博士論文

Doctoral Dissertation

Evaluating the Impact of Automated Vehicles on Activity-based Accessibility and Residential Location Choice: A Case Study of Japanese Regional Areas

自動運転車がアクティビティベースト・アクセシビリティと居住地選択に与える影響の評価

～日本の地方都市におけるケーススタディ～

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ABSTRACT

Automated vehicles (AVs) are expected to be another disruptive transport mobility in the future. With their human yields manual controllability to the robotics and computers, it is assumed that AVs would be "a technological innovation which will allow organizing transport supply in a radically different way" (Soteropoulos et al., 2019).

Recently, extensive research efforts have been dedicated to studying the possible characteristics and potential implications of AVs. However, the existing literature is found limited in both quality and quantity regarding the impacts on land use.

One of the hypotheses concerning AV characteristics that value of travel time or generally, subjective travel impedance would decrease compared to the current Human-driven Vehicles (HVs), is plausible as trip-makers would be able to be free from driver's burden and even enable productive use of the time during an AV travel. This change could carry far-reaching implications in travel demand, such as daily travel mode choice; and subsequently in even land use through the concept of accessibility, following such a Travel-Land Use feedback relationship framework.

Much existing literature has issued warnings of potential urban expansion with the prevalence of AVs in the future, which hence could be a hindrance to those Japanese regional cities that have long called for urban planning of compact cities.

To this end, this dissertation conducts a travel forecasting project on the AV implications within the context of a Japanese regional area, Gunma Prefecture. The state-of-the-art travel forecasting paradigm: activity-based travel demand model and dynamic traffic assignment are structured, estimated, and validated, which is then connected with a residential location choice model to predict the potential changes.

The year 2040 is assumed as the target year for the analyses, where the effects from the decreased population are reflected in the scenario settings, along with some other variables to accommodate the uncertainties in the characteristics of AVs.

The transport methodology framework in this dissertation captures the induced travel by AVs and the feedback effects between the transport supply and demand. As result, for example, from 24% to 48% increase in the total trip distance is found in four AV scenarios where all HV owners are assumed to replace their HV with private AVs. Despite that this can be a signal for worsened network level of service, the median accessibility gains with the introduction of AVs for all the scenarios are found positive. In particular, the outskirt areas would enjoy more gains compared to their city center counterparts.

A residential location model is then estimated and validated with accessibility as one of the variables. The simulation results confirm the potential of urban expansion in the sense of residential locations. It is demonstrated that, compared to Base Scenario, the median distance between the residences to the city center areas expands by at most 10.2% for the four AV Scenarios adopted in this dissertation. Two countermeasures are then applied as the hypothetical policy mandates to mitigate the problem. The results suggest that to provide a 10% subsidy directly to the land price is effective for all the scenarios. Especially for the scenario with the most conservative yet realistic settings, the results of median distance indicators are at similar levels to the results of Base Scenario.

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CHAPTER 1 INTRODUCTION

1.1 Rationale

Automated vehicles or autonomous vehicles (AVs), an emerging transport mobility tool with a driverless feature, are developing at an ever-increasing pace.

High-level driving automation (SAE level 4 and 5; SAE, 2021) assumes the vehicle would completely take over the control of the vehicle without any driver intervention. As such, a considerable decrease in the general cost of travel is expected against human-driven vehicles (HVs), resulting in lower impedance to travel time and distance for drivers (e.g., Fagnant & Kockelman, 2015).

Several other intuitions could be summarized following the ceding of vehicle controllability: for example, more efficient use of road networks with smoother acceleration and deceleration; ability to share with others and therefore reduce vehicle ownership; to induce travels from those who cannot drive themselves like the seniors; and further in a longer period, to impact urban land use pattern in a various way.

In a word, AVs have been hailed as more advanced transport mobility, and thus will impact the current transportation system in a rather profound way. Despite considerable existing literature has been working in this research field, the implications of AVs have not been sufficiently explored enough, especially from a land use perspective (Soteropoulos et al., 2019; Harb et al., 2021).

Unlike the mainstream that conducted their studies in the U.S. or Europe, this study intends to offer insights into the context of Japan, where few studies have been done regarding this research topic. Although Japan shares many similarities with other Western countries, it is also at the forefront of major issues like aging and depopulation. To what degree will AVs impact this nation is definitely of significance from the author’s perspective.

As a developed country with a mature automobile manufacturing industry, Japan is not and cannot afford to be indifferent to AV development. The Ministry of Land, Infrastructure, Transport and

Tourism (国土交通省, MLIT) along with the Ministry of Economy, Trade and Industry (経済産業省, METI) of Japan held their first "Committee on Automated Driving Business (自動走行ビジネス検討会)" dated back to 2015. Since then, the committee has released and updated the "Report on Efforts for Achieving Automated Driving and Policies" to its fifth version (METI, 2021). According to the report, the Japanese Government is committed to deploying level-4 AVs under mixed traffic conditions in various areas by around 2025.

Against this background, this dissertation is aiming at filling one research gap: evaluating the implications of AVs in both senses of transportation and land use in the context of Japan.

Such an investigation involves many causal effects as one would expect, so the author considers it as well a valuable effort in exercising the state-of-the-practice travel forecasting: microsimulation models in a Land Use Transport Integration (LUTI) manner (e.g., Bierlaire et al., 2015), for the Japanese context.

1.2 Definition of Automated Vehicles

In general terms, current experimental AVs employ a "sense-plan-act" design. Under this framework, sensors inside the vehicle first gather and process data from its outside environment. Then these data are used to make plans, which will be later converted to actions for the vehicle control system. This design harnesses the power of developed computation power nowadays and often runs in parallel to improve computation efficiency. Thus, with highly advanced perception and processing ability, automated vehicles are expected to emulate the human driver's behavior and take over the driver's role.

Taxonomy serves more specifically the purpose to define automated vehicles. The Society of Automobile Engineers classification (SAE, 2021) currently is the most well-known and accepted taxonomy for automated vehicles. It describes due duties for humans and vehicles in each level, suggesting the continuum of the research and commercialize steps (Table 1-1).

Table 1-1. The SAE Levels of Automation (adapted from SAE, 2021).

Level	**Name**	**Narrative definition**	**Dynamic driving task (DDT)**		**Dynamic driving task fallback (DDT fallback)**	**Operational design domain (ODD)**
			Sustained lateral and longitudinal vehicle motion control	Object and Event Detection and Response (OEDR)		
Driver performs part of all of the dynamic driving task						
0	**No driving automation**	The performance by the driver of the entire DDT, even when enhanced by active safety systems.	Driver	Driver	Driver	-
1	**Driver assistance**	The sustained and ODD-specific execution by a driving automation system of either the lateral or the longitudinal vehicle motion control subtask of the DDT (but not both simultaneously) with the expectation that the driver performs the remainder of the DDT.	Driver and System	Driver	Driver	limited
2	**Partial driving automation**	the sustained and ODD-specific execution by a driving automation system of both the lateral and longitudinal vehicle motion control subtasks of the DDT with the expectation that the driver completes the OEDR subtask and supervises the driving automation system.	System	Driver	Driver	limited
"System" performs the entire dynamic driving task (while engaged)						
3	**Conditional driving automation**	The sustained and ODD-specific performance by an Automated driving system (ADS) of the entire DDT with the expectation that the DDT fallback-ready user is receptive to ADS-issued requests to intervene, as well as to DDT performance relevant system failures in other vehicle systems and will respond appropriately.	System	System	Fallback-ready user	limited
4	**High driving automation**	The sustained and ODD-specific performance by an ADS of the entire DDT and DDT fallback without any expectation that a user will need to intervene.	System	System	System	limited
5	**Full driving automation**	The sustained and unconditional (i.e., not ODD specific) performance by an ADS of the entire DDT and DDT fallback without any expectation that a user will need to intervene.	System	System	System	Unlimited

According to Table 1-1, the highest SAE level, level 5 is defined to be superior to level 4 in and only in assuming unconditional operational conditions (in the SAE Standard called Operational Design Domain). As this dissertation does not intend to investigate the difference under specific operational conditions, we assumed that AVs are in Level 4 or 5 for the modeling. Therefore, we will hereafter generally describe our assumption for AVs as "high-driving automation".

Two different ownership and operation models, private automated vehicle (PAV) and shared automated vehicle (SAV), are usually distinguished. PAVs are exclusive to one certain person in accord with their ownership attributes, which is similar to the current private human-driven vehicles. SAVs are assumed as a kind of mobility tool with an image of driverless taxis. The fleet is not owned by certain individuals but by, for example, the government or commercial companies. SAVs can be further categorized according to the number of passengers they serve for each ride. Those shared AVs that offer serve to individuals are simply called SAV in this dissertation, while the others offer to serve to multiple passengers each ride are called Shared Automated Rides (SAR). It is expected that SARs would consider picking up other passengers even in the service of one passenger, where extra travel time is usually generated from the detours. See Table 1-2 for a comparison of these operating models.

Table 1-2. Comparison of Operating Models (adapted from Litman, 2021).

	Private Human-Driven Vehicles	Private Automated Vehicles	Shared Automated Vehicles	Shared Automated Rides
Features	Motorists own or lease, and drive, a vehicle.	Households own or lease self-driving vehicles.	Self-driving taxis offer serve individuals.	Micro-transit serves multiple passengers
Advantages	Low costs. Always available. Users can leave gear in vehicles. Pride of ownership.	High convenience. Always available. Users can leave gear in vehicles. Pride of ownership.	Users can choose vehicles that best meet their needs. Door to door service.	Lowest total costs. Minimizes congestion, risk and pollution emissions.
Disadvantages	Requires driving ability, and associated stress.	High costs. Users cannot choose different vehicles for different uses. Likely to increase vehicle travel and associated costs.	Users must wait for vehicles. Limited services (no driver to help passengers carry luggage or ensure safety).	Least speed, convenience and comfort, particularly in sprawled areas.

1.3 Research Objective and Scope

The research objective of this study is to evaluate the implications of private automated vehicles (PAV) in the context of a Japanese regional area. The research considers a land use implication: residential location pattern changes as its final output, to get which travel behavior changes are also quantified and presented.

This study is expected to gain insights into the AV impacts from transport to land use range: for example, number of trips and tours, total travel distance, accessibility, and distance to center areas from residence. It is also designed to test two policies in attempting to mitigate the potential negative effects.

Such an investigation necessitates building models with sufficient responsive properties to produce "quality of the travel forecasts for future and changed conditions" (Davidson et al., 2007). For that purpose, this dissertation is dedicated to estimating and validating transport and land use models that can appropriately reflect the changes induced by AVs. Specifically, an activity-based travel demand model, a dynamic traffic assignment travel supply model, and a land-use model are combined serving the methodologic framework of this dissertation. Activity-based accessibility (Dong et al., 2006) is used to evaluate transport implications in a composite way as the expected utility gained from making daily travel decisions. The application of this concept not only adds a layer of economic analysis to the operational analysis layer of the simulations results, an issue that remains relatively understudied in the existing literature (Soteropoulos et al., 2019) but serves as a connection between the transport and land use models.

To the best knowledge of the author, this study is dedicated to filling several existing knowledge gaps. From the perspective of research purpose, the existing literature is limited on how AV would impact future residential location choice, particularly in a manner connecting transport and land use models (Section 2.3.6). Furthermore, this study built a transport forecasting system within the data from the Japanese context, which has considerable value in being a well-validated state-of-the-practice policy-responsive model that can capture tour-based and daily-schedule-based changes and interactions; can capture short-term travel demand and supply interactions; is able to connect with a residential location model; and is able to measure 1km mesh cell level changes.

Not to be confused with other works, there are some aspects that this dissertation does not intend to address. First, high-driving automation is adopted in this dissertation but forecasting the specific time for its emergence is not one of the objectives. Second, specific consumed energy for AV is not defined, thus those evaluations related to electricity-propelled vehicles, such as charging and recharging issues, are not covered. Third, connected vehicle technology is not considered in this dissertation. Fourth, car-sharing service is not assumed allowed for the service, each time one vehicle can take one passenger only.

1.4 Outline of This Dissertation

This dissertation is organized as follows. Chapter 2 presents a literature review covering three parts: activity-based travel demand model, integrated transportation models, and automated vehicles. Chapter 3 then discusses the methodology adopted in this dissertation with reasonings and major data sources introduced. Chapter 4 and Chapter 5 subsequently give descriptions of the travel demand model and travel supply model with details such as estimation and validation issues. Chapter 6 applies the two models just described in an iterative way to obtain the transport implications of the automated vehicles within four scenarios. Chapter 7 describes the specification, estimation, and validation of the residential location model, as well as the data and sub-models (e.g., a land price hedonic model) used. Chapter 8 presents the application to the residential location model under automated vehicle scenarios, hypothetical policy mandates follow to attempt to mitigate the potential negative effects found in the application results. Finally, Chapter 9 summarizes the research findings and concludes for this dissertation.

CHAPTER 2 LITERATURE REVIEW

This dissertation is finding its roots in so many various concepts or fields of research including automated vehicles, activity-based travel demand models, and land use models, that a multi-faceted literature review is deemed necessary for a better understanding of the subsequent chapters. The review will be written in a somewhat general manner. It is worth noting that, however, the review presented here is in no way exhaustive, but only those being representative are selected and presented.

2.1 Review on Activity-based Travel Demand Model

The idea of activity-based models stems from a very basic characteristic of travel demand: "*the demand of travel is derived, it is not an end in itself*" (Ortuzar & Willumsen, 2011). It is the need to undertake activities at locations different in space that makes people travel. The activity-based approaches as such lay great emphasis on behavioral realism, that is, the underlying decision-making process for trip-making. Another worth-noted characteristic of the activity-based approaches is derived from the point above: measuring travel in a whole day or even whole week frame to allow better capturing of the effects across multiple trips (Kitamura, 1996).

Besides these main concepts that are probably shared by most activity-based models, readers may be cautioned with a caveat that, models described as "activity-based" do not have "*a great deal in common*" (Boyce & Williams, 2015). Level of aggregation, policies meant to address, decision processes to model and validate, etc. could vary much among different models that claim themselves "activity-based".

After all, the activity-based travel demand model is going to play an important role in this dissertation in that it is considered the state-of-the-practice travel demand model, where travel behaviors are captured in a rather advanced way. This argument will be elaborated in the following contents where the evolving process of travel demand models is firstly presented, following a sub-section that intends to focus on the field of activity-based studies and models. The review is expected to provide a basic image of what activity-based models are and why we must use them as one of the methodologies, to which review works of, for example, Pinjari and Bhat (2011), Rasouli and Timmermans (2014), and Li (2015) have been referred.

2.1.1 Conventional Travel Demand Models before Activity-based Models

Travel demand refers to the needs of travel, it contains information such as origins, destinations, time of day, and travel mode to suggest how trip makers reach places to fulfill specific activities or needs. Travel demand modeling, as its name suggests, is to construct models for estimating this information of travel demand. Due to its role in representing the complexity of human behaviors, especially in the sense of decision making, travel demand modeling has been long researched and applied since the 1950s and lies at one of the cores of transportation planning nowadays.

In the beginning, however, the focus of transportation planning was to evaluate long-term transportation infrastructure supply. The 1950s marked the post-war economic expansion when motorization and suburbanization stimulated mass infrastructure construction in the United States (Kitamura, 1996). Following these two trends, surged commuting travel demand was generated in a so unprecedented way that the need for accommodating them came into the focus of transportation planning back then. This very pioneering style is called "supply-oriented planning process" (Pinjari & Bhat, 2011). At that time, information required for transportation planning was relatively simple and forecasting population increase patterns was less difficult than now (Kitamura, 1996), hence predicting travel demand in an aggregate manner would be sufficient. The Four-Step travel demand model emerged against this background, where improvement in computing powers should as well not be ignored.

The Four-Step Model (Mitchell & Rapkin, 1954) was originally proposed by Chicago Area Transportation Study in 1955 under the leadership of Douglas Carroll, whose experience in the Detroit Metropolitan Area Traffic Study two years before was highly valued and used (Boyce &

Williams, 2015). The Four-Step Model system separates the travel demand estimation process into four sequentially connected procedures: trip generation, trip distribution, mode choice, and route choice. First, trip generation measures trip frequency for each geographic unit in the study area. Trips to and from each unit, or called respectively productions and attractions, are estimated separately. Then, in the trip distribution step, productions calculated from the first step are distributed to match the trip attraction for each unit. Next, the mode choice part decides the proportion of trips by different travel modes for each origin-destination (OD) pair. Finally, route choice, or traffic assignment step, assigns the mode-specific trip tables to traffic networks.

The whole Four-Step Model process can be illustrated in Figure 2-1 (McNally, 2007). The "Equilibration" arrow in the figure stands for that in the basic Four-Step Model process, only route choices have an equilibration process. The "Feedback" arrows stand for that in most applications Four-Step Model equilibrates link travel times to the trip distribution and/or mode choice models. Further details are referred to McNally (2007) and Ortuzar and Willumsen (2011).

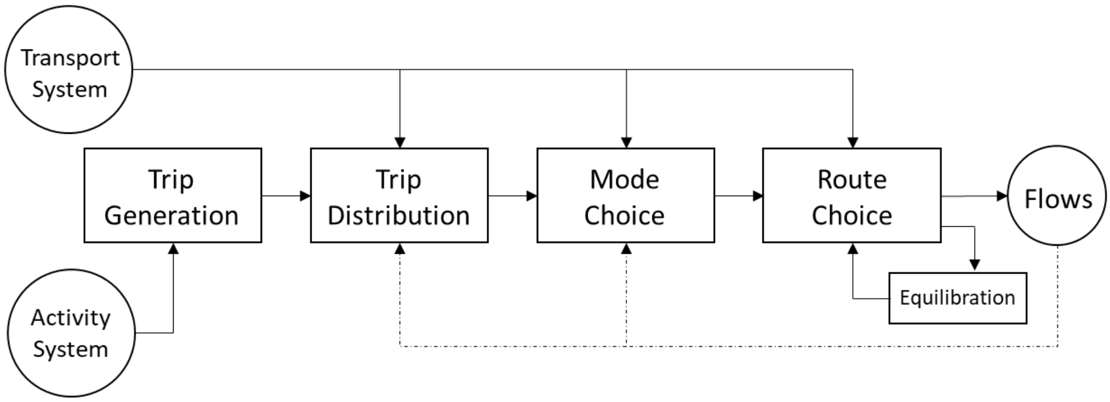


Figure 2-1. Four-Step Model Process (McNally, 2007).

However, many researchers and practitioners voiced against Four-Step Model soon after their popularity in practice. Rasouli and Timmermans (2014) in their informative review paper summarized criticisms of the Four-Step Model in four aspects. First, Four-Step Model lacks integrity: consistency among the sub-models is questioned as, for example, the distance decay function in trip distribution does not necessarily match with the one used in the trip assignment. Second, Four-Step Model lacks dependency: effects from other trips conducted by the same trip maker (this effect could be ignored for Route Choice, Bradley et al., 1999), or from the people in the same household, or from other “steps", cannot be captured; this suggests that Four-Step Model is in its design “inadequate to predict such secondary effects and complex behavioral adaptation patterns in response to external policies”. Third, Four-Step Model has strong aggregate nature: the models are measured in the unit of trips that emanate from traffic zones; all individuals and households from the same zone are considered identical except that they are segmentalized by certain variables, which are often a few given computational burdens. Temporal differences also are usually captured by building two Four-Step Models for peak and off-peak periods only. Fourth, Four-Step Model lacks behavioral realism: no choice mechanisms are underpinned, nor behavioral constraints are considered in the model designs. In Rasouli and Timmermans (2014)’s words as a summary, Four-Step Model is “nothing but a special application of spatial interaction models.”

As such, along with the Four-Step Model prevailing around Metropolitan Planning Organizations (MPOs) in the US and Europe after its introduction, the 1970s to 1980s marked a shift from the supply-oriented transportation planning to statistically-oriented trip-based travel modeling approach (Pinjari & Bhat, 2011). In this period, escalating capital costs led to a relatively saturated infrastructure market and traffic congestion emerged as a side result of the past economic expansion. Consequently, interest in using Transportation Systems Management (TSM) and Travel Demand Management (TDM) has grown among transport planners and modelers. These management measures, such as congestion pricing and ridesharing incentives, focus on either changing transport service characteristics or controlling travel demand to solve transport problems.

Under these circumstances, there was a need for understanding and analyzing policy responses at the disaggregate or individual level. The introduction of Discrete Choice Models (e.g., McFadden, 1973) at that time has been providing a much more useful methodology framework. The method has its root in preserving the notion of “rational decision makers who would make the same choice if repeatedly confronted with a set of choices under the same conditions” (Boyce & Williams, 2015), under which choice makers are assumed to select the option with maximum utility. The utilities are considered by the modeler as a random variable, whose error term attributes to population taste variation, unobserved variables, measurement errors, and proxy variables (McFadden, 1973; Ben-Akiva & Lerman, 1985). The so-called Random Utility Maximization (RUM) theoretical framework derived discrete choice models, such as Multinomial Logit (MNL) dominated the disaggregate behavioral approach in the era. A delineation of MNL will be given in Chapter 3 (Section 3.1).

The discrete choice models, mainly MNL, were widely applied to mode choice in the beginning. For example, a short-term forecasting project led by McFadden and colleagues on the modal share of the Bay Area Rapid Transit project was considerably better than the official forecast, both are compared with the rapid transit's observed share in 1975 (Boyce & Williams, 2015).

Two pioneering works and some subsequent studies that attempted to extend the discrete choice model application to other dimensions of travel demand, i.e., not limited to mode choice or other single aspects, are noted here. This stream of models is called the disaggregate travel demand model or Integrated Trip-based Model (Bowman, 2009) against the aggregate nature of Four Step Models.

Domencich and McFadden (1975) developed a multi-level model to represent optimal choices within a decision hierarchy that is composed of work and residential location choice, vehicle ownership choice, trip or no trip choice, destination choice, time-of-day choice, and mode choice, in that order (Figure 2-2). Each level of decision "can be viewed as being made conditional on fixed preceding decisions and optimal succeeding decisions." To specify, the solid arrows in Figure 2-2 represent the information of the decision from the higher level, the broken arrows represent the expected optimal values, or "Inclusive Value" from the lower level. This multi-level model is, as argued by the authors, compatible with the conventional Four-Step Model (or in the opposite sense) with a trip or no trip choice corresponding to trip generation, and destination choice to trip distribution. Although the work was empirically applied with limited sample size and choice sets, also an inappropriate linear average form of Inclusive Value, the treatment of information from succeeding level decisions has marked a noticeable improvement.

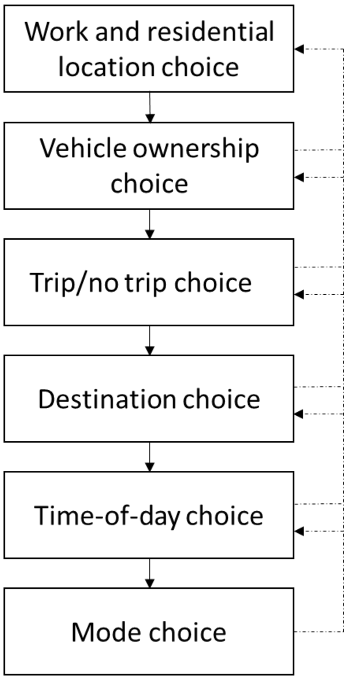


Figure 2-2. Multi-level Travel Behavior Model System in Domemcich and McFadden (1975).

Ben-Akiva and Lerman (1974) extended the work of CRA (1972), a prior report version of Domencich and McFadden (1975), by suggesting the "symmetric" hierarchy of travel demand choices. It was argued by Ben-Akiva and Lerman (1974) that the hierarchy in CRA (1972) requires *a priori* information of the ordering, which represents still a sequential decision-making process. Instead, a "symmetric" hierarchy with a simultaneous or joint decision-making process that treats multiple levels of decisions into a combined choice set, should make more sense in the application. His empirical study of comparing the simultaneous and sequential structure for a travel mode-destination problem suggested that, however, there was little advantage over the other. Whether to use one structure against the other, therefore, remained inconclusive in the period (Stopher & Meyburg, 1975). Nonetheless, there is another important contribution from Ben-Akiva and Lerman (1974) that a form of the natural logarithm of the denominator of the MNL model, later expressed to "logsum", was proposed to be used as the Inclusive Value.

A subsequent work by Ruiter and Ben-Akiva (1978) developed one of the first operational disaggregate travel demand models, which was prepared for the Metropolitan Planning Organization (MPO) in San Francisco, California, the U.S. Its hierarchical structure is similar to what we have introduced in CRA (1972) and Ben-Akiva and Lerman (1974), and the models are connected sequentially or jointly depend on their interrelationship.

Despite these inspirational studies with significant improvements over Four-Step Model, disaggregate travel demand approaches were mostly still, like in the Four-Step Model's case, applied in a trip-based context, which has been receiving many criticisms such as failing to capture complex individual responses. It is to this end that the following development of behaviorally-oriented activity-based approaches is introduced later (Pinjari & Bhat, 2011). We shall introduce them in the following sections.

2.1.2 Seminal Works in Activity-based Context

In the late 1970s, researchers and practitioners raised concerns about the developments of disaggregate travel demand models despite their theoretical superiority over the Four-Step Model. Accumulating evidence collected from revealed individual or group responses at that time showed inconsistency with the results from RUM-based disaggregate discrete choice models (e.g., Heggie & Jones, 1978). The new generation of travel demand approaches, activity-based models, emerged against this backdrop.

The modern development in studying travel in the framework of activities is usually attributed to two seminal studies: Hagerstrand (1970) and Chapin (1974). The work of Hagerstrand examined the role of geographical and temporal constraints in determining choices of activities and travels, whereas Chapin's emphasized the associations between activities and inherent desires as well as societal constraints. Hagerstrand's work might need to be elaborated a little more here as its significance in defining traveling constraints. Hagerstrand (1970), from a standpoint of regional science, proposed three kinds of constraints that trip-makers need to cope with every day: "Capacity constraints", "Coupling constraints", and "Authority constraints". Capacity constraints represent any limits owing to biological or physical requirements such as minimum sleeping hours and a maximum speed of travel mode. Coupling constraints represent those that require grouping of several people at one specific location at a specific time, which refers to a "bundle" of several "paths". Authority constraints stand for any requirements from the accessibility of institutions, such as the opening and closing time of a shop. Of more importance is that Hagerstrand (1970) managed to summarize these constraints into one well-known conceptual framework: the space-time prism. The framework describes an individual's actual behavior as a "path", whose potential space is called a "prism". In this sense, the concept of the prism is also regarded as a Person-based accessibility measure (Geurs & van Wee, 2004). These concepts have inspired many of the subsequent works, especially in the terms of determining feasible activity and travel choices.

Jones (1979) summarized the two studies above and addressed a framework connecting travel, activity, time, and space. In Jones's words: "it is thus probably most productive to combine the two approaches and to view activity 'choice' as a process for satisfying a need or a set of needs, subject to a set of subjective and objective constraints". Jones (1979)'s works identified travel as a derived demand explicitly, and it is his efforts that brought the activity-based ideas one big step further.

Subsequent analyses in the 1980s spanned many varieties such as activity participation, spatial-temporal constraints, interaction in travel decisions, data collection techniques, and operational activity-travel models. Interested readers are referred to Kitamura (1988) for a detailed review of the work conducted in the 1980s.

The various focuses of activity-based approaches have been stretching over their respective research field since then. Categorization of these varieties has not come to a general agreement unfortunately. Kitamura (1988), for example, grouped them into two categories: "activity-based approach as travel behavior science" and "activity-based approach as a planning tool". The former focused on the "theoretical explanation of observed travel behavior" and the latter on transportation planning practice. Bhat and Koppelman (1999), as another example, undertook their review in two categories: “Single Activity Episode Participation” and “Activity Episode Pattern Analysis”, which respectively stands for the participation of individuals in a single activity episode, and multiple activity episodes generation and scheduling. In either case, activity-based research of the latter term is the focus of this dissertation as we are addressing a travel forecasting problem. So, we will address in the rest of this review this specific category, which is in some cases generally called “activity-based models of travel demand” (Rasouli & Timmermans, 2014).

2.1.3 Towards Operational Activity-based Models of Travel Demand

The seminal activity-based theoretical notions shed light on the following development of activity-based models. Although many early models are better described as prototypes which were never put into practical use, considerable progress has been achieved in the models’ deployment by multiple planning organizations across the world.

Since the end of the 1980s, travel demand models in activity-based concepts have been gathering momentum as a move to the next generation of travel forecasting methods in the travel research community. Finally, as a response to the evolving requirements of transport and environmental issues (e.g., requirements from the Clean Air Act Amendments of 1990 and Intermodal Surface Transportation Efficiency Act of 1991 in the United States), the Federal Highway Administration of the U.S. launched the Travel Model Improvement Program (TMIP), which awarded research grants for proposals of “a new generation of travel demand models” to some organizations such as Research Decision Consultants (RDC). As result, since the 2000s, some researchers can assert that activity-based travel demand modeling has attained the academic mainstream, despite the persistence of the conventional Four-Step Method in practical applications (Davidson et al., 2007).

In line with the categorization by Rasouli and Timmermans (2014), three types of activity-based models can be distinguished: Constraints-based Models, Computational Process Models or sometimes called Rule-based models, and Utility-maximizing Models. Some more recent models adopted a form of the hybrid of the latter two types, so they are usually categorized as Hybrid Models. Although these types are not strictly chronologically developed, a general description is to be addressed in this section in the order above. Tour-based models are treated as an independent sub-section to better the clarification. Some exemplary models will be highlighted in detail for their specific significance or for being related to the methodology used in this dissertation.

2.1.3.1 Constraints-based Models

The first type of activity-based model refers to the term "constraints-based" models, which can be traced back to the mid-1970s. These pioneering models, however, do not fit well the field of travel demand model or travel forecasting approach as they are designed to check whether a given daily itinerary is feasible or not, rather than to predict individual- or household-level activity-travel patterns (Rasouli & Timmermans, 2014). This is well explained as some of the constraints-based models emerged even earlier than disaggregate travel demand models. Nevertheless, predicting rudimental behavioral adaptations to policies can also be found in some of the models.

Constraints-based models are mostly derived from the framework of the space-time prism (Hagerstrand, 1970), which defines feasible activity-travel choices amid geographical and temporal constraints. Besides the information from the itinerary, inputs of the model include the opening and ending time of their corresponding facility, available modes of transport, and their travel time between the activity locations. Two typical examples of models are introduced below.

Lenntorp (1976) elaborated the space-time prism concept and developed PESASP model, which was designed for analyzing alternative ways of conducting a given itinerary. It also defined the concept of potential path area: the planar projection of the 3-dimensional prism that has been applied in some following works, for example, to introduce "space-time accessibility" (Burns, 1979).

Following PESASP, Jones et al. (1983) proposed CARLA model for not only generating potential feasible activity patterns given the temporal-spatial constraints but also providing likely schedule adjustments to certain policies. The adjustments are limited to altering activity duration or starting and ending time.

Despite their progress, the constrained-based models have received criticism regarding the behavioral foundation, deterministic treatment for choice situations, and insufficient representation of the travel environment (Rasouli & Timmermans, 2014). Several more recent research has addressed some of the limitations. For example, Kim and Kwan (2003) offered a short review of the efforts in enhancing travel network representation in this context and proposed a Geography Information System (GIS)-based algorithm to even improve so. Also, generalizations of the original space-time prism concept have emerged recently such as accommodating joint activity for multiple trip makers and the effects of social networks (e.g., Neutens et al., 2007). But still, this specific type of model can be hardly said to fit well in the field of forecasting changes in travel demand.

2.1.3.2 Interim Tour-based Models

During the process of the evolution to the operational models, it is worth mentioning that there was an interim stage of the travel demand method that is called tour-based travel demand models (Boyce & Williams, 2015). The tour-based models made an advance upon the conventional trip-based models in that they joined related trips into tours for each sojourn, thus were able to examine the trip-chaining effects associated with policy responses. Among the tour-based models, two works: VISEM (e.g., Fellendorf et al., 1997) and the SIMS (Algers et al., 1996) represent respectively a refinement directly of the Four Step Model and disaggregate travel demand model and will be discussed in the following.

VISEM (Fellendorf et al., 1997) was designed by Germany's company PTV as its regional travel forecasting system, which emphasized its improvement in the trip generation sub-model compared to the Four Step Model. In VISEM's design, a sub-model that predicts the number of tours rather than the number of trips is used to replace the trip generation sub-model. The tours are conceptualized in the form of HXH, HXOH, and HXOH, where H represents home activity, X represents work-related trip and O represents other trips. The model firstly summarized each tour type's occurrence from national or municipal travel survey data and then associated them with each person category that they in advance distinguished so that the distribution of daily number and types of tours can be determined. Some other refinements such as keeping mode continuity in the modal split sub-model by modeling mode of travel at the tour-level are also applied.

SIMS (Algers et al., 1996) was an extension of Ruiter and Ben-Akiva (1978) and was applied in Stockholm, Sweden. It is considered as the state-of-the-practice in the mid-1990s with a sophisticated hierarchical model design that enhanced itself in accommodating more complex substitution patterns. This model had its root in the discrete choice model and considered household task allocation as one of the levels in the hierarchical structure. The concept of logsum was used as representing the expected utility measures across each level of the model. Shopping tour models are exemplary of SIMS features (Figure 2-3).

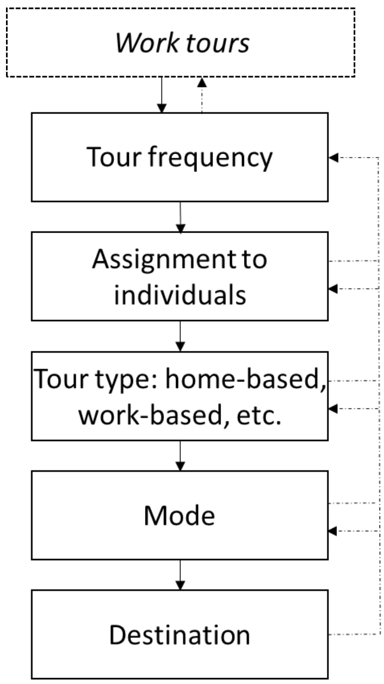


Figure 2-3. Structure of Shopping Tour Model in SIMS (Algers et al., 1996).

From Figure 2-3 we can tell that in SIMS the shopping tour model is determined in an order of 1) the number of tours per household; 2) the allocation of each tour/activity to specific household members; 3) the type of tours; 4) mode of travel; and 5) travel destination. The shopping tour hierarchy is conditioned by work tour decisions which involve a group of decisions. It is thus from these points makes SIMS an advanced version of the disaggregate travel demand model.

2.1.3.3 Rule-based Models

Rule-based models, in some cases called Computational Process Models (CPM, e.g., Kitamura, 1996, Rasouli & Timmermans, 2014), refer to those activity-based models using heuristics to mimic the decision-making process. Although these heuristics are usually context-dependent and thus have so enormous branches that cannot be practically demonstrated in one single model, the rule-based models can be coarsely viewed as an “exhaustive set of rules in the form of condition-action pairs” (Pinjari & Bhat, 2011). These rules or heuristics sometimes do not pursue an “optimal” but instead “non-inferior” or “sub-optimal” decisions during the process to reflect the embedding activity constraints and priorities, which are context dependent as mentioned above.

Representative examples of the rule-based models are introduced as follows, while some models are omitted such as SCHEDULER (Garling et al., 1989) and SMASH (Ettema et al., 1993). See Pinjari and Bhat (2011) and Rasouli and Timmermans (2014), etc. for the information and details of all the models concerned.

STARCHILD (Recker et al., 1986a; 1986b) is considered the first rule-based activity-based modeling framework (Li, 2015). This model differentiates itself from the concept of the constraints-based model by treating the outputs from CARLA (Jones et al., 1983), one of the aforementioned constraints-based models, as part of its choice sets of activity patterns. After choice set generation, alternative grouping, and filtering heuristic procedures, an MNL model is applied to identify the specific personal activity schedule.

AMOS (RDC, 1995; Kitamura et al., 1996) is considered to be the first applicable model of this stream, as it was implemented in Washington, D.C. The model was partly funded by TMIP and thus one of the outputs of the Program. AMOS is developed to simulate trip makers' response towards travel demand management policies such as parking pricing, thus emphasizing itself in rules of policy adaptation, which however requires custom development for each policy. Its whole model structure is shown in Figure 2-4.

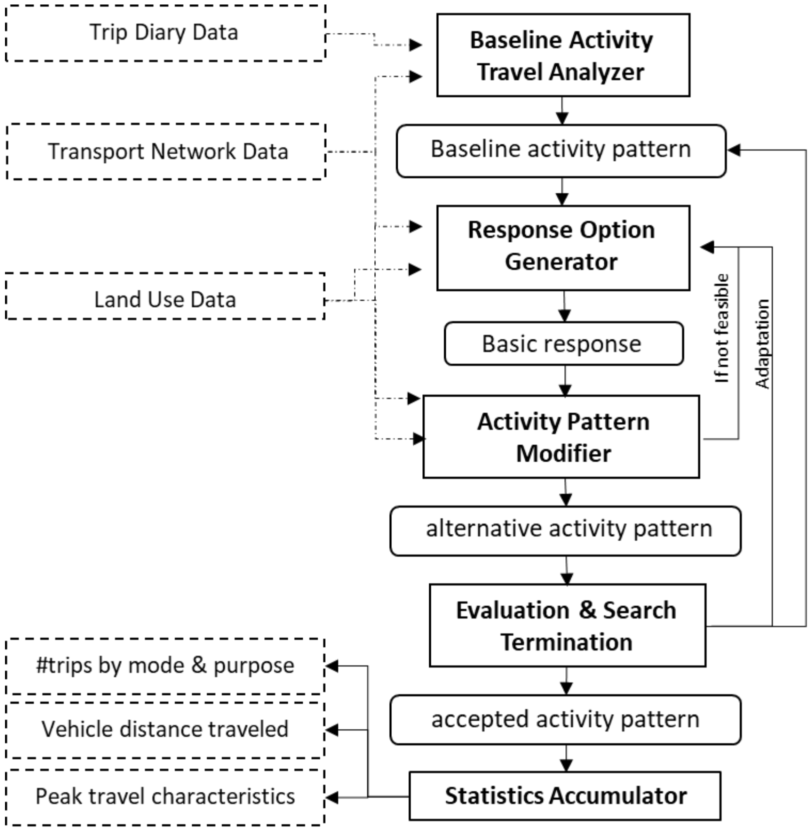


Figure 2-4. AMOS Model Structure (adapted from RDC, 1995).

AMOS is composed of five parts which are shown in bold in Figure 2-4. Among them, Response Option Generator predicts the behavior response to the travel demand management and is the core of AMOS's design. The Generator applies a Neural Network to determine the probabilities of the response options of changing departure time, switching mode of travel, working at home, and doing nothing. After the basic response generated by the Response Option Generator, Activity Pattern Modifier will be applied to simulate secondary responses such as activity re-scheduling, re-linking, and trip re-timing. These phases are applied iteratively until pre-specified criteria based on utility are fulfilled.

PCATS model (Fujii et al., 1997; Kitamura & Fujii, 1998) is an activity-based model that was developed for the Japanese context, partly led by some of the authors of AMOS. PCATS model assumes that an individual's activity engagement can be divided into two types: fixed activities and flexible activities, which can be conducted in blocked periods and open periods, respectively. Given an assumption that individuals have commitments for fixed activities, the PCATS model considers all fixed activities are forming a space-time prism for delineating the feasible area of flexible activities. For each open period, activity type, location, mode, and duration are modeled sequentially with Nested Logit (NL) model or duration model. The improved version of the PCATS model later was integrated with a population synthesizer and re-estimated in the context of Florida, formed into the FAMOS (Pendyala et al., 2005) model.

ALBATROSS (Arentze & Timmermans, 2004) represents an advance in rule-based activity-based models more recently. It was developed for the Dutch Ministry of Transportation and has been implemented in the whole nation of the Netherlands. One important feature of ALBATROSS is treating heuristics endogenous, which is contrary to treating them exogenous as most previous models did. The core of ALBATROSS is a Scheduling Engine that decides generating, sequencing, and timing of fixed and flexible activities sequentially. For each step, a decision tree that is derived from observed diary data to mimic human decision making is employed, where choice sets are delineated considering multiple time-space constraints. The design of the decision trees satisfies the requirements of completeness and consistency, new branches or leaf nodes are achieved by splitting the condition state of several condition variables. Since its original version, ALBATROSS has been improving in various ways. For example, the model incorporates learning mechanisms in the heuristics and thus sometimes considered being agent-based (Pinjari & Bhat, 2011).

TASHA (Miller & Roorda, 2003) stands for the effort of a combination of rule-based models and the utility-maximizing models that is to be introduced in the following section. TASHA is mainly applied in Canada. TASHA applies activity generation and sequencing in a rule-based way while conducting mode choice and destination choice, etc. within the discrete choice model framework. One major difference between TASHA and ALBATROSS is that TASHA draws activity attributes such as its duration from the empirical distribution of the study area.

Another model with the hybrid manner, ADAPTS (Auld & Mohammadian, 2009; 2012) is also worth noting with its feature of not pre-defining order of the modeling process. It thus explicitly considers the dynamics in activity scheduling and planning.

2.1.3.4 Utility-maximizing Models

Utility-maximizing models stand for another stream of activity-based models that have been popular since their introduction in the mid-90s. This stream of models is based on the discrete choice method framework as well as the framework's major premise of Random Utility Maximization in choosing alternatives, from which the stream takes the name.

As introduced in sub-section 2.1.1, there have been many earlier models that employed discrete choice models, exemplified by Domencich and McFadden (1975) and Ruiter and Ben-Akiva (1978). Utility-maximizing models can be regarded as extensions to span the modeling context to at least an entire day by including more dimensions such as daily activity pattern choice and seeking a finer resolution for its applications. Several representative model systems are reviewed below.

The Daily Activity Schedule model (Bowman 1995; Ben-Akiva et al., 1996; Bowman & Ben-Akiva, 2001) constitutes the basis for a group of practical transportation planning projects later and thus serves a vital role in this specific stream of models. The model is of multi-hierarchical NL design (Figure 2-5) which is similar to Ruiter and Ben-Akiva (1978), and also is a part of TMIP. Five levels (or nests) form the structure: daily activity pattern (e.g., home-work-home with one secondary tour); time of day of the primary tour (e.g., AM Peak, Midday, PM Peak, and Other); mode of travel and destination of the primary tour, in zone-level; time of day of the secondary tour; mode of travel and destination of the secondary tour. Designating the primary tour of the day requires a series of pre-defined rules to decide the priority among all the tours during that day. For example, work activities are deemed with higher priority than other activity types. Other tours except the primary tour are defined as secondary tours. By categorizing the tours, modeling the daily activity schedule level became more feasible to deal with. This is one of the features that let the Daily Activity Schedule model system become an inspiration for the later models.

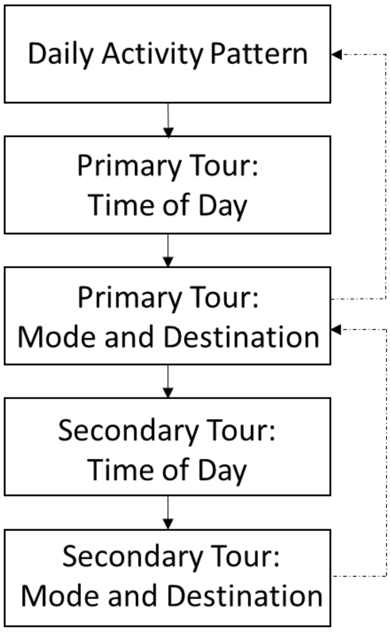


Figure 2-5. Implemented Model Structure of Daily Activity Schedule Model (adapted from Bowman, 1995).

Since the introduction of the original Daily Activity Schedule model, many variants and improvements of this type have been proposed and launched in practice by many MPOs across the United States. The original model prototype analyzed empirically data from Boston Household Diary Survey but have not been used in practice. Soon after that, Bowman (1998) and Bradley et al. (1998) developed Portland Metro Model that extended the levels in its hierarchical design, added at-home activity types into the daily activity pattern choice; level of work-based subtours; and level of intermediate trips. Its production version has in total 114 alternative daily activity patterns, which suggests the increased complexity and sensitivity compared to the original Boston one with around 30 alternatives.

The recent two decades have witnessed subsequent applications including the SFCTA model (Bradley et al., 2001), the SACOG or the SACSIM model (Bradley et al., 2010), the DRCOG model (Sabina & Rossi, 2007), the Oregon statewide model (Brinckerhoff, 2010), the PSRC model (PSRC, n.d.; Bowman & Bradley, 2014), etc., continuously emerges in practice. These models are all derived from the original prototype and shared some similar aspects like the hierarchical econometric model system to represent one entire day using stochastic microsimulation. Some design features distinguish each other, see the table in Bowman (2009) for a detailed comparison. The main differences, according to Bowman (2009), are related to the level of spatial and temporal resolution; varieties of activity purposes; treatment of household interactions; treatment of intermediate stops; interdependency between mode, destination, and time of day; and treatment of expected utility variables across the hierarchy.

Among these subsequent models, the SACSIM model (Bradley et al., 2010) probably merits a few more words of description for its salient features. The SACSIM model is one of the models still in use (for Sacramento, California) with substantial improvements compared to the original prototype and the Portland Model. For example, the SACSIM model reformulates the model level of daily activity pattern into levels of occurrence of tours and stops for each activity purpose. The exact number of tours and stops are separated as independent levels that are predicted after the occurrence model. In this way, the pattern alternative can be greatly reduced and leave the exact numbers to be conditioned by other levels of models. Also, the SACSIM model is the first of this type to adopt a parcel-level spatial resolution and half-hour temporal resolution, both are at a very fine level with the help of improvements in computing power and software design.

Following the Daily Activity Schedule model, especially the SACSIM, Li (2015) designed and estimated a version for the city of Singapore. The model is a part of the development efforts for the SimMobility project (Adnan et al., 2016) as the pre-day travel demand model for the mid-term level. The project is a model system that attempted to integrate an activity-based system, dynamic traffic assignment model, long-term location choice model, etc. Some words of elaboration will be given later. Another notable application of the DAS-type model was found in Yagi and Mohammadian (2010), who developed it for the Jakarta Metropolitan Area in Indonesia, as it is a less common case carried out within the context of a developing country.

One feature of the DAS models in their basic forms is that they explore no more than individual-level daily activity-travel patterns. Since the 2000s, intra-household interactions have been incorporated in, for example, a series of models called CT-RAMP (Vovsha et al., 2011). The CT-RAMP models explicitly incorporate modeling of joint activities, and household task allocation by adding these two levels of sub-models into the choice hierarchy. After defining information on mandatory tours, joint non-mandatory tours as well as maintenance tours are generated and scheduled for the household level, where tour participation for joint non-mandatory tours and allocation for household maintenance tours are modeled, respectively.

Operational models from the CT-RAMP family include the NYBPM (Vovsha et al., 2002), the MORPC Model (Consult PB, 2005), and the Phoenix model (Vovsha et al., 2011), among others. Advanced features have been introduced into some recent models. For example, the Phoenix model incorporated sub-models for visitors' travel and special events such as large-scale concerts. Besides, the latter two models are designed in a time-allocation fashion, where the entire daily activity-travel schedules are generated once each available timeframe has been filled up in order. They emphasized themselves in a tour formation style which is also been adopted in some improved versions of CT-RAMP (e.g., Paleti et al., 2017) though in a more sophisticated way.

The CEMDAP (Bhat et al., 2004; Pinjari & Bhat, 2011) model is another activity-based utility-maximizing model characterized by its "continuous time activity-travel forecasting system". Separate modeling frameworks and sequences are adopted for workers (including students) and non-workers. For workers, daily patterns are defined in terms of five different sub-patterns: Before-Work, representing those undertaken before leaving home to work; Home-Work, representing those conducted during the commuting leaving for work activity; Work-based, representing those undertaken from workspace; Work-Home, representing those pursued during the commuting back home; and After-Work, representing those conducted after arriving home from commuting. For each sub-pattern, attributes of pattern-level, tour-level, and stop-level are determined via various econometric models. For example, the number of tours as a pattern-level attribute is determined by the Ordered Probit model. Travel time from the last stop and activity duration, as stop-level attributes, are determined by regression as continuous choice alternatives. Before the scheduling model system mentioned above, a mechanism called the generation-allocation model system applies to the household level to determine if a specific type of activity, say grocery shopping or pick-up of the children, will be made or not and if so, who is going to conduct it. More than 50 econometric models are required in total. Together, these two model systems are performed in a microsimulation framework with pre-defined order of the decisions. An example of the CEMDAP-based model application along with a long-term choice model and a population synthesizer can be found in Pendyala et al. (2012a) for the southern California area. Also, an improved version of CEMDAP is applied at the household level (Bhat et al., 2013).

2.1.4 Summary

Activity-based travel demand models are in line with one of the most salient features of travel demand that is being derived. This more behaviorally sound model stream has been developed from conceptual frameworks to operational model systems and is becoming the focus of the travel demand models. Behavioral realism is earned by introducing the level of daily activity-travel pattern that is "on the top of" the tour-level decisions. Therefore, the activity-based models enjoy much improved policy sensitivity and cross-substitution patterns within the model.

However, it is summarized here from the literature that there exist various approaches of activity-based models and it is still quite far from reaching common ground, especially, among practitioners. At least two major streams of the models: Rule-based and Utility-maximizing, have been popular in academia. Both approaches showed their respective way to solve the problem of choice of daily activity-travel pattern in a two-stage decision protocol: choice set generation and choice itself (e.g., Manski, 1977) but with different focuses. The Rule-based ones devote themselves to the choice set generation, aiming at yielding a small choice set upon which a simple choice model is always used, while the Utility-maximizing ones focus on the sophisticated representation of the choice model (Ben-

Akiva & Bowman, 1998a).

It seems that Utility-maximizing models, exemplified by the DAS models and the CT-RAMP models, are gradually taking the majority in practice, but it can be asserted for now that still, no one single model has commanded universal appeal (Li, 2015). Nevertheless, activity-based models are still in the way of advancing to methodology with greater behavioral realism, better policy sensitivity, faster deployment, and ease of understanding. Within this process, the distinctions between the two types have narrowed as they sought to accommodate more realistic choice representation in the sense of both choice set generation and choice itself to represent better human behavior (Boyce & Williams, 2015).

Despite the advancements, the increasing complexity of the activity-based model systems has been so formidable to many local planning organizations that models of the earlier generation like the Four-Step model are still taking a considerable share in practice (Boyce & Williams, 2015). Theoretical advantages are not always appreciated by the practitioners unless they can find out how these models of the “new generation” could better address their specific practical needs (Davidson et al., 2007). This might require more empirical analysis and successful implementations to spark more interest, which is considered one of the raisons d’être of this dissertation.

2.2 Review on Integrated Transportation Models

A system is often featured by being composed of multiple various elements that interdependently affect each other. The urban system is undoubtfully an exemplar of the complex interconnected structure, where transportation is no more than one of its components. It is normal to consider the influence of others whenever there is an attempt to analyze one of the components. Integration, nevertheless, asks to combine the involved components together into one holistic mechanism. The concept and necessity of integration of urban systems have long been recognized as conventional wisdom.

Transport planning thus is also required to be analyzed as an integral part. For example, virtually all economic and social activities require the transport of people or goods. In this sense, economics determines most of the forms of transport, while contributions of transport to economics is also playing a significant role there. In both academia and industry, among others, connections between transport and land use planning are deemed more important as being closer to each other. In Banister (2002)'s eloquent words: "transport planning must be seen as part of the land use planning and development process, which requires an integrated approach to analysis and a clear vision of the type of the city and society in which we wish to live".

At a more basic level, the integration of elements within the transport system is also important in the analysis. Integration at this level can refer to the integration of, for example, traffic networks of different modes of travel (Givoni & Banister, 2010), but more often this refers to the integration of travel demand and travel supply. Linkages between the demand and the supply are usually reflected in the traffic assignment procedure that predicts traffic flow conditions under a given pattern of travel demand and other related inputs. The other side of the linkage, namely the effects from transportation level-of-service to travel demand, is usually carried on within the travel demand model. Being less frequently mentioned and conducted for this level of integration is the equilibrium between the demand and the supply, which means iterating the interactions between the two until they converge to a stable state (Pinjari & Bhat, 2011).

These levels of integrations can be illustrated in one general travel demand-supply and land use causal structure (Figure 2-6), where feedback effects are adequately considered, and accessibility plays an important bridging role (see Sub-section 3.2.2).

Unfortunately, this wisdom of integration did not prevail until recent decades as they are hard to operationalize. This dissertation considers it an important aspect of a sound travel forecasting project and finds it necessary to be reviewed. A travel forecasting project like this dissertation usually involves a time frame of years or decades.

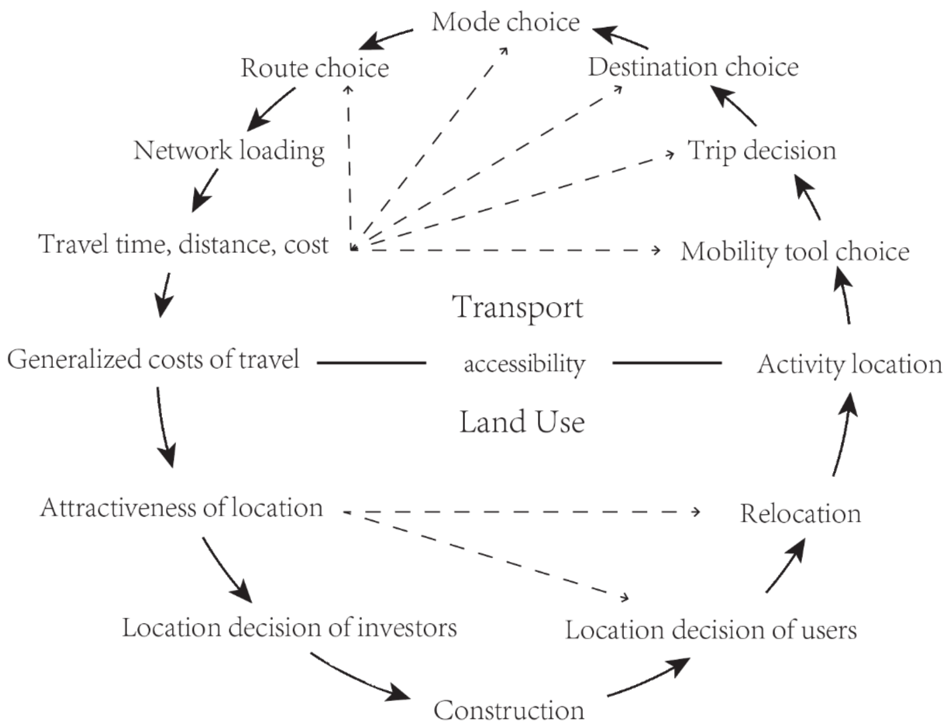


Figure 2-6. Feedback Cycle between Land Use and Transport Systems (adapted from Bierlaire et al., 2015).

Thus, a short review will be given in this section, including two parts: integration with land use, and integration of travel demand and supply. Reviews of residential location choices and dynamic traffic assignment models are also given briefly below. For detailed reviews, refer to Iacono et al. (2008) and Kii et al. (2016) for integration between transport and land use, Lin et al. (2008), and Adnan et al. (2016) for integration between travel demand and supply.

2.2.1 Integrating Transport and Land Use Models

Land use models forecast primarily "the locations where urban activities occur" (Boyce & Williams, 2015), which decides in other words the spatial patterns of activity locations or facilities in the study region. As the land use model determines the distribution of locations around the region, it decides to a large extent the patterns of travel demand by determining the spatial separation pattern among the activity locations. On the other hand, a change in costs of travel would affect the attractiveness of the locations and thus has the potential to change the land use distribution in turn.

Therefore, the relationship between transportation models and land use models has long been recognized as being reciprocal. This reciprocal relationship is usually called the "Transportation-land use link" (Kelly, 1994) or "Land-use transport feedback cycle" (Wegener, 2004). The models aiming at capturing this process are called Land Use Transport Interaction (LUTI) Models.

The basic theory of the Transportation-land use feedback cycle is based on economic concepts such as consumer behavior notions. In the 1960s, Wingo (1961) and Alonso (1964) independently proposed two very similar ideas of attempting to formalize the relationship. In their economic models, they argued that the money spent on commuting and housing is recognized by a rational consumer as a tradeoff: the residential property with the best access to commuting is entitled to the highest prices, all else being equal. Their models are very simple but did establish a fundamental notion that transport accessibility should not be neglected but instead is one of the key elements in the land use model (Kelly, 1994). Transport accessibility is an index to describe the level of access convenience for a geographical unit in the study region. For this specific geographic unit, a traffic zone for example, accessibility is typically calculated as the total travel impedance from this unit to all other available and reachable units via the traffic network. Varieties of accessibility and other details will be elaborated on later in sub-section 3.2.2.

Lowry (1964)'s model is considered to be the first operational urban land use model and merits some brief word of description here to facilitate understanding. The Lowry model falls into a category called the Spatial Interaction model which is derived from the gravity model and the principle of entropy maximization, the same foundations used in some early travel demand models. The Lowry model determines number of workers T_{ij} in zone i while living in zone j as:

$$T_{ij} = \frac{e_i w_j f(t_{ij})}{\sum_j w_j f(t_{ij})}$$

Where e_i is the employment in zone i, w_j is the attractiveness of zone j, and $f(t_{ij})$ is the travel deterrence function that is related to t_{ij}, travel time or other measures of travel impedance between i and j. The most applied form of the deterrence function is:

$$f(t_{ij}) = e^{-\beta t_{ij}}$$

Where β is the marginal utility per time.

Totally, the number of workers residing in zone j is:

$$T_j = \sum_i T_{ij}$$

Besides the workers' residential location choice, the Lowry model is also featured by including service location choice. After the locations have been allocated, the land use model can be coupled with a travel demand model such as the Four-Step model, which in this form becomes the first generation of integrated transport and land use model.

Building on the Lowry and its successors' model, Putman (1983, 1991) developed the well-known ITLUP model that has been used practically at over 40 planning agencies (Boyce & Williams, 2015). ITLUP model is often referred to DRAM/EMPAL framework as it includes two sub-models: DRAM and EMPAL. A basic travel forecasting model that is equipped with trip generation and trip distribution functions is embedded in the DRAM so that travel impedance could be incorporated into modeling activity locations.

Later, some other integration models based on Spatial Interaction formulations such as the IRPUD model (Wegener, 1985) for Dortmund, Germany, the LILT (Mackett, 1983) for Leeds, U.K., and the CALUTAS (Nakamura et al., 1983) for Tokyo, Japan, have been proposed and applied. However, few models of this type remain to the present for their poor forecasting performance (Iacono et al., 2008). This is probably due to mainly the inadequacy of the underpinning theory and limitation in representing broader economic activities (Kii et al., 2016). These criticisms introduced the next generation of transport-land use integration models, which is based on the RUM framework.

LUTI models emerged following the introduction of applying residential location choice with discrete choice models (e.g., McFadden, 1978). Of this model stream, the salient feature is replacing the theoretically flawed gravity model with the RUM-based MNL model. Notwithstanding, some models do have some unique elements that distinguish them from others. The TRANUS (de la Barra,

1989) incorporates explicitly a land development model for developers and improves the travel model by distinguishing traffic flow by the different times of day and travel modes. The TRANUS is also one of the first models to apply logsum type accessibility in bridging the travel model and land use model. The CATLAS (Anas, 1982) is another exemplar of this stream, which uses an NL model form for choosing a workplace, residential location, and travel mode together, from which logsum type accessibility is calculated to indicate the change in household welfare. The CATLAS framework was later evolved into an enhanced model, the METROSIM (Anas & Arnott, 1994) which expands the model function to include such as commercial real estate and non-work traveling. An alternative model, the MUSSA (Martinez, 1992, 1996) has features such as adopting the form of an auction for the land market, players from both sides bid against each other for building stock. This is called the "bid-rent" framework, which has been widely used in some more recent land use models. The MUSSA also emphasizes itself in higher spatial resolution and more detailed transit network representation, which is one remarked improvement with the adoption of random utility theory as it allows for developing models at a disaggregated level.

Since the 1990s, the Intermodal Surface Transportation Efficiency Act (ISTEA) of 1991 of the U.S. and advances in computing power sparked a paradigm shift into the current state-of-the-art type of LUTI model: agent-based microsimulation models. This specific stream of model attempts to simulate the behaviors and interactions dynamically over time at a individual level so that the whole urban system and its changes can be represented from the "bottom-up". These models emphasize especially the feature of being disaggregated as well as dynamic. Two models from this category are introduced here as examples.

The UrbanSim (Waddell, 2000; Waddell et al., 2003; Bierlaire et al., 2015) is the currently most used LUTI model by MPOs in the U.S. (Kii et al., 2016), which suggests that it is one of the most flexible LUTI models to date. The original version of the UrbanSim, according to Iacono et al. (2008), still falls in the category of econometric LUTI model despite having adopted many microsimulation features in some of its sub-models. Its improved version managed to obtain completed microsimulation features and is said to be the only model that succeeded in completing the transition. The UrbanSim pursues parcel-level spatial resolution, which is much finer, if not the finest, than other existing models. Land markets are modeled following the "bid-choice" framework, which is similar to the MUSSA. The whole framework consists of six sub-models: the Real Estate Price model to compute the prices of real estate goods; the Household Transition & Relocation model to describe the evolution of households by time and whether they are planning to move or not; the Household location model to determine the specific location for household moving; the Job Transition & Relocation Model to describe the evolution and willing to move for firms; the Job Location Model to determine the specific location for the firm moving; and the Real Estate Development model to decide the new supply of real estate goods (Bierlaire et al., 2015). All these sub-models apply the MNL model except that the Price model computes the results from a Hedonic Model. Besides, the UrbanSim has been coded into an open-sourced software system that greatly increases its ease of use and transferability, which is found by a survey to be the practitioners' priority in choosing LUTI models (Waddell, 2011). However, one important limitation of UrbanSim is that it does not include a transport model component but rather offers an interface to extend it with an exogenous transport model.

The ILUTE model (Salvini & Miller, 2005) stands for one of the most completed microsimulation models. Four contiguous components represent the core of the ILUTE: land use, automobile ownership, location choice, and activity-travel patterns. Multiple modeling methods are implemented for these components to cope with different choice contexts, these methods including random utility models, rule-based models, learning models, and state transition models. The most worth-mentioned feature of the ILUTE model is explicitly treating land markets in a disequilibrium fashion, which means that no equilibrium is sought and even no market clearing is assumed in their modeling. Also, the activity-travel patterns component in the ILUTE is often coupled with the TASHA, though the travel supply component is absent.

2.2.2 Integrating Travel Demand and Travel Supply

Travel supply refers to transport services provided by the urban system. Specifically, the services are delivered by the combination of infrastructure, vehicles, and the operators or the management system of the former two (Ortuzar & Williumsen, 2011). Sometimes, travel supply also simply refers to the level of the services, or metrics representing the network conditions.

The interaction between travel supply and travel demand can thus be stated in the following terms (Ortuzar & Williumsen, 2011): consider in a transport system, *S* for the level of service, *Q* for the network capacity, *V* for the traffic volume, and *M* the management system, then there can be assumed a relationship that:

$$S = f(Q, V, M)$$

Where network capacity *Q* is expected to be dependent on the management system *M* and levels of investment *I*:

$$Q = f(M, I)$$

As for travel demand *D*, one would expect in most cases need for travel should depend on the spatial pattern of activity facilities *A* and the level of service *S* of the transport system:

$$D = f(S, A)$$

Since traffic volume V is strongly related to travel demand D, combining the above equations would thus lead to a problem of finding the equilibrium point, which is defined as "find(ing) a demand pattern generating network conditions that, in turn, cause the same demand pattern to re-appear" (Nagel & Flötteröd, 2012).

Therefore, seeking the travel equilibrium state would more sufficiently reflect consistent travel forecasting and thus improve its reliability. Although this statement seems correct whatever the policies concerned in one forecasting problem, the task of finding the equilibrium is often not easy due to the complexities of the relationships above.

In the conventional Four-Step Model, the first three steps forecast the changes in the travel demand side while the last step forecasts the influence on the travel supply side. So, if exercised in a full iterative process, the Four-Step Model should serve the purpose of seeking equilibrium (Lin et al., 2008). However, the Four-Step Model usually fails to adequately fulfill this task not only because the basic specification of the Four-Step Model incorporates an iterative process limited to route choice, but more fundamentally also due to its shortcomings in applying trip-based method and static traffic assignment method: e.g., the feedback for the stages of destination, mode, and whether to travel "has often been introduced but not in a consistent and convergent manner" (McNally, 2007).

For the travel demand side, in replace of the trip-based models, activity-based models are considered more appealing with more behavioral reliability. Many operational activity-based travel demand models have been proposed and applied around the world (Section 2.1).

For the travel supply side, static assignment methods have been implemented as a convention for a long time. As mentioned, traffic assignment is the procedure to load the travel OD pairs onto the traffic network, which generally refers to modeling the action of "route swapping" by drivers. This process needs to be solved in iteration (Sheffi, 1985) by repeatedly loading the demands, to reach an equilibrium state for subsequent analyses. Different objective functions adopted throughout the iteration process would lead to different equilibriums in the assignment procedure. For example, when assumed that all routes used should have the same minimum cost, which means no one can unilaterally improve his or her situation, a User Equilibrium would be obtained (Wardrop, 1952). This equilibrium is limited in route choice so should not be confused with the aforementioned travel supply-demand equilibrium, though they can be accommodated in a theoretical framework that "combines" all four steps together in iteration (e.g., Safwat & Magnanti, 1988).

The feature of being "static" in conventional traffic assignments means that neither the OD pairs nor the network conditions are treated as time-dependent. As the conventional trip-based travel demand models usually do not identify temporal variations more than peak and off-period periods, the static traffic assignment should meet most of the requirements then. Apparently, this is no longer the case currently. For example, policies such as congestion pricing intuitively demand a better temporal resolution, this is in essence a call for accommodating travel demand dynamics in the supply model. Against this background, dynamic traffic assignment emerges where both demand and network conditions, and travel times are time-dependent.

Despite the advancements in both demand and supply models, much of the research efforts have been achieved relatively independently (Lin et al., 2008) due to their complexities. To exploit the advantages from both sides and to generally improve the travel forecasting power of a model system, it is essential to execute the travel supply-demand equilibrium process with these two advanced approaches. In this sense of integrating the activity-based travel demand model and dynamic traffic assignment model, a limited number of applications have been published, some exemplars are introduced below.

Integrations in early implementations were undertaken in a so-called sequential integration approach, which means that the activity-based travel demand model and dynamic traffic assignment model are run independently and coupled together in a not rigorous way (Pendyala et al., 2012b). For example, Lin et al. (2008) built an integration of the activity-based model CEMDAP (Bhat et al., 2004) with a cell-transmission-based dynamic assignment model VISTA (Ziliaskopoulos & Lee, 1996) and examined the convergence properties with two experimental grid networks. Other examples include combining PCATS (e.g., Kitamura & Fujii, 1998) and DEBNetS (Kitamura et al., 2005) for the Japanese context (Iida et al., 2000).

Pendyala et al. (2012b) explicitly addressed the naiveness of the sequential integration by running the components into one same framework, called dynamic integration. They proposed the SimTRAVEL, a modeling system adopting the integration of OpenAMOS, an improved version of AMOS (RDC, 1995; Kitamura et al., 1996) and MALTA (Chiu & Villalobos, 2008). The model was evaluated in Arizona, U.S.

Subsequent research projects have sought to develop a model platform where the supply-demand equilibrium is more closely integrated inside so that application efficiency would greatly be improved. This is achieved by better software designs and data constructs.

MATSim (Horni et al., 2016) is an agent-based transport simulation model and is designed to handle large-scale networks and millions of trips. From this standpoint, implementation efficiency has been highlighted. Lies in its core is an iterative process called a population-based co-evolutionary algorithm, which attempts to solve the supply-demand equilibrium problem. The model enjoys the reputation for having been applied widely around the world and is still evolving to incorporate increased functions via its open-source software architecture. One conspicuous limitation of its algorithm exists as the travel demand part fails to account for the trip generation. Partly to this end, some academic integration efforts that employed MATSim as no more than a traffic assignment simulator can be found. For example, Hao et al. (2010) apply a TASHA (Miller & Roorda, 2003) and MATSim integration, and Ziemke et al. (2015) couple the CEMDAP (Bhat et al., 2004) with MATSIM, a simulation platform that will be elaborated in Sub-section 3.2.1.

FEATHERS (Bellemans et al., 2010) is a dynamic agent-based microsimulation framework, designed for Flanders, Belgium to replace its Four-Step Model. It is a platform of modular design where its demand model component (called Schedule Module) can be implemented with different algorithms, such as ALBATROSS (Arentze & Timmermans, 2004).

Auld et al. (2016) integrated ADAPTS (Auld & Mohammadian, 2009; 2012) and a queue-based traffic simulator DTAlite (Zhou & Taylor, 2014) into one unified framework called POLARIS. It emphasizes itself in forming a complete, agile, and extensible software. The use of the Intelligent Transportation System was tested with the model system in the Chicago area, Illinois, the U.S.

Finally, the model system of SimMobility (Adnan et al. 2016) represents one of the most sophisticated model systems of this stream. The Singapore-based model managed its great ambition to integrate long-term land use model UrbanSim (e.g., Waddell et al., 2003), mid-term travel demand model DAS (e.g., Bradley et al., 2010), mid-term dynamic traffic assignment model

DYNAMIT (Ben-Akiva et al., 2010), and a short-term microscopic traffic simulator MITSIM (Yang & Koutsopoulos, 1997) for microlevel vehicle control such as lane change behavior in 0.1-second resolution. These models were respectively enhanced and combined into a model system, which has been adapted to the Singapore context.

2.2.3 Summary

As a complex system, the urban transport system is made up of various dependent sub-model components. These components are intuitively demanded an integration effort to exploit their real potential and yield more reliable travel forecasting results.

Nonetheless, it was not until recent decades that operational integration models emerged. This is of course partly due to the rising need for testing travel policy with increasing complexity, but also partly due to improvement in computation power and data quality. Within this trend, Lee (1973)'s well-known Requiem for Large-Scale Models seems no longer to hold anymore. It is expected that the next-generation travel models with higher forecasting power would be widespread in practice.

Unfortunately, travel forecasting efforts are becoming so sophisticated, if not formidable, that hinder other researchers and practitioners from comprehending the mechanism inside the "black boxes". The complexities of the integrated models are way above the level of the activity-based travel demand model (introduced in the last Section) for they usually involve expertise in other fields such as computer science and software engineering. Therefore, ease of understanding, use, and transferability should deserve more attention, which are sometimes considered more important than theoretical soundness and advancements (Waddell, 2011).

Despite some sense of uneasiness, it still should be confirmed that things are moving in the right direction in this research area. We shall conclude the section with a quote from NRC and TRB (2007): "*Travel models can be improved by being based on a more comprehensive understanding of the activities of households. Also needed is a more complete representation of the supply-side network* *to account for the details of congested operations throughout the day. No one new modeling approach can address these and other needs. Rather, a suite of related approaches, taken together, shows promise for greatly improving modeling practice. These approaches include improved land use modeling, tour-based models, activity-based models, discrete-choice modeling, traffic micro-simulation, and dynamic traffic assignment*".

2.3 Review on Automated Vehicles

The AVs are expected to bear the potential to influence society in a rather complex way: both benefits and side effects have been anticipated by various published research and reports. A basic picture of what the literature has found is deemed necessary.

Forecasting the implications of AVs should not be an exception to the transport demand-supply framework. Impacts on travel demand are assumed to occur following the change in travel supply, while in the longer term, impacts are also likely to extend to land use. Therefore, this review is organized to state the current research efforts that have been done concerning 1) AV's general development background; 2) AV's characteristics as a change in transport supply; 3) AV's impacts on travel demand, or travel behavior; and 4) AV's long-term impacts on land use. These impacts are studied by the existing literature depending on certain AV operating models, i.e., PAVs, SAVs, SARs, or a combination of them. Our focus lies on the PAVs due to the research scope of this dissertation, but several significant works on the other two types will also be mentioned.

Comprehensive reviews can be referred to, for example, Milakis et al. (2017), Soteropoulos et al. (2019), and in particular a comprehensive summary from Harb et al. (2021).

2.3.1 Development of Automated Vehicles

The topic of automated vehicles is not brought up all of a sudden, the conception and development of automated vehicles could be traced back more than a century.

Early efforts of self-driving cars have been devoted to demonstrating the potential of radio technology. After the mass automobile production in America during the early 20th century, in 1925 and 1932, a radio-control sedan was designed to be remotely operated by a person in another car. Although the so-called “Phantom Auto” differs from the current self-contained image of an automated car, it is recorded as the first attempt to operate a vehicle without a driver or occupant (Jenn, 2016).

In the 1950s, people began to envision a world full of driverless cars: a famous advertisement was created by H. Miller in 1957 (Figure 2-7). Its original text stated: “*ELECTRICITY MAY BE THE DRIVER. One day your car may speed along an electric super-highway, its speed and steering automatically controlled by electronic devices embedded in the road. Highways will be made safe—by electricity! No traffic jams…no collisions…no driver fatigue.*”

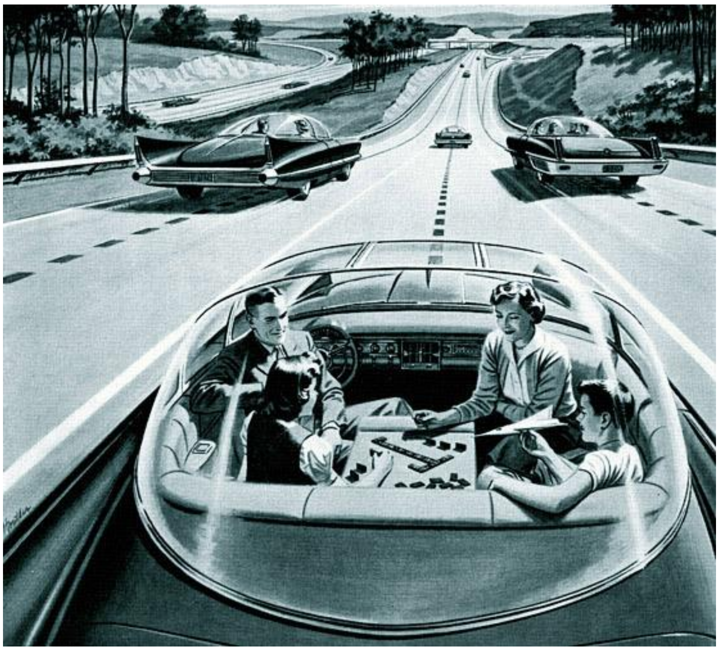


Figure 2-7. Image of Automated vehicles in 1957 (Anderson et al., 2014).

During the 1970s, several attempts that better fit the current automated car image were made. For example, the Stanford Cart was configured successfully as an automated unit. The cart was programmed to move one meter while pausing for ten to fifteen minutes for image processing and route planning. In 1979 it managed to cross a room full of chairs without human intervention in about five hours. The idea to use video information later proved to be a typical input in AV research.

In the 1990s, self-contained vehicles emerged as a result of computer technological advancements. The Ernst Dickmanns team at Bundeswehr University Munich equipped a car with several driverless prototypes (a supercomputer and image analyzing system) and named it VaMP. The VaMP made a highway round-trip travel between Munich, Germany, and Odense, Denmark for 1,758 km in 1995, where 95% of the trip by distance was run automatedly with video cameras.

With these developments' foreshadowing, the DARPA (U.S Defense Advanced Research Projects Agency) Grand Challenge accelerated the developments of automated vehicles remarkably. The prize competitions were held 3 times and heralded a faster pace in AV research & development and invited players from many commercial automobile manufacturers as well. The challenge aroused public awareness of this novel conception to a perhaps unprecedented extent.

In 2009, the launching of the Google Self-Driving Car Project, which later became Waymo, marked another constructive development with the help of the platform of the giant company. The team was initially composed of some of the winners of the Grand Challenge and led by Sebastian Thrun (who was involved in developing Stanford Cart in the 70s) from Stanford University. In late 2018, Waymo became the first company in the world to launch a public self-driving ride-hailing service. Waymo now has claimed more than 20 million self-driven real-world miles on public roads by 2021 (Waymo, 2021).

Aside from Google, the last decade has featured many more players joining the game. Almost all large vehicle manufacturers and some technology companies have been suggesting their interests. These companies have announced their respective ambitious goals for launching Level-4 or higher (SAE, 2021) AVs. For example, in 2012 Sergey Brin, the co-founder of Google, commented that "You can count on one hand the number of years until ordinary people can experience this" (Niccolai, 2012).

Unfortunately, at present these companies have already delayed their timeline. "The latest announcements indicate that the first Level 3 highway systems will hit the market at some point from 2021 to 2024…Technological challenges and regulatory issues are likely to account for most of the delays" (Doll et al., 2020). Litman (2021), in this continuously updated and well-cited technical report, predicts that level 5 AVs could be commercially and legally available by the late 2020s. But it would not be until the 2040s or even longer that AVs become common and affordable so that most impacts can be significant.

To summarize, the current market has become partially a show business during the past several years, which has broadened public awareness and boosted technological advancements. Although still in the struggles, efforts by both academic and industrial fields lead us to believe that this technology is close to maturity and commercialization as more and more testing projects are being exposed. Therefore, we believe to study the implications of AVs in advance is of necessity and significance.

2.3.2 Transport Characteristics of Automated Vehicles

AVs distinguish themselves by a common feature whatever their operating models would be: humans will yield manual controllability to the robotics or computers. All the following AV impacts are derived from this salient feature. To be more specific, this feature can be further clarified by two parts: yielding manual controllability and robotic control, as they presumedly cause some different impact independently. For instance, the impact on capacity can hardly be explained to be caused by merely yielding manual controllability. Instead, it is the robotic control that offers us a smoother traffic flow in most cases. Another distinction between these two characteristics is that most impacts caused by the first characteristic probably appear only after the realization of full automation but the impact from the second could take effect even in partial automation.

With these features, AVs are considered "a technological innovation which will allow organizing transport supply in a radically different way” (Soteropoulos et al., 2019). Changes in transport supply directly indicate potential impacts on generalized travel costs, for example, travel time per se, travel time impedance level (value of travel time), mobility availability, and monetary costs. As AVs are not yet operated in general, empirical data are impossible to be collected hence these transport characteristics vary to a large extent by different assumptions. This section is thus to give a brief review of how these characteristics would presumably be.

2.3.2.1 Safety

The first and most important effect is the general improvement in safety, which is considered the biggest incentive for promoting this technology. By taking over the driving tasks, a fully automated vehicle could avoid most of these human-related crashes with advanced assistance and/or automated technologies. According to the National Motor Vehicle Crash Causation Survey (Table 2-1; Singh, 2015), of the estimated 2,189,000 crash events in the U.S. during 2005-2007, around 94% are attributed to human errors. Among these driver-related crashes, recognition error (e.g., inadequate surveillance, distraction), decision error (e.g., following too closely), performance error (e.g., poor directional control, panic), and non-performance error (e.g., sleep, heart attack) are listed as the reasons.

Table 2-1. Critical Reasons for Vehicle Crashes (adapted from Singh, 2015).

Critical reason attributed to	Estimated	
	Number	Percentage (95% confidence)
Drivers	2,046,000	94% (± 2.2%)
Vehicles	44,000	2% (± 0.7%)
Environment	52,000	2% (± 1.3%)
Unknown Reasons	47,000	2% (± 1.4%)
Total	2,189,000	100%

Focuses of this stream of research lie in proving the effectiveness of driving assistance systems and vehicle-connected technologies. For example, several controller optimization algorithms adapted to vehicle-connected technologies have been evaluated to suggest improved safety. Khondaker and Kattan (2015) designed a variable speed limit control algorithm and used a microscopic approach to achieve multi-objective optimization. A surrogate safety measure "Time to Collision" was employed to measure the safety level. This research showed at most an 11% improvement in "Time to Collision" when applying this algorithm under a 100% AV penetration rate.

Some studies questioned the safety improvements of AVs in partial automation or insufficient market penetration. For example, Strand et al. (2014) experimented with a Level 3 moving base driving simulator involving thirty-six participants, to test their reaction to a sudden automation failure. They found that human reaction time could be no less than 2.2 seconds to resume control, suggesting the potential peril in driving. This, however, should not be a problem in a full-automation context. Also, malicious hacking could impair AV security, which should be of concern (Litman, 2021).

In summary, in a full automation scenario with considerable market penetration, it is believed an improvement in traveling safety is very likely. This benefit, however, is argued to be impossible to confirm and precisely measured until up to hundreds of billions of miles have been driven (Kalra & Paddock, 2016). It also has been rarely considered in measuring other impacts resulting from the AVs, as it is difficult to conceptualize other than in the cases of studying, for example, mode choice preference and crash-related transport delays.

2.3.2.2 Travel Impedance and Value of Travel Time

Value of travel time is a concept defined as the equivalent amount of money a traveler would pay to change one unit of time (e.g., Jara-Diaz, 2007), indicating impedance to travel considering varied income levels and "time value" among travelers.

It is assumed that travel impedance and value of travel time would be reduced (i.e., the disutility of travel time would become less negative) due to yielding manual controllability. Especially, the ability to engage in productive activities while traveling not only generates positive utility in doing so but also eliminates the negative workload of gripping the steering wheel.

There are many studies in the field of traffic psychology: in a review research by de Winter et al. (2014) where a meta-analysis of thirty-two papers was conducted, they reported that self-reported workload (e.g., staying vigilant to monitor the environments) in highly automated driving is around 52% of manual driving, and the number of self-paced in-vehicle display tasks (e.g., menu navigation and figure comparison) completed under highly automated driving is 261% of manual driving's case. Cyganski et al. (2015) conducted a stated-preference survey with 1,000 respondents in Germany, they found that no less than 30% of respondents saw an advantage in working on a fully automated AV, 60% would converse with their companions and 40% would consider to be relaxed and even sleep.

Many published modeling research adopted this hypothesis to assume a decrease in travel impedance, despite great variations in the extent of the change and the treatments in their models. For example, Childress et al. (2015) assumed a 35% decrease in actual travel time for AV users; Liu et al. (2017) assumed a 50% decrease in the impedance parameter of in-vehicle travel time.

Research efforts have been also dedicated to quantifying the specific value of travel time savings, where stated preference (SP) methods are applied commonly. For example, Steck et al. (2018) found that for all low-, middle-, and high-income groups around 31% decrease in the value of travel times in PAV commuting trips can be observed via an SP survey and Mixed Logit model. A reduction rate of 41% was reported by the same research team in another paper (Kolarova et al., 2019). Concerning spatial variability, Zhong et al. (2020) claimed the value of travel time reduction of 18%, 32%, and 24% in PAV mode, for respondents in rural, suburban, and city center areas, respectively.

The reduction rate was observed less for SAV mode: Steck et al. (2018) reported a 10% decrease for all income groups while Zhong et al. (2020) summarized the rates of 8%, 14%, and 13% for the three types of area. An exception here is Krueger et al. (2016), where around 35% and 10% gains in value of travel time for SAV and SAR, respectively, are found via an SP survey in Australia.

It is worth noting that, however, travel impedance and value of travel time are found identical or more “negative” compared to HVs in some literature especially when it comes to the cases such as PAV leisure trips and SAV. For example, Kolarova et al. (2019) reported that the value of travel time for PAV leisure trips is basically the same for all three income groups while for SAV trips even increased slightly; Correia et al. (2019) even found a 29% increase for a PAV that internally designed for leisure activity, but that their revised theoretical framework (Pudāne & Correia, 2020) still suggests a decrease in value of travel time using Jara-Diaz (2007)’s microeconomics model. Regarding the counter-intuitive findings above, Singleton (2019) and Rashidi et al. (2020) provided thoughtful arguments and suggested that whether AV would reduce travel impedance has not yet reached a consensus.

2.3.2.3 Acquisition and Operational Cost

To investigate how the acquisition and operational cost of AV would be is of concern in forecasting car ownership, mode choice, and specific operational models in the future. How AV price would be is highly unsure as for now the equipment required for AV are still in research and development. As general forecasting, Litman (2021) predicts that probably several thousand U.S. dollars (USD) in the vehicle purchase price; hundreds of USD in annual services and maintenance costs, which on average cost 0.80-1.20 USD vehicle mile (55-82 Japanese Yen, or JPY per km) would occur for PAV in the initial stages when AV being commercially available; and 0.60-1.00 USD per vehicle mile (41-68 JPY per km) after the commercialization becomes mature. These predictions coarsely fit with Daziano et al. (2017), who found that the average household is willing to pay (WTP) about 3,500 USD and 4,900 USD for partial automation and full automation, respectively.

In contrast to the likely increasing acquisition cost, the operational cost for in particular SAV is assumed to be far much lower than the current taxis since no labor cost for drivers would be needed anymore. Much literature has been devoted to this issue. To name some recent ones, Bösch et al. (2018) presented a comprehensive and rigorous cost structure analysis of AVs in detail. In considering comprehensive cost forms including cleaning, fuel, maintenance cost, etc., in the Swiss context, they estimated 0.504 Swiss Franc (CHF) and 0.407 CHF per km cost for PAV and SAV, respectively (56 JPY per km or 0.81 USD per mile; 45 JPY per km or 0.66 USD per mile). As such, the PAV cost is just 4% more than its conventional human-driven counterpart, while the SAV cost is about 15% of current taxis.

Additionally, Chen et al. (2016) gave a rigorous financial analysis for shared automated electric vehicles. They argued a total operational cost ranged from 0.417-0.486 USD per mile (29-33 JPY per km) with different settings of battery life and charge required time.

2.3.2.4 Road Capacity

AVs could have a positive effect on free flow capacity, as a result of advanced driving assistance systems (in level 3 or higher). The automated module could allow a short time headway between vehicles, smoother lane change, and accelerating and decelerating behaviors, and thus avoid inefficient start-and-stop traffic behavior. The specific automation algorithm or controller design influences the improvement level a lot.

Many academic efforts have been committed to studying this topic. For example, Huang et al. (2000) designed a driving controller for automated vehicles to simulate mixed traffic with human-driven vehicles. They observed a peak flow of 5,000 vehicles per hour per lane on the freeway under the mixed traffic condition where the share of AVs is no less than 70%. Fernandes et al. (2015) proposed an algorithm to maintain constant spacing among an automated vehicle platoon and tested it with MATLAB and SUMO simulators. According to their results, the capacity of the 8-vehicle platoon could rise to 7,200 vehicles per hour (one passenger per vehicle), which is even higher than the capacity of light rail and bus.

It is also argued that vehicle-connected technology (Cooperation Adaptive Cruise Control, CACC) could increase capacity on freeways to a considerable level (e.g., Shladover et al., 2012), but this effect is quite sensitive to market penetration. In Shladover et al. (2012)'s study, a 100% CACC share would almost double the capacity gain of a 10% CACC share case.

However, some literature suggested the opposite. For example, Le Vine et al. (2015) argued that AV's dynamics (acceleration rate; turning speed) should not surpass those for the light rail transit or high-speed rail as car passengers tend to feel more discomfort than car drivers do. Such settings could produce decreased intersection capacity and increased delay compared to the case of HVs.

2.3.3 Impacts of Automated vehicles on Travel Behavior and Traffic

Impacts on travel behavior refer to potential changes in travel demand, mainly individual- or household-level travel-related choices. Most of these impacts are the associated consequence of many other factors, such as the individual's sociodemographic attributes, the built environment, and the direct impact discussed in the last section. Therefore, these impacts are regarded as "induced" and remain even more uncertain as they depend on the assumptions of the AV characteristics.

2.3.3.1 Vehicle Ownership Choice and Transport Mode Choice

With the addition of a new mobility alternative, the travel mobility market penetration and car ownership in the future would inevitably shift. However, the specific quantified change is far from clear at present.

The choice to own an AV privately or not is majorly dependent on the specific use pattern in the future. Individuals and households could choose among owning a PAV, using SAV every day while not possessing one privately, and combining the former two at the same time. In this sense, vehicle ownership choice is largely associated with transport mode choice, which has long been recognized as one of the conventional wisdom (e.g., Ben-Akiva & Lerman, 1974).

SP methods have been used vastly regarding these personal preferences on these novel mobilities. For example, Haboucha et al. (2017) conducted an SP survey distributed to 721 individuals across Israel, Canada, and the U.S. Three options were presented to the respondents: to keep possessing and using HV; to purchase and use a PAV; to subscript and use SAV system. As result, they found in total 44% chose to keep regular cars, with 32% for PAVs and 24% for SAVs, given the attributes like HV costs 30,000 USD and PAV costs 34,500 USD.

Similar research efforts can be found in Lavieri et al. (2017), who studied future intention on using PAV, SAV, both, or neither, as a function of individual lifestyle preferences, attitudinal factors, and current use of disruptive transportation services. The GHDM approach (Bhat, 2015) based on multinomial Probit kernel model and latent variable structural equation model, etc. was adopted. As result, they found that their respondents were generally not inclined to use AV as 68.5% showed interest in either, with their alternative specific constants being negative; Residents in higher density neighborhoods and with fewer current vehicle ownership tended to favor SAV; People with green lifestyle and technological savviness (latent variables) would embrace both PAV and SAV, etc.

The research above was offered in the scope of preference level while did not suggest general predictions of market penetration. To address this, Bansal and Kockelman (2017), for example, utilized a Monte Carlo simulation based on their survey with a scenario setting with the incremental annual change in WTP and price reduction. According to their research, the market share of level 4 automation in 2030 would be 19.7%, and 37.0% in 2040. Their assumption of the price for automated equipment is $13,947 in 2030 and $4,863 in 2040, given a 10% annual price reduction rate. Lavasani et al. (2016) employed a Bass diffusion model, an estimation based on historical sales of hybrid electric vehicles, to forecast the market penetration of AVs. According to them, the penetration rate is assumed to be 8.0% in 2035 and 36.0% in 2040. Neither research differentiated PAV and SAV in their analyses.

As result, different AV-using patterns would lead to a change in the total level of vehicle ownership. Some studies investigated how many HVs are required to function similarly to one SAV, assuming that travel demand keeps unchanged. Fagnant and Kockelman (2014) applied an agent-based simulation model to examine the feasibility of SAV service in a grid-based synthetic city. In their warming up simulation, they evaluated the optimized fleet size with a rule that generates a new SAV for every traveler who has been waiting for at least 20 min after sending the request. As a result, they found that 1,688 SAV meet the 60,551 agents' demand. With each licensed driver in the US an average generating 3.02 trips per day and owning or leasing 0.99 household vehicles, 19,849 vehicles are presumedly required to meet the 60,551 trip demand. Given that only 1,688 SAVs are required according to their simulation, a replacement rate of 11.8 is derived. Similarly, the replacement rates for SAV of 9.3, 9.0, 10.77 were estimated by Fagnant et al. (2015), Chen et al. (2016, for electric SAV), Fagnant and Kockelman (2018, for SAR), respectively.

Bösch et al. (2016) also examined the optimized fleet size of SAV. By sampling the incremental level of actual Switzerland travel demand and inputting incremental supply level into MATSim, they concluded that a fleet size of 10% of the demand size is necessary to ensure 95% of the requests are served within 10 min in a large-scale demand level.

Few investigations have been done regarding the ownership change for PAV. Vehicle ownership is argued to be potentially reduced as PAV would render more efficient intra-household allocation. Zhang et al. (2018) solved this by using a greedy scheduling algorithm to determine the minimum number of PAV required to satisfy all the travel demands in one specific household. They found that about 18.3% of the households from their survey have the potential to reduce vehicle ownership while maintaining the current travel schedules.

Some other research predicted mode shift through simulation approaches with various assumptions on AV characteristics and ownership ratio. For example, Liu et al. (2017) identified the modal shift effect in SAV via simulation with MATSim. They first calculated the optimized SAV fleet size based on Bösch et al. (2016)'s study and then employed MATSim's iteration process to simulate individual choices. With certain values of travel time settings, they found 50.9% of trips turned into SAV when the fare rate was set at 0.31 USD (34 JPY) per km and 10.5% with 0.62 USD (68 JPY) per km.

To summarize, despite that this research topic have to be conducted based on multiple assumptions of AV characteristics, so far AV mode choice preference has been studied extensively through SP methods. With the preference modeled, applying agent-based simulation methods is widespread to acquire specific modal shift predictions. Yet, with the concerns in the unmatured technique, we might question the results of the modal shift and vehicle ownership from the SP surveys. If the present preferences on ownership would hold, AVs seem very unlikely to prevail. One explanation for that could be the results are subject to hypothetical bias, the deviation from real markets with a stated preference survey (e.g., Hensher, 2010; Fifer et al., 2014). Also, it could be suggested that vehicle ownership choice accumulates more uncertainties and hence SP methods might not be the best idea. We expect further studies assessing AV ownership choice via modeling approaches.

2.3.3.2 Travel Destination Choice, Travel Generation Choice, and Travel Pattern Change

Following the travel demand and supply relationship, AVs are also assumed to have impacts on other travel-related choices including travel destination choice and travel generation choice. With AVs as a new alternative available in travel mode choice, 1) those who cannot or are not willing to drive themselves could reconsider their trip-making decisions; 2) those who suffer from driving burden so chose a convenience store nearby for shopping could select a farther shopping center, etc. These are usually referred to as "induced travel demand". Further, individual- and household-level daily travel patterns could be changed as a result of combining these decision changes.

The existing literature provided very limited understanding concerning these dimensions of choices, except for those induced by those who cannot drive: Harper et al. (2016) established three demand wedges for three groups that might be caused by the adoption of AVs: people who cannot drive for physical, legal, or financial reasons (including who does not have a license); the elderly over 65 and without medical problems; adults who have a medical problem. By applying these wedges to the 2009 National Household Transportation Survey (NHTS), they found in total an upper bound of 295 billion miles or a 14% annual increase.

It is postulated that the scarcity of this research is because most of the agent-based simulation models that are used within the AV topic do not incorporate these dimensions. Both destination choice and travel generation choice are usually involved with a large choice set, which introduces more difficulties compared to travel mode choice. Therefore, activity-based travel demand models are typically employed in examining these issues. Two notable works are introduced below.

Childress et al. (2015) pioneered using an activity-based model to explore the impacts of AVs. The study employed an activity-based travel model, SoundCast (PSRC, n.d.) which is built on DAS structure to the Puget Sound area, Washington, U.S., as its main methodology. Four AV scenarios concerning capacity change, parking cost change, and value of time changes were evaluated to suggest short-term implications. Apart from the modal shift, the authors found at most about a 4.9% increase in daily trip per person, around 14.5% in average trip length, and 19.6% in overall distance traveled, all of which were embedded with the hypothesis that AV could make trips with less impedance.

Vyas et al. (2019) provided some other valuable insights with much more treatments included to incorporate the features of AVs. They presented a scenario-based analysis on potential AV implications in Columbus, Ohio, the U.S. using an activity-based travel demand model CT-RAMP. The analysis enjoyed some sophisticated features of CT-RAMP compared to DAS. For example, a school escorting model was explicitly incorporated so that around a 20% decrease in escorting activities can be observed in their scenarios. While other activities than escorting increased by around 1-3% according to their results. As for the travel distance, increasing rates of around 3% and 4.5% are found in the scenarios of 25% and 50% bonus of travel time impedance, respectively. The results are more conservative than what was found by Childress et al. (2015), the authors argued that it is because of, for example, the incorporation of time-space constraints in the destination choices of CT-RAMP.

Individual daily travel pattern is well-recognized to be subjected to household-level schedule coordination. PAV by its features has the potential to be more efficiently allocated among each household. This should not only affect household vehicle ownership (Zhang et al., 2018) but also could lead to Individual-level daily travel pattern adaptations such as a schedule shift to use AVs. Research regarding this intra-household vehicle sharing problem is few in the AV context so far, some efforts can be found in, for example, Correia and van Arem, (2016), as well as Cokyasar and Larson (2020).

To summarize, despite uncertain changing rates to come, longer and more trips are expected with the prevailing of AVs in the future according to the existing literature.

2.3.3.3 Impacts on Traffic Flow Characteristics

Traffic performance metrics typically refer to those level-of-service indicators such as link travel time, vehicle travel distance, and delays. Extensive literature is available on this topic, especially on travel distance, with the help of agent-based simulation methods.

Vehicle travel distance is often measured by total vehicle distance traveled, the aforementioned studies by agent-based simulation models for SAVs have given many insights: for MATSim or other agent-based simulation studies, induced total vehicle distance traveled of 10.7%, 8.0%, 8.9%, 6.6%, 9.8-15.1% is identified by Fagnant and Kockelman (2014), Fagnant et al. (2015), Fagnant and Kockelman (2018) and Liu et al. (2017), respectively. In Chen et al. (2016), the distance to charge stations is also included in the electric vehicles case, an induced VKT of 14.0% is found with shared automated electric vehicles given 129 km travel per every 30 min charge time. Zhang et al. (2015) focused on parking demand change. By using an agent-based simulation model of a 16 km × 16 km grid hypothetical city, they observed a 63% total distance traveled increase induced by SAV's cruising behavior: when a 30-min empty cruising time is required before stopping (i.e., parking) comparing with a no cruising time scenario.

For the studies above, increased travel distance is mainly the consequence of empty driving of SAV. Factors such as travel destination change were mostly not incorporated. Some exceptions include Childress et al. (2015) and Vyas et al. (2019), which have been introduced in the last sub-section. Another notable research is by Auld et al. (2017), who employed an integrated travel demand and traffic simulation model framework, POLARIS (Auld et al., 2016) to analyze the effects of AVs for Chicago, Illinois, the U.S. At the travel demand component of POLARIS is the activity-based demand model, ADAPTS, where a route choice model is explicitly included so that connected vehicle technology is possible to be evaluated. By setting scenarios of AV ownership, the value of travel time change, and capacity change, the authors observed a board range of VMT increase from 1% to 79%.

Traffic delay is another well-used indicator to suggest the level of congestion in transport research. In the context of AVs, however, this value seems less popular in use. Childress et al. (2015) found that daily average delay hours could at most improve by 58.6% if SAVs are to dominate, but also could deteriorate by 17.7% when all trips are made by PAVs. On the contrary, Vyas et al. (2019) suggested that with the benefits of road capacity improvements, a reduction of delays is found in all their scenarios, from 40.4% to 85.4% and 10.4% to 64.7% for freeways and other roads, respectively.

In all, the effect of congestion seems to vary with the model settings and remains rather unclear on balance with positive and negative components. A more comprehensive analysis and in particular better evaluation metrics are necessary to offer a better understanding.

2.3.4 Impacts of Automated vehicles on Accessibility and Land Use

This sub-section focuses on the induced impact of AVs in the longer term. This concerns land use changes such as residential location choice and infrastructure development choice. Before stepping into land use, one evaluator called accessibility is to be introduced and reviewed as its important role in connecting transport and land use implications.

2.3.4.1 Accessibility Change

Being different from classical mobility-based planning performance indicators such as automobile travel speed and delay, utility-based accessibility (Geurs & van Wee, 2004) corresponds with perceptions of the people in the study area and is typically considered a more composite indicator for evaluation policies (Section 3.2.2).

AV's impact on accessibility has long been discussed in the literature. For example, according to an expert-based experiment (Milakis et al., 2018), some experts considered it likely that induced travel demand might offset the accessibility benefits, while others took a positive position about overall AV accessibility impacts.

Some studies have been conducted to quantify accessibility changes resulting from AV introduction, which are nevertheless limited in quantity. Meyer et al. (2017) studied the impact of AVs on accessibility in Swiss municipalities based on the Swiss National Transport Model. Three nationwide scenarios that differ in AV deployment strategies (i.e., type of roads or areas AVs can operate), AV ownership, and road capacity benefits were examined. Their findings suggest overall considerable accessibility gains in all the scenarios while large cities suffer a small decrease in the fully shared automated scenario. For example, an average 10% increase in accessibility was found in the scenario with induced demand from new customer groups of the young and the old as well as an optimistic capacity change setting of a 40% increase in urban roads and a 270% increase in extra-urban roads. It is noted that a simple network loading model was used in the study, where the level of congestion by introducing AV might be limited.

Childress et al. (2015) measured accessibility changes in their most aggressive AV scenario through the activity-based travel demand model. The Puget Sound Regional Council researchers found that due to the convenience of AVs, logsum accessibility increased from 8.5% to 8.9% for the whole

Seattle area, with considerable higher increases in more remote areas. Similar findings and especially the pattern of changing differences between centers and outskirts can be found in Vyas et al. (2019) and Luo et al. (2019), the former observed in the scenario with a 50% value of travel time bonus at most about 0.5 aggregate accessibility increases, which the authors considered are not extreme. The latter found a total 23-36% increase of trip-based logsum across the study region, with no induced travel incorporated in this simulation study.

Nahmias-Biran et al. (2021) evaluated their SAV simulation work with activity-based accessibility, a more advanced accessibility measure (Dong et al., 2006). The work was implemented with the SimMobility simulator where a DAS-based activity-based travel model is included. Activity-based accessibility was computed as the logsum of the upper-most level of their activity-based travel demand model. As result, in a scenario where SAVs are exclusively operated in Singapore, overall accessibility gain was observed as people with lower income enjoying more.

2.3.4.2 Land Use Change

AVs might have profound impacts on land use patterns on a regional scale. Given a decline in generalized travel cost under the transport-land use feedback relationship, AVs could influence the tradeoff between land values and commuting costs (e.g., Alonso, 1964). In weighing this tradeoff, the willingness to reside or locate homes or firms farther away is assumed to be one of the impacts in the longer term. Therefore, this could encourage a house and firm moving trend toward the outskirt of a city and in consequence a lower-density land use pattern in the future. Given the focus of this dissertation, a review of the impacts on residential location choice is to be highlighted.

Using survey methods is the first common stream of research in studying AV impacts on residential location choice. According to an SP survey of 347 respondents in Austin, Texas, and an ordered Probit model, Bansal et al. (2016) found that respondents with more children, living further from their workplace in a high-density commercial area, and who prefer to drive alone for work trips tend to move further from the city center in Austin, Texas, the U.S. It is perhaps because of lower land prices in suburban areas and more comfort in long commuting time. Also, the respondents with bachelor's degrees or higher and living in high-density neighborhoods as well tend to move further from central Austin, perhaps on account of high land prices in their current neighborhoods. On the contrary, the results indicated that full-time employed males with higher income and annual vehicle miles traveled are likely to move closer to the central area, perhaps to utilize the SAV service more conveniently. Tech-savvy respondents showed a similar propensity to shift closer to the center. 74% of the residents were reported to believe no home location change would be made, while 14% and 12% chose to move closer and farther from the city centers, respectively.

Krueger et al. (2019) investigated this issue by conducting an SP survey of 512 residents in Sydney, Australia. In the survey, the respondents were required to jointly choose a residential location option and a commuting travel mode option from HV, AV, and public transit. They summarized that, after calibrating the data with a Mixed Logit model, the changes in the value of travel time of AVs and the residential location choice preference may be limited.

Kim et al. (2020) also examined the choice of residential location and vehicle ownership bundle in the context of AVs. A cross-nested logit model was estimated based on the results from an SP survey. As result, they found 77.3% of the respondents expected no change in the residential location, though one interesting propensity was revealed that the more people expect AVs to make their time using more productively and flexibly, the more likely they are to move farther away from work and other currently frequently-visited places. The authors remarked that it probably is "because long-term decisions are relatively stable, the ramifications of AVs may still be difficult for many people to imagine, and the nature of the AV era remains profoundly uncertain for everyone".

Some other survey studies quantified the magnitude of the changes in residential locations. Moore et al. (2020) predicted a 68% increase in commute time conditional on relocation based on their Dallas-Fort Worth metropolitan area-based survey. They argued the result suggested the upper range of potential urban sprawl.

Much less evidence is currently available that was applied in travel forecasting modeling and/or simulation paradigm. Four notable works are introduced below.

Gelauff et al. (2019) studied the effects of PAVs and automated public transit on residential location change with a general equilibrium model LUCA, which was designed in a LUTI fashion to connect transport effects with land use. The concept of equilibrium in their model refers to equilibrium in the residential land market between housing supply and demand. Upon the change in the housing demand resulting from transport choice, land prices are adjusted until the housing demand and supply that was exogenously provided are equal again. In total, 3 models: a commuting mode choice model, a job location choice model, and a residential location choice model were combined within an NL paradigm in LUCA, whose parameters were sequentially estimated based on 60,000 Dutch employees. In their model that assumed a 20% reduction of the coefficient on the travel time of privately owned cars for trips longer than 5km, home-job location distance was found to increase by 16.8% across the Netherlands, and the population decreased by about 1% in the four largest cities and 3% in other large cities.

Meng et al. (2019) employed a LUTI simulation platform SimMobility to study the SAV impacts on moving patterns in Singapore. The study combined a long-term housing market model, a job location choice model, and a household vehicle ownership model, where the effects from SAV were reflected as logsums calculated from the transport models proposed in their previous studies. Housing bidding behaviors were explicitly considered. Their results suggested a roughly slight moving-out tendency from the central region under a scenario with SAV added to compete with the existing transport modes. Nevertheless, under a scenario where only SAV and public transits were allowed, 15.6% more people moving into the central region were found.

Zhang and Guhathakurta (2021), on the other hand, focused on residential location choice in exclusively "the era of SAV" where the authors connected an MNL-based residential location model and an agent-based SAV simulation model that was built in Zhang and Guhathakurta (2017). The model for Atlanta, Georgia, the U.S., simulated SAV fleet size determination, SAV passenger assigning and serving, as well as SAV relocation and parking. The trips generated through a Four Step model were used as the input. As result, they found average waiting time for SAV would be less than five minutes in urban areas and longer than ten minutes in suburban areas. Two scenarios where the in-vehicle travel time of SAV becomes 0% and 75% (where all trips are served by SAVs) were assumed. Then, the change in travel cost was reflected in the residential location model, where the costs were included as one of the independent variables. After the simulation, it is found in this study that people all tend to move away from their job location but some may choose to move closer to the CBD area, for example, people younger than forty without kids will relocate further away from the CBD (6.8% increase in median distance) and their job locations (23.4% increase in median distance), while older people with children tend to move closer to the CBD (6.5% decrease in the median distance) but still away from their job location (20.9% decrease in the median distance).

Llorca et al., (2022) studied the potential PAV effects on residential location choice in the context of Munich, Germany. They proposed a combination of a land-use model system, a travel demand model, and a traffic assignment model, as their LUTI methods. They assessed eight AV scenarios covering the effects of changes in the value of travel time, parking restrictions, and traffic congestion. The commuting time changes largely account for the AV impacts connecting the transport models to the land use model. Their results observed urban sprawl. For example, for the full scenario where all the AV effects were included, those who work and also live in the city centers would be 2-3% fewer than in the non-AV scenario.

Apart from the potential change in residence distribution, the change in parking infrastructure toward urban land use patterns is also considerable. Three ways to assess this impact are clarified: first, during the time gap between dropping off its owner and the next request, these vehicles could pilot themselves to a remote parking lot where the parking fee is cheaper. In this way, the amount of parking infrastructure would be reduced in the urban center area (Fagnant & Kockelman, 2015); second, parking capacity can be increased on existing lots since no room for driver access would be required anymore (Childress et al. 2015); third, SAVs would instead not need to park or reduce the frequency to park since they are always busy serving passengers, i.e., operated with higher utilization efficiency (Zhang et al. 2015). Detailed findings on this topic are not covered in this review.

In a summary, AV impacts in the long term have not received sufficient research attention so far. This is reflected in not only the limitation in the quantity of academic research have been published, but also in the opposite envisions proposed and contradicting findings that have been revealed from the existing literature. Regarding residential location choice, despite the LUTI models having been widely applied, appropriately reflecting the changes from AVs in the residential location model is far from reaching a common ground. The results also varied widely depending on the contexts of the study regions. Evaluating the AV impacts in a context that has been missing regarding this topic should offer insights into this unsettled research question.

2.3.5 Literature of Automated vehicles in the Context of Japan

This dissertation considered itself as one of the contributions to the AV research in the context of Japanese society, thus recognizing the necessity to introduce the existing literature within the context in a separate manner.

To the best of the author's knowledge, studies about AV awareness and implications in the context of Japan are limited in quantity thus far.

Most of the existing English-written research has concentrated on the public preferences towards AV ownership and mode choice behaviors that should fall into what has been introduced in Sub-section 2.3.3. For example, Jiang et al. (2019) conducted an SP survey on AV ownership by analyzing 576 car users in Japan. The authors set five types of attributes (AV penetration rates, additional AV purchase cost, AV insurance discount rate, AV parking cost, and release timing of AVs to the market) and found that more than half (53%) of their respondents chose to purchase an HV, while 26% to own AV with Level 4 or higher. Further, a Mixed Logit model was employed to investigate the relationships between the WTP and the assumed AV attributes as well as individual demographic attributes. One interesting finding is that senior respondents are more likely to own AVs compared to younger respondents.

Hao et al. (2019) made similar efforts in measuring the intention and WTP on SAVs by the SP method. An effective sample with 1,036 respondents from Nagoya City, Aichi, was collected. The respondents were directly asked the amount of money they would like to pay for eleven assumed SAV "services" (e.g., easy boarding, short waiting time, larger trunk, etc.). As result, six clusters of respondents are identified: for example, the cluster with mainly middle-aged employed people and in general low interest in SAV shows lower WTP (1.76 USD per SAV trip), which is around 46% less than the cluster with the second lowest WTP (3.81 USD per SAV trip) and 62% less than the cluster with the highest WTP (4.67 USD per SAV trip). Trip heterogeneity was unfortunately not considered in their survey.

Besides the ownership and mode choice, the general AV acceptability concerning some specific facets of public awareness has also been investigated. Chikaraishi et al. (2020) conducted an SP survey from Japan in examining the risk perception levels of AVs. The 1,442 respondents from Hiroshima Prefecture were first presented with randomized combinations of videos about three types of AV-related risks: system error, hacking, and unexpected events. After that, the respondents were asked to self-report three types of information: first, their perceived benefits and risks regarding 20 "risk items" including AVs, nuclear power, smoking, skiing, etc., in relative magnitude to each other; second, their risk level acceptability regarding the risk items; third, perceived characteristics regarding the nine risk items in Likert scale, for example, the extent of knowledge about that specific risk by the public. The results of the perceived risks of AVs were found lower than HVs but higher than railways at large, despite the difference in the perceived risks between partial automation and complete automation being found not significant. While for the risk characteristics, the results reveal that the nine risk items after conducting a factor analysis can be well explained by two aggregate factors: dread and unfamiliarity. The AVs are found within the highest unfamiliarity score but are neutral on the dread scale. The current risk perception of AVs has thus been confirmed to be mainly a result of their strangeness and lack of public exposure, which could explain those intuitively incorrect SP model results in the context of AV generally.

Abe et al. (2020) also investigated the link between safety concerns and AV user acceptance. This group of researchers focused on the impacts of the approach to SAV monitoring which is argued by the authors could affect individuals' perception of emergency management and thus the general safety of SAV. Similarly, SP methods were used from a web-based survey with 1,663 respondents across Japan. Direct questioning about the intention to use automated buses and taxis was first conducted, where six alternatives involving the two modes and three monitoring methods: on-board human monitoring, remote human-based monitoring, and remote system-based monitoring are included. The results show that "more individuals express strong resistance to more advanced remote monitoring". Following that, a stated choice experiment was structured to obtain the mode choice responses to each respondent's last trip, where their actual mode and SAV are provided as the choice alternatives. Estimation results from Panel Mixed Ordered Logit models were used to reveal the relationship between the individual demographics, trip characteristics, monitoring methods, and SP responses. The authors reported no significant effect on intentions to use SAV and the monitoring method variables.

Few English-written existing literature is found discussing other facets of AV in the context of Japan, with Abe (2019) and Luo et al. (2019) being notable exceptions. Abe (2019) analyzed the Japanese context with the method used by Bösch et al. (2018) and found that PAV could cost at least 60 JPY per km (0.85 USD per mile) for the central area and 40 JPY per km (0.57 USD per mile) for the peripheral area; SAV at least about 60 JPY per km (0.85 USD per mile); and SAE at least about 40 JPY per km (0.57 USD per mile). He concluded similarly to Bösch et al. (2018) in comparing conventional vehicles to their automated counterparts. Luo et al. (2019) applied MATSim and scenario analysis for the Gunma Prefecture with both PAV and SAV considered. The research took the advantage of the agent-based traffic simulation function from MATSim and Gunma Person Trip data and hence managed to simulate AVs in a much finer spatial resolution in the context of Japan. The simulation results suggest that, for example, 24.7% share of PAV and 8.2% share of SAV were gained in a scenario with a 30% population possessing PAV; SAV fleet size supplied equal to 5% total population; 25% value of travel time for AVs compared to HVs; and 32 JPY charge for SAV per km. This work also highlighted itself in providing accessibility as one of the evaluators, where on average 31.8% accessibility increase was found in the study area.

Greater diversity is found in Japanese-written existing literature. Early studies such as Kii et al. (2017) have made attempts to evaluate full-automated PAV implications via economic models, which are however limited in assuming too many exogenous inputs and assumptions including deciding trip distance by the assumed city size, fixed and identical number of trips, etc.

Katsuki et al. (2017) analyzed the possibility of SAR introduction for the southern part of Ibaraki Prefecture by matching the trips in the Person Trip (PT) data of the corresponding area within the county level ("small zone"). The difference between the HVs and AVs is limited in concerning the vehicle ownership only: in the HV-ridesharing scenario, a ridesharing trip would be generated only between an HV owner and a non-owner, which is not demanded in AV-related scenarios. The number of supply vehicles is obtained by assuming all the SAR trips are satisfied. The results show more than around 10% trip reduction per vehicle in their AV-related scenarios. Besides, spatial heterogeneity in SAR trip matching offers some valuable insights: for example, industrial areas would have the highest ridesharing share, which is arguably to be explained by more temporally concentrated travel patterns in the area. With the same methodology but different evaluators, the subsequent works of Katsuki et al. (2018a) and Katsuki et al. (2018b) examined the implications of SAR on parking time and emissions, respectively.

Kamijo et al. (2019) followed Luo et al. (2019) in applying the simulation framework of MATSim to evaluate the AV implications. This research highlighted itself in practicing the ride-sharing module in MATSim as SAR and adapting it with some sophisticated vehicle allocation settings to Numata City, Gunma Prefecture. PAV and SAV were also added as the mode choice alternatives along with SAR. One of the major results of this research is that different vehicle allocation algorithms would influence the SAR running efficiency to a great extent.

Furusawa et al. (2020) conducted a simulation-based analysis of automated car-sharing in the context of Japan. The authors first conducted an SP survey for around 390 households residing in the 3km circle from the city center of Kumamoto City, Kumamoto Prefecture. The survey was designed with three objectives: whether the respondent would like to replace one trip of their reported itinerary from the current mode to AV car-sharing; whether the respondent would like to own an AV; and if so, whether the respondent would like to lend it to others. The first question was estimated with a binary Logit model, while the last two were with a Nested Logit model. Then, a rule-based model was built to simulate the potential AV car-sharing demand from the Kumamoto Person Trip data. As result, 720 people (out of 196,322 individuals in Person Trip data) were identified as AV car-sharing service providers, whose vehicles are almost used all the time with a 99.8% utilizing ratio out of 100-day simulations.

Matsunaka et al. (2020) built a simulation model based on a virtual mono-center city targeting the implications of SAV. The trips in the virtual city were generated from the summary statistics from the National Person Trip data, where the OD pairs along with facility locations were determined by a model from a previous work of the authors. The study assumes that all the HV trips generated from the last step are replaced by SAV trips, whose fleet number is decided in a similar way to Fagnant and Kockelman (2014). The main evaluation statistic of the study is a social cost, which is calculated from vehicle running cost (gasoline cost, travel time cost, waiting cost), vehicle maintenance cost, and parking space maintenance cost. The simulation results suggest that by introducing SAVs, the total social cost would reduce by 25 million JPY per day, around 88.7% of the HV case. The improvement is mainly attributed to the reduction in maintenance costs and vehicle running costs.

2.3.6 Summary

The advent of automated vehicles is still looming on the horizon, making the image of the future remains in question.

Extensive research attention has been devoted and is still being devoted to studying the possible characteristics and potential implications of this novel mode of transport. One may expect the predictions of the former to be straightforward given field experiments are currently being implemented vastly. That is, however, not the case according to the review given in this chapter: the costs of AVs are subject to the specific technology equipped and the actual commercial model adopted; benefits in value of travel time seemingly have become controversial in some recent studies. The latter that resulted from the change in the AV characteristics hence is observed with even wider discrepancy: many respondents of the SP survey were observed to declare no change in vehicle ownership and residential location choice would be made, while the simulation modeling works suggested this would probably not to be the case.

The issues are found even unclear in the context of Japan. The existing AV-related literature for Japan is limited in quantity and scope: though many have looked into the public awareness of AVs using SP survey data from Japanese people, few works have paid attention to other aspects such as destination choice, travel generation choice, and long-term implications.

We here borrow the categorization from Harb et al. (2021) to categorize the potential AV impacts: 1) the impacts whose direction is consistent across the existing literature of adequate quantity, despite the magnitude varies; 2) the impacts with limited evidence but consistent results, albeit the range varies; 3) the impacts with limited evidence where findings are also conflicting; and 4) the impacts with very few studies ever address.

Table 2-2 summarized the reviewed impacts with consideration of the author and the results from Harb et al. (2021).

Table 2-2. Categorization of AV Impacts from the Existing Literature.

Category	AV impacts	Category	AV impacts
1	Safety. Costs. Road capacity. Traffic flow characteristics. Mode choice preference and willingness to pay.	**2**	Value of travel time and in-vehicle behavior. Destination choice. Travel generation choice. Accessibility changes. Parking supply changes.
3	Residential location choice. Operating models preference: SAV and PAV.	**4**	Job location choice. Idle vehicle using pattern;

CHAPTER 3 METHODOLOGY AND DATA

Following the literature reviewed in the last chapter, this chapter is intended to clarify the specific methodology framework that is going to be used in this dissertation in a general way as well as to provide some reasonings for choosing such a framework. Further clarifications and specifications of the methodologies are to be covered in Chapters 4, 5, and 7. Two sections introducing the study region and data are also provided in this Chapter.

3.1 Methodology Framework

This study should fall into the general category of travel forecasting, as the objective is to forecast AV impacts in the future. The implications to be concerned involve different periods, so a multi-hierarchical model system is adopted as the methodology framework of this dissertation (Figure 3-1).

This model system mainly consists of three models: an activity-based travel demand model, DAS (Bowman and Ben-Akiva, 2001; Bradley et al. 2010); an agent-based dynamic traffic simulation model, MATSim (Horni et al., 2016); and an MNL-based residential location model. As Figure 3-1 shows, the DAS models the travel demand and MATSim models the travel supply part. These two models are integrated in a manner that is similar to Lin et al. (2008) to capture the travel demand-supply interactions: the outputs from both models, respectively time-specific OD pairs data and network conditions data, are exchanged across the two models. The procedure of exercising travel demand-supply equilibrium is necessary in, for example, measuring indirect effects such as increased travel time due to the induced travel from the introduction of AVs. After the two models converge to a demand-supply equilibrium, a concept of activity-based accessibility (Dong et al., 2006) is calculated as a composite change from the transportation system to be passed to the long-term residential location choice as one of its inputs. The approach to incorporate the activity-based accessibility used in this research references mostly Ben-Akiva and Bowman (1998b). The use of accessibility in residential location choice models is a common practice. For example, in the DRAM model (Putman, 1983; 1991) a similar concept was included as a measure of the aggregate benefit households could receive from locating at a specific residential zone.

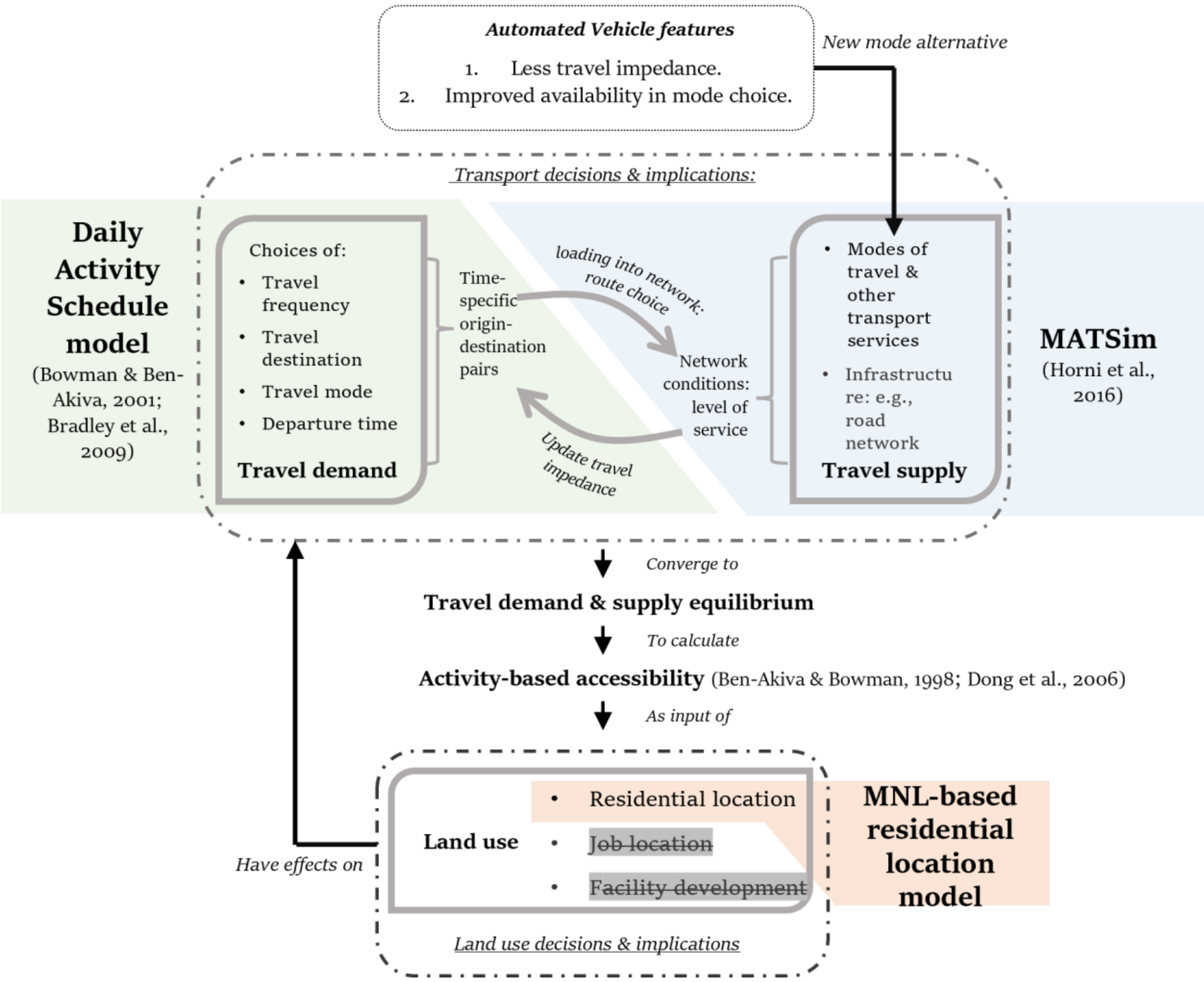


Figure 3-1. Overall Methodology Framework.

Three texts in the grey background: infrastructure, job location, and facility development are the factors considered exogenous, i.e., either unchanged or set by scenarios.

AVs are incorporated in this model system as a new travel mode alternative with two key assumptions: 1) to have less travel impedance, and 2) improved availability in mode choice, that is, becoming available for those unable to drive and used by another household member when in idle. The choices on the travel demand side then reflect adaptions to this new mode alternative in the adopted activity-based demand model, following which the changes are passed back to the supply model to form the iteration. Specific treatments following this change are also to be elaborated in the following chapters (e.g., Section 6.1).

The frequently mentioned method of Logit model is briefly introduced here. The family of Logit models is conceptualized in Probabilistic Discrete Choice Theory with Random Utility Maximization approach (e.g., Manski, 1977). This approach adopts a perspective that the choice probability of alternative *i* from the choice set C_n of individual *n* equals to the probability of *i*'s utility U_{in} is no less than all other alternatives in C_n (Ben-Akiva & Lerman, 1985):

$$P(i|C_n) = Pr[U_{in} \geq U_{jn}, \forall j \in C_n]$$

The utilities U_{in} for all i in C_n are all considered random because mainly the observational deficiencies of the modelers in obtaining the "true" form of utilities. Manski (1977) identified four sources of randomness: unobserved attributes; unobserved taste variations; measurement errors; and instrumental variables. Therefore, the random utility is expressed as the sum of an observable component, V_{in} (often called systematic component), and an unobservable component, ε_{in} (often called disturbance):

$$U_{in} = V_{in} + \varepsilon_{in}$$

Then, by assuming that all the disturbances ε_{in} are independently and identically distributed type I extreme value (i.e., Gumbel distribution) with a scale parameter μ, we can derive a choice model paradigm with a form of:

$$P_n(i) = \frac{e^{V_{in}}}{\sum_{j \in C_n} e^{V_{jn}}}$$

This model is called Multinomial Logit (MNL) model, where conventionally V_{in} are structured linearly with the following types of terms for individual *i* and alternative *j* (Croissant, 2020):

1. Alternative specific constants α_j (to capture the average effect not included in the model).
2. Alternative specific variable t_j with generic coefficient θ.
3. Individual or choice-situation specific variable z_i with alternative specific coefficient γ_j
4. Alternative and individual or choice-situation specific variable x_{ij} with generic coefficient β.
5. Alternative and individual or choice-situation specific variable w_{ij} with alternative specific

coefficient δ_j.

As only the difference of utility matters in the structure of Logit models, we can thus obtain the utility difference for alternative *j* and *k* as:

$$V_j - V_k = (\alpha_j - \alpha_k) + \theta(t_j - t_k) + (\gamma_j - \gamma_k)z_i + \beta(x_{ij} - x_{ik}) + (\delta_j w_{ij} - \delta_k w_{ik})$$

Note that within the formula above, at most *J*-1 alternative specific coefficients can be recognized with *J* alternatives in total. Hence in the estimation, a base alternative would be arbitrarily selected which is usually the most selected one from observations for the convenience of demonstration.

Despite that MNL is subjected to limitations such as a property of Independence from Irrelevant Alternative, the application of MNL has been widespread since its introduction due to its great tractability.

3.2 Reasoning behind the Methodology

As reviewed in the previous chapter, the combination of activity-based travel demand model and dynamic traffic assignment model is considered the state-of-the-art paradigm in travel forecasting. Hence, advanced model reliability and sensitivity are expected compared to its traditional counterparts at large. How these advantages can be gained in specific in the DAS and MATSim combination is first summarized below. Then, the superiority of activity-based accessibility over traditional accessibility measures follows.

3.2.1 Advantages of MATSim and DAS model

The major advantage and the reason to use MATSim in this research is its spatial and temporal resolution which are one of the finest levels currently available. This model was built on basis of the knowledge and experience from the TRANSIMS project (Smith et al., 1995), one major contributor of which, Kai Nagel, later become one of the initiators of MATSim.

The launch of the TRANSIMS was one of the initiatives to develop a new forecasting method stimulated by the ISTEA legislation in 1991 by the U.S. government, paralleling the innovations of activity-based travel demand models. The ambition of the TRANSIMS project was to contain modules of a population synthesizer, an activity demand generator, and an intermodal route planner, together in an iterative microsimulation approach. Nevertheless, the probably most significant feature of TRANSIMS was the unprecedented resolution and scale at the time in its proposed methods: second-by-second microsimulation over 24 hours within an "all-streets" network in the scale of entire cities (Boyce & Williams, 2015).

The methodology framework and the features of TRANSIMS have been succeeded by MATSim to a large extent but also with some advances: for example, MATSim replaced cellular automata model with a queueing model for the network loading part.

Briefly, the improved network representations are considered necessary to match the precision of travel behaviors generated by advanced activity-based demand models. Besides, from a practical perspective, the reputation of MATSim in being employed in the existing literature studying AV behaviors, as well as its open-source nature that offers good access, have also contributed to the decision of adopting it as one of the methods in this dissertation.

The use of the DAS model also requires words of reasoning here. Despite that MATSim, as reviewed, is originally designed as an integrated transport demand and supply model, this research purposely choose to not enjoy MATSim's full function. The main reason for that is the travel demand module, i.e., the so-called Operators that are applied in MATSim could not provide sufficient model sensitivity that is required in examining AV impacts: namely the induced travels of AVs in both sense of travel more and travel longer, which mean the demand for accommodating trip generation and trip destination choices. This research expects that the induced travels would influence the congestion effect and accessibility, thus being an important factor in evaluating the AV implications. According to the literature review, it is found that the induced travel has been so far relatively focused on those caused by empty trips of SAVs. In this regard, a separate activity-based demand model is adopted to generate daily demand including the “trip generation” and “trip destination” steps.

The reason why the activity-based travel demand model is chosen over other conventional travel demand models (i.e., the Four Step Model, the Integrated Trip-based Models, and the Tour-based Models; see Section 2.1) can be summarized simply in that, especially for the DAS type, it allows “consistent generation of all tours and trips made during a person-day” (Vovsha et al., 2005). Compared to the Four Step model, the trip generation in activity-based models (so do the Integrated Trip-based Models and Tour-based Models) is sensitive to the change in travel impedance so that being responsive to the induced travel. While compared to the other trip-based and tour-based models, activity-based models provide a new modeling dimension: the daily pattern level, so that it could not only give a greater level of output detail but also accommodate the interactions between the tours made during one entire day.

To this end, we choose the DAS model, one representative of the utility-maximizing models, among all the activity-based models that have been proposed and applied. The reasons why the rule-based activity-based models were not adopted are that most of the rule-based models focus on activity scheduling and sequencing while considering activity generating to be exogenous (Pinjari & Bhat, 2011).

To choose the DAS model, among other activity-based models, is at first because of a practical reason that DAS type models are one of the most applied travel demand models in the real world. This is presumably due to its utility-maximizing protocol and hierarchical model structure being easier to understand and validate so that they get more chances to be appreciated by the practitioners and policymakers.

The DAS model is also considered by the author to be one of the most maturely developed activity-based model systems nowadays. DAS model was structured based on trip- and tour-based discrete choice models (e.g., Ruiter & Ben-Akiva, 1978), where interactions among the travel decisions were captured via expected utilities. These model systems have been extensively applied, validated, and extended, suggesting their "ability to perform reasonably well in forecasting" (Bowman, 1998). As an extension, the DAS model managed to accommodate trips and tours into one larger level of so-called "day pattern" (through some innovative designs to reduce the number of its original formidably large alternative set), so that allows more policy sensitivity to the pattern-level choices. Despite comprehending to this more complex choice hierarchy could introduce difficulty and even new sources of bias in forecasting, it is thus chosen by the author as a balance between the model sophistication and model sensitivity.

3.2.2 Accessibility as an Evaluation Measure

The use of accessibility has been widespread in transportation planning, urban planning, and other academic fields for decades, for assessing composite benefits from the transport system.

The definition of accessibility varies to its application context, but in its essence refers to "*the potential of opportunities for interaction*" (Hansen, 1959) at large. Another definition of "*the extent to which land-use and transport systems enable individuals to reach activities or destinations by means of transport modes*" (Geurs & van Wee, 2004) might offer impressions in a slightly more specific fashion. By using the word "opportunities", it means that having accessibility does not require any actual use of the services and activities, but the potential is valued (Nahmias-Biran & Shiftan, 2016).

The existing literature seemed not unanimous in the way of measuring accessibility. Geurs and van Wee (2004) provided a review and classification of the accessibility measures: infrastructure-based measure for analyzing the level of service of transport infrastructure, such as level of congestion and average travel speed; location-based measure for analyzing the level of access to locations typically on a macro-level, such as the number of jobs could be reached within 30 minutes traveling from the origin; person-based measure for analyzing accessibility on an individual level, such as the activities an individual can participate at a given time; and utility-based measure for analyzing the economic benefits that people can gain from the activities.

The utility-based measure, in specific, the logsum is adopted in this dissertation. This measure offers an interpretation of accessibility as the "expected utility associated with a choice situation" (Ben-Akiva & Lerman, 1985) which is similar to an economic concept of indirect utility. Within the RUM framework, the expected utility refers to the systematic component of the maximum utility. In MNL, it equals the natural logarithm of the denominator:

$$A_n = \frac{1}{\mu}\ln\left(\sum_{i \epsilon C_n} e^{\mu V_{in}}\right) + C$$

Where A_n denotes the accessibility of individual *n*, μ the scale parameter, *i* the alternative in the choice set C_n, V_{in} the systematic component of the utility of *i* for *n*, and *C* an unknown constant that represents the absolute value of utility in that MNL specification.

Although the logsum measure suffers from shortcomings such as failing to capture temporal constraints, i.e., the available time of facilities and time budget of individuals, it satisfies most of the theoretical criteria proposed by Geurs and van Wee (2004), including being sensitive to changes in both transport and land use system, taking individual's heterogeneity into account, and being relatively easy to operate and interpret. Of even more significance is that the logsum is, by its foundation, linked to microeconomic theory so makes itself appropriate for economic evaluations. An indicator of social welfare, consumer surplus can be easily transformed from logsum by dividing it by a travel cost coefficient (Geurs & van Wee, 2004; de Jong et al., 2007). As argued and suggested by de Jong et al. (2007), the logsum measure of consumer surplus is more accurate than the traditional Rule-of-a-half practice, which is based on assuming incorrect linear demand curves and cannot correspond to the situation where there is a change occurred in the number of alternatives.

There is one technical issue required for the application of the logsum measure that the logsum must be normalized before any comparisons across individuals are to be made (Ben-Akiva & Lerman, 1985; Dong et al., 2006). To achieve this, Level Condition and Scale Condition must be satisfied in any utility-based measure (Dong et al., 2006), the former asks logsum to have a consistent benchmark utility, i.e., to drop that unknown constant that could vary with heterogeneity across individuals; the latter requires logsum to share the same unit/scale. Level Condition can be satisfied by computing the differences of the same model specifications with different inputs value. Scale Condition can be satisfied by converting the utility units to a comparable model variable, e.g., travel time or cost.

The applications of logsum measure in practical appraisals of transport project was limited until 2000 (de Jong et al., 2007), and the applications involved mode-destination choice mainly (e.g., Niemeier, 1997). As an extension to that, Dong et al. (2006) formulated a concept called "Activity-based Accessibility" (ABA) that was first presented by Ben-Akiva and Bowman (1998b). The key difference between the ABA and mode-destination accessibility is that the former is generated from the DAS model, so it examines all trips and activities in the whole-day range instead of a single trip.

In specific, ABA still follows the formula of logsum above, where the choice set is a set of activity schedules rather than a single trip's mode-destinations for specific trip purposes. This allows ABA to reflect the influence of trip chaining and scheduling and thus to provide evaluations with higher sensitivity. For example, Dong et al. (2006) compared the ABA with mode-destination logsum accessibility on a work trip when imposed with a peak-hour toll. They found that on average the magnitude of decrease in logsum is lower in ABA than the traditional trip-based logsum, the authors argued that it is because the ABA is able to reflect "the full array of adjustments" in not only the peak-hour commuting work trip other than mode-destination choice dimension but also in other trips, whatever their trip purpose, in the individual's daily schedule.

3.3 Study Region

This article uses Gunma Prefecture of Japan as the study region to examine potential AV implications in the context of regional areas in Japan. Gunma is a landlocked prefecture that belongs to the Kanto region, with its prefectural government located approximately 100km away from Tokyo Station (Figure 3-2). It covers 6,363 km^2 and has a total population of 1,940,333 as of 2020 (Statistics Bureau of Japan, 2020), with a population density of 304.9 people per km^2. This value is slightly less than the average population density in Japan of 338.4 people per km^2 (Statistics Bureau of Japan, 2020).

Figure 3-2. Location of Gunma Prefecture. Source: OpenStreetMap.

Gunma prefecture consists of thirty-five municipalities that vary a lot in characteristics. The prefectural capital Maebashi and the most populous city Takasaki together hold a 36.4% share of the whole population, the value would increase to 64.3% when considering other major cities, namely Ota, Isesaki, and Kiryu (all are shown in Figure 3-2). The urbanization pattern in Gunma is skewed to its southeast, which is close to the Tokyo Metropolitan Area. Its rural area is covered largely by mountains and forests, with around 14% of the total land of Gunma designated as the National Parks of Japan.

It is accurate to describe Gunma as a car-dependent society. Gunma is the prefecture with the highest average private four-wheeled vehicle ownership in Japan with 70.5 vehicles per 100 persons (AIRIA, 2021). According to a summary report of Gunma Person Trip Data (Inahara et al., 2017), private cars accounted for 77.9% of the modal share in the area, while train, bus, bicycle, walk and others, took 2.5%, 0.3%, 8.6%, and 10.7%, respectively.

3.4 Data Sources

Multiple data sources are employed in this research, their basic information is introduced here.

3.4.1 Land Use Data

The analysis spatial resolution of this study is 1km^2 mesh cell, which is called Tertiary Mesh (3次メッシュ) cell in Japan. Such a level is considered by the author appropriate as a balance between the requirement of spatial resolution and computational cost.

Land use data for each mesh cell are obtained from mainly mesh cell level analysis (Statistics Bureau of Japan, 2019) for Japanese National Census 2015 (国勢調査) and Economy Census 2016 (経済センサス－活動調査). Basic data processing treatments are implemented to the mesh cell level data, including removing those whose size of mesh cell is less than 0.3 km^2 (caused by prefectural border trimming); removing those whose number of households is less than 5 (as 15 percent quantile); removing those whose number of employees is less than 3 (as 5 percent quantile); and removing those whose centroid is outside Gunma; These were done with "sf" package (Pebesma, 2018) from the programming language of R (R Core Team, 2021). After the processing, two mesh cell level data are obtained, namely *Resident's Mesh Dataset* and *Activity System Mesh Dataset*, the former contains all mesh cells having at least one household residing there while the latter contains all mesh cells having at least one employee working there. By the definitions, most of the mesh cells can be found in both datasets while some only appear in either. The two sets will serve different purposes in the subsequent analyses. For example, the choice set of residential location choice should be sampled from Resident's Mesh Dataset, but the choice set of destination choice should be sampled from Activity System Mesh Dataset. A summary of the attributes collected is shown in Table 3-1 below.

Table 3-1. Summary of Land Use Mesh Data Sets.

Dataset	Variables	Type	Mean	Median	Min	Max	Standard Deviation
Resident's Mesh Dataset	#Residents	Continuous	757.7	273	6	7246	1094.6
Resident's Mesh Dataset	#Households	Continuous	297.9	96	5	3606	466.6
Activity System Mesh Dataset	#Employee	Continuous	368.8	98	3	14237	766.1
Activity System Mesh Dataset	#Office	Continuous	37.3	13	1	1225	71.5
Both	City (by the location of mesh's centroid)	Categorical	-	-	-	-	-
Note: #Mesh cells in Resident's Mesh Dataset = 2794; #Mesh cells in Activity System Mesh Dataset = 2611.							

The spatial distribution of the number of households in Resident's Mesh Dataset and the number of employments in Activity System Mesh Dataset are shown in Figures 3-3 and 3-4 as examples.

Two other important concepts of land use: Urban Function Attraction Area (UFAA, "都市機能誘導区域") and Dwelling Attraction Area (DAA, "居住誘導区域") that will be frequently used in evaluations are introduced here. These concepts are extracted from Location Optimization Plan (MLIT, 2021, "立地適正化計画") as the target areas to attract respectively urban functional facilities and residents to achieve compact city designs. They are used to define the urban center areas for urban functional facilities (e.g., commercial, educational, and medical facilities) and dwelling facilities, respectively. The spatial distribution by 1km mesh cell of UFAA and DAA are shown[1] in Figures 3-5 and 3-6.

[1] UFAA and DAA are designated by the municipal-level governments, but some of them have not disclosed their area designation as of Nov. 2021. These include Shibukawa, Numata, Midori, Annaka, Shinto, Ueno, Kanna, Shimonita, Nanmoku, Kanra, Nakanojo, Higashiazuma, Naganohara, Tsumagoi, Kusatsu, Takayama, Katashina, Kawaba, Showa, Minakami, Tamamura, Itakura, Oizumi, and Ashikaga from Tochigi Prefecture. This should be one limitation of the evaluation.

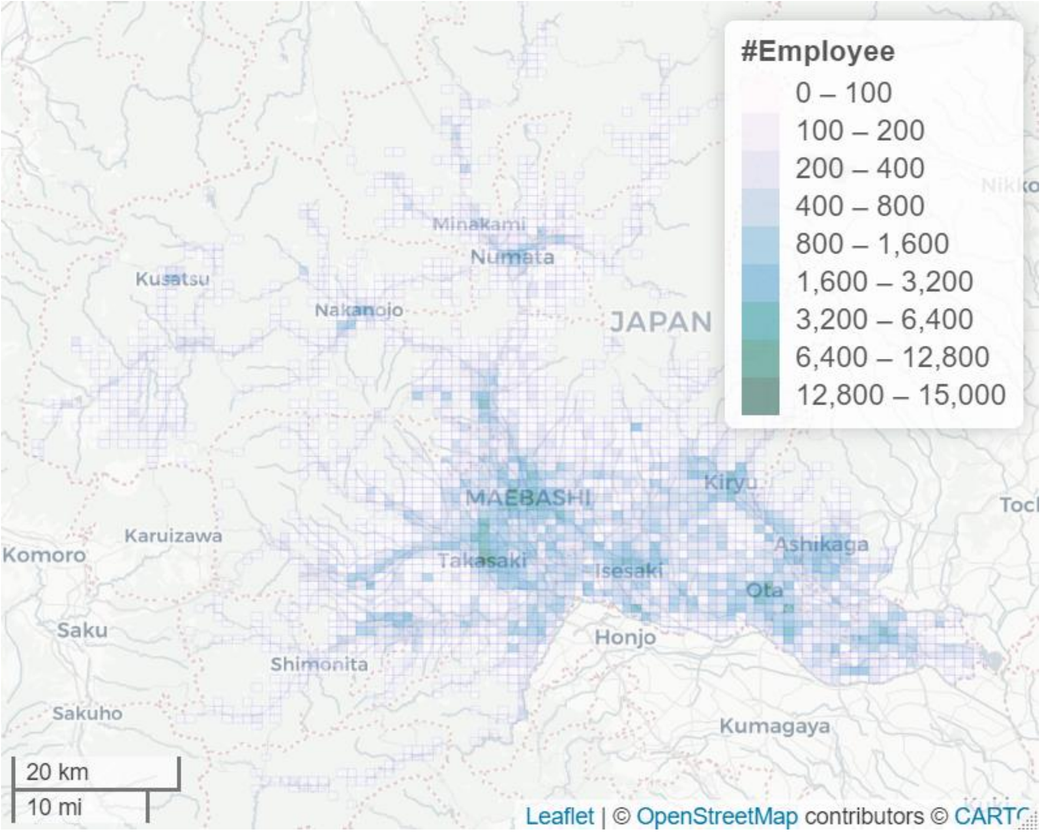


Figure 3-3. Spatial Distribution of Number of Employees by Mesh Cells in Gunma PT Area.

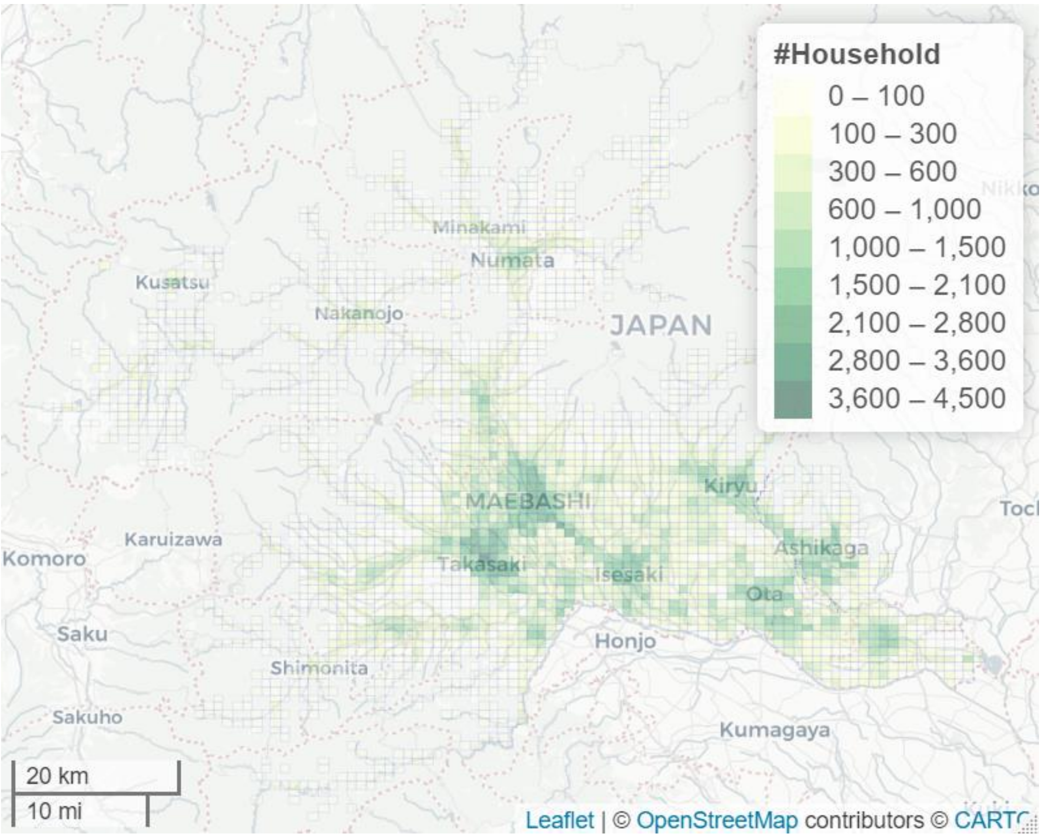


Figure 3-4. Spatial Distribution of Number of Households by Mesh Cell in Gunma PT Area.

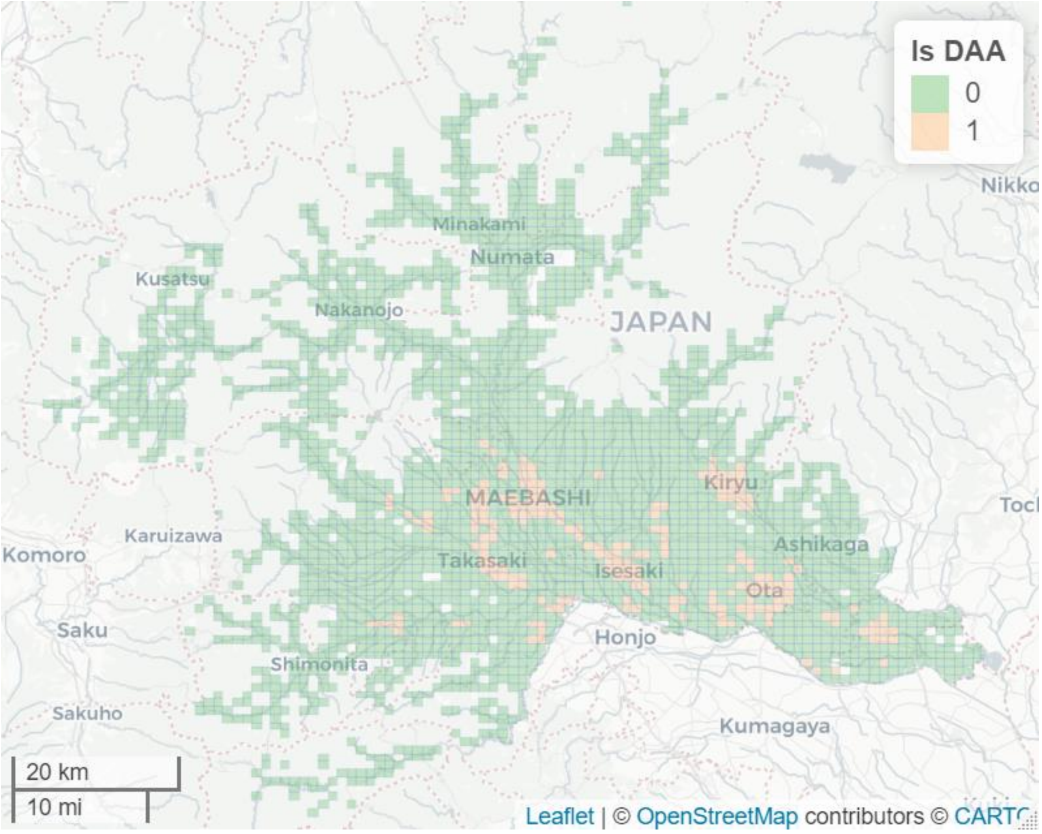


Figure 3-5. Distribution of Dwelling Attraction Areas (DAA) in Gunma PT Area.

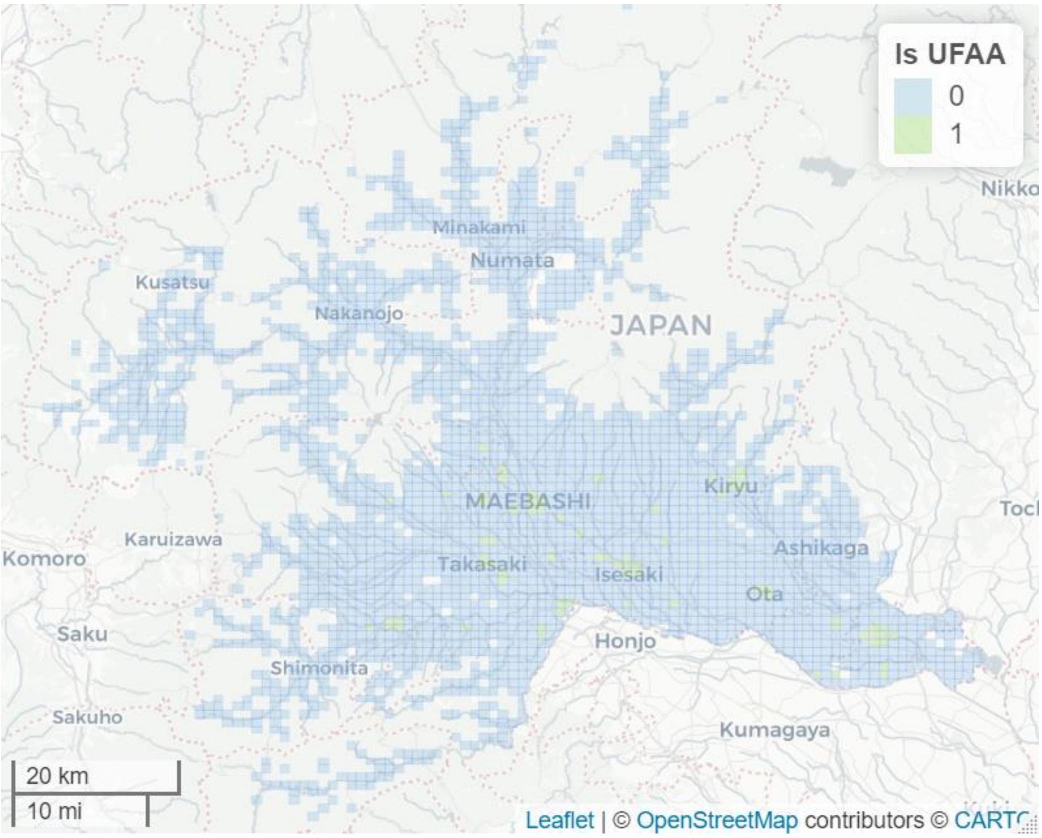


Figure 3-6. Distribution of Urban Function Attraction Areas (UFAA) in Gunma PT Area.

Other sources of data are also employed in this dissertation but are limited to the scope of the residential location choice. These include information on housing stock and land development regulation type, details are to be presented in Chapter 7.

3.4.2 Initial Travel Demand and Residential Locations

Gunma 2015 Person Trip Survey data (Gunma PT data) is used as the initial travel demand and residential location input. The prefectural government-hosted survey was conducted by distributing questionnaires to randomly sampled around 242,000 households in Gunma prefecture plus Ashikaga City in Tochigi prefecture (Figure 3-2) across 2015 and 2016. The questionnaires first collected demographic and socioeconomic information, then asked each household to record their information on trips across one day, including trip purpose, coordinates of origins and destinations, mode of travel, departure times, etc. Note that this survey was not intentionally designed to collect information at the tour level, and some valuable information was not collected such as individual income, financial and time budget, which either will be a handicap to further analysis or will introduce extra data processing in, for example, tour forming.

The PT Data was pre-processed with filters applied at the household level, which means if any data was found missing or inexplicable for one individual, the individual along with all his or her household members would be removed. This somewhat greedy way of filtering was applied to ensure the integrity of each household, which is the analyzing level of the residential location choice (Chapter 7). One exception is that all individuals with ages less than or equal to six are removed as they are considered to be not able to independently make choices that are related to either travel or residential location, with their other household members kept (if data quality of those people would suffice). To be noted, the processing work was done using the programing language of R (R Core Team, 2021) with the package of "data.table" (Dowle & Srinivasan, 2021) and "stringi" (Gagolewski, 2021), among others.

A summary of the pre-processing procedures is given in Table 3-2.

Table 3-2. Summary to the Pre-Processing Procedures Regarding to PT Data.

Filter types	Related variables	Filtered #household by each step. *(origin# = 62,398)*
Missing values	Driving license or car availability	1,834
	Household car ownership	9,167
	Home location	3
	Job type	2,173
	Type of employment	1,317
	Trip departure time	12,867
	Mode of Travel	1,018
	Trip duration	1,030
	Destination coordinates	9,559
	Driving state	312
Inexplicable	Origin equal to Destination	284
	Origin or Destination not in Activity System Mesh Dataset	102
	Home not in Resident's Mesh Dataset	35
	Education-purpose Trip went to mesh cell with No Educational Facility (attribute from Activity System Mesh Dataset)	668
	Trips with Purposes of Shopping, Leisure, etc., went to mesh cell with No Facility in Tertiary Sector (Attribute from Activity System Mesh Dataset)	9
	"Go back home" activities only	164
	"Go back home" activities but not heading home	28
	First trip of the day does not start from home	446
	Last trip of the day does not back home	234
Assumptions made by the author	Unemployed or student did work-purpose trip, or non-student did education-purpose trip	440
	Used inapplicable modes of travel: train, bus, motorbike, and others.	1,196
	People who require accompany for activities all day	1,295
	People who drove car or bicycle not in a round-trip way, i.e., not consistently through one tour (done after the tour forming procedure).	534
Extreme value	Bicycle or walking trip exceed mode-specific 99 percent quantile of trip distance, respectively	76

Note: some records may meet multiple filters, so the filtered number is subject to the filtering order (the applied filtering order is exactly the order of variables shown here).

The four filters listed above should be considered as the assumptions of this research. These are applied mostly for computational convenience: for example, removing those who take public transits saved the efforts to retrieve travel impedance data for public transits, which could be laborious given the 1km mesh cell spatial level has been adopted.

Besides the filtering procedures described, another important filter has also been implemented.

Since a majority of PT original data was removed, mostly due to the missing or inexplicable travel-related data, there is a concern about over-sampling no trip data, i.e., respondents who reported that no trip was made at all on the surveying day. Therefore, no-trip data was randomly removed until the ratio of the person with no trip was equal to the corresponding ratio in the original data.

Finally, a data set of 16,425 households with 33,300 persons are adopted as the effective initial travel demand and residential location data in this research. Approximately, the sample size is 1.57% of the whole target population in 2015 (Statistics Bureau of Japan, 2015). A descriptive summary of the effective PT data sample with major variables is given in Table 3-3.

Table 3-3. Summary to the Demographic Attributes in the Effective PT Data Sample.

Level	Variables	Data Type	Descriptive summary				
			Mean	Median	Min.	Max.	Standard Deviation
Household *(Total #households = 16,425)*	Has household member whose age is < 20	Binary	True: 16.0%; False: 84.0%				
	Has household member whose age is > 65	Binary	True: 33.5%; False: 66.5%				
	#Household member	Continuous	2.41	2	1	9	1.20
	Bike ownership	Continuous	0.55	0	0	10	0.86
	Car ownership	Continuous	1.80	2	0	12	0.88
	Home location	Coordinates	-				
	Work or School Location	Coordinates	-				
Individual *(Total #individuals = 33,300)*	Holds license or not	Binary	True: 84.4%; False: 15.6%				
	Car availability by individual	Categorical	Always available: 78.5%; Shared with other household members: 4.8%; Not available: 16.7%				
	Age	Continuous	49.00	50	7	100	19.95
	Gender	Binary	Female: 51.3%; Male: 48.7%				
	Job type	Categorical	Tertiary sector: 38.9%; Secondary sector: 17.4%; Primary sector: 1.8%; Student: 10.1%; Other: 0.6%; Homemaker: 12.8%; Unemployed (excluding students): 18.4%				
	Type of employment (among employees)	Categorical	Full time worker: 59.8%; Temporary worker: 2.1%; Part-time worker: 21.5%; Board members: 3.9%; Self-employed worker: 7.3%; Family worker: 3.2%; Others: 2.2%				
	#Trips in the day	Continuous	1.02	1	0	13	0.84

Notes: Temporary worker refers to paid employee who are hired through dispatched labor; Family worker refers to employee who are hired in a family business either paid or unpaid.

3.4.3 Road Network

Network data is extracted from the OpenStreetMap (OpenStreetMap contributors, 2021) through Java OpenStreetMap Editor. The study area bounding box covers totally 13,680km^2 where the whole Gunma Prefecture and Ashikaga City are completely included. Pruning effort is not executed, that is, the road network is adopted as the "all-street" way, except the toll roads as it is difficult to calculate the fare and most of the trips using them are presumably associated with extra-prefecture travels. Plus, road capacity for all the roads was scaled down by a factor to match the sample and population ratio.

CHAPTER 4 TRAVEL SUPPLY MODEL SPECIFICATION

This chapter focuses on the supply component in travel equilibrium, regarding which some general introductions, specific ways of applying, and validations to prove the reliability are presented.

4.1 Introduction to MATSim

In this dissertation, an agent-based travel simulation model, MATSim (Multi-Agent Transport Simulation. Horni et al., 2016) is employed as the travel supply model.

As what has been discussed in Chapter 3, MATSim was designed as an integrated simulation toolkit to model travel equilibrium, which requires MATSim to be able to model both transport demand and supply part. To this end, MATSim adopts a co-evolutionary iterative loop to converge to the equilibrium (Figure 4-1).

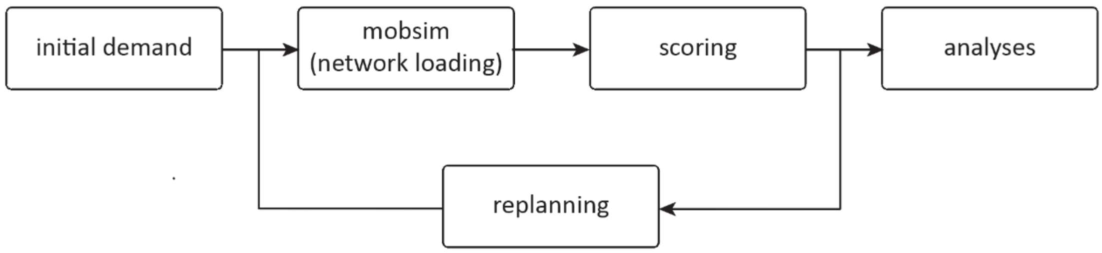


Figure 4-1. MATSim Iterative Loop (Horni et al., 2016).

The loop starts with an initial travel demand in the form of daily activity and trip chains for every individual. The activity and trip chains are loaded to the road network in the Mobsim phase. After the end of one simulation day, a score is calculated for each agent's activity chains (i.e., plans). In the final step of replanning, every agent possesses a collection of plans generated from their previous plans and must choose one based on their scores to execute in the next iteration.

In the network loading part, a traffic flow model QSim is adopted in MATSim. The QSim applies a computationally efficient queue-based approach (Figure 4-2). Basically, when vehicles enter a road segment, they follow the behaviors described below: first, go through the link with time of the link length and velocity ratio; second, the vehicle is inserted into the tail of the queue of the road; and finally leaves the road according to flow capacity attribute of the road.

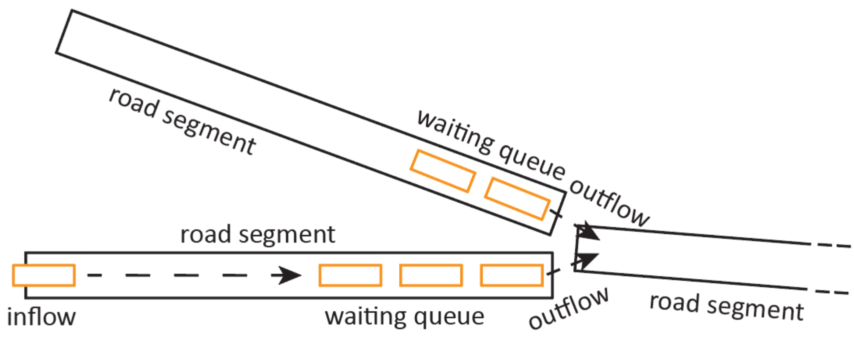


Figure 4-2. Microscopic Traffic Flow Operational Mechanism in MATSim (adapted from Horni et al., 2016).

In the scoring and replanning part, a score is formulated in a generalized utility fashion, to offer a criterion for differentiating a "better" and a "worse" plan for each agent. Based on the score, the replanning part applies Genetic Algorithm (or called Evolutionary Algorithm) that "breeds" a new plan completely based on previous plans, i.e., plans it has conducted by the specific agent. Two operators, mutation and selection operator are generally used in the application. Mutation operator modifies a certain component in the previously executed plan and adopted this modified (i.e., mutated) plan for the next iteration.

In its default configurations, three types of mutators that correspond to three components: route choice, departure time choice, and mode choice are applied in MATSim. Reroute Mutator re-computes the fastest path for each trip in the specific agent's plan according to time-specific link travel times, which are calculated from the simulation of the previous iteration. Time Allocation Mutator randomly draws a value from a uniform distribution from minus 30min to plus 30min, then shifts the activity end time for the first activity and activity duration for the other activities with this value. Mode Choice Mutator changes travel mode to a random mode in the agent's ownership.

There are multiple types of Selectors available in MATSim, depending on the equilibrium state that a modeler intends to achieve. Best Reply Selector simply selects the best plan from the last iteration. An MNL Selector applies the plan selection approach in a discrete choice way, which accounts for stochasticity in agents' behavior:

$$\mathrm{P(i)} = \frac{e^{\mu S_i}}{\sum_j e^{\mu S_j}}$$

Where *i* stands for the plan to examined, *j* is the plan the agent possesses in memory and μ is the scale parameter which is normalized to be 1.

A sequence of the three phases of mobsim, scoring, and replanning forms one iteration for the model. One can consider the MATSim iteration process as an extension to a route assignment loop, becoming a generalized "supernetwork" (Sheffi, 1985) in an activity chain context. It means that the model process is designed to involve not only route assignment but also other choice dimensions, such as mode choice and departure time choice, to reach a joint equilibrium. If a probabilistic Selector is applied, the stable state at convergence is formalized in an agent-based Stochastic User Equilibrium, which is defined as *"a system state where agents draw from a stationary choice distribution and where the resulting distribution of traffic conditions re-generates that choice distribution."* (Nagel & Flötteröd, 2012). For each traveler, a collection of plans is maintained, with which the population evolves simultaneously to converge to equilibrium. The so-called population-based co-evolutionary algorithm is stated formally as follows (Table 4-1):

Table 4-1. Population-based Co-evolutionary Algorithm (adapted from Nagel & Flötteröd, 2012).

1. **Initiation**: Generate at least one plan for every agent.
2. **Iterations**: Repeat the following many times.
(a) **Selection/Choice**: Select one of the plans for every agent.
(b) **Scoring**: Obtain a score for every agent's selected plan by executing all selected plans simultaneously in a simulation and attaching some performance measure to each executed plan.
(c) **Generation of new plans (innovation)/Choice set generation**: For some of the agents, generate new plans; for example, as "best replies" or as mutations of existing plans.

The convergence of the equilibrium is guaranteed from a Markov Chain perspective. Following the algorithm introduced above, one iteration of the MATSim iteration process requires only information about the previous iteration's outcome, thus by definition the process is characterized by Markov Chain (Flötteröd, 2016). One important feature of Markov Chain is that, if both properties of aperiodicity and irreducibility satisfy, given any initial state, there must be a unique stationary distribution that can be attained after sufficient iterations. To assure the properties, MATSim usually applies certain settings in configuration, which is to be introduced in the next section.

4.2 MATSim as Travel Assignment Model

Despite MATSim's efficiency and portability in simulating a large-scale agent-based simulation, this study decides not to enjoy MATSim's full function but instead to use it to model travel supply only. As mentioned in Chapter 3, the reason for this is that MATSim by default cannot manage trip/tour generation independently. To be noted, MATSim is equipped with destination innovation as an extension module (Horni, 2013), but it seemed to be limited in discretionary location.

MATSim is thus used as a travel route assignment model for HVs and PAVs in this dissertation. For this purpose, Reroute Mutator is the only mutator applied, with MNL Selector serving the MATSim replanning phase operators for this analysis. The share of agents (or possibility) to execute Reroute Mutator and MNL Selector is set at 0.6 and 0.4, respectively. The mutators are switched off in the final 10% of the simulation to guarantee the irreducibility property as a Markov Chain (Section 4.1) and thus the existence and uniqueness of the solutions to the converged state. Irreducibility refers to the property that every possible system state can be reached by the simulation (Flötteröd, 2016). Apparently, irreducibility cannot hold when mutators are switched on because the replaced previous plan (and its state subspace) is impossible to be reached unless that plan is "bred" again. It should be noted that, however, the algorithm in MATSim is not rigorously irreducible (Flötteröd, 2016).

After assessing a different number of iterations, we set the number of MATSim iterations to 30 in balancing the performance of convergence and computational cost. Score statistics records (Figure 4-3) indicate that measures such as average executed score become "flat" at around iteration 25. The marginal scores of modes and activities are basically in line with the default settings in MATSim. The Mutators are switched off since iteration 27 (i.e., 90% of 30).

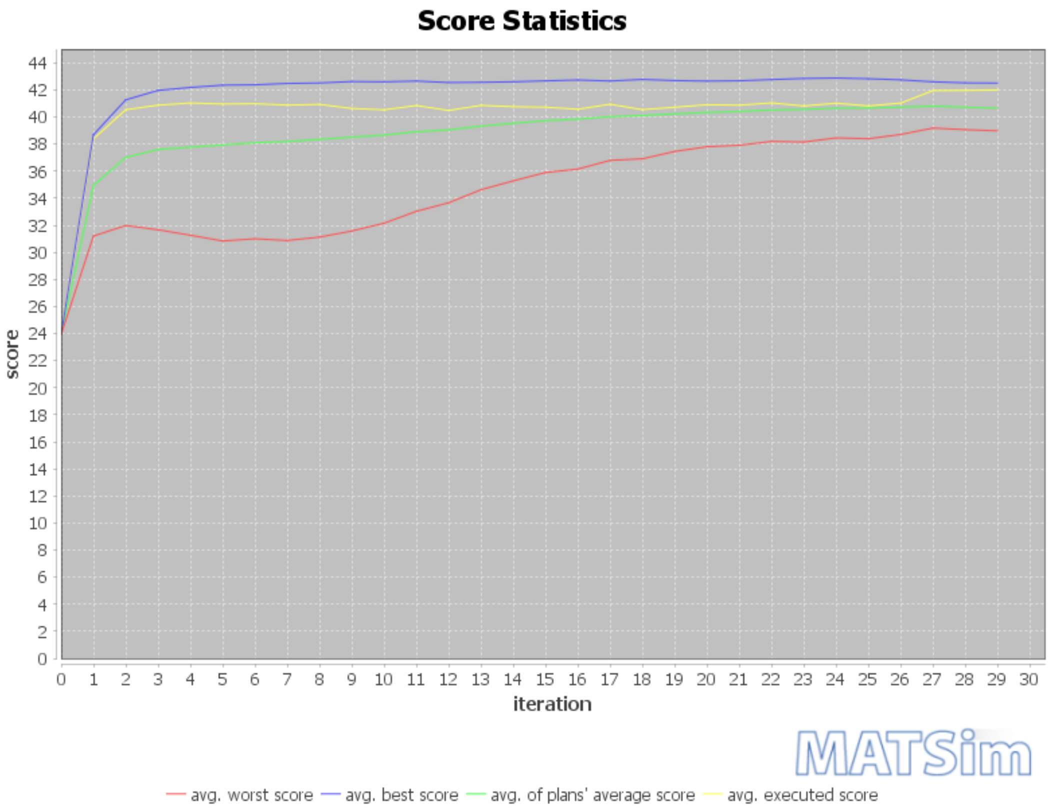


Figure 4-3. Score Statistics by MATSim Iterations.

As mentioned in the last section, MATSim adopts a queue-based approach to simulate traffic flow. Queue-based approaches model traffic dynamics with waiting queues, without using more sophisticated car following models. The way it compromises to not use a more detailed model is undoubtedly due to the concerns of computational efficiency. It is also due to this reason that in this specific application, traffic signals and other existing MATSim modular extensions relating to traffic control are not incorporated. Instead, a general capacity factor of 0.66 is applied to the road network data to reflect the delay effects from such as intersections. Note that this factor is applied combining with another capacity to reflect the sample population ratio (Section 3.4.3), which was set at 0.0166, a number slightly higher than the ratio of the effective size and entire population in the study region. The main reason for the difference is that it yields better validation results, which are presented in the next section.

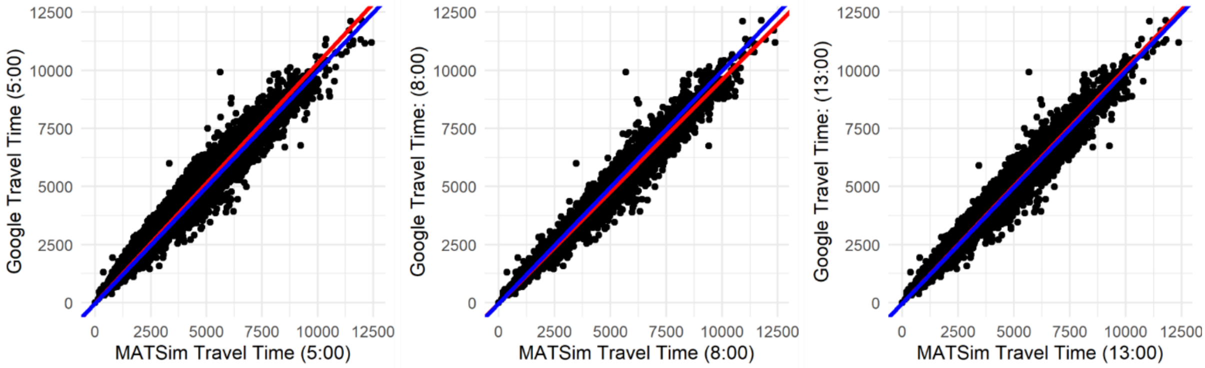
After the 30 iterations, we programmed MATSim to perform the shortest path calculation to retrieve the congested travel impedance by building a Least Cost Path Tree (Lefebvre & Balmer, 2007) for each of the five time-of-day periods adopted in this study. For each time-of-day period, travel time and distance of 3001 × 2617 mesh cell pairs (combining mesh dataset of Resident's Mesh Dataset and Activity System Mesh Dataset × Activity System Mesh Dataset) are calculated, which are to be used as inputs for the travel demand model.

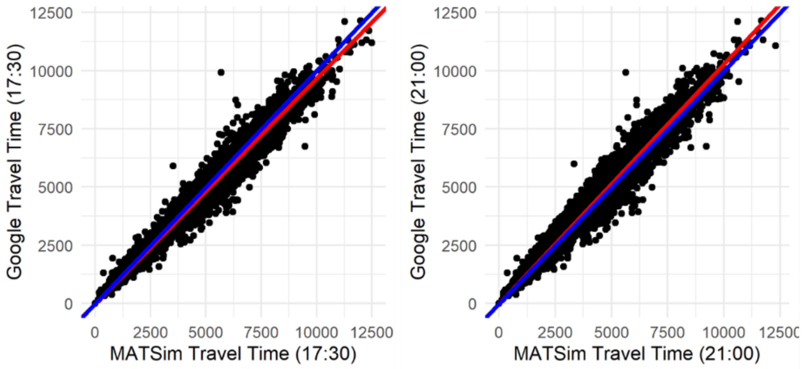
4.3 Model Validation

External validations are conducted to demonstrate the appropriateness of MATSim as an assignment model. 5,000 mesh cell centroid pairs are randomly drawn from a combining dataset of Resident's Mesh Dataset and Activity System Mesh Dataset. For each pair, we collected the actual travel times and distances using the Google Matrix Distance API and compared them with the travel times and distances generated from MATSim. The comparisons are made for five time points (i.e., five o'clock; eight o'clock; thirteen o'clock; half past seventeen; and twenty-one o'clock) which are the representative times for the five time-of-day periods used.

Comparisons between the MATSim data and Google API data are illustrated below in Figure 4-4 for travel time and Figure 4-5 for travel distance. Linear regression results are plotted in red lines along with blue lines standing for the identity line. The intercepts in the models are constrained to zero to demonstrate the deviation more clearly between the data from the two different sources.

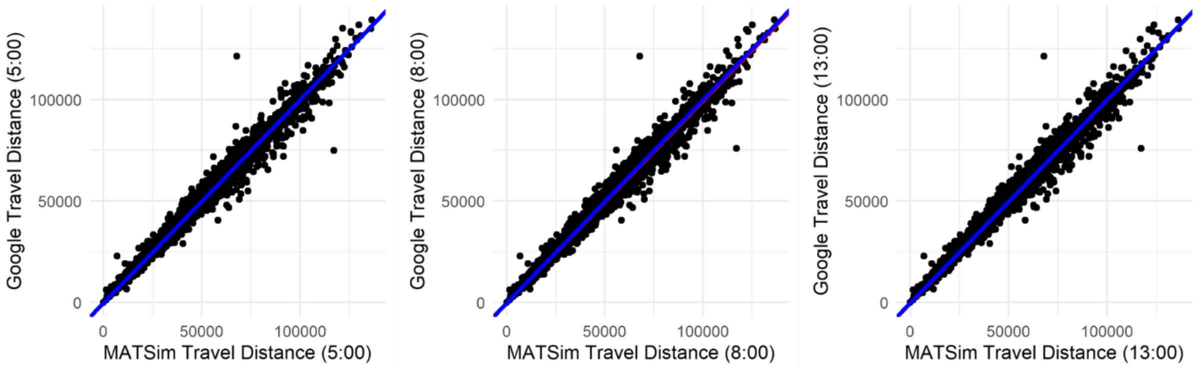
A general conclusion drawn from the results is that both travel time and distance comparisons suggest that MATSim is adequate to predict the travel impedance data.

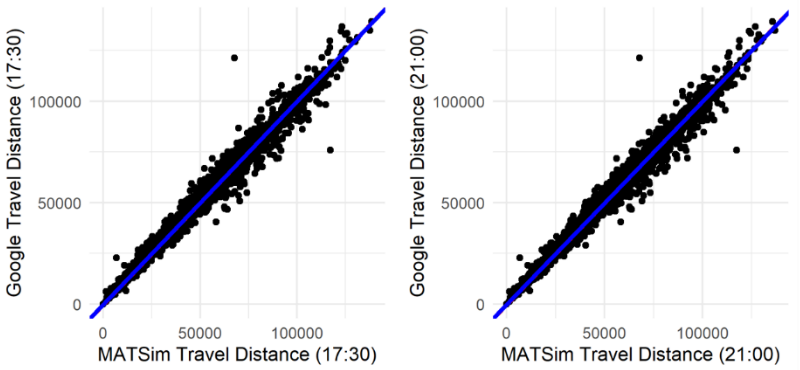




Time Points	Slope	R^2
5:00	1.0319	0.990
8:00	0.9622	0.993
13:00	1.0114	0.992
17:30	0.968	0.993
21:00	1.0297	0.991

Figure 4-4. Summary of MATSim Model Validation: Travel Time.





Time Points	Slope	R^2
5:00	1.0001	0.997
8:00	0.9950	0.997
13:00	1.0014	0.997
17:30	1.0015	0.997
21:00	1.0004	0.997

Figure 4-5. Summary of MATSim Model Validation: Travel Distance.

CHAPTER 5 TRAVEL DEMAND MODEL SPECIFICATION

This chapter focuses on the demand component in travel demand-supply equilibrium, regarding which a general introduction and data processing procedures are first presented, and estimation and validation results then follow.

5.1 Daily Activity Schedule Model as Travel Demand Model

In this dissertation, an activity-based travel demand model based on the Daily Activity Schedule model (DAS model. Bowman, 1995; Bowman, 1998; Bowman & Ben-Akiva, 2001) is employed as the travel demand model.

As introduced in Chapters 2 and 3, the DAS model adopts a utility-maximizing discrete-choice protocol to forecast travel itinerary for an individual at a whole-day level. By this protocol, the travel decisions, i.e., demands are "viewed as a utility maximizing individual's choice of one day activity schedule from a discrete choice set of all possible schedules" (Bowman, 1998). The definitions of the "schedule" alternative vary among different DAS model specifications, but a main idea is shared that tour decisions are and should be conditioned as well as constrained by the trip maker's activity pattern decision. These two form the choices of "schedule" together.

The utility of the pattern alternative is also dependent on its conditional tours through the expected utilities of the tours. By doing so, the sensitivity of pattern choice to the change in tour characteristics is captured.

Specifically, the DAS structure applied in this dissertation is shown in Figure 5-1. This structure is much closer to what was applied by Bradley et al. (2010) and Li (2015), both of which have been mentioned in Section 2.1 as the subsequent DAS versions to the original ones. Three levels of decisions: pattern-level decisions, tour-level decisions, and trip-level decisions (or stop-level decisions) form the whole structure. Each level has multiple models concerning different facets of one's daily schedule: persons are assumed to draw an overall image of what activities they are going to do that day, then for those activities with higher priority several home-based tours are planned, while those activities with less priority are either performed in other home-based tours or as an intermediate stop or subtour trip based on the location of the primary activity. All the levels are structured within the MNL framework, though the way of defining the alternatives may vary for the two "generation" models for subtours and intermediate trips.

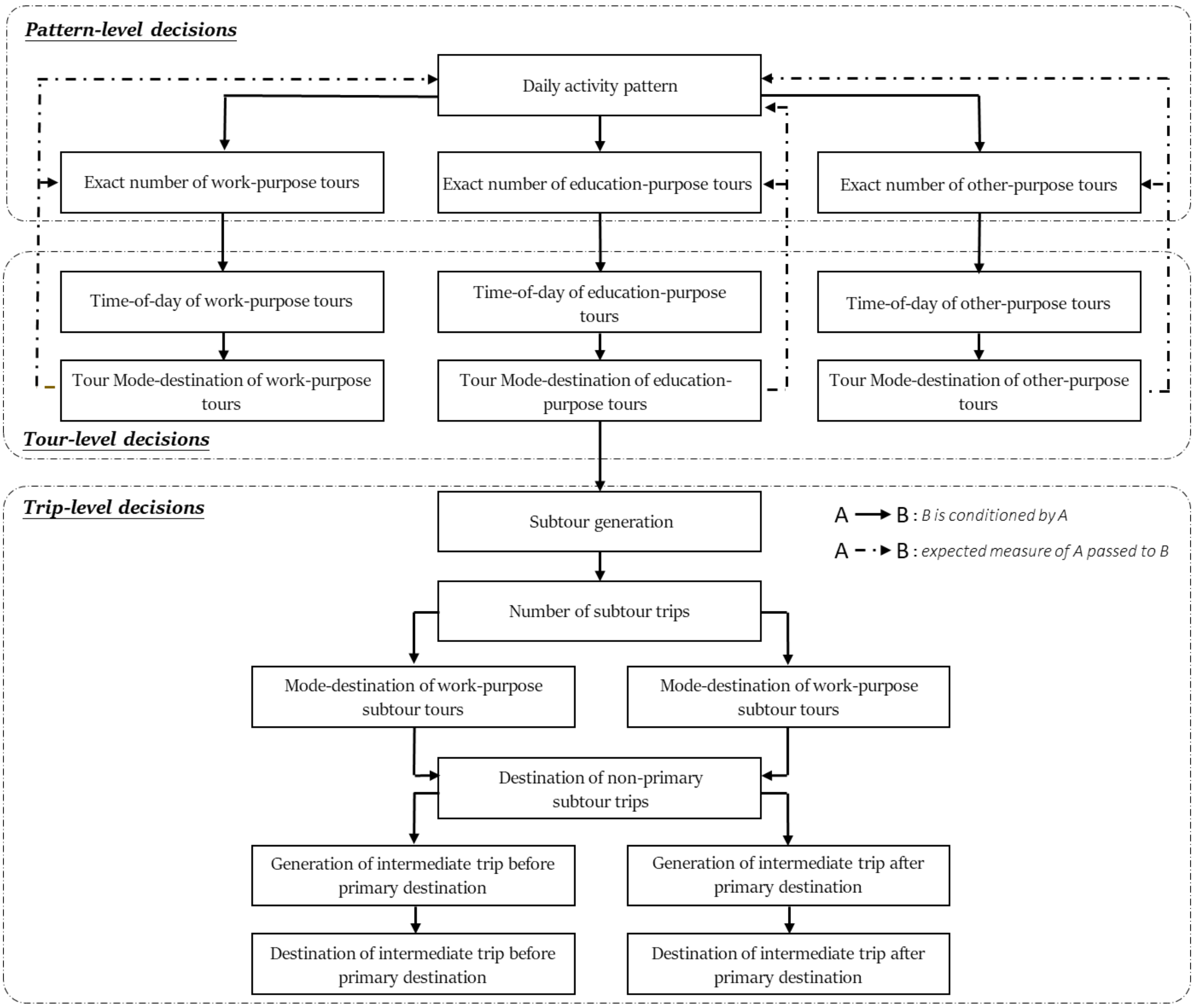


Figure 5-1. DAS-type Travel Demand Model Structure.

The interrelationship across the decisions and models is indicated by the arrows in Figure 5-1. As the legend suggests, the solid arrows in Figure 5-1 represent that the lower models are conditioned by (i.e., receive model inputs from) the models pre-defined over them, while the dashed arrows represent that pattern-level models are dependent on the expected maximum utility from some certain lower models, whose actual decisions are to be made subsequently.

Daily pattern level decisions include two models: Day Activity Pattern model to predict whether or not to participate in tours and stops (i.e., intermediate trips and subtour trips) for each activity purpose; and Exact Number of Tours model to predict in this day the exact number of tours of certain activity purpose that is predicted true in the previous Day Activity Pattern model. This level offers to model of substitution effects between extra tours and extra stops.

The number of stops for each tour is not predicted at this level, which is intentionally mentioned in the technical memos of the Sacramento model (Bowman & Bradley, 2006) as a feature that differentiated it from previous model designs. Instead, the exact allocation (to tours) and the number of stops are handled with the information of tours is already known, which means after the modeling of tour-level decisions. This design could offer better stop-level sensitivities as the changes in tour-level characteristics are reflected.

Tour-level decisions also include two models for predicting the time of day and mode-destination of each tour. Tours in this research are defined as a series of trips where the origin of the first trip and the destination of the last trip are both homes. The time of day model predicts jointly departure time of day (in five levels of temporal resolution, Early, AM Peak, Midday, PM Peak, and Late) of two phases in each tour: the time point of the tour departs from home and leaves for home. For example, AM Peak-PM Peak represents a tour that departs home at AM Peak and leaves for home at PM Peak. The mode-destination model predicts jointly the primary destination mesh cell of each tour and the mode of travel for it.

Stop-level decisions include multiple models to complement the trip-level information for each tour. Besides the primary activity in one tour, trip-makers are sometimes observed to make extra stops during the tour. These include subtour: any round trips with an anchor that is not home, and intermediate trips: any detours to perform extra activity on the way to or back from the primary activity destination. The exact number of these two types of stops and their mode-destination information is modeled in the order shown in Figure 5-1.

5.2 Tours and Activity Pattern Processing and Identification

To be applied in the subsequent forecasting, this model system is estimated with Gunma PT Data to reflect the preferences of the study area. However, the PT data was collected with a traditional trip-based survey so should be no exception from extensive data pre-processing. The most important is to convert trips to tours and to identify other tour-level features such as subtours. This procedure is necessary because in trip-based surveys respondents did not report explicitly the information of his or her activity priorities and corresponding tour formation considerations.

The procedures listed in Table 5-1 explain the specific rules adopted in this research for "translating" observed survey data to a form that is suitable for the following model estimation. Most of them reference Bowman (1995; 1998) and Li (2015).

After tours and other day pattern level attributes are defined from the procedures above, a descriptive analysis regarding travel-related characteristics of the demand data is given below in Tables 5-2 and 5-3.

Several insights have been gained from the descriptive analysis of the processed Gunma PT data. The respondents from the PT data on average generate 2.38 trips and 0.98 tours per person, and 2.43 trips per tour. These all exceed their Singapore counterparts with 1.81, 0.80, and 2.26, respectively (Li, 2015), which suggests a relatively higher willingness to travel and potentially more versatile tour patterns in Gunma. Being most noteworthy feature is that people in Gunma perform only around half (50.1%) of their tours without making extra stops (i.e., "simple" tours that contain only one leaving-home trip and one back-home trip), which is presumably caused by and more sparse distribution of facilities in Gunma area so that people would drop by more.

Table 5-1. Tour and Activity Pattern Identification Procedures.

Pre-defining trip attributes.

1. For each trip, categorize and aggregate activity purpose: work-purpose trip; education-purpose trip; other-purpose trip; and back-home-purpose trip.
2. For each trip, define its following activity duration as the difference between the arrive time of the trip and the start time of its subsequent trip.

Begin.

3. Define tours:
   {loop on persons}
   - *Set initially ID index of tour as by default one.*
   - *{loop on trips}*
     - *{If the trip is of back-home-purpose}*
       - *Assign the current tour ID to the looped trips with no tour ID; tour ID is incremented by one.*
   - *{end loop on trips}*

   {end loop on persons}
4. Define attributes: number of trips per tour; number of tours per person by counting.
5. Define primary activity type by person: assuming priority is work/education > other, i.e., if a work- or education-purpose activity observed, the primary activity type is assigned accordingly, else the primary activity type is other-purpose.
6. Define primary trip by each tour:
   {loop on persons}
   - *{loop on tours}*
     - *Record the destinations of each trip.*
     - *Record the following activity durations of each trip.*
     - *{if any trip is heading for usual work or school location (reported from the survey)}*
       - *Record the first trip that satisfies the requirement, as primary trip of the tour.*
     - *{else}*
       - *Record the most-visited destination, with most total following activity duration serves the tiebreaker.*
       - *Record the trip that headed for the most-visited destination, as primary trip of the tour, with trip sequence serves the tiebreaker.*
   - *{end loop on tours}*

   {end loop on persons}
7. Define attributes: locations of primary trips by each tour; (*Boolean*) whether the trip is heading for primary location of the tour; first and last trip heading for primary location of the tour.
8. Define primary trip by each person:
   {loop on persons}
   - *{if only one tour observed}*
     - *Record the primary trip of the tour as the primary trip of the person.*
   - *{else, loop on primary trip of tours}*
     - *{if any primary trip of tours is heading for usual work or school location}*
       - *Record the trips that satisfies the requirement and with most total following activity duration, as primary trip of the person.*
     - *{else}*
       - *Record the trips with most total following activity duration, as primary trip of the person.*
   - *{end loop on primary trip of tours}*

   {end loop on persons}
9. Define attributes: primary tour of the person, as the tour with the primary trip of the person.
10. Define attributes: secondary tour of the person, as the tour(s) other than the primary tour.
11. Define intermediate trips:
    {loop on persons}

Table 5-1 Continued.

{loop on tours}

{if the primary trip of the tour is not the first trip of the tour}

Record all the trips between the first trip and the preceding trip of the primary trip, as the intermediate trips before the primary destination.

{if the subsequent trip of the last trip that headed to the primary destination of the tour is not directly heading home}

Record all the trips between the subsequent trip of last trip to the primary destination and the last trip of the tour, as the intermediate trips after the primary destination.

{end loop on tours}

{end loop on persons}

12. Define subtour trips:

{loop on persons}

{loop on tours}

{if any, loop on trips between the first and the last trip to the primary destination}

Set initially ID index of subtour as by default one。

{if the trip is heading to primary destination of the tour}

Assign the current subtour ID to the looped trips with no subtour ID; subtour ID is incremented by one.

{end loop on trips}

{end loop on tours}

{end loop on persons}

13. Define primary trip of subtour:

{loop on persons}

{loop on tours}

{loop on subtours}

Record the following activity durations of each trip in the subtour.

Record the trip with most following activity durations as the primary trip for this subtour, with trip sequence serves the tiebreaker.

{end loop on subtours}

{end loop on tours}

{end loop on persons}

14. Define attributes: number of tours of work-, education-, and other-purpose per person; number of subtour, subtour trips, and intermediate trips per tour per person.

End.

Some interesting findings of the processed sample include that, for example, students on average generate around 10% more tours but around 5% fewer trips than full-time workers.

In summary, a general descriptive analysis of Gunma people suggests relatively more complex travel patterns there, particularly in the sense of making extra stops. More specific distributions regarding each level of decisions in Figure 5-1 are presented in the next section.

Table 5-2. Summary to the Individual level Travel-related Attributes in the Effective PT Data.

<table>
<tr><th>Level</th><th colspan="2">Segment</th><th>Average #Tours</th><th>Average #Trips</th></tr>
<tr><td rowspan="19">Individual
(Total #individuals = 33,300)</td><td colspan="2">Total</td><td>0.98</td><td>2.38</td></tr>
<tr><td rowspan="8">Job & Employment Type</td><td>Full-time worker</td><td>1.04</td><td>2.57</td></tr>
<tr><td>Temporary worker</td><td>1.01</td><td>2.41</td></tr>
<tr><td>Part-time worker</td><td>1.19</td><td>2.89</td></tr>
<tr><td>Board member</td><td>1.04</td><td>2.84</td></tr>
<tr><td>Self employed</td><td>0.83</td><td>2.08</td></tr>
<tr><td>Family worker</td><td>0.86</td><td>2.08</td></tr>
<tr><td>Student</td><td>1.14</td><td>2.45</td></tr>
<tr><td>Unemployed or homemaker</td><td>0.79</td><td>1.95</td></tr>
<tr><td colspan="2">Male</td><td>0.98</td><td>2.35</td></tr>
<tr><td colspan="2">Female</td><td>0.98</td><td>2.40</td></tr>
<tr><td colspan="2">Has kids younger than 6 in the household</td><td>1.23</td><td>3.09</td></tr>
<tr><td colspan="2">Has no kid younger than 6 in the household</td><td>0.97</td><td>2.36</td></tr>
<tr><td colspan="2">Segment</td><td colspan="2">Count and Ratio of the segment</td></tr>
<tr><td colspan="2">People who made no tour</td><td colspan="2">6,083 (18.3%)</td></tr>
<tr><td colspan="2">People who made only 1 tour</td><td colspan="2">22,798 (68.4%)</td></tr>
<tr><td colspan="2">People who made 2 tours</td><td colspan="2">3,659 (11.0%)</td></tr>
<tr><td colspan="2">People who made 3 or more tours</td><td colspan="2">760 (2.3%)</td></tr>
</table>

Table 5-3. Summary to the Tour and Trip Level Travel-related Attributes in the Effective PT Data.

<table>
<tr><th>Level</th><th colspan="3">Segment</th><th>Count and Ratio of the segment</th><th>Average #trip per tour</th></tr>
<tr><td rowspan="12">Tour (Total #tours = 32,532)</td><td colspan="3">Total</td><td>32,532 (100.0%)</td><td>2.43</td></tr>
<tr><td rowspan="3">Primary activity purpose</td><td colspan="2">Work</td><td>16,567 (50.9%)</td><td>2.48</td></tr>
<tr><td colspan="2">Education</td><td>3,171 (9.8%)</td><td>2.14</td></tr>
<tr><td colspan="2">Other</td><td>12,794 (39.3%)</td><td>2.44</td></tr>
<tr><td rowspan="7">Tour Pattern</td><td colspan="2">Simple tour (no stop made at all)</td><td>16,293 (50.1%)</td><td>2.00</td></tr>
<tr><td rowspan="2">Has subtour or not</td><td>Yes</td><td>1,212 (3.7%)</td><td>5.14</td></tr>
<tr><td>No</td><td>31,320 (96.3%)</td><td>2.33</td></tr>
<tr><td rowspan="4">Has intermediate trip or not</td><td>Neither</td><td>24,983 (76.8%)</td><td>2.10</td></tr>
<tr><td>Only before primary destination</td><td>1,657 (5.1%)</td><td>3.34</td></tr>
<tr><td>Only after primary destination</td><td>4,934 (15.2%)</td><td>3.40</td></tr>
<tr><td>Both before and after primary destination</td><td>958 (2.9%)</td><td>4.60</td></tr>
<tr><td rowspan="4">Trip (Total #trips = 79,166)</td><td colspan="2" rowspan="4">Activity purpose</td><td>Work</td><td>19,722 (24.9%)</td><td>-</td></tr>
<tr><td>Education</td><td>3,178 (4.0%)</td><td>-</td></tr>
<tr><td>Other</td><td>23,734 (30.0%)</td><td>-</td></tr>
<tr><td>Back home</td><td>32,532 (41.1%)</td><td>-</td></tr>
</table>

5.3 Model Description and Estimation

This section presents the estimation results for all the models introduced in Figure 5-1 with the datasets from Section 3.4. Maximum Likelihood Estimation is employed for all the models within the programming language of R (R Core Team, 2021). For each model, the definition, the alternative availability, and the observed distribution of the alternatives (i.e., the choice set) are described and presented, followed by tables of the estimation results and several basic discussions.

The whole demand dataset is separated randomly by household to an 80% estimation sample and a 20% validation sample for the subsequent validation procedure (Section 5.5). Note that all the observed distributions (e.g., Figure 5-2) shown below refer to the distribution of the whole dataset. Coefficients with a 90% confidence level (t value being larger than 1.645) are kept by the author's judgment.

In model designs, a summary of the types of variables applied is shown in Table 5-4, which suggests that variables selection in this application of DAS is made in a rather parsimonious way in particular for trip-level models.

5.3.1 Day Activity Pattern Level

This level of the model is designed to predict the occurrence of tours and stops (i.e., subtour or intermediate trip) for each individual in the PT dataset. The definition and availability of the alternatives are summarized below:

Table 5-4. Summary of Variable Types Included in Each Level of Models.

Model	Variable used: demographics	Variable used: trip characteristics	Variable used: land use characteristics	Variable used: logsum	Are variables from higher-level models included
Variable category *(Section 3.1)*	3	5	2	4	-
Daily activity pattern	*Yes*			*Yes: from Tour mode and destination level.*	
Exact number of tours	*Yes*			*Yes: from Tour mode and destination level.*	*Yes: whether the tour has extra stop(s) only.*
Tour time of day	*Yes*				*Yes: whether the tour has extra stop(s) only.*
Tour mode and destination	*Yes*	*Yes*	*Yes*		*Yes: whether the tour has extra stop(s) only.*
Subtour generation		*Yes.*			*Yes: primary activity type of its home-based tour; number of tours remained, etc.*
Number of subtour trips		*Yes.*			*Yes: number of tours remained; number of subtours have done, etc.*
Subtour mode and destination		*Yes*	*Yes*		*Yes: primary mode of its home-based tour only.*
Destination of nonprimary subtour trips		*Yes*	*Yes*		*Yes: is the same city as the tour and subtour's primary destination only.*
Intermediate trip generation	*Yes. Full-time worker or not only*				*Yes: time of day of its home-based tour; number of tours remained, etc.*
Destination of intermediate trips		*Yes*	*Yes*		*Yes: is the same city as the home and tour's primary destination only.*

Note: blank means not incorporated, omitted for readability.

- Alternative definition: a 6-bit form of whether tour and stop of each 3 activity types: work-, education- and other-purpose, in that order, would occur. For example, "100-001" means a pattern having work-purpose tour and work-purpose occur. The hyphen mark is set for convenience. The patterns that are assumed contradictory (e.g., 110-000 as work activity and education activity cannot coexist) or not observed (e.g., 010-011) are excluded. See Table 5-5 for a summary of the alternatives.
- Alternative availability: Work-purpose tour/stop: available to employees only; Education-purpose tour/stop: available to students only; Other-purpose tour/stop: available to everyone.

Table 5-5. Look-up Table of the Definition of Daily Activity Pattern.

Daily Activity Pattern	**Occurrence of**					
	Work-purpose tour	Education-purpose tour	Other-purpose tour	Work-purpose stop	Education-purpose stop	Other-purpose stop
000-000	*Stay at home all day*					
100-000	Yes					
100-001	Yes					Yes
100-100	Yes			Yes		
100-101	Yes			Yes		Yes
101-000	Yes		Yes			
101-001	Yes		Yes			Yes
101-100	Yes		Yes	Yes		
101-101	Yes		Yes	Yes		Yes
010-000		Yes				
010-001		Yes				Yes
010-010		Yes			Yes	
011-000		Yes	Yes			
011-001		Yes	Yes			Yes
001-000			Yes			
001-001			Yes			Yes
Note: blank means "No", omitted for readability.						

- Base characteristics for reference in estimating demographic variables: Female full-time worker or board member in tertiary sector industry with age larger than 22 and no more than 35, who does not have a kid with age less than 6 for work-purpose and other-purpose related alternatives; Middle school or high school students for education-purpose related alternatives.

Find below Figure 5-2 for a summary for the observed alternative distribution and Tables 5-6 to 5-9 for the estimation results.

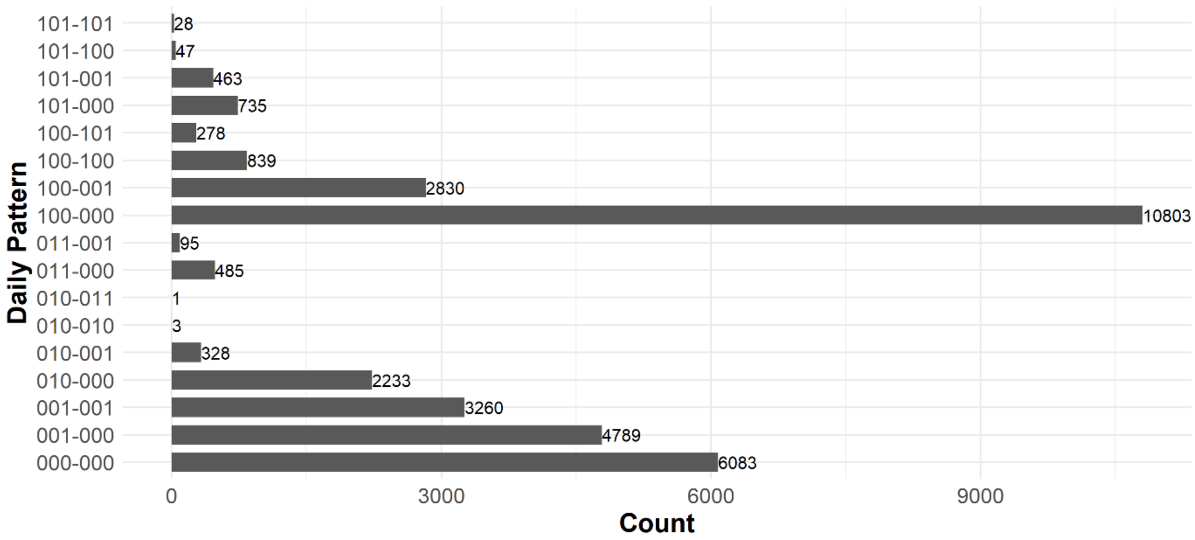


Figure 5-2. Observed Count Distribution for Day Activity Pattern Model.

Table 5-6. Estimation Results for Day Activity Pattern Model (Part 1).

Variable	**Alternative-specific constant**		**Age∈ [6, 22]**		**Age∈ (35,)50]**		**Age∈ (50, 65)**		**Age∈ [65, 100]**	
Variable#	#1-1		#1-2		#1-3		#1-4		#1-5	
Alternative	Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
000-000	*Base alternative*		*Base alternative*		*Base alternative*		*Base alternative*		*Base alternative*	
100-000	1.08	*3.52*		*-0.86*	0.36	*4.59*	0.38	*4.77*	-0.56	*-6.03*
100-001		*0.45*	-1.39	*-3.97*	0.57	*6.20*	0.45	*4.74*	-0.33	*-2.77*
100-100	-2.30	*-7.00*		*-1.45*	1.02	*6.83*	1.36	*9.02*	0.72	*3.99*
100-101	-2.75	*-7.59*		*-0.81*	0.96	*4.13*	1.27	*5.46*	0.81	*2.87*
101-000	-4.38	*-11.33*		*-0.28*	1.22	*7.89*	1.10	*6.84*	0.48	*2.56*
101-001	-4.51	*-11.67*		*-0.10*	1.19	*6.82*	0.59	*3.03*	-0.35	*-1.33*
101-100	-8.75	*-7.98*		*-0.09*	2.77	*2.68*	2.94	*2.84*	2.26	*2.09*
101-101	-7.31	*-9.91*		*-0.08*	1.41	*2.18*		*1.20*		*0.49*
010-000	2.52	*17.32*								
010-001	-0.51	*-2.30*								
010-010	-4.63	*-7.47*	*Not applied*		*Not applied*		*Not applied*		*Not applied*	
011-000	-1.11	*-4.95*								
011-001	-2.67	*-9.84*								
001-000	-2.75	*-16.89*		*-1.64*	0.29	*3.18*	0.42	*4.77*	0.35	*4.14*
001-001	-2.79	*-17.21*	-1.08	*-3.62*	0.25	*2.54*	0.34	*3.55*		*0.76*

Table 5-7. Estimation Results for Day Activity Pattern Model (Part 2).

Variable	Temporary worker or part-time worker		Self-employed		Family worker		Male		Has kid age less than 6	
Variable#	#1-6		#1-7		#1-8		#1-9		#1-10	
Alternative	Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
000-000	Base alternative		Base alternative		Base alternative		Base alternative		Base alternative	
100-000		*-0.77*	-2.60	*-26.88*	-2.57	*-18.41*	0.69	*11.59*		*0.55*
100-001		*-1.03*	-2.73	*-17.42*	-2.89	*-12.82*	-0.19	*-2.66*	0.91	*4.56*
100-100	-1.01	*-6.04*	-2.01	*-12.76*	-1.94	*-6.58*	1.26	*11.08*		*0.74*
100-101	-1.20	*-4.76*	-1.79	*-7.26*	-2.65	*-4.43*	0.41	*2.57*		*0.94*
101-000	0.71	*5.70*	-1.81	*-9.29*	-1.56	*-6.02*		*0.93*		*0.27*
101-001	0.98	*6.65*	-1.39	*-5.30*	-1.44	*-4.13*	-0.40	*-2.79*	1.05	*3.74*
101-100		*-0.41*	-1.62	*-3.51*	-1.29	*-1.65*	1.14	*3.09*	*Not observed*	
101-101		*-0.73*	-1.64	*-2.40*	*Not observed*			*1.46*		0.47
010-000	*Not applicable*		*Not applicable*		*Not applicable*		*Not applicable*		*Not applicable*	
010-001										
010-010										
011-000										
011-001										
001-000	0.33	*2.77*	-0.72	*-5.76*	-0.26	*-1.74*		*1.31*	0.70	*3.77*
001-001	0.51	*4.10*	-0.89	*-6.11*	-0.60	*-3.22*		*1.49*	0.68	*3.45*

Table 5-8. Estimation Results for Day Activity Pattern Model (Part 3).

Variable	Work in primary sector industry		Work in secondary sector industry		Primary school student		University student	
Variable#	#1-11		#1-12		#1-13		#1-14	
Alternative	Coef.	T value	Coef.	Coef.	Coef.	T value	Coef.	T value
000-000	*Base alternative*		*Base alternative*		*Base alternative*		*Base alternative*	
100-000	-0.39	*-2.81*	0.20	*2.72*	*Not applicable*		*Not applicable*	
100-001	-0.66	*-3.03*		*1.39*				
100-100	-1.12	*-3.65*	-0.44	*-3.75*				
100-101	*Not observed*		-0.45	*-2.49*				
101-000		*-0.87*		*-1.18*				
101-001	-1.04	*-1.99*		*-1.26*				
101-100		*-0.02*	-1.46	*-2.73*				
101-101		*-0.05*		*-1.43*				
010-000	*Not applicable*		*Not applicable*		0.89	*3.46*	-2.35	*-10.35*
010-001					2.24	*7.49*	-1.39	*-4.20*
010-010					*Not applied*		*Not observed*	
011-000					1.29	*4.70*	-4.02	*-9.27*
011-001					1.31	*3.79*	-3.40	*-5.24*
001-000		*-1.26*	-0.45	*-3.89*	0.72	*1.69*	-0.81	*-2.06*
001-001	-0.47	*-2.12*	-0.58	*-4.48*		*0.31*	-1.07	*-1.95*

Table 5-9. Estimation Results for Day Activity Pattern Model (Part 4).

Variable	**Homemaker**		**Unemployed**		**Logsum from mode-destination of work tour**		**Logsum from mode-destination of education tour**		**Logsum from mode-destination of other tour**	
Variable#	#1-15		#1-16		#1-17		#1-18		#1-19	
Alternative	Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
000-000	*Base alternative*		*Base alternative*		*Base alternative*		*Base alternative*		*Base alternative*	
100-000					0.072	*2.36*				
100-001					0.072	*2.36*			*Not applicable*	
100-100					0.072	*2.36*				
100-101					0.072	*2.36*	*Not applicable*			
101-000					0.072	*2.36*			0.24	*16.38*
101-001					0.072	*2.36*			0.24	*16.38*
101-100	*Not applicable*		*Not applicable*		0.072	*2.36*			0.24	*16.38*
101-101					0.072	*2.36*			0.24	*16.38*
010-000							0.19	*4.19*		
010-001							0.19	*4.19*	*Not applicable*	
010-010							0.19	*4.19*		
011-000					*Not applicable*		0.19	*4.19*	0.24	*16.38*
011-001							0.19	*4.19*	0.24	*16.38*
001-000	0.31	*3.44*		*0.61*			*Not applicable*		0.24	*16.38*
001-001	0.21	*2.17*		*-0.66*					0.24	*16.38*

Table 5-10. Summary Statistics for Day Activity Pattern Model Estimation Results.

Observations	26,688
Initial likelihood	-52,244.25
Final likelihood	-33,917.83
Adjusted rho squared	0.348

The estimation results above can be explained as, for example, by checking Variable #1-6 we can find that compared to full-time workers, temporary or part-time workers are more likely to conduct other-purpose activity as separate home-based tour rather than as a stop, when they already had a work-purpose tour made.

In summary, many demographic variables are found significant in the likelihood of choosing different day activity patterns. Mode-destination logsum variables were estimated for three types of activity purposes, they are found positively related to the likelihood of traveling to these activities.

5.3.2 Exact Number of Tours Level

This level of the model is designed to predict the exact number of tours for each individual. The definition and availability of the alternatives are summarized below:

- Alternative definition:
    - Work-purpose tour model: 1 work-purpose tour; 2 work-purpose tours; 3 or more work-purpose tours.
    - Education-purpose tour model: 1 education-purpose tour; 2 education-purpose tours.
    - Other-purpose tour model: 1 other-purpose tour; 2 other-purpose tours; 3 other-purpose tours; 4 or more other-purpose tours.
- Alternative availability: all considered available unless no tour for the specific purpose was made at all.
- Base characteristics for reference in estimating demographic variables:
    - Work-purpose and other-purpose tour model: female full-time worker or board member with age larger than 22 and no more than 35, who does not have a kid with age less than 6.
    - Education-purpose tour model: Middle school or high school students.

Find below Figure 5-3 for a summary for the observed alternative distribution and Table 5-11 to Table 5-13 for the estimation results.

The estimation results of this level also confirm the relationships between the individual-level demographics and the number of tours made. For example, those who are self-employed or being family workers are more likely to make multiple work tours compared to full-time workers (Variable #2-8 and Variable #2-9), which is presumably attributed by more working flexibility of them and higher frequency to do work-related errands out home. Inference could also be drawn from the number of other-purpose tour model by the similar way. However, the results from the number of education-purpose tour model provide very limited insights, with only coefficient of logsum found significant. This is not surprising as education-purpose tours are found mostly conducted only once a day (Figure 5-3), and a very high rho squared indicates that alternative-specific constant and the logsum are adequate to explain the features of the two alternatives.

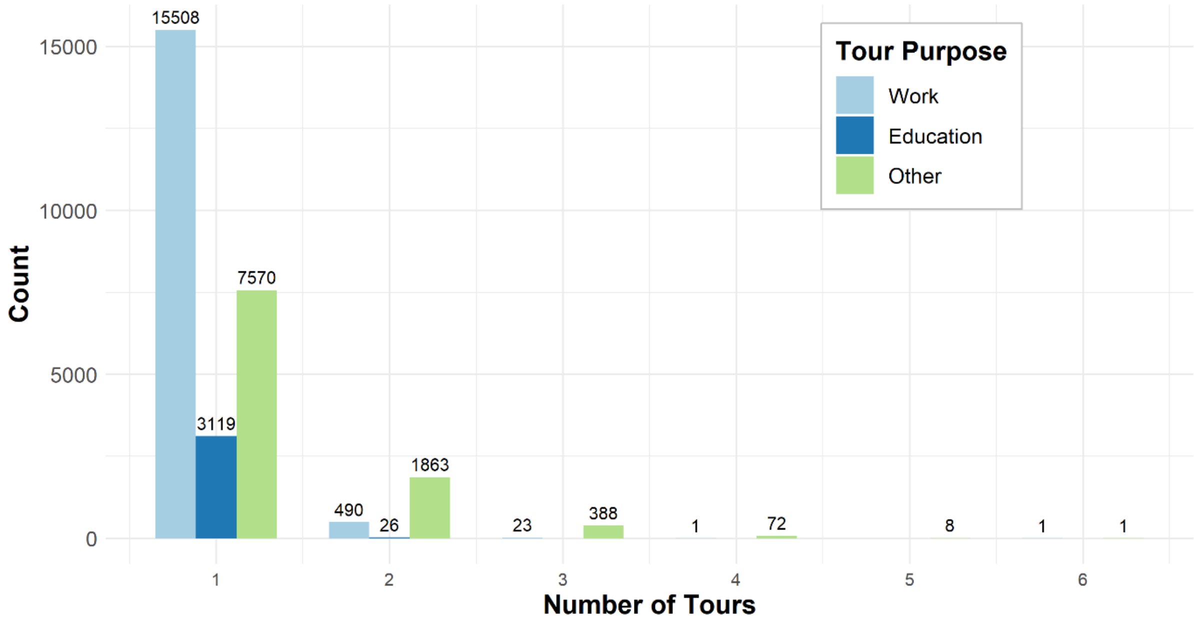


Figure 5-3. Observed Count Distribution for Exact Number of Tours Models.

To be noted, logsum variable is not found significant for the number of work-purpose tour model, which suggests that being more accessible to the work-related facilities from the anchor (i.e., home) does not induce more tours for this activity purpose. This is not the case for the number of education- and other-purpose models, where more activity flexibilities are presumably enjoyed. Presumably, the reason for this is the less flexibility of work-related activities than those with education or other purposes.

Table 5-11. Estimation Results of Exact Number of Work-purpose Tours.

Variable	Variable#	1 work tour		2 work tour		3 or more work tours	
		Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#2-1	*Base alternative*		-4.22	*-6.26*	-12.23	*-3.55*
Logsum from mode-destination model of work-purpose tour	#2-2				*-0.17*		*0.96*
Age∈ [6, 22]	#2-3				*0.97*	*Not observed*	
Age∈ (35, 50)	#2-4			0.39	*2.11*		*0.80*
Age∈ (50, 65)	#2-5			0.69	*3.71*		*0.41*
Age∈ [65, 100)	#2-6			1.27	*6.24*		*1.46*
Temporary worker or part-time worker	#2-7			0.54	*4.06*		*0.84*
Self-employed	#2-8			2.04	*13.64*	3.86	*5.47*
Family worker	#2-9			1.92	*8.20*	4.43	*5.31*
Male	#2-10			-0.22	*-1.81*		*1.12*
Has kid age less than 6	#2-11				*-1.50*	*Not observed*	
Has work-purpose stop	#2-12			0.43	*2.68*		*-1.15*
Has other-purpose stop	#2-13				*1.07*		*0.20*
#Observations	12,770						
Initial likelihood	-14,050.15						
Final likelihood	-1,753.26						
Adjusted rho squared	0.874						

Table 5-12. Estimation Results of Exact Number of Education-purpose Tours.

Variable	Variable#	1 education tour		2 education tour	
		Coef.	T value	Coef.	T value
Alternative-specific constant	#2-14	*Base alternative*		-5.85	*-11.06*
Logsum from mode-destination model of education-purpose tour	#2-15			0.48	*2.90*
University student	#2-16				*0.52*
Primary school student	#2-17				*0.17*
Has education-purpose stop	#2-18				*-0.05*
Has other-purpose stop	#2-19				*0.37*
#Observations	2,514				
Initial likelihood	-1,742.57				
Final likelihood	-127.66				
Adjusted rho squared	0.923				

Table 5-13. Estimation Results of Exact Number of Other-purpose Tours.

Variable	Variable #	1 other tour		2 other tours		3 other tours		4 or more other tours	
		Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#2-20			-2.96	*-10.10*	-4.99	*-8.41*	-7.29	*-6.54*
Logsum from mode-destination model of other-purpose tour	#2-21			0.21	*6.97*	0.25	*4.07*	0.31	*2.51*
Age∈ [6, 22]	#2-22			-0.78	*-3.22*	*Not observed*			
Age∈ (35, 50)	#2-23				*1.25*	0.42	*2.24*		
Age∈ (50, 65)	#2-24			-0.39	*-3.39*	-0.66	*-3.05*		
Age∈ [65, 100)	#2-25			-0.36	*-3.30*	-0.81	*-3.97*		
Temporary worker or part-time worker	#2-26				*1.57*	0.45	*1.86*		
Self-employed	#2-27	*Base alternative*			*-0.86*	-1.02	*-1.91*		
Family worker	#2-28				*-0.67*	0.61	*1.67*		
Homemaker or unemployed	#2-29				*0.68*		*0.70*	*Not applied or observed (few observations)*	
Male	#2-30				*0.15*	0.26	*1.87*		
Has kid age less than 6	#2-31			0.55	*3.09*	1.00	*3.82*		
Has work- or edu-purpose tour	#2-32			-0.85	*-7.36*	-2.03	*-7.22*		
Has work- or edu-purpose stop	#2-33			-1.08	*-1.80*		*0.30*		
Has other-purpose stop	#2-34				*1.51*	0.23	*1.91*		
#Observations	8,013								
Initial likelihood	-11,108.37								
Final likelihood	-5,234.97								
Adjusted rho squared	0.526								

5.3.3 Tour Time of Day Level

This tour level consists of three models to predict departure and back-home time for each tour with the three types of activity purposes.

Due to the concern of computational burdens, a relatively coarse temporal resolution: time of day is chosen as the basic unit for the modeling alternatives. By looking into the distribution of trip start time (Figure 5-4), we can recognize two peaks and three valleys from the current travel patterns.

Therefore, the time points are aggregated to five time periods called "time of day":

- 3:00 AM to 6:59 AM as "Early".
- 7:00 AM to 9:00 AM as "AM Peak".
- 9:01 AM to 3:59 PM as "Midday".
- 4:00 PM to 7:00 PM as "PM Peak".
- 7:00 PM to 2:59 AM as "Late".

The aggregation is shown with color in Figure 5-4.

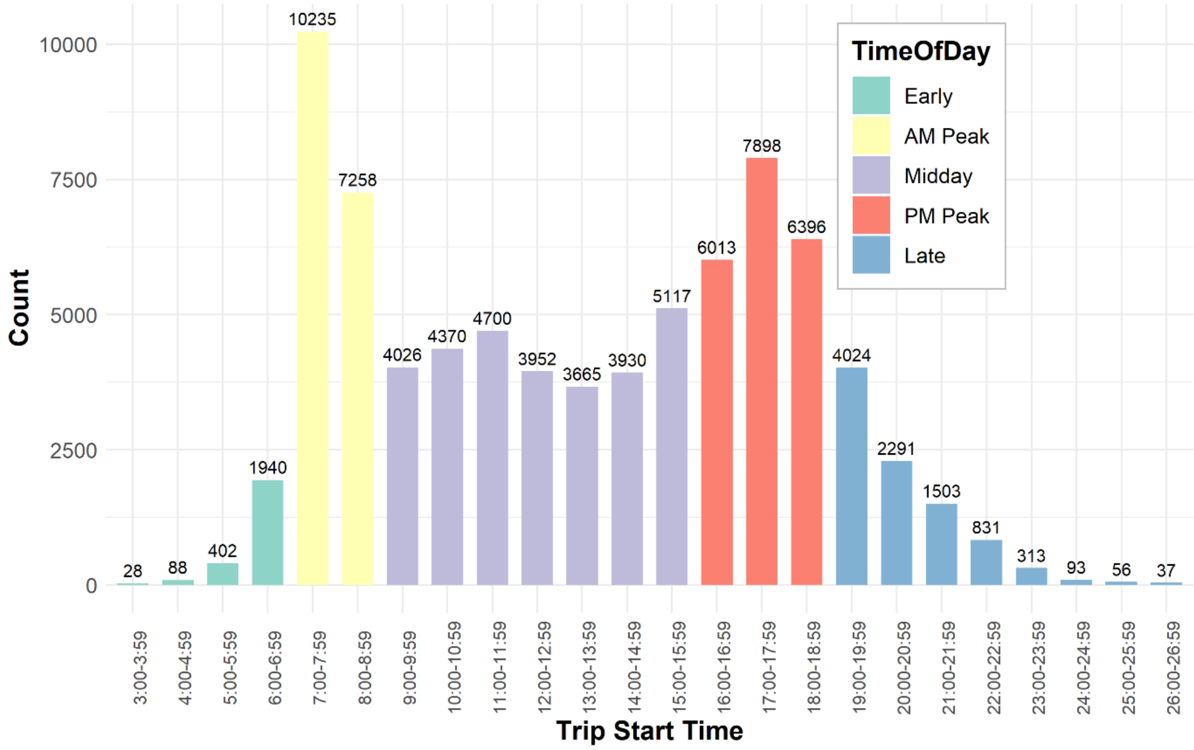


Figure 5-4. Observed Trip Start Time Distribution.

The definition and availability of the alternatives are summarized below:

- Alternative definition: time of day combinations of the trip departure from home (i.e., the first trip of the tour) and the trip leaving for home from the primary destination.
- Alternative availability: all alternatives are available unless found overlapped with time-of-day of the tour(s) that have been made. For example, alternative of Midday-Midday would not be available as the second tour of one certain individual if he or she had made an AM

Peak-PM Peak tour previously.

Find below Figure 5-5 for a summary for the observed alternative distribution, and Table 5-14 to Table 5-16 for the estimation results.

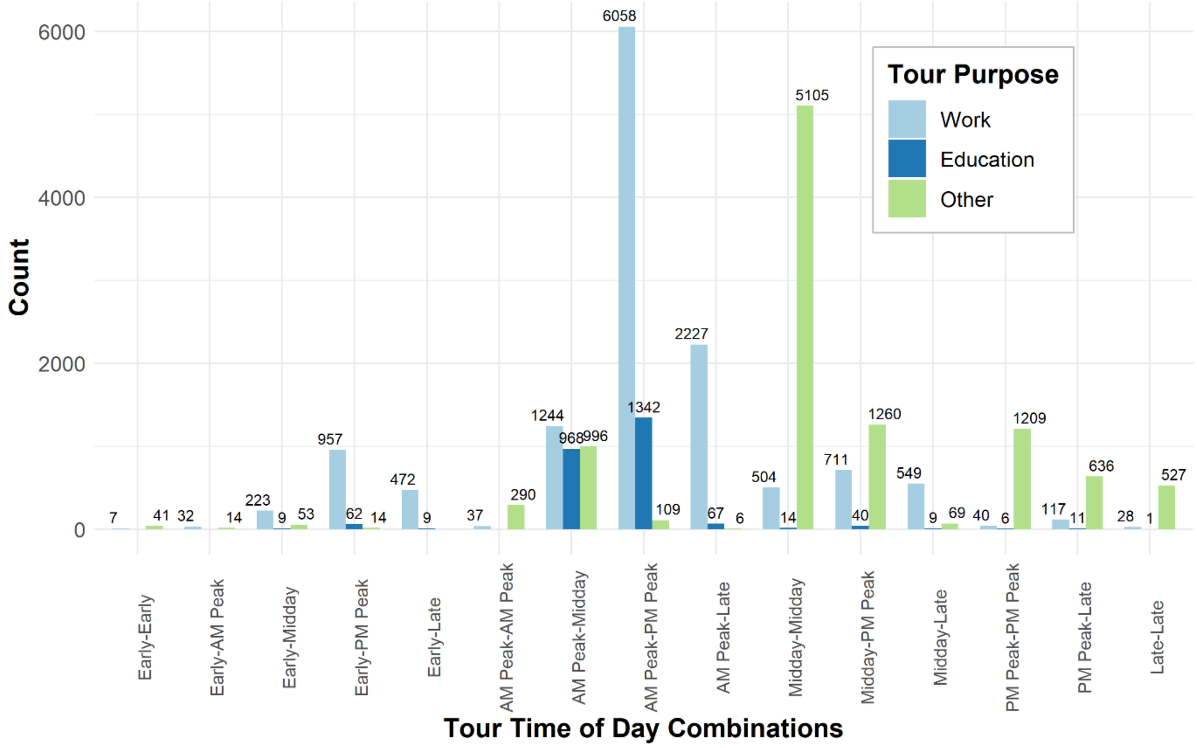


Figure 5-5. Observed Count Distribution for Time of Day Models.

Explanations to the time of day models are straightforward as they are built in a relatively simple way, with one exception: variable whether the person planned a stop in that given day as an effect passed from the activity pattern level models. For example, the results found those people who have planned to make extra stop tend to make short work tours (in the sense of time) around midday for (Variable #3-4), which can be explained from two different perspectives: one possibility is that people tend to make work-related errands with multiple short trips involved at midday; another is that people tend to make their tour not across many time periods, as they need to save the time budget for another tour with stops in other time of the day. This discrepancy is caused by the limitation of the day activity pattern level in this specific model design, as we assume that the trip makers at this point have no information which tour are attached with extra stop(s) if they are predicted to make at least one.

Table 5-14. Estimation Results of Time of Day Model for Work-purpose Tours.

Variable	**Alternative-specific constant**		**Full-time worker or board member**		**Is not primary tour**		**Has stop in this day**	
Variable#	#3-1		#3-2		#3-3		#3-4	
Alternative	Coef.	T value	Coef.	Coef.	Coef.	T value	Coef.	T value
Early-Early	-6.55	*-10.05*		*-1.12*	*Not observed*			*0.85*
Early-AM Peak	-4.35	*-18.52*	-2.30	*-5.57*	6.54	*9.00*		*-1.30*
Early-Midday	-2.63	*-25.45*	-1.29	*-9.31*	4.44	*6.03*		*1.09*
Early-PM Peak	-2.28	*-25.54*	0.68	*7.08*	*Not observed*		-0.42	*-4.97*
Early-Late	-3.75	*-20.57*	1.59	*8.46*		*-0.20*	-0.72	*-5.67*
AM Peak-AM Peak	-5.17	*-17.11*	-1.09	*-3.26*	6.06	*8.22*	1.13	*3.40*
AM Peak-Midday	-0.99	*-19.29*	-2.16	*-29.36*	5.65	*9.51*	0.75	*10.68*
AM Peak-PM Peak	*Base alternative*							
AM Peak-Late	-1.93	*-25.30*	1.26	*15.72*	*Not observed*		-0.54	*-8.89*
Midday-Midday	-2.03	*-26.80*	-2.51	*-21.48*	6.57	*11.00*	0.95	*9.40*
Midday-PM Peak	-1.46	*-23.91*	-2.00	*-22.18*	6.05	*10.15*	0.28	*3.05*
Midday-Late	-1.91	*-25.76*	-0.79	*-8.49*	3.62	*5.38*	-0.44	*-3.97*
PM Peak-PM Peak	-5.48	*-16.49*	-2.47	*-6.74*	8.63	*12.62*	0.83	*2.45*
PM Peak-Late	-3.18	*-24.38*	-2.28	*-10.45*	6.71	*10.76*		*-1.51*
Late-Late	-5.42	*-15.94*	-1.74	*-4.38*	7.94	*11.31*		*0.26*
#Observations	13,206							
Initial likelihood	-35,520.00							
Final likelihood	-20,688.50							
Adjusted rho squared	0.416							

Another major limitation of time of day models is that no logsum variables from the lower models are included[2]. Designs with logsum freely estimated were tested but some are found not significant or in incorrect sign. This might be caused by relatively low overall congestion level in the study region.

5.3.4 Tour Mode and Destination Level

This tour level consists of, again, three models to predict jointly mode of travel and destination for each tour corresponding to respectively the three types of activity purposes. The definition and availability of the alternatives are summarized below:

[2] In other words, the coefficients of logsum variables are constrained to 1.0.

Table 5-15. Estimation Results of Time of Day Model for Education-purpose Tours.

Variable	Alternative-specific constant		University student		Primary school student		Has stop in this day	
Variable#	#3-5		#3-6		#3-7		#3-8	
Alternative	Coef.	T value	Coef.	Coef.	Coef.	T value	Coef.	T value
Early-Early	*Alternative not observed*							
Early-AM Peak	*Alternative not observed*							
Early-Midday	-5.01	*-14.97*	*Not observed*		*Not applied (Few observations)*		*Not applied (Few observations)*	
Early-PM Peak	-2.64	*-18.72*	-1.31	*-1.80*		*-0.41*		*1.28*
Early-Late	-5.00	*-14.97*	*Not observed*		*Not observed*		*Not applied (Few observations)*	
AM Peak-AM Peak	*Alternative not observed*							
AM Peak-Midday	-1.38	*-17.58*		*-1.31*	1.79	*18.25*	0.57	*4.18*
AM Peak-PM Peak	*Base alternative*							
AM Peak-Late	-3.03	*-18.07*	1.69	*5.97*	-1.41	*-2.95*		*-0.56*
Midday-Midday	-6.26	*-9.74*	3.94	*5.65*		*-0.16*		*0.66*
Midday-PM Peak	-7.57	*-7.28*	6.15	*5.87*	2.75	*2.49*	1.11	*2.69*
Midday-Late	-5.52	*-15.02*	*Not applied (Few observations)*		*Not observed*		*Not observed*	
PM Peak-PM Peak	-6.51	*-13.44*	*Not observed*		*Not applied (Few observations)*		*Not applied (Few observations)*	
PM Peak-Late	-5.91	*-14.81*	*Not applied (Few observations)*		*Not applied (Few observations)*		*Not observed*	
Late-Late	-8.31	*-8.01*	*Not observed*		*Not observed*		*Not observed*	
#Observations	2,538							
Initial likelihood	-6,285.09							
Final likelihood	-2,237.74							
Adjusted rho squared	0.640							

- Alternative definition: mode-destination pairs combining one of the travel modes from Car driver, Car passenger, Bicycle, and Walk; and one of the mesh cells from a 100-mesh-cell set sampled out of the total 2611 mesh cells in Activity System Mesh Dataset.
- Alternative availability:
  - Travel modes:
    - Car driver: available to car availability attribute being "Always available" or "Shared with other household members" (Table 3-3).
    - Car passenger and walking: available to all.

    - Bicycle: available to members in a bicycle owned household.

- Travel destination: Available to all unless those distance from the origin exceed mode-specific 99 percent quantile (before the filtering, see Table 3-2) which are 16.647 km for bicycle mode and 3.710 km for walking mode.

Table 5-16. Estimation Results of Time of Day Model for Other-purpose Tours.

Variable	**Alternative-specific constant**		**Age∈ (65, 100)**		**Is not primary tour**		**Has stop in this day**	
Variable#	#3-9		#3-10		#3-11		#3-12	
Alternative	Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
Early-Early	-5.97	*-15.70*	0.79	*2.42*	1.68	*4.84*	-0.67	*-1.83*
Early-AM Peak	-6.27	*-11.56*		*-0.34*	1.00	*1.80*		*-0.40*
Early-Midday	-4.60	*-17.17*		*1.52*		*-0.45*		*-0.51*
Early-PM Peak	-6.34	*-8.74*	1.55	*2.03*		*-0.12*		*-1.23*
Early-Late	*Alternative not observed*							
AM Peak-AM Peak	-3.51	*-25.17*	-0.93	*-5.86*	1.67	*11.64*		*-1.40*
AM Peak-Midday	-1.80	*-26.90*	0.28	*3.99*		*-0.07*	0.27	*3.86*
AM Peak-PM Peak	-3.48	*-20.52*		*0.57*	-2.71	*-2.70*		*-0.40*
AM Peak-Late	-6.13	*-9.35*		*-0.96*		*-0.10*		*0.46*
Midday-Midday	*Base alternative*							
Midday-PM Peak	-1.44	*-24.86*		*-0.96*	0.21	*3.00*		*1.05*
Midday-Late	-3.90	*-19.46*	-0.96	*-3.57*	-1.13	*-2.83*	0.41	*1.68*
PM Peak-PM Peak	-1.89	*-27.70*	-0.60	*-7.84*	1.44	*19.65*	-0.47	*-6.36*
PM Peak-Late	-2.37	*-26.94*	-1.27	*-10.83*	1.41	*14.59*	-0.44	*-4.59*
Late-Late	-3.21	*-24.78*	-1.95	*-10.88*	2.26	*16.66*	-0.49	*-4.59*
#Observations	10,329							
Initial likelihood	-25,626.51							
Final likelihood	-15,020.26							
Adjusted rho squared	0.412							

Alternative sampling procedures are elaborated slightly here. It has been proved by McFadden (1978) that maximization of conditional likelihood function with a subset of the universal choice set yields consistent estimates of the unknown parameters under regularity conditions. Specifically, method of Importance Sampling with Replacement (Ben-Akiva & Lerman, 1985) is used in the estimation and subsequent model simulation for the destination choice. This method draws from the whole choice set a sample *j* for individual *n* with probability:

$$q_{jn} = E_j e^{-\frac{2d_{jn}}{mean(d)}}$$

Where E_j is the number of employees of mesh cell j; d_{jn} is the network distance to j from the home of individual n; and *mean(d)* is the average observed tour distance of that specific activity purpose. The form of q_{jn} is reference to what suggested by Ben-Akiva and Lerman (1985). The alternative sampling procedure was implemented separately for work-, education-, and other-purpose tours as different types of number of employees are associated: all employees, employees in educational sector, employees in tertiary sector, are applied for the three models, respectively.

Two bias correction terms are added to the utility functions due to the using of alternative sampling and aggregation of alternatives to ensure consistent parameter estimation (Ben-Akiva & Lerman, 1985). First, a natural log of the inverse of the sampling probability q_{jn} is required to cancel out the extra information earned from sampling alternatives with high q_{jn}. Second, a nature log of the term representing the size, i.e., the number of elemental alternatives, of each aggregate alternative is required to concern the difference in scale among the aggregated alternatives. Specifically, a nature log of number of offices in each mesh cell was applied. Different office types are considered in different models of activity purpose as done in the alternative sampling. The second term is also called Size Variable despite no coefficient is required to estimate in the case of including only single measure.

Find below Figure 5-6 for a summary for the observed alternative distribution, and Tables 5-17 to 5-19 for the estimation results. Note that travel time for bicycle and walking are calculated from car distance by assuming a distance factor of 0.9 and speed of 10km/h and 4.5 km/h, respectively.

The major findings of this level include that the coefficients of travel time for car, bicycle, and walking are found in an expected order, and most of the land use variables and demographic variables are found significant. Also, whether travel stop is made in the day are found significant (Variable #4-5; #4-15; #4-23), which suggests that basically compared to drive a car, trip makers are less likely to choose walking or bicycle if they knew that they would make a stop.

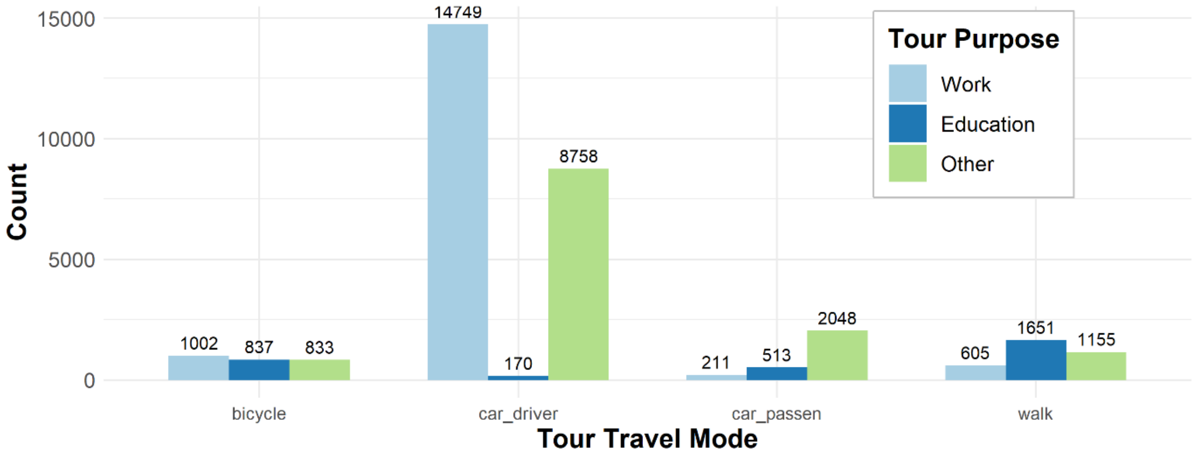


Figure 5-6. Observed Count Distribution for Tour Mode.

Table 5-17. Estimation Results of Mode-destination Model for Work-purpose Tours.

Variable	Variable#	Car Driver		Bicycle		Walk		Car Passenger	
		Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#4-1				*0.94*	2.35	*19.62*	-3.34	*-19.28*
Age∈ [6, 35]	#4-2	*Base alternative*		0.60	*6.32*		*-0.44*		*-0.34*
Male	#4-3			0.28	*3.28*	0.19	*1.92*	-0.94	*-5.50*
Is not primary tour	#4-4				*-0.37*	1.23	*7.03*	0.90	*2.87*
Has stop in the day	#4-5			-0.73	*-6.79*	-1.27	*-8.32*		*0.02*
Travel time (hour)	#4-6	-5.86	*-98.00*	-6.70	*-35.78*	-14.44	*-31.41*	-8.57	*-15.81*
#Employees of tertiary sector[3]/size variable	#4-7	0.026	*45.72*	0.026	*45.72*	0.026	*45.72*	0.026	*45.72*
#Employees of primary and secondary sector[4]/size variable	#4-8	0.027	*62.55*	0.027	*62.55*	0.027	*62.55*	0.027	*62.55*
Is the same city as origin's	#4-9	0.86	*35.66*	0.86	*35.66*	0.86	*35.66*	0.86	*35.66*
Size variable: #Offices	-	1.00	-	1.00	-	1.00	-	1.00	-
#Observations	13,206								
Initial likelihood	-82,169.88								
Final likelihood	-57,839.20								
Adjusted rho squared	0.296								

[3] Corresponding to industry category F-R from the data of Economy Census 2016. See also https://www.soumu.go.jp/toukei_toukatsu/index/seido/sangyo/02toukatsu01_03000044.html#o (in Japanese) for the Japanese Standard Industry Category ("日本標準産業分類" in Japanese).

[4] Corresponding to industry category A-E from the data of Economy Census 2016.

Table 5-18. Estimation Results of Mode-destination Model for Education-purpose Tours.

Variable	Variable#	Car Driver		Bicycle		Walk		Car Passenger	
		Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#4-10	-1.78	*-1.90*	-2.89	*-20.93*	*Base alternative*		-3.93	*-21.76*
Is university student	#4-11	*Not applicable (car drivers all satisfy)*		2.50	*3.14*			2.50	*2.88*
Is primary school student	#4-12	*Not observed*		-6.28	*-10.71*				*-0.70*
Male	#4-13	-1.20	*-1.94*		*1.30*			-0.29	*-2.05*
Is not primary tour	#4-14		*1.32*		*0.45*			2.74	*4.62*
Has stop in the day	#4-15	2.47	*3.19*	1.94	*6.17*			3.74	*19.28*
Travel time (hour)	#4-16	-4.96	*-5.70*	-8.23	*-41.47*	-13.24	*-49.86*	-34.54	*-34.67*
#Employees of education sector[5]/size variable	#4-17	0.030	*39.69*	0.030	*39.69*	0.030	*39.69*	0.030	*39.69*
Size variable: #Offices of education sector	-	1.00	-	1.00	-	1.00	-	1.00	-
#Observations	2,538								
Initial likelihood	-14,586.94								
Final likelihood	-6,376.88								
Adjusted rho squared	0.561								

Table 5-19. Estimation Results of Mode-destination Model for Other-purpose Tours.

Variable	Variable#	Car Driver		Bicycle		Walk		Car Passenger	
		Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#4-18	*Base alternative*		1.19	*10.58*	2.98	*30.13*	-2.57	*-32.48*
Age∈ [6, 25]	#4-19			-1.21	*-3.71*	-2.53	*-7.43*	1.14	*3.92*
Age∈ [65, 100]	#4-20				*0.89*		*0.51*	0.60	*7.89*
Male	#4-21				*-0.89*		*-1.29*	-1.02	*-12.19*
Is not primary tour	#4-22			-0.27	*-2.67*	0.65	*8.15*	-0.37	*-4.51*
Has other-purpose stop in the day	#4-23			-0.44	*-4.45*	-0.74	*-8.55*	0.23	*3.23*
Travel time (hour)	#4-24	-14.50	*-108.10*	-18.39	*-38.60*	-19.86	*-48.48*	-12.19	*-64.91*
#Employees of tertiary sector/size variable	#4-25	0.024	*31.23*	0.024	*31.23*	0.024	*31.23*	0.024	*31.23*
Is the same city as origin's	#4-26	0.87	*27.88*	0.87	*27.88*	0.87	*27.88*	0.87	*27.88*
Size variable: #Offices of tertiary sector	-	1.00	-	1.00	-	1.00	-	1.00	-
#Observations	10,329								
Initial likelihood	-66,540.42								
Final likelihood	-41,842.51								
Adjusted rho squared	0.371								

[5] Corresponding to industry category O (“教育，学習支援業” in Japanese) from the data of Economy Census 2016.

5.3.5 Subtour Generation Level

This level of the model is applied in a repeated so-called stop-and-go process (Li, 2015). Each time the model predicts to generate a new work-purpose, or other-purpose subtour (no education-purpose subtour was observed), or to quit the repeating process. The main reason to adopt this process is to save the efforts to model number of different activity purpose separately.

Another feature of this model is that not only work-based subtours are included (as did by many existing research) due to the versatility of travel pattern in Gunma (Table 5-20).

Table 5-20. Observed Count for Activity Purpose of Primary Tour Activity by Each Subtour.

Activity Purpose of Primary Tour Activity by Each Subtour	Count
Work	1,132
Education	247
Other	3

The definition and availability of the alternatives are summarized below:

- Alternative definition: to generate a work-purpose subtour; to generate an other-purpose subtour; to quit.
- Alternative availability: subtour are available to who the occurrence of stop of corresponding activity purpose is predicted true in Day Activity Pattern Model.

Find below Table 5-21 for a summary for the observed number of subtours by each tour, Figure 5-7 for the observed distribution of subtour choice outcomes, and Table 5-22 for the estimation results. Note that those who made either a work- or other-purpose stop but are observed to make no subtour, (i.e., chose to make intermediate stop) are included in the estimation dataset as quit choice.

Multiple variables that are conditioned by higher model are included, whose results are found intuitively correct. For example, the longer distance between the primary destination and home, the less possibility to make a subtour (Variable #5-4); the longer time window the tour has, the higher probability to make a subtour (Variable #5-5), both irrespective of the subtour purpose.

Table 5-21. Observed Counts of Subtour Numbers by Each Tour.

Number of subtours by each tour	Count
0	31,320
1	1,064
2	131
3	14
4	2
6	1

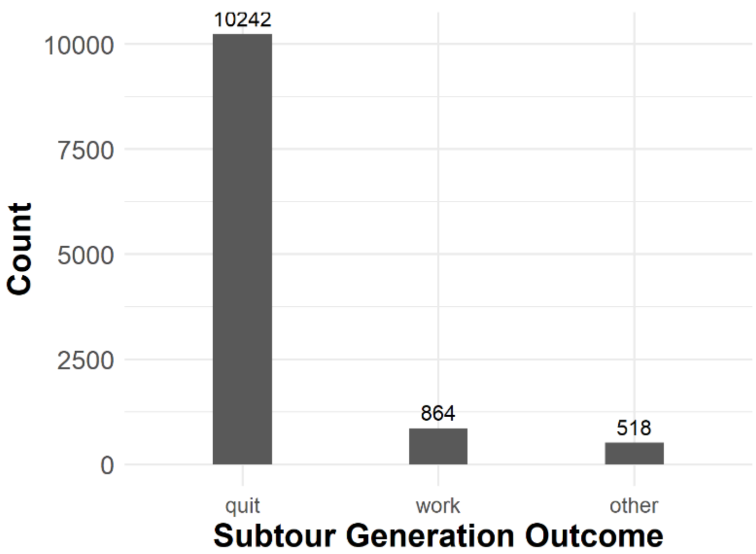


Figure 5-7. Observed Subtour Choice Outcome Distribution.

Table 5-22. Estimation Results of Subtour Generation Model.

Variable	**Variable#**	**Quit**		**Generate Work-purpose Subtour**		**Generate Other-purpose Subtour**	
		Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#5-1			-2.66	*-11.10*	-4.17	*-28.76*
Number of home-based tours remained	#5-2				*1.21*	-0.41	*-2.67*
Primary activity type of its home-based tour is work or education	#5-3			*Not applicable*		-2.44	*-13.72*
Distance between primary destination and home (km)	#5-4	*Base alternative*		-0.04	*-4.96*	-0.03	*-3.33*
Time difference between departure home and back home trips (min)	#5-5			0.37	*15.36*	0.43	*18.43*
Number of subtour have been done	#5-6			-2.52	*-18.43*	-1.23	*-5.78*
Its home-based tour is not primary tour	#5-7				*-0.83*	0.59	*3.22*
#Observations	9,287						
Initial likelihood	-6,613.58						
Final likelihood	-2,254.06						
Adjusted rho squared	0.657						

5.3.6 Number of Subtour Trips Level

This level is a relatively simple one to predict the number of trips in each subtour, with a very similar design to Exact Number of Tours Level. It is necessary to include this level of the model because a considerable share of subtours is observed associated with multiple trips. The definition and availability of the alternatives are summarized below:

- Alternative definition: 1 trip; 2 trips; 3 or more trips (the trip back to the primary destination does not count).
- Alternative availability: All considered available.

Find below Figure 5-8 for the observed distribution of the number of subtour trips, and Table 5-23 for the estimation results.

Mode results of this level suggest relatively limited insights compared to the subtour generation model as many variables are found insignificant. But still, a larger time window is found positively related to the possibility of making 3 or more trips compared to the base alternative of a single trip (Variable #6-6). Also, the more subtours have been done, the less likely would the trip maker to make a subtour with 3 or more subtour trips (Variable #6-7).

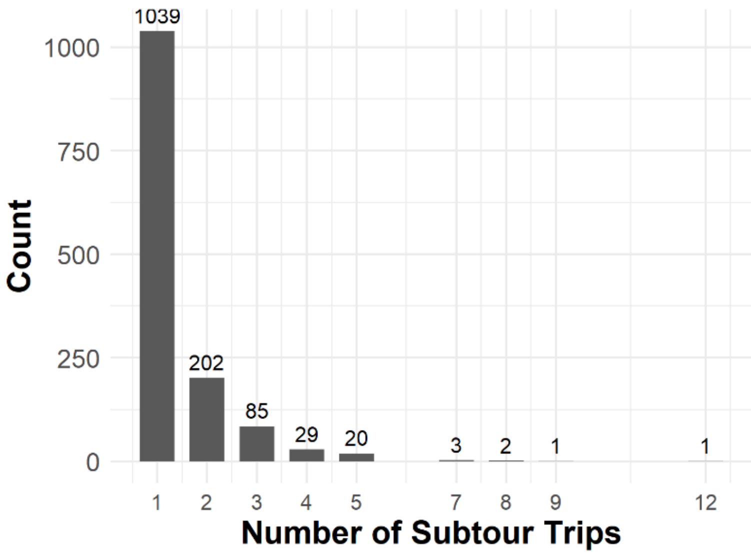


Figure 5-8. Observed Number of Subtour Trips Count Distribution.

Table 5-23. Estimation Results of Number of Subtour Trips Model

Variable	Variable#	1 trip		2 trips		3 or more trips	
		Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#6-1	*Base alternative*		-1.57	*-6.09*	-3.40	*-8.04*
Activity type of subtour is work	#6-2			0.79	*2.86*	0.72	*2.34*
Primary activity type of its home-based tour is work	#6-3			-1.20	*-3.39*	-0.82	*-1.78*
Primary activity type of its home-based tour is education	#6-4				*-0.09*		*-0.11*
Distance between primary destination and home (km)	#6-5				*-0.50*		*-1.11*
Time difference between departure home and back home trips (min)	#6-6				*1.17*	0.17	*3.65*
Number of subtour have been done	#6-7				*1.44*	-0.58	*-1.71*
#Observations	12,770						
Initial likelihood	-1,218.36						
Final likelihood	-763.31						
Adjusted rho squared	0.362						

5.3.7 Subtour Mode and Destination Level

The primary mode and destination for each subtour are estimated in this level, with a similar design to the Tour Mode and Destination Model. Two models are estimated corresponding to the two observed subtour activity types. The definition and availability of the alternatives are summarized below:

- Alternative definition: mode-destination pairs combining one of the travel modes from Car driver, Car passenger, Bicycle, and Walk; and one of the mesh cells from a 100-mesh-cell set sampled out of the total 2,611 mesh cells in Activity System Mesh Dataset.
- Alternative availability:
    - Travel modes:
        - Car driver: available to whose primary mode is car driver.
        - Car passenger and walking: available to all.
        - Bicycle: available to whose primary mode is bicycle.

- Travel destination:
    - Available to all unless those distance from the origin exceed mode-specific 99 percent quantile of subtour trips which are 6.177 km for bicycle mode and 2.100 km for walking mode.

Destination alternative sampling was also applied with the same method introduced in Tour Mode and Destination Model, and so do the correction terms.

Find below Figure 5-9 for the observed distribution of the number of subtour trips, and Tables 5-24 and 5-25 for the estimation results.

Explanations and findings are basically similar to its home-based tour counterparts, except that the information on the travel mode used by its corresponding home-based tour was added as Variable #7-2 and Variable #7-8. However, only the effect of car passenger mode in the other-purpose model is found significant, which suggests a tendency to still let others drive you in the subtour when that is the case in the corresponding primary tour.

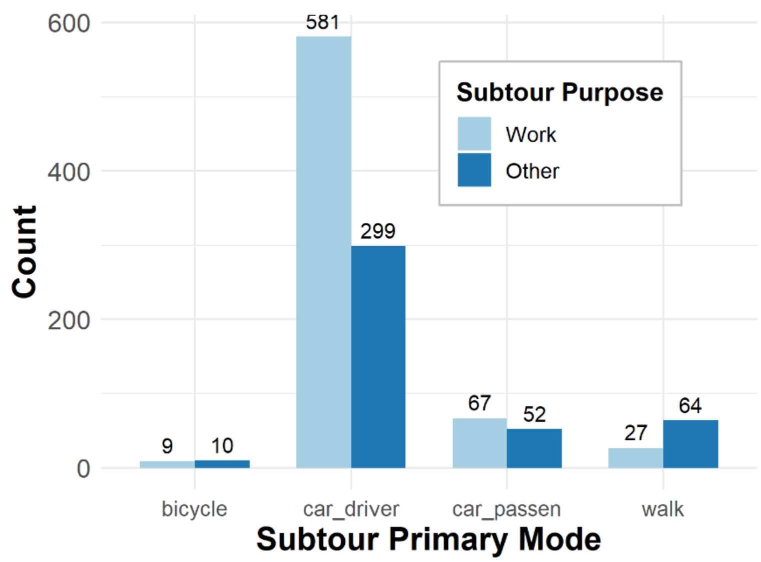


Figure 5-9. Observed Subtour Primary Mode Count Distribution.

Table 5-24. Estimation Results of Work-purpose Subtour Mode-destination Model.

Variable	Variable#	Car Driver		Bicycle		Walk		Car Passenger	
		Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#7-1	*Base Alternative*		3.48	*3.52*	3.98	*8.58*	-2.63	*-12.51*
Is same with mode of its home-based tour	#7-2			*Not applicable*			*0.46*		*0.28*
Travel time (hour)	#7-3	-5.06	*-20.69*	*-23.73*	-3.56	*-26.61*	*-7.21*	-3.82	*-8.92*
#Employees of tertiary sector/size variable	#7-4	0.020	*5.12*	0.020	*5.12*	0.020	*5.12*	0.020	*5.12*
#Employees of primary and secondary sector/size variable	#7-5	0.021	*8.06*	0.021	*8.06*	0.021	*8.06*	0.021	*8.06*
Is the same city as origin	#7-6	1.22	*11.06*	1.22	*11.06*	1.22	*11.06*	1.22	*11.06*
Size variable: #Offices	-	1.00	-	1.00	-	1.00	-	1.00	-
#Observations	684								
Initial likelihood	-3,973.50								
Final likelihood	-2,811.88								
Adjusted rho squared	0.289								

Table 5-25. Estimation Results of Other-purpose Subtour Mode-destination Model.

Variable	Variable#	Car Driver		Bicycle		Walk		Car Passenger	
		Coef.	T value	Coef.	T value	Coef.	T value	Coef.	T value
Alternative-specific constant	#7-7	*Base Alternative*		1.78	*2.06*	5.11	*13.74*	-3.47	*-11.58*
Is same with mode of its home-based tour	#7-8			Not applicable			*0.50*	2.24	*3.36*
Travel time (hour)	#7-9	-12.73	*-21.30*	*-19.25*	*-3.94*	*-34.01*	*-10.37*	*-8.42*	*-11.95*
#Employees of tertiary sector/size variable	#7-10	0.025	*6.62*	0.025	*6.62*	0.025	*6.62*	0.025	*6.62*
Is the same city as origin's	#7-11	0.84	*5.54*	0.84	*5.54*	0.84	*5.54*	0.84	*5.54*
Size variable: #Offices of tertiary sector	-	1.00	-	1.00	-	1.00	-	1.00	-
#Observations	425								
Initial likelihood	-2,637.54								
Final likelihood	-1,565.59								
Adjusted rho squared	0.402								

5.3.8 Destination of Non-Primary Subtour Trips Level

This level predicts the destinations in subtour trips for those that are not the primary ones, so called "non-primary subtour trips", which can also be considered as the "intermediate trips in subtours".

An assumption that people do not modify their mode of travel inside a subtour has been imposed so that modes in these non-primary subtour trips are not included. One important difference in this level is that travel impedance for the alternative *j* is a difference term as d'_j:

$$d'_j = d_{jp} + d_{js_p} - d_{ps_p}$$

Where *p* is the tour primary destination, S_p is the subtour primary destination. The d'_j can be called "detour distance".

The definition and availability of the alternatives are summarized below:

- Alternative definition: meshes from a 100-mesh-cell set sampled out of the total 2,611 mesh cells in Activity System Mesh Dataset.
- Alternative availability: all considered available.

Destination alternative sampling is also applied with the same method introduced in Tour Mode and Destination Model, and so do the correction terms. Find Table 5-26 for the estimation results.

Table 5-26. Estimation Results of Destination of Non-Primary Subtour Trip Model.

Variable	Variable#	Coef.	T value
Detour distance (km)	#8-1	-0.18	*-20.76*
#Employees of tertiary sector/size variable	#8-2	0.025	*4.88*
#Employees of primary and secondary sector/size variable	#8-3	0.020	*4.86*
Is the same city as tour primary destination's	#8-4		*0.93*
Is the same city as subtour primary destination's	#8-5	0.96	*7.25*
Size variable: #Offices	-	1.00	-
#Observations	439		
Initial likelihood	-2,010.59		
Final likelihood	-1,623.21		
Adjusted rho squared	0.190		

The coefficient of detour distance is found significant and has the expected sign from the results (Variable #8-1). Some other interesting finding includes that non-primary trips seem to tend to go to cities the same as the subtour primary destination but not the tour primary destination (Variables #8-4 and #8-5), suggesting that non-primary subtour trips generally are shorter trips compared to the primary one.

5.3.9 Intermediate Trip Generation Level

This level generates intermediate trips for each tour. Two categories: intermediate trips before and after the primary destination are modeled separately. The stop-and-go process used in Subtour Generation Model is also adopted here. The definition and availability of the alternatives are summarized below:

- Alternative definition[6]: to generate a work-purpose intermediate trip; to generate an other-purpose intermediate trip; to quit.
- Alternative availability: intermediate trip generation are available to who the occurrence of stop with corresponding activity purpose is predicted true in Day Activity Pattern Model.

Those who are predicted to make stops but are observed to make no intermediate stop, (i.e., chose to make subtours instead) are included in the estimation dataset as a quit choice.

Find below Figure 5-10 for a summary of the observed number of intermediate trips by each tour, Figure 5-11 for the observed distribution of intermediate trip generation choice outcomes, and Tables 5-27 to 5-28 for the estimation results.

Effects from time window pressure are also observed in the intermediate trip generation: the longer its home-based tour lasts, the more possibility for the individual to make work- and other-purpose intermediate trips before the primary destination (Variable #9-4) as well as other-purpose intermediate trip after the primary destination. But this is not the case for work-purpose intermediate trips (Variable #9-18), which could be explained by an unwillingness to perform any

[6] Education-purpose intermediate trips are not included as an alternative for simplicity, though observed (Figure 5-11).

other work-related activities when leaving for home.

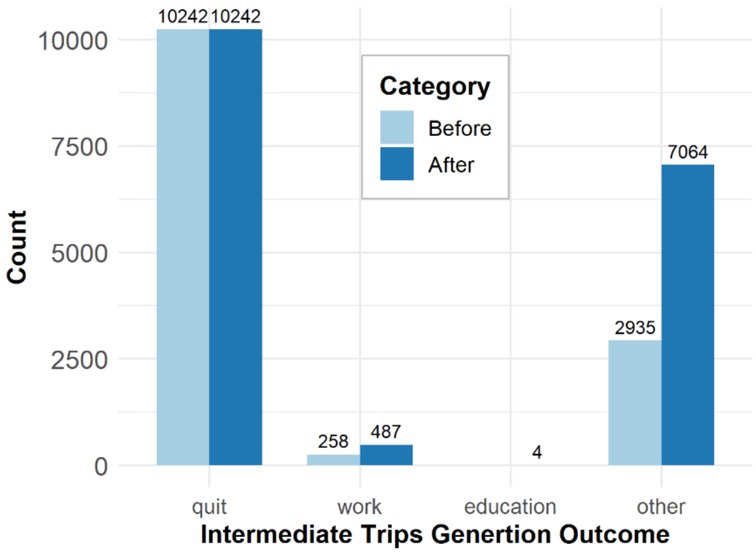


Figure 5-10. Observed Intermediate Trips Generation Outcome Count Distribution.

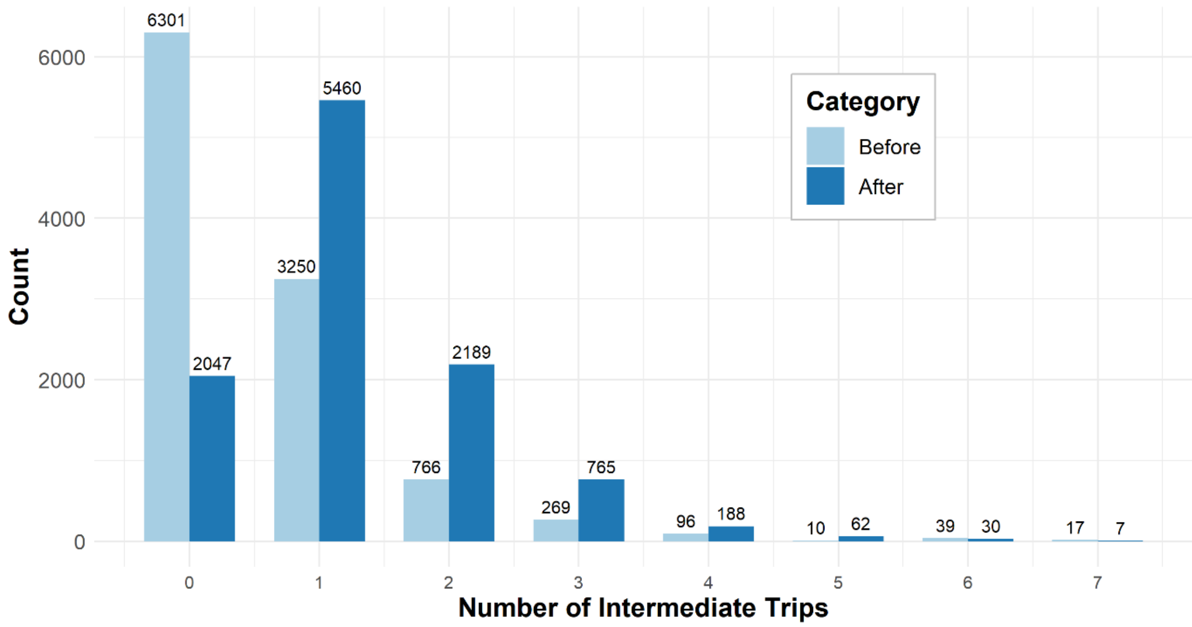


Figure 5-11. Observed Number of Intermediate Trips Count Distribution.

Table 5-27. Estimation Results of Intermediate Trips Generation (Before Primary Destination) Model.

Variable	Variable#	Quit	Generate Work intermediate trip		Generate Other intermediate trip	
		- -	Coef.	T val.	Coef.	T val.
Alternative-specific constant	#9-1		-2.43	*-7.48*	-1.33	*-13.86*
Number of home-based tours remained	#9-2		-0.53	*-1.72*	-0.15	*-2.59*
Distance between primary destination and home (km)	#9-3		0.018	*2.14*	0.0070	*2.13*
Time difference between departure home and back home trips (min)	#9-4		0.15	*5.13*	0.11	*8.64*
Time of day of the first half tour is Early	#9-5			*-1.32*	-0.64	*-3.96*
Time of day of the first half tour is Midday	#9-6	*Base alternative*	1.33	*5.61*	0.62	*8.09*
Time of day of the first half tour is PM Peak	#9-7			*-0.04*	0.24	*1.86*
Time of day of the first half tour is Late	#9-8			*-0.07*	-0.83	*-2.71*
Full-time worker or board member	#9-9			*-0.29*		*-1.55*
Number of intermediate trips have been done	#9-10			*0.69*	-0.58	*-11.77*
Its home-based tour is not primary tour	#9-11			*-0.88*	-0.44	*-5.31*
Its home-based tour has subtour	#9-12		-2.45	*-10.24*	-0.80	*-6.71*
Its home-based tour is of work purpose	#9-13		*Not applicable*		-0.86	*-9.38*
Its home-based tour is of education purpose	#9-14		*Not applicable*		-2.60	*-9.60*
#Observations	10,712		**Initial likelihood**	7,590.37		
Adjusted rho squared	0.274		**Final likelihood**	-5,485.47		

Table 5-28. Estimation Results of Intermediate Trips Generation (After Primary Destination) Model.

Variable	Variable #	Quit	Generate Work intermediate trip		Generate Other intermediate trip	
		- -	Coef.	T val.	Coef.	T val.
Alternative-specific constant	#9-15		1.00	*2.51*		*1.13*
Number of home-based tours remained	#9-16		-0.70	*-4.00*	-0.76	*-15.38*
Distance between primary destination and home (km)	#9-17		0.023	*3.13*	0.013	*4.59*
Time difference between departure home and back home trips (min)	#9-18		-0.074	*-2.27*		*1.59*
Time of day of the last half tour is Early	#9-19		4.46	*4.41*		*0.09*
Time of day of the last half tour is Midday	#9-20	*Base alternative*		*0.68*	0.46	*2.12*
Time of day of the last half tour is PM Peak	#9-21		-0.89	*-1.97*		*-1.34*
Time of day of the last half tour is Late	#9-22		-2.65	*-4.51*	-0.89	*-3.84*
Full-time worker or board member	#9-23		0.49	*2.97*	*0.23*	*4.24*
Number of intermediate trips have been done	#9-24		-1.28	*-11.63*	-1.61	*-42.62*
Its home-based tour is not primary tour	#9-25		-1.74	*-5.68*	-0.79	*-11.00*
Its home-based tour has subtour	#9-26		-2.57	*-10.91*	-1.14	*-12.46*
Its home-based tour is of work purpose	#9-27		*Not applicable*		0.64	*9.07*
Its home-based tour is of education purpose	#9-28		*Not applicable*		0.55	*5.03*
#Observations	14,198		**Initial likelihood**	-10,100.16		
Adjusted rho squared	0.214		**Final likelihood**	-7,910.00		

5.3.10 Destination of Intermediate Trips Level

This level of the model determines the destinations of the intermediate trips that are just generated from the previous level of models. Its design is very similar to Destination of Non-Primary Subtour Trips Level as the concept of "detour distance" is as well applied as the travel impedance variable (in this case, is the detour distance compared to the home and the primary destination).

The definition and availability of the alternatives are summarized below:

- Alternative definition: mesh cells from a 100-mesh-cell set that are sampled out of the total 2611 meshes in Activity System Mesh Dataset.
- Alternative availability: all considered available.

Destination alternative sampling is applied with the same method introduced in Tour Mode and Destination Model, and so do the correction terms. Find below Table 5-29 for the estimation results where the two categories (before and after the primary destination) are separately estimated.

Table 5-29. Estimation Results of Destination of Intermediate Trip Model.

Variable	Before Primary Destination			After Primary Destination		
	Variable#	Coef.	T value	Variable#	Coef.	T value
Detour distance (km)	#10-1	-0.48	*-86.82*	#10-6	*-0.53*	*-127.73*
#Employees of tertiary sector/size variable	#10-2	0.031	*12.83*	#10-7	0.031	*19.80*
#Employees of primary and secondary sector/size variable	#10-3	-0.023	*-3.75*	#10-8	-0.018	*-4.67*
Is the same city as tour home's	#10-4	0.58	*9.01*	#10-9	*0.63*	*15.14*
Is the same city as primary destination's	#10-5		*0.64*	#10-10	*-0.11*	*-2.57*
Size variable: #Offices	-	1.00	-	-	1.00	-
#Observations	2,534			6,020		
Initial likelihood	-11,234.4			-27,690.29		
Final likelihood	-7,859.12			-19,205.75		
Adjusted rho squared	0.300			0.306		

Detour distance coefficients are found negative in both models as expected. One interesting finding is that the number of employees in the primary and secondary sectors has a negative influence on intermediate trip destination choice, both before and after the primary destination. This can be explained by that intermediate trip are mostly related to other-purpose activities (Figure 5-11) such as shopping and leisure where the number of employees in the primary and secondary sectors is low.

5.4 Model Simulation

After finishing the estimation of the DAS models, some logic to generate the "Time-specific OD pairs" (Figure 3-1) were designed. Instead of the classic sample enumeration method which enumerates all possible combinations of model outcomes and multiplies fractional probabilities in multi-dimensional arrays, stochastic simulation is adopted that applies the probabilities in Monte Carlo method to predict a single set of tours, destinations and modes, and other travel attributes for each individual in the sample. Despite suffering from random sampling error, the stochastic simulation is argued to be advantageous as it allows a greater level of output details which resembles a travel diary better (Bradley et al., 1999). The basic structure of the simulation is described below in Table 5-30, where attributes recording and updating are not listed for readability. The whole simulation process is run with the language of R (R Core Team, 2021).

It is noted that certain procedures (Steps 3, 7, 10, 32, and 33) have been introduced and implemented in attempting to have a more realistic vehicle using patterns among the households. Household vehicle ownership is explicitly controlled so that intra-household car sharing (but not ridesharing) is captured through these steps, which are detailed below. These steps are especially important in modeling AVs in the next chapter (Section 6.1) for reflecting better on the feature of AVs and for generating zero-occupancy trips (empty trips).

In Step 3, each household is defined as "vehicle sufficient" or "vehicle insufficient" by checking whether the vehicle ownership of the household is greater or equal to the number of household members excluding those who do not hold a driving license. For each person who holds a driving license in a vehicle insufficient household, the vehicles are assigned in the order of employment status and age. For example, in a one-income nuclear family owning only one car, we assume the worker would have the priority in using the vehicle; while in a dual-income nuclear family with one car, the priority would be assigned to the older worker. The vehicle (as a driver) availability is assumed as false for those who have no vehicle assigned at this step.

In Step 7, the vehicle (as a driver) availability of each household is updated. After simulating Day Activity Pattern model, information of who is planning to stay at home all day (i.e., "zero-trippers", "000-000" in Table 5-5) is counted and the vehicles that have been assigned to these people are reallocated to other members in their respective household. For those who are assigned a vehicle, their vehicle (as a driver) availability is assumed as true.

In Step 10, whole tour data are separated into two groups, 1) those who are car available or hold no driving license; 2) those who are not car available but hold a driving license; and are simulated sequentially. This is because the car availability of the second group should be dependent upon the simulation result of the first one, that is, the tours/people in the second group (Group 2) still have opportunities to use HV during the time of day when any HV has been returned home with its former user as they finished (one of) his or her tour(s).

After the simulation of Group 1, in Steps 32 and 33, the vehicle usage patterns are summarized for Group 1 people to collect the information of tour time of day (and thus idle time of day) and the user ID for each vehicle. The idle time of day of each vehicle is then matched with the time of day (decided in Step 9) of each tour of people in Group 2. Those who match a tour within the same household of the vehicle user will be reassigned (as only intra-household sharing is considered), as such the tour is considered a car available in its subsequent model simulations.

Table 5-30. Simulation Procedures of DAS Model.

Begin.

1. Read person data with demographic variables, model coefficients, mesh land use data, mesh LOS matrices.
2. Pre-calculate logsum for each individual.
3. Car Availability Related: define whether each household is "vehicle sufficient" and based on which define the mode availability for car driver (see Section 5.4 for detail).

{for person data}

4. Apply **Daily Activity Pattern Model**: Generate individual-specific probabilities and randomly draw one of the alternatives as the simulation outcome (*same for all the "Apply", omitted below*).
5. Apply **Exact Number of Tours Model** for 3 purposes.
6. For whom without precise outcome (e.g., "3 or more tours"), randomly sample one based on the observed distributions.
7. Car Availability Related: count the number of zero-trippers of each household and based on which update the mode availability for car driver (see Section 5.4 for detail).
8. Generate simulated tour data by expanding the person data with the simulated number of tours.

{for tour data}

9. Apply **Tour Time of Day Model** for 3 purposes.
   a. Remove conflicted time of day alternatives each time for the simulation of next tour within the same person.
10. Car Availability Related: separate the whole tour data into two groups, 1) those who are car available or hold no driving license; 2) those who are not car available but hold driving license.
11. Apply **Tour Mode and Destination model** for 3 purposes for Group 1.
    a. Sample the destination alternatives.
    b. Use travel impedance data corresponding to the simulated time of day.
12. Predict destination coordinates by randomly sampling from the predicted destination mesh cell for Group 1.
13. Predict specific departure and back home time point inside the predicted time of day by randomly sampling for Group 1.
    a. Solve time conflicts across the tours by repeatedly sampling.
14. Apply **Subtour Generation Model** for Group 1.
15. Generate subtour data (Group 1) by expanding the tour data (Group 1) with the simulated number of subtours.

{for subtour data (Group 1)}

16. Apply **Number of Subtour Trips Model.**
17. For whom without precise outcome (e.g., "3 or more subtours"), randomly sample one based on the observed distributions.
18. Apply **Subtour Mode and Destination Model.**
    a. Those who did not choose car (driver) as primary mode of the tour cannot choose car (driver) for the subtour mode choice.
19. Predict destination coordinates by randomly sampling from the predicted destination mesh cell.
20. Generate subtour trip data (Group 1) by expanding the subtour data (Group 1) with the simulated number of subtour trips.

{for subtour trip data (Group 1)}

21. Predict time of day for subtour trips by randomly sampling from the observed distribution.
22. Apply **Destination of Un-primary Subtour Trip Model.**
23. Predict destination coordinates by randomly sampling from the predicted destination mesh cell.

Table 5-30. Continued.

{for tour data (Group 1)}

24. Divide the data to the departure home half-tour data and back home half-tour data.
25. Apply **Intermediate Trip Generation Model** to the two half-tour data.
26. Generate intermediate trip data (Group 1) by expanding the half-tour data with the simulated number of intermediate trips.

{for intermediate trip data (Group 1)}

27. Apply **Destination of Intermediate Trip Model** to the intermediate trip data.
28. Predict destination coordinates by randomly sampling from the predicted destination mesh cell.
29. Combine tour data, subtour data, and intermediate trip data to trip data (Group 1).

{for trip data (Group 1)}

30. Predict specific trip start time inside the predicted time of day by randomly sampling.
    a. Solve time conflicts across the trips by repeatedly sampling.
31. Assign attributes such as travel time and distance between the trips.
32. Car Availability Related: summarize tour & idle time of day for each vehicle.

{for tour data (Group 2)}

33. Car Availability Related: check whether the tour match the idle time of day that summarized in previous step for tour 1. If so, assign car availability of the tour as true.

Simulate Step 11-31 for Group 2 data (**Omitted**).

End.

5.5 Model Validation

As mentioned above, efforts are also devoted to validating the estimation results to demonstrate their reliability. Due to the lack of data, only internal validations are conducted. Internal validation is defined following Parady et al. (2021) as the evaluation of the reproducibility of the model, that is, the extent to which the model maintains its predictive accuracy in a different sample from the same population. In lieu of a different sample, the holdout method is used, where the dataset is randomly split into two, in this case at the household level (80 % estimation, 20 % validation). The validation dataset was run through the stochastic simulation procedures with their demographics as the inputs, and then the simulated results are compared to the observed ones. All the results are averaged from 10 times repeated simulations to mitigate random sampling error. The validation results are shown in Figures 5-12 to 5-28, results of some trip-level models are not conducted for simplicity.

According to the internal validation results, the estimated DAS model for Gunma generally demonstrates good predictive accuracy. However, the results of several models show noticeable discrepancies that might lead to biased forecasting, they are summarized below.

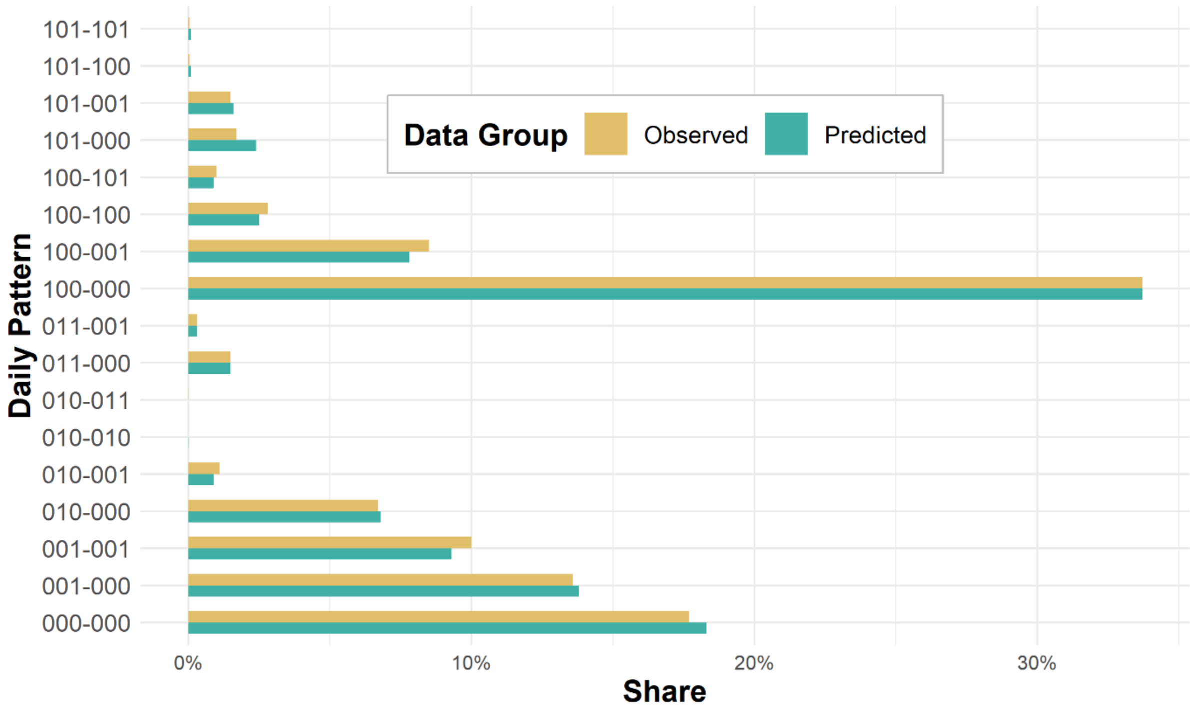


Figure 5-12. Validation Results of Day Activity Patterns.

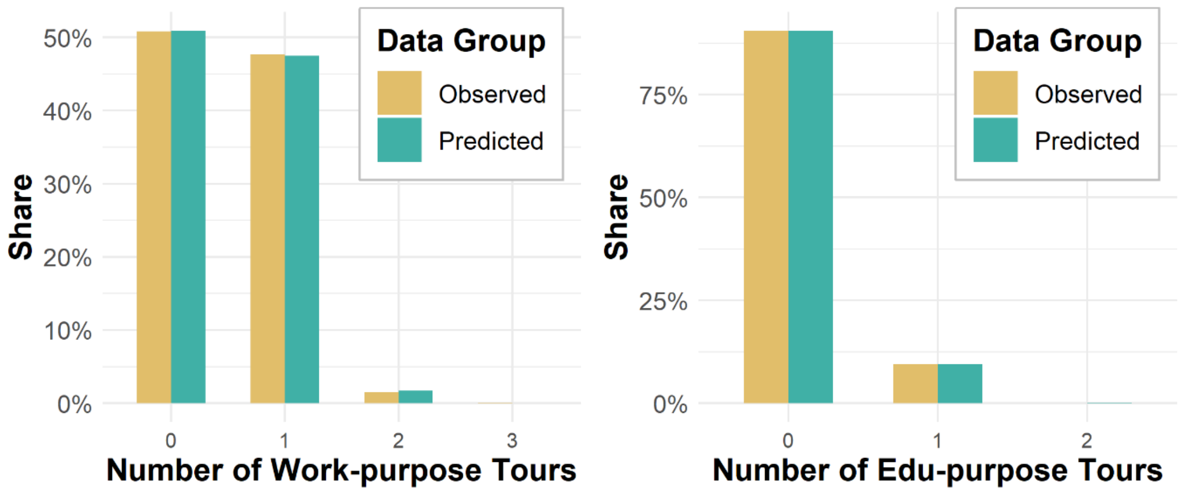


Figure 5-13. Validation Results of Number of Work Tours & of Education-purpose Tours.

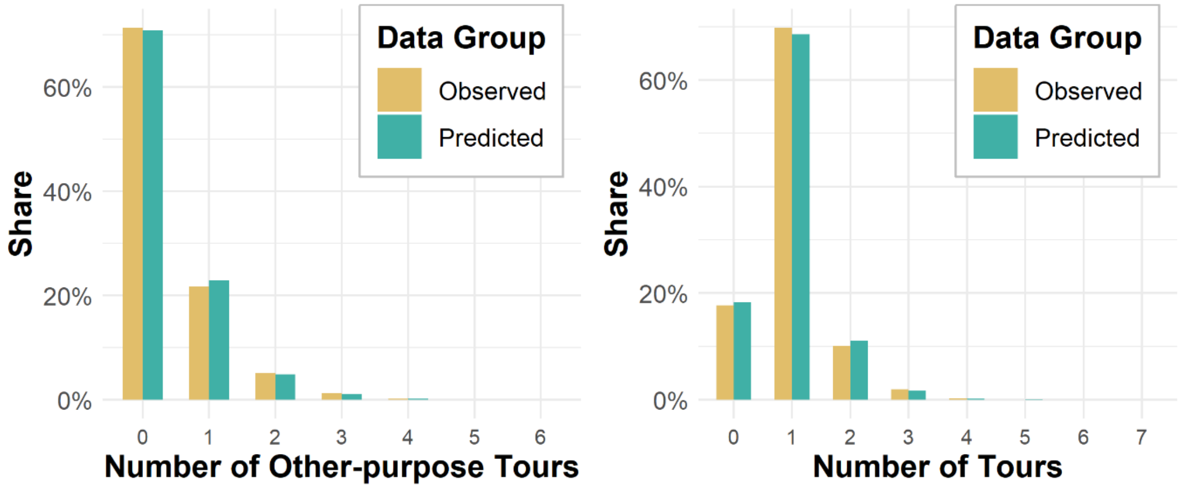


Figure 5-14. Validation Results of Number of Other-purpose Tours & of All Tours.

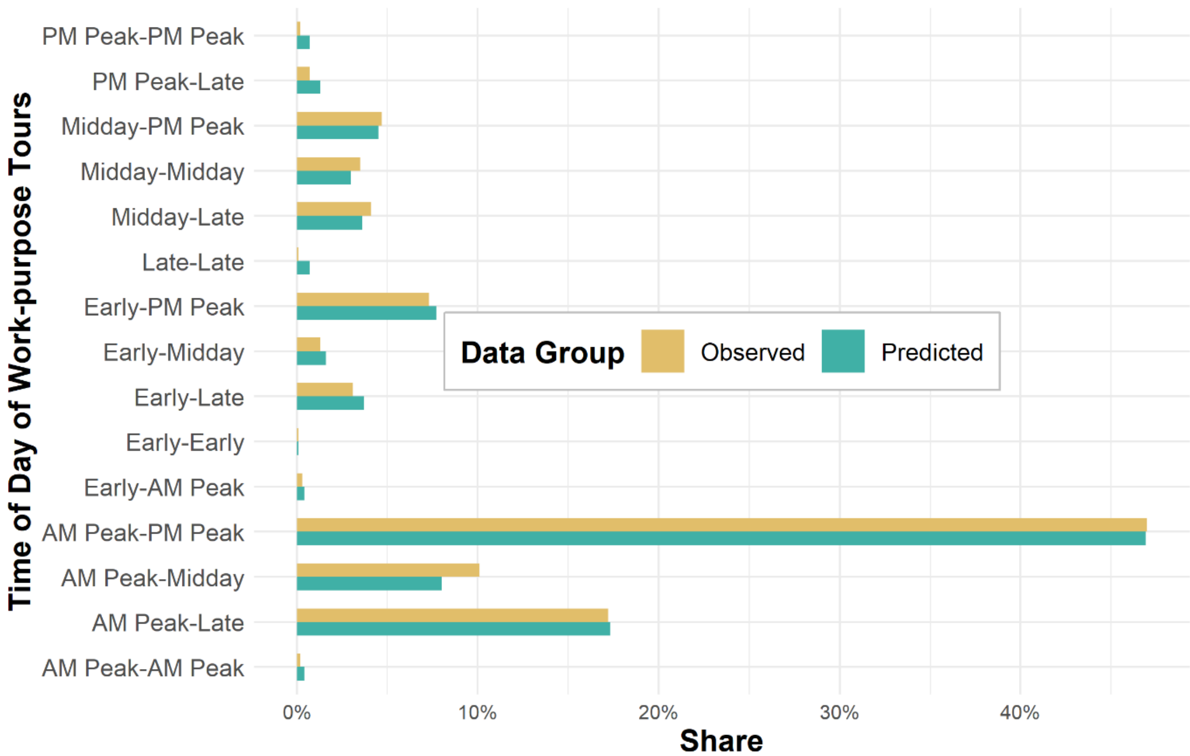


Figure 5-15. Validation Results of Time of Day of Work-purpose Tours.

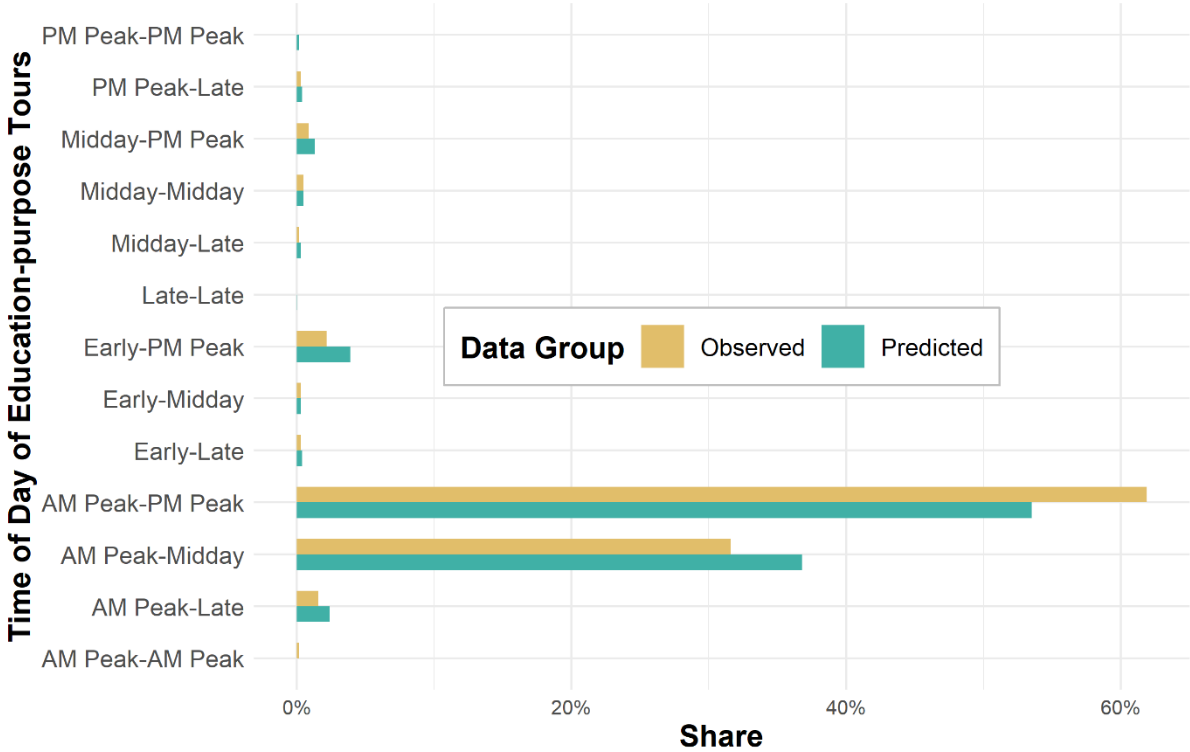


Figure 5-16. Validation Results of Time of Day of Education-purpose Tours.

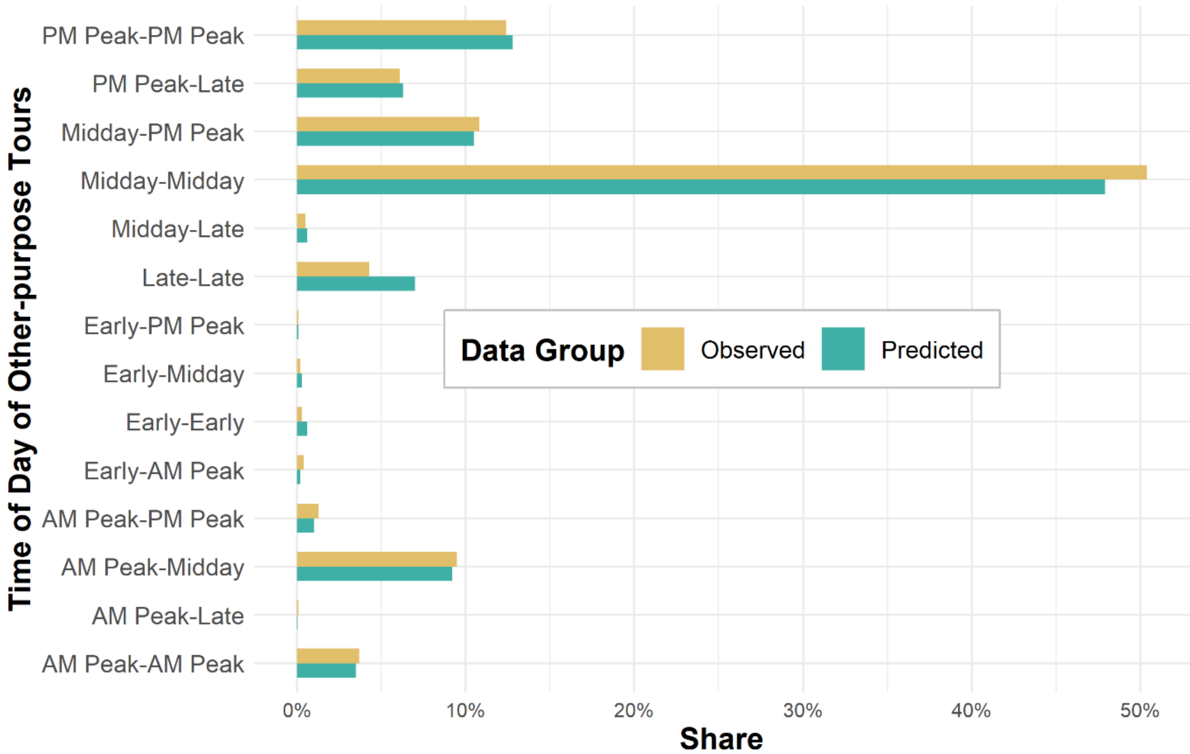


Figure 5-17. Validation Results Time of Day of Other-purpose Tours.

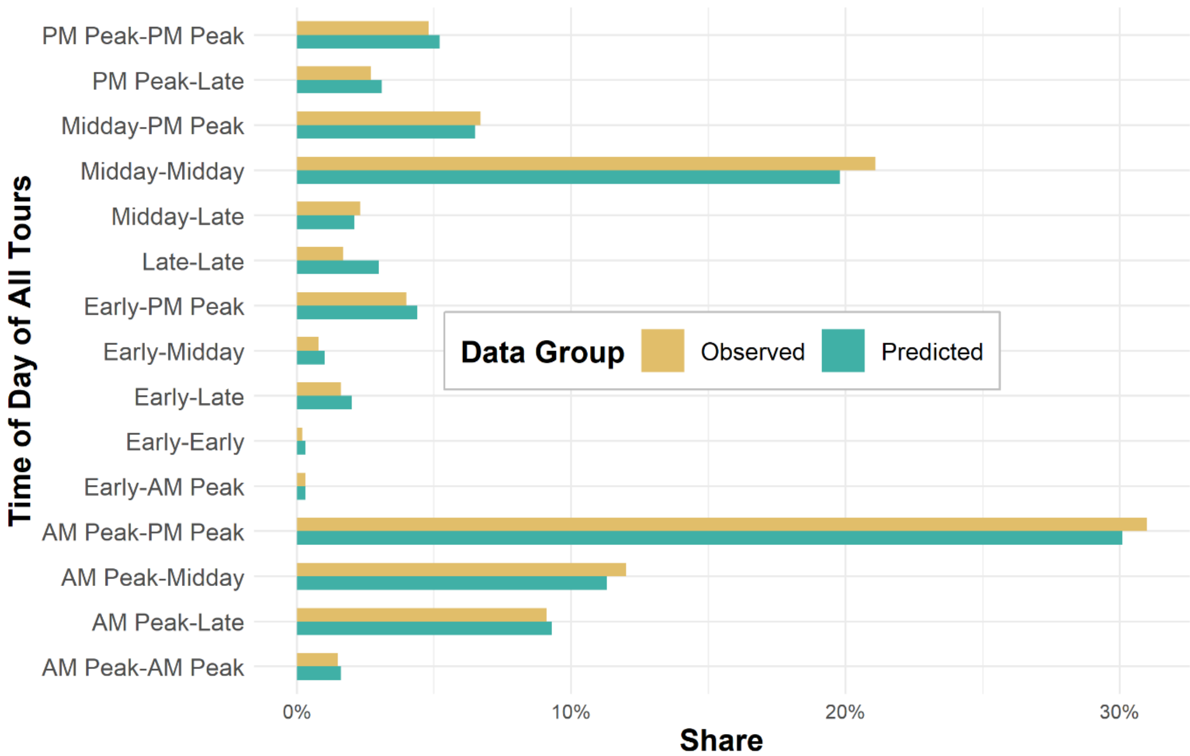


Figure 5-18. Validation Results of Time of Day of All Tours.

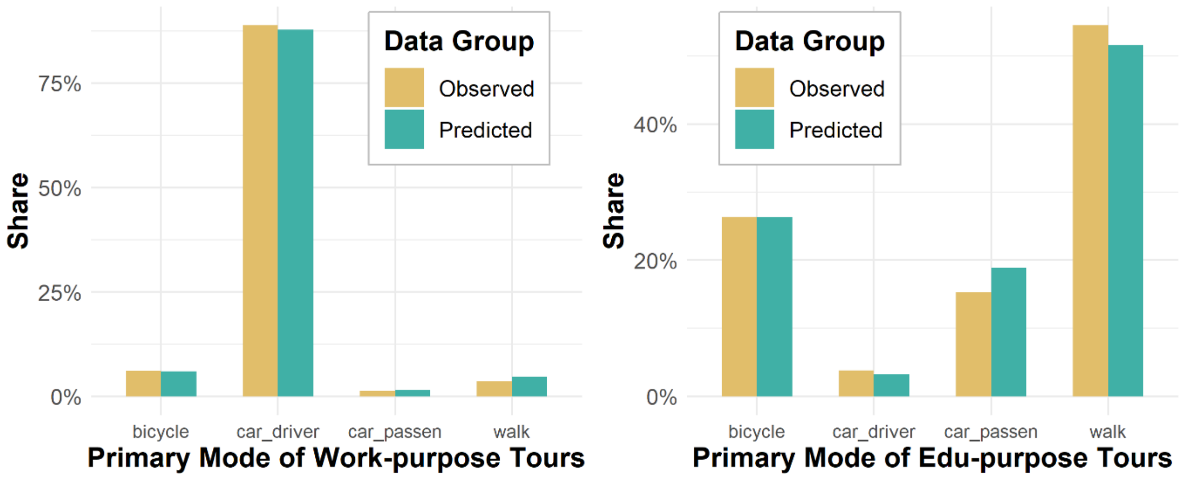


Figure 5-19. Validation Results of Travel Mode of Work-purpose Tours & Education-purpose Tours.

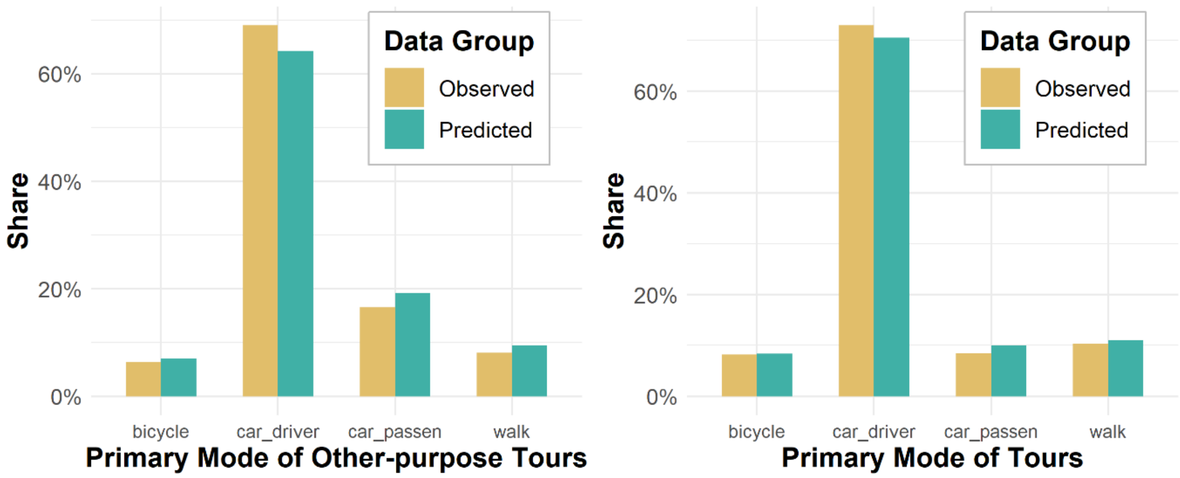


Figure 5-20. Validation Results of Travel Mode of Other-purpose Tours & All Tours.

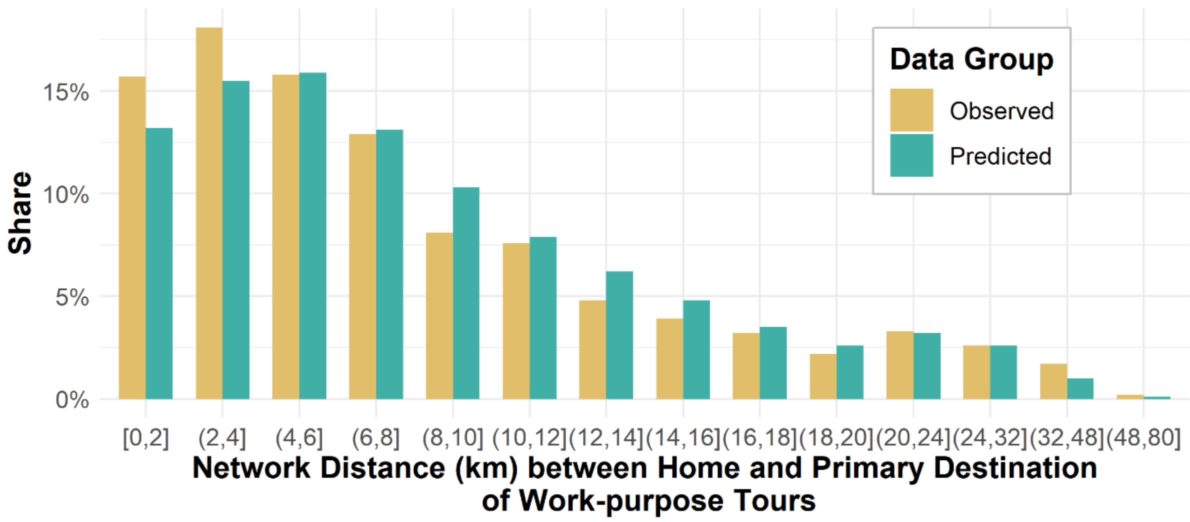


Figure 5-21. Validation Results of Travel Distance (km) of Work-purpose Tours.

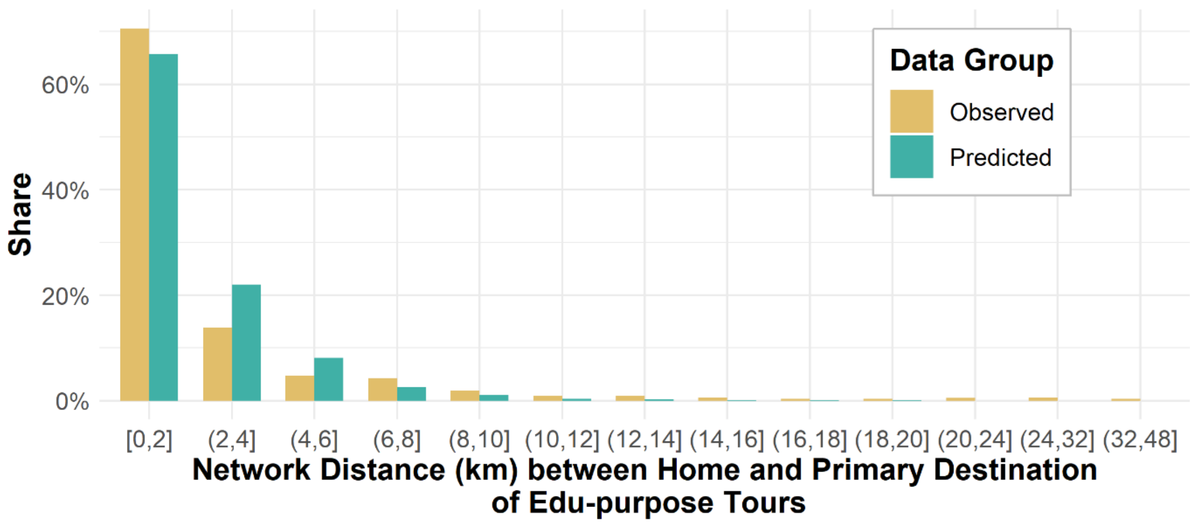


Figure 5-22. Validation Results of Travel Distance (km) of Education-purpose Tours.

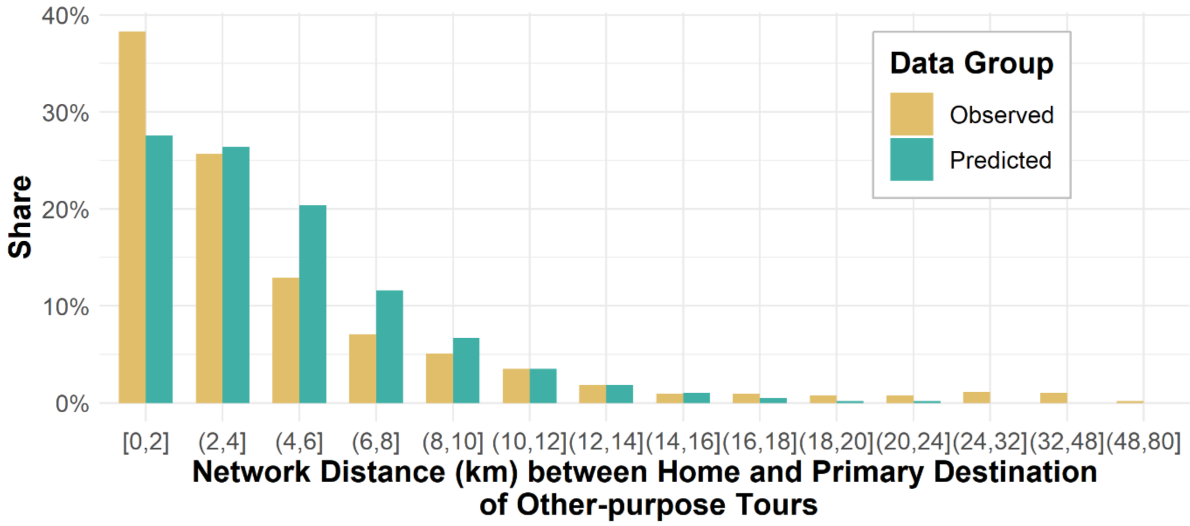


Figure 5-23. Validation Results of Travel Distance (km) of Other-purpose Tours.

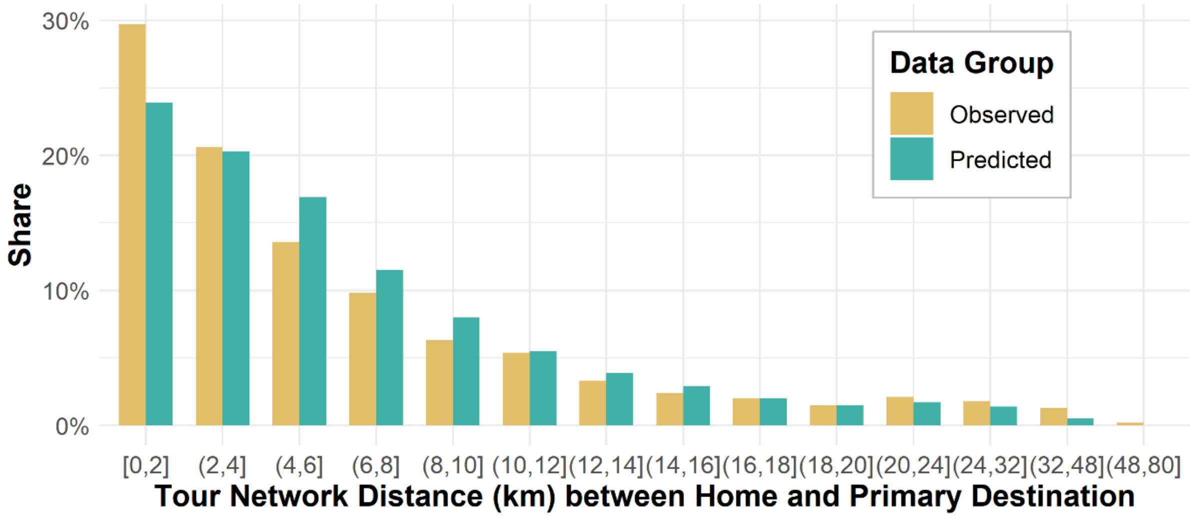


Figure 5-24. Validation Results of Travel Distance (km) of All Tours.

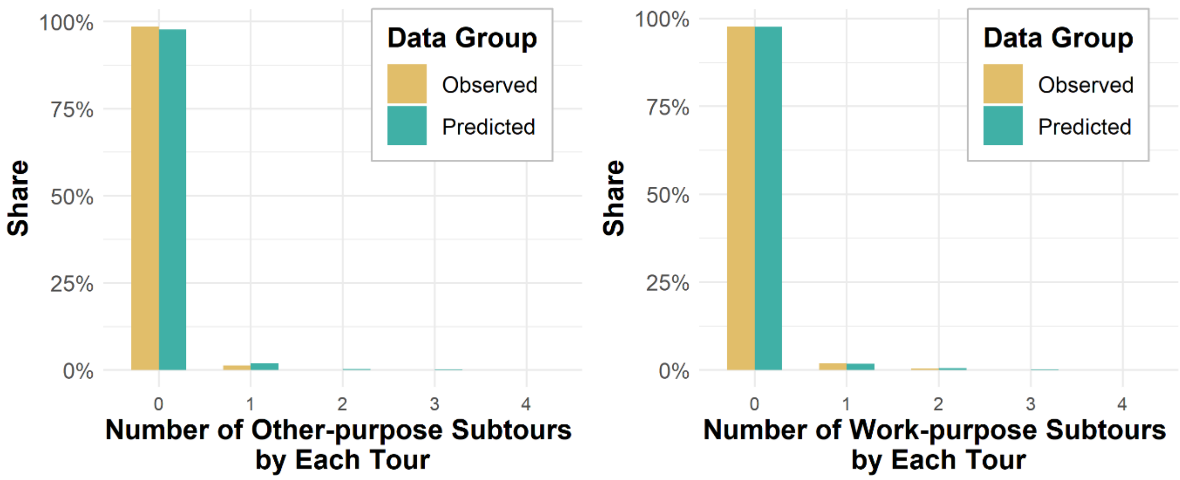


Figure 5-25. Validation Results of Number of Work-purpose & Other-purpose Subtours.

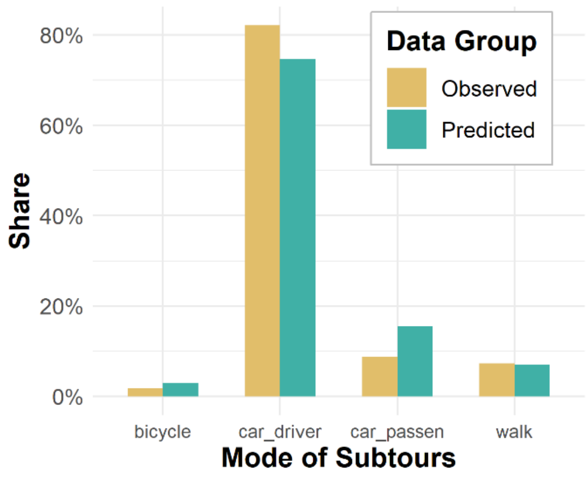


Figure 5-26. Validation Results of Subtour Modes.

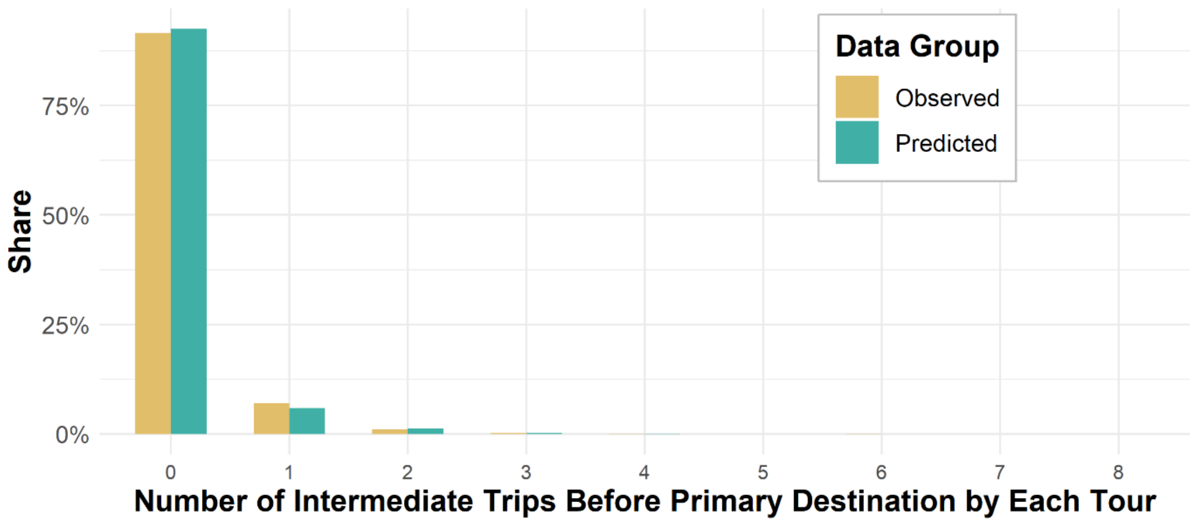


Figure 5-27. Validation Results of Number of Intermediate Trips Before Primary Destination.

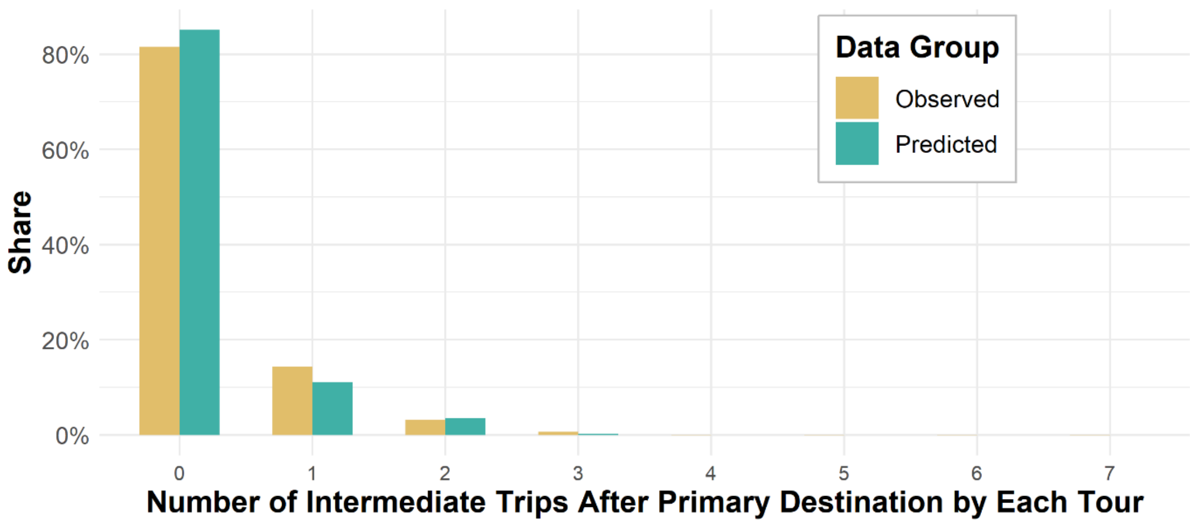


Figure 5-28. Validation Results of Number of Intermediate Trips After Primary Destination.

First, regarding travel modes, there founds a tendency to over-predict the share of passengers in both home-based tours (Figures 5-19 and 5-20) and subtours (Figure 5-26). An obvious reason behind the discrepancy is that the mode availability for passenger mode adopted in this DAS model of Gunma is quite naïve: simply all the trip makers whose household own cars are considered available for being a vehicle passenger. It is more realistic to consider the trip matching issues in the mode choice, which means one must be matched with another individual who is car available at the time to chauffeur him or her to make the car passenger mode alternative available. This complex information is, unfortunately, not explicitly reported in the Gunma PT Survey so this dissertation decides to not incorporate this feature. Therefore, the over-predicting issue here has to be left as a limitation of this study.

Second, the distances between the home and primary activity destination are found, as expected, to have the most value discrepancies among the whole DAS model system. This is a common issue because not only the largest choice set in this decision but also many factors such as spatial resolution issues (e.g., Modifiable Areal Unit Problem) are playing roles in the decision making that would introduce more sources of error. Specifically in this research, the mode-destination models (Figures 5-21; 5-22; 5-23; and 5-24) are found to under-predict the frequency in the interval less than 2km, while over-predict the intervals between 4km and 16km. It is speculated here that the discrepancies are caused by the travel impedance retrieval method and the spatial unit of 1km mesh cells used in this research. The transport supply model generates the cell-to-cell car-based travel time and distance that are measured with mesh cell centroids, which means that the accuracy of the impedance data can be quite low when the demands are facing destination alternatives that locate just in their vicinities or the same mesh cell as the origin. In the case of the same mesh cell with the origin, travel time data are randomly sampled from a Triangle Distribution between 30 seconds and 210 seconds. This should be left as one of the limitations. Nevertheless, the discrepancies seem to offset each other to some extent: the average value of the distance between the home and primary activity destination from the simulated results is 6,357m, a value slightly smaller than the observed

6,412m.

In summary, the estimated model shows sufficient reproducibility and is adequate for forecasting. However, cautions are required to attempt to evaluate the metrics for each activity purpose separately, and the spatial distribution of travel distance.

CHAPTER 6 TRANSPORT MODEL APPLICATIONS AND EVALUATIONS

This chapter introduces the procedures to incorporate AVs into the demand and supply models. The implications of the AV introduction are then evaluated through conducting scenario analysis, where one base scenario and four AV scenarios are involved.

6.1 Scenario Settings and Assumptions about Automated Vehicles

As discussed in the literature review of AVs in Section 2.3, there is still much uncertainty about the characteristics AVs will possess. To reflect the potential variation in the characteristics, scenario analysis has been extensively used in the existing literature by assuming a combination of different characteristics.

In this study, the forecast year for the scenario analysis is 2040, a time point assumed for the prevalence of AVs (Litman, 2021). To reiterate, predicting the specific time of AV prevalence is beyond the scope of this dissertation (Section 1.3).

A scenario without AVs but only population changes is included as the benchmark case, hereafter called Base Scenario. A ratio of 82.45% to the current population in Gunma Prefecture and Ashikaga City is assumed for 2040 based on the predictions made by the National Institute of Population and Social Security Research of Japan (NIPSSR, 2018). The demographic patterns across the population are assumed the same as of 2015, which means no household transition model was incorporated.

Four AV scenarios are defined with different levels of value of travel time and levels of road capacity assumed (Table 6-1). Scenario 1 is the most conservative in terms of AV characteristics, where values of travel time are set as 75% and 85% compared to HV for commuting and other-purpose travels, respectively. No AV-induced benefit in road capacity is assumed. Scenario 2 also assumes no change in road capacity, but the decreased levels of values of travel time are doubled. Scenario 3 and Scenario 4 apply the same value of travel time patterns as Scenario 1 and 2, respectively, but assumes a 20 % increase in road capacity for the AVs. The values of travel time for commuting purposes (i.e., work and education) and other purpose are differentiated according to the findings of the existing literature from SP surveys (Kolarova et al., 2019).

Table 6-1. Summary of Scenario Settings.

Scenario	Population change	PAV ownership	PAV or HV availability	Value of travel time for AV compared to HV (drivers)		Road Capacity for AVs of HVs
				Commuting-purpose tours and subtours	Other-purpose tours and subtours	
Base Scenario	82.45% to the current	-	Requiring driving license & depending on vehicle ownership (Section 5.4)	-	-	-
Scenario 1		The same as of HV ownership patterns	Depending on vehicle ownership (Section 6.1)	75%	85%	1.0
Scenario 2				50%	70%	1.0
Scenario 3				75%	85%	1.2
Scenario 4				50%	70%	1.2

The different levels of AV characteristics are adopted for two purposes. For Scenarios 1 and 3, the values of travel time level (around 20% decrease) are basically set in line with the findings of the existing literature (Section 2.3), hence these two scenarios are intentionally conceived for evaluations in relatively “realistic” futures in a sense of following the current academic findings. While Scenarios 2 and 4, where the decreased levels of value of travel time are more optimistically set compared to their counterparts, are proposed as relatively “extreme” cases.

The level of road capacity benefit might be associated with extra uncertainties from specific vehicle running patterns (e.g., in the platoon) and technology (e.g., Connected Vehicles), as well as for the concern of passenger comfort (e.g., Le Vine et al., 2015). Therefore, only a single moderate level (20%) of improvement (Shladover et al., 2012) is applied to Scenarios 3 and 4. From a perspective of policy making, it is also possible that one considers the different levels of road capacity benefit as leverage for AV introduction. Compared to the value of travel time, which is somewhat “subjective” and hard to control, road capacity benefits could be more flexible as being a more "objective" concept. Such a perspective will be discussed in the subsequent contents briefly (Sections 8-2 & 8-4).

For all the AV scenarios, the human-driven vehicles currently owned by households are assumed to switch to PAVs with the same ownership level, and all the members in these households are assumed to have access to an available/idle PAV irrespective of their driving license status. Certain rules are proposed below to define the availability/idleness of AVs.

The way to define vehicle availability of PAVs is different from those of HVs (Section 5.4). The main PAV feature that they can drive themselves is assumed to impact the vehicle usage patterns in two aspects: 1) PAVs require no driving license anymore; 2) PAVs can move back home without any occupant to serve another household member. Therefore, those people belonging to a "vehicle insufficient" household under the PAV case should have two opportunities to access a PAV when:

- Any PAV has been returned home with its former user (inside the same household). As did in the HV simulation.
- Any PAV has returned home by itself during idle time when its (primary) user is not using (e.g., staying in the office from AM Peak – PM Peak).

The simulation steps (Table 5-30) related to car availability are modified accordingly:

- In the steps (Steps 3, 7, and 10 in Table 5-30) defining "vehicle sufficient" household, the members holding no driving license are not counted anymore.
- In Steps 32 and 33, the occupied times of day in trip level (instead of the time of day of the whole tour) are summarized. The idle time now expands to those time of day not occupied by the primary user. The tours in Group 2 data are matched with the idle time time-of-day in order to decide their PAV availabilities.

For example, consider the following household owning only one PAV (Table 6-2):

Table 6-2. Hypothetical Activity Schedule for PAV Mode Availability Explanation.

Person ID by Household	Tour ID by Person	Trip ID by Tour	Trip Time of Day	Trip Purpose	PAV Availability	Tour Mode Choice
1	1	1	AM Peak	Work	True	PAV
1	1	2	PM Peak	Back home		
2	1	1	Midday	Shopping	?	?
2	1	2	Midday	Back home		
2	2	1	Late	Shopping	?	?
2	2	2	Late	Back home		

In the HV case, the second tour of Person 2 should have access to HV as the vehicle has been returned home by Person 1, while the first tour is not car available. Nonetheless, in the PAV case, the first tour of Person 2 is also considered car (PAV) available as PAV could drive itself home after the first trip of Person 1.

These trips AV drive itself without an occupant for intra-household sharing, are called zero-occupancy trips (or empty trips), which are expected to add extra vehicle distance traveled to the whole transport system.

Another source of zero-occupancy trips is that, in some rare cases that a trip maker chooses to use PAV for a subtour but did not use PAV for its corresponding home-based tour (car availability for the subtour would be false in HV case if no HV was used for the tour). In this case, we assume PAV would drive itself from home to the primary destination of the tour and drive back after serving subtour.

6.2 Model Simulation Results of Base Scenario as Benchmark

Base Scenario is presented firstly to illustrate the impacts of population decrease. The initial travel demand in the base scenario is obtained by randomly selecting 82.45% of the households from the original effective PT data sample of 16,425 households. The resulting dataset contains 13,542 households and 27,350 persons.

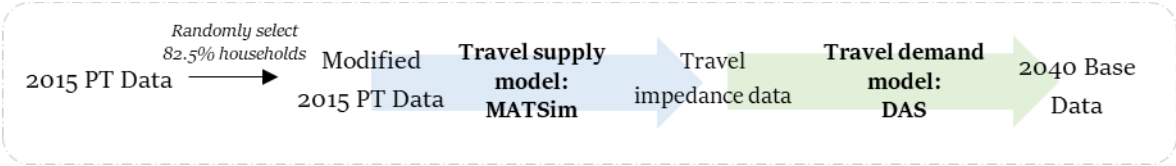


Figure 6-1. Simulation Running Flow for Generating 2040 Base Data.

One iteration between the MATSim and DAS is performed to reflect the change in travel impedance following the decreased population (Figure 6-1). The 13,542 household dataset is hereafter called 2040 Base Data.

The travel-related simulation results for Base Scenario are shown below in Table 6-3 with a comparison with the effective PT data sample in 2015 that is used for the DAS model building. Two conclusions can be drawn from this comparison: first, AM Peak time average speed increased by 4.0% suggesting less congestion in Base Scenario; this is intuitive since the existing road infrastructure would be enjoyed by less population. Second, despite the better level of service, the differences in trip making metrics between the PT data and the 2040 Base data were so small that are probably compounded with simulation random errors, especially for the average travel frequency measures. Care must be taken in interpreting these measures.

Table 6-3. Comparison between PT Data Sample and Simulated Base Data for 2040.

Dataset	#Households	Share of Persons Made travel			Average #Tours per person			Average speed in city centers (among DAA mesh cells, see Sub-section 3.4.1)	
		Overall	Residing in DAA		Overall	Residing in DAA		In AM Peak time	In Early time
			Yes	No		Yes	No		
PT Data (2015)	16,425	81.7%	82.7%	81.1%	0.98	1.00	0.96	32.28 km/h	39.15 km/h
2040 Base Data	13,542	81.7%	83.2%	80.7%	0.97	1.01	0.95	33.57 km/h	39.26 km/h

6.3 Model Simulation Results of Automated Vehicle Scenarios

AV scenarios (Table 6-1) are simulated with the DAS-MATSim loop with the 2040 Base Data as the initial travel demand. The running flow process and terms for the iterations are shown in Figure 6-2.

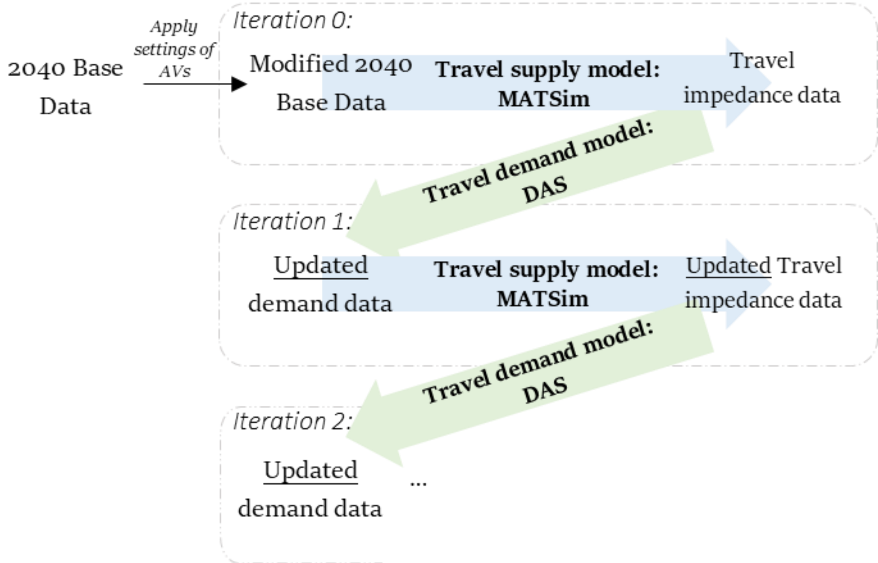


Figure 6-2. Simulation Running Flow for Scenarios with Automated Vehicles.

Records of the total distance traveled of each iteration and their changing rates are presented in Table 6-4. We assumed as convergence criteria three-iteration moving average smaller than 0.10%. Based on that criterion, convergence is reached in Iterations 6, 4, 5, and 5 for the four AV scenarios, respectively.

According to the results in Table 6-4, the comparisons between Iteration 0 and the final Iteration for the AV scenarios indicate the necessity to exercise the transport supply-demand loop. The statistics in equilibrium do vary compared to a one-time model exercise, let alone in the case of no interaction between supply and demand considered. For example, the trip distances in the final iterations decrease by up to around three percent from Iteration 0, except for Scenario 3 where the combination of moderate PAV settings and road capacity benefit probably played a role. For other scenarios than Scenario 3, the results suggest the adaptations from the trip makers for travel congestions resulted from the increased distance.

Table 6-4. Simulated Total Trip Distance by Iteration.

	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
Iteration #	Total distance traveled in 100km (% change)	% change moving average	Total distance traveled in 100km (% change)	% change moving average	Total distance traveled in 100km (% change)	% change moving average	Total distance traveled in 100km (% change)	% change moving average
Base	3,994	-	3,994	-	3,994	-	3,994	-
0	5,081 (+27.21%)	-	5,978 (+49.68%)	-	5,080 (+27.40%)	-	5,978 (+49.9%)	-
1	4,890 (-3.76%)	-	5,761 (-3.64%)	-	5,098 (+0.34%)	-	5,859 (-2.00%)	-
2	4,906 (+0.34%)	+7.93%	5,784 (+0.41%)	+15.48%	5,086 (-0.23%)	+9.17%	5,887 (+0.49%)	+16.13%
3	4,966 (+1.22%)	-0.73%	5,746 (-0.66%)	-1.30%	5,103 (+0.32%)	+0.14%	5,873 (-0.24%)	-0.58%
4	4,928 (-0.77%)	+0.26%	5,759 (+0.23%)	-0.01%	5,076 (-0.52%)	-0.14%	5,883 (+0.16%)	+0.14%
5	4,932 (+0.08%)	+0.18%	-	-	5,088 (-0.23%)	+0.01%	5,897 (+0.24%)	+0.05%
6	4,957 (+0.51%)	-0.06%	-	-	-		-	-
% change of final iteration against Base		+24.1%	+44.2%		+27.6%		+47.9%	
% change of final iteration against Iteration 0		-2.4%	-3.7%		+0.1%		-1.4%	

A summary of the simulation results is shown in Table 6-5.

Some insights into the AV implications can be gained from the simulation results: in general, the increase of the considered indicators' values is higher in Scenarios 2 and 4 than in Scenarios 1 and 3, which is as expected because of a more optimistic AV value of travel time decrease. While the difference among the scenarios with only road capacity changes seems much more moderate. Specific analyses are presented below.

Table 6-5. Simulation Results Summary of Transport Evaluators.

Measures		Base Scenario Value	Scenario 1 Value (% change against base)	Scenario 2 Value (% change against base)	Scenario 3 Value (% change against base)	Scenario 4 Value (% change against base)
#Persons who conducted at least one tour		22,333	22,289 (+0.2%)	22,360 (+0.1%)	22,317 (-0.1%)	22,426 (+0.4%)
#Tours		26,566	26,560 (-0.02%)	26,850 (+1.1%)	26,685 (+0.4%)	26,805 (+0.9%)
#Trips		64,642	67,792 (+4.9%)	68,408 (+5.8%)	68,152 (+5.4%)	68,266 (+5.6%)
Mode share (by trips)	PAV or Car (driver)	71.7%	86.4%	89.2%	87.0%	89.3%
	Bicycle	7.5%	4.1%	3.2%	3.8%	3.1%
	Walk	9.9%	4.9%	3.9%	4.7%	3.9%
	Car (passenger)	10.9%	4.6%	3.6%	4.4%	3.6%
Total distance traveled (100km)	PAV or Car (driver)	3,401	4,679 (+37.5%)	5,541 (+62.9%)	4,815 (+41.6%)	5,676 (+66.9%)
	Bicycle	136	74 (-45.6%)	61 (-55.1%)	74 (-45.6%)	58 (-57.3%)
	Walk	79	43 (-45.6%)	33 (-58.2%)	40 (-49.4%)	34 (-57.0%)
	Car (passenger)	372	161 (-56.7%)	124 (-66.7%)	159 (-57.3%)	129 (-65.3%)
Average trip distance (m)	PAV or Car (driver)	7,339	7,987 (+8.8%)	9,076 (+23.7%)	8,121 (+10.7%)	9,307 (+26.8%)
	Bicycle	2,792	2,681 (-4.0%)	2,756 (-1.3%)	2,813 (+0.8%)	2,746 (-1.6%)
	Walk	1,240	1,304 (+5.2%)	1,230 (-0.8%)	1,250 (+0.8%)	1,235 (-0.4%)
	Car (passenger)	5,287	5,134 (+2.9%)	5,028 (-4.9%)	5,246 (-0.8%)	5,288 (+0.02%)
Average speed among DAA mesh cells in AM Peak time (km/h)		33.57	31.63 (-5.8%)	31.06 (-7.5%)	33.07 (-1.5%)	32.36 (-3.6%)
%PAV Trips by persons unable to drive of total trips		-	10.4%	10.8%	10.7%	10.5%
%Tour that PAV or Car (driver) availability reassigned through Intra-household sharing		1.1%	10.8%	10.4%	10.7%	10.3%
%PAV zero-occupancy trips of total trips		-	4.8%	4.8%	4.9%	4.8%
%Total distance traveled attributed to PAV zero-occupancy trips		-	5.4%	5.3%	5.6%	5.6%

We first observed few changes in the number of persons who conducted at least one tour. The sensitivity of daily patterns seems relatively low for the applied DAS model, this will be explained more in the following (Figure 6-3). The increase of the scenarios with the more optimistic value of travel time settings (i.e., Scenario 2 and 4) is found to be larger compared to the other scenarios.

Regarding the number of trips, we found that PAV zero-occupancy trips account mostly for the increase. According to the second last row of Table 6-5, there are around 5% of the total trips are run by PAVs without occupants, all in their way to serve a certain member of the household. The ratios of PAV zero-occupancy trips are basically the same among the AV Scenarios, simply because AV features mentioned in Table 6-1 have no impact on the intra-household vehicle sharing behavior in this model system.

As for the modal share, as expected, PAV dominates all scenarios, taking more than 86% of all trips. An interesting finding is that among the PAV trips, 10.4%, 10.8%, 10.7%, and 10.5% in each AV scenario are performed by those who cannot drive at the current time, which means that a majority of the modal shifts can be attributed to the feature that AV requires no driving license anymore.

Total distances traveled show much larger changes than the number of tours and trips with 24.1%, 44.2%, 27.6%, and 47.9% overall increases (Table 6-4) estimated for Scenarios 1 to 4, respectively. The benefits from road capacity improvement are smaller by around an order of magnitude than the change in the value of travel time, similar to the findings by Auld et al. (2017). The increases in total distance traveled by PAV or car driver modes range from 37.5% up to 66.9% (Table 6-5), which are within the upper bounds of the results reported from the existing literature: 19.6% and 35.3% increases in vehicle miles traveled were reported by Childress et al. (2015, a scenario with 30% capacity increase and 35% perceived travel time benefit) and Auld et al. (2017, a scenario with 75% AV penetration, 50% value of travel time decrease, and no road capacity benefit), respectively.

We argue that the new PAV trips as a result of modal shifts and induced demand from those who cannot drive contribute considerably to the observed increases in PAV distances traveled. For

Scenario 1, the modal share of PAV increased from 71.7% to 86.4% with consequent decreases in other modes. Childress et al. (2015), for example, found at most a 1.1% increase in modal share. Regarding increases in trip distances, average trip distances increased by 8.8% in Scenario 1 and at most 26.8% under the most optimistic Scenario 4. This is in line with findings from the literature, where for example, Childress et al. (2015) found a 12.9% increase in average trip distances in the scenario mentioned above. Less travel impedance allows people to be able to choose somewhere more distant but with more activity facilities, including commuting.

Different geographical contexts and/or existing travel patterns (as compared to the contexts the literature has focused on) should also account for the differences in total distances traveled. For example, the average trip distance of 7.3km (Table 6-5) by car driver mode in Base Scenario is much smaller than the two aforementioned literature in American contexts.

PAV zero-occupancy trips as well contribute to more than 5% of the total distance traveled. As a result of PAV intra-household sharing, this is sometimes ignored by the existing literature, such as in a previous study of this dissertation (Luo et al., 2022).

At any rate, it is important to note that given the wide variety of models, data, and assumptions used in the literature, straightforward comparisons are somewhat difficult and should be done with a clear understanding of these limitations. On the other hand, given that the DAS model in this study did not explicitly control for time budgets in the choice set definition, there is a risk of overestimation of travel distances, in that some individuals may choose destinations that are so far away that they reduce the available time for undertaking their next activities. Further analysis is required to address this issue, such as incorporating an activity duration model in the system.

We also showed the results of average speed among the DAA mesh cells in Table 6-5 to evaluate the impacts on traffic flow characteristics. With longer total distances traveled, the average speed in the central area of Gunma is found reduced in all AV scenarios, as expected. The magnitude of changes is found to deteriorate by around 2% in the scenarios with more optimistic values of travel time settings (e.g., -1.5% in Scenario 3 and -3.6% in Scenario 4), which causes longer total distance traveled. However, the benefits from road capacity increased the average speeds by around 3 to 4% (e.g., -3.6% in Scenario 4 compared to -7.5% in Scenario 2), suggesting the results were more sensitive to changes in road capacity.

A comparison of daily pattern choice among the three scenarios is shown in Figure 6-3. It seems that no substantial changes occur by and large. Presumably, the reason for this is that Day Activity Pattern level of the DAS model set the logsum coefficients (which reflect the changes from AVs) identical across patterns with the same purpose of tours, which is a convention in such types of models to be estimated as an "informal" nested logit manner (Li, 2015).

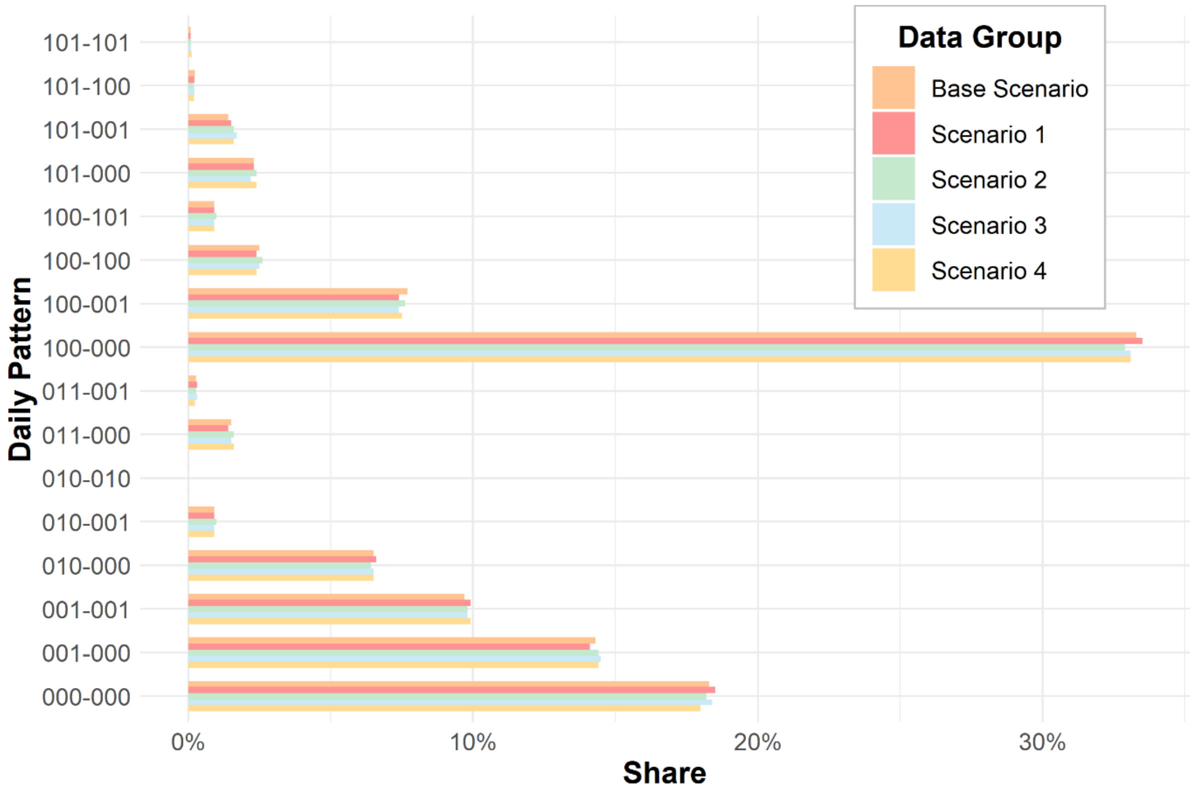


Figure 6-3. Comparisons of Simulation Results of Daily Pattern Choice.

Given the substantial increase in total distance traveled, vehicle emission implications can also be expected to be considerable. We here provide a basic calculation of AV's environmental impacts on the basis of the model suggested by the National Institute for Land and Infrastructure Management (Dohi et al., 2012) that has been regressed from observed data in the Japanese context:

$$EF = \frac{A}{v} + B \times v + C \times v^2 + D$$

Where *EF* is the emissions per kilometer released along with vehicle running, v is the average running speed (km/h), *A, B, C, and D* are the regression parameters (Dohi et al., 2012) varying with the emission types and other contexts.

By assuming the average speed among the DAA mesh cells in AM Peak time as the representative values and a fleet of vehicles with the 2015 ratio of hybrid vehicles and ordinary internal combustion engine vehicles (hybrid vehicles account for 7.2% of the fleet as of 2015; AIRIA, 2022), we show the emission implication results for the scenarios in Table 6-6.

These results indicate substantial emission increases of all types. As expected, the increasing rates are largely similar to the ones of total distance traveled, which is considered the major contributor to the emission outcomes. Note, however, that in this calculation, specific patterns of vehicle acceleration and deceleration, as well as cold starts and warm starts were not incorporated. Nonetheless, we believe these results could provide a basic image and some caveats for the future AV introduction regarding the environmental impacts, which is difficult to be measured even in some composite indicators such as accessibility that are to be discussed in the next section.

Table 6-6. Environmental Impacts of AVs.

Environmental Impact (kg)	**Base Scenario**	**Scenario 1**	**Scenario 2**	**Scenario 3**	**Scenario 4**
	Value	Value (% change against base)	Value (% change against base)	Value (% change against base)	Value (% change against base)
CO_2	41,828.0	53,383.5 (+27.6%)	62,556.7 (+49.6%)	53,659.5 (+28.3%)	62,827.3 (+50.2%)
NO_x	22.0	28.5 (+29.5%)	33.5 (+52.3%)	28.4 (+29.1%)	33.4 (+51.8%)
SPM (Suspended Particulate Matter)	1.4	1.7 (+21.4%)	2.0 (+42.9%)	1.8 (+28.6%)	2.1 (+50.0%)
CO	301.1	403.7 (+34.1%)	479.8 (+59.3%)	391.2 (+29.9%)	466.4 (+54.9%)
SO_2	1.9	2.5 (+31.6%)	2.9 (+52.6%)	2.5 (+31.6%)	2.9 (+52.6%)

It is important to note that as the Japanese government pushes for Well-to-Wheel Zero Emissions automobile transport through the wide adoption of hybrid, electric, and hydrogen vehicles (METI, 2018), the negative environmental implications of PAVs are expected to be partially mitigated, however, a detailed analysis of these changes is beyond the scope of this article.

6.4 Activity-based Accessibility Analysis

For the AV Scenarios, individual specific Activity-based Accessibility (ABA, see Sub-section 3.2.2) is then computed to offer a more comprehensive measure for the AV implications in transport. The ABA for individual *n* is formulated as:

$$ABA_n = \ln\left(\sum_{dp \epsilon C_n} e^{V_{dp_n}}\right) + C$$

Where *dp is* the daily activity pattern in the pattern choice set C_n, V_{dp_n} the systematic component of utility of *dp* for *n*, and *C* the constant represents the absolute value of utility in that MNL specification.

Normalization is done following Dong et al. (2006) and Nahmias-Biran et al. (2021) to make ABA satisfy both Level Condition and Scale Condition as:

$$ABA_n^{normalized} = \frac{ABA_n - ABA_n^{original}}{\alpha_{nt}}$$

Where α_{nt} is the scaling factor that approximates the marginal utility of travel time *t* by measuring the change in ABA with 1 unit change of *t* (1min is adopted for the convenience of analysis):

$$\alpha_{nt} = \frac{ABA_n^{\Delta t} - ABA_n}{\Delta t}$$

And $ABA_n^{original}$ is the original ABA before the change in policy or the transport system, which means the normalized ABA value is calculated against Base Scenario in this dissertation. Note that since logsum from the Time of Day level is not incorporated in the applied DAS model, travel impedance from AM Peak is used in the ABA calculation.

Based on this procedure, the travel-time-based normalized ABA can thus be interpreted as the change in travel-time-based utility (utility-equivalent time) with the introduction of PAVs for each individual under the scenario settings.

The change distributions of ABA under the four AV Scenarios across the whole demand sample are shown in Figure 6-4, and descriptive statistics are shown in Table 6-7.

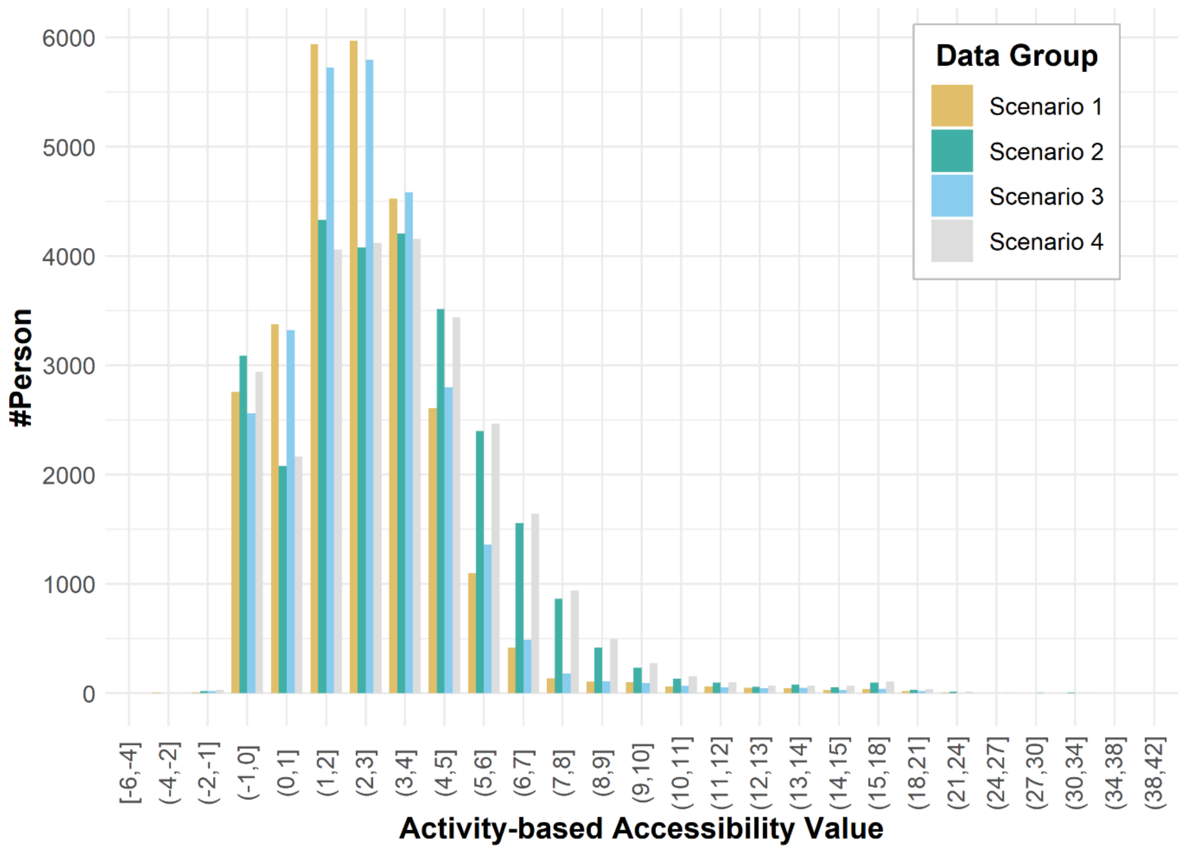


Figure 6-4. Distribution of Activity-based Accessibility under AV Scenarios against Base.

Table 6-7. Summary to Activity-based Accessibility under AV Scenarios against Base.

Normalized ABA values against Base Scenario (min)	Descriptive summary				
	Mean (95% confidence level)	Median	Min.	Max.	Standard Deviation
Scenario 1	2.48 (± 0.025)	2.26	-5.54	35.65	2.15
Scenario 2	3.32 (± 0.033)	3.02	-2.46	40.24	2.79
Scenario 3	2.58 (± 0.026)	2.36	-4.24	36.05	2.18
Scenario 4	3.41 (± 0.034)	3.09	-2.91	40.81	2.85

The ABA is found on average to increase by around 2 and 3 min, respectively, across the entire study region in the four AV scenarios. Yet, the variance in ABA seems to be large across the demand sample and the level of gain is highly dependent on each individual's demographic characteristics and residence location. For example, according to Figure 6-4, there are a group of people negatively affected by the prevalence of PAVs as their ABA being less than zero. By investigation, those who found with negative ABA can be classified into three groups: the first being those whose households have no access to an HV in original and by assumption are not PAV available, thus enjoying nothing from PAV but suffering from the congestion (Table 6-5); the second being those who reside in the relatively urban center area where most likely to bear more congestion effect induced by PAV for lower road network level of service; the third being those who had access to HV but not to PAV as a result of the changes in vehicle use priority rules in the household level (Sections 5.4 & 6.1)

As for other demographics, Figure 6-5 and Table 6-8 show the ABA changes under Scenario 4 by the segment of employment status.

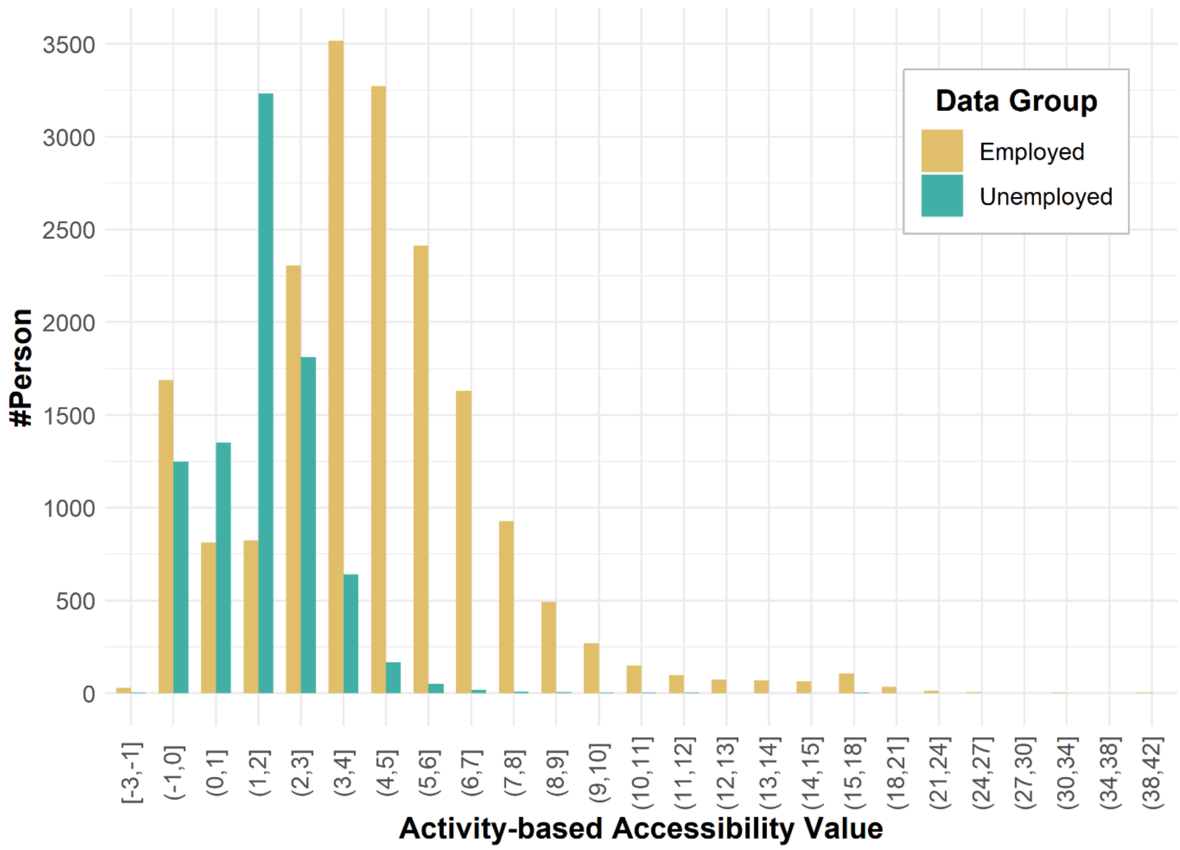


Figure 6-5. Distribution of Activity-based Accessibility under Scenario 4 by Employment Status.

Table 6-8. Summary to Activity-based Accessibility under Scenario 4 by Employment Status.

Normalized ABA values versus Base Scenario under Scenario 4 (min)	Descriptive summary				
	Mean (95% confidence level)	Median	Min.	Max.	Standard Deviation
Employed people	4.25 (± 0.042)	4.06	-2.91	40.81	2.97
Unemployed people	1.57 (± 0.027)	1.54	-1.87	21.82	1.29

It suggests that employed people benefit more than the unemployed, which is intuitive as the utility gains for the unemployed are limited to other-purpose tours. On the other hand, the employed people combine their gains from multiple types of tours.

To evaluate the spatial pattern of changes in ABA more clearly while controlling for the effects of all the covariates, we estimated ABA for a representative individual. Specifically, this representative individual was replicated and assigned to reside on each mesh cell (one per cell), respectively, in the resident's mesh dataset, being the anchors for calculating ABA. A 39-year-old full-time male worker who has no kid and has access to bicycle and car (HV and PAV depending on the scenario) is selected. The ABA under Scenario 4 of the representative person across the study region is shown in Figures 6-6 and 6-7. Note that normalization was not conducted as we are examining the "same" individuals.

As expected, the absolute level of ABA (Figure 6-6) across the region indicates that urban centers have higher travel accessibility compared to the outskirts. However, when looking at relative changes (Figure 6-7), the ABA gains are higher in the suburbs and outskirts of the region. In other words, it could be expected to have less difference in the sense of transport accessibility between the urban centers and other areas in the time of AVs. This is one of the basic rationales of this research to examine the change in residential locations with the prevalence of AVs (Luo et al., 2019; Gelauff et al., 2019). The following chapters will investigate this issue in detail.

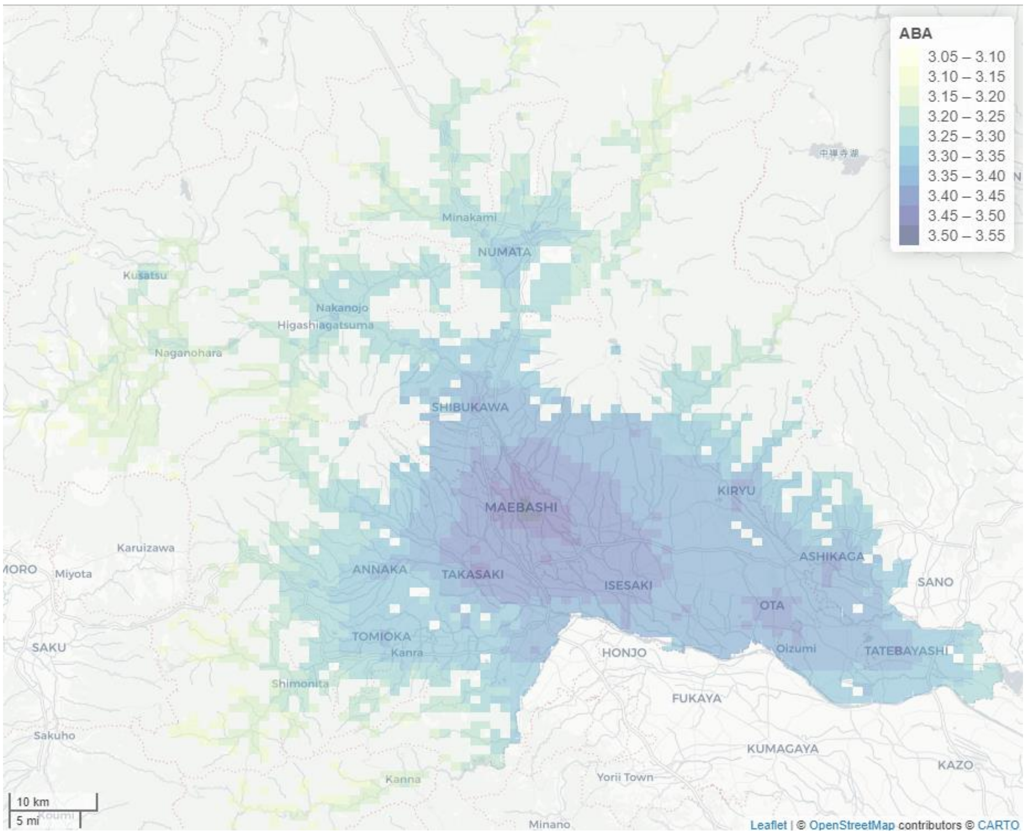


Figure 6-6. Activity-based Accessibility of Representative Person under Scenario 4.

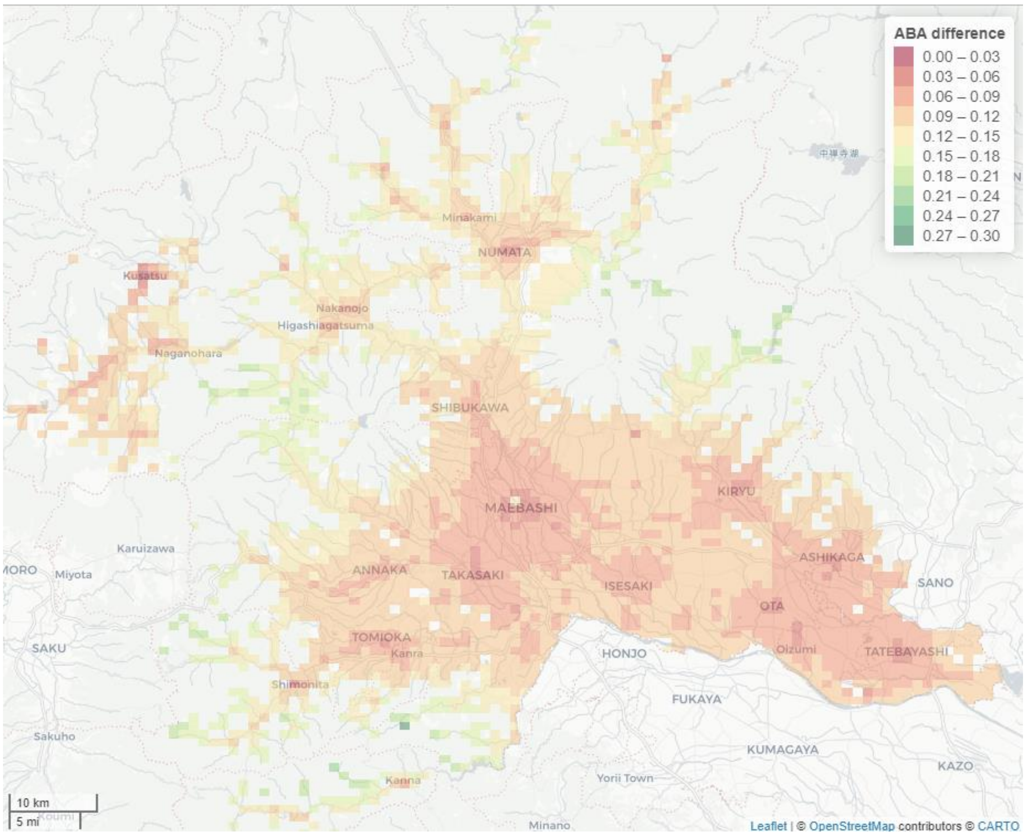


Figure 6-7. Activity-based Accessibility of Representative Person under Scenario 4 against Base.

CHAPTER 7 RESIDENTIAL LOCATION MODEL SPECIFICATION

This chapter focuses on the residential location model for long-term forecasting. Before presenting the model specification and estimation results, land use data processing is first conducted to prepare some necessary attributes besides those that have been used for the DAS model. Following the estimation, a simple validation is also presented to demonstrate the reliability of the model.

7.1 Housing Stocks and Land Price Model

Although two types of land use datasets called Resident's Mesh Dataset and Activity System Mesh Dataset have been processed and prepared in the transport model calibrations (Sub-section 3.4.1), there are some other attributes are considered necessary in modeling residential locations. Among others, the number of housing stocks and land price per mesh cell are considered of more significance as they represent measurements from the supply side in the urban residence market.

The number of housing stock data is currently not available in the Tertiary Mesh level in Japan[7]. Hence, they must be approximated by allocating city-level data with other mesh-level attributes as the weights. This research adopts the land use type area ratio by mesh cell from Land Use Mesh Data (MLIT, 2018a) as well as Land Use Subdivided Mesh Data of Urban Area (MLIT, 2018b) to serve the weight. The former gives information on the ratio of buildings per each mesh cell across Japan without details, while the latter provides the ratio of buildings for the urban area within four categories: area of buildings with more than 4 floors; area of buildings with less than 3 floors; area of densely distributed buildings with less than 3 floors; and area of industrial buildings. We adopt an empirical practice to calculate the weight of buildings for mesh cell m in the study region as:

$$w_m = a_{building_{low-floor}} + 3 \times a_{building_{densely-low-floor}} + 2 \times a_{building_{high-floor}}$$

[7] An attempt to collect and aggregate parcel-level data, such as Zmap-TOWN Data from ZENRIN Co., Ltd. (https://www.zenrin.co.jp/product/category/gis/basemap/zmaptown/index.html) has been made. Unfortunately, the attributes of the building names (for speculating the type of the building) and the number of floors (for speculating the dwelling density of the building) are missing to a great amount, hence it is decided to not use them in this dissertation.

Where, w_m is the weight of buildings for mesh cell *m*, *a* is the area of buildings of the specific category just mentioned above, which are annotated in the subscript. The coefficients of each *a* are identified through multiple empirical tests as a "practically good" combination in the sense of matching the population distribution from the Japanese National Census 2015.

For those outside the urban area, where no data is available from Land Use Subdivided Mesh Data, the weight of` building is simply the area of buildings. This should make sense as we expect that the density and floors do not vary so much in suburban or country areas as in urban areas.

Housing stock data at the city-level is obtained from the Housing and Land Census 2018 of Japan (Statistics Bureau of Japan, 2018). The results of allocated housing stock by each mesh cell are shown in Figure 7-1. Note that even the city-level data on housing stock is not complete, data from some small cities are absent. For these cities, the city-level data are allocated from the prefecture-level data by the sum of the weight of buildings (calculated above) for each city.

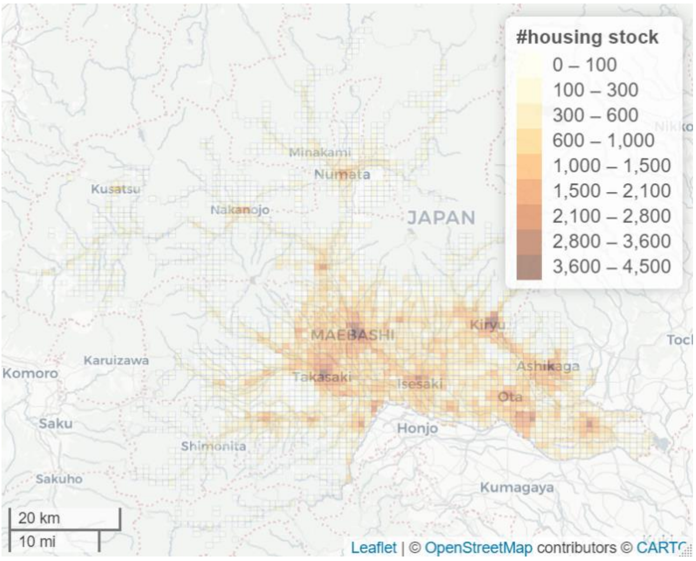


Figure 7-1. Approximated Housing Stock by Mesh Cell in Gunma PT Area.

Land price data are available from Land Value Publication Data (MLIT, 2016), a dataset containing values for "standard sites" that are selected by the governments to guide the transactions in the land market. The data for the year 2016 was used as it is the year the 2015 Gunma PT survey finished. In total, land prices of 824 sites that locate inside Gunma and Ashikaga city are obtained and are illustrated in Figure 7-2.

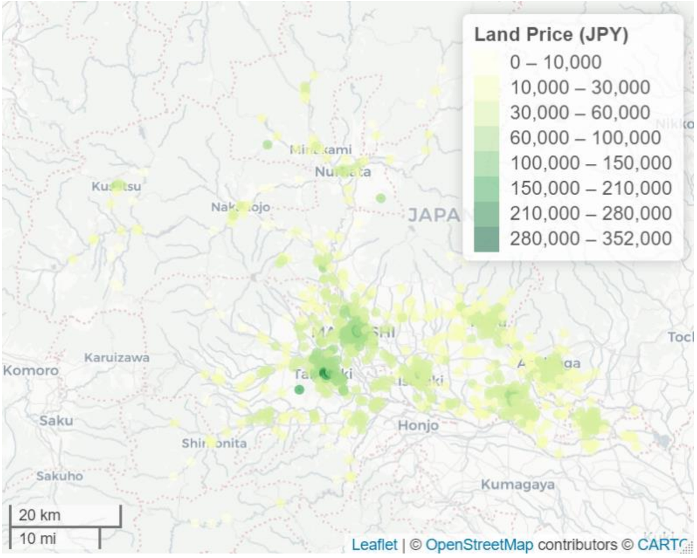


Figure 7-2. Land Prices for the Standard Sites in Gunma PT Area.

To get the land price data at the mesh cell level, a simple Hedonic Model was developed and estimated. The land price data of the Standard Sites are considered as the observed values which are then spatially merged with the Resident's Mesh Dataset (take the average price value if multiple sites are found in one mesh cell).

The Hedonic Model of land price is structured in linear regression, based on 557 mesh cells with the merged land price values. Its estimation results are shown in Table 7-1. For simplicity, spatial issues such as spatial dependence and spatial heterogeneity are not considered.

Three logsum variables are added as independent variables in the Hedonic Model. They are calculated from the Tour Mode and Destination Level of the DAS model (Sub-section 5.3.4) to represent the tour-based transport accessibility for the specific mesh cell. Representative individual demographics are assumed for the calculations of each tour purpose:

- Tour-based Logsum of work-purpose and other-purpose: 30-year-old males with both car and bicycle available.
- Tour-based Logsum of education-purpose: 10-year-old female primary school students with neither car nor bicycle available.

Plus, the tours with work- and education-purpose are assumed to be the primary tour, while other-purpose tours are not the case. Also, at least one trip stop is assumed to be made for the work-purpose tour, yet the other two types have none.

Table 7-1. Estimation Results of Mesh Cell Level Land Price Hedonic Model.

Dependent variable: natural log of land price (JPY per meter squared)			
Data Source	**Variable**	**Coefficient**	**T Value**
-	Intercept	7.83	*27.52*
Housing and Land Census 2018 (Processed)	#Housing stock		*-0.64*
DAS model	Tour-based logsum of work-purpose	0.15	*5.02*
	Tour-based logsum of education-purpose	0.043	*6.91*
	Tour-based logsum of other-purpose	0.13	*4.91*
Boundary Data in Economic Census Data 2016	Is Takasaki City	0.30	*6.37*
	Is Maebashi City	0.21	*4.37*
	Is Ota City		*-0.34*
	Is Isesaki City		*-0.89*
	Is Kiryu City	-0.11	*-1.81*
Land Use Mesh Data	Ratio of agricultural use area	-0.48	*-3.80*
	Ratio of forest area		*-0.46*
	Ratio of freshwater use area		*-0.15*
Land Use Subdivided Mesh Data of Urban Area	Ratio of industrial use area	-0.58	*-2.27*
#Count	557		
Adjusted R squared	0.728		
F statistic	115.4		

The high R squared shown in Figure 7-1 suggests a good performance in fitting the training data. As result, a mesh cell being transport accessible for all three types of tour, and with fewer areas used for either agricultural or industrial use are likely to have high land prices. Being in Takasaki or Maebashi City is considered as a merit, but not so if the mesh cell belongs to Kiryu City, all else being equal.

The predicted land price by each mesh cell based on the estimated Hedonic Model is presented in Figure 7-3. The land price will be used in the residential location model as one of the land use variables and to be a proxy for residence price. The failure to retrieve mesh cell level residence price should be considered as one limitation of this study.

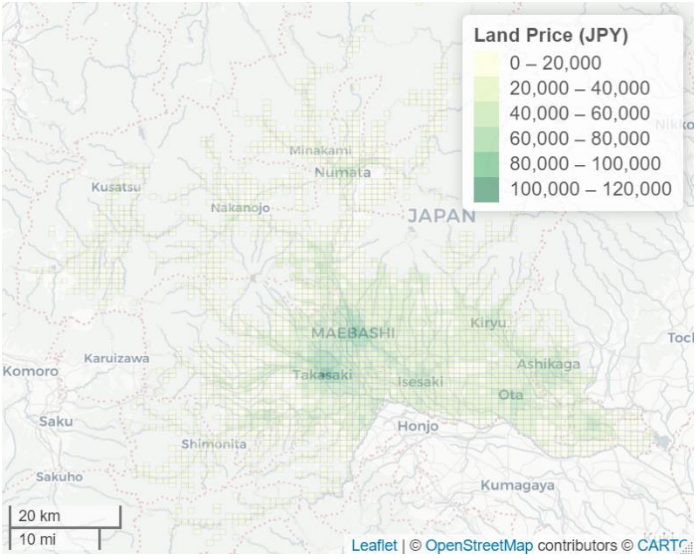


Figure 7-3. Predicted Land Price by Mesh Cell in Gunma PT Area.

7.2 Model Specification and Estimation

This research follows the residential location model specification that was proposed by Ben-Akiva and Bowman (1998) as an integrated model connected to an activity-based model system. The residential model is specified as an MNL model at household level, where the observed component of the utility of residential location *l* for household *i* is of two parts:

$$V_{il} = \beta X_l + \alpha A_{i|l}$$

Where X_l is the attributes of *l*, $A_{i|l}$ is Activity-based Accessibility value (Section 6.4): the expected utility calculated from the Day Activity Schedule model, the top level of DAS model, of household *i* given residential location *l, and* α, β are coefficients to be estimated. Specifically, three types of $A_{i|l}$ are included in this research:

$$A^{W}{}_{i|l} = \frac{\sum_{w \in W_i} A_{w|l}}{W_i}$$

$$A^{S}{}_{i|l} = \frac{\sum_{s \in S_i} A_{s|l}}{S_i}$$

$$A^{U}{}_{i|l} = \frac{\sum_{u \in U_i} A_{u|l}}{U_i}$$

Where $A^w{}_{i|l}$, $A^s{}_{i|l}$, $A^u{}_{i|l}$ are the average Activity-based Accessibility for workers, students, and unemployed people in the household *i,* respectively. These three terms are pre-calculated and estimated as three independent variables with corresponding coefficients α. The average ABA term of each person type would not be included in the utility function if that household has no member with the specific person type. The ABA of each household member is normalized following the calculations introduced in Section 6.4, the original ABA for individual $n\ ABA_n{}^{original}$ in this case refers to the ABA of *n* given the current home location of *n*'s household.

This residential location choice model is conducted on the 1km-mesh-cell level, the same as what has been applied in the destination choice levels of the DAS model (e.g., Sub-section 5.3.4). The choice alternatives for residential location are the 2,794 1km mesh cells in Resident's Mesh Dataset (Sub-section 3.4.1). For each household 50 alternatives are sampled from the whole mesh set with Importance Sampling with Replacement (Ben-Akiva & Lerman, 1985), the observed alternative would randomly replace one sampled alternative if it is not found in the alternative set. Only one attribute, mesh cell level land price, is used as the sampling weight in this procedure. Two correction terms concerning aggregated alternatives and alternative samplings are added (Sub-section 5.3.4): the housing stocks of each mesh cell are used as the size variable; the natural log of the inverse of the sampling probability is used to cancel out the bias in the alternative sampling.

The same estimation data sample that has been used in the DAS model (Section 5.3) is applied for the residential model estimation. 13,140 households in the dataset are exogenously divided into five market segments with similar sizes by the age of the household head and the number of household members to accommodate the heterogeneity by demographics. Two levels of the age: 50 and 65, and one level of the number of household members: 3, are applied for the segmentation following an assumption that these two household-level characteristics have effects on the residential location patterns. For example, one could expect a two-member household with a household head younger than 50 would consider differently (for example, tend to consider a more "temporary" residence) than a three-member household with a household head older than 50 in terms of accessibility and other land use characteristics.

The estimation results, as shown in Table 7-2, demonstrate expected coefficient signs of household average ABA and land price, which indicate that the trade-off between transportation and housing cost is well captured. Besides that, all households are found to prefer a mesh cell with fewer buildings, fewer farmlands, more forests, and fewer number no matter the job category, and is governed by the two big cities in the study region, Takasaki and Maebashi, all else being equal. The preferences also vary across different market segments: for example, those small-size households with a senior head in age (Segment #4 and #5) do not take transport accessibility for students into concern for their residential location choices. This makes sense as students in these two types of households are usually absent.

The segmented models are checked if they outperform their corresponding pooled model by a Chi-square test (Ben-Akiva & Lerman, 1985) of:

$$-2\left(LL_{pooled} - \sum_{g \in G} LL_g\right) \sim X^2_{(\sum_{g \in G} K_g) - K_{pooled}}$$

Where LL_{pooled} and LL_g are the log likelihood with parameter coefficients from the pooled model structure and the segmented model *g*, respectively. *G* is the total number of the market segment used and K_{pooled}, K_g, are the number of parameters in the pooled model and segmented model, respectively. As result, the chi-square test score is calculated[8] as 3,554.36, a value higher than $X^2_{45,0.001}$ of 80.08. Hence, we can reject the null hypothesis that the segmented models are no better than the pooled one.

[8] The estimation results for the pooled model are omitted here, its log likelihood is -37809.84.

Table 7-2. Estimation Results of Residential Location Model.

Market segments	Segment #1		Segment #2		Segment #3		Segment #4		Segment #5	
Age of the head of household[9]	(6,50]		(6,50]		(50,100]		(50,65)		[65,100]	
#Household members[10]	3 or more		1 or 2		3 or more		1 or 2		1 or 2	
Variable	Coef.	T Val.	Coef.	T Val.	Coef.	T Val.	Coef.	T Val.	Coef.	T Val.
Household average ABA for workers	0.63	*57.86*	0.62	*57.91*	0.40	*45.24*	0.43	*45.93*	0.33	*34.65*
Household average ABA for students	0.060	*8.35*	0.12	*6.36*	0.026	*2.47*		*0.60*		*0.98*
Household average ABA for unemployed people	0.17	*10.45*	0.28	*11.43*	0.24	*19.18*	0.37	*23.56*	0.61	*49.91*
Land price (10,000 JPY per km^2)	-1.24	*-21.81*	-0.74	*-13.89*	-0.84	*-17.05*	-0.82	*-15.57*	-0.73	*-16.73*
Ratio of buildings use area	-1.17	*-10.89*	-1.21	*-11.84*	-0.56	*-5.67*	-0.75	*-7.34*	-0.58	*-6.90*
Ratio of agricultural use area	-2.09	*-10.26*	-1.77	*-8.45*	-0.92	*-4.99*	-1.25	*-6.12*	-0.85	*-5.04*
Ratio of freshwater area		*-0.06*		*1.15*	0.31	*1.91*		*0.98*	0.41	*2.66*
Ratio of forest use area	0.74	*3.34*	0.70	*3.13*	1.18	*6.43*	1.16	*5.78*	1.41	*8.76*
Is Takasaki city	0.73	*5.86*		*0.038*	0.42	*3.91*	0.30	*2.51*	0.64	*6.57*
Is Maebashi city	0.24	*2.28*		*-0.42*	0.26	*2.93*	0.29	*2.98*	0.73	*9.14*
Is Ota city	-0.73	*-7.97*	-0.59	*-6.67*	-0.48	*-5.90*	-0.40	*-4.58*	0.13	*1.82*
Is Isesaki city	-0.69	*-7.39*	-0.61	*-6.60*	-0.54	*-6.26*	-0.52	*-5.61*		*-0.94*
Is Kiryu city	-0.37	*-3.15*	-0.32	*-2.67*	-0.24	*-2.54*	-0.35	*-3.21*		*-1.56*
#Employees of Primary and Secondary Sector	-0.10	*-13.31*	-0.054	*-9.30*	-0.065	*-8.86*	-0.067	*-8.70*	-0.023	*-4.55*
#Employees of Tertiary Sector	-0.033	*-9.08*	-0.038	*-11.87*	-0.047	*-11.42*	-0.022	*-6.97*	-0.048	*-47.82*
Size variable: Housing stock	1.00	-	1.00	-	1.00	-	1.00	-	1.00	-
#Observations	2,630		2,554		2,578		2,192		3,186	
Initial likelihood	-9,477.81		-9,128.47		-9,407.29		-7,953.38		-11,534.37	
Final likelihood	-6,406.43		-6,142.27		-7,586.59		-6,335.93		-9,561.44	
Adjusted rho squared	0.322		0.325		0.192		0.201		0.170	

[9] The first respondent for each household in the PT survey, called "世帯主" in Japanese.

[10] Household members with ages less than six are counted, but not included in logsum calculation.

7.3 Model Validation

Validation of the residential location model is also performed to prove its reliability. The validation sample data, as used in Section 5.4, with a 20% random sample of the effective 2015 PT data are used for the purpose.

The first type of indicator used for the validation is network distance to the closest center area, to represent the feature of the residence pattern in a polycentric area like Gunma. The concepts of Urban Function Attraction Area (UFAA) and Dwelling Attraction Area (DAA) introduced in Sub-section 3.4.1 are considered appropriate to define these center areas by their definitions. Therefore, the network distance from a residence to its closest UFAA and DAA, respectively, are taken as the major evaluation metrics.

Validation results are obtained as the average values of 10-time Monte Carlo simulations of the residential location choice model. Shown in Tables 7-3 and 7-4 are summaries of the statistics, and Figures 7-4 and 7-5 are illustrations of the spatial distributions.

Table 7-3. Validation Results of Network Distance to the Closest DAA (m).

Network distance to the closest Dwelling Attraction Area (m)	Mean	Median	Standard Deviation
Observed	3,172	1,237	7,308
Simulated	2,265	1,222	5,425
Observed (data farther than 10,000m removed)	1,658	1,158	2,149
Simulated (data farther than 10,000m removed)	1,561	1,195	1,928

Table 7-4. Validation Results of Network Distance to the Closest UFAA (m).

Network distance to the closest Urban Function Attraction Area (m)	Mean	Median	Standard Deviation
Observed	4,297	2,298	7,245
Simulated	3,458	2,170	5,567
Observed (data farther than 10,000m removed)	2,712	2,067	2,299
Simulated (data farther than 10,000m removed)	2,626	2,059	2,220

According to the comparisons of the summary statistics in Tables 7-3 and 7-4, the estimated residential location choice model has good reproducibility in predicting the median value of the distance to both the nearest UFAA and DAA.

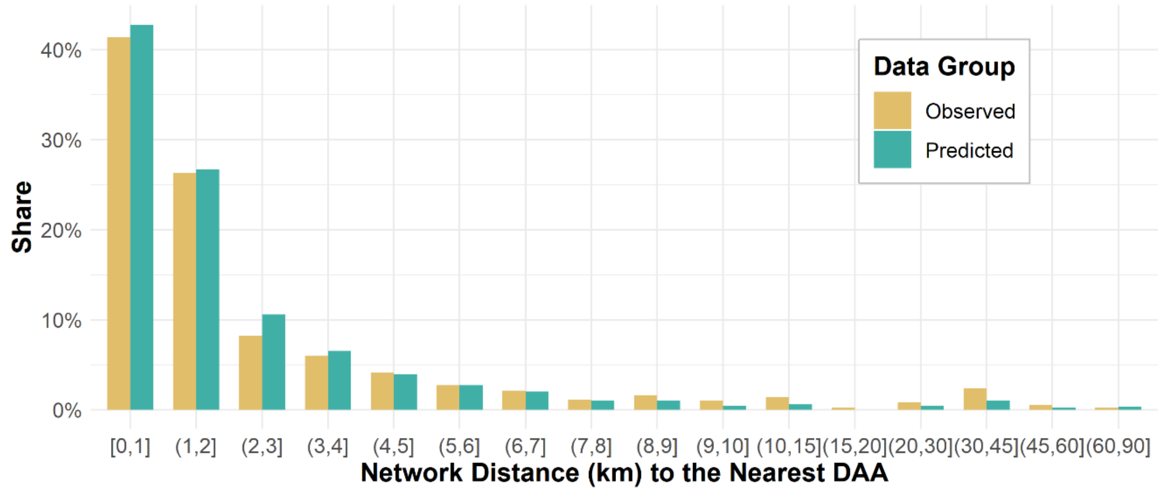


Figure 7-4. Validation Results of Distribution of Distance to the Nearest DAA (m).

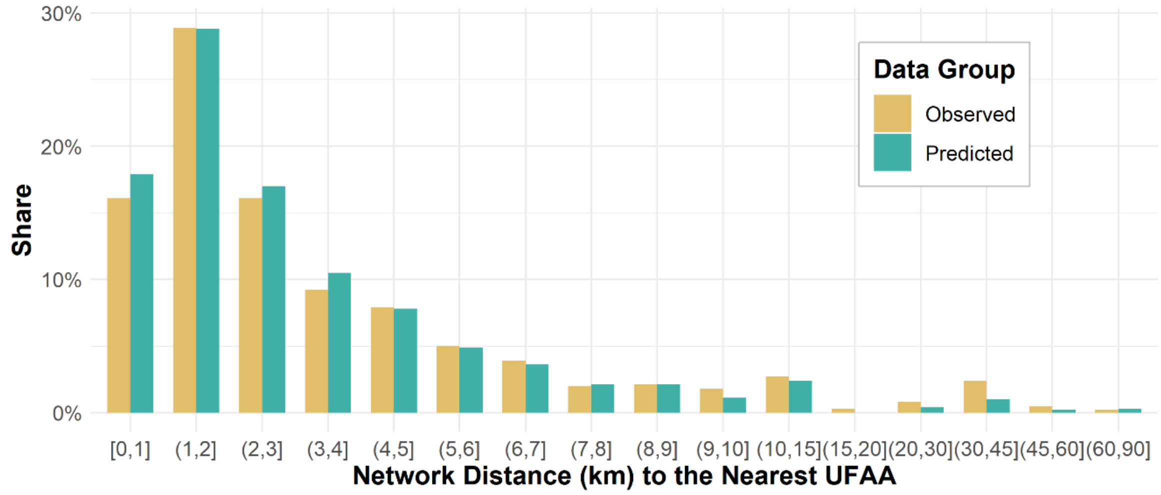


Figure 7-5. Validation Results of Distribution of Distance to the Nearest UFAA (m).

However, it is not the case for mean values where the simulated value is around 20% smaller than the observed one. The discrepancies are well explained by Figures 7-6 and 7-7, where the share of those who reside more than 10,000m and 20,000m away from their closest UFAA or DAA, respectively, are underpredicted by more than 50%. These extreme values affect to a great extent the mean values, hence causing discrepancies in the validation. Some variables concerning the historical influence (e.g., some seniors might just prefer to keep living in remote areas where their ancestors have long been residing) could be advised to be added to the model estimation in the future, as we are currently not accessible to such data. Also shown in Tables 7-3 and 7-4, the difference between the mean values after removing those that are farther than 10,000m is much narrower, which should support the speculation above.

Another simpler indicator: the ratio and count of households residing in DAA are also assessed, which is more straightforward to comprehend and will serve as one of the policy evaluators. Its validation results are shown in Table 7-5, where the simulated values are also averaged from 10 time repeated simulations.

Table 7-5. Validation Results of Ratio of Household Residing in DAA.

Ratio and Count of Household Residing in Dwelling Attraction Area	Count	Ratio (total #household = 3,285 in the validation dataset)
Observed	1,328	40.4%
Simulated (data farther than 10,000m removed)	1,344	40.9%

In summary, the estimated model shows sufficient reproducibility and is adequate for forecasting. However, as bias caused by the extreme values is confirmed, the subsequent analyses will focus on the median statistic for the distance indicators.

CHAPTER 8 RESIDENTIAL LOCATION MODEL APPLICATIONS AND EVALUTIONS

This chapter simulates the residential location model built in the previous chapter to assess the residential location pattern change under the AV Scenarios. Two hypothetical policy mandates are then imposed as attempts to mitigate the potential side effects of the AV introduction.

8.1 Model Application Settings

The four AV Scenarios plus Base Scenario proposed in Section 6.1 (Table 6-1) are applied to the residential location model proposed in Chapter 7 in a stochastic microsimulation way (Section 5.4). The inputs for all the scenarios are in their transport convergence states (Section 6.3). The worth mentioning settings and assumptions that are used through the simulation process are presented as follows.

Regarding the residence moving choice, we assumed that the households would decide to move or not every five years following the observed moving choice results currently in the study region. To elaborate, the moving choice is applied based on the data from the National Census (Statistics Bureau of Japan, 2015) that recorded the probability of whether households still reside where they were 5 years ago. The probability of whether a household would move by 2040 is calculated as:

$$P_a = 1 - {R_a}^5$$

Where, P_a is the probability of moving by 2040 for the category *a* by the age of the head of household. R_a is the ratio of household stayed between 2010 and 2015 for category *a*. The fifth power means that there are five periods of five years between 2015 and 2040. R_a and the results of P_a for each *a* are shown in Table 8-1. Monte Carlo simulations are then run to decide whether the household would move before simulating the residential location choice.

Table 8-1. Probability of Residence Moving Behavior.

Age of the head of household	(0,15)	[15,19]	[20,24]	[25,29]	[30,34]	[35,39]	[40,44]	[45,49]
Ratio of the not moved last five years	0.500	0.0360	0.0542	0.135	0.262	0.467	0.648	0.755
Probability of moving by the target year	0.969	1.000	1.000	1.000	0.999	0.978	0.885	0.755
Age of the head of household	[50,54]	[55,59]	[60,64]	[65,69]	[70,74]	[75,79]	[80,84]	[85,)
Ratio of the not moved last five years	0.827	0.878	0.911	0.931	0.947	0.957	0.962	0.965
Probability of moving by the target year	0.612	0.478	0.372	0.302	0.237	0.197	0.177	0.161

This treatment of moving behavior should be considered a limitation of this approach as the moving choice is supposed to be formulated as a model dependent on various demographics of the household, its current (or even earlier) residential location, etc. Such model structure can be found, for example, in the updated version of UrbanSim (Bierlaire et al., 2015). Incorporating this dimension of choice would yield more realistic forecasts for future residential location patterns. In this case, one can consider the moving choice is executed via a very fundamental model, which assumes the current behavioral preference to hold in the next 25 years with only one variable considered.

Second, as mentioned in also Section 6.1, the demographic patterns across the population in 2040 are assumed the same as in 2015. This could seriously limit the long-term forecasting reliability and policy response sensitivity.

Third, for each household, 25 sampled alternatives of mesh cells are provided as the choice set with the same sampling methods and correction terms as having been done in model estimation (Section 7.2).

Fourth, Activity-based Accessibility is pre-calculated for each sampled alternative in the choice set given the AV settings. The original ABA for individual *n* (${ABA_n}^{original}$) in the normalization procedure (Sections 3.2.2 & 6.4) refers to the ABA of *n* given the current home location of *n*'s household with the HV settings. One minute of travel time is still applied to satisfy the Scale

Condition and for the convenience of the following analyses.

Fifth, land prices are updated for each scenario before the residential location simulation. This is necessary because the impedance levels, which vary with different scenario settings, affect the tour-based logsum calculation, which is used in the land price model (Section 7.1).

Last, the land use loop in Figure 3-1 is not implemented for the current simulation results due to the high computational burdens. Ideally, the effects of the changed residential location choice should be captured to provide more reliable forecasts in transport, and land use as well.

8.2 Model Simulation Results of Automated Vehicle Scenarios

After Monte Carlo simulations, we have predicted the residential location for each household in 1km mesh cell level for Base and AV Scenarios.

The distributions of the number of households by mesh cell are firstly shown in Figures 8-1 to 8-5 for Base and AV Scenarios. The results under AV scenarios are presented with difference values against the Base Scenario. The legends for the AV Scenarios are shown with the same legend for the purpose of comparison.

Compared to the Base Scenario, moving trends from the center areas (Sub-section 3.4.1) can be found in all four AV Scenarios, with Scenarios 2 and 4 found with higher extents.

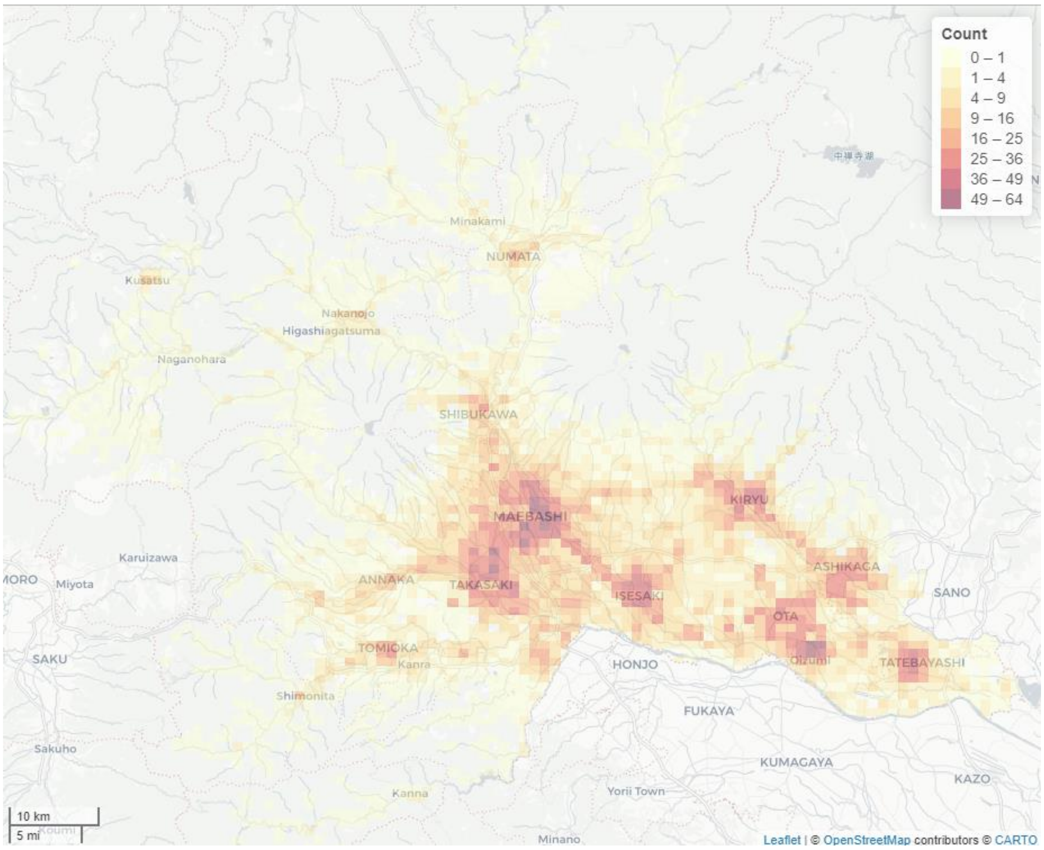


Figure 8-1. Number of Households by Mesh Cell of Base Scenario.

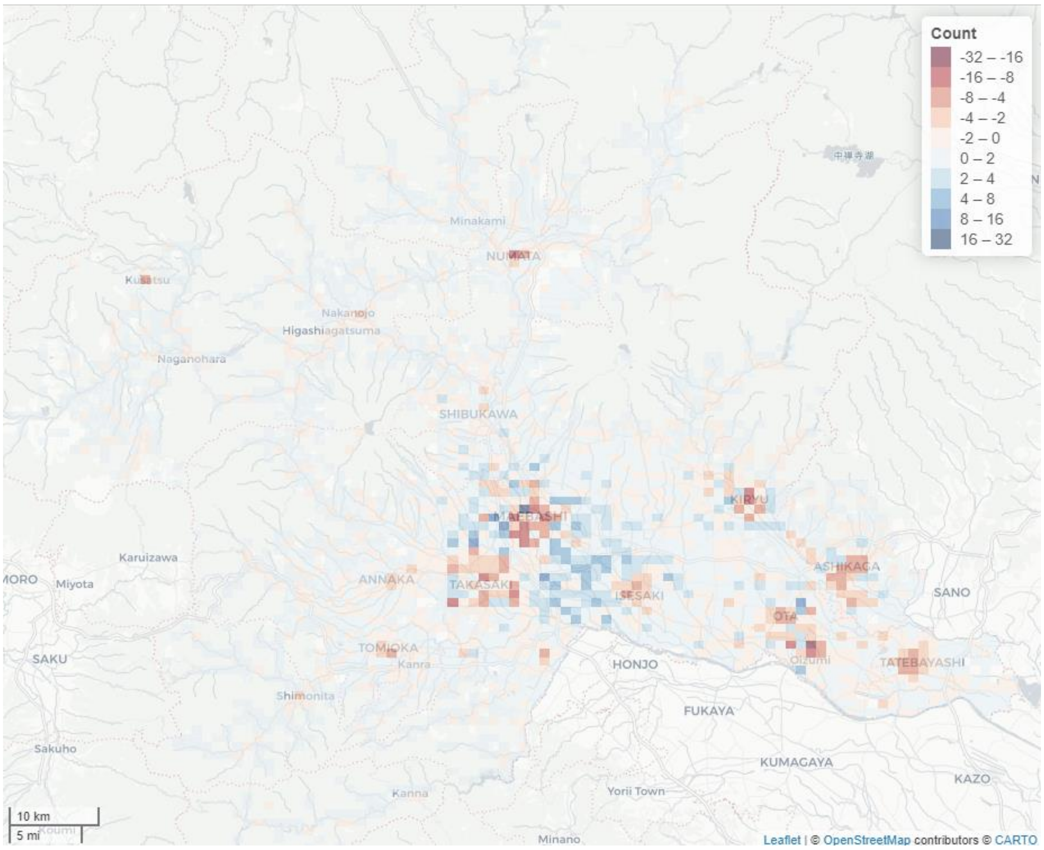


Figure 8-2. Number of Households by Mesh Cell of Scenario 1 against Base Scenario.

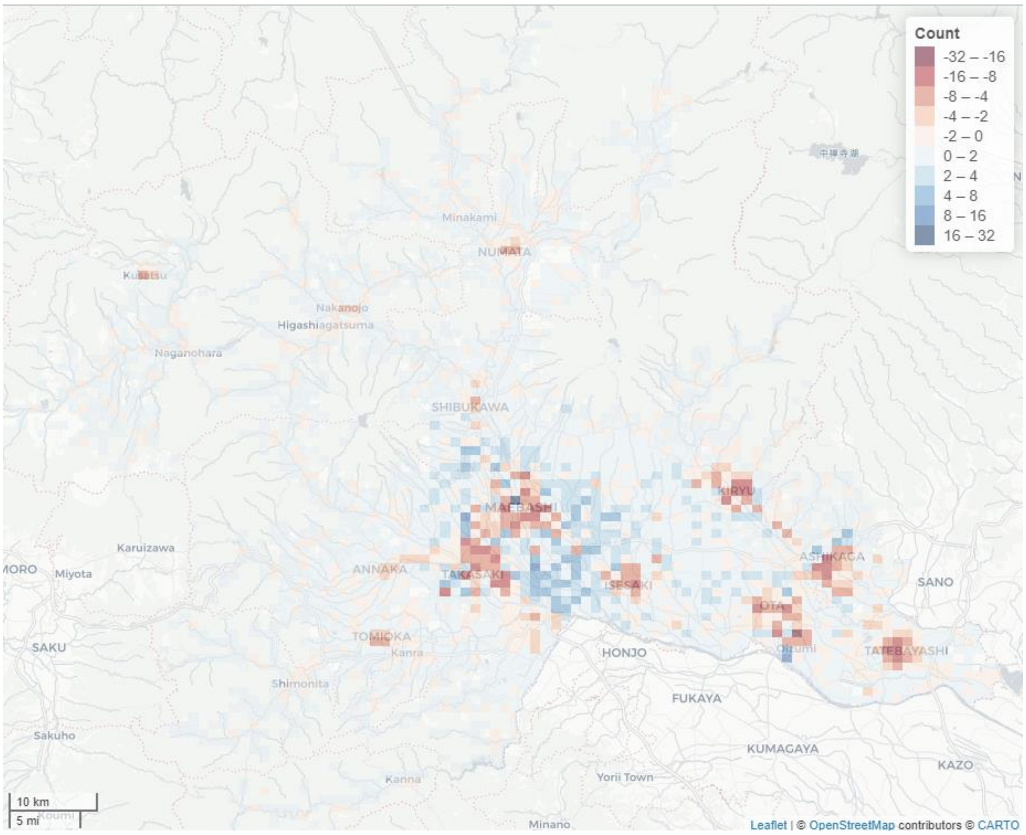


Figure 8-3. Number of Households by Mesh Cell of Scenario 2 against Base Scenario.

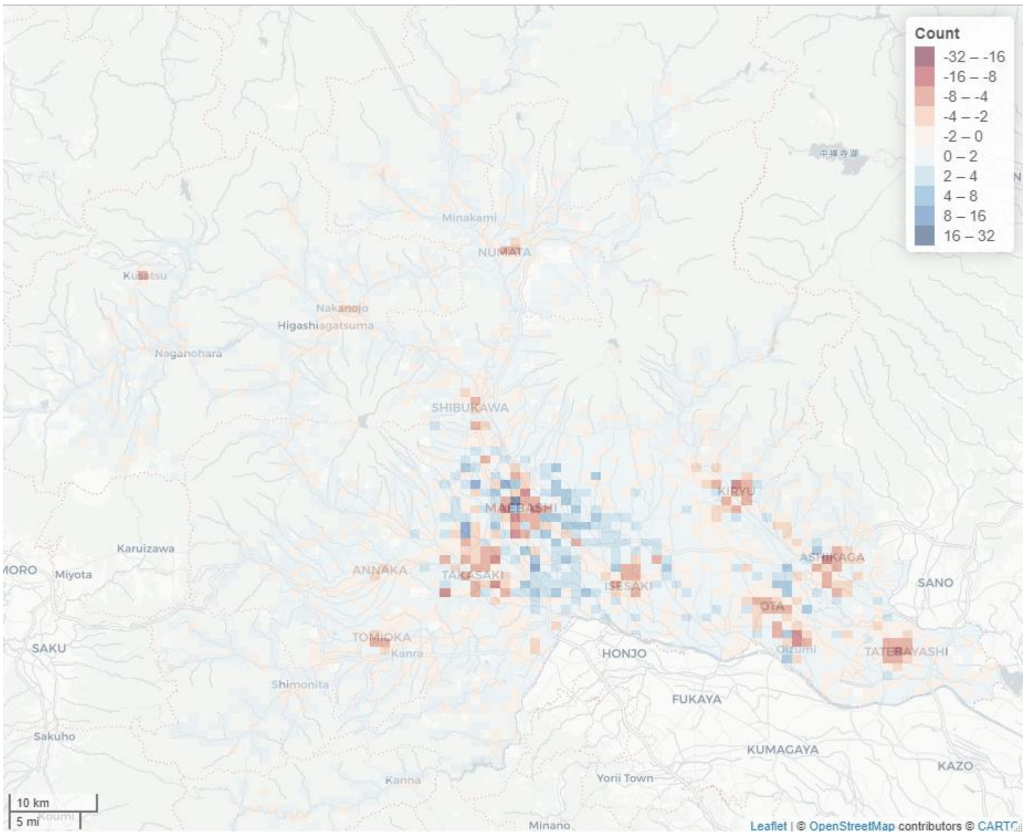


Figure 8-4. Number of Households by Mesh Cell of Scenario 3 against Base Scenario.

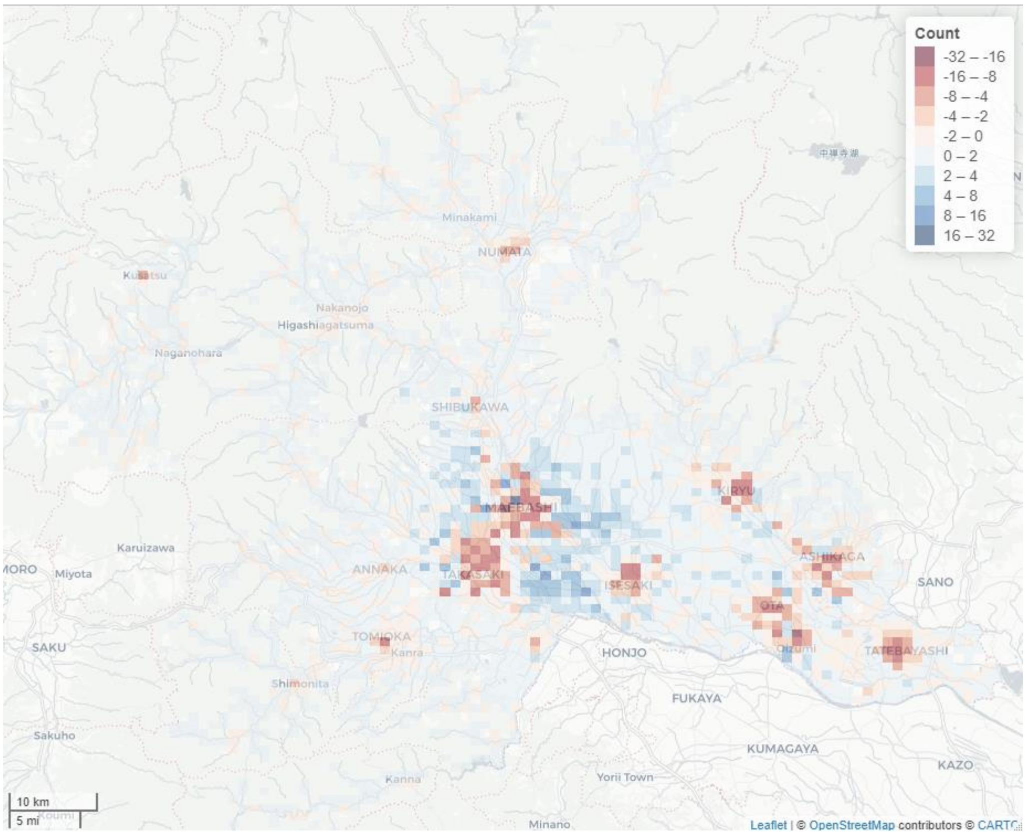


Figure 8-5. Number of Households by Mesh Cell for Scenario 4 against Base Scenario.

The indicators proposed in Section 7.3, network distance to the closest UFAA and DAA, and ratio of households residing in the DAA are then evaluated to identify the moving trend more clearly. The summary results of the evaluators are shown in Table 8-2. The data are all averaged from 10-time simulation runs.

Table 8-2. Simulation Results of Residential Location Model.

Measures	2015 PT Data	Base Scenario	Scenario 1	Scenario 2	Scenario 3	Scenario 4
	Value	Value (% change against PT)	Value (% change against Base)	Value (% change against Base)	Value (% change against Base)	Value (% change against Base)
Median Value of network distance to the closest DAA (m)	1,243	1,326 (+6.7%)	1,363 (+2.8%)	1,401 (+5.7%)	1,399 (+5.5%)	1,435 (+8.2%)
Median value of network distance to the closest UFAA (m)	2,328	2,507 (+7.7%)	2,571 (+2.6%)	2,685 (+7.1%)	2,700 (+7.7%)	2,762 (+10.2%)
Ratio of Household Residing in DAA	40.2%	36.8%	34.5%	33.1%	34.3%	32.8%

From the results, we can again identify clear moving trends to reside where are more distant to both DAA and UFAA. Even for Base Scenario that differs from the PT data only in population size, the median value to the residents' nearest DAA and UFAA are found to increase by around 7% presumably due to the improved level of service in the road network. With the introduction of PAVs, these two values against Base Scenario escalate to up to at most 8.2% and 10.2%, respectively, under Scenario 4. The residents are attracted by the increased accessibility and lower land price so they decide to live farther from the city centers. As for the ratio of residents in DAA, all AV Scenarios witness decreases against Base Scenario, dropping at most to 32.8% from 36.8%.

As expected, both AV characteristics (value of travel time and road capacity benefit) contribute to the moving trend as Scenario 4 shows results with the highest increase rate. It is interesting to find that Scenarios 2 and 3 show similar performance in the two median distance evaluators. This suggests that the effect of road capacity benefit is at a similar level to the more optimistically set value of travel time, which is not anticipated as the effects from road capacity benefit is generally smaller for evaluators in transport (Section 6.3). However, when comparing the ratio of residents in DAA, the result of Scenario 3 is still at a similar level to Scenario 1, but not Scenario 2, which indicates that the two AV characteristics could contribute to the moving trend in a different way. We will revisit the issue with the following illustrations.

Figures 8-6 to 8-9 show the shares of residence by distance to the nearest DAA and UFAA for detailed changing patterns of residential locations.

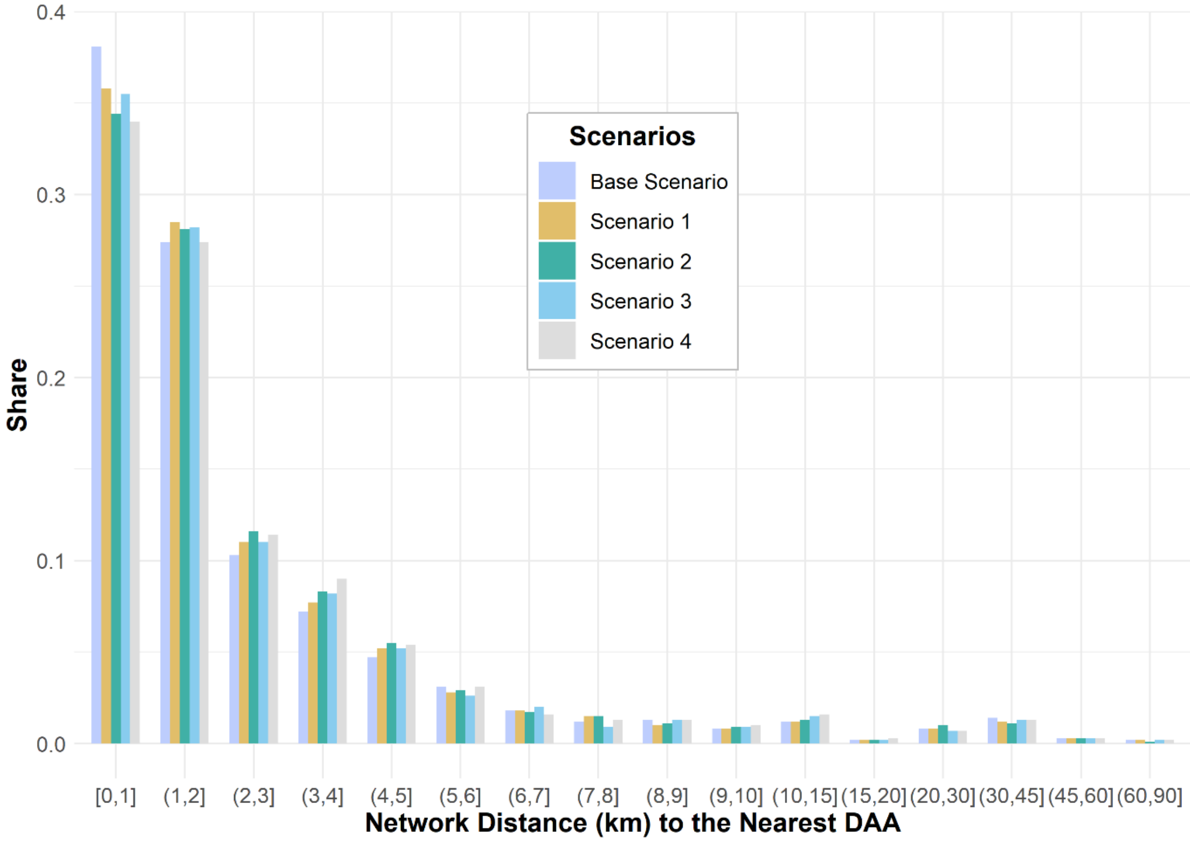


Figure 8-6. Distribution of Distance to the Nearest DAA.

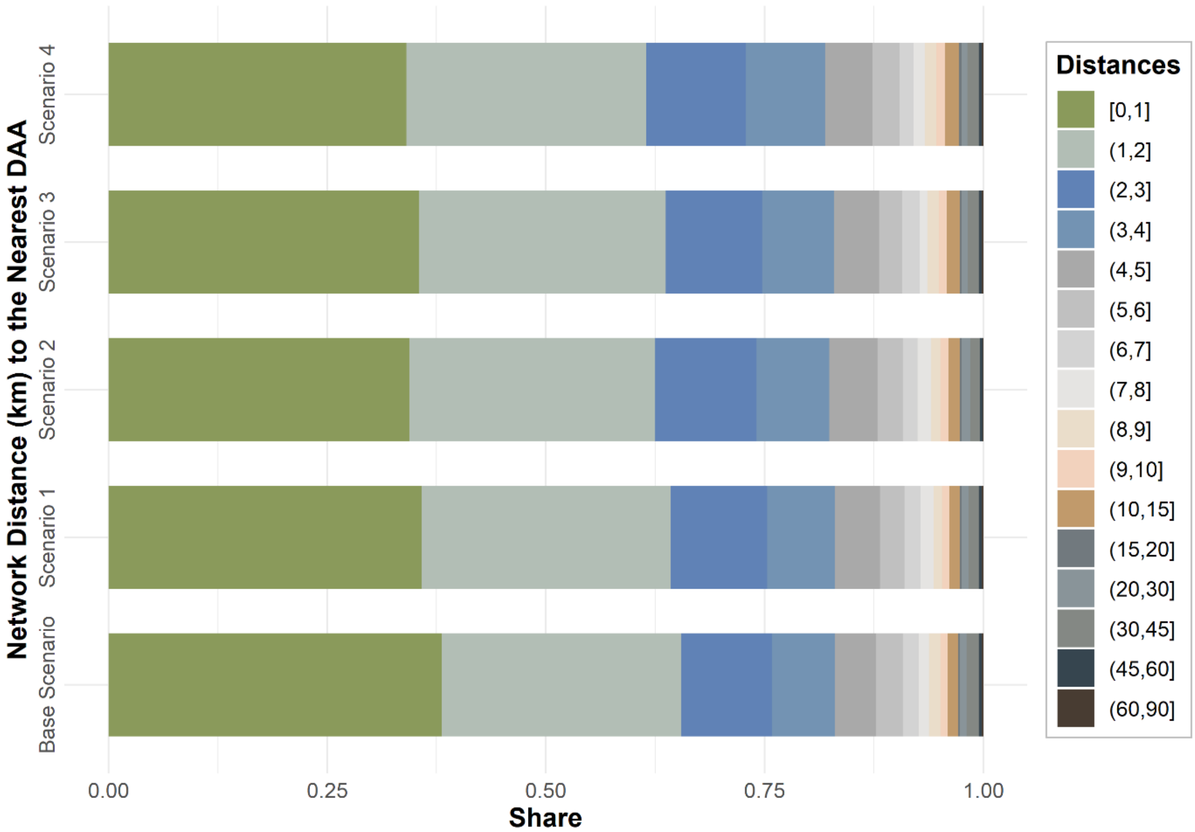


Figure 8-7. Distribution of Distance to the Nearest DAA (Stacked by Scenarios).

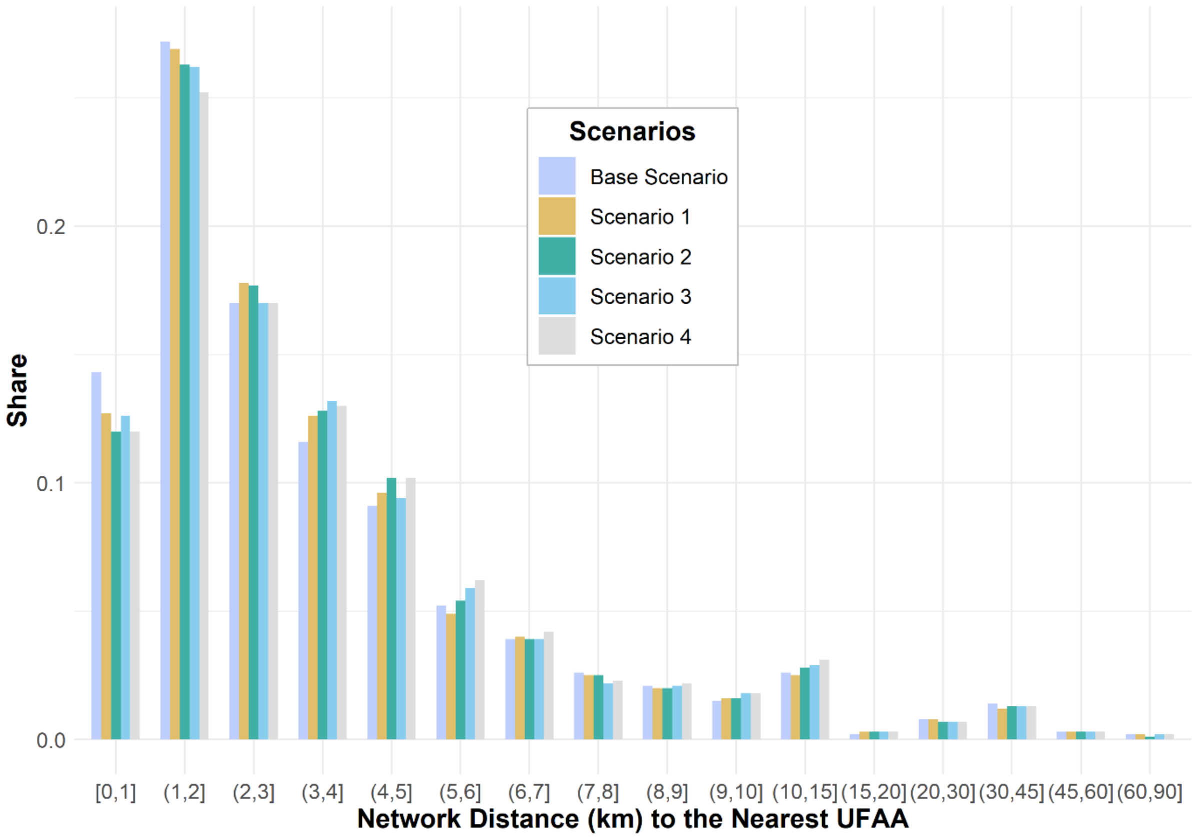


Figure 8-8. Distribution of Distance to the Nearest UFAA.

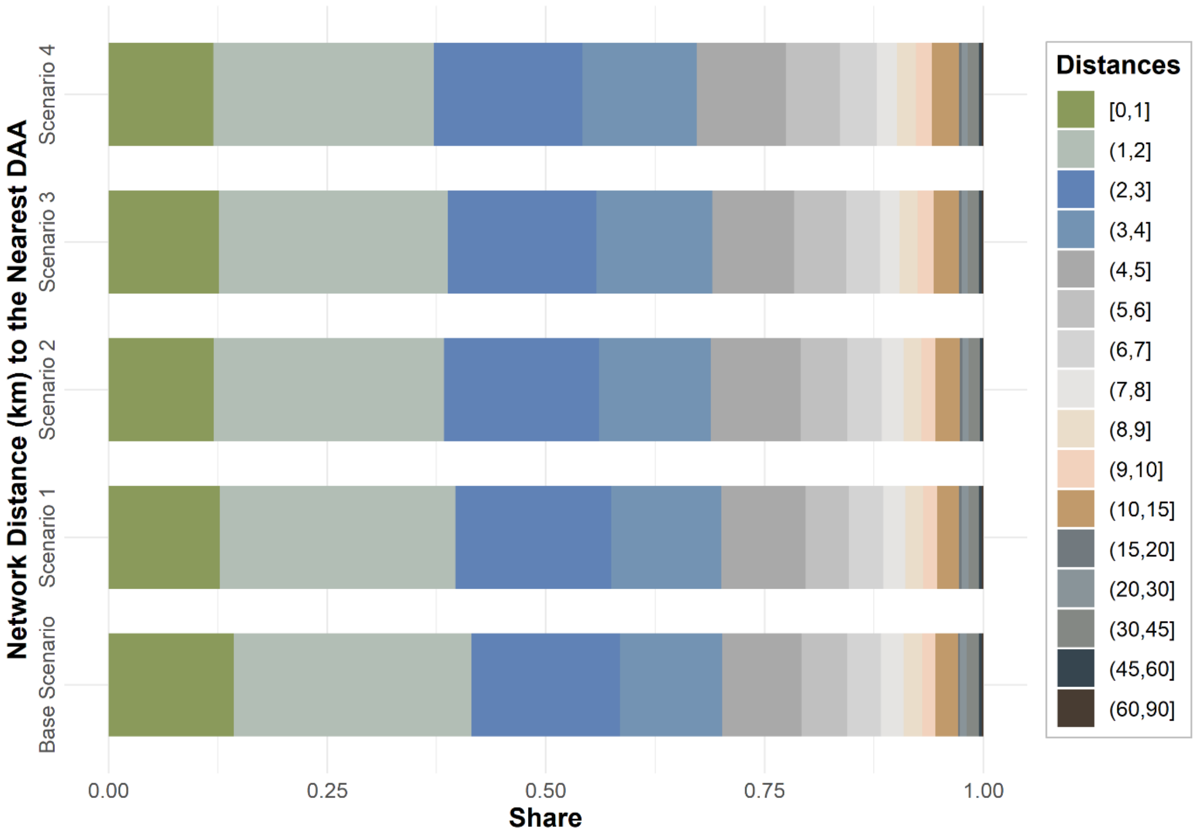


Figure 8-9. Distribution of Distance to the Nearest UFAA (Stacked by Scenarios).

The distribution results generally confirm the findings from Table 8-2. In particular, it is found that the residents tend to shift to the areas that are 2km to 6km apart from the nearest DAA and 3km to 7km apart for the nearest UFAA, but not further in all the AV scenarios. This suggests where the new housing and transport cost balance occurs.

It is noted that when comparing Scenarios 1 and 3 in Figures 8-6 and 8-8, the distance results of the two scenarios regarding the nearest DAA are basically similar but show discrepancies between 2km and 6km regarding the nearest UFAA. However, the results from Scenarios 1 and 2 show discrepancies in both distance evaluators. The difference suggests that, with road capacity benefits, people are moving away from UFAA to an extent that is not as much as being away from DAA. We argue that these results are intuitive as road capacity benefits improved average speed among the DAA cells (Table 6-5) so that accessibility of these areas should improve compared to no road capacity benefit assumed for Scenario 1.

We also calculated the Activity-based Accessibility on relocated residences for an image of surplus earned approximately after the relocation. The results of the four AV Scenarios are shown in Table 8-3 and Figure 8-10, where the normalization procedure is now taken against the original residence location of each person. In this sense, the accessibility values show the "expected utility-equivalent time trip-makers could gain from making daily travel schedules from the relocated residence with PAV introduction, compared to the situation without relocation”.

According to the results, it is interesting to find that most people still have positive accessibility gains, though decreased by mean and median compared to the results in Table 6-7 (for example, accessibility value decreases from 3.09 to 2.38). This suggests that even by average and median people are moving to where transport convenience should be lower, they still have positive gains from the PAV introduction for the study region.

To reiterate, the accessibility applied here suggests only those expected utilities from transport, which means those monetary related are not concerned. Since neither cost coefficient nor household/individual monetary budget data are available, this should remain a future task.

Table 8-3. Summary to Activity-based Accessibility under AV Scenarios after Relocation.

Normalized ABA values versus Base Scenario in Original Home Address (min)	Descriptive summary				
	Mean (95% confidence level)	Median	Min.	Max.	Standard Deviation
Scenario 1	1.96 (± 0.053)	1.74	-24.34	69.93	4.43
Scenario 2	2.65 (± 0.057)	2.30	-25.86	70.03	4.81
Scenario 3	2.04 (± 0.053)	1.78	-26.52	74.14	4.46
Scenario 4	2.69 (± 0.058)	2.38	-40.06	125.28	4.90

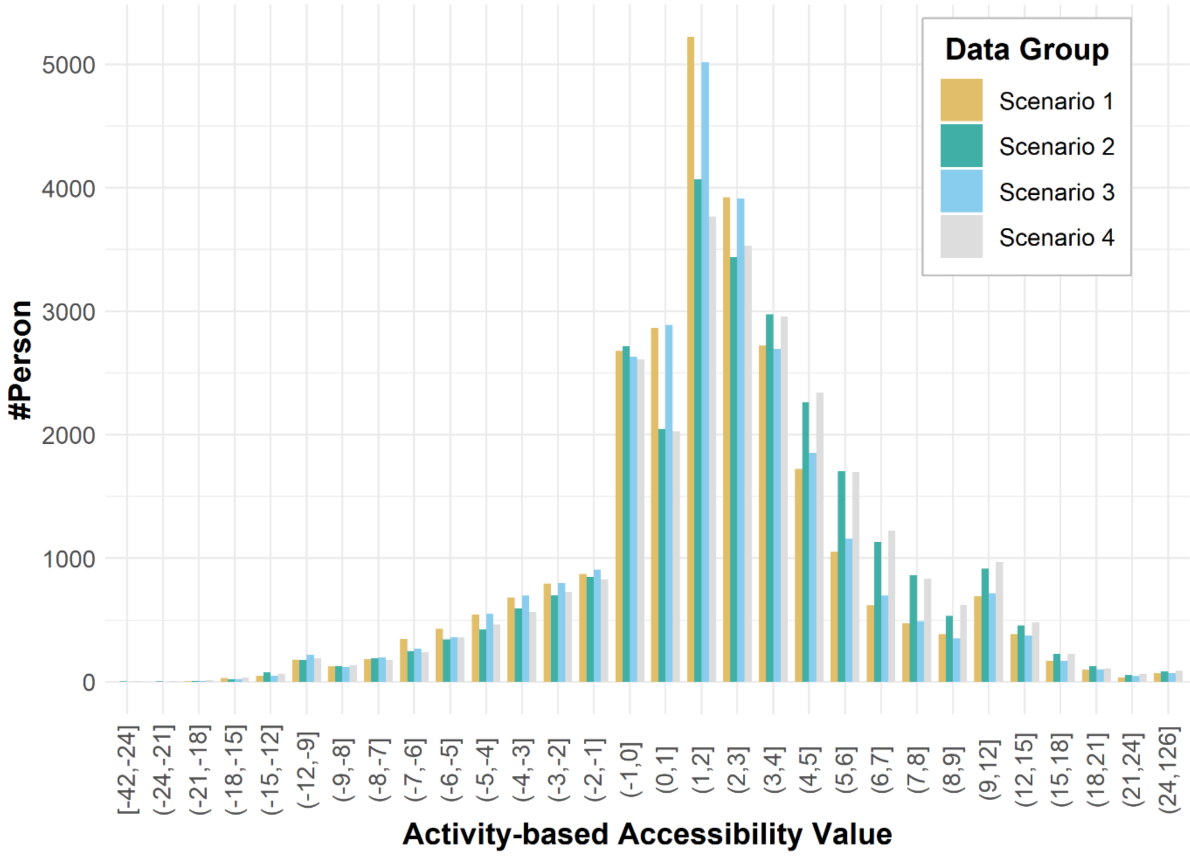


Figure 8-10. Distribution of Activity-based Accessibility after Relocation under AV Scenarios against Base.

8.3 Policy Mandates to Mitigate Residential Location Expansion

Gunma Prefecture, like other Japanese regional areas, is suffering from a population decrease and vacant existing facilities. Urban Planning of Gunma 2020 (Gunma Prefectural Government, 2020) explicitly mentioned pursuing compact city designs as one of their visions. Low-density areas have been putting much pressure on the local government finance, and it would be even worse if that pattern held hereafter. The application of Local Optimization Plan (MLIT, 2021; see also Sub-section 3.4.1) was emphasized, as one of the policies outlined in Urban Planning of Gunma 2020 to address the problem. Local Optimization Plan is a municipal-level plan aiming at attracting facilities and residents to the designated area in the city centers. One main feature of the Plan is that not "to regulate" but "to attract" are considered as the measures.

Recall that there are two specific types of attraction areas defined in Local Optimization Plan: Urban Function Attraction Area (UFAA) and Dwelling Attraction Area (DAA), differentiated by the attracting targets of them. Specific measures to achieve the targets vary by each municipality. For example, the Local Optimization Plan of Maebashi City (Maebashi Municipal Government, 2019), the prefectural capital of Gunma, proposed some measures that are summarized in Table 8-4 for attracting residents to DAA.

Table 8-4. Measures of Maebashi City to Attract Residents to DAA.

Attraction Targets	Target and category of measures	Measures for the area
Residents	Maintaining the urban infrastructure in DAA	Reconstruction of decrepit buildings. Utilization of vacant land and housing stock. Embarking redevelopment businesses. Promoting land categorization.
	Improving the living environment in DAA	Subsidizing residence developers and rents for students.
	Attracting residents outside Maebashi	Benefits to those outsiders who are seeking jobs in Maebashi.

The idea from the first two categories of measures in Table 8-3 applies to the methodology framework adopted in this dissertation, though in a more general way: not within the resolutions as fine as what proposed by the municipal government as parcel-level treatments are not manageable given the adopted methods in this dissertation.

As such, we applied two policies for the AV Scenarios to gain insights into possible countermeasures to attempt to mitigate the residential location expansion issues found in the previous section:

1. To grant tax exemptions for land development in DAA.

2. To attract the number of tertiary-sector employees from non-UFAA to UFAA.

They are evaluated and discussed in the following as Policy 1 and Policy 2, respectively.

The rationale behind Policy 1 is simply to attempt to re-balance the transport and housing cost trade-off in the residential location choice so that to mitigate the negative effects of increasing accessibility in suburban areas. The change in land price will have no impact on the transport choices, so the application of Policy 1 is straightforward by modifying the land price attributes for the mesh cells in DAA (Figure 3-4).

The value of 10% is proposed because it turned out to be the level that could obtain similar performance to the Base Scenario for Scenario 1 (Section 8.4), the most conservative scenario adopted in this dissertation. So at least for Scenario 1, this specific level could be interpreted as the effective level to offset the expansion effect. Plus, it is considered that values higher than 10% would be less realistic to be achieved through imposing such a policy mandate, which means attempting to offset all the expansion effects in other scenarios was not pursued.

The rationale behind Policy 2 is that by making UFAA more attractive, the accessibility of DAA which are generally spatially close to UFAA would increase. Meanwhile, reducing the corresponding part of employees in the non-UFAA would make these areas enjoy less accessibility, thus decreasing people's willingness to move there. One level: 30% is assumed to be increased in the UFAA from its original value. The value of 30% is proposed simply because it is the extreme value that could be imagined to be the result of imposing such a policy mandate.

Under Policy 2, the number of tertiary sector employees in the UFAA is expanded by 30%, then the sum of the increased values from the UFAA is considered as the total that must be offset by non-UFAA, whose values are decreased accordingly by the weight of their respective original values of the number of tertiary sector employees.

Compared to Policy 1, this policy is expected to impact the whole system in a relatively more complex way. First, the number of employees is one of the independent variables in the Destination models (Section 5.3), hence a re-running of the DAS-MATSim loop is required. Second, the number of employees also impacts the tour-based logsums, independent variables in the Land Price model (Section 7.1), hence updates in land price are required.

The simulation results of transport models under Policy 2 for the AV scenarios are shown in Table 8-5 in a brief form for simplicity. The counterpart results with no policy imposed (Table 6-5) are added for comparison. The four AV scenarios converge at Iterations 4, 5, 5, and 6, respectively.

Table 8-5. Simulation Results Summary of Transport Evaluators under Policy 2.

Measures	Base Scenario	Scenario 1		Scenario 2		Scenario 3		Scenario 4	
	Value	Value (% change against base)		Value (% change against base)		Value (% change against base)		Value (% change against base)	
		No policy	Policy 2	No policy	Policy 2	No policy	Policy 2	No policy	Policy 2
#Tours	26,566	26,560 (-0.02%)	26,676 (+0.4%)	26,850 (+1.1%)	26,897 (+1.2%)	26,685 (+0.4%)	26,734 (+0.6%)	26,805 (+0.9%)	26,877 (+1.2%)
#Trips	64,642	67,792 (+4.9%)	67,586 (+4.6%)	68,408 (+5.8%)	68,630 (+6.2%)	68,152 (+5.4%)	68,123 (+5.4%)	68,266 (+5.6%)	68,338 (+5.7%)
Mode share (by trips) of PAV or Car (driver)	71.7%	86.4%	86.6%	89.2%	89.3%	87.0%	86.8%	89.3%	89.4%
Total distance traveled (100km) of PAV or Car (driver)	3,401	4,679 (+37.5%)	4,754 (+39.8%)	5,541 (+62.9%)	5,674 (+66.8%)	4,815 (+41.6%)	4,792 (+40.9%)	5,676 (+66.9%)	5,699 (+67.6%)
Average trip distance (m) of PAV or Car (driver)	7,339	7,987 (+8.8%)	8,119 (+10.6%)	9,076 (+23.7%)	9,263 (+26.2%)	8,121 (+10.7%)	8,101 (+10.4%)	9,307 (+26.8%)	9,329 (+27.1%)
Average speed among DAA mesh cells in AM Peak time (km/h)	33.57	31.63 (-5.8%)	32.42 (-3.4%)	31.06 (-7.5%)	31.70 (-5.6%)	33.07 (-1.5%)	33.18 (-1.2%)	32.36 (-3.6%)	32.40 (-3.5%)
%Trips heading for UFAA mesh cells (excluding those back home and zero-occupancy trips)	15.7%	16.3%	19.7%	16.3%	19.8%	16.2%	20.0%	15.7%	19.9%

From the simulation results, we basically observed a longer total distance traveled and average trip length under Policy 2. This is because more trips under Policy 2 headed for UFAA mesh cells as a result of more bustling urban centers (see the last row of Table 8-5). However, the changing rate of Scenarios 3 and 4 are much more moderate (the results of Scenario 3 decreased slightly in fact) compared to those of Scenarios 1 and 2. Presumably, the reason for these is that the road capacity benefits have already, in the no policy case, generated trip patterns that span across the urban centers (which is difficult to identify specifically) where the congestion levels are lower than the other two AV scenarios. As such, the trip distance traveled barely changed even though around 4% more trips are now heading to UFAA, and hence the average speed changed just slightly as well.

Similar changing patterns can be found also in average speed among DAA mesh cells, where those of the scenarios having no road capacity benefit improved more than those of the scenarios assuming road capacity benefit compared to the no policy case. Although the difference in the changes among the AV scenarios could be attributed to what have discussed above, it is counterintuitive that the average speeds improved compared to the no-policy case. As 4% more trips are now heading to UFAA, we expected the congestion level among the city centers would be worse. We speculate that this is because as the trips are more concentrated to UFAA under Policy 2, the trips among the DAA mesh cells are not necessarily increased as they are not the target of this policy. Also, the average speed among those spatially separated DAA mesh cells (Figure 3-4) probably has improved as more trips are heading to the UFAA.

To summarize, the effects of Policy 2 are indeed more complex as they seemingly are impacting the transport system in various ways, which can make the land use model results under Policy 2 more difficult to interpret.

8.4 Model Simulation Results of Automated Vehicle Scenarios under Policy Mandates

The simulation results of the AV scenarios under the two policies along with the results under no policy (Table 8-5) are shown in Tables 8-6 and 8-7.

Table 8-6. Simulation Results of Residential Location Model under Policy Mandates (Scenarios 1 & 2).

Measures	Scenario 1 Value (% change against Base)			Scenario 2 Value (% change against Base)		
	No policy	Policy 1	Policy 2	No policy	Policy 1	Policy 2
Median Value of network distance to the closest DAA (m)	1,363 (+2.8%)	1,296 (-2.3%)	1,398 (+5.4%)	1,401 (+5.7%)	1,348 (+1.7%)	1,430 (+7.8%)
Median value of network distance to the closest UFAA (m)	2,571 (+2.6%)	2,477 (-1.2%)	2,662 (+6.2%)	2,685 (+7.1%)	2,562 (+2.2%)	2,739 (+9.3%)
Ratio of Household Residing in DAA	34.5%	38.3%	34.6%	33.1%	36.8%	32.9%

Table 8-7. Simulation Results of Residential Location Model under Policy Mandates (Scenarios 3 & 4).

Measures	Scenario 3 Value (% change against Base)			Scenario 4 Value (% change against Base)		
	No policy	Policy 1	Policy 2	No policy	Policy 1	Policy 2
Median Value of network distance to the closest DAA (m)	1,399 (+5.5%)	1,351 (+1.9%)	1,392 (+5.0%)	1,435 (+8.2%)	1,387 (+4.6%)	1,428 (+7.7%)
Median value of network distance to the closest UFAA (m)	2,700 (+7.7%)	2,578 (+2.8%)	2,650 (+5.7%)	2,762 (+10.2%)	2,679 (+6.9%)	2,734 (+9.1%)
Ratio of Household Residing in DAA	34.3%	37.7%	34.6%	32.8%	36.4%	33.0%

As just argued, the simulation results suggest that granting tax exemption can significantly alleviate the residence expansion problem. For Scenario 1 where the characteristics of PAVs are assumed relatively conservative, the three indicators are found to be able to achieve even better levels than what was observed in Base Scenario.

For the other three AV Scenarios with more optimistic AV assumptions, all the metrics under Policy 1 are found to improve compared to the no-policy case. For example, the median value distance to the nearest DAA dropped from a 5.7% increase to a 1.7% increase in Scenario 2. The ratio of households residing in DAA in all the scenarios except Scenario 4 is equal to or better than Base Scenario. This suggests that people tend to relocate to the edge (compared to Base Scenario) of DAA to enjoy the benefits from both PAV and Policy 1. Therefore, the designation of the policy target area, from the results, should merit more attention.

Figures 8-11 and 8-12 show the shares of residence by distance to the nearest DAA and UFAA, respectively, under Policy 1. The results confirm that many households have relocated inside DAA compared to the no-policy case.

Overall, it can thus be summarized that providing a subsidy on the land price or its equivalents could be effective to mitigate urban expansions. However, the cost to impose such a policy mandate is expected to be enormous. By a rough calculation, the total cost that the prefectural government would pay for Policy 1 per 1m2 is the sum of the housing stock of each DAA mesh cell (Section 7.1) × land price of each DAA mesh cell (Section 7.1) × 10%, which for Scenario 1 as an example is approximately 1.4 billion JPY. The calculated value then should multiply the average area of housing stock, which is 106 m2 according to the Statistics Bureau of Japan (2018), and we can derive a total amount of 148 billion JPY, around 15.6% of the yearly expense of the prefecture in 2021 (Gunma Prefectural Government, 2022).

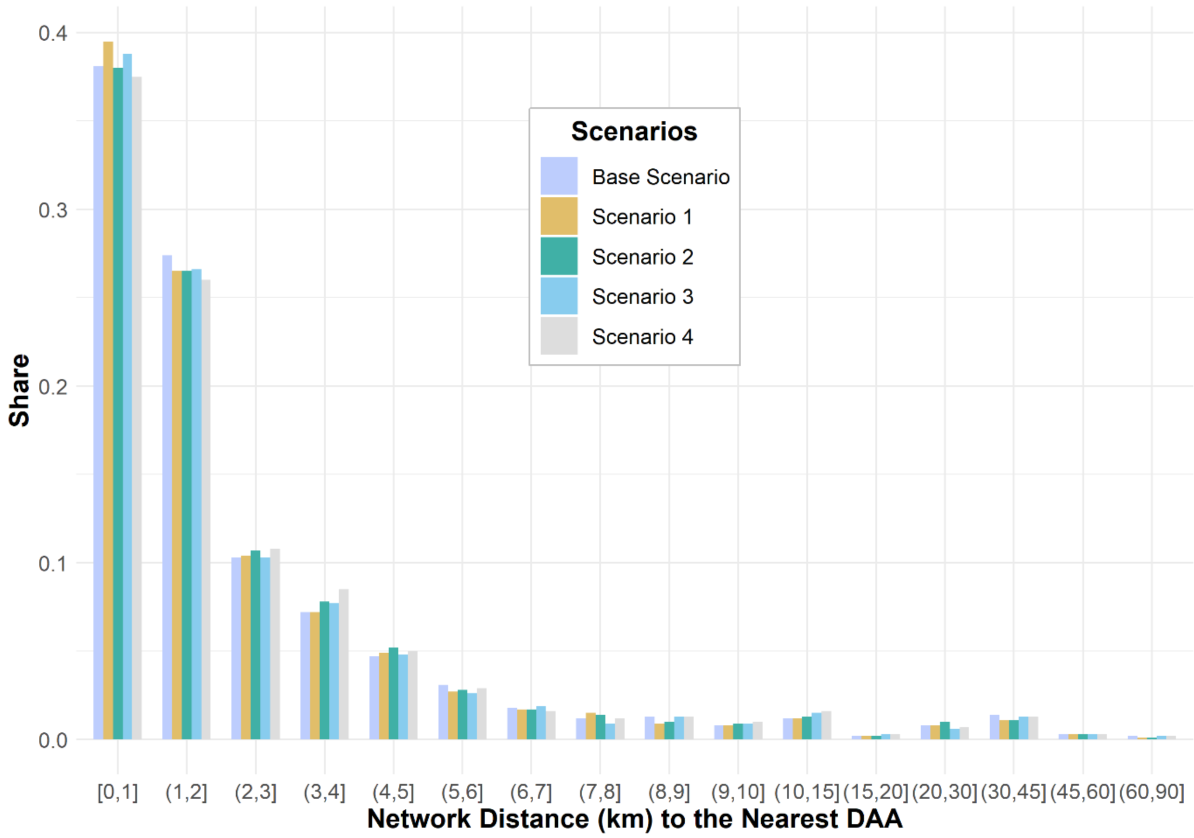


Figure 8-11. Distribution of Distance to the Nearest DAA Under Policy 1.

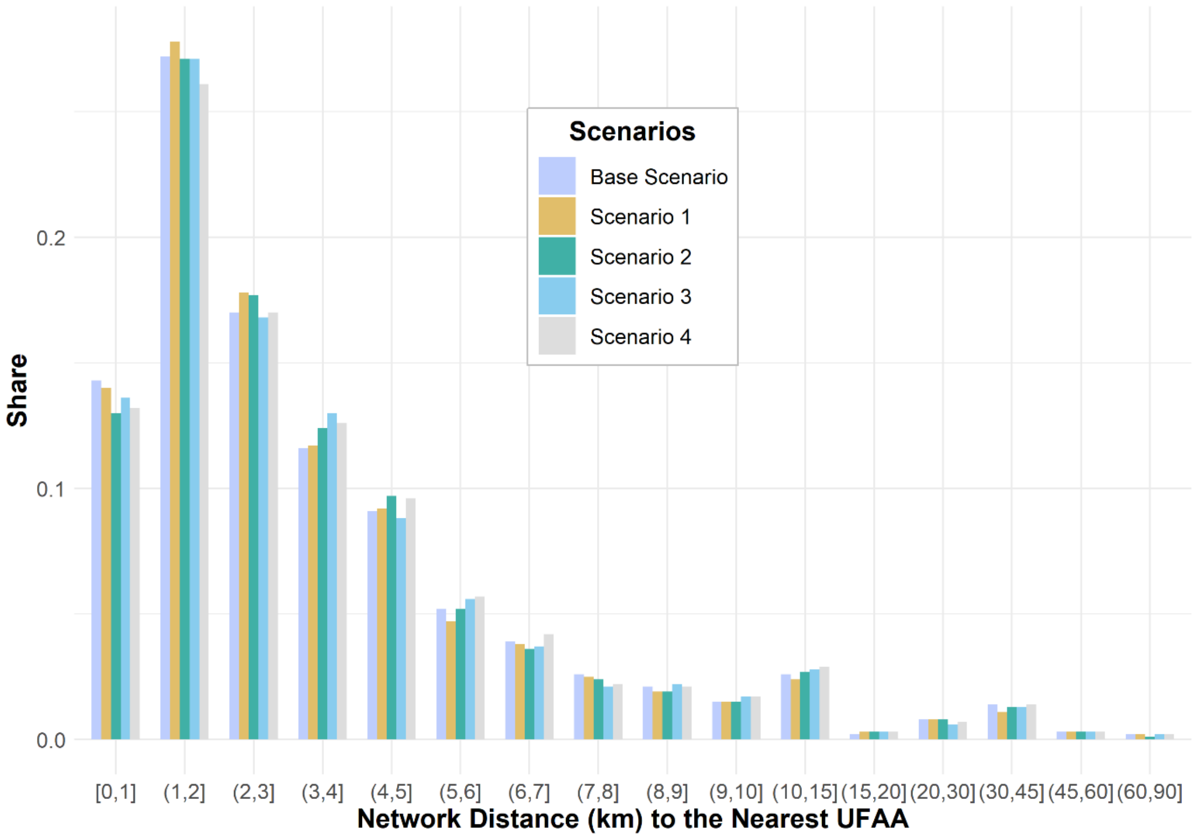


Figure 8-12. Distribution of Distance to the Nearest UFAA Under Policy 1.

For the results under Policy 2, the measuring indicators are surprisingly found to deteriorate in Scenarios 1 and 2 compared to the results without any policy imposed. The results in Scenarios 3 and 4 improved compared to the results under no policy but to a fewer extent than Policy 1.

To investigate, the distribution of shares of the distance to the nearest DAA and UFAA are shown in Figure 8-13 and Figure 8-14. By comparing these two figures with Figure 8-6 and Figure 8-8, two speculations are presented in the following to explain the results.

First, despite that the distributions regarding distance to the nearest DAA do not show substantial changes (Figures 8-6 & 8-13), we can identify some differences in, for example, the shares of distance longer than 1km but no more than 2km, the results of Scenarios 1 and 2 under Policy 2 decreased slightly compared to the no-policy case, while the shares of distance longer than 3km but no more than 6km, the results yet increased. These suggest that the road network level of service around UFAA decreased hence has reduced the accessibility and the willingness to relocate there. This is, however, not the case for Scenarios 3 and 4, where road capacity benefits of AVs should offset the negative effects.

Second, in general for all AV scenarios, the decrease in the number of employee level in the non-UFAA to some extent increase the chance to move there as the number of employees is a parameter with a negative coefficient in the residential location choice model (Table 7-2); this reasoning also applies to decreased land price through the re-calculation of the land price model (Table 7-1) where the tour-based logsum variables are reduced with fewer employees for non-UFAA.

In summary, Policy 2 of attracting tertiary-sector employees seems to be not as effective as Policy 1, as its effects on both transport and land use could lead to a complex changing pattern from the models adopted. Nevertheless, the results of Scenarios 3 and 4 do have slight improvement compared to no policy imposed. It is instructive to learn from this point as road capacity benefit, as mentioned in Section 6.1, can be the AV characteristic that is more flexible in future policy making.

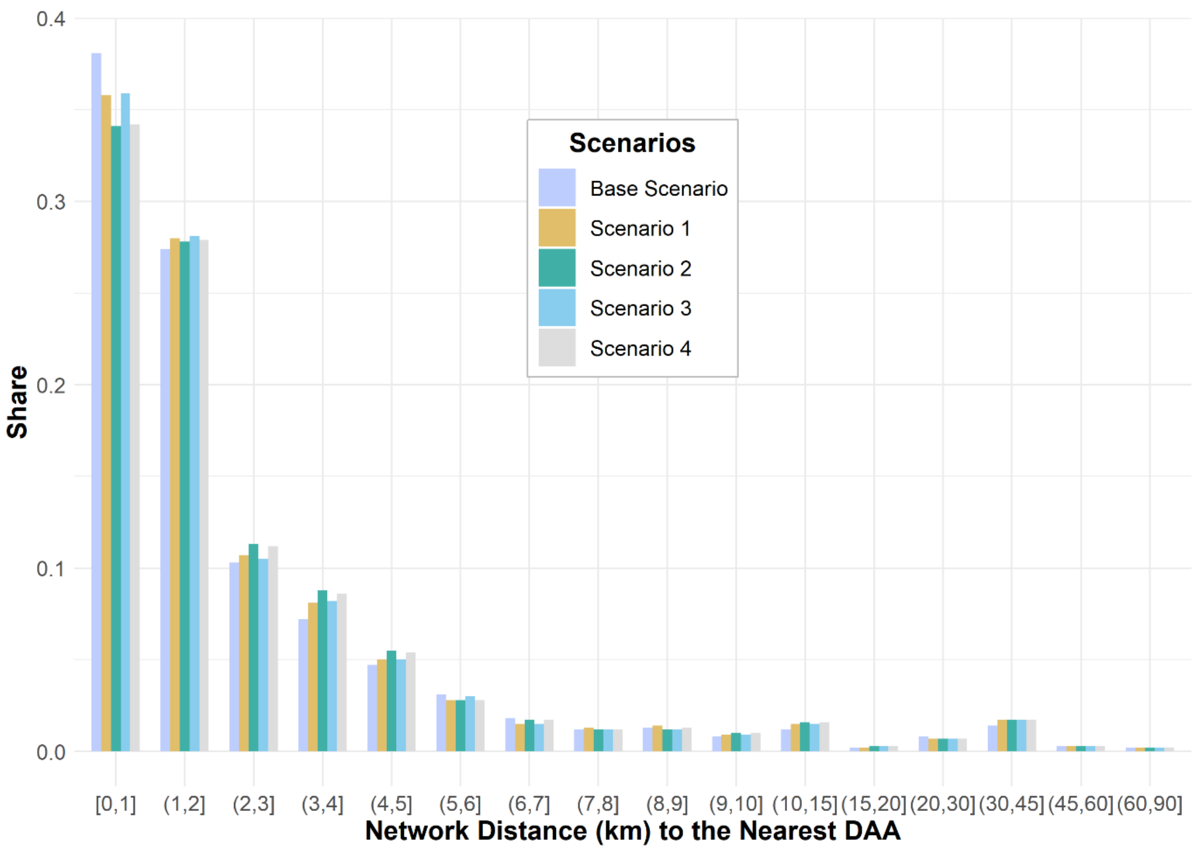


Figure 8-13. Distribution of Distance to the Nearest DAA under Policy 2.

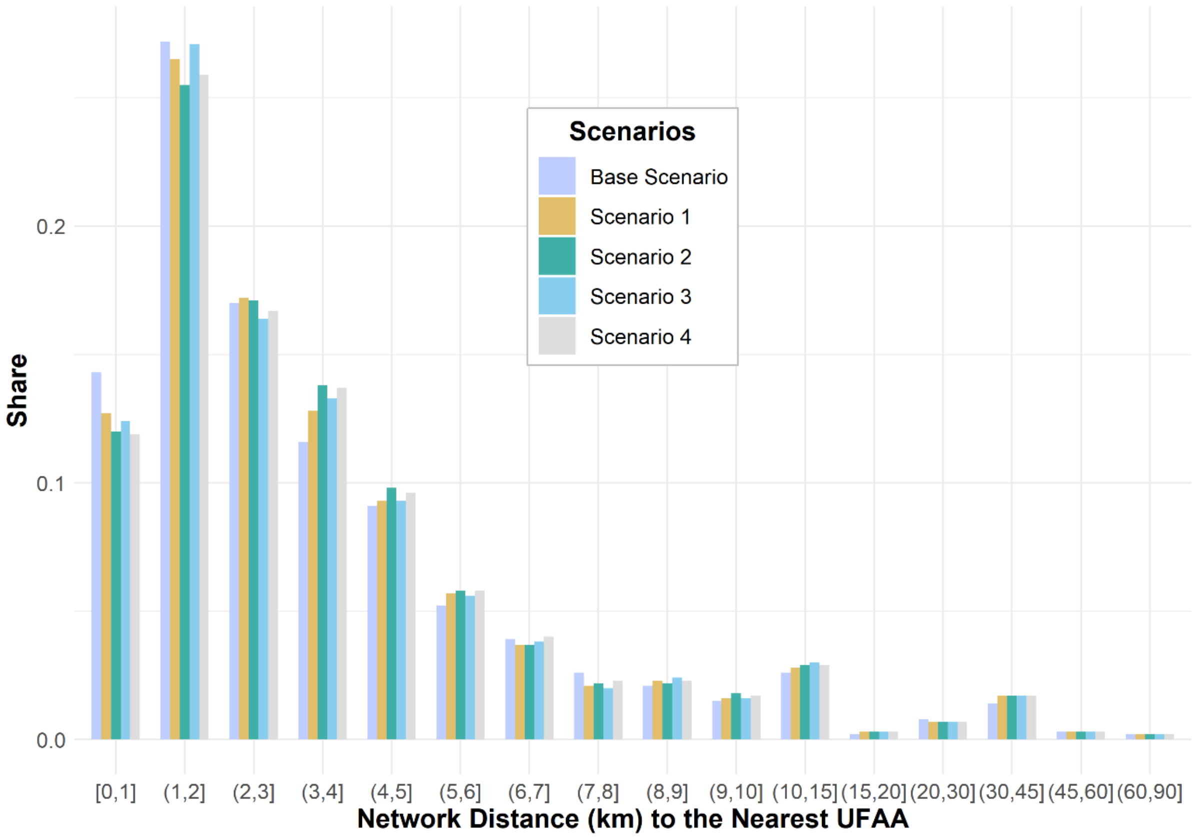


Figure 8-14. Distribution of Distance to the Nearest UFAA under Policy 2.

CHAPTER 9 CONCLUSIONS AND LIMITATIONS

This chapter first summarizes the whole dissertation, then presents several limitations that this work failed to cover, and gives a brief discussion on the future work to address them.

9.1 Summary

This dissertation conducted a travel forecasting project with the background of potential prevalence of automated vehicles in a Japanese regional area. The rationale and originality behind such a topic are presented in Chapters 1 and 2: after an introductory Chapter 1 stating the information such as the rationale and the research objective of this dissertation, Chapter 2 presents a relatively comprehensive literature review on three aspects, namely activity-based travel demand model, integrated transportation model, and automated vehicles. Some conclusions drawn from the literature review include that first, building a combined framework of activity-based travel demand model and dynamic traffic assignment model is significant in examining transport impacts; second, AV impacts can be categorized by the extent of investigation made so far, where implications in land use are so inadequate that deserve much more academic efforts.

To address the topic, a methodology framework combining an activity-based travel demand model, a dynamic traffic assignment model, and a discrete-choice-based residential location model is adopted and introduced in Chapter 3. The reasoning behind the method and sources of data are also described. The methodology framework can be separated into two transport models and one residential location model. The “bridge” connecting these two components is a concept called activity-based accessibility, which has not been applied much despite the general form of accessibility being considered common practice.

Chapter 4 and Chapter 5 then provide elaborations on the travel demand model and travel supply models, respectively. Considerable efforts have been devoted to the model estimations and validations for both chapters. As result, two well-validated models are built and should serve the transport forecasting in good temporal and spatial resolutions.

The major outputs of this dissertation besides these well-validated models are the simulation results of automated vehicles in both transport and land use. Chapter 6 clarifies the way of simulating and interacting with these two transport-related models and shows the simulation running results as well as analyses under four automated vehicle scenarios with different levels of features. It is found from the results that, the prevalence of private automated vehicles in such a currently car-dependent study region would carry implications in a rather complex way: a lower network level of service was observed while the median value of activity-based accessibility (as the expected utility from activity-travel schedules in a whole day) was found positive. Despite that this has been recognized in the existing literature, few ever discussed it with the feedback effect considered, as what has been done in this dissertation. Through the transport demand-supply loop framework, adaptations to avoid traffic made by the trip makers with automated vehicles were discovered. In this sense, the necessity to exercise the loop has been confirmed.

Chapter 7 gave the specification of an MNL-based residential location model with estimation and validation procedures emphasized as well. Applications of the residential location model are shown in the following Chapter 8. The findings of the land use model seem to be relatively more straightforward. All the scenarios reported negative shifts in all three indicators of median distance to the nearest Dwelling Attraction Area (DAA), to the nearest Urban Function Attraction Area (UFAA), and the ratio of the households residing in DAA. The shifts are considered as the new balance of the trade-off between the housing costs and the transport costs since the moving household are found to concentrate in distance zones just around 2km more distant (in the sense of the distance to the nearest DAA) than their original pattern. The ability to use the DAA and UFAA as validation and policy testing objects is at large because of the fine spatial resolution of the 1km level used in this study. Two hypothetical policy mandates are also evaluated as attempts to mitigate the moving trends. As result, granting subsidies for the land prices in DAA is found effective, but not so for the policy to attract the number of tertiary-sector employees to the UFAA. These findings should suggest insights into values for future policy makings.

9.2 Limitations and Future Works

In general, a transport forecasting project like what was done in this dissertation can never be perfect. This statement is especially true when it is extended to land use forecasting. This work is subjected to many limitations, besides those that have been mentioned in the body of this dissertation, some representatives are discussed or even reiterated below.

First, as a study on the implications of private automated vehicles, this dissertation focuses on three assumed changes in vehicle characteristics compared to human-driven vehicles. However, some more sophisticated behaviors with the AV introduction are not measured. For example, despite that PAV intra-household sharing behavior has been deployed with the simulation models, how would the sharing induce more travels is not incorporated in the current model system. A more sophisticated modeling tool would be required to examine those potential changes.

Second, the limitations of the activity-based travel demand model adopted (i.e., the DAS model), should be shared. For the model specification used in this study, at least two obvious points can be improved in the future: one is that individual-specific time budget has not been explicitly incorporated; the other is that the logsum variable fails to reflect changes from the time of day and other trip-based level choices. Both points have considerably impaired the reliability of the model results and conclusions. Especially, if well managed, the time budget constraint should produce more realistic induced travel distance results. An improved version of DAS is expected to solve the limitation, such as in the empirical analysis by Vyas et al. (2019) where another activity-based travel demand model CT-RAMP was used. Also, the sensitivity of this model specification to the policies seems to be not adequate, as the daily activity pattern under AV scenarios does not demonstrate significant changes (Figure 6-3).

Third, "More data beats clever algorithms" (Peter Norvig), limitations related to the currently accessible data should be another source of error in the prediction. For example, the Person Trip data used as the initial travel demand are collected in a trip-based way. Although much existing literature and this study have managed to convert the survey data to a tour-based or even day-pattern-based, biases are in no way to be neglected through the data processing work. It hence would be better to use tour-based travel demand data directly for such forecasting efforts, so it is urged to conduct surveys with these concerns. Besides, more types of land use data in the resolution of mesh cell level or even finer should allow not only higher model reliability but also greater potential in improving responsive properties to policies. The lack of data at the mesh cell level has made the policy testing analysis limited in this dissertation.

Fourth, to better reflect the characteristics of automated vehicles, investigations such as a Stated Preference survey might be advised. However, as argued in the literature review, such surveys are supposed to be designed very carefully to prevent any unexpected results[11].

Fifth, besides private automated vehicles, the methodology framework of this research is also suitable for accommodating shared automated vehicles as one of the study objects. The supply model of MATSim has been adopted in much existing literature as a simulation tool for modeling shared automated vehicles. However, in that case, appropriately calculating the accessibility for shared mobility would become another challenge, which could also be extended to public transit.

Finally, there is a large room for improvement in the land use model adopted in this research. Despite that increases in both model complexity and data requirements should be expected, aspects such as job location choice, development choice of housing or other facilities (Figure 3-1), etc. are better to be incorporated to acquire more realistic forecasting in the long term. A life-cycling model to reflect the demographic changes in the long term is also desirable in acquiring more reliable forecasts. Furthermore, the land use loop in Figure 3-1 is advised to be performed in the future. It is expected that the negative effects such as urban expansion could be mitigated through the long-term loop: people relocating further away from the city centers would probably deteriorate the traffic level of service there thereby lead to a tendency to move back in turn.

[11] In fact, a failed attempt of conducting an SP survey was made by the author.

The End.

REFERENCES

Abe, R. (2019). Introducing automated buses and taxis: Quantifying the potential benefits in Japanese transportation systems. *Transportation Research Part A: Policy and Practice*, 126, 94-113.

Abe, R., Kita, Y., & Fukuda, D. (2020). An experimental approach to understanding the impacts of monitoring methods on use intentions for automated vehicle services: Survey evidence from Japan. *Sustainability*, 12(6), 2157.

Adler, T., & Ben-Akiva, M. (1979). A theoretical and empirical model of trip chaining behavior. *Transportation Research B: Methodological*, 13, 243–257.

Adnan, M., Pereira, F. C., Azevedo, C. M. L., Basak, K., Lovric, M., Raveau, S., Zhu, Y., Ferreira, J., Zegras, C., & Ben-Akiva, M. (2016). Simmobility: A multi-scale integrated agent-based simulation platform. *In 95th Annual Meeting of the Transportation Research Board Forthcoming in Transportation Research Record*.

Algers, S., Daly, A., Kjellman, P., & Widlert, S. (1996). Stockholm Model System (SIMS): Application. Volume 2: Modelling Transport Systems. In: D. Hensher, J. King, and T. Oum (eds.), *World Transport Research*, 345-361. Pergamon, Amsterdam.

Alonso, W. (1964). *Location and Land Use*, Harvard University Press, Cambridge.

Anas, A. (1982). Residential Location Markets and Urban Transportation. *Economic Theory, Econometrics and Policy Analysis with Discrete Choice Models*. New York: Academic Press.

Anas, A., & Arnott, R. J. (1994). The Chicago prototype housing market model with tenure choice and its policy applications. *Journal of Housing Research*, 23-90.

Anderson, J. M., Nidhi, K., Stanley, K. D., Sorensen, P., Samaras, C., & Oluwatola, O. A. (2014). *Automated Vehicle Technology: A Guide for Policymakers*. Rand Corporation.

Arentze, T. A., & Timmermans, H. J. (2004). A learning-based transportation oriented simulation system. *Transportation Research Part B: Methodological*, 38(7), 613-633.

Auld, J., & Mohammadian, A. K. (2009). Framework for the development of the agent-based dynamic activity planning and travel scheduling (ADAPTS) model. *Transportation Letters*, 1(3), 245-255.

Auld, J., & Mohammadian, A. K. (2012). Activity planning processes in the Agent-based Dynamic Activity Planning and Travel Scheduling (ADAPTS) model. *Transportation Research Part A: Policy and Practice*, 46(8), 1386-1403.

Auld, J., Hope, M., Ley, H., Sokolov, V., Xu, B., & Zhang, K. (2016). POLARIS: Agent-based modeling framework development and implementation for integrated travel demand and network and operations simulations. *Transportation Research Part C: Emerging Technologies*, 64, 101-116.

Auld, J., Sokolov, V., & Stephens, T. S. (2017). Analysis of the effects of connected–automated vehicle technologies on travel demand. *Transportation Research Record*, 2625(1), 1-8.

Automobile Inspection Registration Information Association. (2021). Car Ownership Summary by Prefecture. URL: https://www.airia.or.jp/publish/file/r5c6pv000000wkrb-att/r5c6pv000000wkrq.pdf (In Japanese). *Accessed Jun. 2022.*

Automobile Inspection Registration Information Association. (2022). Hybrid and Electric Car Ownership Summary. URL: https://www.airia.or.jp/publish/file/r5c6pv000000wkqb-att/04_HV_EV.pdf (In Japanese). *Accessed Jun. 2022.*

Balmer, M., Rieser, M., Meister, K., Charypar, D., Lefebvre, N., & Nagel, K. (2009). MATSim-T: Architecture and simulation times. In: A. Bazzan and F. Klügl (eds.), *Multi-Agent Systems for Traffic and Transportation Engineering* (pp. 57-78). IGI Global.

Bansal, P., Kockelman, K. M., & Singh, A. (2016). Assessing public opinions of and interest in new vehicle technologies: An Austin perspective. *Transportation Research Part C: Emerging Technologies*, 67, 1-14.

Bansal, P., & Kockelman, K. M. (2017). Forecasting Americans' long-term adoption of connected and automated vehicle technologies. *Transportation Research Part A: Policy and Practice*, 95, 49-63.

Bansiter, D. (2002). *Transport Planning*. Second Edition. Routledge.

Bellemans, T., Kochan, B., Janssens, D., Wets, G., Arentze, T., & Timmermans, H. (2010). Implementation framework and development trajectory of FEATHERS activity-based simulation platform. *Transportation Research Record*, 2175(1), 111-119.

Ben-Akiva, M. E., & Lerman, S. R. (1974). Some estimation results of a simultaneous model of auto ownership and mode choice to work. *Transportation*, 3(4), 357-376.

Ben-Akiva, M. E., & Lerman, S. R. (1985). *Discrete Choice Analysis: Theory and Application to Travel Demand*. The MIT Press, Cambridge.

Ben-Akiva, M. E., Bowman, J. L., & Gopinath, D. (1996). Travel demand model system for the information area. *Transportation*, 25, 241–266.

Ben-Akiva, M. E., & Bowman, J. L. (1998a). Activity based travel demand model systems. In: P. Marcotte and S. Nguyen (eds.), *Equilibrium and Advanced Transportation Modelling*, 27-46. Springer, Boston, MA.

Ben-Akiva, M. E., & Bowman, J. L. (1998b). Integration of an activity-based model system and a residential location model. *Urban Studies*, 35(7), 1131-1153.

Ben-Akiva, M., Koutsopoulos, H. N., Antoniou, C., & Balakrishna, R. (2010). Traffic simulation with DynaMIT. In: J. Barceló (ed.), *Fundamentals of Traffic Simulation*. 363-398. Springer, New York, NY.

Bhat, C. R., & Koppelman, F. S. (1999). Activity-based modeling of travel demand. In: R. Hall (ed.), *Handbook of transportation Science*, 35-61. Springer, Boston, MA.

Bhat, C. R., Guo, J. Y., Srinivasan, S., & Sivakumar, A. (2004). Comprehensive econometric microsimulator of daily activity-travel patterns. *Transportation Research Record.* 1894 (1), 57–66.

Bhat, C. R., Goulias, K. G., Pendyala, R. M., Paleti, R., Sidharthan, R., Schmitt, L., & Hu, H. H. (2013). A household-level activity pattern generation model with an application for Southern California. *Transportation*, 40(5), 1063-1086.

Bhat, C. R. (2015). A new generalized heterogeneous data model (GHDM) to jointly model mixed types of dependent variables. *Transportation Research Part B: Methodological*, 79, 50-77.

Bierlaire, M., De Palma, A., Hurtubia, R., & Waddell, P. (2015). *Integrated transport and land use modeling for sustainable cities* (No. BOOK). EPFL Press.

Bösch, P. M., Ciari, F., & Axhausen, K. W. (2016). Automated vehicle fleet sizes required to serve different levels of demand. *Transportation Research Record*, 2542(1), 111-119.

Bösch, P. M., Becker, F., Becker, H., & Axhausen, K. W. (2018). Cost-based analysis of automated mobility services. *Transport Policy*, 64, 76-91.

Bowman, J. L. (1995). *Activity Based Travel Demand Model System with Daily Activity Schedules.* (Master Thesis). Massachusetts Institute of Technology, Cambridge, MA.

Bowman, J. L. (1998). *The Day Activity Schedule Approach to Travel Demand Analysis.* (Ph.D. thesis). Massachusetts Institute of Technology, Cambridge, MA.

Bowman, J. L., & Ben-Akiva, M. E. (2001). Activity-based disaggregate travel demand model system with activity schedules. *Transportation Research A*: *Policy and Practice*, 35, 1–28.

Bowman, J. L., & Bradley, M. A. (2006). *Activity-Based Travel Forecasting Model for SACOG: Technical Memos Numbers 1-11*. URL: https://github.com/RSGInc/DaySim/wiki/John-Bowman-Website-Archive. *Accessed Nov. 2021.*

Bowman, J. L. (2009). Historical development of activity based model theory and practice. *Traffic Engineering & Control*, 50(2), 59-62.

Bowman, J. L., & Bradley, M. A. (2014). *Soundcast Activity-based Travel Forecasting Model for PSRC: Model System Design*. Puget Sound Regional Council. URL: *https://www.psrc.org/sites/default/files/ soundcastdesign2014.pdf. Accessed Nov. 2021.*

Boyce, D. E., & Williams, H. C. (2015). *Forecasting Urban Travel: Past, Present and Future*. Edward Elgar Publishing.

Bradley, M. A., Portland Metro, Bowman, J. L., & Cambridge Systematics (1998). *A System of Activity-Based Models for Portland, Oregon*. USDOT report number DOT-T-99-02, prepared for the Travel Model Improvement Program of the USDOT and EPA, Washington, D.C.

Bradley, M. A., Bowman, J.L., & Lawton, K. (1999). A comparison of sample enumeration and stochastic microsimulation for application of tour-based and activity-based travel demand models. *27th European Transport Conference*, Cambridge, England.

Bradley, M. A., Outwinter, M., Jonnalagadda, N., & Ruiter, E. (2001). Estimation of an activity based micro simulation model for San Francisco. *In: Proceedings of the 80th Annual Meeting of the Transportation Research Board*, Washington, D.C., USA.

Bradley, M. A., Bowman, J. L., & Griesenbeck, B. (2010). SACSIM: An applied activity-based model system with fine-level spatial and temporal resolution. *Journal of Choice Modelling*, 3(1), 5-31.

Brinckerhoff, P. (2010). *Oregon Statewide Integrated Model (SWIM2): Model Description*. URL: https://www.oregon.gov/ODOT/Planning/Documents/SWIM2-Model-Description.pdf. *Accessed Nov. 2021.*

Burns, D. (1979). *Transportation, Temporal, and Spatial Components of Accessibility*. Lexington Books, Lexington.

Chapin, F. S. (1974). *Human Activity Patterns in the City: Things People Do in Time and Space*. Wiley, New York.

Charypar, D., Balmer, M., & Axhausen, K. W. (2009). High-performance traffic flow microsimulation for large problems. In: *88th Annual Meeting of the Transportation Research Board*, Washington, D.C.

Chen, T. D., Kockelman, K. M., & Hanna, J. P. (2016). Operations of a shared, automated, electric vehicle fleet: Implications of vehicle & charging infrastructure decisions. *Transportation Research Part A: Policy and Practice*, 94, 243-254.

Chikaraishi, M., Khan, D., Yasuda, B., & Fujiwara, A. (2020). Risk perception and social acceptability of automated vehicles: A case study in Hiroshima, Japan. *Transport Policy*, 98, 105-115.

Childress, S., Nichols, B., Charlton, B., & Coe, S. (2015). Using an activity-based model to explore the potential impacts of automated vehicles. *Transportation Research Record*, 2493(1), 99-106.

Chiu, Y. C., Villalobos, J. A., & Board, T. R. (2008). The anisotropic mesoscopic simulation model on the interrupted highway facilities. In *Symposium on the Fundamental Diagram* (Vol. 75).

Cokyasar, T., Larson, J., (2020). Optimal assignment for the single-household shared autonomous vehicle problem. *Transportation Research Part B: Methodological*, 141, 98-115.

Consult, P. B. (2005). *The MORPC Travel Demand Model Overview and Summary*. URL: [https://www3.drcog.org/documents/archive /MORPC.pdf](https://www3.drcog.org/documents/archive/MORPC.pdf). *Accessed Nov. 2021.*

Correia, G. H., & van Arem, B. (2016). Solving the User Optimum Privately Owned Automated Vehicles Assignment Problem (UO-POAVAP): A model to explore the impacts of self-driving vehicles on urban mobility. *Transportation Research Part B: Methodological*, 87, 64-88.

Correia, G. H., Looff, E., van Cranenburgh, S., Snelder, M., & van Arem, B. (2019). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey. *Transportation Research Part A: Policy and Practice*, 119, 359-382.

Croissant, Y. (2020). Estimation of random utility models in R: the mlogit package. *Journal of Statistical Software*, 95(1), 1-41.

Davidson, W., Donnelly, R., Vovsha, P., Freedman, J., Ruegg, S., Hicks, J., Castiglione, J., & Picado, R. (2007). Synthesis of first practices and operational research approaches in activity-based travel demand modeling. *Transportation Research Part A: Policy and Practice*, 41(5), 464-488.

Daziano, R. A., Sarrias, M., & Leard, B. (2017). Are consumers willing to pay to let cars drive for them? Analyzing response to automated vehicles. *Transportation Research Part C: Emerging Technologies*, 78, 150-164.

de Jong, G., Daly, A., Pieters, M., & Van der Hoorn, T. (2007). The logsum as an evaluation measure: review of the literature and new results. *Transportation Research Part A: Policy and Practice*, 41(9), 874-889.

de la Barra, T. (1989). *Integrated Land Use and Transport Modelling: Decision Chains and Hierarchies* (Cambridge Urban and Architectural Studies). Cambridge University Press, Cambridge.

de Winter, J. C., Happee, R., Martens, M. H., & Stanton, N. A., (2014). Effects of adaptive cruise control and highly automated driving on workload and situation awareness: A review of the empirical evidence. *Transportation Research Part F: Traffic Psychology and Behavior*, 27, 196-217.

Dohi, M., Sone, S., Takimoto, M., Ogawa, T., Namikawa, Y. (2012). Evidence of automobile emission factors for road environmental impact assessment. National Institute for Land and Infrastructure Management. URL: http://www.nilim.go.jp/lab/bcg/siryou/tnn/tnn0671.htm (In Japanese), *Accessed Jun. 2022.*

Doll, G., Ebel, E., Heineke, K., Kellner M., & Wiemuth, C. (2020). *Private automated vehicles: the other side of the robo-taxi story.* McKinsey & Company. URL*: https://www.mckinsey.com/industries/automotive-and-assembly/our-insights/private-automated-vehicles-the-other-side-of-the-robo-taxi-story. Accessed Nov. 2021.*

Domencich, T. A., & McFadden, D. (1975). *Urban Travel Demand: A Behavioral Analysis.* North-Holland Publishing, Amsterdam.

Dong, X., Ben-Akiva, M. E., Bowman, J. L., & Walker, J. L. (2006). Moving from trip-based to activity-based measures of accessibility. *Transportation Research Part A: Policy and Practice*, 40(2), 163-180.

Dowle, M., & Srinivasan, A. (2021). *Data.table: Extension of `Data.frame`*. R package version 1.14.2. URL: https://CRAN.R-project.org/package=data.table. *Accessed Nov. 2021.*

Ettema, D., Borgers, A., & Timmermans, H. (1993). Simulation model of activity scheduling behavior. *Transportation Research Record.* 1413 (1), 1-11.

Fagnant, D. J., & Kockelman, K. M. (2014). The travel and environmental implications of shared automated vehicles, using agent-based model scenarios. *Transportation Research Part C: Emerging Technologies*, 40, 1-13.

Fagnant, D. J., & Kockelman, K. M. (2015). Preparing a nation for automated vehicles: opportunities, barriers and policy recommendations. *Transportation Research Part A: Policy and Practice*, 77, 167-181.

Fagnant, D. J., Kockelman, K. M., & Bansal, P. (2015). Operations of shared automated vehicle fleet for Austin, Texas, market. *Transportation Research Record*, 2563(1), 98-106.

Fagnant, D. J., & Kockelman, K. M. (2018). Dynamic ride-sharing and fleet sizing for a system of shared automated vehicles in Austin, Texas. *Transportation*, 45(1), 143-158.

Fellendorf, M., Haupt, T., Heidl, U., & Scherr, W. (1997). PTV Vision: Activity-based demand forecasting in daily practice. In: D. Ettema and H. Timmermans (eds.), *Activity-Based Approaches to Travel Analysis*, 55-72. Pergamon, Oxford.

Fernandes, P. & Nunes, U. (2015). Multiplatooning leaders positioning and cooperative behavior algorithms of communicant automated vehicles for high traffic capacity. *IEEE Transactions on Intelligent Transportation Systems*, 16(3), 1172-1187.

Fifer, S., Rose, J. & Greaves, S., (2014). Hypothetical bias in Stated Choice Experiments: Is it a problem? And if so, how do we deal with it?. *Transportation research part A: Policy and Practice*, 61, 164-177.

Flötteröd, G. (2016). MATSim as a Monte-Carlo Engine. In: A. Horni, K. Nagel, and K. W. Axhausen (eds.), *The Multi-Agent Transport Simulation MATSim*, 327-336. Ubiquity Press. London.

Fujii, S., Otsuka, Y., Kitamura, R., & Monma, T. (1997). A micro-simulation model system of individuals' daily activity behavior that incorporates spatial, temporal and coupling constraints. *Infrastructure Planning Review*. 14, 643-652. (*In Japanese*. 藤井聡, 大塚祐一郎, 北村隆一, & 門間俊幸. 1997. 時間的空間的制約を考慮した生活行動軌跡を再現するための行動シミュレーションの構築. 土木計画学研究・論文集, 14, 643-652.)

Furusawa, Y., Mizokami, S., & Yae, R. (2020). A simulation analysis on introducibility of automated vehicle car-sharing service. *Journal of Japan Society of Civil Engineers D3: Infrastructure Planning and Management*. 76(2), 168-179. (In Japanese. 古澤悠吾, 溝上章志, 森俊勝, & 八戸龍馬. 2020. 完全自動運転カーシェアサービスの導入可能性に関するシミュレーション分析. 土木学会論文集 D3 (土木計画学), *76*(2), 168-179.)

Gagolewski, M. (2021). *Stringi: Fast and Portable Character String Processing in R*. R package version 1.7.5, URL: https://stringi.gagolewski.com/. *Accessed Nov. 2021.*

Gärling, T., Brännäs, K., Garvill, J., Golledge, R. G., Gopal, S., Holm, E., & Lindberg, E. (1989). Household activity scheduling. *Selected Proceedings of The Fifth World Conference on Transport Research*, 4, 235–248. Western Periodicals. Ventura, CA.

Gelauff, G., Ossokina, I., & Teulings, C. (2019). Spatial and welfare effects of automated driving: will cities grow, decline or both?. *Transportation Research Part A: Policy and Practice*, 121, 277-294.

Geurs, K. T., & Van Wee, B. (2004). Accessibility evaluation of land-use and transport strategies: review and research directions. *Journal of Transport Geography*, 12(2), 127-140.

Givoni, M., & Banister, D. (2010). The need for integration in transport policy and practice. In: M. Givoni and D. Banister (eds.), *Integrated transport: From Policy to Practice*. 17-28. Routledge.

Gunma Prefectural Government (2020). *Urban Planning of Gunma 2020*. URL: https://www.pref.gunma.jp/06/h5800002.html. (In Japanese. 「ぐんまの都市計画２０２０」). *Accessed Nov. 2021.*

Gunma Prefectural Government (2022). *Fiscal 2021 Gunma Prefecture*. URL: https://www.pref.gunma.jp/site/gunmazaisei/100269.html (In Japanese. 「令和3年度群馬県の決算」). *Accessed Feb. 2023.*

Haboucha, C.J., Ishaq, R. and Shiftan, Y. (2017). User preferences regarding automated vehicles. *Transportation Research Part C: Emerging Technologies*, 78, 37-49.

Hägerstrand, T. (1970). What about people in Regional Science?. *Papers of the Regional Science Association,* 24, 6–21.

Hague Consulting Group (1992). *The Netherlands National Model, 1990: The National Model System for Traffic and Transport*. Ministry of Transport and Public Works, The Netherlands.

Hansen, W. G. (1959). How accessibility shapes land use. *Journal of the American Institute of Planners*, 25(2), 73-76.

Hao, J. Y., Hatzopoulou, M., & Miller, E. J. (2010). Integrating an activity-based travel demand model with dynamic traffic assignment and emission models: Implementation in the Greater Toronto, Canada, area. *Transportation Research Record*, 2176(1), 1-13.

Hao, M., Li, Y., & Yamamoto, T. (2019). Public preferences and willingness to pay for shared automated vehicles services in Nagoya, Japan. *Smart Cities*, 2(2), 230-244.

Harb, M., Stathopoulos, A., Shiftan, Y., & Walker, J. L. (2021). What do we (not) know about our future with automated vehicles?. *Transportation Research Part C: Emerging Technologies*, 123, 102948.

Harper, C. D., Hendrickson, C. T., Mangones, S., & Samaras, C. (2016). Estimating potential increases in travel with automated vehicles for the non-driving, elderly and people with travel-restrictive medical conditions. *Transportation Research Part C: Emerging Technologies*, 72, 1-9.

Heggie, I. G., & Jones, P. M. (1978). Defining domains for models of travel demand. *Transportation*, 7(2), 119-125.

Hensher, D. A., (2010). Hypothetical bias, choice experiments and willingness to pay. *Transportation Research Part B: Methodological*, 44(6), 735-752.

Horni, A. (2013). *Destination Choice Modeling of Discretionary Activities in Transport Microsimulations*, (Ph.D. Thesis), ETH Zurich, Zurich.

Horni, A, Nagel, K., & Axhausen, K. W. (2016). The Multi-Agent Transport Simulation MATSim. Ubiquity Press, London.

Huang, S., Ren, W., & Chan, S. C. (2000). Design and performance evaluation of mixed manual and automated control traffic. *IEEE Transactions on Systems, Man, and Cybernetics Part A: Systems and Humans*, 30(6), 661-673.

Iacono, M., Levinson, D., & El-Geneidy, A. (2008). Models of transportation and land use change: A guide to the territory. *Journal of Planning Literature*, 22(4), 323-340.

Iida, Y., Iwabe, M., Kikuchi, A., Kitamura, R., Sasaki, K., Shiromizu, Y., Nakagawa, D., Hatoko, M., Fujii, M., Morikawa, T., & Yamamoto, T. (2000). Micro-Simulation Based Travel Demand Forecasting System for Urban Transportation Planning. Infrastructure Planning Review, 17, 841-847. (*In Japanese*. 飯田祐三, 岩辺路由, 菊池輝, 北村隆一, 佐々木邦明, 白水靖郎, 中川大, 波床正敏, 藤井聡, 森川高行, 山本俊行. (2000). マイクロシミュレーションアプローチによる都市交通計画のための交通需要予測システムの提案. 土木計画学研究・論文集, 17, 841-847).

Inahara, H., Daimon, H., Hayashi, K., Sekimoto, M., Akimoto, M., Amamori, E. & Ito, M. (2017). Consideration on Future Urban Transport Policy in Regional Metropolitan Area - Picturing the Future of Japan Based on the Results of Gunma Person Trip Survey. *The Institute of Behavioral Sciences (IBS) Annual Report*. (*In Japanese*. 稲原宏、大門創、林健太郎、関本稀美、秋元伸裕、雨森恵理子、伊藤 京. (2017). 地方都市圏のこれからの都市交通政策を考える ～群馬県PT調査結果から読み解く日本の将来～. *IBS研究活動報告*).

Javanmardi, M., Auld, J., Omer. V., 2018. Analyzing intra-household fully automated vehicle sharing," in Proceedings of the 97th Annual Meeting of the Transportation Research Board.

Jara-Díaz, S. R. (2007). Allocation and valuation of travel-time savings. In: D. Hensher and K. Button (eds.), *Handbook of Transport Modelling*, 363-379. Emerald Group Publishing Limited.

Jenn, U. (2016). *The Road to Driverless Cars: 1925 – 2025*. Engineering.com. URL: https://www.engineering.com/IOT/ArticleID/12665/The-Road-to-Driverless-Cars-1925--2025.aspx. *Accessed Nov. 2021.*

Jiang, Y., Zhang, J., Wang, Y., & Wang, W. (2019). Capturing ownership behavior of automated vehicles in Japan based on a stated preference survey and a mixed logit model with repeated choices. *International Journal of Sustainable Transportation*, 13(10), 788-801.

Jones, P. M. (1979). New approaches to understanding travel behaviour: the human activity approach. In: D. Hensher and P. Stopher (eds.), 45-71. *Behavioural Travel Modelling*, Routledge.

Jones, P. M., Dix, M. C., Clarke, M. I., & Heggie, I. G. (1983). *Understanding Travel Behaviour*. Gower: Aldershot.

Kalra, N., & Paddock, S. M. (2016). Driving to safety: How many miles of driving would it take to demonstrate automated vehicle reliability?. *Transportation Research Part A: Policy and Practice*, 94, 182-193.

Kamijo, Y., Luo, L., Parady, G. T., Takami, K., & Harata, N. (2019). Scenario evaluation of automated vehicle spread using agent-based simulation. *Journal of Japan Society of Traffic Engineers*, 5(2), A_142-A_151. (In Japanese. 上条陽, 羅力晨, 髙見淳史, & 原田昇. (2019). エージェントベースシミュレーションを用いた自動運転車普及シナリオの評価. *交通工学論文集*, *5*(2), A_142-A_151).

Katsuki, H., Azuma, K., & Taniguchi, M. (2017). Introducing shared automated driving for universal service for suburban transportation: Emphasis on spatioemporal and personal characteristics of trips. *Journal of the City Planning Institute of Japan*, 52(3), 769-775. (In Japanese, 香月秀仁, 東達志, & 谷口守. 2017. 郊外間交通へのシェア型自動運転車の導入可能性トリップの時空間特性・個人属性の観点から. 都市計画論文集, 52(3), 769-775).

Katsuki, H., Azuma, K., Takahara, I., & Taniguchi, M. (2018a). Down size of parking spatioemporal spaces by shared mobility with automated driving. *Journal of the City Planning Institute of Japan*. 53(3), 544-550. (In Japanese, 香月秀仁, 東達志, 高原勇, & 谷口守. 2018. シェア型自動運転交通" Shared-adus" 導入による駐車時空間削減効果. 都市計画論文集, 53(3), 544-550).

Katsuki, H., Azuma, K., Takahara, I., & Taniguchi, M. (2018b). Change of vehicle utilization by shared mobility with automated driving: environmental footprint effects of vacant trip time. *Journal of Japan Society of Civil Engineers D3: Infrastructure Planning and Management*. 74(5), 889-896. (In Japanese. 香月秀仁, 東達志, 高原勇, & 谷口守. 2018. シェア型自動運転車による自動車利用変化—空走時間発生による環境負荷への影響—. 土木学会論文集 D3 (土木計画学), 74(5), 889-896).

Kelly, E. D. (1994). The transportation land-use link. *Journal of Planning Literature*, 9(2), 128-145.

Khondaker, B., & Kattan, L. (2015). Variable speed limit: A microscopic analysis in a connected vehicle environment. *Transportation Research Part C: Emerging Technologies*, 58, 146-159.

Kii, M., Nakanishi, H., Nakamura, K., & Doi, K. (2016). Transportation and spatial development: An overview and a future direction. *Transport Policy*, 49, 148-158.

Kii, M., Yokota, A., Gao, Z., & Nakamura, K. (2017). The effect of urban conditions on dissemination of shared fully-automated vehicles. *Journal of Japan Society of Civil Engineers D3: Infrastructure Planning and Management*, 73(5), 507-515. (In Japanese. 紀伊雅敦, 横田彩加, 高震宇, & 中村一樹.

2017. 共有型完全自動運転車両の普及に関する基礎分析. 土木学会論文集 D3 (土木計画学), 73(5), 507-515).

Kim, H. M., & Kwan, M. P. (2003). Space-time accessibility measures: A geocomputational algorithm with a focus on the feasible opportunity set and possible activity duration. *Journal of geographical Systems*, 5(1), 71-91.

Kim, S. H., Mokhtarian, P. L., & Circella, G. (2020). Will automated vehicles change residential location and vehicle ownership? Glimpses from Georgia. *Transportation Research Part D: Transport and Environment*, 82, 102-291.

Kitamura, R. (1988). An evaluation of activity-based travel analysis. *Transportation*, 15(1), 9-34.

Kitamura, R., E.I. Pas, C.V. Lula, T.K. Lawton, & P.E. Benson (1996). The sequenced activity mobility simulator (SAMS): an integrated approach to modeling transportation, land use and air quality. *Transportation*, 23, 267-291.

Kitamura, R. (1996). Challenges for Travel Demand Forecasting: Toward the Development of Next-Generation Model Systems. *Journal of Japan Society of Civil Engineers*, (530), 17-30. *(In Japanese.* 北村隆一. 交通需要予測の課題: 次世代手法の構築にむけて. 土木学会論文集, (530), 17-30).

Kitamura, R., & Fujii, S. (1998). Two computational process models of activity-travel choice. In *T. Gärling, T. Laitila, & K. Westin (eds.), Theoretical foundations of travel choice modelling*, 251–279. Elsevier, Oxford.

Kitamura, R., Kikuchi, A., Fujii, S., & Yamamoto, T. (2005). An overview of PCATS/DEBNetS micro-simulation system: Its development, extension, and application to demand forecasting. In: R. Kitamura, and M. Kuwahara (eds.), *Simulation Approaches in Transportation Analysis*, 371-399. Springer, Boston, MA.

Kolarova, V., Steck, F., & Bahamonde-Birke, F. J. (2019). Assessing the effect of automated driving on value of travel time savings: A comparison between current and future preferences. *Transportation Research Part A: Policy and Practice*, 129, 155-169.

Krueger, R., Rashidi, T. H., & Rose, J. M. (2016). Preferences for shared automated vehicles. *Transportation Research Part C: Emerging Technologies*, 69, 343-355.

Krueger, R., Rashidi, T. H., & Dixit, V. V. (2019). Automated driving and residential location preferences: Evidence from a stated choice survey. Transportation Research Part C: Emerging Technologies, 108, 255-268.

Lavieri, P. S., Garikapati, V. M., Bhat, C. R., Pendyala, R. M., Astroza, S., & Dias, F. F. (2017). Modeling individual preferences for ownership and sharing of automated vehicle technologies. *Transportation Research Record*, 2665(1), 1-10.

Le Vine, S., Zolfaghari, A. & Polak, J. (2015). Automated cars: The tension between occupant experience and intersection capacity. Transportation Research Part C: Emerging Technologies, 52, 1-14.

Lee Jr, D. B. (1973). Requiem for large-scale models. *Journal of the American Institute of Planners*, 39(3), 163-178.

Lefebvre, N., & Balmer, M. (2007). Fast shortest path computation in time-dependent traffic networks. *Arbeitsberichte Verkehrs-und Raumplanung*, 439.

Lenntorp, B. (1976). Paths in space-time environments: A time-geographic study of movement possibilities of individuals. *Lund Studies in Geography, Series B, Human Geography number 44*. The Royal University of Lund, Sweden.

Li, S. (2015). *Activity-based Travel Demand Model: Application and Innovation* (Ph.D. thesis). National University of Singapore, Singapore.

Lin, D. Y., Eluru, N., Waller, S. T., & Bhat, C. R. (2008). Integration of activity-based modeling and dynamic traffic assignment. *Transportation Research Record*, 2076(1), 52-61.

Litman, T. (2017). *Evaluating Accessibility for Transport Planning*. Victoria Transport Policy Institute.

Litman, T. (2021). *Automated Vehicle Implementation Predictions: Implications for Transport Planning*. Victoria Transport Policy Institute.

Liu, J., Kockelman, K. M., Boesch, P. M., & Ciari, F. (2017). Tracking a system of shared automated vehicles across the Austin, Texas network using agent-based simulation. *Transportation*, 44(6), 1261-1278.

Llorca, C., Moreno, A., Ammar, G., & Moeckel, R. (2022). Impact of autonomous vehicles on household relocation: An agent-based simulation. *Cities*. 126: 103692.

Lowry, I. S. (1964). *A model of metropolis*. Santa Monica, CA: Rand Corporation.

Luo, L., Parady, G. T., Takami, K., & Harata, N. (2019). Evaluating the Impact of Automated vehicles on Accessibility Using Agent-Based Simulation—A Case Study of Gunma Prefecture. *Journal of Japan Society of Civil Engineers*, 7(1), 100-111.

Luo, L., Parady, G., & Takami, K. (2022). Evaluating the impact of private automated vehicles on activity-based accessibility in Japanese regional areas: A case study of Gunma Prefecture. *Transportation Research Interdisciplinary Perspectives*, 16, 100717.

Mackett, R. L. (1983). *The Leeds Integrated Land-use Transport Model (LILT).* Transport and Road Research Laboratory, Crowthorne.

Maebashi Municipal Government (2019). *Local Optimization Plan of Maebashi City*. URL: https://www.city.maebashi.gunma.jp/soshiki/toshikeikakubu/toshikeikaku/oshirase/23361.html. (In Japanese.「前橋市立地適正化計画」). *Accessed Nov. 2021.*

Manski, C. F. (1977). The structure of random utility models. *Theory and Decision*, 8(3), 229.

Martinez, F. J. (1992). The bid—choice land-use model: an integrated economic framework. *Environment and Planning A: Economy and Space*, 24(6), 871-885.

Martinez, F. J. (1996). MUSSA: land use model for Santiago city. *Transportation Research Record*, 1552(1), 126-134.

Matsunaka, R., Oba, T., & Sumikawa, S. (2020). Analyzing social benefits obtained from the spread of shared automated vehicle using urban traffic simulation. *Journal of the City Planning Institute of Japan*, 55(2), 115-125. (In Japanese. 松中亮治, 大庭哲治, 住川俊多. 2020. 都市内交通シミュレーションを用いた共有型完全自動運転車両の普及による社会的便益に関する研究. 都市計画論文集, 55(2), 115-125).

McFadden, D. (1973). Conditional logit analysis of qualitative choice behavior. In: P. Zarembka (ed.), *Frontiers in Econometrics*, 105-142, Academic Press, New York, NY.

McFadden, D. (1978). Modelling the choice of residential location. In: A. Karlqvist, L. Lundqvist, F. Snickars, and J. Weibull (eds.), *Spatial Interaction Theory and Planning Models,* 75-96. North-Holland Publishing, Amsterdam.

McNally, M. G. (2007). The Four-Step Model. In: Hensher, D.A. and Button, K.J. (eds.), *Handbook of Transport Modelling*, 33-53. Emerald Group Publishing Limited, Bingley.

Meyer, J., Becker, H., Bösch, P. M., & Axhausen, K. W. (2017). Automated vehicles: The next jump in accessibilities?. *Research in Transportation Economics*, 62, 80-91.

Meng, Z., Le, D. T., Zegras, P. C., & Ferreira, J. (2019). Impacts of automated mobility on demand on long-term mobility choices: A case study of Singapore. *In 2019 IEEE Intelligent Transportation Systems Conference*, IEEE, 1908-1913.

Milakis, D., Van Arem, B., & Van Wee, B. (2017). Policy and society related implications of automated driving: A review of literature and directions for future research. *Journal of Intelligent Transportation Systems*, 21(4), 324-348.

Milakis, D., Kroesen, M., & van Wee, B. (2018). Implications of automated vehicles for accessibility and location choices: Evidence from an expert-based experiment. *Journal of Transport Geography*, 68, 142-148.

Miller, E. J., & Roorda, M. J. (2003). Prototype model of household activity-travel scheduling. *Transportation Research Record*, 1831(1), 114-121.

Ministry of Economy, Trade and Industry (2018). Japan Promotes Electrified Vehicle (xEV) Strategy ahead of 2050. URL: https://www.meti.go.jp/english/mobile/2018/20180911001en.html. *Accessed Jul. 2022.*

Ministry of Economy, Trade and Industry (2021). Report on Efforts for Achieving Automated Driving and Policies Version 5.0. URL: https://www.meti.go.jp/shingikai/mono_info_service/jido_soko/20210430_report.html. (In Japanese. 自動走行ビジネス検討会 - 報告書「自動走行の実現及び普及に向けた取組報告と方針Version5.0」～レベル4自動運転サービスの社会実装を目指して～). *Accessed Nov. 2021.*

Ministry of Land, Infrastructure, Transport and Tourism (2016). *Land Value Publication Data*. URL: https://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-L01-v3_0.html; and https://nlftp.mlit.go.jp/ksj/gml /datalist/KsjTmplt-L02-v3_0.html (In Japanese. 「国土数値情報（地価公示データ & 都道府県地価調査データ）」（国土交通省）). *Accessed Nov. 2021.*

Ministry of Land, Infrastructure, Transport and Tourism (2018a). *Land Use Mesh Data*. URL: https://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-L03-a.html. (In Japanese. 「国土数値情報（土地利用メッシュデータ）」（国土交通省）). *Accessed Nov. 2021.*

Ministry of Land, Infrastructure, Transport and Tourism (2018b). *Land Use Subdivided Mesh Data in Urban Area*. URL: https://nlftp.mlit.go.jp/ksj/gml/datalist/KsjTmplt-L03-b-u.html. (In Japanese. 「国土数値情報（都市地域土地利用細分メッシュデータ）」（国土交通省）). *Accessed Nov. 2021.*

Ministry of Land, Infrastructure, Transport and Tourism (2021). *Local Optimization Plan*. URL: https://www.mlit.go.jp/en/toshi/city_plan/compactcity_network.html. (In Japanese. 立地適正化計画制度, 国土交通省). *Accessed Nov. 2021.*

Mitchell, R. B., & Rapkin, C. (1954). *Urban Traffic: A Function of Land Use*. Columbia, University Press, New York, NY.

Moore, M. A., Lavieri, P. S., Dias, F. F., & Bhat, C. R. (2020). On investigating the potential effects of private autonomous vehicle use on home/work relocations and commute times. *Transportation Research Part C: Emerging Technologies*. 110: 166-185.

Nagel, K., & Flötteröd, G. (2012). Agent-based traffic assignment: Going from trips to behavioural travelers. In: *Travel Behaviour Research in an Evolving World–Selected papers from the 12th international conference on travel behaviour research*. 261-294. International Association for Travel Behaviour Research.

Nahmias–Biran, B. H., & Shiftan, Y. (2016). Towards a more equitable distribution of resources: Using activity-based models and subjective well-being measures in transport project evaluation.

Transportation Research Part A: Policy and Practice, 94, 672-684.

Nahmias-Biran, B. H., Oke, J. B., Kumar, N., Lima Azevedo, C., & Ben-Akiva, M. (2021). Evaluating the impacts of shared automated mobility on-demand services: an activity-based accessibility approach. *Transportation*, 48(4), 1613-1638.

Nakamura, H., Hayashi, Y., & Miyamoto, K. (1983). A land use-transport model for metropolitan areas. *Papers of the Regional Science Association* 51(1), 43-63. Springer-Verlag.

National Institute of Population and Social Security Research (Japan). (2018). *Prediction of Future Population in Japan by Areas*. URL: https://www.ipss.go.jp/pp-shicyoson/j/shicyoson18/2gaiyo_hyo/gaiyo.asp. (*In Japanese.* 国立社会保障・人口問題研究所. 日本の地域別将来推計人口』（平成 30（2018）年推計）). *Accessed Nov. 2021.*

National Research Council (US). Committee for Determination of the State of the Practice in Metropolitan Area Travel Forecasting, & Transportation Research Board. (2007). *Metropolitan Travel Forecasting: Current Practice and Future Direction--Special Report 288 (No. 288).* Transportation Research Board.

Niemeier, D. A. (1997). Accessibility: an evaluation using consumer welfare. *Transportation*, 24(4), 377-396.

Niccolai, J. (2012). *Self-driving cars a reality for 'ordinary people' within 5 years, says Google's Sergey Brin.* Computerworld. URL: *https://www.computerworld.com/article/2491635/self-driving-cars-a-reality-for--ordinary-people--within-5-years--says-google-s-sergey-b.html*. *Accessed Nov. 2021.*

Neutens, T., Witlox, F., Van De Weghe, N., & De Maeyer, P. H. (2007). Space–time opportunities for multiple agents: a constraint-based approach. *International Journal of Geographical Information Science*, 21(10), 1061-1076.

OpenStreetMap contributors. (2021). *Planet Dump*. URL: *https://planet.openstreetmap.org*.

Ortúzar, J. D. D., & Willumsen, L. G. (2011). *Modelling Transport*. Wiley, New York.

Paleti, R., Vovsha, P., Vyas, G., Anderson, R., & Giaimo, G. (2017). Activity sequencing, location, and formation of individual non-mandatory tours: application to the activity-based models for Columbus, Cincinnati, and Cleveland, OH. *Transportation*, 44(3), 615-640.

Parady, G., Ory, D., & Walker, J. (2021). The overreliance on statistical goodness-of-fit and under-reliance on model validation in discrete choice models: A review of validation practices in the transportation academic literature. *Journal of Choice Modelling* 38, 100257.

Pebesma, E. (2018). Simple Features for R: Standardized Support for Spatial Vector Data. The R Journal, 10(1), 439-446,

Pendyala, R. M., Kitamura, R., Kikuchi, A., Yamamoto, T., & Fujii, S. (2005). Florida activity mobility simulator: overview and preliminary validation results. *Transportation Research Record*, 1921(1), 123-130.

Pendyala, R. M., Konduri, K. C., Chiu, Y. C., Hickman, M., Noh, H., Waddell, P., Wang, L., You, D., & Gardner, B. (2012a). Integrated land use–transport model system with dynamic time-dependent activity–travel microsimulation. *Transportation Research Record*, 2303(1), 19-27.

Pendyala, R. M., Bhat, C. R., Goulias, K. G., Paleti, R., Konduri, K. C., Sidharthan, R., Hu, H., Huang, G., & Christian, K. P. (2012b). Application of Socioeconomic Model System for Activity-Based Modeling: Experience from Southern California. *Transportation research record*, *2303*(1), 71-80.

Pinjari, A. R., & Bhat, C. R. (2011). Activity-based travel demand analysis. In: A. de Palma, R. Lindsey, E. Quinet and R. Vickerman (eds.), *A Handbook of Transport Economics*, 213-248. Edward Elgar Publishing.

Pudāne, B., & Correia, G. (2020). On the impact of vehicle automation on the value of travel time while performing work and leisure activities in a car: Theoretical insights and results from a stated preference survey–A comment. *Transportation Research Part A: Policy and Practice*, 132, 324-328.

Puget Sound Regional Council (n.d). *Activity-Based Travel Model: SoundCast*. URL: https://www.psrc.org/activity-based-travel-model-soundcast. *Accessed Nov. 2021*.

Putman, S. H. (1983). *Integrated Urban Models*. Pion, London.

Putman, S. H. (1991). *Integrated Urban Models 2*. Pion, London.

R Core Team (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. URL: https://www.R-project.org/. *Accessed Nov. 2021.*

Rashidi, T. H., Waller, T., & Axhausen, K. (2020). Reduced value of time for automated vehicle users: Myth or reality?. *Transport Policy*, 95, 30-36.

Rasouli, S., & Timmermans, H. (2014). Activity-based models of travel demand: promises, progress and prospects. *International Journal of Urban Sciences*, 18(1), 31-60.

Recker, W. W., McNally, M. G., & Root, G. S. (1986a). A model of complex travel behavior: Part I—Theoretical development. *Transportation Research Part A: General*, 20(4), 307-318.

Recker, W. W., McNally, M. G., & Root, G. S. (1986b). A model of complex travel behavior: Part II—An operational model. *Transportation Research Part A: General*, 20(4), 319-330.

Resource Decision Consultants (1995). *Activity-based Modeling System for Travel Demand Forecasting,* US Department of Transportation, Washington, D.C. URL: https://www.mobilityanalytics.org/uploads/5/0/5/4/5054275/amos.pdf. *Accessed Nov. 2021.*

Ruiter, E. R., & Ben-Akiva, M. E. (1978). Disaggregate travel demand models for the San Francisco bay area, *Transportation Research Record*, 673, 121-128.

Sabina, E., & Rossi, T. (2007). Denver's activity-based model project: status report, lessons learned so far, and advice on how you can do it better than we have. In: *11th TRB National Transportation Planning Applications Conference*, Florida.

Safwat, K. N., & Magnanti, T. L. (1988). A combined trip generation, trip distribution, modal split, and trip assignment model. *Transportation Science*, 22(1), 14-30.

Society of Automobile Engineers (2021). *Standard J3016: Taxonomy and Definitions for Terms Related to Driving Automation Systems for On-Road Motor vehicle*. SAE International.

Salvini, P., & Miller, E. J. (2005). ILUTE: An operational prototype of a comprehensive microsimulation model of urban systems. *Networks and Spatial Economics*, 5(2), 217-234.

Sheffi, Y. (1985). *Urban Transportation Networks.* Prentice-Hall, Englewood Cliffs, NJ.

Shladover, S., Su, D. & Lu, X.Y., (2012). Impact of cooperative adaptive cruise control on freeway traffic flow. *Transportation Research Record*, 2324, 63-70.

Singh, S. (2015). *Critical Reasons for Crashes Investigated in the National Motor Vehicle Crash Causation Survey*. National Highway Traffic Safety Administration, Washington D.C., Report No. DOT HS 812 115.

Singleton, P. A. (2019). Discussing the "positive utilities" of automated vehicles: will travellers really use their time productively?. *Transport Reviews*, 39(1), 50-65.

Smith, L., Beckman, R., & Baggerly, K. (1995). *TRANSIMS: Transportation analysis and simulation system* (No. LA-UR-95-1641). Los Alamos National Lab., NM.

Soteropoulos, A., Berger, M., & Ciari, F. (2019). Impacts of automated vehicles on travel behaviour and land use: an international review of modelling studies. *Transport Reviews*, 39(1), 29-49.

Statistics Bureau of Japan (2015). *National Census*. URL: https://www.stat.go.jp/data/kokusei/2015/index.html. (In Japanese. 総務省統計局「平成27年国勢調査結果」*). Accessed Nov. 2021.*

Statistics Bureau of Japan (2018). *Housing and Land Census*. URL: https://www.stat.go.jp/data/jyutaku/index.html. (In Japanese. 総務省統計局 平成30年住宅・土地統計調査*). Accessed Nov. 2021.*

Statistics Bureau of Japan (2019). *Regional Mesh Statistics*. URL: https://www.stat.go.jp/data/mesh/index.html. (In Japanese. 総務省統計局 地域メッシュ統計*). Accessed Nov. 2021.*

Statistics Bureau of Japan (2020). *National Census*. URL: https://www.stat.go.jp/data/kokusei/2020/index.html. (In Japanese. 総務省統計局「令和2年国勢調査結果」*). Accessed Nov. 2021.*

Steck, F., Kolarova, V., Bahamonde-Birke, F., Trommer, S., & Lenz, B. (2018). How automated driving may affect the value of travel time savings for commuting. *Transportation Research Record*, 2672(46), 11-20.

Strand, N., Nilsson, J., Karlsson, I. M., & Nilsson, L. (2014). Semi-automated versus highly automated driving in critical situations caused by automation failures. *Transportation Research Part F: Traffic Psychology and Behaviour*, 27, 218-228.

Vovsha, P., Petersen, E., & Donnelly, R. (2002). Microsimulation in travel demand modeling: Lessons learned from the New York best practice model. *Transportation Research Record*, 1805(1), 68-77.

Vovsha, P., Bradley, M., & Bowman, J. L. (2005). Activity-based travel forecasting models in the United States: Progress since 1995 and prospects for the future. In: H. Timmermans (ed.), *Progress in Activity-based Analysis*, 389-414. Elsevier, Oxford.

Vovsha, P., Freedman, J., Livshits, V., & Sun, W. (2011). Design Features of Activity-Based Models in Practice: Coordinated Travel–Regional Activity Modeling Platform. *Transportation Research Record*, 2254(1), 19-27.

Vyas, G., Famili, P., Vovsha, P., Fay, D., Kulshrestha, A., Giaimo, G., & Anderson, R. (2019). Incorporating features of automated vehicles in activity-based travel demand model for Columbus, OH. *Transportation*, 46(6), 2081-2102.

Waddell, P. (2000). A behavioral simulation model for metropolitan policy analysis and planning: residential location and housing market components of UrbanSim. *Environment and Planning B: Planning and Design*, 27(2), 247-263.

Waddell, P., Borning, A., Noth, M., Freier, N., Becke, M., & Ulfarsson, G. (2003). Microsimulation of urban development and location choices: Design and implementation of UrbanSim. *Networks and Spatial Economics*, 3(1), 43-67.

Waddell, P. (2011). Integrated land use and transportation planning and modelling: addressing challenges in research and practice. *Transport Reviews*, 31(2), 209-229.

Wardrop, J. G. (1952). Road paper. some theoretical aspects of road traffic research. *Proceedings Of the Institution of Civil Engineers*, 1(3), 325-362.

Waymo. (2021). *Waymo Safety Report*. URL: https://storage.googleapis.com/waymo-uploads/files/documents/safety/2021-12-waymo-safety-report.pdf *Accessed Feb. 2023.*

Wegener, M. (1985). The Dortmund housing market model: a Monte Carlo simulation of a regional housing market. In: K. Stahl (ed.), *Microeconomic Models of Housing Markets*, 144-191. Springer, Berlin, Heidelberg.

Wegener, M. (2004). Overview of land use transport models. In: D. Hensher, K. Button, K. Haynes, and P. Stopher (eds.), *Handbook of Transport Geography and Spatial Systems*, 127-146. Emerald Group Publishing Limited.

Wingo, L. (1961). *Transportation and Urban Land*. Routledge.

Yagi, S., & Mohammadian, A. K. (2010). An activity-based microsimulation model of travel demand in the Jakarta metropolitan area. *Journal of Choice Modelling*, 3(1), 32-57.

Yang, Q., & Koutsopoulos, H. N. (1996). A microscopic traffic simulator for evaluation of dynamic traffic management systems. *Transportation Research Part C: Emerging Technologies*, 4(3), 113-129.

Zhang, W., Guhathakurta, S., Fang, J., & Zhang, G. (2015). Exploring the impact of shared automated vehicles on urban parking demand: An agent-based simulation approach. *Sustainable Cities and Society*, 19, 34-45.

Zhang, W., & Guhathakurta, S. (2017). Parking spaces in the age of shared automated vehicles: How much parking will we need and where?. *Transportation Research Record*, 2651(1), 80-91.

Zhang, W., Guhathakurta, S., & Khalil, E. B. (2018). The impact of private automated vehicles on vehicle ownership and unoccupied VMT generation. *Transportation Research Part C: Emerging Technologies*, 90, 156-165.

Zhang, W., & Guhathakurta, S. (2021). Residential location choice in the era of shared automated vehicles. *Journal of Planning Education and Research*, 41(2), 135-148.

Zhong, H., Li, W., Burris, M. W., Talebpour, A., & Sinha, K. C. (2020). Will automated vehicles change auto commuters' value of travel time?. *Transportation Research Part D: Transport and Environment*, 83, 102303.

Zhou, X., & Taylor, J., (2014). DTALite: a queue-based mesoscopic traffic simulator for fast model evaluation and calibration. *Cogent Engineering*. 1(1), 964345.

Ziemke, D., Nagel, K., & Bhat, C. (2015). Integrating CEMDAP and MATSim to increase the transferability of transport demand models. *Transportation Research Record*, 2493(1), 117-125.

Ziliaskopoulos, A. K., & Lee, S. (1996). A cell transmission based assignment-simulation model for integrated freeway/surface street systems. In: *75th Annual Meeting of the Transportation Research Board*, Washington, DC.