in describing myopic behavior in detail, and (2) there is a large body of empirical data for model estimation. Note that this model cannot calculate the evaluation of the use of urban street space using the consumer surplus.

In Chapter 5, we focus on the *global domain* of *public space* shown in **Figure 2.2**. Specifically, using the dynamic discrete choice model described in section 2.3.1, we construct a pedestrian model that comprehensively describes moving and staying, while taking into account micro interactions between moving (or staying) and between moving and staying (e.g., collision avoidance and leader-following). Furthermore, using the proposed model, we perform numerical simulations assuming an urban street space where there is interaction between moving and staying. Through this simulation, the differences in pedestrian (i.e., travelers and sojourners) use of the urban street space are precisely evaluated based on the consumer surplus described in section 2.4.1, taking into account the interaction between moving and staying.

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Chapter 3: Analysis of the Effect of Recall Time on Preference Survey Choice Result

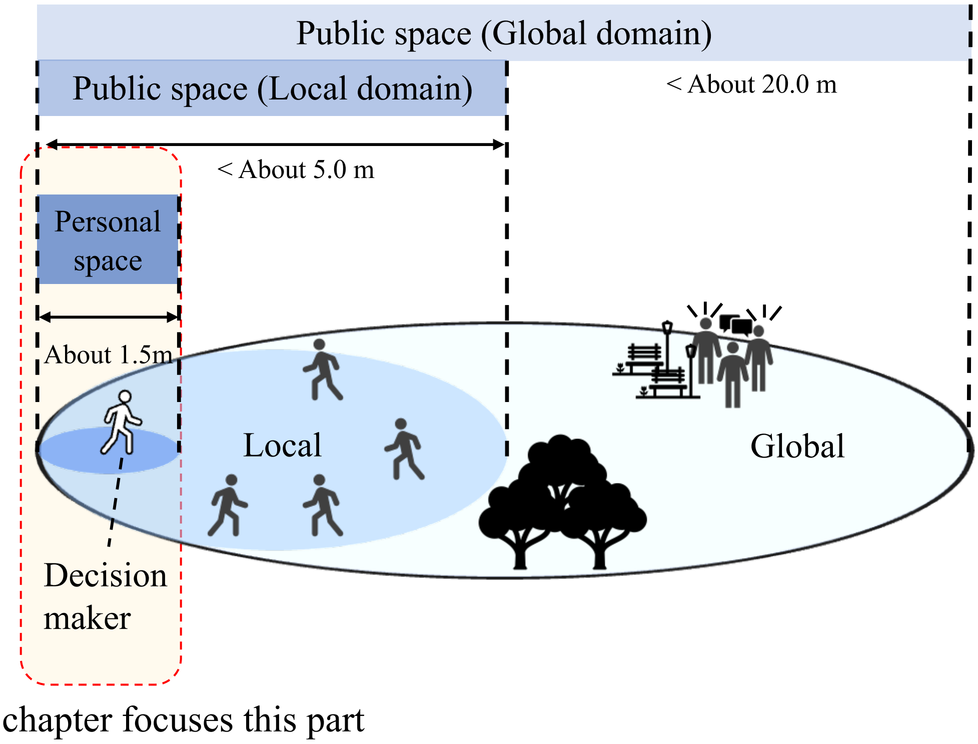

Figure 3. 1 Area of urban street space focused on in this chapter (red dashed line)

3.1. Introduction

This chapter focuses on the observation of user perception in *personal space* in the urban street space, as shown in **Figure 3.1**. To observe user perception, we pay particular attention to location-specific preference surveys. This survey method generates preference survey attribute levels based on behavioral factors. Various methods have been used in existing studies (Lee-Gosselin, 1996; Rose et al., 2008; Train and Wilson, 2008; Sadakane et al., 2010; Danaf et al., 2019; Feneri et al., 2021; Safira et al., 2022). In these approaches, users are asked to respond based on the actual behavioral context of the user. The advantage of these surveys is that they can accurately capture preferences because they can take into account various contextual factors such as user behavioral constraints (Feneri et al., 2021). The development of preference surveys using the Web and smartphones has made it possible to easily incorporate behavioral factors into preference surveys and to immediately observe user preferences as they complete their actions within the policy intervention area. In the context of urban street space, it is possible to observe user preferences for location-specific measures such as the installation of benches and tree planting.

In the above survey method, the accuracy of the observation depends greatly on the accuracy of the user memory of past behaviors. An index to measure the accuracy of memory recall of past behaviors is the time difference between when to complete behavior and when to answer a question (referred to as "*recall time*" in this dissertation). In other words, the longer the *recall time*, the more difficult it is for users to accurately recall the context of the behavior. As will be briefly discussed in the next section, there are many studies on designing preference surveys based on behavioral data, some of which focused on the *time interval* between repeating preference surveys (Kitamura et al., 2001) or the *response time* of preference surveys (Haaijer et al., 2000; Rose and Black, 2006). However, to the best of our knowledge, there are no studies that address how *recall time* affects responses in preference surveys.

The purpose of this study is to quantitatively analyze the effect of *recall time* in location-specific preference surveys on the choice results of preference surveys. In addition, we utilize a location-specific preference survey, and in our case which can immediately reflect the results of actions in the preference survey (Puspitasari et al., 2021). In this survey, users are asked about the following six behavioral changes in response to a hypothetically introduced congestion pricing: (1) keep the present trip under a road pricing scheme; (2) cancel the trip; (3) change the time of day; (4) change the destination; (5) change the travel mode; and (6) change the route. The first and sixth alternatives have little effect on the activity-travel schedule after the trip, while the other options may affect the decision-making for the rest of the day's trips. Specifically, "cancel the trip" and "change the destination" could affect the destination of the next trip due to a significant change in plans at the time of departure; "change the travel mode" from car to public transit may make it difficult to reach some of the destinations where public transit services are not available; and "change the time of the day" could potentially force them to cancel some of the trips they had planned to do after the current one.

In summary, some of the alternatives in this study involve substantial schedule changes (i.e., high scheduling costs) for users, while others would not. Such scheduling costs (e.g., behavioral context) are easy to recall in the preference survey immediately after a trip, but users may have difficulty recalling the behavioral context after some time has passed. Thanks to the diffusion of smartphones, now we can easily ask the users to answer the preference answer immediately after the trip using a push notification function (the details are explained in section 3.3).

In order to investigate the direct and indirect effects of the *recall time* on the choice results, the following three hypotheses are formulated in this chapter. **Figure 3.2** shows a schematic diagram of the hypotheses.

H1. The greater the *recall time*, the greater the systematic bias in the choice result.

H2. The greater the *recall time*, the more difficult it becomes for the users to recall the memory of behavior context in answering preference questions, i.e., the *recall time* acts as a moderator variable that reduces the effects of the behavioral attributes on the choice result.

H3. The greater the *recall time* the more hypothetical (and the less real) the choice context becomes, resulting in a more dominant influence of the preference attributes on the choice result, i.e., the *recall time* acts as a moderator variable that increases the effects of the preference attributes on the choice result.

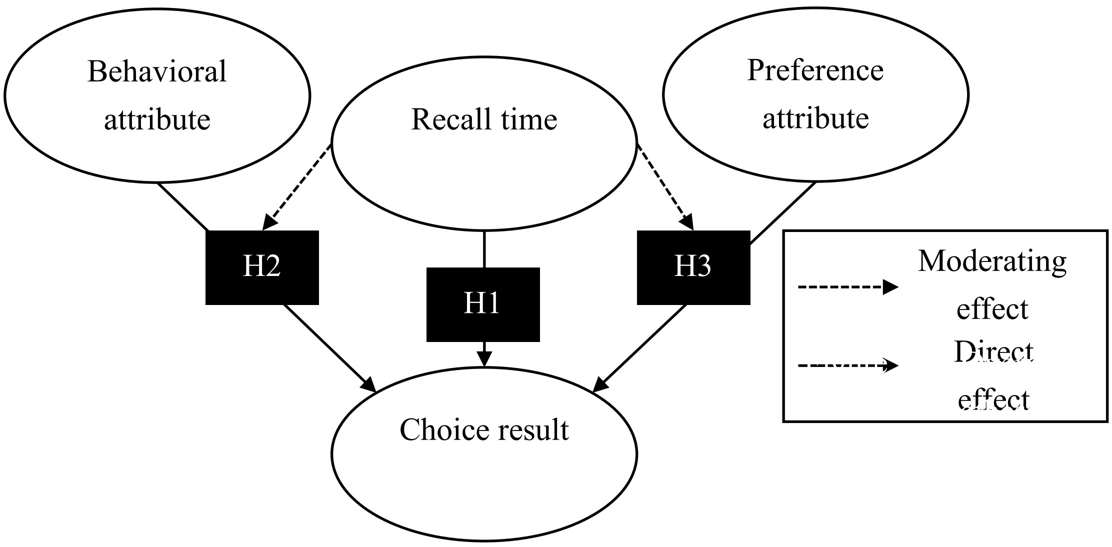

Figure 3. 3 Overview of three hypothesis

For the first hypothesis, we test the possibility of systematic bias in choice result attributed to the *recall time*. Reasons for systematic biases could be (1) social desirability bias, (2) not being context aware, and/or (3) lack of real penalties/gains from the choice. Although we could not identify the reasons, we test for the null hypothesis where the added *recall time* variables do not affect the choice.

Regarding the second and third hypotheses, we test the hypothesis that the relative effects of behavior and preference attributes on the choice gets weaker (or stronger) as the *recall time* increases (or decreases), i.e., by evaluating the effect of the *recall time* as a moderator variable. Essentially, we investigate whether longer *recall time* led users to rely predominantly on preference attributes while disregarding the effects of the behavior context.

In this study, although it is not possible to obtain data from surveys of pedestrian behavior in the context of urban street space, observing the effect of a policy intervention at a specific location (i.e., the zone in this study) is equivalent to observing pedestrians' perceptions of nearby vehicles and objects at a specific point (time) in the urban street space. However, in the case of the urban street space, it is necessary to analyze the differences in the effects of *recall time* over a shorter range because the target behavior is shorter in the urban street space.

The structure of this research is as follows. Section 3.2 provides a literature review, while section 3.3 describes data utilized. The results of the basic analysis are presented in section 3.4. Section 3.5 describes the model used in the estimation. Section 3.6 presents the estimation results using data, and section 3.7 concludes this chapter by discussing key findings, contributions, and directions for future research.

3.2. Literature review

3.2.1. Studies on preference survey based on behavior factors

In order to make alternatives more realistic (i.e., more behavior-based), many preference survey methods utilizing behavioral data have been proposed. One of them is the "*pivoting preference survey*" (Hensher, 2008; Rose et. al., 2008). In this method, the attribute levels of the preference survey are set by increasing or decreasing the attribute levels of the users obtained in the behavioral survey. However, in the pivoting preference survey, the behavioral factors are only used to make the attribute levels in the preference survey realistic and are not designed to consider the behavioral context. For example, in the case of "*moving quickly to attend an important meeting*", the placement of a bench is likely to be an obstacle. Ignoring such behavioral contexts has been observed to introduce biases in choice results, for example, overestimating preferences for new modes of transportation (Huynh, N.A et. al., 2017-a, b).

The location-specific preference surveys have been proposed as another way to combine the behavioral survey and the preference survey (Danaf et. al., 2019; Feneri et.

al., 2021; Safira et. al., 2022). This location-specific preference survey is designed to reflect the actual behavioral context and experience of the users, allowing for preference survey responses based on the behavioral context. Similarly, the survey method proposed by Train and Wilson (2008) also aims to observe users' preferences in terms of behavioral context. However, in the location-specific preference survey, the larger the time difference between when the behavior is completed and when the survey is completed (i.e., *recall time*), the more difficult it becomes for users to accurately recall the behavioral context. Therefore, when the *recall time* becomes large, location-specific preference surveys cannot observe responses that fully account for the influence of the action context. We have developed a survey method that can observe *recall time* and reflects the behavioral context in real-time (Puspitasari et. al., 2021). In this location-specific preference survey, users can answer the preference survey immediately while utilizing behavioral information. However, to the author's knowledge, there are no existing studies that focus on "*recall time*" in preference surveys. As mentioned above, many studies have been conducted on "*time*", which is different from "*recall time*". For example, some studies focus on the "*time interval*" when repeating the preference survey (Kitamura et. al., 2001) and the "*response time*" of the preference survey (Haaijer et. al. 2000; Rose and Black, 2006).

3.2.2. Studies on analysis of the effect of response time on choice results

Several studies have analyzed the effect of response time on choice in preference surveys. For example, research on paper-based preference surveys has shown that when users were provided with self-reported reflection time, (i.e., time to reconsider whether their answers were correct or not) their preference for new goods decreased (Cook et. al., 2012). On the other hand, in web-based preference surveys, it was observed that an increase in response time increased the preference for new goods (Börger, 2016). Furthermore, in the preference survey, a longer response time was observed to decrease the variance of error terms and the variance of randomly distributed taste parameters in a mixed logit model (Haaijer et. al., 2000; Rose and Black, 2006). However, another study found contrary evidence and observed that response time increased error variance (Bech et. al., 2006).

It should be noted that the response time discussed in the above studies is different from the *recall time* treated in this study. Specifically, two different mechanisms can be considered for the time difference between the behavior and preference surveys: (1) "*Memory effect*" (also called *recall time* effects in this study), where a larger timing gap makes it more challenging for the users to accurately recall the behavioral context, and (2) "*Time to think effect*", where more time spent contemplating the choice task may lead to more precise preference answers. While the latter effects cannot be disregarded for complex choice tasks (such as selecting different environmental policy options affecting individual and collective welfare), we assume that the former effects dominate in the context of behavioral adaptations to a hypothetical congestion pricing scheme. This is because the survey primarily focuses on individual preferences and in principle, do not directly involve others' preferences. Additionally, the time-to-think effects are expected to manifest within a relatively short time gap (e.g., whether the users take an additional 5 minutes to think), while the memory effects are expected to arise with longer time gaps (e.g., whether the users answer preference questions today or the following day). This study mainly focuses on relatively longer time gaps that would allow us to consider the influence of time gap as memory or *recall time* effects. Similarly, in the context of urban street space, the time to think effect is relatively small, and the memory effect is considered to account for the majority of the time difference.

3.3. Data collection method

A location-specific preference survey was conducted in Kumamoto and Hiroshima metropolitan areas during January and February 2020. The survey included 150 people selected from both cities who regularly pass through or visit the city center by car. Each user was requested to install a mobile phone application on their device, which recorded their behavioral histories, including travel times, for all trips made over the subsequent two weeks. The users were asked to fill in a behavior survey before each trip to record their travel mode and purpose. During each trip, the users received a push notification to answer the preference question immediately, if he or she met the following three conditions: a) using a car, b) passing through the congestion charging area, departed from the area, or arrived at the area (**Figure 3.3**), and c) traveling during a specific time of day (from 6:00 to 19:00). This push notification allows users to answer the question in real-time. The preference survey recorded two distinct time points: the moment the participant pressed the button upon concluding the trip and the time when the preference response was successfully submitted. In this study, "*recall time*" is defined as the time interval between these two recorded instances.

In the preference survey, participants were presented with a hypothetical scenario involving the payment of a congestion charge to enter and move around the city center.

They were then asked to answer questions on behavioral changes. The preference survey displayed various combinations of attributes to the users on their smartphone screens, as shown in **Figure 3.4**. The survey included four preference attributes: 1) travel time reduction, 2) basic pricing level, 3) pricing level during off-peak hours, and 4) start time of off-peak hours. Based on the above-mentioned attributes, the travel time reduction and the congestion charge were calculated using formulas in **Table 3.1**. Two different plans were utilized to compare user preferences for different pricing schemes. In plan 1, the congestion charge was set randomly, while in plan 2, the congestion charge was calculated based on travel time in the congestion charging area (see **Table 3.1**). The users were divided into two user groups, and both congestion pricing schemes were implemented for each group during different time periods of the survey, as shown in **Figure 3.5.** The survey included six alternative options for behavioral change: 1) keep the present trip under congestion pricing scheme, 2) cancel the trip, 3) change the time of day, 4) change the destination, 5) change the travel mode, and 6) change the route.

Figure 3.3 shows an example of a preference choice scenario presented to the user in Hiroshima (translated from Japanese to English in the figure) after completing their trip. The question is presented to them via a push notification once their trip is completed. In this particular example, the congestion charge was set at 500 JPY, travel time reduction would be 6 min (30 min of total travel time), and they made the trip between 09:00- 16:00. The users were then asked to choose from the six alternatives mentioned above.

After data cleaning, 1,846 preference responses were used in the following analysis. Since the number of users was 150, each user answered preference questions 12.3 times on average, where the minimum is one time, and the maximum is 46 times. The missing rate of preference question is 1.96%, which is quite low, thanks to the incentive provided. Note that, in some cases, the users answered preference questions for trips on the way to the office and on the way back from the office. In this case, these two behavioral adaptations should be consistent: for example, if they choose a car on the way to the office, a different travel mode should not be chosen on the way back. Checking this inconsistency can be a useful index to check the quality of the data, but we could not implement it, since attribute levels shown to the users were different between these two choice contexts, making it difficult to judge the inconsistency just by comparing the choice results. In the future, to confirm the consistency of their preference answer, it would be worth setting the attribute level for each trip chain, instead of for each trip.

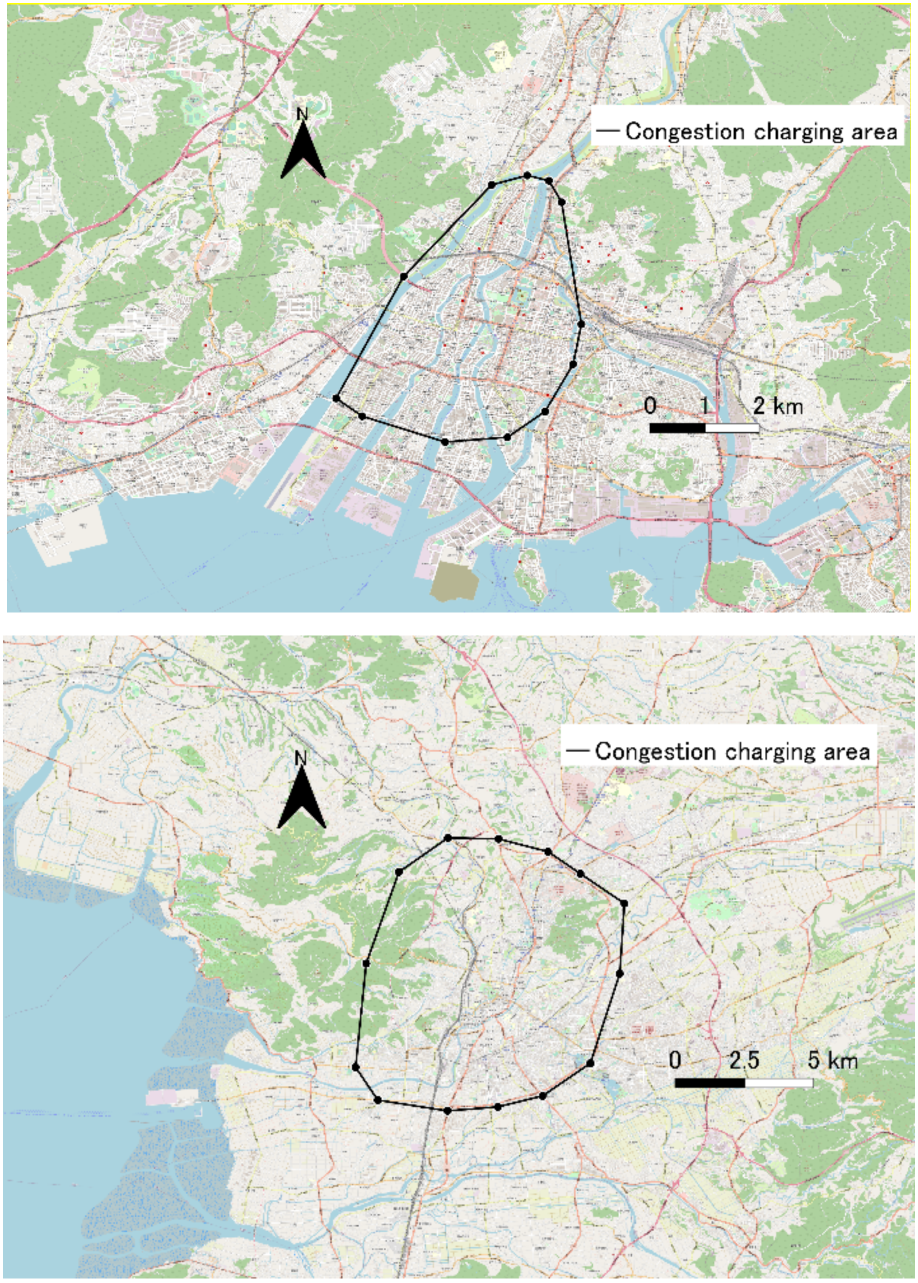

Figure 3. 4 The metropolitan areas of Hiroshima (top) and Kumamoto (bottom)

Table 3. 1 Attribute settings in the preference survey

	Plan1	Plan2
Travel time reduction	$\boxed{z \times x}$(minute)	$\boxed{z \times x}$(minute)

Congestion charge	1. [6:00 – t] $\boxed{y}$ (JPY) 2. [t – 16:00] $\boxed{y \times m}$ (JPY) 3. [16:00 – 19:00] $\boxed{y}$(JPY) 4. others $\boxed{0}$ (JPY)	1. [6:00 – t] $\boxed{z/30 \times y}$(JPY) 2. [t – 16:00] $\boxed{z/30 \times y \times m}$(JPY) 3. [16:00 – 19:00] $\boxed{z/30 \times y}$(JPY) 4. others $\boxed{0}$ (JPY)

z: Travel time in the pricing area

y: Preference attribute representing the basic pricing level. {50, 100, 250, 500, 1000}

m: Preference attribute representing the price level during off-peak. {0.3, 0.4, 0.5}

t: Preference attribute representing start time of off-peak. {9:00, 10:00, 11:00}

x: Preference attribute representing travel time reduction. {0.1, 0.2, 0.3, 0.4}

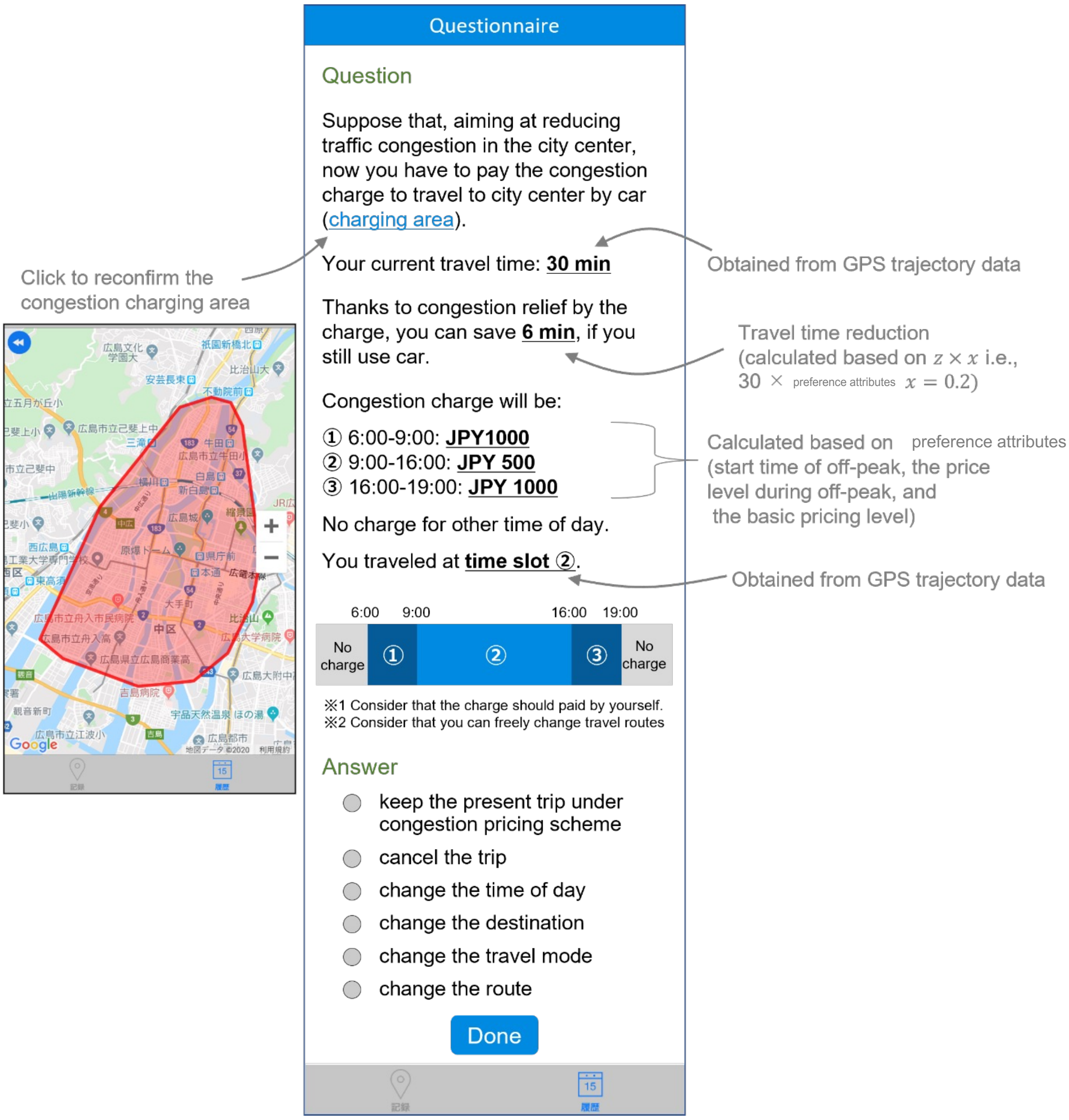

Figure 3. 5 Screen of preference survey (translated from Japanese to English)

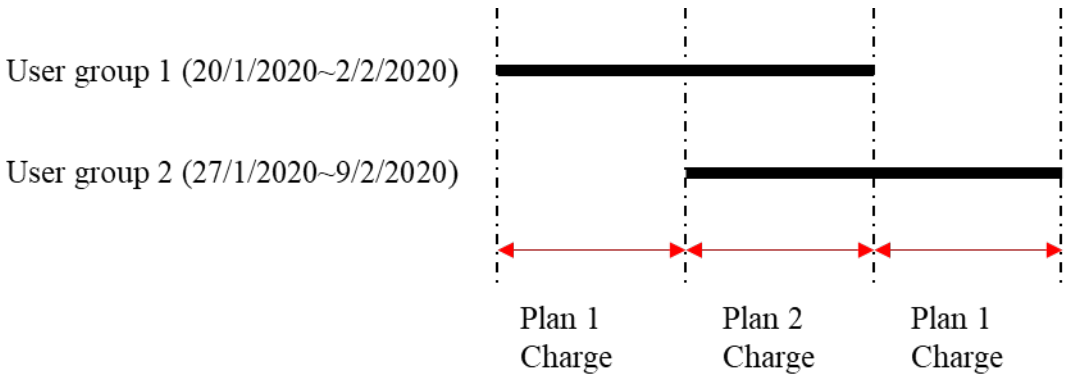

Figure 3. 6 Preference survey implementation time period for different congestion pricing plans

3.4. Basic analysis

Table 3.2 presents the distribution of preference responses, which can be categorized into unchanged and changed options. In one-third of preference scenarios, users chose "unchanged", indicating their intention to continue the current trip and pay the congestion charge. Meanwhile, in the remaining two-thirds of preference scenarios, users chose "changed", which included five different behavioral changes. These results indicate that the congestion pricing scheme has a non-negligible impact on travel behavior. Among the travelers who opted to change their behavior, a relatively small number of people chose "cancel the trip" (2nd alternative) and "change the destination" (4th alternative). This could be attributed to the challenges involved in cancelling or altering plans for commuting and business trips, as they would require significant adjustments to schedules. Conversely, users who chose "change the route" (6th alternative) were the largest, which implies that travelers tend to keep the original departure time, destination, and travel mode, but change their route to avoid the congestion charge. **Figure 3.6** shows the relationship between preference choices and trip purpose. Users with duty purpose (business trips) showed the highest percentage (42.4%) for the 1st alternative, i.e., "no behavior change and pay the congestion charge". Meanwhile, users traveling for commute purpose have the lowest percentage of selecting the 1st alternative (30.8%). This suggests that for business travelers, it is more difficult to change their travel behavior patterns (routes and travel modes) and they prefer to pay the congestion charge instead. On the other hand, commuters avoid the charge by changing their travel behavior more often as compared to other travel purposes. **Figure 3.7** shows the relationship between preference choices and the levels of congestion charge. It was observed that as the congestion charge increased, the percentage of users choosing to pay the charge and continuing with their current behavior (i.e., "no behavior change and pay the congestion charge") decreased. Additionally, when the congestion charge level was less than 100 JPY, the percentage of people who chose to pay the charge was extremely high (50.6%). **Figure 3.8** demonstrates the relationship between preference choices and *recall time*. It was observed that a *recall time* corresponded to a higher percentage of users choosing the 1st alternative ("no behavior change and pay the congestion charge"). This suggests that a longer *recall time* may diminish the effect of the congestion charge, indicating the presence of potential systematic bias in choice result.

Table 3. 2 Distribution of choice result

	Alternative	Total	
Unchanged	1 Keep the present trip under congestion pricing scheme	635 (34.4%)	
Changed	2 Cancel the trip	43 (2.3%)	1211 (65.6%)
	3 Change the time of day	150 (8.1%)	
	4 Change the destination	51 (2.8%)	
	5 Change the travel mode	144 (7.8%)	
	6 Change the route	823 (44.6%)	
	Total	1846 (100%)	

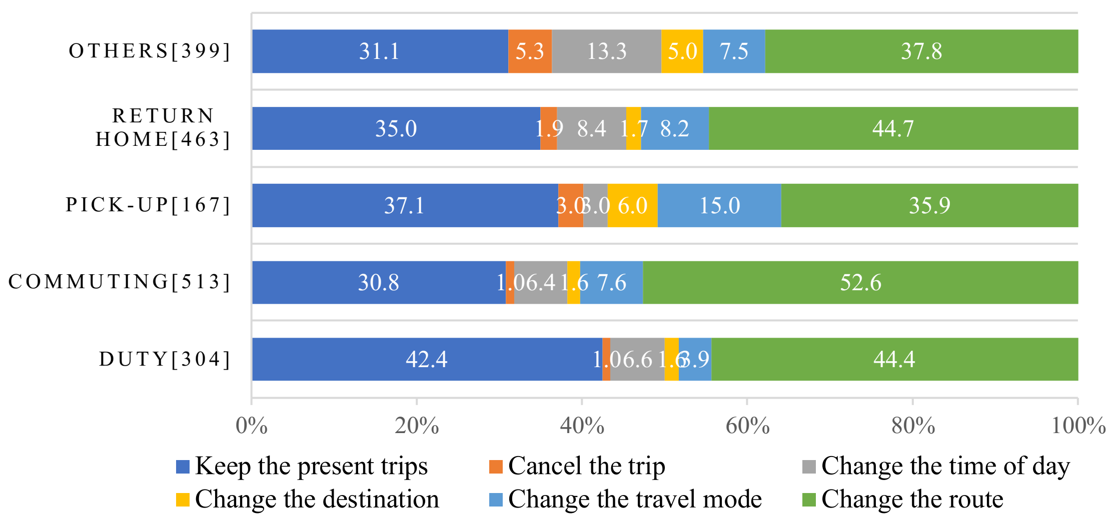

Figure 3. 7 Relationship between choices and trip purpose [sample size]

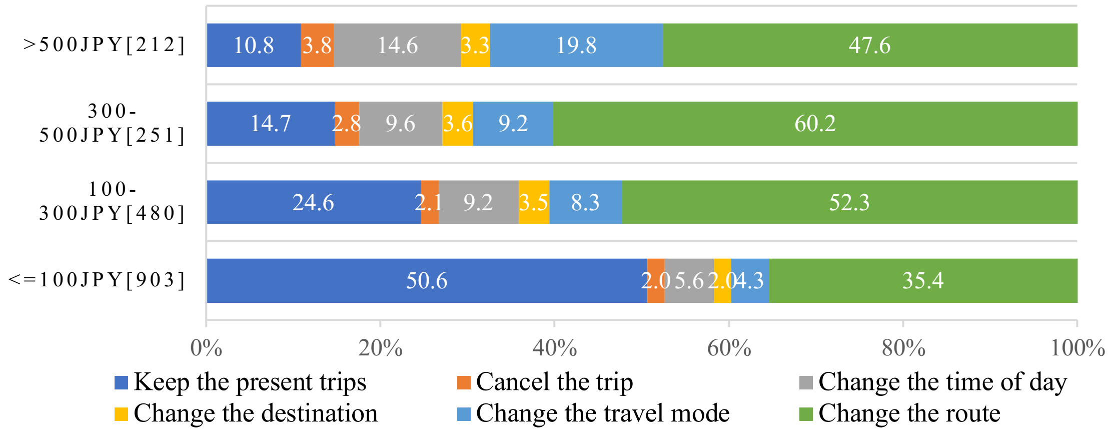

Figure 3. 8 Relationship between choices and congestion charge [sample size]

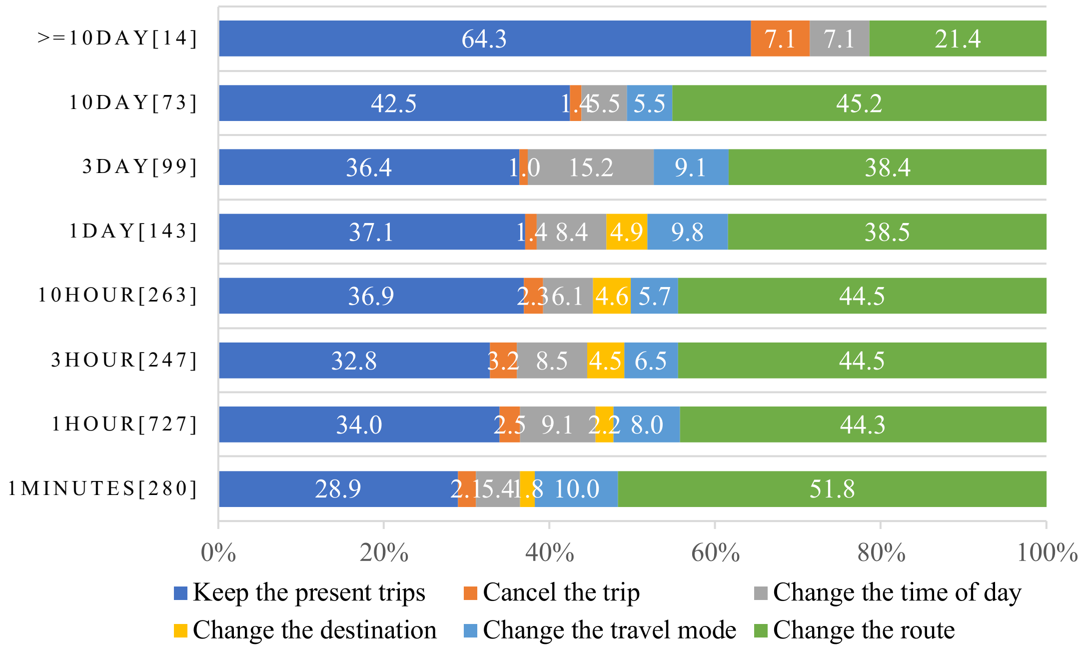

Figure 3. 9 Relationship between choices and recall time [sample size]

3.5. Model framework

To test the three hypotheses mentioned in section 3.1, we utilize the data from the real-time location-specific preference survey to model behavioral changes resulting from the introduction of a congestion pricing scheme. Although the survey presented six adaptation options to the users, for the purpose of modeling the behavioral change, we merged them into three alternatives based on the cost of scheduling adjustment: (1) “no behavioral change”, which is used as a base alternative, (2) “change the route”, and (3) “other behavior change”, which includes options 2-5 (cancel the trip, change the time of day, change the destination and change the travel mode). The 3rd alternative entails a higher schedule adjustment cost, while the 2nd alternative (change the route) incurs a relatively lower schedule adjustment cost. Since the location-specific preference survey involves multiple trips made by the same users, it results in multiple preference answers from each user. This would cause correlations across answers from the same user. To account for this correlation, we employ a panel mixed logit model (MXL model). We compare the estimation results of the MXL model with that of a multinominal logit model (MNL model). Note that, instead of merging alternatives into three as mentioned above, we could also remove the 2nd and 4th alternatives from the analysis since these alternatives were chosen only by less than 3% of the users. However, we decided not to do that, since removing those options from the choice set may underestimate the number of users who choose options that involve the higher cost of scheduling adjustment.

3.5.1. MNL model

In the formulation of the MNL model with *recall time* effects, the random utility function is defined as:

$$U_{ikj} \ = \ V_{ikj} + \varepsilon_{ikj} \tag{3.1}$$

where V_{ikj} represents the deterministic part of the utility function for individual i’s k-th choice scenario (for k -th trip) of alternative j, and ε_{ikj} is an error term following the standard Gumbel distribution. It is worth noting that in the location-specific survey, the error term (unobserved factor) would contain unobserved behavior contextual information. Furthermore, the effect of such behavior elements is expected to decrease as the *recall time* increases due to the memory gap. To account for this, we formulate the systematic utility function V_{ikj} as follows:

$$V_{ikj} = \theta_{ik}^{HP} \ \beta_j^{HP} x_{ikj}^{HP} + \theta_{ik}^{BH} \beta_j^{BH} x_{ikj}^{BH} + \beta_j^{At} x_i^{At} + \gamma_j \ ln(L_{ik}) + \beta_j^{const} \tag{3.2}$$

where x_{ijk}^{HP} and x_{ijk}^{BH} are vectors of explanatory variables obtained from the preference and behavior surveys, respectively. L_{ik} is the *recall time* in minutes for individual i during the choice context k, and β_j^{HP} and β_j^{BH} are vectors of coefficient parameters for the preference and behavioral variables, respectively. X_i^{At} is a vector of explanatory variables representing individual attributes, while β_j^{At} is a vector of coefficient parameters for X_i^{At}. β_j^{const} is a constant term for each alternative, and γ_j is the parameter coefficient for the *recall time*. In this research, we introduce the scale parameters θ_{ik}^{HP} and θ_{ik}^{BH} to quantify the influence of the *recall time* on the effects of preference and behavioral attributes. The scale parameters θ_{ik}^{HP} and θ_{ik}^{BH} are expressed as follows:

$$\theta_{ik}^{HP} = \exp\left(\alpha^{HP} \ln(L_{ik})\right) \tag{3.3}$$
$$\theta_{ik}^{BH} = \exp\left(\alpha^{BH} \ln(L_{ik})\right) \tag{3.4}$$

where, α^{HP} and α^{BH} are unknown parameters to be estimated, which capture the effect of *recall time* on the scale parameters θ_{ik}^{HP} and θ_{ik}^{BH}. Overall, by directly including the *recall time* as an explanatory variable and introducing scale parameters for preference and behavioral attributes as functions of the *recall time*, we aim to confirm the presence of systematic bias due to the *recall time* (hypothesis 1) and quantify the influence of the *recall time* on the effects of preference and behavioral attributes on the choice results (hypotheses 2 and 3).

3.5.2. MXL model

In this research, we incorporate the unobserved inter-individual heterogeneity using a MXL model. The MXL model accounts for this heterogeneity through an additional error term η_{ij}. The random utility function is defined as:

$$U_{ikj} = V_{ikj} + \eta_{ij} + \varepsilon_{ikj} \tag{3.5}$$

where η_{ij} is an error term that varies across alternatives and individuals, following a normal distribution with a mean of 0 and standard deviation of σ_j. The MXL model uses the same idiosyncratic error term ε_{ikj} and equations for the systematic utility V_{ikj} as the MNL model.

3.6. Estimation result

The explanatory variables representing behavioral attributes (x_{ikj}^{BH}) and individual attributes (x_i^{At}) are shown in **Table 3.3**. Since the primary focus of this study was to examine the influence of *recall time* on choices and its moderation on the effects of behavioral and preference variables, only two dummy variables representing individual attributes were included in the models, specifically to test the impact of age and income (one dummy variable for each attribute). Meanwhile, reference attributes (x_{ikj}^{HP}) consist of the congestion charge (JPY) and time saving (min) variables, as explained in Section 3.3.

The estimation results are shown in **Table 3.4** for the MNL model and **Table 3.5** for the MXL model. Comparing the two models, the MXL model demonstrates improved performance with higher log final likelihood and adjusted ρ^2 values, indicating an improved model performance. This also suggests that the effect of unobserved heterogeneity among individuals is likely to be present.

The estimation results reveal two major findings. Firstly, as shown in **Table 3.4** and **Table 3.5**, the parameter representing the recall time (γ_j) is significant with a negative sign for alternatives 2-5 (cancel the trip, change the time of day, change the destination, and change the travel mode), as well as alternative 6 (change the route) in both the MNL and MXL models. This implies that the users are more likely to choose alternative 1 (no behavioral change) as *recall time* increases. This tendency suggests that the *recall time* introduces systematic bias in the preference data and diminishes the impact of the congestion pricing scheme on the user's choices. Secondly, the results of both models show that the estimated parameters α^{HP} and α^{BH} are positive and negative, respectively. Furthermore, α^{BH} is statistically significant for MNL model. This indicates that when the *recall time* is large, the preference attributes have a larger impact on the users' choices, while the behavioral attributes have smaller impacts. These estimation results support the three hypotheses presented in section 3.1 regarding the effect of *recall times*. However, it should be noted that the parameter α^{HP} was not statistically significant.

To visualize the effect of the *recall time* on the contribution of preference attributes, behavioral attributes, individual attributes, and the error term towards the total variance of utility differences, we employed the variance decomposition (Chikaraishi et. al., 2010) and represented it graphically. The variance decomposition serves as a valuable tool to elucidate the distinct influences and the contribution of various sets of explanatory variables on the total variance of utility difference between an alternative and the base alternative. In this study, we analyzed the change in the contribution of each attribute in response to a change in *recall time* using this method. **Figure 3.9** illustrates the results for MNL, where the vertical axis shows the proportion of variance attributed to preference attributes, behavioral attributes, individual attributes (At), and the error term, with the sum set to 100. The results for MXL, which also include the error term for individual heterogeneity (η_{ij}), are presented in **Figure 3.10**. It is worth noting that the error term (white noise) may include unobserved behavioral contextual factors, and thus we anticipate that its contribution will decrease as the *recall time* increases. It is worth noting that our formulation can capture changes in the relative contribution of the error term. Specifically, we can test whether, as the *recall time* increases, users tend to pay less attention to contextual factors that are mainly captured by the error term, resulting in the lower contribution of unobserved factors (see Appendix A). The horizontal axis of both figures represents the *recall time*, indicating the time elapsed between presenting the preference survey questions to the users and their actual response (1[minute], 1[hour], 3[hour], 1[day], 3[day], 10[day]).

With regard to the proportions of variances explained by different variables, both MNL and MXL models showed that behavioral attributes accounted for a relatively small proportion compared to preference attributes. As the *recall time* increased for all alternatives, the proportion of preference attributes increased, while the proportions of behavioral attributes, individual attributes, and error terms decreased. Based on the results, we observed that the proportion of the contribution of preference attributes in explaining the variance for the alternatives 2-5 (cancel the trip, change the time of day, change the destination, and change the travel mode) was larger than that for alternative 6 (change the route), so we could say that the proportion of preference attributes for the alternatives 2-5 was larger than that for alternative 6 where "pay the fee and perform the same action as the current one" is the base alternative. These findings suggest that users tend to consider behavioral context more when responding to preference questions with shorter *recall time*. Additionally, the contribution of the unobserved variables, which might include other unobserved behavioral contextual factors, also tend to decrease with an increase in the value of *recall time*. These findings highlight the importance of real-time responses in encouraging users to consider the behavioral context effectively. Finally, it was observed that the effect of the idiosyncratic error term representing unobserved inter-individual heterogeneity is higher than the effect of unobserved inter-trip heterogeneity.

Note that the behavioral attribute may act as a covariate that influences both the *recall time* and the choice result, which can introduce potential bias in the estimation results (Hoshino, 2009). To address this issue and ensure the robustness of our findings, we conducted additional estimation considering the impact of behavioral contextual covariates using propensity scores. The method and estimation results can be found in Appendix B. Overall, the results suggest that although there are some differences in the estimated parameters, the effect of *recall time* on the choice outcome and the signs of the parameters α^{HP} and α^{BH} are consistent with the results obtained without considering the propensity score.

In summary, our findings highlight that when the *recall time* is large, the preference attributes have a larger impact on the users' choices, while the behavioral attributes have smaller impacts as shown in **Tables 3.4** and **3.5**. Simultaneously, **Figures 3.9** and **3.10** show that as the *recall time* increased for all alternatives, the proportion of contribution of preference attributes increased, while the proportions of behavioral attributes decreased, supporting the hypotheses stated in the Introduction.

Table 3. 3 Behavioral attribute and individual attribute

Variable name	Type of Variable	Variable description
Age	Individual attribute	1: ≤ 35 years old 0: > 35 years old
Income	Individual attribute	1: $\geq$ 10 million JPY/year 0: $<$ 10 million JPY/year
Arrival time to destination	Behavior attribute	1: between 6 am - 9 am 0: otherwise
Commuting	Behavior attribute	1: if trip purpose is commuting 0: otherwise
Duty	Behavior attribute	1: if trip purpose is duty 0: otherwise
Pick-up	Behavior attribute	1: if trip purpose is pick-up or drop-off 0: others

Table 3. 4 Estimation result (MNL)

Choice	Change the route		Other behavior change	
	Estimation	**t value**	**Estimation**	**t value**
Constant	-1.34×10^{-1}	-0.85	-6.55×10^{-1}	-3.72**

Congestion Charge (JPY)	2.89×10^{-3}	4.22**	3.07×10^{-3}	4.34**
Time saving (min)	-2.07×10^{-2}	-3.39**	-2.79×10^{-2}	-3.01**
Commuting	9.59×10^{-1}	3.10**	-2.77×10^{-1}	-0.833
Duty	-2.44×10^{-1}	-1.03	-1.36	-3.63**
Pick-up	-1.88×10^{-1}	-0.562	-7.82×10^{-2}	-0.229
Arrival time to destination	-5.50×10^{-1}	-2.04+	-2.55×10^{-1}	-0.827
Age	4.90×10^{-1}	3.91**	4.72×10^{-1}	3.16**
Income	-4.92×10^{-1}	-2.71**	-2.00×10^{-1}	-0.971
γ	-7.41×10^{-2}	-2.92**	-8.04×10^{-2}	-2.77**
α^{HP}	4.11×10^{-2} (0.949)			
α^{BH}	-1.34×10^{-1} (-2.68**)			
Initial likelihood	-2028.038			
Final likelihood	-1796.161			
Number of observations	1846			
Adjusted ρ^2	0.1035			

Note: "Other behavior change" include cancel the trip, change the time of day, change the destination and change the travel mode. Significance levels: '**' 1%, '*' 5%, '+' 10%. "Pay the fee and perform the same action as the current one" was the base alternative.

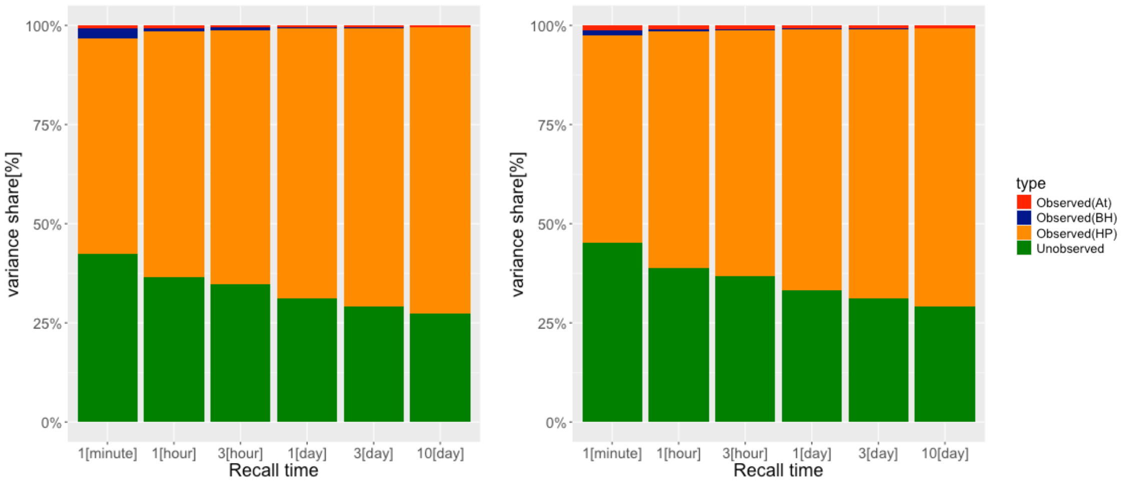

Figure 3. 10 Variance decomposition in the MNL model: route choice (left) and other behavioral changes (right)

Table 3. 5 Estimation result (MXL)

Choice	Change the route		Other behavior change	
	Estimation	t value	Estimation	t value
Constant	-5.33×10^{-1}	-1.09	-8.52×10^{-1}	-2.13*
Congestion Charge (JPY)	4.21×10^{-3}	4.40**	4.28×10^{-3}	4.38**
Time saving (min)	-3.57×10^{-2}	-2.86**	-3.45×10^{-2}	-2.43*
Commuting	3.86×10^{-1}	0.672	-8.55×10^{-1}	-1.85+
Duty	-3.59×10^{-1}	-0.640	-1.87	-2.97**
Pick-up	6.01×10^{-2}	0.077	-1.93×10^{-1}	-0.353
Arrival time to destination	-3.54×10^{-1}	-0.812	-1.40×10^{-1}	-0.326
Age	6.75×10^{-1}	1.05	4.94×10^{-1}	0.885
Income	-1.25	-2.37*	-1.14	-2.39*
γ	-7.00×10^{-2}	-1.81 +	-1.44×10^{-1}	-3.08**
σ	2.92	9.83**	2.29	10.4**
α^{HP}	5.28×10^{-2} (1.51)			
α^{BH}	-1.24×10^{-1} (-1.21)			
Initial likelihood	-2028.038			
Final likelihood	-1329.283			

Number of observations (Users)	1846 (150)
Adjusted ρ^2	0.3327

Note: "Other behavior change" include cancel the trip, change the time of day, change the destination and change the travel mode. Significance levels: '**' 1%, '*' 5%, '+' 10%. "Pay the fee and perform the same action as the current one" was the base alternative.

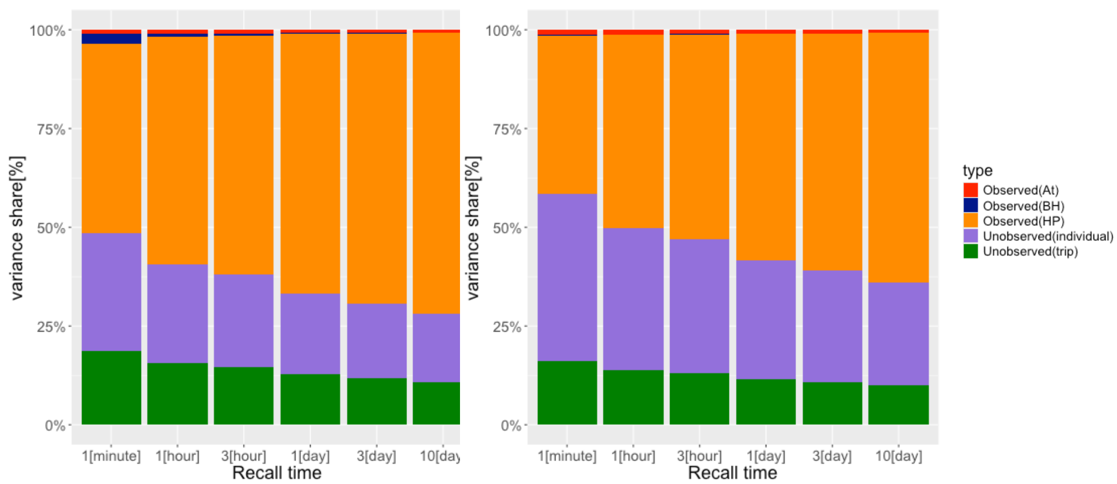

Figure 3. 11 Variance decomposition in the MXL model: route choice (left) and other behavioral changes (right)

3.7. Conclusion

In this study, we evaluated the effect of *recall time* on choice behavior using data from location-specific preference survey conducted in Kumamoto and Hiroshima metropolitan areas in January and February 2020. The findings of this research support the hypotheses formulated in Section 3.1. The key findings can be summarized as follows:

1. The discrete choice models show significant negative effect of *recall time* on choices of other alternatives (including cancel the trip, change the time of day, change the destination and change the travel mode) and route change, relative to paying the congestion charge. These findings support the first hypothesis, which suggests that a longer *recall time* leads to a larger systematic bias in the choice results.

2. The analysis of variance decomposition provided insights into the changes in the contribution of different attributes with varying *recall time*. The results support the second hypothesis, indicating that as the *recall time* increases, the effect of behavioral attributes on the choice result tends to decrease.
3. Finally, it was observed that as the *recall time* increases, the effect of preference attributes on the choice result tends to increase, supporting the third hypothesis.

Based on the results of this study, it can be said that as the *recall time* increases in the location-specific preference surveys, users place more importance on preference factors than on the behavioral context. This leads to a bias in the results of user responses and their influence on subsequent measures. For example, when *recall time* increases, it is suggested that users often choose not to change their behavior even for a high congestion pricing system. However, the decision-making process in congestion pricing schemes is likely to take place well before the start of the trip. This is especially true for regular daily commuter trips, where users can more carefully prepare for behavior change while taking congestion pricing into account.

The findings of this study are also very useful in the context of observing user perception of the urban street space. This is because (1) the use of the urban street space (e.g., pedestrian behavior) changes sequentially and (2) the decision-making process of users requires a short span (i.e., small spatial scale). Therefore, it is important to observe the pedestrian's perception at this point in time and space. In other words, a survey design that can provide real-time responses with a short *recall time* may be necessary in the pedestrian context.

The results of this study, which demonstrate the importance of *recall time* on the choice results of a preference survey, provide valuable suggestions for the development of preference survey applications. Such survey applications can be designed to encourage users to answer a question with a shorter *recall time* by (1) providing incentives to encourage a shorter *recall time*, and (2) imposing constraints on *recall time*. The first potential application of this location-specific preference survey is a commercial application that can integrate real-time preference questions into a smartphone-based travel diary survey. The development of such an application is extremely important to obtain more reliable preference data. A further potential application is the observation of user perception in response to policy interventions such as the installation of benches in urban street spaces or the planting of trees. Since this survey can be combined with preference and behavioral data, it would be possible to incorporate user perceptions of vehicles and objects into the pedestrian model discussed in the following chapters.

This study suggests several directions for future research. First, we analyzed the occurrence of systematic bias through the estimated parameters of *recall time*, but systematic bias should be analyzed by comparing actual and predicted choices. Next, an attempt should be made to estimate a model that takes the trip chain into account. This is because users may answer the preference survey questions collectively (after all the trips in the trip chain have been completed), and if the trip chain is complex, the *recall time* may be large. Another issue for future research is to simultaneously address the "memory effect" and the "time to think effect" discussed in section 3.2. In the case of urban street space design, users may be interested in more than one option (design). To account for response time, it is necessary to observe three different timings: (1) the time when the push notification is sent, (2) the time when the user starts to answer the question, and (3) the time when the user finishes answering the question.

3.8. References

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Chapter 4: Modeling Approach: Interactions between Autonomous Vehicles and Pedestrians Using Real Data

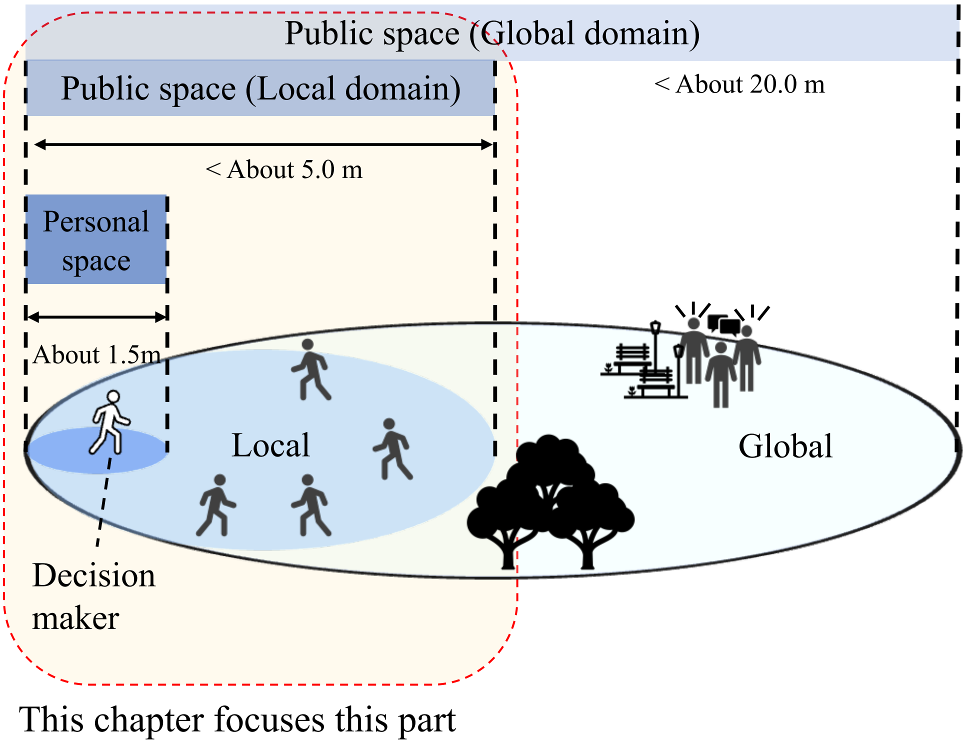

Figure 4. 1 Areas of urban street space focused on in this chapter (red dashed line)

4.1. Introduction

In Chapter 3, we focused on the observation of user perception in the *personal space* of the urban street space. In this chapter, we focus on *local domain* of *public space* and (**Figure 4.1**), and in particular on the local effect (i.e., micro interaction between pedestrian and vehicle) in a space where pedestrians and vehicles coexist. As Hans Monderman (2008) points out, in such a space where pedestrians and vehicles coexist, it is necessary to facilitate communication between pedestrians and drivers with minimal traffic rules and no traffic signals or signs. In other words, the design of pedestrian-vehicle coexistence spaces requires an understanding of what kind of micro interactions between vehicles and pedestrians will occur. With the introduction of new mobility devices such as Autonomous Vehicles (AVs) in recent years, the design of pedestrian-vehicle coexistence spaces is accelerating, so the analysis of micro interactions between new vehicles and pedestrians is considered to be very important.

We propose a pedestrian model to describe the interactions between pedestrians, AVs, and Conventional Vehicles (CVs) (e.g., motorcycles, bicycles, and cars) in order to analyze the differences in pedestrian behavior toward vehicles. In this chapter, we apply the model framework, proposed by Robin et al. (2009), because (1) it can describe micro interactions in continuous space, (2) the factors in the pedestrian decision process are clear, and (3) it can be extended to a model that calculates consumer surplus based on Random Utility Maximization (RUM) theory (i.e., since this model describes sequential pedestrian behavior, it is difficult to calculate consumer surplus from origin to destination, but the model framework itself can be extended to the model in Chapter 5). As a modeling challenge, the model put forward by Robin et al. (2009) model only describes pedestrian-pedestrian interactions (i.e., collision avoidance and leader follower) and needs to be extended to a model that describes interactions with vehicles (i.e., collision avoidance). Furthermore, collision avoidance frameworks constructed using other models, such as social force models (Anvari et al., 2015; Dias et al., 2018a and 2018b; Yang et al., 2020), need to be applied to this model framework to validate whether collision avoidance methods for cars can be used in the case of AVs. In order to address these challenges, we add the utility function regarding the collision avoidance with vehicles that includes four components: likelihood of collision, perception of vehicle behavior, risk at collision, and safety distance to collision. In this function, the pedestrian is assumed to make a decision regarding a collision with a vehicle, taking into account factors such as distance from the vehicle, relative speed with the vehicle, and the vehicle behavior (i.e., deceleration or acceleration). In addition, two types of likelihood of collision situations are considered. The first is a situation in which the pedestrian does not estimate the speed of the vehicle and judges whether or not a collision will occur based on his/her direction and the vehicle, and the second is a situation in which the pedestrian estimates the speed of the vehicle and judges whether or not a collision will occur based on the estimated future location of the vehicle and him/herself. We test the hypotheses about the four elements and confirm which elements are valid under the conditions observed in this chapter. We also analyze the differences in pedestrian behavior toward different vehicles.

To obtain data for model estimation, observations of pedestrian and vehicle behavior are conducted. Specifically, the trajectories of pedestrians and vehicles (i.e., AVs, cars, bicycles, and motorcycles) at pedestrian crossings are measured in conjunction with an AV driving experiment conducted at the Higashi-Hiroshima Campus of Hiroshima University.

The structure of this study is as follows. Section 4.2 provides a literature review of

(1) existing studies analyzing pedestrian reactions to AVs in virtual or real space, and (2) studies on pedestrian models for pedestrians and vehicles. Section 4.3 describes the observation and trajectory data generation methods. Section 4.4 provides an overview of the pedestrian models used in this study. Section 4.5 presents the basic analysis results using the trajectory data. Section 4.6 presents the estimation results using the observed data. Section 4.7 provides a summary of this study.

4.2. Literature review

4.2.1. Analysis of pedestrians' perceptions of AVs

Many studies have been conducted which analyze of pedestrian's reactions towards AVs using psychological and behavioral perspectives. These studies compromise of mainly two types of studies: (1) scenario-based studies and (2) empirical studies. The scenario-based studies mainly use preference surveys (Deb et al., 2017; Hulse et al., 2018; Hafeez et al., 2022) or Virtual Reality (VR) (Deb et al., 2018; Velasco et al., 2019; Jayaraman et al., 2019; Camara et al., 2021), or agent-based simulation (Gupha et al., 2019; Predhumeau et al., 2022; Trumpp et al., 2022; Rashid et al., 2024).

Studies using preference surveys have focused on pedestrian risk perception towards AVs. Deb et al. (2017) show that pedestrians tend to perceive AVs as safe, while they would take different behaviors toward AVs: (1) conservative (i.e., cooperative with other road users) and (2) aggressive (i.e., cross the road without paying attention). Hulse et al. (2018) also show that pedestrians perceive AVs as less risk than conventional vehicles, but females perceived higher risks compared to males.

Studies using VR have mainly focused on pedestrian crossing behavior in front of AVs in signalized or unsignalized area. Velasco et al. (2019) show that pedestrians are more concerned with large time gap size and the presence of a crosswalk, rather than vehicle type. Jayaraman et al. (2019) show that trust in AVs depend on presence of traffic signals. Similarly, Deb et al. (2018) show that the use of eHMI (i.e., communication tool between vehicles and pedestrians) improves pedestrian receptivity toward AVs when crossing. In summary, studies using preference surveys have found that pedestrians would consider the AVs as safe. In addition, the VR experiment suggests pedestrians' trust in AVs is exogenously influenced by the infrastructure and signs of AVs when crossing.

Regarding agent-based simulation, previous studies have focused on the behavioral perspective on AVs. Rashid et al. (2024) conducted a simulation of pedestrian interaction with AVs under several conditions based on different parameters such as different pedestrian types (i.e., risk taking, cautious, and distracted) and different vehicle sensor types (i.e., varying error percentage of pedestrian detection varies). The simulation analyzes the minimum distance accepted by a pedestrian during a road crossing scenario. Predhumeau et al. (2022) also conduct a simulation of pedestrian interaction with AVs in shared space considering different factors such as perception size and speed.

On the other hand, there are fewer empirical studies compared to scenario-based studies. The empirical studies have focused on analysis about pedestrians' reactions towards AVs using video camera from outside (e.g., telephone pole) or from AVs. Madigan et al. (2019) conducted AVs demonstrations in France and Greece and explored factors influencing pedestrian behavior towards AVs. This study found that correct infrastructures (e.g., road width, traffic signals) support the safe introduction of AVs (i.e., some infrastructures cause the emergence of risky behaviors). Rothenbucher et al. (2016) conducted an AV running experiment (i.e., an experiment created the illusion of a driverless situation by disguising the driver seats to appear that it had no driver) in California and analyzed the impact of driverless vehicles on pedestrian behavior. This study concluded that pedestrians interact with the AVs smoothly unless there was a breakdown in expectations. However, to our best knowledge, few studies analyze interactions between pedestrians and AVs on actual space using a pedestrian model.

From the above, many studies have analyzed pedestrians' physical and psychological reaction towards AVs in virtual scenarios, but creating a virtual scenario similar to the real environment is challenging, and this causes discrepancies between the pedestrian responses and the actual responses. Therefore, it is necessary to observe and analyze pedestrian behavior towards actual AVs to provide knowledge for improving the algorithm of AVs and urban street design. However, it is possible that only limited experimental observations (e.g., speed limit or wrapping) may be possible due to legal and technical issues.

4.2.2. Pedestrian model describing the interaction between pedestrians and vehicles

In terms of models describing the micro-interactions between pedestrians and vehicles, existing studies have focused on models that assume a pedestrian-vehicle coexistence space, and signalized or unsignalized crosswalks using social force model and CA model.

Regarding the pedestrian-vehicle coexistence space, many pedestrian models have been proposed to account for the complex behavior of vehicles (Anvari et al., 2015; Dias et al., 2018a and 2018b; Yang et al., 2020). For example, Dias et al. (2018a) and Dias et al. (2018b) describe the interactions between pedestrians, personal mobility, and bicycles using the social force model. However, these models for pedestrian-vehicle coexistence spaces often describe pedestrian behavior in a limited experimental or virtual space to ensure safety. On the other hand, for pedestrian crossings, many models (Liu et al., 2017; Zeng et al., 2017; Chen et al., 2018) have been proposed to describe collision avoidance between vehicles and pedestrians moving in a specific direction (e.g., when turning right or left at a crosswalk). For example, Zeng et al. (2017) uses the social force model to describe the interaction between pedestrians and right-turning vehicles, with the addition of signal cycle constraints.

We discuss what factors are considered in the above model for the collision avoidance with vehicles. Many models based on the social force model describe collision avoidance with vehicles using the repulsive force, and calculate the likelihood of collision in terms of pedestrian and vehicle direction vectors. Anvari et al. (2015), Liu et al. (2017) and Rashid et al. (2024) describe the magnitude of the repulsive force using the decay function of the distance between the pedestrian and vehicle. Dias et al. (2018a and 2018b) represent the repulsive force as a repulsive potential on an ellipse using the current speed and angle, and consider the predicted time (i.e., how far the pedestrian linearly interpolates the current into the future). Yang et al. (2020) consider distance decay and anisotropy (i.e., pedestrians moving away from the vehicle have a less impact on the collision). In other models, Schönauer et al. (2012) use a Stackelberg game instead of the repulsive force and utilize terms describing the utility of stopping, avoiding, and maintaining the current state. On the other hand, these social force models are often used in parallel with other models calculated, for example, the possibility of crossing using Time to Collision (TTC) (Liu et al., 2017), or the optimal speed and direction to the destination in the absence of obstacles (Anvari et al., 2015; Liu et al., 2017).

In this study, we focus on behaviors of pedestrian and vehicle at crosswalks and use a discrete choice pedestrian model (Robin et al., 2009) to describe the micro interactions between pedestrians and vehicles (AVs, cars, bicycles, and motorcycles) based on actual trajectory data (see section 4.3). The description of collision avoidance uses a utility function that introduces four elements: 1) likelihood of collision, 2) perception of vehicle behavior (i.e., acceleration or deceleration), 3) risk at collision (i.e., relative speed of vehicle and pedestrian), and 4) safety distance to collision. In addition to the likelihood of collision, distance decay and relative speed, discussed above, a perception of vehicle behavior term (i.e., a signal from the vehicle to the pedestrian) is introduced in order to communicate with the vehicle when crossing. This study aims to analyze the differences in pedestrian behavior toward different vehicles using this idea of the collision avoidance with vehicle.

4.3. Data

4.3.1. Measurement about behaviors of pedestrians and vehicles

The social experiment about AV driving was conducted for about one year from March 2021 to May 2022 at Hiroshima University. These AVs, named "HIROMOBI" ran around road space (about 3.5 km) on Higashi-Hiroshima campus. This HIROMOBI is almost level 3 autonomous driving (i.e., a driver controls it instead of the machine if unexpected situation occurs). Using this opportunity, we set a video camera to observe the behavior of AVs, pedestrians, and other vehicles from the 2nd floor of the Science Faculty at Hiroshima University (around 5.2m above the ground). The crossing area was selected as the measurement area where vehicles and pedestrians may have conflict, as shown in **Figure 4. 2**.

Figure 4. 2 Measurement area

4.3.2. Data process

After this measurement, we create trajectory data using several processes, as shown in **Figure 4.3**.

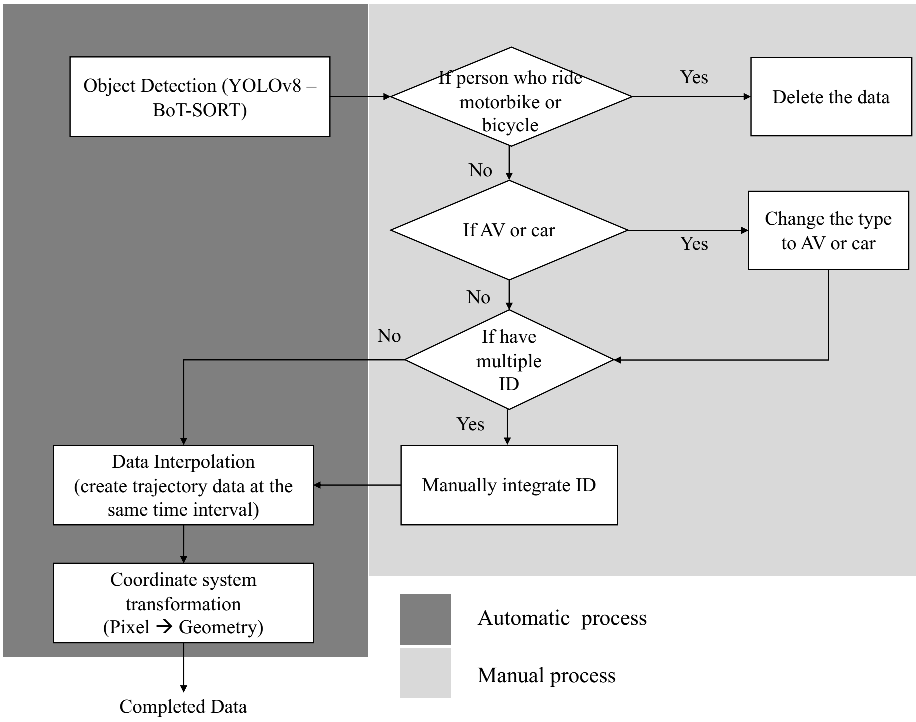

Figure 4. 3 Flow chart of data process

First, object detection used the python package YOLOv8 integrated with the BoT-SORT tracker in the PyTorch deep learning library, which used the COCO dataset (i.e., pedestrians, bicycles, motorcycles, car, truck, and bus were extracted) as the dataset. The object detection outputs were (1) video data and (2) text data. The video data contained object IDs, object labels, and confidence scores (i.e., ranging from 0 to 1). The confidence score was better detection when it was closer to one. The text file contained frame, object IDs, object labels, pixel coordinates of the object at the center of the bounding box and bounding box size (i.e., height and width). In addition, the objects pixel coordinate were calculated as the center bottom of the bounding box. However, this text data had two issues: (1) duplicated object label, and (2) multiple IDs of an object. To solve these issues, we conducted the following manual process.

For the duplicated object label of motorcycles and bicycles, YOLOv8-BoT-SORT detected both the vehicles and the riders as separate objects. We kept data pertaining to motorcycles and bicycles (i.e., we delete riders' data). Next, for AVs, the COCO dataset did not have an image of the HIROMOBI, and the same AV was categorized as multiple object labels such as "truck", "car" and "bus". Similarly, for cars, the same car was categorized as multiple object labels such as "truck", "car" and "bus". This issue occurred despite the overlap of bounding boxes for trucks and cars being large. In such cases, the detected object was reclassified into its correct category (i.e., "AV" and "car"). Moreover, for multiple IDs of an object, these IDs were manually integrated into a single ID.

However, it was difficult to detect objects that were far away or hidden by obstacles such as trees or other pedestrians. We conducted data interpolation at the same time interval of 0.5 seconds to create the trajectory data.

To convert pixel coordinates into geographic coordinates, a method involving small boxes, outlined by yellow dashed lines (excluding the blue areas) was employed (see **Figure 4.4**). At each corner of the box, longitude and latitude was determined using Google Maps. To incorporate both the pixel coordinates and the geographic coordinates, the linear interpolation was conducted along the x-axis and y-axis directions (see **Figure 4.5**). The corresponding equation was as follows:

$$z_i = \frac{y_2 - y_i}{y_2 - y_1}\left(z_{11}\frac{x_2 - x_i}{x_2 - x_1} + z_{21}\frac{x_i - x_1}{x_2 - x_1}\right) + \frac{y_i - y_1}{y_2 - y_1}\left(z_{12}\frac{x_2 - x_i}{x_2 - x_1} + z_{22}\frac{x_i - x_1}{x_2 - x_1}\right) \quad (4.1)$$

where, x_i and y_i represented pixel coordinates of targeted location i. $\boldsymbol{x} = (x_1, x_2)$ and $\boldsymbol{y} = (y_1, y_2)$ represented pixel coordinates of each box with a targeted location. $\boldsymbol{z} = (z_{11}, z_{12}, z_{21}, z_{22})$ represented the geographic coordinates according to corner of box. The trajectory data was completed after converting coordinates from pixel to geometry.

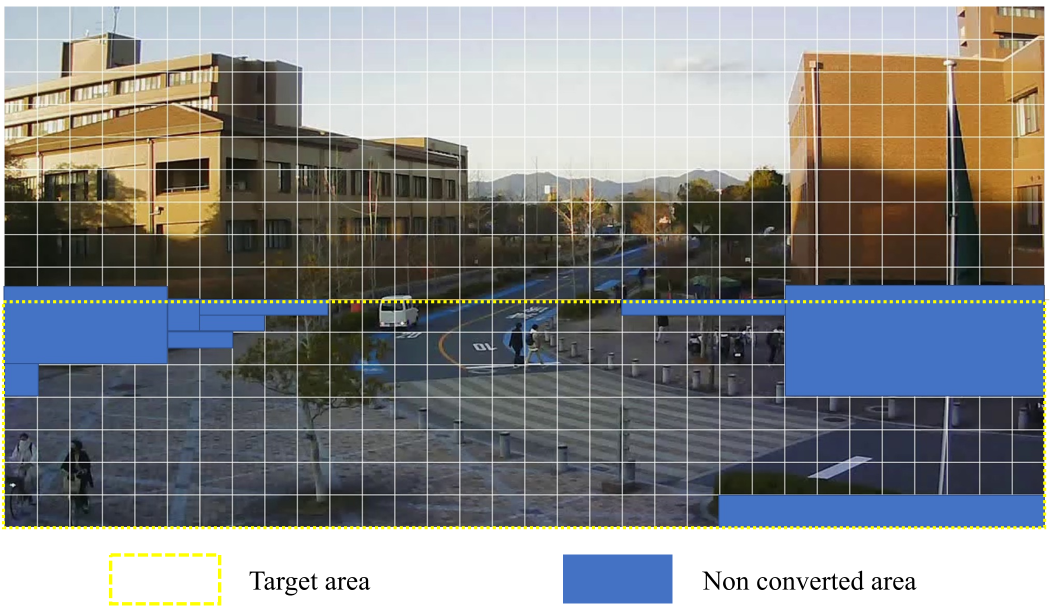

Figure 4. 4 Box for linear interpolation

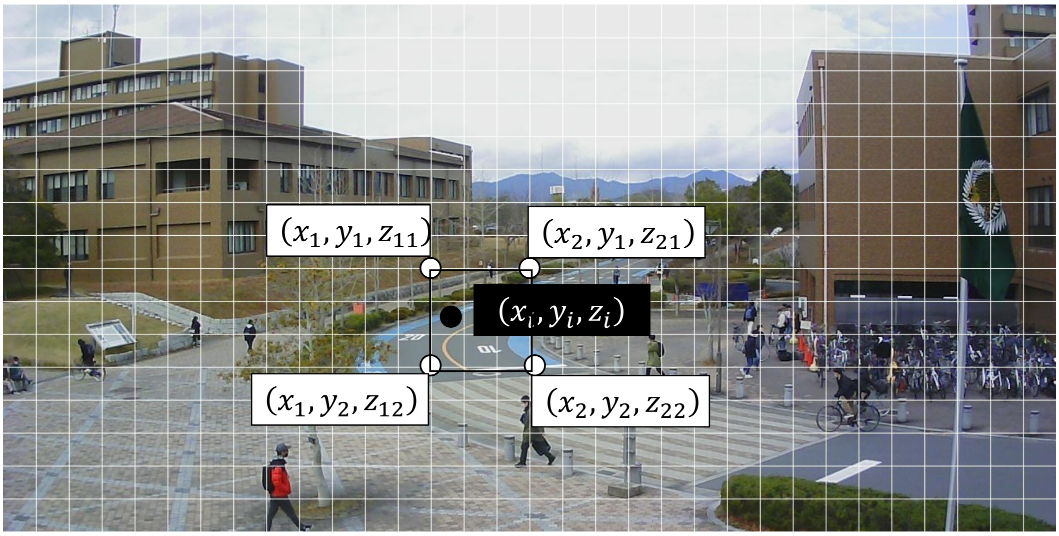

Figure 4. 5 Linear interpolation explanation

4.4. Modeling framework

4.4.1. Behavioral assumptions

This study extended the discrete choice pedestrian model (Antonini et al., 2006; Robin et al., 2009) to include the factor about interactions between pedestrians and vehicles (AVs, cars, motorcycles, and bicycles). The model assumed sequential pedestrian behaviors between time steps Δt. Specifically, a decision maker n at the current time t_k choose the next point from the discretized space (i.e., choice set) at the next time $t_{k+1}(= t_k + \Delta t)$.

The choice set consisted of 33 alternatives[3] which considered visual angle and reachable maximum distance (i.e., $1.75\ v_n \Delta t$) of the pedestrian based on their current speed v_n and angle θ_{d_n} as shown in **Figure 4.6**. Here, θ_{d_n} is the angle between the decision maker's vector d_n (i.e., $|d_n| = 1$) and the north vector. This study assume that visual angle of the pedestrian was $170°$. Based on the visual angle, it was divided into 11 cones (see **Figure 4.7a**) with the angle of $10°$ in the center, followed on either side by cones $10°, 10°, 15°, 20°$ and $25°$, where the smaller the cone, the clearer the visual of the pedestrian.

Then, this study considered three speed regimes (see **Figure 4.7b**), consisting of (1) decelerate regime (i.e., from $0.25 v_n \Delta t$ to $0.75 v_n \Delta t$), (2) constant speed regime (i.e.,

[3] The 33 alternatives may not be suitable, while the extreme sides (i.e., angle over 20°) are important to consider the behavior of avoiding vehicles.

from $0.75v_n\Delta t$ to $1.25v_n\Delta t$), and (3) accelerate regime (i.e., from $1.25v_n\Delta t$ to $1.75v_n\Delta t$). Note that we do not consider the stop regime (i.e., from 0 to $0.25v_n\Delta t$) due to its minimal size and complicate segmentation of the speed regimes and direction cones.

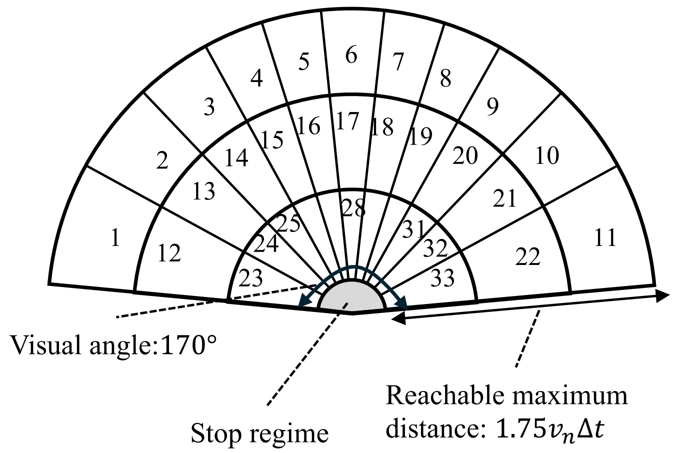

Figure 4. 6 Overview of choice set

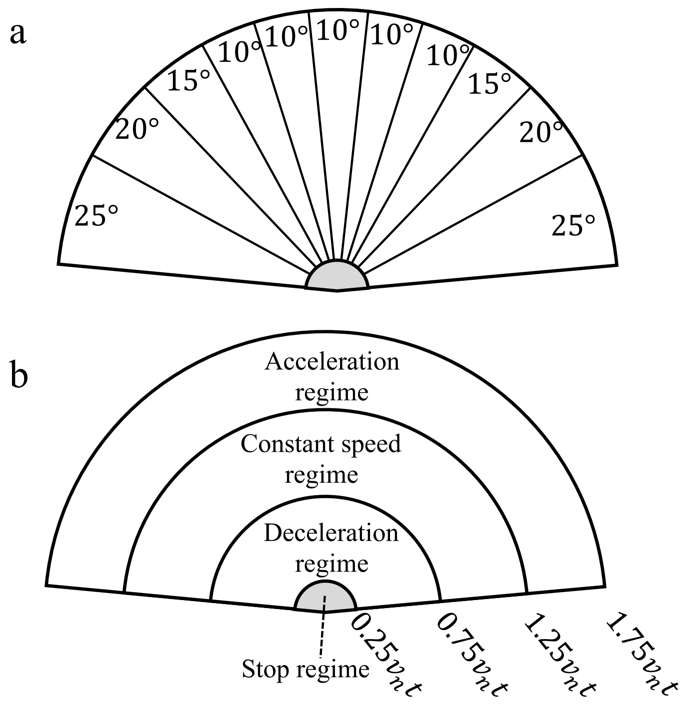

Figure 4. 7 Space discretization, a: direction cones; b: speed regimes

4.4.2. Utility functions

The decision maker n chose an alternative ij (i.e., i is an angle cone and j is a speed regime) that maximizes utility function V_{ijn}. The utility function V_{ijn} has mainly two behavioral factors: (1) unconstrained factors, (2) constrained factors (see **Figure 4.8**). The former one means behavioral factor which are independent of the presence of other pedestrians and are generated by subjective and/or unobserved factors: (a) *keep direction* (b) *toward destination*, (c) *free flow.* The latter one means factors which are induced by interactions with other individuals nearby and vehicles. In existing work of Robin et. al. (2009), they consider two factors: (d) *leader follower*, (e) *collision avoidance*. This study adds another factor, i.e., (f) *collision avoidance with vehicles* which is designed to capture the effects of possible collisions with vehicles on the current trajectory of the decision maker.

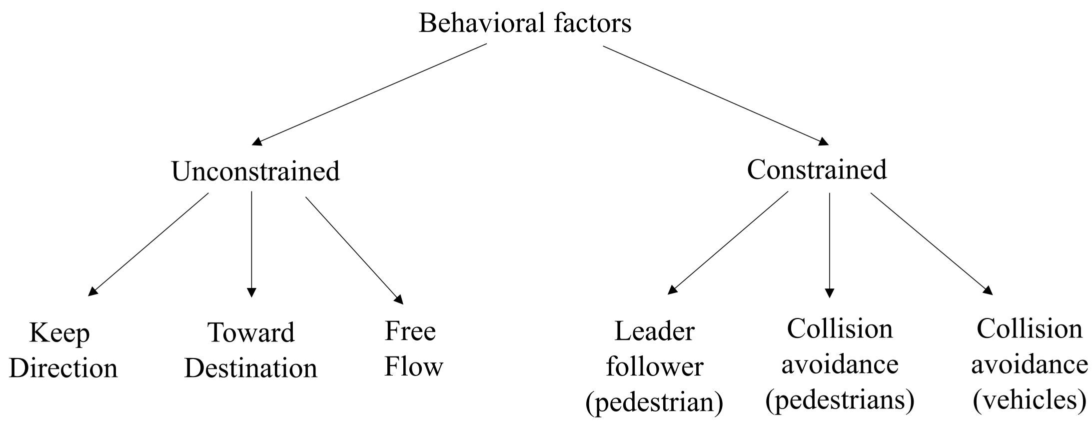

Figure 4. 8 Pedestrian behavioral factors

Table 4.1 summarizes the structure of the utility functions and behavioral hypotheses for the unconstrained and constrained factors (i.e., leader follower, collision avoidance with pedestrians). The following sections 4.4.2.1 to 4.4.2.5 provide a detailed explanation. In the following explanations, we focus on pedestrian n and a certain alternative ij. However, the computation of each explanatory variable is repeated for each decision maker and each alternative.

Table 4. 1 Utility functions for unconstrained and constrained factors (interactions with pedestrians), explanations of behavior, hypotheses

	Utility function	Behavioral explanation	Hypothesis
Keep direction	$\beta^{cent}\exp\left(\rho^{cent}\theta_{d_{ij}d_n}\right)I_{ij}^{cent}$ $+\beta^{ncent}\exp\left(\rho^{ncent}\theta_{d_{ij}d_n}\right)I_{ij}^{ncent}$	The pedestrian maintains direction so that the angle from the direction of travel becomes smaller.	$\beta^{cent}>0,\beta^{ncent}<0$ $\rho^{cent}<0,\rho^{ncent}>0$
Toward destination	$\beta^{ddist}\lvert d_{ijdest}\rvert$	The pedestrian behaves in such a way that the distance to the destination becomes smaller.	$\beta^{ddist}<0$
Free flow	$\beta^{dec}I_{ij}^{dec}(v_n/v_{max})^{\lambda^{dec}}$ $+\beta^{acc}I_{ij}^{acc}(v_n/v_{max})^{\lambda^{acc}}$	The higher the pedestrian's speed, the more the pedestrian accelerates, and the lower the speed, the more the pedestrian decelerates.	$\beta^{dec}>0,\beta^{acc}<0$ $\lambda^{dec}<0,\lambda^{acc}>0$
Leader follower	$I_i^L\alpha^L\left(1/(D_L+1)\right)$	The pedestrian follow the leader walking in the same direction. The smaller the distance, the more likely he/she is to follow the leader.	$\alpha^L>0$
Collision avoidance with pedestrian	$I_i^{CP}\alpha^{CP}\left(1/(D_{CP}+1)\right)$	The pedestrian behave in a way that avoids a front collider walking in the opposite direction. The smaller the distance, the more likely the avoidance behavior will occur.	$\alpha^{CP}<0$

4.4.2.1. Keep direction

In *Keep direction*, we divide the directions into two groups: (1) center group, which represents the cones with an angle of $10°$, (2) non-center group, which represents the cones with an angle of $15°, 20°$, and $25°$:

$$\beta^{cent} \exp\left(\rho^{cent}\theta_{d_{ij}d_n}\right) I_{ij}^{cent} + \beta^{ncent} \exp\left(\rho^{ncent}\theta_{d_{ij}d_n}\right) I_{ij}^{ncent} \tag{4.2}$$

where, the dummy variable I_{ij}^{cent} which is 1 if ij is in the center group and 0 otherwise, and the dummy variable I_{ij}^{ncent} which is 1 if ij is in the non-center group and 0 otherwise. β^{cent}, ρ_i^{cent} and β^{ncent}, ρ_i^{ncent} are unknown parameters about the center group and the non-center group. The term $\theta_{d_{ij}d_n}$ is the angle between d_{ij} (i.e., the vector connecting between the central point of the alternative ij and the decision maker) and the vector d_n as shown in **Figure 4.9**. Note that d_{ij} has same direction regardless of j. Since pedestrians tend to choose center, and furthermore, to choose the alternative with the smallest angle, β^{cent} and ρ^{ncent} are expected to be positive while β^{ncent} and ρ^{cent} are expected to be negative.

4.4.2.2. Toward destination

In *Toward destination*, the associated term is as follows:

$$\beta^{ddist}\left|d_{ijdest}\right| \tag{4.3}$$

where, $\left|d_{ijdest}\right|$ is the distance between the center point of the alternative ij, and the destination (i.e., length of the vector connecting between the central point of the alternative ij and the destination (*dest*)) as illustrated in **Figure 4.9**. The unknown parameters, β^{ddist}, represents the tendency of walking behaviors toward the decision maker's destination. Since pedestrians behave in such a way that the distance to their destination is smaller, the sign of β^{ddist} is expected to be negative.

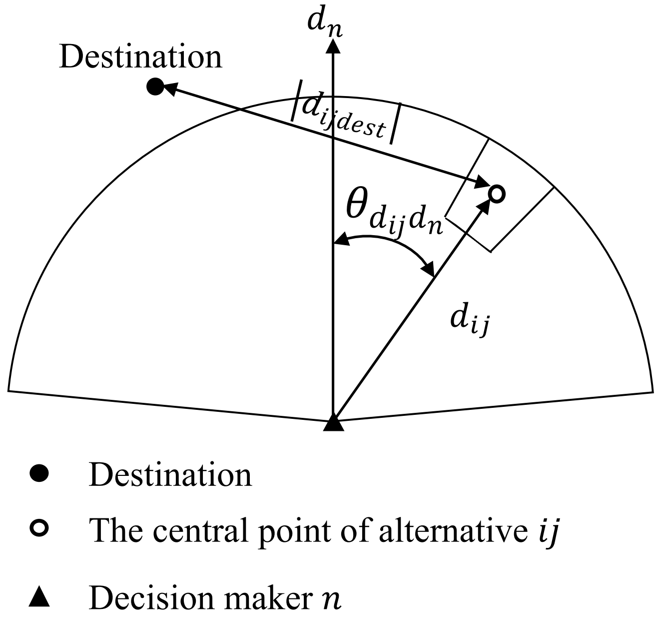

Figure 4. 9 Description of the term for "keep direction" and "toward the destination"

4.4.2.3. Free flow

In *Free flow*, the associated term is as follows:

$$\beta^{dec} I_{ij}^{dec} (v_n/v_{max})^{\lambda^{dec}} + \beta^{acc} I_{ij}^{acc} (v_n/v_{max})^{\lambda^{acc}} \tag{4.4}$$

where, the first part of the term corresponds to deceleration and the second part corresponds to acceleration. The dummy variable $I_{ij}^{dec}(I_{ij}^{acc})$ is 1 if ij is in the accelerate (decelerate) regime and 0 otherwise. The unknown parameters β^{dec} and β^{acc} are corresponding to free flow deceleration and acceleration respectively. v_{max} is the maximum speed in data. $\lambda^{dec}, \lambda^{acc}$ are the elasticity considering nonlinearity for deceleration and deceleration. Since the higher the pedestrian's speed, the more it accelerates, and the lower the speed, the more it decelerates, as the current speed approaches the maximum speed, the utility of deceleration (or acceleration) is expected to increase (or decrease). The sign of β^{dec}(or β^{acc}) is expected to be positive (or negative).

4.4.2.4. Leader follower

In *Leader follower*, we explore potential leaders at each cone and choose the closest person among them as a leader, using the following steps. To avoid getting the same potential leaders, we focus on each cone i regardless of j. First, we set up an extended fan with a radius (D_{th}) 10 times larger than the radius ($D_{max} = 1.75 v_n \Delta t$) as shown in **Figure 4.10**. Within each cone of the extended fan, we identify a set of potential leaders. The selection of potential leaders is based on the following criteria:

$$I_i^{\mu} = \begin{cases} 1 \;\; if\ d_{n\mu} = s_1 d_i^l + s_2 d_i^r \\ \quad and\ s_1, s_2 \geq 0 \\ \quad and\ 0 < |d_{n\mu}| \leq D_{th} \\ \quad and\ 0 < |\theta_{\mu}| \leq \ 10° \\ 0 \;\; otherwise \end{cases} \tag{4.5}$$

where, d_i^l and d_i^r represent left and right vectors of the cone i, and $d_{n\mu}$ is the vector connecting the pedestrian μ and decision maker n. θ_{μ} is the angle between the vector d_i which represents the direction of center of cone i and the vector d_{μ} of pedestrian μ. If I_i^{μ} is 1, the pedestrian μ become one of the potential leaders.

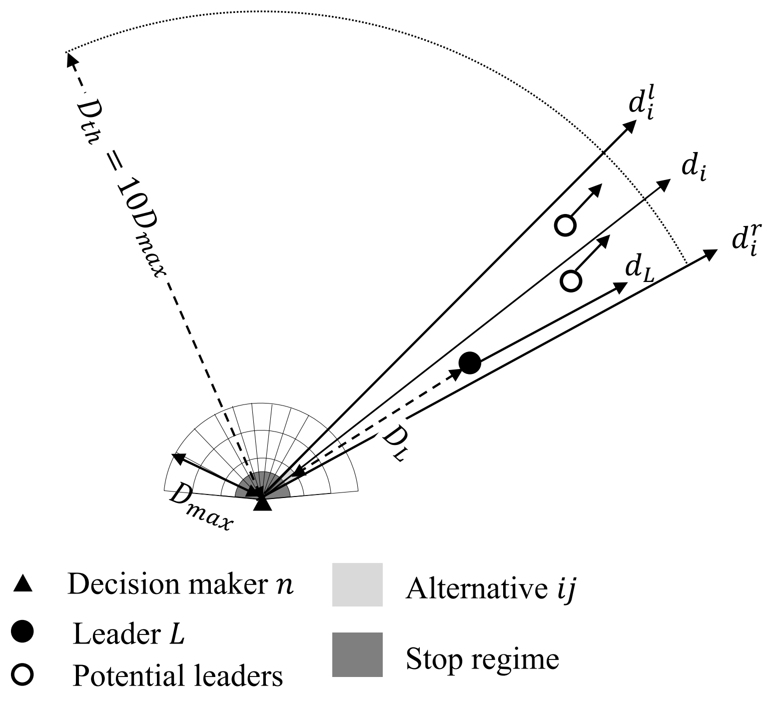

Figure 4. 10 Description of the term used for "leader follower"

After the process for selecting potential leaders, we choose the closest person as the leader l. The term leader follower regarding the leader l is defined as follows:

$$I_i^L \alpha^L \left({}^{1}/_{(D_L + 1)} \right) \tag{4.6}$$

where, dummy variable I_i^L is 1 if the leader is in the cone i and 0 otherwise. D_L is the distance between the alternative ij and the leader. α^L is unknown parameter. Since pedestrians tend to follow the leader's behavior, α^L is expected to be positive.

4.4.2.5. Collision avoidance with pedestrians

In *Collision avoidance with pedestrian*, as leader follower, we explore potential colliders at each cone and choose the closest person among them as a collider, using the following steps. To avoid getting the same potential collider, we focus on each cone i regardless of j. First, we set up an extended fan with a radius (D_{th}) 15 times larger than the radius ($D_{max} = 1.75 v_n \Delta t$) as shown in **Figure 4.11**. Within each cone of the extended fan, we identify a set of potential colliders. The selection of potential colliders is based on the following criteria:

$$I_c^{\acute{\mu}} = \begin{cases} 1 \; if \; d_{n\acute{\mu}} = s_1 d_i^l + s_2 d_i^r \\ \quad and \; s_1, s_2 \geq 0 \\ \quad and \; 0 < \left| d_{n\acute{\mu}} \right| \leq D_{th} \\ \quad and \; \pi/2 < \left| \theta_{\acute{\mu}} \right| \leq \pi \\ 0 \;\; otherwise \end{cases} \tag{4.7}$$

where, d_i^l and d_i^r represent left and right vectors of the cone i, and $d_{\acute{\mu}}$ is the direction indicating the position of pedestrian $\acute{\mu}$. $D_{\acute{\mu}}$ is the vector connecting between pedestrian $\acute{\mu}$ and decision maker n, and $\theta_{\acute{\mu}}$ is the angle between the vector of pedestrian $d_{\acute{\mu}}$ and the vector d_n. If $I_C^{\acute{\mu}}$ is 1, pedestrian $\acute{\mu}$ becomes one of the potential colliders.

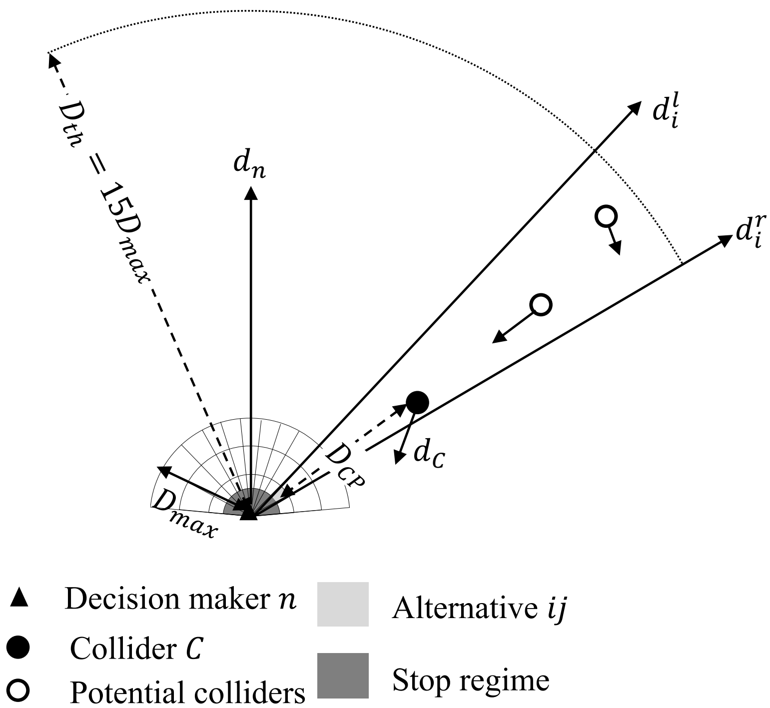

Figure 4. 11 Description of the term used for "collision avoidance with pedestrians"

After the process for selecting potential colliders, we choose the closest person as the collider C. The term collision avoidance with pedestrians regarding the collider C is defined as follows:

$$+I_i^{CP}\alpha^{CP}\left(1/(D_{CP}+1)\right) \tag{4.8}$$

where, dummy variable I_i^{CP} is 1 if the collider is in the cone i and 0 otherwise. D_{CP} is the distance between the decision maker and the alternative ij. α_{CP} are the unknown parameters. Since pedestrians tend to avoid the nearby collider, α_{CP} is expected to be negative.

4.4.2.6. Collision avoidance with vehicle

In *Collision avoidance with vehicles*, we consider the utility functions, explanations of behavior, and behavioral hypotheses shown in **Table 4.2.**

Table 4. 2 Utility functions, behavioral explanations, and hypotheses regarding collision avoidance with vehicles

Utility function
$\sum_{q \in C_V} \left(I_{ijnq} \left(\left(1 - I_q^D\right)\beta_q + \alpha_q \right) \left(v_n + v_q\right)^{\sigma_q} \left(\frac{1}{\left(\left(D_{ijnq}\right)^{\gamma_q} + 1\right)} \right) \right)$
Behavioral explanation
1. Under the likelihood of collision① (or ②), pedestrian avoidance behavior (i.e., acceleration/deceleration or change of direction) is more likely to occur when the vehicle does not decelerate. 2. Pedestrian avoidance behavior is unlikely to occur when the vehicle decelerates. 3. Pedestrian avoidance behavior is less likely to occur when the relative speed between a pedestrian and a vehicle is small. 4. Pedestrian avoidance behavior is more likely to occur when the distance between a pedestrian and a vehicle becomes shorter.
Hypothesis
1. $\beta_q + \alpha_q < 0$ when I_q^D is 0 2. $\alpha_q > 0$ when I_q^D is 1 3. $\gamma_q > 0$ 4. $\sigma_q < 0$

The utility function includes four components (i.e., likelihood of collision, pedestrian perception of vehicle behavior (i.e., acceleration), risk at collision, and safe distance to collision). **Figure 4.12** outlines the above four components. The likelihood of collision indicates whether or not there is a collision (i.e., collision area) based on the speed and angle of the pedestrian and vehicle, and the safe distance to collision indicates the effect of the distance to the collision area In addition, the perception of vehicle behavior represents the effect of differences in vehicle behavior (i.e., acceleration) and risk at collision represents the magnitude of the impact at the time of collision based on the relative velocities.

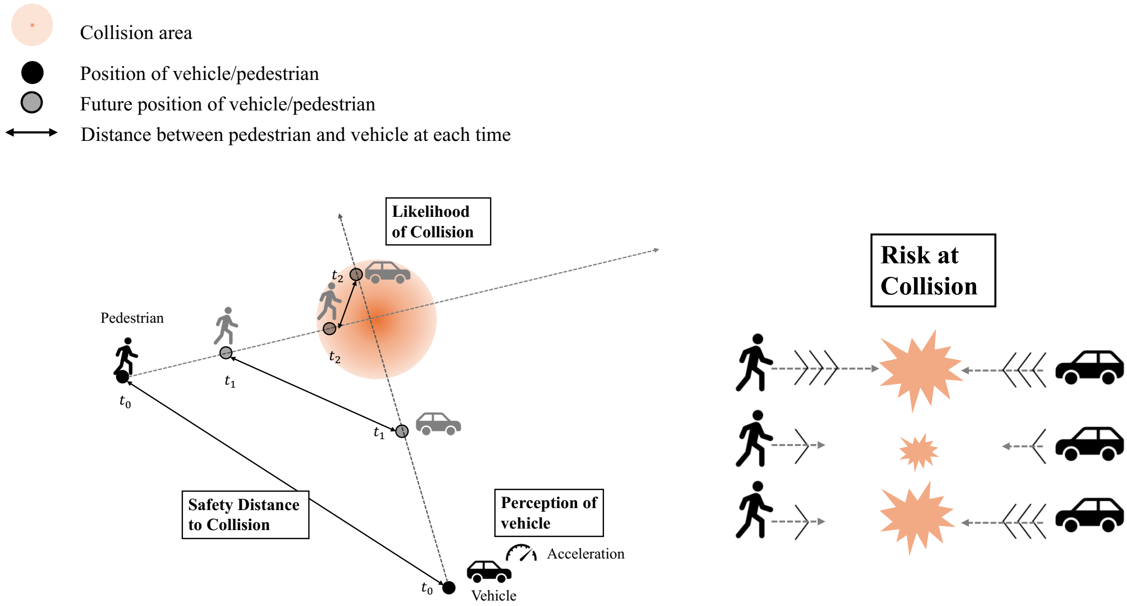

Figure 4. 12 Four components of collision avoidance with vehicles

The utility function for likelihood of collision represents uses $I_{ijnq}\left(\left(1 - I_q^D\right)\beta_q + \alpha_q\right)$. I_{ijnq} is a dummy variable representing the likelihood of a collision (1 if the acceleration threshold (I_{ijnq}^{th}) or less, 0 otherwise), I_{ijnq} is a dummy variable for vehicle deceleration, and β_q and α_q are unknown parameters. β_q and α_q are unknown parameters. Under a potential collision situation, $\beta_q + \alpha_q$ are considered negative values because pedestrian avoidance behavior (i.e., acceleration/deceleration or change of direction) is more likely to occur when the vehicle does not decelerate. On the other hand, when the vehicle decelerates, α_q is considered to be positive because it is less likely to occur when the vehicle decelerates.

Two types of likelihood of collision (① and ②) are considered. In likelihood of collision ①, for each option, whether or not a collision occurs (whether or not there is an intersection) is calculated using the directions of the pedestrian and vehicle. Specifically, whether a pedestrian n and a vehicle q collide is determined by the following three conditions (**Equation 4.9**): (1) whether the pedestrian and the vehicle are moving in opposite directions, (2) whether the vehicle is in front of the pedestrian, and (3) whether the vehicle and the decision maker have an intersection.

$$I^{C}_{ijnq} = \begin{cases} 1 & if\ d_n \cdot d_q \leq 0 \\ & and\ d_{nq} \cdot d_n \geq 0 \\ & and\ \delta_1 \geq 0, \delta_2 \geq 0 \\ & where\ d_n = \delta_1 d_{ij} + \delta_2 d_{nq} \\ 0 & others \end{cases} \tag{4.9}$$

where, as shown in **Figure 4.13**, d_n is the current direction vector of the decision maker, d_q is the current direction vector of the vehicle, d_{nq} is the vector connecting the decision maker and the vehicle, and d_{ij} is the vector of alternatives. I^{C}_{ijqn} is 1 if all vectors satisfy the condition. As a further condition, the threshold for the distance between the vehicle and the pedestrian alternatives (D^{C}_{ijqn}) is set to D^{vc}_{th} [m].

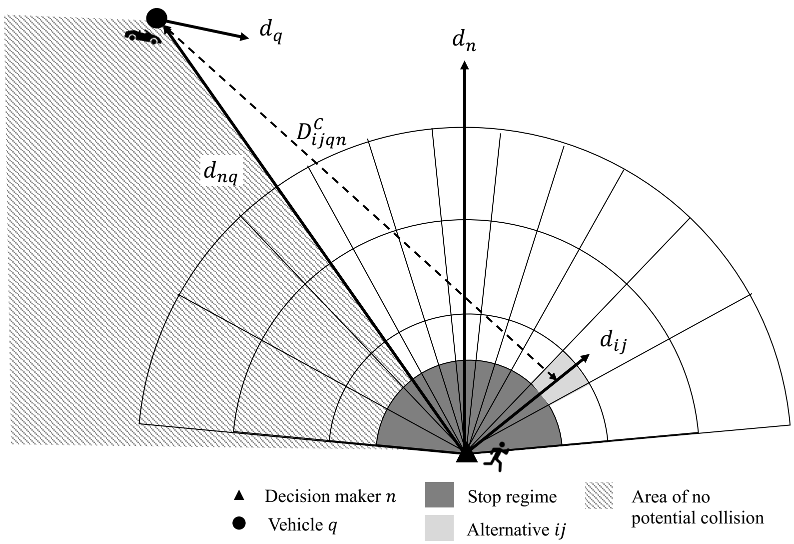

Figure 4. 13 Overview chart of likelihood of collision ①

In likelihood of collision ②, the future positions of pedestrians and vehicles are predicted using their speeds and angles to determine whether or not a collision is likely to occur. Basically, it is the same as TTC concept, which is widely used in traffic engineering. If I^{C}_{ijnq} is 1, there is an intersection between a pedestrian and a vehicle, so the distance and time to reach the intersection are calculated, and further restrictions are imposed on the conditional equation. **Figure 4.14** shows an overview of likelihood of collision ②. Specifically, the current speeds of the vehicle and pedestrian ($v_{nji\tau}, v_{q\tau}$) are used to calculate the time ($T_{nij\tau}, T_{q\tau}$) for the pedestrian and vehicle to reach the collision area. This arrival time is the same as TTC. Here, the current speed of the pedestrian, $v_{nji\tau}$, is changed according to the speed region to which each choice belongs. For example,

$v_{nji\tau} = 1.5v_n$ for the option that belongs to the acceleration region. The minimum arrival time to the collision area is defined as $T_c = \min(T_{nij\tau}, T_{q\tau})$, where τ is the index of the time it takes for one of them to reach the area. The time is incremented by 0.5 from 0 to T_c. The minimum distance D^s_{ijqn} between the vehicle and the decision maker's position at T_c is calculated. Further, the threshold of D^s_{ijqn} is set to D^{vs}_{th} [m] for non-bicyclists and D^{vsb}_{th} [m] for bicycles, and the threshold of T_c is set to T^{vs}_{th}[s] for non-bicyclists and T^{vsb}_{th}[s] for bicycles. The dummy variable for likelihood of collision considering these constraints is I^s_{ijnq}.

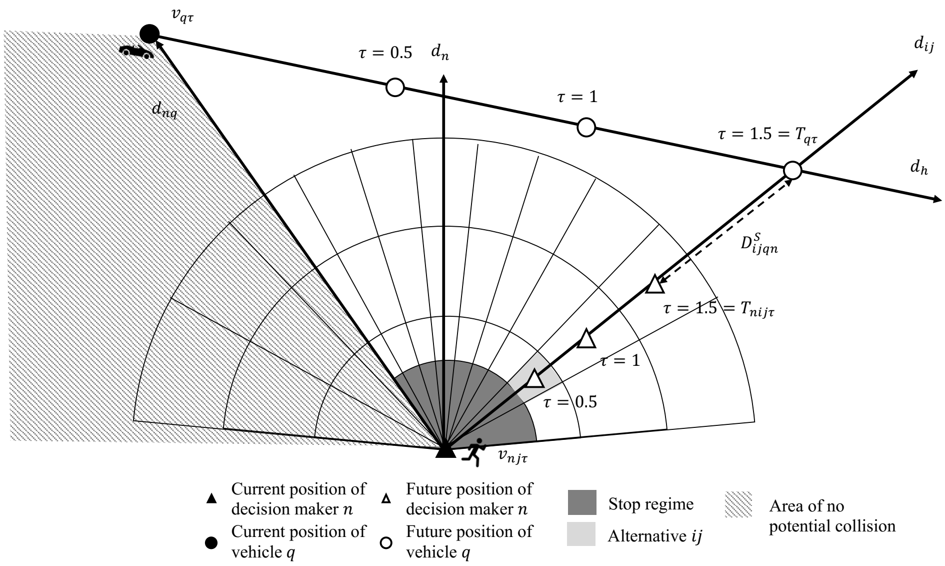

Figure 4. 14 Overview chart of likelihood of collision ②

I_{ijnq} utilizes I^C_{ijnq} or I^s_{ijnq} depending on the type of likelihood of collision (① or ②). The crash risk represents the magnitude of the impact of the collision and uses $\left(v_n + v_q\right)^{\sigma_q}$ as the utility function. $v_n + v_q$ is the relative velocity between pedestrian n and vehicle q, and σ_q is an unknown parameter representing resilience. In this term, σ_q is positive because pedestrian avoidance behavior is assumed to be less likely to occur when the relative velocity between pedestrian and vehicle is small. For the safe distance to collision, we use $1/(\left(D_{ijnq}\right)^{\gamma} + 1)$ as the utility function, where D_{ijnq} is the distance between pedestrian n and vehicle q, and γ is an unknown parameter that represents resilience. In this term, γ is assumed to be negative because pedestrian avoidance behavior is assumed to be less likely to occur when the relative velocity between pedestrian and vehicle is small. D_{ijnq} can be one of two possible distances, specifically the distance D^D_{ijnq} between the current pedestrian (i.e., choice) and the vehicle or the distance D_{ijnq}^{S} between the pedestrian's location and the vehicle's location in the future. However, the speed of the vehicle and the distance to the vehicle in this utility function are treated as endogenous variables when there is a vehicle model, so they must be described within the framework of the model shown in Chapter 5. In this chapter, since there is no vehicle model, they are introduced into the utility function exogenously.

4.4.3. Model structure

As mentioned earlier in this study, there are 33 choices concerning the directions, while speeds are distributed into five nests: three nests related to the speed direction consist of "Acceleration" (i.e., alternative 1-11), "Constant speed" (i.e., alternative 12-22), and "Deceleration" (i.e., alternative 23-33) as shown in **Figure 4.7b**; two nests related to directions consist of "Center" which represents the cones with an angle of $10°$, and "Not center" which represents the cones with an angle of $15°, 20°$, and $25°$ as shown in **Figure 4.7a**. All alternatives are attributed with overlap to both the direction nests and the speed nests.

This study uses the cross-nested logit (CNL) model (Wen and Koopelman, 2001) to consider the correlation structure because the CNL model permits alternatives to appear in numerous nests, allowing for more flexible correlation patterns than the nested logit. The generating function of CNL is shown as follows:

$$G(y_1, \dots, y_{33}) = \sum_{m=1}^{M} \left(\sum_{\acute{a} \in C_m} (\alpha_{\acute{a}m} y_{\acute{a}})^{1/\mu_m} \right)^{\mu_m} \tag{4.10}$$

where $m = 1, \dots, M$ is the number of the nests and alternatives a belong to nest m is defined by the allocation parameter α_{am}. C_m is the set of alternatives in nest m and μ_m is the scale parameter for nest m. To be consistent with random utility theory, $\alpha_{am} \geq 0 \; \forall \, a, m$ and$\sum_{m=1}^{M} \alpha_{am} = 1 \; \forall \, m$. $y_{\acute{a}}$ is $\exp(v_a)$. This formulation yields the following expression for the choice probability formula:

$$P(a) = \sum_{m=1}^{M} \frac{(\alpha_{\acute{a}m} y_{\acute{a}})^{1/\mu_m}}{\sum_{\acute{a} \in C_m} (\alpha_{\acute{a}m} y_{\acute{a}})^{1/\mu_m}} \frac{\left(\sum_{j \in C_m} (\alpha_{jm} y_j)^{1/\mu_m}\right)^{\mu_m}}{\sum_{n=1}^{M} \left(\sum_{j \in C_n} (\alpha_{jn} y_j)^{1/\mu_n}\right)^{\mu_m}} \tag{4.11}$$

4.5. Basic analysis

We use the observational data during lunchtime on some days in April and May 2022. The data had 228 pedestrian trajectories, for a total of 7,158 observations (i.e., total time steps of all pedestrians).[4] The speed of histogram was as shown in **Figure 4.15**. The mean of speed was 1.25 m/s (i.e., 4.50 km/h) and the standard deviation was 0.48. This average walking speed is slightly slower than walking speed (Robin et al., 2009) due to potential collision avoidance with vehicles. The standard deviation was slightly large because this data had several behaviors such as running.

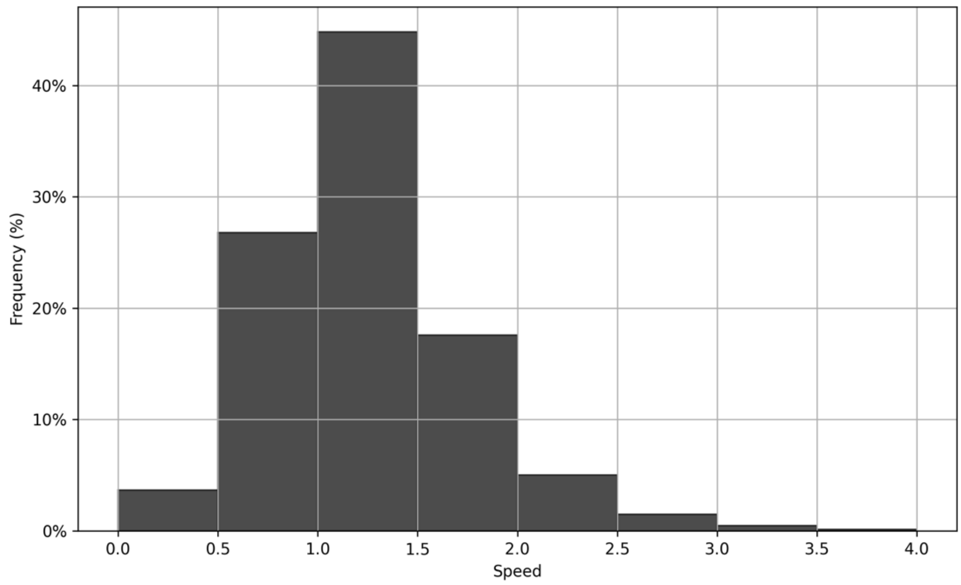

Figure 4. 15 Speed histogram

Figure 4.16 showed the distribution of alternatives chosen. The percentage of alternatives 16-18 was very high, indicating that pedestrians tend to choose constant speed and center (i.e., keep their current speed and direction). This trend can also be seen in **Figure 4.17**, where the percentage of "constant speed" was about 80% and the percentage of "center" was over 95%. Despite interactions with vehicles, pedestrians did not significantly change their speed and direction because they believe the vehicle will stop.

[4] In this study, we removed data where the pedestrian speed was below 0.3 or above 4 [m/s], outside the fan, and within the stop regime (see **Figure 4.6**).

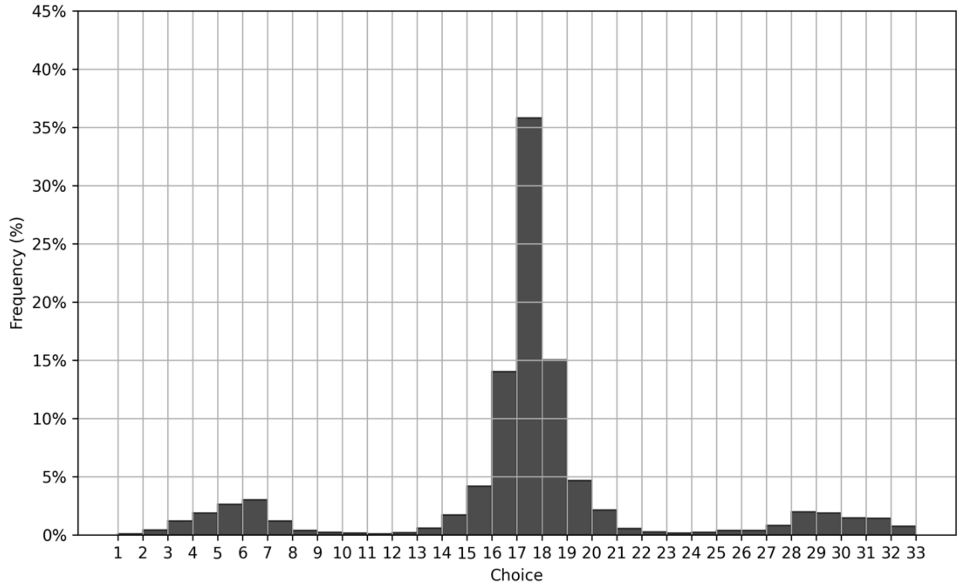

Figure 4. 16 Distribution of choice

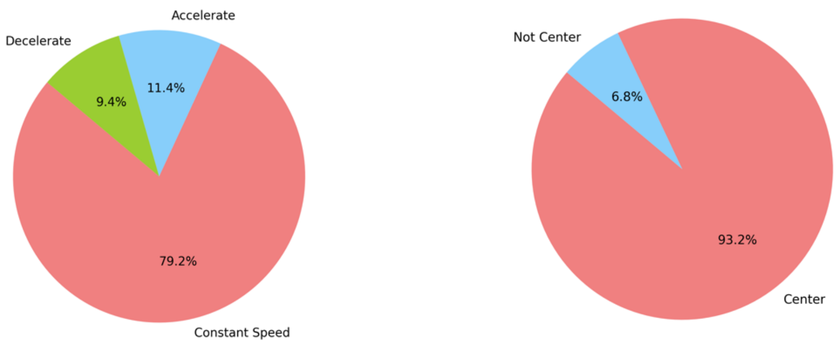

Figure 4. 17 Pie chart of speed regime (left) and direction cone (right)

Table 4. 3 Distribution of vehicle speeds

	AV	Car	Bicycle	Motorcycle
Average	0.83	1.45	1.75	1.52
Standard error	0.92	1.23	0.81	1.12
Median	0.51	1.30	1.68	1.27

Minimum	0.00	0.00	0.09	0.01
Maximum	4.56	5.36	5.58	3.77

Table 4.3 shows the distribution of vehicle speeds. Since these data show how vehicles behave at intersections, the overall speeds tend to be low. The average speed of AVs is the smallest because AVs are limited to 19 km/h (5.3m/s) and behave cautiously to avoid pedestrians. On the other hand, the average speed of bicycles is almost the same as that of cars, and their standard error of them is small. This means that cyclists tend to behave aggressively and do not slowing down despite at the crossing area. In addition, the average speed of motorcycles is greater than that of cars, indicating that motorcycles also tend to behave aggressively. However, due to the small sample size of motorcycles, the small change in speed may affect the average speed.

4.6. Estimation result

When estimating the parameters, the allocation parameter α_{am} was set to 0.5. This means that each choice has an equal probability of belonging to either the speed or direction nest. Of the five nest parameters, the parameters for “Not center” and “Acceleration” exceeded 1, so we set both nest parameters to 1. In this estimation, bicycles and motorcycles were excluded from the sample because they have a smaller sample size and their behavior is more complex than that of cars and AVs, and it is difficult to describe them with the same utility function equation for collisions. The upper limit of the distance between D_L, D_{CP} is set to 2[m] for collision avoidance between pedestrians and leader-following distance. In addition, we estimated a total of nine models: three combinations with different thresholds for distance, TTC, and acceleration for collision avoidance with vehicles, and three combinations with distance D^D_{ijqn} for likelihood of collision ① and distance D^D_{ijqn} and D^S_{ijqn} for likelihood of collision ②.

Meanwhile , β_{cent}, ρ_{ncent} are statistically significant with a positive sign, and β_{cent}, ρ_{ncent} are statistically significant with a negative sign. These signs mean that the pedestrians tend to keep their current directions. β_{ddist} is statistically significant with negative sign, indicating that the pedestrians tend to go directly to their destination. These estimated parameters are as expected. Moreover, β_{acc} is statistically significant with a negative sign, and λ^{acc} is less than 1, indicating that pedestrians tend to accelerate when the current speed is low. On the other hand, β_{dec} is statistically significant with a positive sign, and λ^{dec} is more than 1, indicating that pedestrians tend to decelerate when the current speed is large. As for leader following, α^L is statistically significant and positive, suggesting that the presence of a leader has a positive influence on decision makers. These parameters support the hypotheses presented in **Table 4.1**. However, α_{cp} is positive, which is contrary to the hypothesis. This suggests that decision makers are not likely to unexpectedly avoid a collider and that pedestrians are likely to maintain their own trajectory unaffected by a collider.

The estimation results for the nine models are shown in **Table 4.4**, with little change in model accuracy or parameters across definitions of TTC, distance, thresholds for deceleration, collision likelihood, and distance. It is possible that pedestrians' decision-making did not differ significantly between collision likelihoods ① and ②. For the avoidance of collision with a car, the sum of β_{car} and $\alpha_{car}$was negative and α_{car} was positive in most of the models. This result supports the two hypotheses in **Table 4.2**. In other words, when the car does not decelerate, the pedestrian's avoidance behavior is likely to occur, and when the car decelerates, the pedestrian's avoidance behavior is unlikely to occur. On the other hand, the sum of β_{AV} and α_{AV}, as well as α_{AV}, were positive in many of the models for collision avoidance with AV. These results support only the hypothesis that pedestrian avoidance behavior is less likely to occur when the vehicle is decelerating. However, since the parameter related to the vehicle not decelerating (β_{AV}) is negative, there is a possibility that pedestrians take evasive action when the AV does not decelerate. Nevertheless, the positive influence of a parameter (α_{AV} unrelated to the acceleration/deceleration of the AV is stronger (i.e., the sum of β_{AV} and α_{AV} is positive), suggesting that pedestrians relatively tend not to take avoidance action against the AV. There are several reasons for this result: (1) pedestrians tend not to take evasive action because they assume that an AV will stop (i.e., pedestrian trust AVs more), (2) the speed of AVs are slower than the that of cars.

The utility functions used in this chapter, which include the four factors of collision likelihood, perception of vehicle deceleration, risk at collision, and safe distance to collision, enabled us to analyze the difference in pedestrian behavior with respect to collision avoidance between pedestrians and cars or AVs. On the other hand, the parameters related to the elasticity of relative velocity and speed (σ_q and γ_q) are difficult to estimate, so the utility function needs to be modified. Specifically, the term related to the safe distance to collision could be changed from the product form to the sum form, or only the pedestrian speed could be used instead of the relative speed.

Table 4. 4 Results related to avoiding collisions with vehicles

	Criteria	Model specification	Result	Final LL
Model 1	$I_{ijnq}^{th} = 0.7$ $D_{th}^{vc} = 10$	Likelihood of collision: ① I_{ijnq}^{D} Distance: D_{ijqn}^{D}	$\beta_{AV} + \alpha_{AV} > 0, \beta_{car} + \alpha_{car} < 0$ $\alpha_q > 0, \alpha_{AV}$ is significant, $\beta_q < 0$	-16230.66
Model 2	$I_{ijnq}^{th} = 0.7$ $D_{th}^{vs} = 10, T_{th}^{vsb} = 6$	Likelihood of collision: ② I_{ijnq}^{S} Distance: D_{ijqn}^{S}	$\beta_{AV} + \alpha_{AV} > 0, \beta_{car} + \alpha_{car} < 0$ $\alpha_q > 0,\ \beta_q < 0$	-16231.51
Model 3	$I_{ijnq}^{th} = 0.7$ $D_{th}^{vs} = 10, T_{th}^{vsb} = 6$	Likelihood of collision: ② I_{ijnq}^{S} Distance: D_{ijqn}^{D}	$\beta_{AV} + \alpha_{AV} > 0, \beta_{car} + \alpha_{car} < 0$ $\alpha_q > 0, \alpha_{AV}$ is significant, $\beta_q < 0$	-16229.34
Model 4	$I_{ijnq}^{th} = 0.8$ $D_{th}^{vs} = 10, T_{th}^{vsb} = 6$	Likelihood of collision: ① I_{ijnq}^{D} Distance: D_{ijqn}^{D}	$\beta_{AV} + \alpha_{AV} > 0, \beta_{car} + \alpha_{car} < 0$ $\alpha_q > 0,\ \beta_q < 0$	-16231.76
Model 5	$I_{ijnq}^{th} = 0.8$ $D_{th}^{vs} = 10, T_{th}^{vsb} = 6$	Likelihood of collision: ② I_{ijnq}^{S} Distance: D_{ijqn}^{S}	$\beta_{AV} + \alpha_{AV} > 0, \beta_{car} + \alpha_{car} < 0$ $\alpha_q > 0,\ \beta_q < 0$	-16231.26
Model 6	$I_{ijnq}^{th} = 0.8$ $D_{th}^{vs} = 10, T_{th}^{vsb} = 6$	Likelihood of collision: ② I_{ijnq}^{S} Distance: D_{ijqn}^{D}	$\beta_{AV} + \alpha_{AV} > 0, \beta_{car} + \alpha_{car} < 0$ $\alpha_q > 0, \alpha_{AV}$ is significant, $\beta_q < 0$	-16230.5
Model 7	$I_{ijnq}^{th} = 0.7$ $D_{th}^{vc} = 8$	Likelihood of collision: ① I_{ijnq}^{D} Distance: D_{ijqn}^{D}	$\beta_{AV} + \alpha_{AV} > 0, \beta_{car} + \alpha_{car} < 0$ $\alpha_q > 0,\ \beta_q < 0$	-16231.74
Model 8	$I_{ijnq}^{th} = 0.7$ $D_{th}^{vs} = 8, T_{th}^{vsb} = 6$	Likelihood of collision: ② I_{ijnq}^{S} Distance: D_{ijqn}^{S}	$\beta_{AV} + \alpha_{AV} > 0, \beta_{car} + \alpha_{car} < 0$ $\alpha_{AV} > 0, \alpha_{car} < 0, \beta_q > 0$	-16232.06
Model 9	$I_{ijnq}^{th} = 0.7$ $D_{th}^{vs} = 8, T_{th}^{vsb} = 6$	Likelihood of collision: ② I_{ijnq}^{S} Distance: D_{ijqn}^{D}	$\beta_{AV} + \alpha_{AV} > 0, \beta_{car} + \alpha_{car} < 0$ $\alpha_q > 0,\ \beta_q < 0$	-16231.19

4.7. Conclusion

In order to focus on the local effect with vehicles and pedestrians in the urban street space, this study developed a pedestrian model describing the interaction between pedestrians, AVs, and CVs (i.e., motorcycles, bicycles, and cars) to analyze pedestrian behavior toward AVs. We extended the discrete choice pedestrian model (Robin et. al., 2009) to include interactions with vehicles. The model has the following advantages: (1) it can simultaneously describe pedestrian-pedestrian interactions and vehicle-pedestrian interactions by introducing multiple interaction factors into the same deterministic utility, and (2) it can clarify decision factors such as why a collision was avoided due to the difference in utilities between the alternatives. In this study, the trajectories of pedestrians and vehicles were observed at an intersection where AVs and other vehicles were running on the Higashi-Hiroshima Campus of Hiroshima University, and model estimation was conducted using the observed data. The utility function for avoiding a collision with a vehicle considered four main factors: likelihood of collision, perception of vehicle behavior, risk at collision, and safety distance to collision. In addition, two types of likelihood were assumed: (1) a situation in which the pedestrian does not estimate the speed of the vehicle and judges whether a collision will occur based on his/her direction and the vehicle, and (2) a situation in which the pedestrian estimates the speed of the vehicle and judges whether a collision will occur based on the estimated future positions of the vehicle and him/herself. We tested several hypotheses regarding these factors.

In the estimation results, we focused only on cars and AVs, and the parameters related to the risk at collision and the safe distance to collision were fixed. The estimation results support the hypotheses that "pedestrians are more likely to avoid a collision with a car when the car does not decelerate" and "pedestrians are less likely to avoid a collision with a car when the car decelerate". On the other hand, only the hypothesis that "pedestrians" avoidance behavior is less likely to occur when the AV is decelerating" was supported for AV and collision avoidance. This result suggests that pedestrians may not take avoidance action relative to AVs, while pedestrians may take avoidance action against vehicles when the vehicle is decelerating. From the above results, multiple behavioral assumptions of pedestrians toward vehicles can be verified by using a utility function that includes four elements. Moreover, we can confirm the difference in pedestrian behavior toward AV and cars using the same idea of collision avoidance with vehicles. On the other hand, this estimation assumes that the pedestrian's avoidance behavior "does not choose a choice with interaction", and considers acceleration/deceleration or change of direction in the aggregate. Therefore, in order to analyze pedestrian behavior in detail, it is necessary to estimate pedestrian avoidance behavior separately for "acceleration/deceleration", "change of direction", and "linear constant". In addition, the assumptions for TTC and distance need to be changed so that the estimation can include bicycles and motorcycles.

From this study, there are several issues with this model could be identified (i.e., issues when applying the model of Robin et al. (2009) to collision avoidance with vehicles). Specifically, in this model, the stopping behavior (i.e., behavior with a fairly small velocity) is considered a "constant speed" region because the stopping behavior does not change position much in small time steps. In this study, the stopping behavior is removed from this model, but this behavior must also be taken into account in order to properly describe pedestrian behavior. In addition, the same pedestrian is treated as a different sample from frame to frame, so it is not possible to describe behaviors that follow the same pedestrian's past walking history. Specifically, once a pedestrian avoids a vehicle, he/she may not take any further avoidance actions. To address these issues, we can create new options for stopping behavior, change the choice set based on absolute speed, or extend the model framework to the one discussed in Chapter 5.

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Chapter 5: Modeling Pedestrian Behavior Representing Interactions Between Moving and Staying in Urban Street Space: A Numerical Simulation

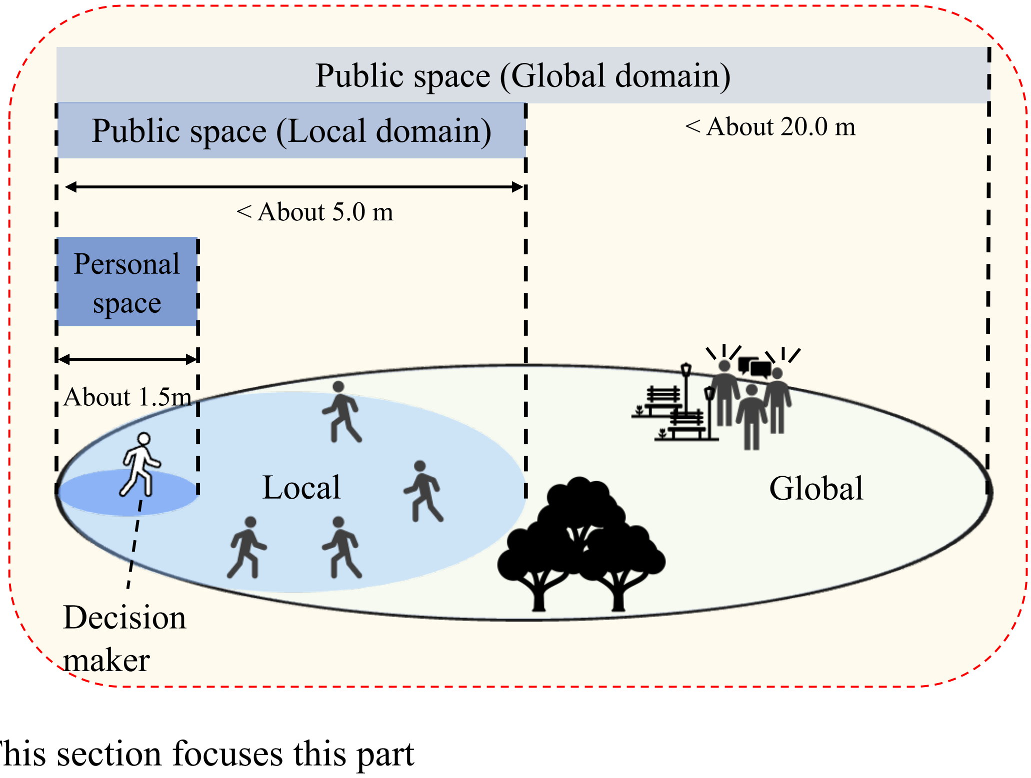

Figure 5. 1 Areas of urban street space focused on in this chapter (red dashed line)

5.1. Introduction

In Chapter 4, we focused on the *local domain* of urban street space on *public space*. In this chapter, in addition to the *local domain* of the *public space*, we also focus on the *global domain* of the *public space* (e.g., crowding going to the destination) (**Figure 5.1**) and aim to develop a methodology to evaluate the use of the urban street space. Specifically, we focus on the interaction between moving and staying, among staying (or moving) in the urban street space considering *Travel function* and *Place function* (Jones and Boujenko, 2009). Specifically, meeting places such as the "Golden Clock" at Nagoya Station (see **Figure 5.2**) naturally attract people, but such clusters of people who stay can interfere with people who move, which may reduce the *Travel function*.

Figure 5. 2 Pedestrian behavior around the "Golden Clock" at Nagoya Station (Source: Authors)

Pedestrian models (Teknomo, 2006; Asano et al., 2009; Robin et al., 2009) that describe these complex interactions are very important, because when complex interactions such as those in **Figure 5.2** occur, counterintuitive use may occur. Furthermore, for a decision support tool for policy makers, the model must have a clear theoretical foundation and evaluation indicators must be able to be calculated directly from the model. In this chapter, we develop a model that describes the interaction between moving and staying, and among moving (or staying) based on the framework of a dynamic discrete choice model. To the best of the authors' knowledge, no study has developed such a model, and the following problems exist.

The following problems exist. In the situation above (**Figure 5.2**), consider two types of agents: travelers and sojourners, as shown in **Figure 5.3**. Travelers have only one moving state, while sojourners have both moving and staying states. An agent transitions to the next state when it moves from one state to another. When an agent transitions to the next state, the state transition cost is strongly influenced by the micro interactions between the agents, as shown in **Figure 5.4**. There are interactions that consist of internal and external, and positive and negative interactions between states of agents (i.e., moving and staying). Specifically, the internal interactions would include: (1) a person who moves tends to follow the person ahead, causing positive interactions among moving, (2) a person who moves also tends to avoid the conflict with the person moving in the opposite

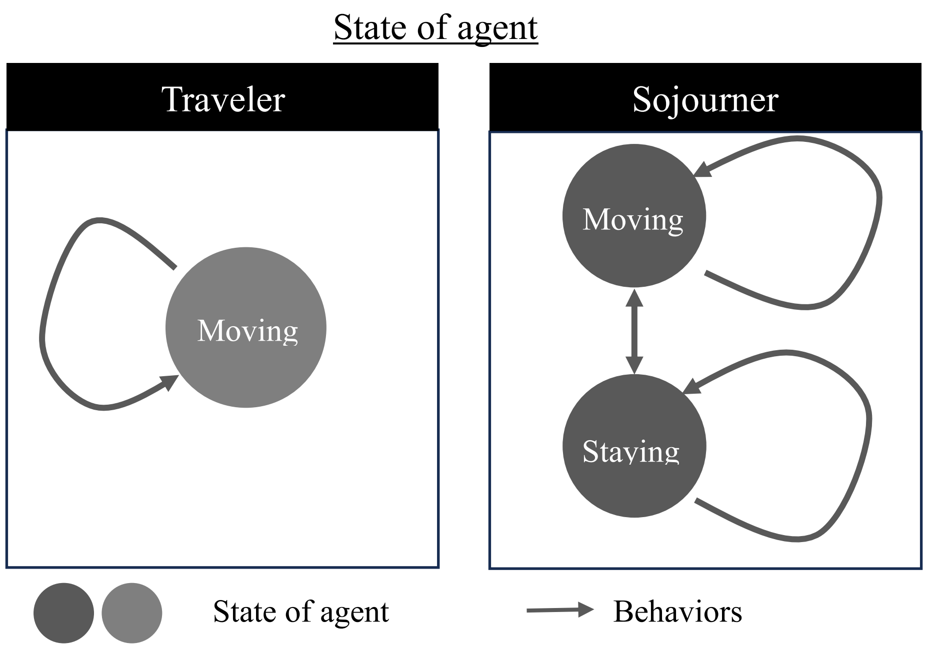

Figure 5. 4 State of agent

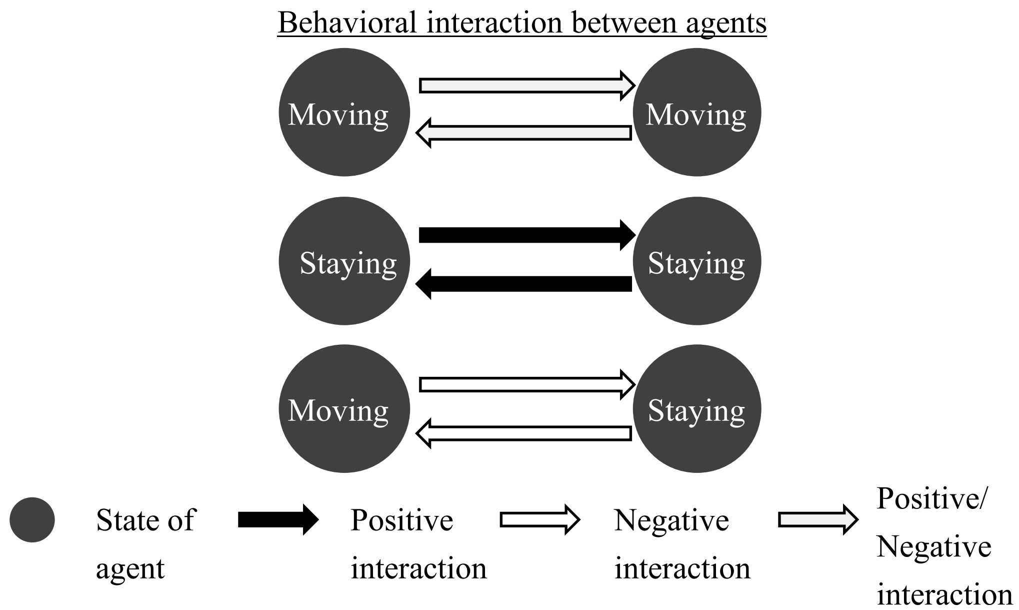

Figure 5. 3 Interaction between agents

direction, causing negative interactions among moving, and (3) increase in a person who stays, could further attract more people to stay, causing positive interactions among staying. The external interactions would include: (1) people who stay could be obstacles for people who move by reducing the effective space for moving, while (2) people who move could reduce the utility of staying in the space by increasing the potential conflicts between people who move and people who stay, causing negative interactions between moving and staying. In summary, there would exist internal positive and negative interactions among staying and moving, as well as external negative interactions between staying and moving. These complex interactions make it difficult to understand the consequences of the model system.

Broadly speaking, there are two approaches to address this issue. The first is to explore the theoretical properties of the model system. The second is to use a computational simulation to understand the behavior of the model system.

In existing works following the first approach, the properties of equilibria, including stability, uniqueness, and convergence, have been explored. After the seminal work of Sandholm (2010), evolutionary game theory (developed in economics) became one of the main tools to achieve it. A major approach is to use the deterministic approximation of stochastic evolutionary process with the assumption of the sufficiently large population size (See Chapter 10 of Sandholm (2010) for the details). This approximation allows us to use an ordinary differential equation to represent evolutionary process under the existence of interactions. Among many existing works exploring theoretical properties using this approximation, the work done by Iryo and Watling (2019) is closely related to the current study. They explored theoretical properties of equilibria for two alternatives and two user groups under the existence of both internal and external interactions. Notably, they classified interactions into nine patterns based on (1) whether internal/external interactions are negative or positive, and (2) whether internal interactions are stronger than external interactions, and confirmed the theoretical properties of equilibria in all cases. The results show that the asymmetric feature of the external interactions may cause the non-existence of a stable equilibrium solution, while most cases can have multiple equilibria. This indicates that equilibria of the model representing interactions between moving and staying which would have asymmetric external interactions, would be very complex. Note that the deterministic approximation may not be appropriate for modeling the pedestrian behavior considered in this study mainly because the interactions locally occur just among a limited (i.e., countable) number of persons.

For the model system, whose theoretical properties are difficult to explore, the second approach, i.e., computational simulation, is often used. Adami et al. (2016) emphasized the importance of using simulation to understand the behavior of the consequences of complex interactions, given that the first approach often assumes unrealistic environments, including infinite population size and perfectly mixed population. The use of simulation is popular in evolutionary biology and economics, and the approach has also been widely used in the transportation field (Asano et al., 2009; Robin et al., 2009; Hoogendoorn et al., 2015; Kneidl et al., 2013). Alsaleh and Sayed (2021) modeled interactions between pedestrians and cyclists (i.e., two user groups) using a multi-agent adversarial inverse reinforcement learning approach (Yu et al., 2019). However, while the framework proposed by Alsaleh and Sayed (2021) can be used to predict the trajectories of pedestrians and cyclists, its theoretical foundation is unclear, making it difficult to compute indices for policy evaluation. Another limitation is that they only considered the moving, and the staying lay outside of their scope.

Given the above considerations, this study first proposes a pedestrian behavior model representing competition between travelers and sojourners based on the dynamic discrete choice modeling framework. The developed model can be characterized as follows. First, we consider two agent types, i.e., travelers and sojourners (see **Figure 5.3**). Second, we consider the interactions within/between moving and staying, including (1) positive and negative internal interactions among moving, (2) positive and negative internal interactions among staying, and (3) positive and negative external interactions between moving and staying. Third, the proposed model is consistent with the RUM theory, allowing us to compute consumer surplus (Ben-Akiva and Litman,1985). These characteristics allow consumer surplus to be used to relect the use of urban road space where there is an interaction between moving and staying.

Through simulation, we will observe how behavioral outcomes and consumer surplus change over time and iteratively in situations with complex interactions between moving and staying (i.e., whether consumer surplus remains within a certain range despite changes in the actual use of space). Next, we analyze the differences in space use patterns between travelers and sojourners by comparing the behavioral outcomes and consumer surplus across scenarios (i.e., object placement and pedestrian flow).

This study is organized as follows. Section 5.2 provides a brief review of existing pedestrian models and highlight the feature of the proposed model system. Section 5.3 introduces the dynamic discrete choice model of pedestrian behavior, together with how we embed internal and external interactions into the model. Section 5.4 presents the numerical simulation analysis focusing on the locations of the objects. Section 5.5 summarizes the conclusions and future prospects.

5.2. Existing pedestrian model

As mentioned in Chapter 2, there are several pedestrian models which focuses on travelers and effectively describes positive and negative internal interaction among those moving in a continuous space, such as the work of Helbing and Molnár (1995), Kwak et al. (2013), Robin et al. (2009) and Asano et al. (2009). In particular, Helbing and Molnár (1995) describes repulsive and attractive forces between pedestrians using equations of motion and consider positive and negative interactions such as collision avoidance and leader follower. Robin et al. (2009)'s model describes sequential speed and angle choice behavior using a logit model framework and also considers positive and negative interactions. Asano et al. (2009) proposed a similar model as Robin et al. (2009), which describes negative internal interactions by incorporating game theory.

By describing route choice behaviors on a network, and employing RUM theory and a logit model framework, Fosgerau et al. (2013) conducted a seminal work confirming that route choice behavior in a discrete state space can be modeled using a dynamic discrete choice framework, called the recursive logit (RL) model as the Markov equilibrium assignment model. The RL modeling framework has been used in many transportation studies, including route choice analysis of pedestrians (van Oijen et al., 2020; Oyama, 2023; 2024). Specifically, a multinomial logit model of route choice behavior in a network can be decomposed into the sequences of link choices using the Bellman equation (Bellman, 1957). This decomposition technique allows us to efficiently compute the expected maximum utility obtainable from the origin point to the destination using the conventional consumer surplus. Also, since the RL model is an implicit route choice model, the expected maximum utility (value function) does not depend on the choice set of the route. However, the RL model has an inherent difficulty in representing staying behavior, essentially because of its inability to handle positive instantaneous utilities that sojourners may acquire (Oyama, 2023). Oyama and Hato (2016) proposed the Prism constrained RL model (Prism-RL), which extends the RL model from a physical network to time structured network, and showed that this model can describe both moving behavior and staying behavior in a network.

In summary, our model employs the model of Oyama and Hato (2016) and incorporates the following three things: (1) consistency with RUM theory and logit model framework (i.e., whether the expected maximum utility obtainable from the origin point to the destination can be computed as a consumer surplus), (2) consideration of both staying and moving, and (3) consideration of positive and negative, and internal and external interactions among moving, among staying, and between staying and moving.

5.3. Model framework

5.3.1. Behavioral assumptions

Pedestrian behavior could be modeled either in (1) a continuous time and continuous space (e.g., Helbing and Molnár, 1995), (2) a discrete time and discrete space (e.g., Oyama and Hato, 2016), and (3) a discrete time and continuous space (Robin et al., 2009). As discussed above, to properly describe physical conflicts among pedestrians, representing pedestrian behavior in a continuous space is necessary. In this study, we employ the third modelling approach, where we consider the continuous space, while time step is discrete. The following is the summary of the approach we took.

First, we changed the deterministic state transition used in Oyama and Hato (2016) to stochastic state transition, where discrete location choices are distributed across a continuous space. This allowed us to identify each pedestrian specific location at each point in time, which enables us, for example, to identify possible collisions among pedestrians in a physical space. Specifically, we assume a physical network (i.e., cross section of time structured network) that is discretely partitioned across a continuous space by grid lines in **Figure 5.5**. The pedestrian's location is randomly distributed within subspace associated with the representative point (i.e., the discrete point that pedestrians chose).

Next, we describe how the trajectory of a time-structured network where both time and space are discretized as shown in **Figure 5.5.** Initially, the pedestrian chooses the link between discrete points and the current location in the time-structured network. Then, similar to the dynamics of continuous space into the network, the pedestrian location is randomly distributed within subspace from the representative point (i.e., the edge of chosen link). In this network, moving is described as diagonal movement and staying as as vertical movement in **Figure 5.5.**

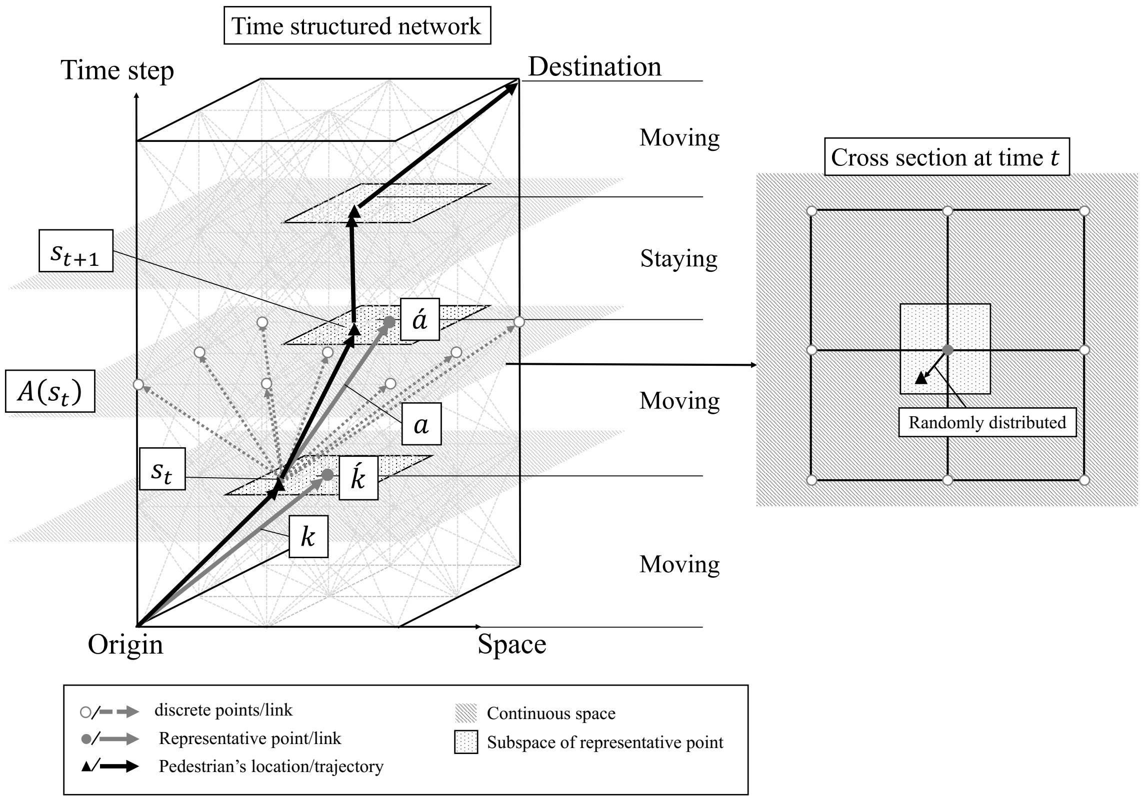

Figure 5. 5 Targeted pedestrian behavior

5.3.2. Pedestrian behavior in the framework of a dynamic discrete choice model

To model pedestrian behavior in a discrete time and continuous space, let $t \in T$ is treated as the time step (i.e., representing discrete time), T represents time budget that means the maximum time step to destination (i.e., pedestrian arrive at the destination until T), and the state space at the time step t, denoted as $s_t = l \in L$. Here l is the location (i.e., the edge of link) at s_t in the target area L (i.e., the area that pedestrian can reach). The path σ of individual n is defined as a state sequence $[s_0, \ldots, s_t, \ldots, s_T]$ from choice stages 0 to T. Note that σ and T are varying across individuals, while subscripts n have been omitted for brevity. The initial state s_0 and the absorbing state s_T are the inflow (origin) and outflow (destination) points of the urban street space. This study defines the absorbing state s_T by adding a dummy link d without successors from destination point. Let $a \in A(s_t)$ be the action that individual n, choose at state s_t, where $A(s_t)$ represents the choice set at state s_t which includes both stay and move actions. We also define $\Lambda = |A(s_t)|$ as the number of actions available to an agent in state s_t. In this model, as shown in **Figure 5.5**, we assume that the pedestrian chooses link a from link set, which are lines between discrete points and state s_t. The next state s_{t+1} is stochastically determined from the subspace of the representative point $\acute{a}$ (i.e., the edge of link a), and the stochastic determination is following with transition probability $q_t(s_{t+1}|s_t, a)$.

However, the transition probability $q_t(s_{t+1}|s_t, a)$ to move to the next state s_{t+1} given a and s_t is used only when the pedestrian chooses a move action. Specifically, the pedestrian' state s_{t+1} is uniformly distributed over the subspace from the representative point $\acute{a}$ when the traveler moves to another subspace. When the pedestrians choose the link a connecting among the same subspace (i.e., choosing stay action), the location of s_{t+1} is exactly the same as that of s_t, so the location of s_{t+1} is determined using location of s_t without transition probability $q_t(s_{t+1}|s_t, a)$.Thanks to this stochastic treatment of state transition, we can define the exact location of pedestrians, enabling, for example, the calculation of possible conflicts with other pedestrians in physical space.

Individual n at state s_t is assumed to choose action a that maximizes the sum of instantaneous utility $u_t(a|s_t)$ and the expected value of the value function $EV_t(s_t, a)$ to absorbing state s_T (i.e., destination). The utility $u_t(a|s_t)$ consists of the deterministic component $v_t(a|s_t)$ and the error component $\varepsilon_t(a)$. The expected value function $V_t(s_t)$ (i.e., the expected maximum utility) is calculated by the following Bellman equation:

$$V_t(s_t) = \max_{a \in A(s_t)} \left(v_t(a|s_t) + EV_t(s_t, a) + \mu\varepsilon_t(a) \right) \tag{5.3}$$

where $\varepsilon_t(a)$ is the error term following the standard Gumbel distribution and μ is the scale parameter. $EV_t(s_t, a)$ is given as:

$$EV_t(s_t, a) = \int_{\check{s}} \left(q_t(\check{s}|s_t, a)\, \bar{V}_{t+1}(\check{s}) \right) \, dq_t(\check{s}|s_t, a) \tag{5.4}$$

where $\bar{V}_t(s_t)$ is the expected maximum utility. Since $\varepsilon_t(a)$ follows Gumbel distribution, $\bar{V}_t(s_t)$ is given by the following consumer surplus:

$$\bar{V}_t(s_t) = \log\left(\sum_{a \in A(s_t)} e^{v_t(a|s_t) + EV_t(s_t,a)}\right) \tag{5.5}$$

As mentioned earlier, we approximate the value function computation using the value obtained from a conventional time-structured network, that is, we do not consider the transition probability $q_t(s_{t+1}|s_t, a)$ for this value function computation, but for the simulation.[5] In this case, **Equation (5.3)** is approximated to the following equation:

$$V_t(k) = \max_{a \in A(s_t)}\left(v_t(a|k) + V_t(a) + \mu\varepsilon_t(a)\right) \tag{5.6}$$

where, k (representative link) is chosen link at t. With the distributional assumption on ε_t, **Equation (5.6)** further reduces to the following consumer surplus:

$$V_t(k) = \log\left(\sum_{a \in A(s_t)} e^{v_t(a|k) + V_t(a)}\right) \tag{5.7}$$

Equation (5.7) shows the consumer surplus from one inflow point in the urban street space to a dummy link. In this study, to quantitatively evaluate of the use of urban street space, the consumer surplus of all inflow points in the discretized street space is calculated using **Equation (5.7)**, and the expected value of this value is used. **Equation (5.7)** is equal to the following equation:

$$e^{V_t(k)} = \sum_{a \in A(s_t)} e^{v_t(a|k) + V_t(a)} \tag{5.8}$$

Equation (5.8) can be written as the following equation:

---

[5] Although approximation of the value function does not allow considering the utility about exact location on continuous space (e.g., utility about collision avoidance with other pedestrians), this study assumes that pedestrians do not consider the effect of going to the destination in detail and that the value function is substituted by values at discrete points. On the other hand, the value function is approximated to discrete points in its calculation, but the effect of continuous space is taken into account in the instantaneous utility.

$$\boldsymbol{z}_t = \boldsymbol{M}_t \boldsymbol{z}_{t+1} + \boldsymbol{b} \quad \forall t \in \{0, \ldots, T-1\} \tag{5.9}$$

where $z_{t,k} = e^{V_t(k)}$, and $M_{t,ka} = e^{v_t(a|k)}$. Also, b_k equals one if s_t is destination and zero otherwise. To solve **Equation (5.9),** simple backward calculation with T iterations are applied. We initialize the vector of the value function: $z_{T,d} = 1$ and $z_{t,k}, \forall (t,k) \neq (T,d)$, and start at $t = T-1$ and update the value function by

$$\boldsymbol{z}_t \leftarrow \boldsymbol{M}_t \boldsymbol{z}_{t+1} + \boldsymbol{b} \tag{5.10}$$

and repeat updating backward in choice stage until $t = 0$ is computed. The probability of choosing action a from state s_t is defined as a logit model form:

$$P_t(a|s_t) = \frac{e^{\frac{1}{\mu}(v_t(a|s_t) + V_t(a))}}{\sum_{a \in A(s_t)} e^{\frac{1}{\mu}(v_t(a|s_t) + V_t(a))}} \tag{5.11}$$

The above probability is the function of the current location in a continuous space. Thus, $\boldsymbol{P}(s_t) == \left(P_t(1|s_t), \ldots, P_t(\Lambda|s_t)\right) = \frac{\widetilde{\boldsymbol{M}}_{t,s_t} \circ z_t^T}{\widetilde{\boldsymbol{M}}_{t,s_t} z_t}$ where $\widetilde{\boldsymbol{M}}_{t,s_t} = \left(\ldots\ldots, e^{v_t(\Lambda|s_t)}\right)$.

5.3.3. Internal and external interactions in the model

The instantaneous utility of each model is defined as follows:

$$v_t(a|s_t) = \begin{cases} \boldsymbol{\beta}^{mo} \boldsymbol{x}_t^{mo}(a|s_t) + \boldsymbol{\gamma}^{mo} \boldsymbol{w}_t^{mo}(a|s_t) & \text{if } a \text{ is move action} \\ \boldsymbol{\beta}^{st} \boldsymbol{x}_t^{st}(a|s_t) + \boldsymbol{\gamma}^{st} \boldsymbol{w}_t^{st}(a|s_t) & \text{if } a \text{ is stay action} \end{cases} \tag{5.12}$$

where the subscripts, *mo* and *st* denote move and stay, respectively. $\boldsymbol{\beta}^{mo}, \boldsymbol{\gamma}^{mo}, \boldsymbol{\beta}^{st}, \boldsymbol{\gamma}^{st}$ are unknown parameter vectors, where $\boldsymbol{x}_t^{mo}(a|s_t)$ and $\boldsymbol{x}_t^{st}(a|s_t)$ are the exogenous variable vectors, $\boldsymbol{w}_t^{mo}(a|s_t)$ and $\boldsymbol{w}_t^{st}$ are the endogenous variable vectors. When choosing action a at state s_t, pedestrians get $\boldsymbol{\beta}^{mo} \boldsymbol{x}_t^{mo}(a|s_t) + \boldsymbol{\gamma}^{mo} \boldsymbol{w}_t^{mo}(a|s_t)$ for move action and $\boldsymbol{\beta}^{st} \boldsymbol{x}_t^{st}(a|s_t) + \boldsymbol{\gamma}^{st} \boldsymbol{w}_t^{st}(a|s_t)$ for stay action. The detailed variable specifications are given in Section 5.3.4.

5.3.4. Pedestrian type: *traveler* and *sojourner*

In this study, we consider two pedestrian types as mentioned above. The first is the *traveler* who just passes through the urban street space. For the travelers, we set the utility for stay action as $-\infty$, meaning that traveler will never stay in the space. The second is the *sojourner* who can both travel and stay in the space under a certain time budget constraint T following the instantaneous utility defined in **Equation (5.12)**.

5.4. Numerical simulation

Numerical simulations are performed for six scenarios based on the location of the objects and the number of incoming travelers and sojourners, assuming constant urban street space and object size. In this numerical simulation, the following two analyses are performed: (i) an analysis of the changes in behavioral outcomes and consumer surplus over time and across trials caused by the model system with complex interactions, and (ii) an analysis of the actual usage of travelers and sojourners in the urban street space in terms of changes in behavioral outcomes and consumer surplus across scenarios.

In the former analysis, the distribution of pedestrians changes within/across trials, but the utility due to congestion is expected to remain within a certain range, so we hypothesize that "the behavioral outcome (where sojourners stay) changes within/across trials but remains within a certain constant range". To test this hypothesis, we perform (1) an Augmented Dickey-Fuller (ADF) test and (2) an ANOVA test to analyze the stationarity of consumer surplus within/across trials and compare it to the graph of behavioral outcome and consumer surplus.

In the latter analysis, we hypothesize that "differences in object placement and the number of incoming sojourners have a significant impact on consumer surplus and behavioral outcomes", because we believe that differences in object placement and the distribution of sojourner cohesion and pedestrian flow will cause significant changes in consumer surplus and behavioral outcomes. To test this hypothesis, we compute the standard deviation and mean of consumer surplus over time (and all times and trials), and behavioral indicators such as travel time and dwell time over time (and all times and trials), and then compare them across scenarios.

5.4.1. Simulation setting

The following setting is used in the simulation:

- The urban street space is assumed to be 10[m] × 20[m] (see **Figure 5.6**). For convenience, the space is discretized into 200 cells (each cell has 1[m] × 1[m])
- Pedestrians flow in and out from both sides of the space. Each pedestrian randomly selects one starting point from 10 cells on each side.
- A pedestrian is assumed to make a route choice decision every 1.0 second.
- Before implementing the simulation, we randomly place 20 people who stay within 2m around object(s) following a uniform distribution. The location of assigned to them is fixed in all simulation trials.

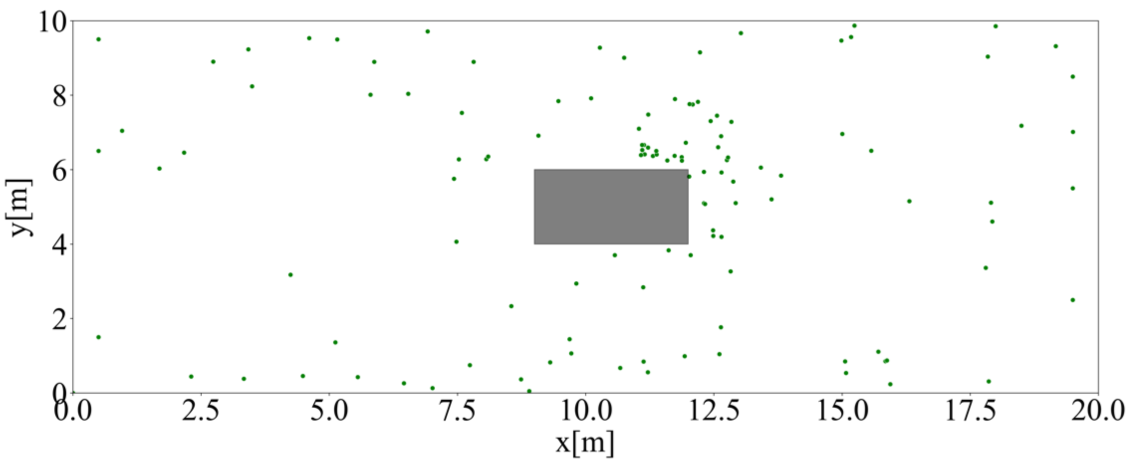

Figure 5. 6 An example of the urban street space in this simulation. The gray rectangle represents an object, and the green dots represent pedestrians.

5.4.2. Definition of variables

In the simulation analysis, the endogenous variables include three interactions: (1) internal interaction among the moving (positive: leader followers; negative: collision avoidance with people who move), (2) internal interaction among the staying (attractiveness generated by sojourners concentration), (3) External interaction between staying and moving (collision avoidance from people who stay or people who move). The exogenous variables include attractiveness of objects, collision avoidance with objects, travel time and transition cost. Note that travel time can also be considered as endogenous, but in this study, we consider it as an exogeneous variable for simplification. The detailed specifications are given in **Table 5.1 and Figure 5.7.** We define the choice set as the set of links connecting points within 2[m] from the current point toward the destination (e.g., the number of alternatives is 10 for the sojourners in **Figure 5.7**).

Table 5. 1 Table of definition of variables.

Endogenous variables			
Internal interaction among moving	Move	Collision avoidance (with people who move) [*negative*]	$w^{cam}(a_n \mid s_{n,t}) \coloneqq \min_{\acute{n}} D(\dot{a}_n, s_{\acute{n},t};\ \acute{n} \in O_a, \acute{n} \neq n)$ $\dot{a}$: the location of edge of link a D: distance function O_a : a set of people who move in the opposite direction within a radius of 3 m in front when taking action a
	Move	Leader follower [*positive*]	$w^{le}(a_n \mid s_{n,t})$: dummy variable 1 if individual n has a leader $\tilde{n} \in F_a$ who satisfies the following two conditions, otherwise 0. $\left\lvert \theta_{a_n} - \theta_{s_{\acute{n},t}} \right\rvert \leq 10°$ $D(\dot{a}_n, s_{\acute{n},t}) \leq 1$ F_a: a set of people who move in the forward direction θ_{a_n}: the angle of a_n, $\theta_{s_{\acute{n},t}}$: the angle of $s_{\acute{n},t}$
External interaction between staying and moving	Move	Collision avoidance (with people who stay) [*negative*]	$w^{cas}(a_n \mid s_{n,t}) := Max(\log(\lvert H_a \rvert), 0)$ H_a : a set of people who stay within a radius of 2 [m]
	Stay	Stay avoidance (with people who move) [*negative*]	$w^{sa}(a_n \mid s_{n,t}) := 1/\min_{\acute{n}} D(\dot{a}_n, s_{\acute{n},t};\ \acute{n} \in O'_a, \acute{n} \neq n)$ O'_a : a set of people who move within a radius of 3 [m]

Internal interaction among staying	Stay	Attractiveness generated by people who stay concentrated [*positive*]	$w_{\square}^{as}(a_n \| s_{n,t}) := Max(\log(\|H_a\|), 0)$
Exogenous variables			
Influences from other sources	Stay	Attractiveness of objects	$x_{\square}^{so}(a_n \| s_{n,t}) := 1/\min_{k} D(\dot{a}_n, OB_k;\ k \in K)$ OB_k: the location of object k K: a set of objects
	Move	Collision avoidance (with objects)	$x_{\square}^{cao}(a_n \| s_{n,t}) := 1/\min_{k} D(\dot{a}_n, OB_k;\ k \in K)$
	Move	Travel time	$x_{\square}^{tt}(a_n \| s_{n,t}) := D(s_{n,t}, \dot{a}_n),\ a_n \in A(s_{n,t})$
	Stay	Transition cost (from staying to moving)	$x_{\square}^{stm}(a_n \| s_{n,t})$: dummy variables if 1 from staying to moving, otherwise 0.
	Move	Transition cost (from moving to staying)	$x_{\square}^{mts}(a_n \| s_{n,t})$: dummy variables if 1 from moving to staying, otherwise 0.

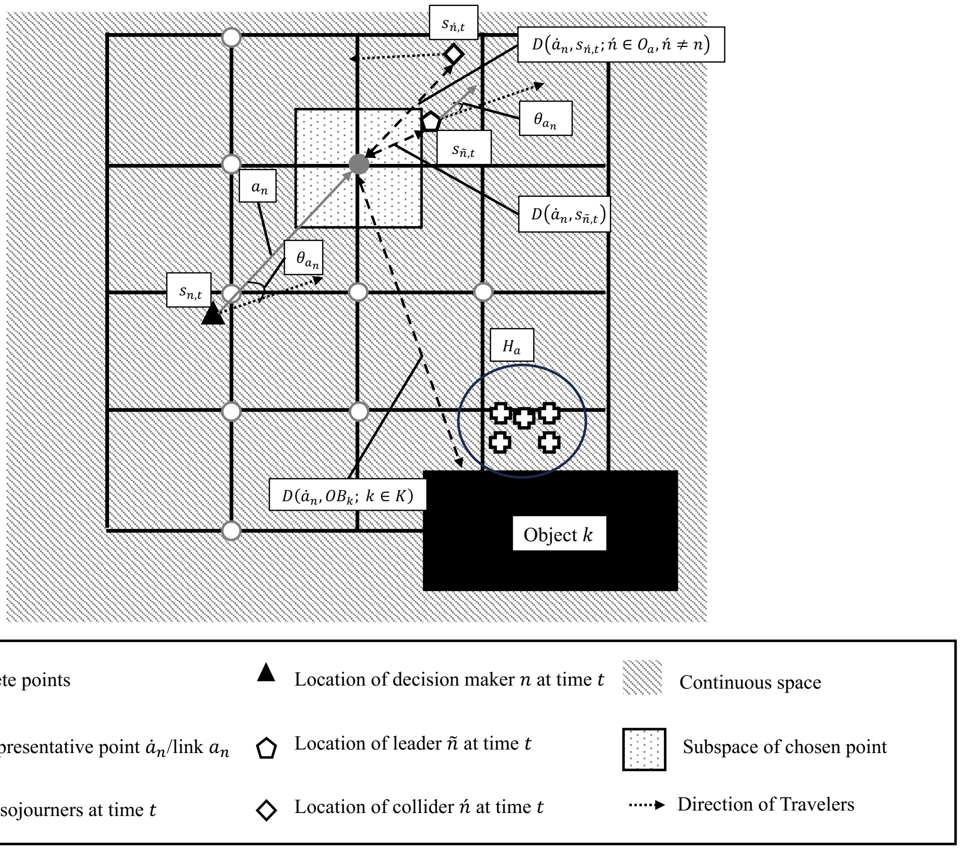

Figure 5. 7 Overview of pedestrian behavior in this simulation. This figure explains the interaction of leader follower, collision avoidance with a person who moves, concentration of sojourners, and an object

5.4.3. Parameters

We set the parameters for each pedestrian type as follows.

Sojourners' parameters

$$[\gamma^{cam}, \gamma^{le}, \gamma^{cas}, \gamma^{sa}, \gamma^{as}, \beta^{so}, \beta^{cao}, \beta^{tt}, \beta^{stm}, \beta^{mts}] = [-1.0, 0.1, -1.2, -1.0, 1.2, 1.0, -0.1, -0.1, -0.1, -0.1] \tag{5.13}$$

Travelers' parameters

$$\begin{aligned}&[\gamma^{cam}, \gamma^{le}, \gamma^{cas}, \gamma^{sa}, \beta^{cao}, \beta^{stm}] \\ &= [-10, 10, -10, -10, -10, -10]\end{aligned} \tag{5.14}$$

It is assumed that the travelers do not take stay action.

This simulation conducted trials using only the above parameters to assume the situation where sojourners tend to concentrate. We explain some other situations by changing the parameters: (1) if the parameter γ^{as} become small, the likelihood of the sojourners taking stay action is reduced due to reducing the stay utility, (2) if the parameter γ^{cas}, becomes small negatively, travelers may not avoid concentrating sojourners who stay, indicating that the travelers' routes will be come close to the location of where sojourners are concentrated.

5.4.4. Simulation flow

The pedestrian behavior is simulated following the process shown in Algorithm 1. Both travelers and sojourners depart between 0 and 200 seconds. Each pedestrian randomly selects one starting point in each simulation trial. This simulation flow is repeated until all pedestrians arrives at their destination.

ALGORITHM 1 Flow of Simulation

LET N_t is a set of pedestrians in the space at time t ($|N_0| = 20$),
IN_t is a set of pedestrians who just depart from the origin at t ($|IN_0| = 0$),
OUT_t is a set of pedestrians who just arrived at destination at t ($|OUT_0| = 0$),
T is the maximum number of steps ($T = 30$ for the current study) to the destination.

SET $t = 1$, flow rate IN_t and IN_s, and $MAX\_ITERATION = 200$.
WHILE $|N_t| > 0$
    COMPUTE $N_j \longleftarrow N_{t-1} \cup IN_{t-1} \setminus OUT_{t-1}$
    FOR $n = 1, \ldots, |N_t|$ DO
        COMPUTE $\boldsymbol{M}$ and $\widetilde{\boldsymbol{M}}$ (updating endogenous variables)
        COMPUTE $\boldsymbol{z}_T \longleftarrow \boldsymbol{b}$
        FOR $i = T - 1, \ldots, 1$ DO
            COMPUTE $\boldsymbol{z_i} \longleftarrow \boldsymbol{M_i} \circ \boldsymbol{z_{i+1}} + \boldsymbol{b}$

```
        COMPUTE  P(s_{n,i}) ← (M̃_{i,s_{n,i}} ∘ z_i^T) / (M̃_{i,s_{n,i}} z_i)
            END FOR
            COMPUTE  a~P(a|s_{n,t})
            COMPUTE  s_{n,t+1}~q(a, s_{n,t})
        END FOR
        COMPUTE  OUT_t
        COMPUTE  IN_t ← IN_t ∪ IN_s  if  t ≤ MAX_ITERATION,
         IN_t ← 0  if  t > MAX_ITERATION.
        INCREMENT  t
    END WHILE
```

5.4.5. Simulation scenario

In this simulation, six scenarios are used, with differences in object location (i.e., center or top and bottom) and the number of pedestrians (i.e., travelers and sojourners) per second (i.e., 2 or 4), as shown in **Table 5.2**. Note that the total object sizes for the center and top and bottom cases are the same. This indicates that the size of the urban street space where people can stay and move is consistent across all scenarios.

Table 5. 2 Table of definitions for six scenarios

	Object location	The number of sojourners: N_s	The number of travelers: N_m
Scenario 1	Center	4 [persons/s]	4 [persons/s]
Scenario 2	Top and bottom	4 [persons/s]	4 [persons/s]
Scenario 3	Center	2 [persons/s]	4 [persons/s]
Scenario 4	Top and bottom	2 [persons/s]	4 [persons/s]
Scenario 5	Center	4 [persons/s]	2 [persons/s]
Scenario 6	Top and bottom	4 [persons/s]	2 [persons/s]

5.4.6. Simulation result

We made 50 simulation trials using **Algorithm 1** for each scenario. Note that, since (1) we do not have any travelers in the space at the initial stage, and (2) it will take some people to form the spot(s) with concentrations of sojourners, we consider 1–89[s] as a burn-in period. All discussions below are based on using the simulation results between 90–200[s].

5.4.6.1. The stationary state of simulation result

First, we check the stationary state of the simulation results for scenarios 1 and 2, focusing on behavioral outcome (i.e., distribution of pedestrians in the space) and consumer surplus, both (1) within each trial and (2) across trials. The behavioral outcome is illustrated in **Figures 5.8 and 5.9**, showing the trajectories of the travelers and the location of sojourners during their stay. Each line traces the traveler's movement for the last five seconds. The yellow line (black line) traces the traveler's trajectory departing from the left side (right side). Blue areas indicate kernel density and orange dots indicate sojourners who stay. We check the difference of behavioral outcomes (i.e., location concentrating sojourners) within each trial and between trials from these graphs.

Figures 5.10 and 5.11 depict the variation of consumer surplus for travelers and sojourners across 50 trials for both scenarios, displaying expected consumer surplus of 10 starting points on each side. The top graph shows the consumer surplus for travelers and the bottom graph shows the consumer surplus for sojourners. **Table 5.3** shows the ADF test[6] results (i.e., whether consumer surplus is stationary or not) for the 50 trials. **Table 5.4** shows the ANOVA test[7] results (i.e., p-value and average square about times, trials, and residual) for both scenarios.

These results show that, while locations with concentration of sojourners vary across trials, once they are concentrated, they do not shift to other locations (**Figures 5.7-(a, b), 5.8-(a, b)**). In reality, when too many sojourners gather in one place, disutility occurs, leading to the possibility of moving to another location, which slightly deviates from this phenomenon. This phenomenon is due to parameters setting in such a way that the

[6] The ADF test is a unit root test used to determine whether the targeted data has a unit root. If the p-value is statistically significant, the data can be considered stationary.

[7] The ANOVA test is used to explore significant differences between the means of three or more groups and to identify the effects of factors and residuals on these differences. If the p-value is statistically significant, it indicates that the means of the groups differ due to the effects of the factors. Additionally, if the mean square is large, it suggests that the group means differ significantly because of the factors' effects.

interaction among sojourners has a significant impact (i.e., congestion by concentrations of sojourners is not considered disutility). We also found that the consumer surplus is stationary in both object locations (**Table 5.3**). Therefore, both the consumer surplus and the behavioral outcome are stationary within the trial. Note that (1) in both scenarios, there are a few trials that where location of the concentration changes over time (**Figures 5.7-(c) and 5.8-(c)**), and (2) for travelers, the number of trials with stationary consumer surplus for scenario 2 (i.e., the top and bottom case) tends to be smaller than that for scenario 1 (i.e., the center case).

We also found that the locations of concentrations of sojourners vary across trials, as shown in **Figures 5.8 and 5.9**. Additionally, the consumer surplus varies across trials as shown in **Table 5.4**. These results can be attributed to the existence of multiple equilibria. However, the consumer surplus shows little variation across trials and falls within a small range (see **Figures 5.10 and 5.11**). This phenomenon is analogous to the phenomenon of escalator use. Specifically, it is known that there are two equilibria, i.e., priority lane is given to the left or right side, but the overall performance remains the same between two equilibria. This indicates that under the current setting, the urban street space can be evaluated stably using the consumer surplus.

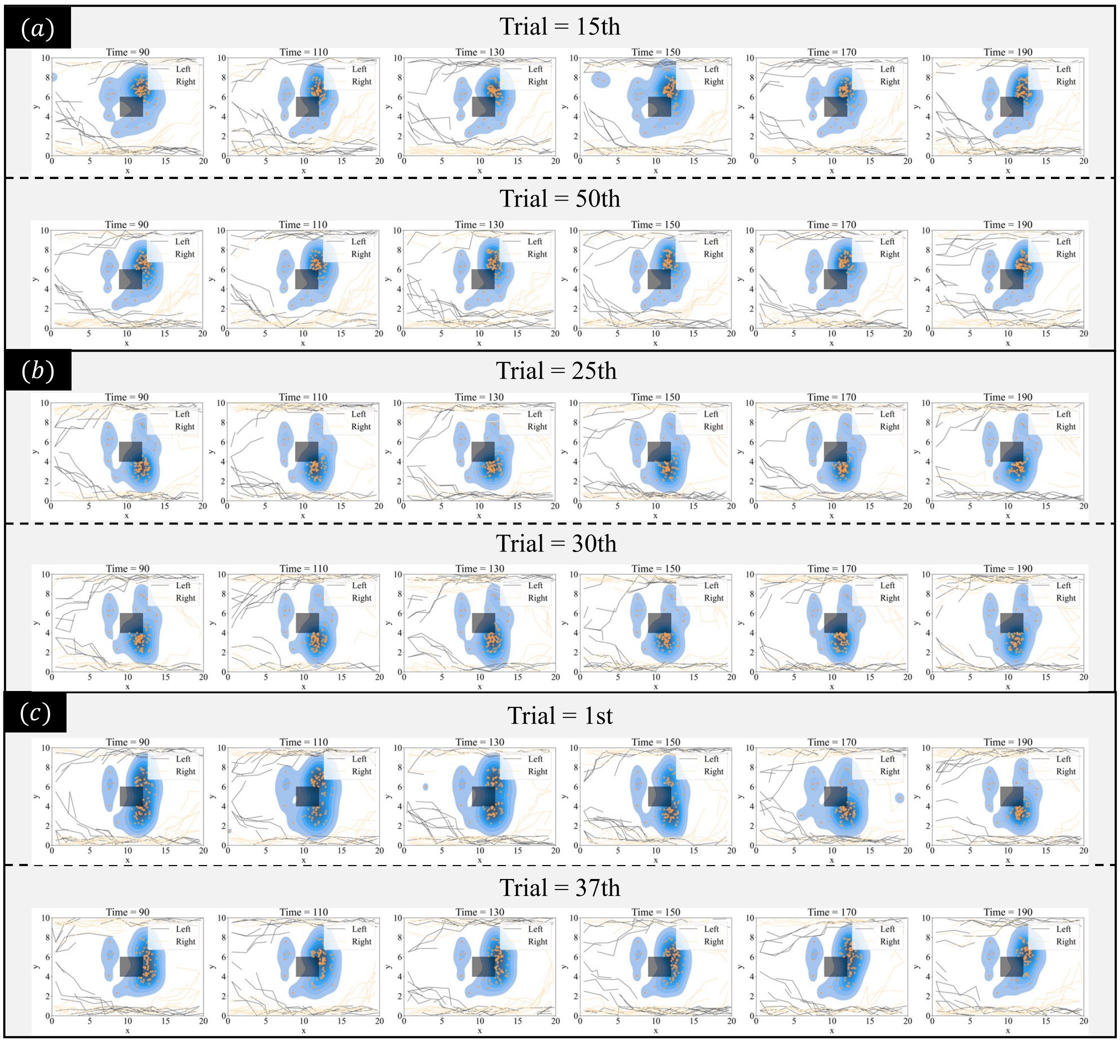

Figure 5. 8 The trajectories of travelers and kernel density of sojourners staying at some trials of scenario 1

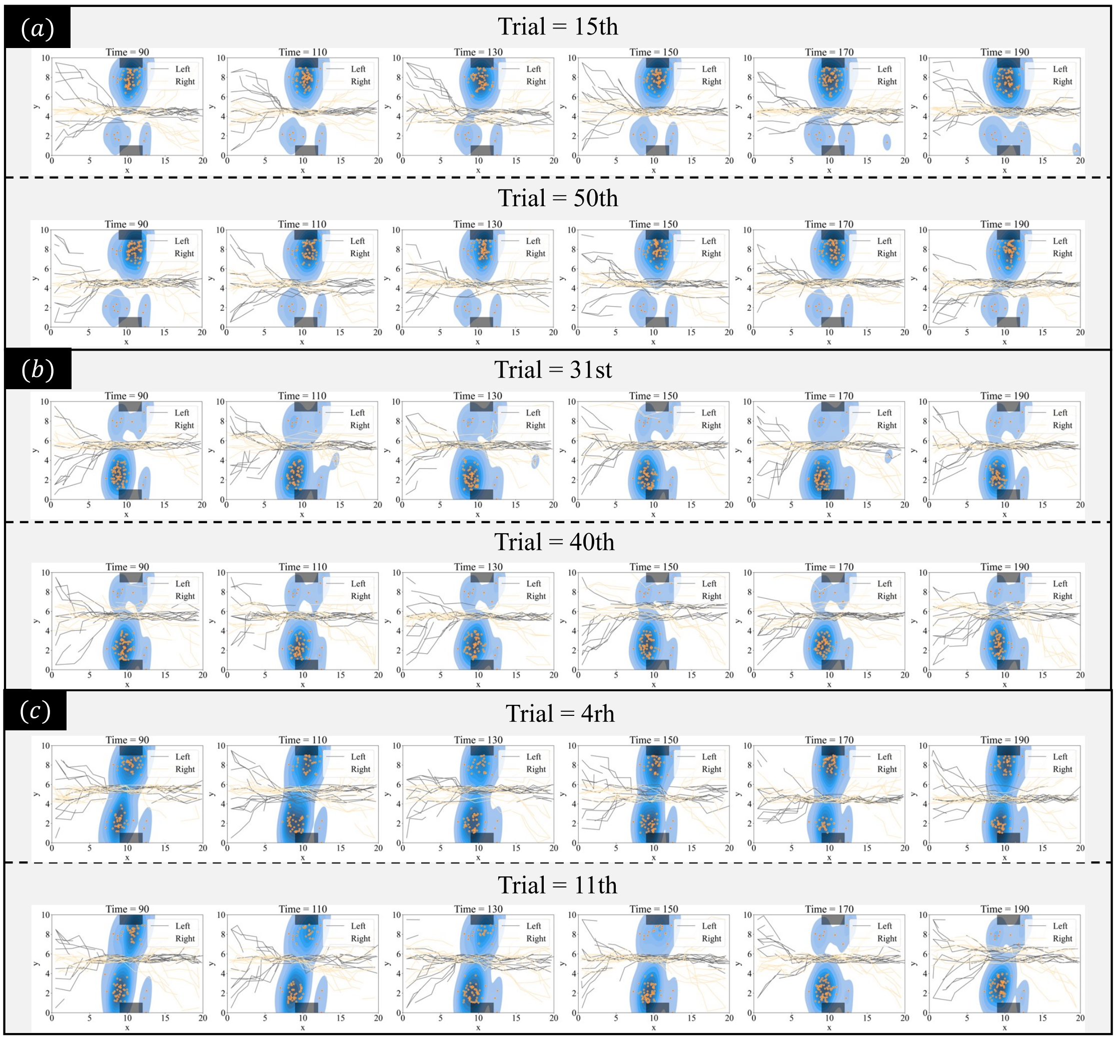

Figure 5. 9 The trajectories of travelers and kernel density of sojourners staying at some trials of scenario 2

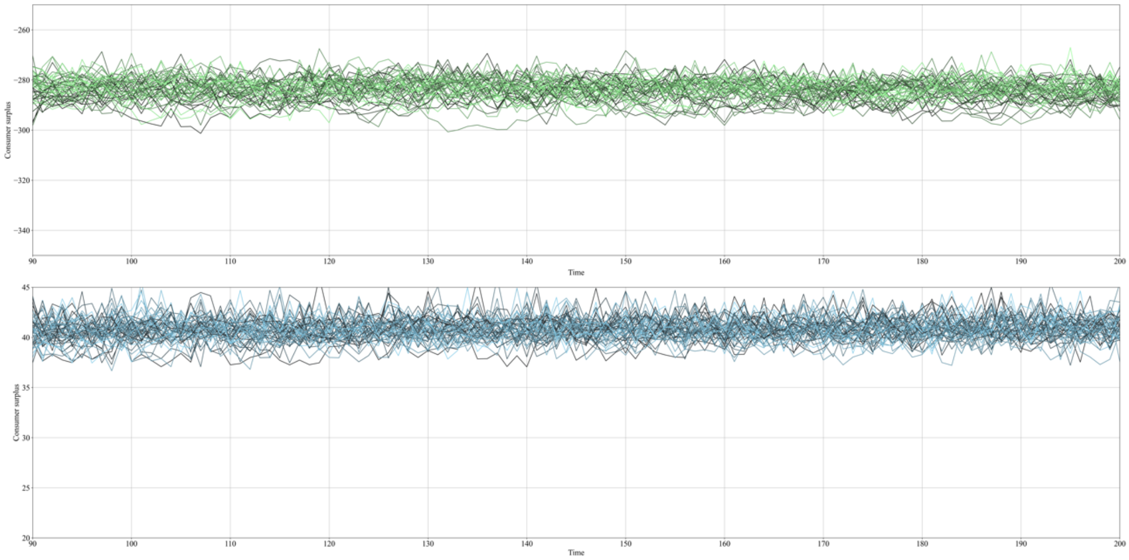

Figure 5. 10 Changes in consumer surplus over 50 trials in Scenario 1: (top) travelers, (bottom) sojourners

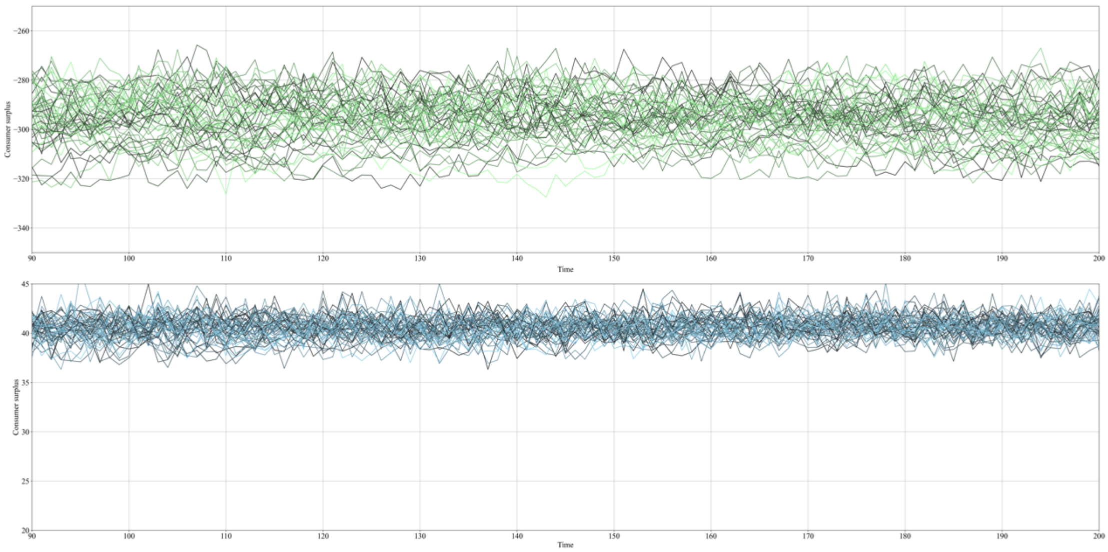

Figure 5. 11 Changes in consumer surplus over 50 trials in Scenario 2: (top) travelers, (bottom) sojourners

Table 5. 3 Result of ADF test about consumer surplus

	Travelers				Sojourners			
Significance levels	<=1 %	<=5%	<=10%	>10%	<=1%	<=5%	<=10%	> 10

								%
Scenario 1	38	6	3	3	46	0	0	4
Scenario 2	13	8	11	18	45	1	0	4

Table 5. 4 Result of ANOVA test about consumer surplus

Scenario		1		2	
		p-value	average square	p-value	average square
travelers	Times	5.49×10^{-1}	14.3	0.735	53.08
	Trials	0	8.34×10^{2}	0	5.03×10^{3}
	residual	-	14.6	-	58.3
sojourners	Times	2.23×10^{-1}	1.50	5.21×10^{-4}	1.97
	Trials	1.24×10^{-128}	22.7	5.70×10^{-135}	22.7
	residual	-	1.37	-	1.30

5.4.6.2. Simulation results in six scenarios

In this section, scenario analysis is conducted using the proposed model. In total, we prepared six scenarios. The evaluation criteria employed include the mean and standard deviation (SD) of (1) consumer surplus for travelers, (2) consumer surplus for sojourners, (3) total travel time, (4) total travel distance, (5) duration of stay, and (6) the number of sojourners who stay (see **Table 5.5**). The SD consists of (1) SD of the trial means (i.e., the difference across trials) and (2) SD across all times and trials (i.e., the difference under each scenario).

First, we confirmed that the average consumer surplus for both travelers and sojourners is greater for the center placement scenarios (i.e., scenarios 1, 3 and 5), compared to top and bottom scenarios (i.e., scenarios 2, 4 and 6). Also, these center scenarios have smaller SD for the consumer surplus of travelers compared to the top and bottom ones. This indicates that the center placement scenarios in general outperform the top and bottom placement scenarios in terms of utility gains for *both* travelers and sojourners. This might be because the center placement is makes it easier for the sojourners to identify a place to stay, which in turn contributes to give space to travelers (see **Figure 5.12**). This finding is further supported by other metrics: the center placement scenarios have shorter travel time (travelers), shorter travel distance (travelers), longer duration of stay (sojourners), and a larger number of sojourners who stay (sojourners), all of which contribute to increasing utilities.

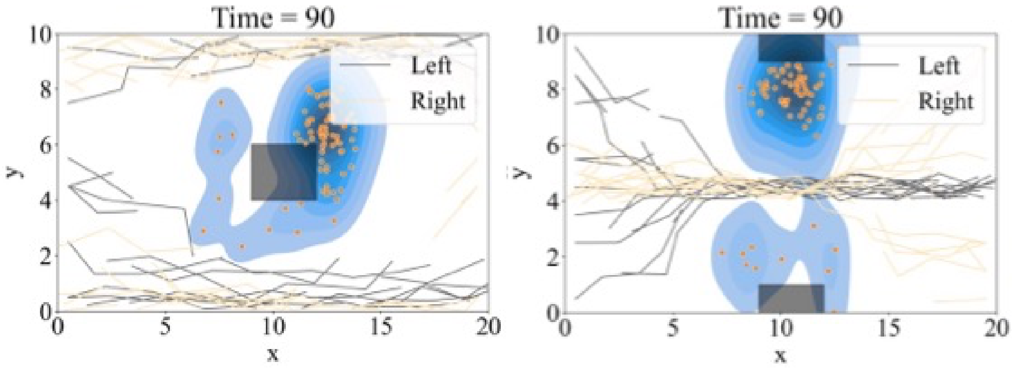

Figure 5. 12 Different location of the object(s): left one is center case and right one is top and bottom case.

Second, from the results of scenarios 3 and 4, we confirm that the reduction in the number of sojourners increases the consumer surplus for travelers, while reducing the consumer surplus for sojourners, as expected. On the other hand, travel time and travel distance for travelers are not much changed from scenarios 1 and 2, indicating that the utility gain for travelers mostly comes from the reduction of conflicts with sojourners who stay rather than passing through the space faster. For the sojourners, they reduce the duration of stay considerably, and the average number of sojourners who stay are smaller than that in scenarios 1 and 2, while they increased the SD (across all times and trials and of the trial means) of the duration of stay and consumer surplus for sojourners. This suggests that the utilities obtained from the concentration of sojourners decrease, leading to more varied staying patterns.

Third, from the results of scenarios 5 and 6, we can confirm that the reduction in the number of travelers increases the travelers' consumer surplus under the center placement scenario, while it slightly decreases travelers' consumer surplus under the top and bottom placement scenario. This means that as the number of people walking decreases, the Level of Service (LOS) of the space usually tends to increase because it becomes easier to walk. However, in the top and bottom cases, as the number of people walking increases, the LOS of the space decreases, making it harder to walk. This would possibly happen because the sojourners who stay under the top and bottom placement scenario could spread out toward the center due to (1) the reduction of pressure from the travelers and (2) the attraction of the object on the other side. This implies that to maintain the travel function under the top and bottom placement scenario, we may need certain number of travelers. We also found that sojourners' consumer surplus increased in both scenarios.

In summary, we find that (1) consumer surplus is stationary within and across trials despite the existence of multiple equilibria in a given scenario, and (2) the center placement and change of the number of sojourners affect consumer surplus and behavioral outcomes (i.e., the mean of the duration of stay and the mean of the number of sojourners who stay). The change in the number of inflows of travelers also creates a paradox in the change in consumer surplus of travelers between the center case and the top and bottom case. These results suggest that the proposed model can effectively evaluate the behavioral consequences of differences. Furthermore, they show that the proposed model has the ability to capture intuitively incomprehensible behaviors caused by differences in the location of objects and the number of pedestrian inflows. In this way, the proposed model describes complex pedestrian behavior in urban street spaces and may provide useful insights for decision making regarding urban street space design.

Table 5. 5 Result of scenario analysis about evaluation criteria

Scenario		1	2	3	4	5	6
Object location		Center	Top and bottom	Center	Top and bottom	Center	Top and bottom
The number of sojourners: N_s		$N_s = 4$	$N_s = 4$	$N_s = 2$	$N_s = 2$	$N_s = 4$	$N_s = 4$
The number of travelers: N_t		$N_t = 4$	$N_t = 4$	$N_t = 4$	$N_t = 4$	$N_t = 2$	$N_t = 2$
Consumer surplus (travelers)	Mean across all times and trials.	-283.8	-295.2	-278.1	-281.7	-280.9	-295.7
	SD of the trial means.	5.3×10^{-1}	1.0	5.4×10^{-1}	9.5×10^{-1}	6.0×10^{-1}	1.5
	SD across all times and trials.	4.7	10.1	3.9	7.2	4.6	10.1
Consumer surplus (sojourners)	Mean across all times and trials.	40.8	40.6	35.0	35.0	40.9	40.7
	SD of the trial means.	1.7×10^{-1}	2.0×10^{-1}	2.1×10^{-1}	2.8×10^{-1}	2.3×10^{-1}	1.8×10^{-1}
	SD across all times and trials.	1.2	1.2	1.5	1.5	1.3	1.2
Travel Time (travelers)	Mean across all times and trials.	12.4	12.6	12.4	12.6	12.4	12.5
	SD of the trial means.	7.0×10^{-2}	1.0×10^{-1}	5.4×10^{-2}	6.7×10^{-2}	8.3×10^{-2}	1.2×10^{-1}
	SD across all times and trials.	1.2	1.1	1.2	1.1	1.2	1.1
Travel Distance (travelers)	Mean across all times and trials.	21.5	21.6	21.4	21.6	21.5	21.6
	SD of the trial means.	9.0×10^{-3}	1.2×10^{-2}	6.0×10^{-3}	5.0×10^{-3}	6.0×10^{-3}	1.0×10^{-3}
	SD across all times and trials.	9.7×10^{-1}	9.2×10^{-1}	9.4×10^{-1}	8.9×10^{-1}	9.9×10^{-1}	9.1×10^{-1}
The duration of stay (sojourners)	Mean across all times and trials.	14.2	14.0	13.2	12.8	14.2	14.1
	SD of the trial means.	8.1×10^{-2}	9.5×10^{-2}	2.9×10^{-1}	4.1×10^{-1}	1.3×10^{-1}	1.4×10^{-1}
	SD across all times and trials.	1.3	1.4	2.9	3.1	1.6	1.4
The number of sojourners who stay (sojourners)	Mean across all times and trials.	57.2	56.4	26.8	26.0	56.9	56.5
	SD of the trial means.	3.0×10^{-1}	1.8×10^{-1}	4.6×10^{-1}	6.9×10^{-1}	4.1×10^{-1}	5.0×10^{-1}
	SD across all times and trials.	2.0	2.4	1.9	2.1	2.1	2.2

5.5. Conclusion

To establish a theoretical foundation for policymakers' decision-making tools, this study proposed a pedestrian behavior model representing interactions between moving and staying based on the dynamic discrete choice modeling framework. The developed model has the following characters: (a) it considers two agent types, i.e., travelers and sojourners; (b) it considers interactions within/between moving and staying, including (1) positive and negative internal interactions among moving, (2) positive internal interactions among staying, and (3) negative external interactions between moving and staying; and (c) it is consistent with the random utility maximization theory and logit model framework, allowing us to compute consumer surplus.

We conducted a numerical simulation with six scenarios based on object location and the number of pedestrian inflows, and 50 trials were performed for each scenario. In this simulation, we found two main things: (1) the consumer surplus is stationary within each trial and across trials despite the existence of multiple equilibria (i.e., different locations of concentrations of sojourners) in the specific scenarios, and (2) the center placement and change of the number of sojourners affect the consumer surplus and behavioral outcomes. Specifically, consumer surplus for the center case was larger, and decreasing the number of sojourners reduced the mean of the duration of stay and the mean of the number of sojourners. In addition, a change in the number of travelers unexpectedly caused a paradox of the consumer surplus for travelers at top and bottom case (i.e., fewer pedestrians walking, which should have increased the consumer surplus, but instead decreased it). From these findings, this model can evaluate the different usage of space by travelers and sojourners, depending on the number of pedestrians who move through and the location of objects, even in the same space size. Moreover, this model also captures the behavioral phenomena that are not intuitively understood due to the complexity of interactions.

In terms of urban street space design, from these findings we suggest that (1) the center case is better for travelers and sojourners because the clearer spatial design allows sojourners to identify the place to stay, which in turn contributes to space for travelers, and (2) a certain number of travelers is necessary for the travel function in the case of top and bottom case because they can show the clear route for them.

However, this proposed model has several limitations: (1) it does not assume some interactions between moving and staying, or among moving (staying), such as negative interactions among stayers (e.g., too many people staying in the area make it difficult to stay in the opposite direction), (2) it focuses only on pedestrians such as those who have predetermined their purpose, (3) it assumes that everyone has rational behavior (i.e., it is necessary to consider randomness among individuals). Related to the first limitation, in order to accurately describe group formation of those who stay, we need to apply the ideas of the models that focus on interactions such as attraction and repulsion (Kwak et al., 2013), which are used in the field of social organization. Moreover, as discussed by Miura et al. (2023), interactions are different before, during, and after the staying (e.g., stopping by), so it is necessary to change the description separately for each time point.

Several future research directions can be considered. First, since the parameters used are not realistic, we need to conduct sensitivity analyses by varying several parameters and perform the parameter estimation using observational data. Second, we need to conduct simulations that consider different scenarios, such as situation where pedestrians and vehicles coexist, imposing physical separation (e.g., bicycle lanes and pedestrian lanes), or dynamic design (e.g., objects or shops moving to different locations). These limitations should be taken into account to increase the robustness of this evaluation framework.

5.6. References

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Chapter 6: Conclusion

6.1. The contributions of each chapter to the development of an evaluation framework for the urban street space design takes into account *Travel function* and *Place function*

In this section, we discuss the contribution of each chapter in the evaluation for the urban street space design considering *Travel function* and *Place function* and the integration of each chapter (i.e., how to bring the idea of Chapter 3 and 4 into Chapter 5).

6.1.1. Contribution of Chapter 3

In Chapter 3, we focused on the observation of user perception within the *personal space* of urban street space. The observation of perception is essential for considering both *Travel function* and *Place function*, because understanding the perception of vehicles that are close to the pedestrian (e.g., whether the pedestrian feels danger or not) is important for the space design to improve safety, such as limiting speed, and understanding the perception of objects (e.g., whether the pedestrian feels something is attractive or not) is important for the space design to create a feeling of liveliness by changing the location of objects. Furthermore, since the use of urban street space changes moment by moment, it is considered important to observe pedestrian perception at their current specific location. In Chapter 3, we analyzed the effect of *recall time* (i.e., the time difference between completing a behavior and completing a response) on choice results. The data from a location-specific preference survey conducted in Hiroshima and Kumamoto, which observed preference for congestion pricing scheme, were used for the analysis. The analysis revealed two key findings: (1) the longer the *recall time*, the stronger the tendency for systematic bias in choice results, and (2) the longer the *recall time*, the greater the tendency for users to choose responses that emphasize preference factors rather than behavioral context. These results suggest that longer *recall time* may directly and indirectly affect the accuracy of choice results. Similarly, in the context of observing pedestrian behavior, we assume that longer *recall time* reduces the accuracy of observation, i.e., observing mixed perceptions at multiple points in time. In other words, it is important to consider the *recall time* to maintain a high accuracy in observing the user perception. Moreover, as mentioned earlier, since the *recall time* includes *response time* (i.e., time to think), we need to record the time of the push notification for the completion of the behavior survey and the start and end time of the response in the preference survey. In other words, we need to analyze the impact of both times on choice result, for example, analyze which influence is responsible for the loss of observation accuracy.

6.1.2. Contribution of Chapter 4

In Chapter 4, we focused mainly on the *local domain* of *public space* in urban street space, i.e., the model framework for micro interaction (i.e., collision avoidance) between pedestrians and vehicles. This is related to the improvement of safety in the *Travel function*. We extended the existing model of Robin et al. (2009) to describe pedestrian-vehicle interaction, and then we analyzed the difference in pedestrian behavior toward vehicles. For the interaction with the vehicle, we introduced a utility function that took into account four factors (i.e., likelihood of collision, perception of vehicle behavior, risk at collision, and safety distance to collision). The data was taken from observations of trajectories of pedestrians and vehicles (i.e., AV, car, bicycle, motorcycle) at crosswalks on the Higashi-Hiroshima campus of Hiroshima University.

The analysis revealed three main findings: (1) pedestrians tend to engage in avoidance behaviors when the car does not decelerate, (2) pedestrians tend to engage in non-avoidance behaviors when the car does decelerate, (3) pedestrians tend to engage in relatively little avoidance behaviors, even when an AV does not decelerate. These findings suggest that pedestrians behave differently toward AVs and cars. There are two possible reasons: (1) the speeds of cars and AVs are different (i.e., the speed of AVs speed is slower than the speed of cars), and (2) pedestrians trust that AVs will always stop.

These results suggest that the difference in pedestrian behavior toward vehicles can be analyzed by the extended model based on Robin et al. (2009). In general, such differences in pedestrian behavior can be attributed to differences in risk perception toward vehicles (e.g., pedestrian perceived safety for AVs, as in Deb et al., 2017). Although the model proposed in Chapter 4 does not directly clarify which factors (e.g., vehicle speed, distance between vehicles, and perceived risk toward vehicles) are responsible for differences in pedestrian behavior, it is possible to analyze differences in behavior, including risk perception, indirectly through differences in parameters and model accuracy. In the future, to design of pedestrian-vehicle coexistence space, we need to analyze the difference in pedestrian behavior toward bicycles and motorcycles using the same modeling framework.

6.1.3. Contribution of Chapter 5

Chapter 5 focused on the *global domain* of *public space,* i.e., evaluation of the effect on getting to the destination. Specifically, we focused on the interactions between moving and staying, which is related to the trade-off between *Travel function* and *Place function*. To do this, we developed the pedestrian model that describes the internal/external, positive/negative interactions of moving and staying using a dynamic discrete choice model framework. The proposed model can evaluate the actual use of urban street space considering these interactions in terms of changes in consumer surplus. Using the proposed model, numerical simulations (including 50 trials for each scenario) were conducted for six scenarios based on changes in the placement of objects and the number of pedestrians.

The analysis revealed two key findings: (1) the change in consumer surplus remained within a certain range, despite variations in the location of sojourners, and (2) when the number of travelers moving through was reduced, the consumer surplus unexpectedly decreased in the case of the top and bottom cases (i.e., it was expected to be easier to walk with fewer travelers, but it was harder to walk). Therefore, this evaluation framework, which considers interactions between moving and staying, among moving (or staying), can evaluate the phenomena (e.g., as an increase in travel time when the number of sojourners decreases or when an increase in the number of sojourners makes it easier for sojourners to stay in the area) that are consistent with existing studies. Moreover, this framework can also evaluate the unexpected phenomena (e.g., fewer travelers were expected to make walking easier, but it was harder).

The evaluation framework proposed in Chapter 5 is a basic framework for evaluating the use of urban street space in terms of changes in consumer surplus from the behavioral aspect. On the other hand, the “equity” of the evaluation framework presented on in this dissertation must also be considered. In other words, the consumer surplus is a clear indicator and aids in efficient decision-making among stakeholders, but it is does not account for all users of urban street space (e.g., different individuals perceive travel time differently). Therefore, when using consumer surplus to evaluate urban street space, it is necessary to also consider factors outside the evaluation framework, such as culture and history.

6.1.4. Integration of each chapter

Here, some of the requirements and challenges in extending the model in Chapter 4 to the framework in Chapter 5 are described below. First, it is necessary to develop models for multiple agents (e.g., pedestrians, cars, bicycles). A major challenge in this process is the development of vehicle models. Two methods are considered: (1) using the social force model proposed in existing research, (2) using the Robin et al. (2009) model. In the second case, since vehicles have more difficulty making in changing their behavior (e.g., speed, angle) over short time intervals compared to pedestrians, we need to consider the difference in time steps (i.e., decision making timing) and the difference in choice set between pedestrians and vehicles. For example, in the Chapter 4, pedestrians have 33 alternatives and a 170° visual angle, whereas for vehicles, we need to reduce the number of alternatives and the visual angle.

Second, it is necessary to describe the multiple interactions between agents and to consider the equilibrium of the interaction in a given situation. In other words, as the number of agents (i.e., road users) increases, the optimal behavior of each agent depends on the behavior of the other agents and the environment of the space, since the situation becomes highly uncertain (i.e., complex interactions occur). For example, using the Markov Game framework (Alsaleh and Sayed, 2021; Ogawa and Hato, 2021), road users can learn and model their behaviors simultaneously, allowing for evaluation of urban street space that accounts for the interactions among agents. In other words, the equilibrium between multi-agents need to be considered under the RUM framework. On the other hand, when using the RUM framework, we need to create the utility function with prior assumption about the agents' interaction type considered for the modeling such as collision avoidance and leader follower, compared to a model like AIRL, where the reward function is restored according to the observed trajectory.

Next, some of the requirements and challenges in extending the model in Chapter 3 to the framework in Chapter 5 are described below. As discussed by Ettema et al. (2010) and Suzuki et al. (2012), user perceptions such as subjective well-being are described as experienced utility, which is distinct from decision utility (e.g., travel time). Since these two utility functions are often different due to lack of information and cognitive biases, the evaluation of pedestrian measures (e.g., installation of benches) based on utility maximization theory (i.e., using only decision utility) cannot reflect the experienced utility. Therefore, the main challenge is how to construct a utility function given the observed user perceptions. To directly use experienced utility is, we need to, for example, observe user perception in a crowded space and separate the utility function according to the perception of the crowded space (e.g., introduce the crowding as a negative/positive effect in the utility function if the user feels uncomfortable/comfortable with the crowding). Similarly, in a mixed space with pedestrians and vehicles, the utility function should be divided according to the difference in perception towards vehicles.

On the other hand, when the use of the urban street space changes from moment to moment, e.g., the liveliness disappears after 20 seconds, it is necessary to capture the uncertain effect of the time change (e.g., the perception at the moment is different than when approaching tens of seconds later/the pedestrian cannot capture the future effect due to incomplete information) in terms of expected utility. There are methods to account for this effect: (1) introducing a discounted rate (Oyama and Hato, 2017), (2) capturing local effects (e.g., the effects of time-varying behavioral phenomena or perception) as instantaneous utility and global effects (e.g., the effects of object location) as expected utility (Oyama, 2024), and (3) introducing stochastic variables (e.g., introducing several travel times within a state) in to account for uncertain information (Mai et al., 2021).

6.2. Future tasks

The current research has led to the identification of several future tasks. The first is to design a survey design for observing pedestrian behavior. Given that observations of pedestrian behavior in urban street space are made on a smaller scale (e.g., a small facility such as station) or for a shorter period, there is a need for a data collection system that can be answered on the spot, such as (1) a system that sends questions as you approach an object and allows immediate response or (2) instant feedback systems such as "HappyOrNot" (https://www.happy-or-not.com/en/, viewed August 6, 2024). In the former case, the survey design should provide higher incentives for time constraints or shorter *recall time* in order to obtain immediate responses. However, there are two types of perceptions (i.e., emotions) (Kahneman and Sugden, 2005; Ettema et al., 2010): (1) emotional reactions in the moment and (2) changes in emotions during the duration of the event. The findings in Chapter 3 apply to the latter. In the former case, issues such as the overlapping perception of multiple objects must be addressed by repeating observations over short periods of time. Looking at the case of short *recall time*, the same analysis as in Chapter 3 should be verified using a survey that takes these factors into account.

Next, as described above, using the model in Chapter 5 allowed us to evaluate the phenomena consistently with existing studies and unexpected phenomena. However, it is also necessary to check whether the described phenomena (i.e., traveler behaviors) are consistent with the traffic engineering indicators (i.e., Fundamental Diagram, or FD). To do this, we need to consider the issue of spatial and temporal aggregation units, which is important in pedestrian flow analysis such as FD. For example, one problem is that pedestrian density calculations vary depending on the method, such as Voronoi or grid-based approaches (Duives et al., 2015; Nikolic and Bierlaire, 2018). Another problem is that flow rates increase with finer discretization (Fu et al., 2018) and do not satisfy realistic FD (Kircher et al., 2004). In the context of this evaluation framework, it is necessary to determine the unit of discretization, taking into account the combination of the computational cost of consumer surplus and discretization.

Moreover, how the movement of the sojourners related to the *Place function* changes (i.e., whether multiple equilibria exist) while satisfying the theory of traffic engineering (i.e., *Travel function*) is an important discussion point. In other words, it is necessary to analyze the change in the location of concentrating sojourners who stay (i.e., whether the expected phenomenon will occur) while the travelers satisfy the FD.

Third, while we developed a framework for evaluating the use of urban street space considering interactions between moving and staying in Chapter 5, urban street space design needs to consider the entire urban street network in which urban street space is embedded. In this dissertation, *Travel function* and *Place function* in the urban street space are considered to be in a “*competition*”, interfering with each other. On the other hand, on the urban street network, a natural segregation of both functions occurs (i.e., when one function is given priority in one urban street space, the other function is complemented in another space), and both functions have “*complementarity*”. Specifically, in an urban street network, travelers tend to avoid routes that are crowded with many sojourners, while sojourners tend to gather in spaces where other sojourners gather and where there is a lot of activity. By considering this complementary relationship, the urban street space design can be based on the interactions on the urban street space while also considering the demand for the entire network.

A framework for evaluating the use of urban street space while also evaluating the urban street network as a whole has been proposed by Chikaraishi et al. (2019). In this framework, the cost of each link (i.e., urban street space) in the network is defined in terms of the consumer surplus calculated from the path choice model describing the pedestrian behavior within the link, allowing for an evaluation that takes both scales into account simultaneously. As mentioned earlier, this model does not consider the *Place function* and micro-interactions, so we need to extend this model to integrate the model of Chapter 5.

One major issue is the computational cost. Specifically, the need to compute consumer surplus (i.e., the value function) for multiple urban street spaces in parallel requires an efficient method for computing value functions such as approximating the consumer surplus for a particular urban street space by using consumer surplus for a huge number of situations. In consideration of the above points, it is necessary to construct a more advanced evaluation method.

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Appendix

Appendix A An alternative formulation for scale parameters

The first two components in **Equation (3.2)** can be rewritten as follows:

$$\theta_{ik}^{HP}\beta_j^{HP}x_{ikj}^{HP} + \theta_{ik}^{BH}\beta_j^{BH}x_{ikj}^{BH} = \theta'_{ik}\left\{\beta_j^{HP}x_{ikj}^{HP} + \theta''_{ik}\beta_j^{BH}x_{ikj}^{BH}\right\} \qquad (\mathrm{A.}\,1)$$

where, $\theta'_{ik} = \theta_{ik}^{HP} = \exp(\alpha^{HP}\ln(L_{ik}))$, and $\theta''_{ik} = \frac{\theta_{ik}^{BH}}{\theta_{ik}^{HP}} = \exp\left((\alpha^{BH} - \alpha^{HP})\ln(L_{ik})\right)$. This indicates that the original model with (1) scale parameter for behavior, and (2) scale parameter for preference can be translated into the model with (1) overall scale parameter for both preference and behavioral variables, and (2) parameter which determines relative importance of behavior with respect to preference. The overall scale parameter determines the relative contribution of unobserved components. It can be expected that as *recall time* increases, respondents pay less attention to contextual factors that are mainly captured by the error term, resulting in the lower contribution of unobserved factors.

Appendix B Testing the robustness of the results using propensity scores

When estimating the model in section 3.5, it was assumed that behavioral attributes only influence the choice result. However, in reality, behavioral attributes may also affect the *recall time* as well, leading to differences in *recall time* depending on trip-related contextual factors. For instance, commuters may find it more challenging to respond in the morning compared to the evening. To address this, the behavioral attribute is represented as a covariate **X** that affects the recall time and choice result, the *recall time* is considered as a treatment variable **Z**, and the choice result is considered as an outcome variable **Y**. Using propensity scores, the study empirically examines the influence the behavioral attribute on both the *recall time* and the choice result.

Since the processing variable **Z** (i.e., *recall time*) is a continuous variable in this study, the propensity score method for continuous quantities as proposed by Imai et al. (2004)

is applied. A propensity score function is characterized by θ. Firstly, the estimated value of $\hat{\theta}(\boldsymbol{X}) = \boldsymbol{X}^T\boldsymbol{\zeta}$ is calculated by employing a linear regression model using the covariate **X**, treatment variable **Z** and an unknown parameter $\boldsymbol{\zeta}$. This estimated value serves as the propensity score. Subsequently, the propensity scores are used to stratify the data, dividing it into different strata based on the estimated propensity scores. The weight, denoted as W_{kl}, for a particular *recall time* k in stratum l, is calculated by dividing the number of individuals (n_{kl}) with that *recall time* in the stratum by the total number of individuals (N_l) in the stratum. This weight calculation is performed using **Equation (B.1)**.

$$W_{kl} = \frac{n_{kl}}{N_l} \tag{B.1}$$

The estimation process incorporates a weighted likelihood function to account for the propensity score weights. The weight for individual i at *recall time* k in stratum l, denoted as w_{kli}, is the reciprocal of W_{kl} divided by the expected value of W_{kl}. This weight is used to weigh the contributions of each individual in the likelihood function,

$$LL = \sum_{k=1}^{} \sum_{j=1}^{} w_{kli} * d_{ij} * \ln P_i(j) \tag{B.2}$$

where, $P_i(j)$ is the probability of individual i choosing alternative j and d_j is a dummy variable which indicates whether individual i chose alternative j or not. The results of the model estimation using the above equations are shown in **Table B.1**. Meanwhile, the results of variance decomposition are shown in **Figure B.1**. The results show that α^{BH} is negative and statistically significant, indicating a similar trend as the results obtained without considering the propensity score. Similarly, for variance decomposition, the results are similar to that of the models without considering the propensity score. These results confirm that the three hypotheses are supported in this model, as they were in the case without propensity score consideration.

Table B. 1 Estimation result of behavioral change model using MNL model with propensity score

Choice	Change the route		Other behavior change	
	Estimation	t value	Estimation	t value
Constant	-6.16×10^{-2}	-0.348	-6.79×10^{-1}	-3.49**
Congestion charge	3.79×10^{-3}	4.87**	3.89×10^{-3}	4.96**
Time saving	-2.79×10^{-2}	-3.66**	-3.06×10^{-2}	-3.00**
Commuting	7.91×10^{-1}	2.32*	-2.56×10^{-1}	-0.682
Duty	-1.30×10^{-1}	-0.509	-1.42	-3.34**
Pick-up	-2.90×10^{-1}	-0.812	-9.48×10^{-2}	-0.253
Arrival time to destination	-4.48×10^{-1}	-1.45	-1.61×10^{-1}	-0.466
Age	5.00×10^{-1}	3.59**	4.88×10^{-1}	2.98**
Income	-4.48×10^{-1}	-1.92+	-2.24×10^{-1}	-0.855
γ	-8.68×10^{-2}	-3.25**	-8.22×10^{-2}	-2.61**
α^{HP}	1.59×10^{-2} (0.401)			
α^{BH}	-1.12×10^{-1} (-1.91+)			
Initial likelihood	-2028.038			
Final likelihood	-1772.592			
Number of observations	1846			
Adjusted ρ^2	0.1151			

Note : Choices 2-5 are to cancel the trip, change the time of day, change the destination and change the travel mode. Significance levels: '**' 1%, '*' 5%, '+' 10%, "Pay the fee and perform the same action as the current one" was the base alternative.

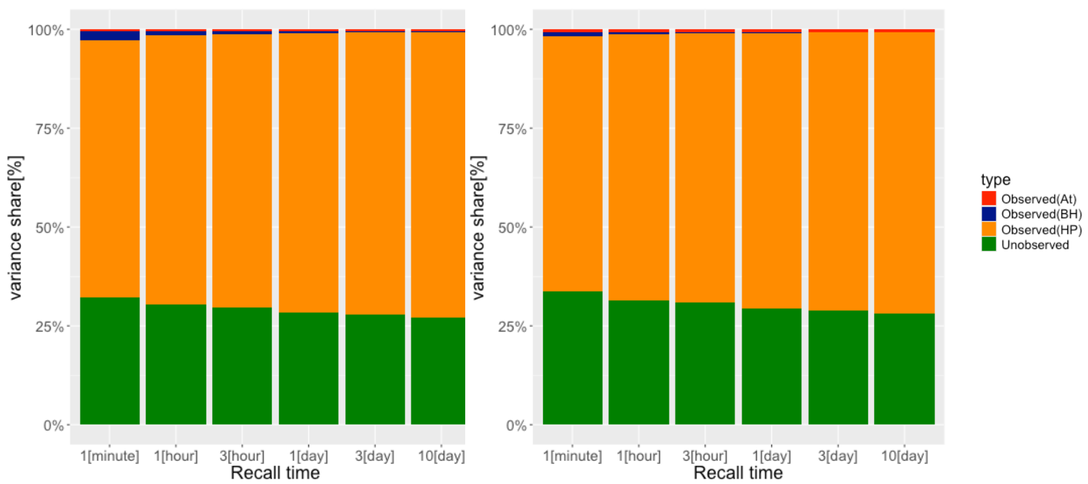

Figure B. 1 Variance decomposition of MNL model with propensity score for other behavior change (including cancel the trip, change the time of day, change the destination and change the travel mode) (left) and 6 (change the route) (right)

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