Nagaoka University of Technology

ATTITUDE-BASED LATENT VARIABLES FOR RESIDENTIAL SELF-SELECTION AND TRAVEL BEHAVIOR CHANGE: COVID-19 EFFECT STUDY CASE

Dissertation of doctoral course
of energy and environment science

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Abstract

Residential self-selection is the mechanism involved in various elements that impact residential location and are related to travel behavior. Residential self-selection is relevant to the decision-making process in terms of relocation and travel behavior. Moreover, in the decision process, planned behavior theory explores attitudes toward the behavior relative to the behavior. In contrast, the cognitive dissonance theory says that a change in attitude leads to a change in behavior. This illustrates the effects of COVID-19 on attitudes that might have effects on travel behavior and relocation in long-term decisions. Furthermore, residential self-selection specifically of residential attitudes allows for a more in-depth study of the relationship between travel attitudes and travel behaviors.

This research aims to investigate the relationship between residential self-selection of hypothesis setting. In order to study causal relationships in statistics, the method is based on structural equation modeling (SEM), which is a data analysis technique that combines path analysis and factor analysis. To explore, uncover, and identify relationships and confirm hypothesis testing, The relationship was revealed to evaluate the overall residential self-selection hypothesis, and the integration of estimates and tests of a variety of hypotheses involving conditional indirect effects was applied. Further, pre-test and post-test designs of experiments in which measurements are taken on decisions before and after were applied to the situation change of the pandemic case study. As specified by attitude-based, Chi-Square Automatic Detection (CHAID) was developed to identify the segmentation of the residential self-selection dimension under decision-making attitude-based.

The results on residential self-selection relationships, in particular of residential attitudes, strongly affected travel attitudes and were found to have a long-term impact on residential attitudes and an indirect effect on travel behavior. In addition, this confirms that attitude has a significant impact on travel behavior more than socio-demographic and other characteristics. In the catchment area, people used mass transit and public transport mainly, so the specific characteristics were the walking distance from residence to the nearest station and the number of transport cards owned. Furthermore, due to the tendency of study results, people will be more aware of residential relocation and that will lead to relocation in the future based on the COVID-19 effect, which makes travelers and residents uncertain in decision-making regarding relocation.

Keywords: Residential self-selection, travel behavior, attitude-based, decision-making, COVID-19, mass transit, SEM, moderated mediation, CHAID, pre-test and post-test.

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1 INTRODUCTION

This chapter introduces the overall research statement, the framework of research, the research question in the field of study area, the research gap, the research objective, and the overall hypothesis of study, all of which are expressed and discussed in detail.

1.1 Research Statement

In the study of travel behavior research, the complex relationship between travel behavior and resident choice or household decision of location by considered a place for living related to travel behavior is called “residential self-selection”. In the term residential self-selection1 refers to ‘‘the tendency of people to choose locations based on their travel abilities, needs, and preferences’’ [1]. Furthermore, when combined with the built environment and residential self-selection was found to be a significant predictor of daily travel, and this may be true for some other long-term choices [2]. Due to the residential built environment, walkability, and regional accessibility all have a direct impact on the active transport modes available and the distance traveled. While residential self-selection, or the decision to live in a certain neighborhood, has an indirect effect on travel attitudes and satisfaction [3], [4].

Studies on residential self-selection frequently emphasize the importance of the built environment on travel behavior due to the impact the built environment on travel behavior has causal mechanism on relocation. However, the psychological attitudes that are important to understanding the decision-making process in behavior are the more advanced research methodology and implications for policy and planning. It was found that the effect of travel preferences on residential self-selection and attitudes might be related to the use of travel modes [5], [6]. In particular, by considering the travel attitudes and motives for relocation were examined and it was discovered that the reasons for moving were related to travel [7].

Consequently, an objective-subjective division in understanding travel behavior: hard factors such as urban form and socioeconomic factors are recognized as having an impact on various aspects of travel behavior [6], and soft factors are used in travel behavior research to consider the impact on travel behavior, such as attitudes and preferences for various modes of transportation or neighborhood characteristics [8]. Additionally, personal characteristics and travel-related attitude were found to be significant predictors of how people evaluate their travel [9]. Nevertheless, changes in travel behavior might be a result of socio-economic and psychological changes. Various studies have shown evidence of the psychological impact on travel behavior, such as personal lifestyles and attitudes [6]. Furthermore, housing and neighborhood characteristics are more important than travel-related attitudes, which have influenced travel behavior and also through residential choice [10].

The residential neighborhood has a significant impact on how people travel. People living in compact, mixed-use neighborhoods with good public transportation frequently walk, cycle, or take public transportation, whereas those who live in low-density, single-use neighborhoods with limited public transportation use private cars for most of their trips. As a result, encouraging people to live in urban areas is frequently recommended as a means of reducing the usage of cars [11]. In addition, the population and employment density, land use mix diversity, and intermodal connection all had a beneficial effect on subway ridership in subway catchment areas, particularly around the station area. [12]. The residents’ preference for traveling by train moved to live nearer to the stations and became regular passengers [13].

Nonetheless, each area's characteristics dictate has their travel patterns. According to research that classified travel behavior across the United States based on demographic variables, people who live in low-income urban areas are more likely to be public transit riders [14]. While it is evident that the large majority of inner-city residents travel shorter distances than suburban residents [15].

COVID-19 has been found all over the world since late 2019. People's lifestyles, behaviors, and attitudes are changing as a result of the changes across the globe to avoid the spread of pandemics, and people are becoming more aware and concerned about pandemics. The COVID-19 pandemic affected several changes and occurred in a variety of fields, such as the economy, society, politics, government, population, disease control management, etc. In addition, the pandemic has directly affected people's daily travels. Travel has been affected by outbreaks of diseases, particularly for emerging infections. Travelers have been considered a major component of the surveillance process [16]. In the short term, changes in workday travel behavior will gradually occur as a consequence of the pandemic control measures, as well as restrictions on the use of public transportation services. Restricted measures of public transportation services have been restricted to avoid or minimize a pandemic of COVID-19. This might result in an increase in the number of people shifting to more frequently private car use. People may decrease their travel and prefer active modes or cars over public transport services as a result of COVID-19 [17].

According to a study of changes in travel behavior caused by the COVID-19 pandemic throughout the world, there was a major shift from public transportation to private car and non-motorized modes [17]. COVID-19's first wave in Switzerland [22] reported that it reduced average daily distance by more than 60% and public transport by more than 90% [18]. In the Netherlands, it was discovered that Dutch people chose not to use public transport in daily life [19]. Passenger numbers on Hong Kong's subway declined by 42 percent, 86 percent, 73 percent, and 48 percent, respectively, for adults, children, students, and senior citizens [20]. As with an economic crisis, such a situation has changed travel behavior. The research in Athens, Greece, revealed that during economic crises, people' travel patterns change, especially in urban areas [21]. The previous MERS epidemic was also examined in Korea. MERS decreased public transport ridership by over 10% [22]. That means travel has decreased significantly throughout the epidemic and the economic crisis in the same direction.

However, the effects were evident in the short-term on travel behavior that has changed during the COVID-19 pandemic, and the assumption about the effect of COVID-19 on residential self-selection has not yet been proven in the case of people who live near mass transit stations and have easy access to the stations. Furthermore, concentrating on residential location analyses, transportation system resiliency, and long-term aspects of pandemic situations should be considered in policy implementations and future insight [23].

In consideration of the possibility that the COVID-19 pandemic is being triggered by changes in people's behavior, it is probable that residential concerns for the suburban area will be considered. People are concerned about congestion in urban areas or there is

the possibility of relocating to a location nearer to the urban area due to the ease of accessing utilities and various facilities within the city limits bases on preference and need, which may be demonstrated by the relocation of residents in the future. In terms of the tendency to relocate, it will be beneficial for land use planning and design, as well as for accessibility modes of transportation, because that will be able to explore the direction of urban development policy more efficiently.

1.2 Research Question

Despite cities expand and mass transit is developed, generally people will likely choose to live near a mass transit network under some travel preference, especially if there is an incident such as COVID-19. Does this have an impact on their future behavioral decisions on relocation or not? This study focuses on residential self-selection affected by travel behavior, and the impact of travel attitudes and residential attitudes, which leads to the decision-making process on relocation in the future. To identify the impact of attitude, change on residential self-selection, this study considers the following research question:

1. Is it possible that changes in travel behavior will have a long-term effect on the attitude toward residential decision-making?
2. What is the relationship between attitudes and travel behavior for future relocation intentions?
3. What is the interaction and intervention between the relationship of attitudes and travel behavior in decision-making?
4. What are the characteristics of travelers and residents around mass transit station areas affected by COVID-19?

1.3 Research Gap

The research gap focuses on the theoretical residential self-selection hypothesis and relationships between variables related to travel behavior and relocation that may be sensitive to psychological attitudes and intervention of phenomenal. The gaps in research synthesis include:

1. Most research emphasizes on travel behavior, travel preference, and travel attitude. Less research considers the long-term decision of relocation with residential attitude.

Previous research examines the complex relationship between the built environment, travel behavior, travel attitude, and neighborhood of residential on residential choices and travel choices, regardless of residential attitude, according to residential self-selection. The residential attitude is an attitude toward residential in the dimensions of accessibility, neighborhood, environment, etc. to represent the attitude of future residential intention.

2. Based on the walking distance to access station, less research considers on direct and indirect effect on walking distance interaction on relationship of travel mode.

The accessibility of mass transit station access significantly influences mode choice, and the distance from home to a mass transit station influences the travelers' mode of

choice behavior [24]. Most of the research is clearly on travel behavior and mode choice to understand the difference between walking distance access and mode choice. However, there have been fewer studies on attitude-based hypotheses of the relationship between walking distance and travel mode.

3. Little research has been considered on attitude-based segmentation to understand the inside from the psychological perspective on residential self-selection.

Previous research has focused on travel behavior and socio-demographics to categorize travelers based on clusters of car ownership, travel time, and so on in order to propose strategies and policies. However, based on the fact that inner-city residents travel shorter distances than suburban residents [15], the segmentation of travelers and residents around mass transit station areas needs to be more evident to show a difference in characteristics.

4. There are many empirical studies on the impacts of COVID-19 on travel behavior research. Nevertheless, the long-term impact of residential self-selection has been less evident.

The majority of the research on the COVID-19 effect has concentrated on the short-term impact of travel behavior, with less research addressing the tendency of long-term impact on relocation coordinated with travel behavior, which is one of the most important factors in transportation and urban planning policy.

1.4 Research Objective

The overview of this research is divided into 4 parts according to the research objectives as follows:

Relationship

1. To evaluate the impact of COVID-19 influence on attitudes and travel behavior due to the factors that were affected by COVID-19.
2. To Identify relationship between travel behavior (short term decision) and residential self-selection (long term decision), SEM was used to confirm relationship with sensitivity of pandemic situation on COVID-19.

Direct and indirect effect

1. To investigate the attitude factor structure of indicators and latent variables of attitude toward travel mode and attitude toward residence.
2. To explore the relationships of intervention variable of attitude toward residence and interaction variables of walking distance to nearest mass transit station on a causal relationship between travel mode behavior and attitude toward travel mode.
3. To examine the effects of COVID-19 on hypothesis relationship by using moderated mediation model to understand behavior change.

Pre/post relationship

1. To investigate the impact of COVID-19 on behavior and attitude by attitude toward relocation of attitude toward residential location area, and attitude toward residential accessibility on the travel mode associated with travel behavior which leads to future relocation decisions.
2. To confirm the relationship between the effect of attitude toward residential accessibility and the attitude toward residential location areas, pre-test and post-test designs were applied to investigate the relationship of intervention variables from the COVID-19 pandemic.

Classification and segmentation

1. To identify and categorize the segmentation of travelers and residents around mass transit station area characteristics based on attitude change in the dimensions of the short-term decision of attitude toward residential accessibility of the travel mode and concern for using public transportation, and the long-term decision of attitude toward residential location area and concern for living in an urban area.

1.5 Research Hypotheses

The hypothesis of this research addresses residential self-selection to explore the relationship among variables of direct and indirect effect. To answer research question, the relationship was considered by variables as following:

1. Observed variable, including socio-demographic, resident and traveler characteristics, and travel and residential attitude.
2. Unobserved variables, as latent variables of travel attitude and residential attitude, are considered case by case for each objective study.
3. The hypothesis of this study mainly focuses on travel behavior, travel attitude, and residential attitude, with various in-depth relationship analyses conducted on some of these variables.
4. The proposed hypothesis for this study is interested in the relationship between travel attitude and resident attitude as well as the different effects of these attitudes on travel behavior in different situations.

1.6 Research Framework and Organization of Thesis

This thesis is organized into eight chapters. Chapter 1 provides an overview of the study along with details on the research area. Chapter 2 reviews research related to this study's theory and methodology. The theoretical methodology, framework, and study area for setting model development are included in Chapter 3. Chapters 4, 5 and 6 contain hypotheses studied in different analyses, which are the primary research studies. Further studies in market segmentation are provided in Chapter 6. Lastly, Chapter 7 illustrated the overall study results, limitations, and suggestions as shown in Figure 1-1.

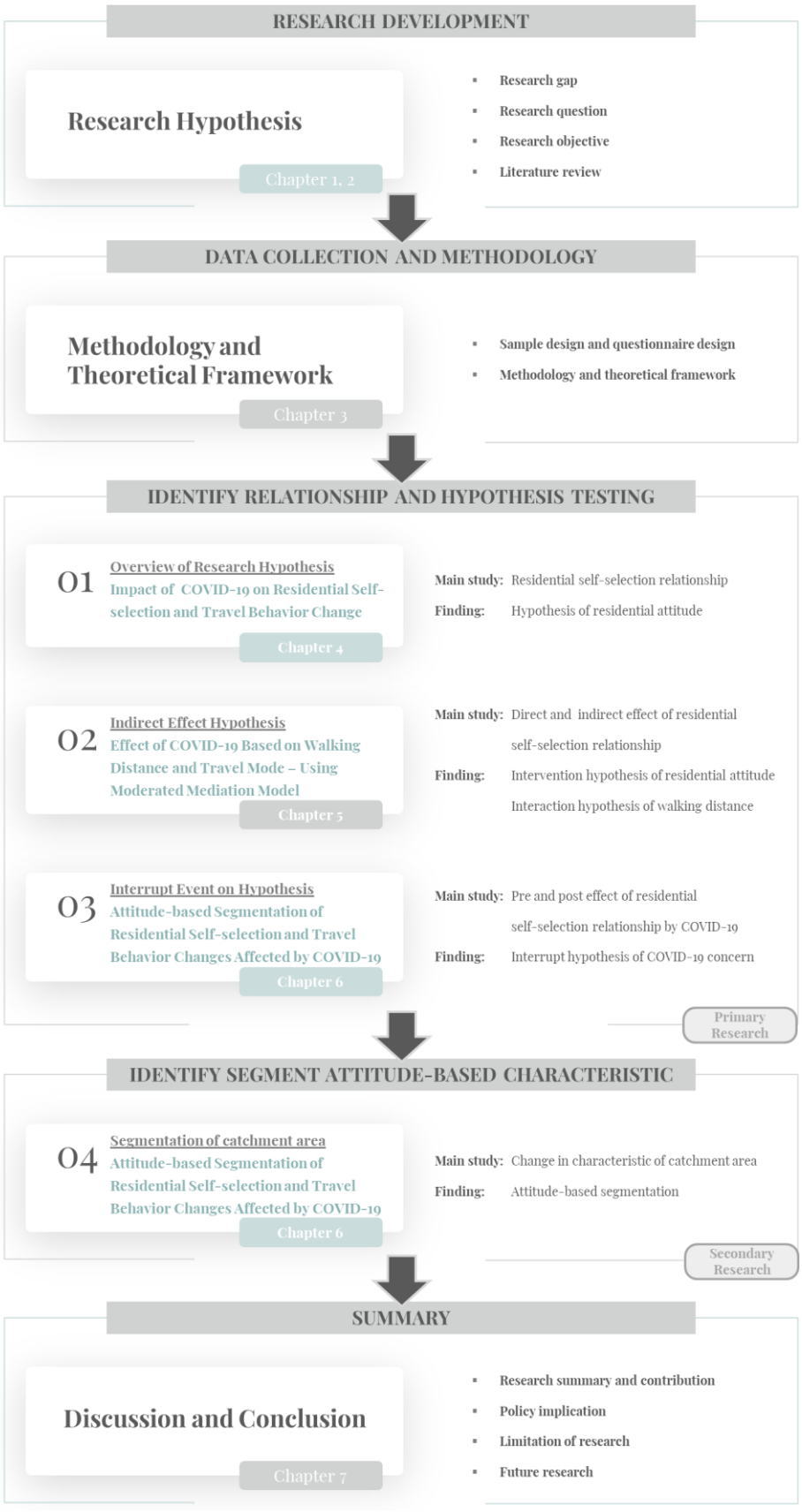


Figure 1-1 The framework and organization of research

2 LITERATURE REVIEW

In terms of residential self-selection, various elements influence travel behavior. This chapter reviews the relevant theories and empirical research about residential self-selection and travel behavior. Previous research associated with the methodology used in this research is discussed in this chapter. Further, the phenomenon of COVID-19 effects and the phenomenon's impact on travel behavior are discussed in this chapter.

2.1 Residential Self-selection

The influence relationship between land use and transportation is particularly important for the mobility of people's activities. Whereas people make decisions on where to live based on their travel needs and personal preferences [25] the tendency for individuals to choose locations based on actual travel abilities, desires, and preferences [1], this is called residential self-selection. The impact of residential self-selection on travel behavior was a debate regarding considering residential self-selection or relocation in past transportation research, which was marked by an objective-subjective division in understanding travel behavior [16]. 1) Hard factors such as urban form and socioeconomic factors are recognized as having an impact on various aspects of travel behavior [8]. 2) Soft factors [6] are used in travel behavior research to consider the impact on travel behavior, such as attitudes and preferences for various modes of transportation or neighborhood characteristics [8]. However, considering the influence of travel behavior on residential self-selection could indicate discussion as follow:

2.1.1 Residential Self-selection and Travel behavior

Human travel behaviors generally influenced by a variety of factors, including the spatial form of a city, land use, as well as road networks [27]. For transportation policy and planning considerations, the impact of the built environment on travel behavior is of significant relevance. Because it is the most visible limiting factor in determining whether or not individuals have the ability to make specific decisions through their own behavior [28]. The dimension of residential self-selection is related to the significance and direction of the relationships between travel behavior and land-use patterns, as well as the existence of causal relationships between them [29]. However, when spatial self-selection is considered in the context of abilities and needs associated with socioeconomic and attitude factors, land-use patterns have a significant impact on travel behavior.[30]. Furthermore, among the various land use variables, accessibility to regional centers is the most important factor in people's travel behaviors [31].

Due to the general low density and diversity of suburban areas, long distance travel and the use of private cars could see an increase and vice versa, urban area of compact city and mix land use make a shorter distance, along with available of public transport services could reduce car ownership of household in urban area [32]. In considering the factors of residential location related to travel behavior, the availability of public transit is demonstrated to be the most important factor influencing current residential location choices, followed by living in a good neighborhood and housing affordability [33]. In addition, relocations and associated changes in the built environment generate significant changes in car ownership and travel mode use, and household structure changes that probably with relocations have a substantial effect on travel behavior [34].

Mode of travel was shown to be associated with residential relocation, with statistically significant relationships between modal shift and selected explanatory factors. The ownership of a car, the purchase of an additional car, income, a particular housing type and size, the type of relocation, the convenience of taking the subway or bus for commuting, the change in commute distance, and the distance to subway station variables

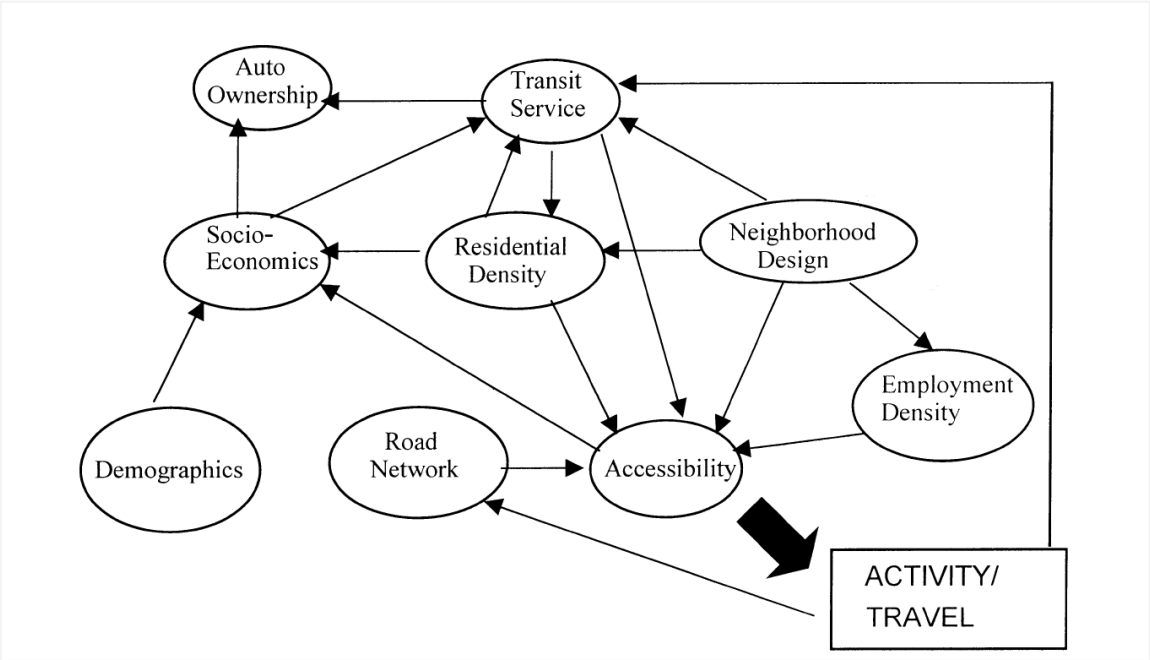
were important considerations when making the decision to switch from using a private car to taking public transport [35]. Nevertheless, the type of residential location had little effect on travel behavior, while attitude and lifestyle variables had an outstanding impact on travel demand [36]. In addition, the relationship between changes in the built environment, changes in vehicle ownership, and changes in travel behavior revealed that relocating to areas closer to destinations or with alternative transport mode choices could lead to less driving and more walking [37].

Previous research on residential self-selection emphasizes the significance of the built environment in influencing travel behavior. Moreover, many previous studies have examined preferences for travel modes and residential choices. The results show that mode preference seems to be strongly associated with both travel behavior and residential choice [38]. In 1990s until recent study, travel attitudes affect travel behavior and resident location choice; in addition, the residential environment affects attitudes toward specific modes of travel [39]. Residential self-selection, or the decision to live in a certain neighborhood, has an indirect effect on travel attitudes and satisfaction [3], [4]. Residential choices are determined by travel attitude. Some research suggests that the type of residential neighborhood affects the choice of commuting mode [40]. This is evident from the relationship between residential self-selection and travel behavior, as well as the built environment and attitude. To emphasize the influence factor on residential self-selection, built environment, and psychological attitude, the following literature is provided as follows:

2.1.2 Built Environment

Travel behavior is affected by the relationship between travel behavior and the built environment, as well as the role played by personal decisions in residential locations [37]. According to various studies found that the built environment has a significant impact on residential choice, travel mode, and travel behavior. The relationship between socioeconomics and urban form is important for understanding the decision-making process of travel behavior [42]. In the majority, empirical studies of the relationship between the built environment and travel behavior have shown that residents of dense, diverse land uses make fewer trips and use more public transportation and active transportation modes. In addition, the built environment was considered by residential neighborhoods in the dimensions of density, diversity, and design, which are called 3Ds [43]. Moreover, neighborhood densities had a stronger effect than mixed land-uses on all commuting mode choices, excluding walking and bicycling, and within 300 feet of grocery shops and other consumer services, it is possible to encourage mass transit commuters [44].

Badoe & Miller (2000) show the influence of urban form on travel in the context of human behavior, which includes location decisions (residence, job location), vehicle ownership decisions, and activity/travel decisions as follows: for the built environment, 1) residential density impacts, 2) employment density impacts, 3) accessibility impacts, 4) neighborhood design impacts, and other factors. 5) auto ownership, 6) socioeconomics, 7) transit supply [42] (see Figure 2-1).



Source: Badoe & Miller (2000) [42].

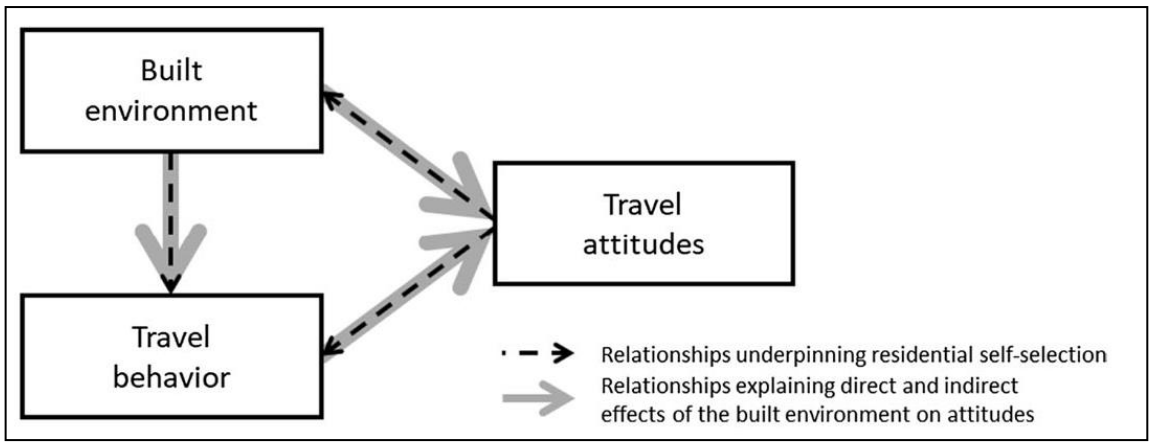
Figure 2-1 Urban form impart of activity and travel.

The perspective of built environment has been shown influence on travel behavior such as residents who prefer to walk and may consciously choose to live in walking-friendly neighborhoods, resulting in more walking [3]. Also, the built environment has a direct and indirect effect on travel mode choice [45]. Furthermore, the types of active transportation that are available and the distance traveled have been impacted by the residential built environment, walkability, and regional accessibility [46].

2.1.3 Attitudes

In order to comprehend human behavior, Ajzen (1985) established the theory of planned behavior and suggested that behavior is determined by intents, attitudes, and subjective norms between perceived behavioral control and behavior [47] which frequently applied psychological theory on travel behavior. In travel behavior research, the importance of perceptions and attitudes has been more considered and travel attitudes play a significant impact in determining travel mode [36]. According to previous study, attitudes and preferences towards travel, as well as residential neighborhoods, are the most accurate predictors of travel patterns [25]. Empirical studies showed that travel-related attitudes have influenced travel behavior directly and also through residential choice, although the variety of housing and neighborhood attributes is of more importance [10]. In addition, personal characteristics and travel-related attitudes were identified as important predictors of how people evaluated their travel [9].

Nevertheless, psychological factors have been demonstrated to be crucial in describing behavioral decisions more accurately for travel behavior studies. The attitudes might be related to the use of travel modes [4], [5]. Consequently, travel attitudes and motives for relocation were examined and it was discovered that the reasons for moving were related to travel [7]. Research on attitudinal influences on residential self-selection most emphasizes attitudes toward travel, attitudes towards mode of travel, and attitudes towards travel-related location. For example, attitudes toward travel modes have a significant determinant in explaining differences in travel behavior, suggesting the existence of a residential self-selection effect [49]. In addition, attitudes toward various modes of transportation demonstrated a significant effect on built environment characteristics that directly affected trip making through residential self-selection [50] as demonstrated in Figure 2-2. For urbanites, attitudes toward public transport have a greater impact on public transportation [51]. Moreover, a positive attitude toward public transport affected the use of public transport for those who do not live in TODs [52].



Source: De Vos et al. (2021) [39].

Figure 2-2 Relationship between the built environment, travel behavior and attitudes.

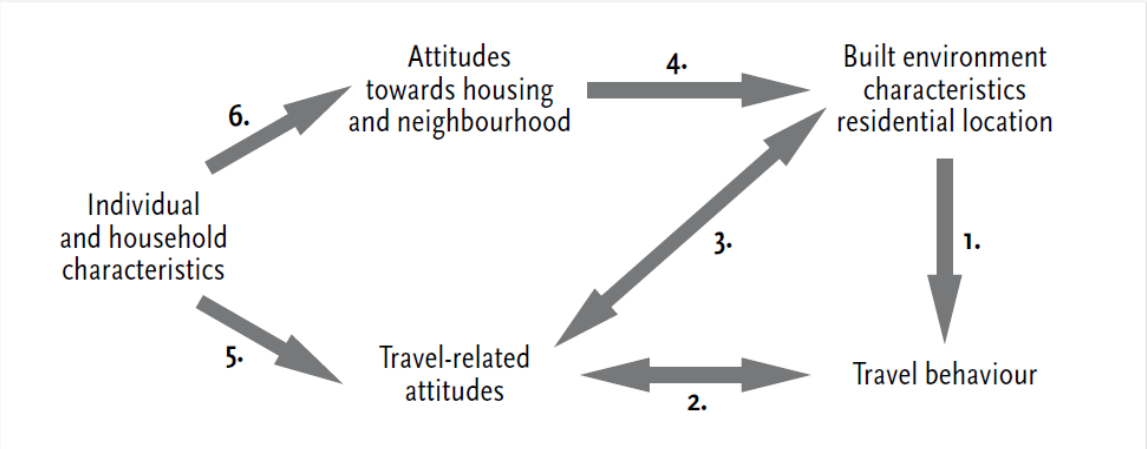
However, the travel attitudes of individuals may change after a home relocation because the built environment has a significant impact on travel preferences [41]. In addition, people might change their attitudes toward their current residential neighborhood by relocating. If people are experiencing cognitive dissonance (Festinger, 1957) [53], they will not only change their behavior but also their attitudes. Travel-related attitudes may adjust to residential choices when dissonance occurs. As is the case, residents' preferences for rail travel have been discovered, particularly those of people who have relocated closer to the stations and become regular travelers [13].

2.2 Structural Equation Model: SEM

2.2.1 SEM on Travel Behavior Research

The structural equation model (SEM) is a methodology for analyzing travel behavior and psychological attitudes. It is focused on the latent variable to identify relationships between variables as well as the direction of causality, direct and indirect relationships. It has several advantages over other methodologies. In the study of travel behavior, SEM is used in the correlation analysis and the impact of travel behavior. For example, considered the relationship between land use that affects weekend travel compared to workday travel, using SEM to confirm the opposing role of land use in travel mode choice and trip frequency on weekdays and weekends [54]. Studied the relationship between the built environment and travel attitude in travel behavior by using SEM to estimate the residential self-selection framework and the environment determination framework [55]. Furthermore, some study applied SEM to analyze sensitivity to changes in the travel utility of mode choice behavior [56]. SEM has been applying to many research that can evaluate relationships and very useful for the transportation field especially for human behavior of subjective norm.

In addition, the relationship between the built environment and travel attitude was employed in the structural equation model (SEM) to estimate the residential self-selection and environmental determination frameworks in the context of travel behavior. According to the findings of a study conducted using SEM to investigate relations between neighborhood design and travel behavior, changes in neighborhood characteristics lead to changes in travel choices, and neighborhood characteristics affect travel behavior. The influence of neighborhood characteristics on car ownership has an additional effect on travel behavior [57]. Additionally, travel attitudes have a significant influence on travel behavior, evidently all directly and indirectly through residential location choice [37].



Source: Bohte (2010) [10].

Figure 2-3 Conceptual of the influence of attitude
and residential self-selection on travel behavior

Figure 2-3 summarizes the conceptual study conducted by Bohte (2010) [10] to investigate the complex relationship between attitudes and residential self-selection on travel behavior using structural equation modeling. The findings demonstrated that people in the Netherlands who have more positive attitudes toward using public transportation drive their cars less frequently as a result of direct attitudes toward travel mode usage.

2.3 Market Segmentation

"Market segmentation is the identification of groups or segments with similarities in characteristics or needs" [58]. In the market segmentation, there are various segment-based objectives, targets, strategies, etc. As shown in Table 2-1, the main market segment is broken down into 9 main approaches.

Market segmentation in travel behavior has been used to increase ridership, implement strategies and policies, improve services, etc. Traveler segmentation can be based on multiple dimensions, such as identifying segments by different types of workers based on the predictability of their travel behavior over multiple days to understand changes in working patterns [59], or by commute patterns to effectively support the planning and operation of public transportation networks [60].

Table 2-1 Basics of market segmentation

Basis	Description	Authors
Geographic	Dividing a market into different geographical units such as nation, states, regions, cities or neighborhoods. For example, tourism markets may be segmented into international and domestic visitors.	Kotler et. Al., 2001 Kelly & Nankervis, 2001
Demographic	Dividing a market based on demographic variables such as age, gender, family size, family life-cycle, income, occupation, education, religion or nationality. For example, luxury resorts may target high-income earners while caravan parks may target middle-income families.	Kotler et. Al., 2001 Kelly & Nankervis, 2001 Blattberg et. Al. 1976
Psychographic /Lifestyle	Dividing markets based on consumer values, attitudes, interests, opinions. For example, adventure tourism operators may target consumers who have a strong interest in outdoor pursuits while epicureans are the target market for food and wine trails and cooking schools.	Kropp et. Al., 2005, Alpert, 1972 Frank et. Al. 1972 Pessemier et. Al, 1967 Lazer, 1963 Plummer, 1974 Yankelovich, 1964
Benefits	Dividing the market into groups according to the different benefits that consumers seek from the product or service. An example of benefit segmentation can be seen in the rise of spa resorts targeting consumers who seek rejuvenation and improved health and well being from their holiday experience.	Leisen, 2001 Haley 1968 Myers, 1976
Usage	Dividing markets based on usage patterns such as non-user, ex-user, potential user, first-time user, regular user, high volume user. For example destination-marketing programs may use one message strategy to communicate with repeat	Bowen, 1998 Twedt, 1964 Young et al. 1978

Basis	Description	Authors
	visitors and a different approach for people who have never visited.	
Loyalty	Dividing markets based on brand loyalty to a particular hotel chain or destination.	Yelkur, & DaCosta, 2001, Grover & Srinivasan, 1989
Image	Dividing markets based on the affective associations relating to brand image. For example the affective associations associated with the French Riviera are likely to be very different from affective associations with the Australian outback.	Leisen, 2001 Evans, 1959 Sirgy, 1982
Situation	Related to usage segmentation, situation segmentation divides markets on the basis of the consumption or purchase situation of consumers. For example travelers may find one destination suitable for a short break and a different style of holiday appropriate for a long holiday.	Gehrt & Shim, 2003 Dickson, 1982
Behavioral	Dividing markets based on consumer's knowledge of, attitude toward, uses for and responses to a product or service.	Kotler et.al., 2001

Source: Janet Hanlan and Don E. Fuller and Simon J. Wilde (2006) [61]

2.3.1 Psychographic Segmentation

Psychological segmentation or psychographic segmentation is the use of customers' psychological characteristics, their beliefs, or their values as segmentation criteria. Examples include travel motivations, desired product benefits, personality traits, and risk aversion [62]. Since market segmentation based on socioeconomic characteristics may be unable to represent and capture differences in attitudes and behaviors. Likewise, Li et al. (2013) examined the socioeconomic characteristics of travelers in each market segment and discovered that most socioeconomic factors do not demonstrate obviously distinctive characteristics between market segments [63].

Recently attitude-based market segmentation has found increased use in transportation research to get inside from psychological perspective. The findings of the research on attitude-based target group approach in forecasting the ecological effect of mobility behavior revealed that the predictive power of the attitude-based approach was greater than segmentation based on socio-demographic and geographic factors [64]. In addition, attitudinal market segments studied were employed to evaluate stated preferences of mode choice and found differences between market segments based on sensitivity to travel stress or the desire to assist the environment [65]. Additionally, an attitude-based approach could help identify target groups of cyclists based on attitudes toward the mode of travel, which can help explain the segment based on preconceived notions of image, status, and constraints in each group [66]. Also, it could identify travelers with similar personal and household characteristics were identified, as were similar needs, desires, and attitudes toward trains and competing for intercity transportation service characteristics [67]. The usefulness of market segmentation-based attitude analysis is clearly predicated on the fact that the same behaviors might occur for different reasons and that similar attitudes can lead to dissimilar behaviors [68]. Nevertheless, disadvantage of the

psychographic approach is the difficulty in identifying customer segmentation. Also, the psychographic approach's power is largely dependent on the empirical measurements' reliability and validity [62].

2.3.2 Decision Tree on Travel Behavior Research

There are numerous types of market segmentation analysis, and one in-depth data analysis that is used in segmentation studies is the decision tree approach, which is based on classification analysis. There are several statistical algorithms for building decision tree models. Table 2-2 shows the decision tree method widely used. However, CART and CHAID represent classification and regression trees, respectively, and employ nonparametric statistical techniques that could be applied to both categorical and continuous data.

Table 2-2 The different decision tree algorithms

Methods	CART	CHAID	QUEST
Measure used to select input variable	Gini index; Twoing criteria	Chi-square	Chi-square for categorical variables; J-way ANOVA for continuous/ordinal variables
Pruning	Pre-pruning using a single-pass algorithm	Pre-pruning using Chi-square test for independence	Post-pruning
Dependent variable	Categorical/ Continuous	Categorical	Categorical
Input variables	Categorical/ Continuous	Categorical/ Continuous	Categorical/ Continuous
Split at each node	Binary; Split on linear combinations	Multiple	Binary; Split on linear combinations

Source: Song & Lu (2015) [69]

In transportation research, some studies used CART and CHAID in association with logistic regression to classify attribute variables more precisely, such as applying CART analysis to obtain the attribute levels of comfort, speed, and travel cost, which proved to be efficient for later applications [70]. Jang and Ko (2019) employed CHAID analysis to identify commute time ranges of significantly different compositions of satisfied and dissatisfied commuters by partitioning the dataset by travel time range [71]. Levin and Zahavi (2001) studied CHAID using the logistic regression model as a benchmark and found that automatic segmentation methods may substitute judgmentally based segmentation methods for response analysis [72]. The effectiveness of the CHAID approach could be highlighted by the fact that the variables were effectively classified and some details of the data were lost [73] compared with other methodologies.

In a study of travel behavior models, CHAID was also investigated using segmentation analysis and was used to examine the rates of household trip generation. The model's predictive capability was verified, and the results suggested that CHAID can be used as an exploratory technique to aid model development, or as a model in and of itself [74]. In addition to the trip distribution model, CHAID applied traditional gravity models

to estimate destination choices and compared them to the decision tree (CHAID and CART) approaches. The results shows that the CHAID algorithm produced the best fit for real destination choices. They indicated that decision tree methods could be used to improve traditional trip distribution models by including the impacts of disaggregated variables [75].

2.4 The Phenomena Impact on Travel Behavior

2.4.1 Economic Crisis

Such a situation has caused a change in travel behavior, as in the case of an economic crisis. According to the study of Christoforou et al. (2011) [21] of Athens, Greece, stated during periods of an economic crisis that there are changes in users' travel patterns, especially in urban areas. Due to the overall cost of transportation, the number of trips was reduced for one in five people, and one in two reported a decline in private car use. In 2008, the financial crisis in Reykjavik, the capital region of Iceland, affected travel behavior. In 2009, they found 30% make fewer trips since the crisis, due in part to reduced income and/or unemployment, and 20% perceive bus transit as more important than [76]

However, during the economic crisis, factors that had not played an important role before the crisis became critically important during the crisis. As a result of the economic crisis, Table 2-3 shows how the intensity and duration of the crisis affect households' reactions to mobility and housing. According to research conducted by Papagiannakis et al. (2018) on the influence of the Greek economic crisis on urban mobility in relation to household income, a decline in expenses resulted in the relocation of certain households, which was most apparent for those with the lowest incomes [77]. However, the economic crisis has been more effective in reducing the use of personal cars because people have reduced the frequency of their trips.

Table 2-3 Economics crisis and consequences for households

Category of economic crisis	**Consequences for households**			
	Mobility behavior	**Residential location**	**Consumption and activities**	**Preservation of changes**
Short term / low intensity	Decrease of travel expenses	No change	Budget optimization, limited use of savings	No
Long term / low intensity	Suppression of some trips, but no change of transport mode	No change	Reduction of activities in order to preserve the current status of living, fragile financial balance	No
Short term / high intensity	Deeper mobility changes	No change	Economic adjustments anticipating a longer crisis	Yes, temporally
Long term / high intensity	Structural and profound changes in travel patterns	At risk	Significant changes in the consumption habits, and income reductions	Yes, permanent

Source: Papagiannakis et al. (2018) [77]

2.4.2 Pandemic Crisis

However, the previous MERS pandemic was studied in South Korea. MERS decreased the number of passengers on public transportation by more than 10 percent. 14 percent and 9 percent declines in trips were observed to impacted area and other areas, respectively. [22]. That means travel during the pandemic and crisis has decreased significantly.

In the past, travel has affected the spread of infectious diseases and emerging infections. Travelers have been seen as a crucial component of the surveillance process. [16]. According to a research by Abdullah et al. (2020), due to COVID-19, people would travel less and prefer active modes or cars over public transport services [17]. In the short term, the change of workdays travels behavior will gradually change because of the control of pandemic and various measures as well as limitation of the service of public transport.

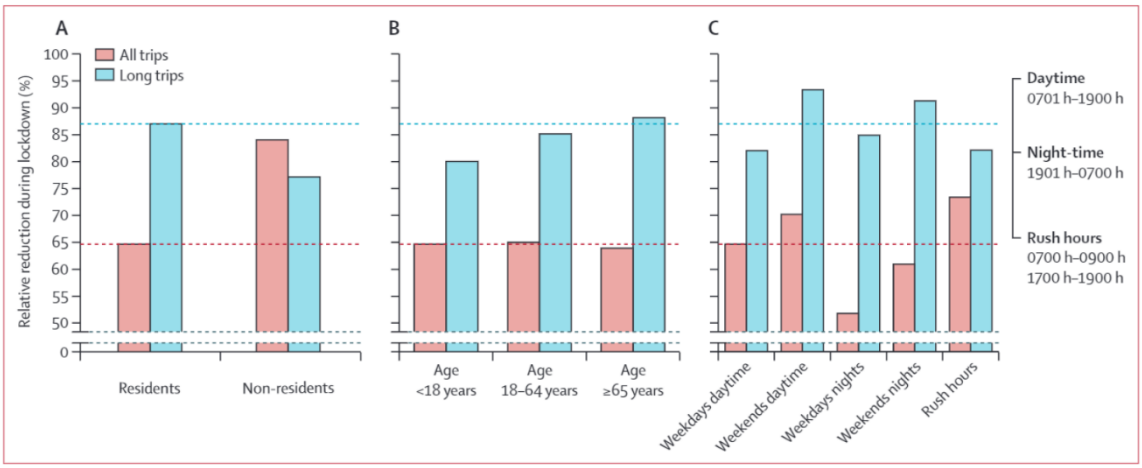
The pandemic has had a major impact on public transport due to concerns about being in contact with, or close to people at risk of infection, and policy responses to disease control. Regarding the level of hygiene on public transportation, it was found that 58 % of passengers have been more concerned about it post-COVID-19 than earlier [78]. Evidently, people are concerned about using the public transport system and their travel intentions have been disturbed. The first wave of COVID-19 in Switzerland reduced the average commuting distance by approximately 60 % and public transport usage by over 90 % [79]. Moreover, COVID-19 appears to have an influence on daily public transport ridership in Sweden. Ridership on public transit declined by 40–60 percent in the study area when compared to other modes of transportation. Additionally, passengers shifted from purchasing monthly period tickets to purchasing single tickets and travel funds [80].

Additionally, the huge average decreases in travel and public transport usage as a result of the pandemic and associated policy responses mask major differences across socioeconomic groups, with the average travel decreasing less among the less educated and lower-income groups [81]. According to a study on public transport use in the United States, lower-income transit passengers reduced their travel less than others who were unwilling to use transit because of the risk of infection. However, mask usage and reducing crowding may increase transport users' willingness to utilize it [14]. People's preferences for housing types may change as a consequence of COVID-19, and the quality of living environments will almost certainly become a significant factor [82].

2.4.3 COVID-19 Crisis

One of the health crises that has spread over the globe is the COVID-19 disease. The epidemic not only affects people's physical health but also has the potential to cause issues with their mental health. Concerns about the pandemic's ability to spread have been seen both in the short term and in the long term in dimensions of residents living in urban areas, such as a dramatic reduction in the amount of time spent traveling long distances for daily trips. As shown in Figure 2-4, the mobility effect in France in March 2020 during the lockdown period decreased overall by 65% for residents and 85% for non-residents,

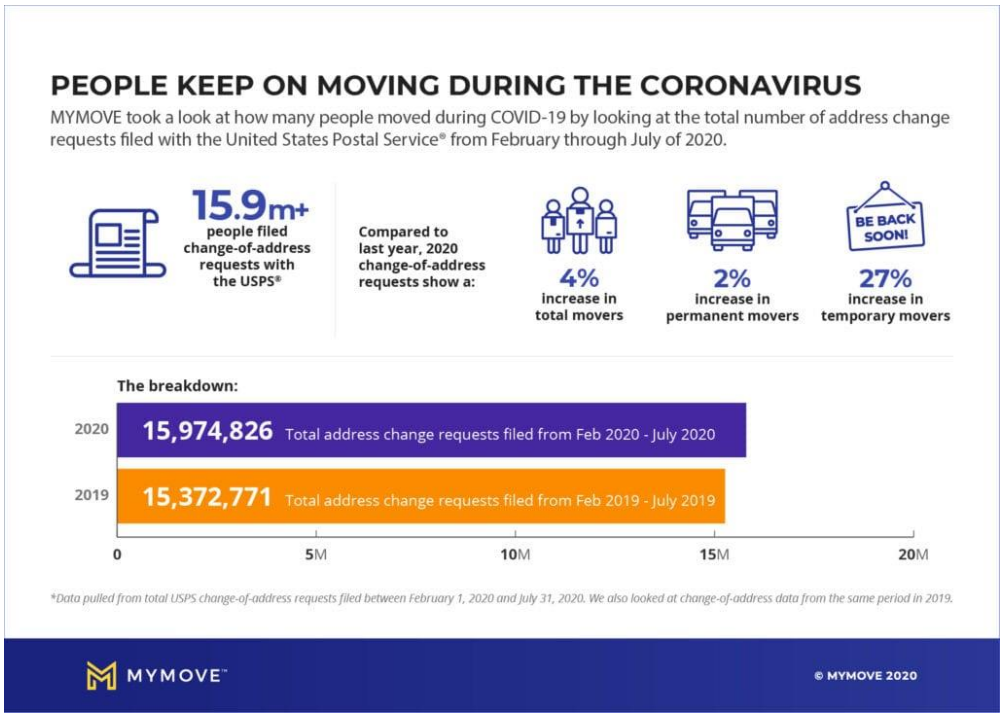
with those aged more than 65 years old reducing overall trips by 64%, and most of the trip reduction was weekday night movement [83].



Source: Pullano et al. (2020) [83]

Figure 2-4 Mobility reduction during lockdown on COVID-19 pandemic

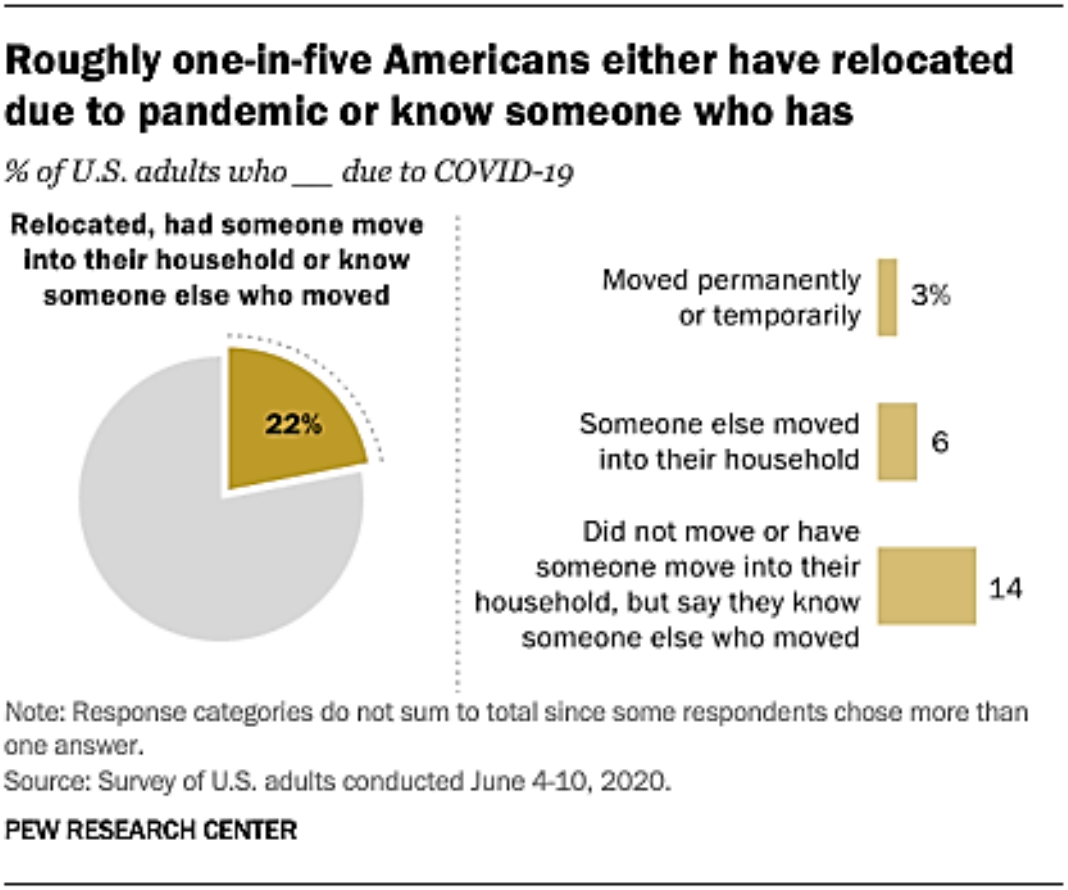
Furthermore, the effect of COVID-19 reflects the decision to relocation on some people. For the American people, the increase in the change of address by USPS (United States Postal Service) data from February to July 2020 compared to February to July 2019. The data provided for the permanent and temporary moves (for the second location or less than six months move) reports by MYMOVE found a 4% increase in total movers, a 2% increase in permanent movers, and a 27% increase in temporary movers as shown in Figure 2-5 [84].



Source: MYMOVE, LLC. (2022) [84]

Figure 2-5 The change of address during COVID-19

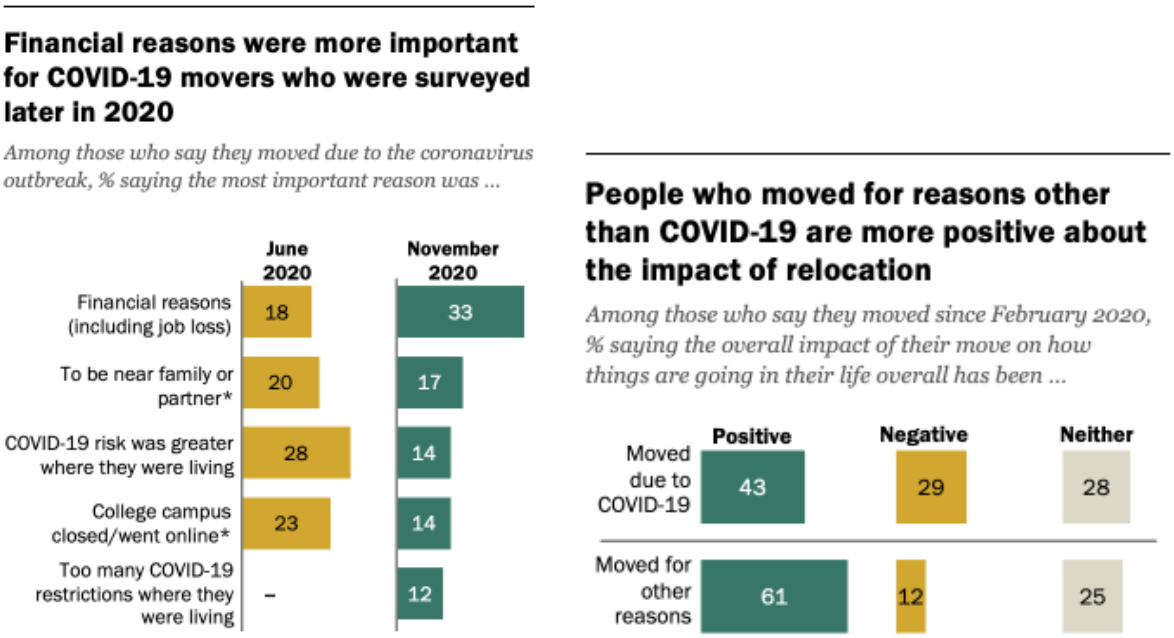
Based on the moving trends of American people, according to a Pew Research Center study surveyed in June 2020, because of COVID-19, they relocated to move out of dormitories that were unexpectedly closed, communities that they felt were unsafe, or housing unaffordable to them. They found overall, 22% changed their residences due to the COVID pandemic and 37% of those aged between 18 and 29 years old moved residences [85] as shown in Figure 2-6.



Source: Pew Research Center [85]

Figure 2-6 Due to the pandemic, one in five U.S. adults has relocated

However, during the early stages of the COVID-19 pandemic, millions of people escaped communities because they feared getting infected. In late 2020, in the spring, those interviewed were more relocated due to financial stress [86]. As shown in Figure 2-7 (left), comparing the survey in June and November 2020, found in November that people moved because of financial problems by 15% from June 2020. Therefore, the survey conducted in November 2020 found that people were still concerned about infection and relocated by 43%, but conversely, 61% moved by unrelated to the infection of COVID-19 (see Figure 2-7 right).



Source: Pew Research Center

Figure 2-7 The reasons of relocation during COVID-19

3 METHODOLOGY AND THEORITICAL FRAMEWORK

The purpose of this research is to explore the relationship between residential self-selection and travel behavior through the application of SEM and to classify the characteristics of residents and travelers through the application of CHAID in order to conduct a results of the research. However, in the case of investigating relationships, the methodology emphasizes in-depth SEM analysis, which is each methodology provides an in-depth effect and result. Figure 3-1 illustrates the overview of the research methodology.

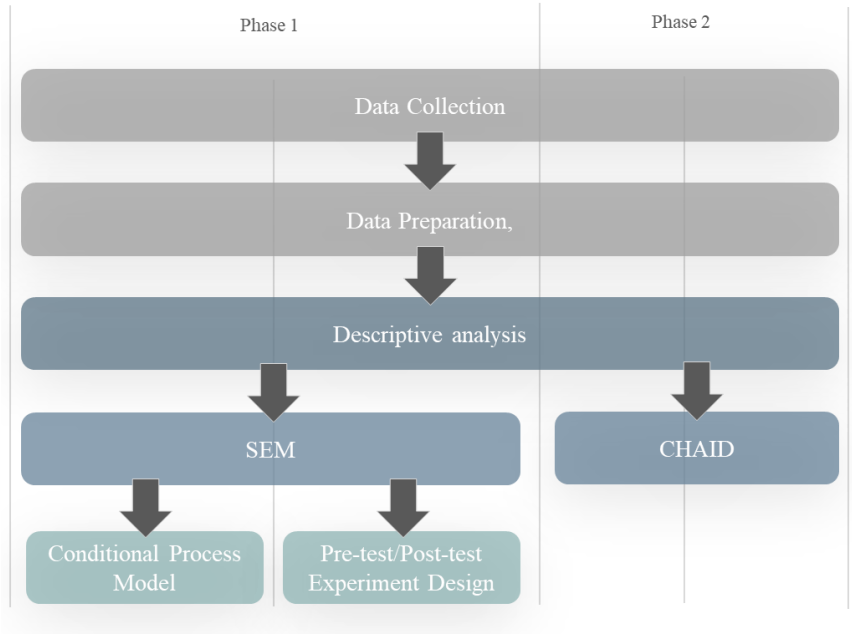


Figure 3-1 Overview of research methodology

3.1 Study Area and Data Collection

3.1.1 Study Area

In this study has been focused on the catchment areas of mass transit stations, as this is the easiest mode of transport to access in urban areas, and people tend to live along mass transit routes. Bangkok, Thailand, is one of the cities that problems with traffic congestion. According to the INRIX Global Traffic Scorecard rated 2019 data, marginal time in Bangkok spend around 90 hours per year from the traffic congestion [87]. The Thailand and Bangkok profiles are shown in Figure 3-2. The gross domestic product (GDP) per capita value was 501,794,961 USD in 2020. According to the National Statistical Office of Thailand data, Thailand has a total population of 68,152,065 in 2020, with 8,854,718 in Bangkok [88]. When the first mass transit operated, the population of Bangkok was 5,662,197 and increase of 56.38%.

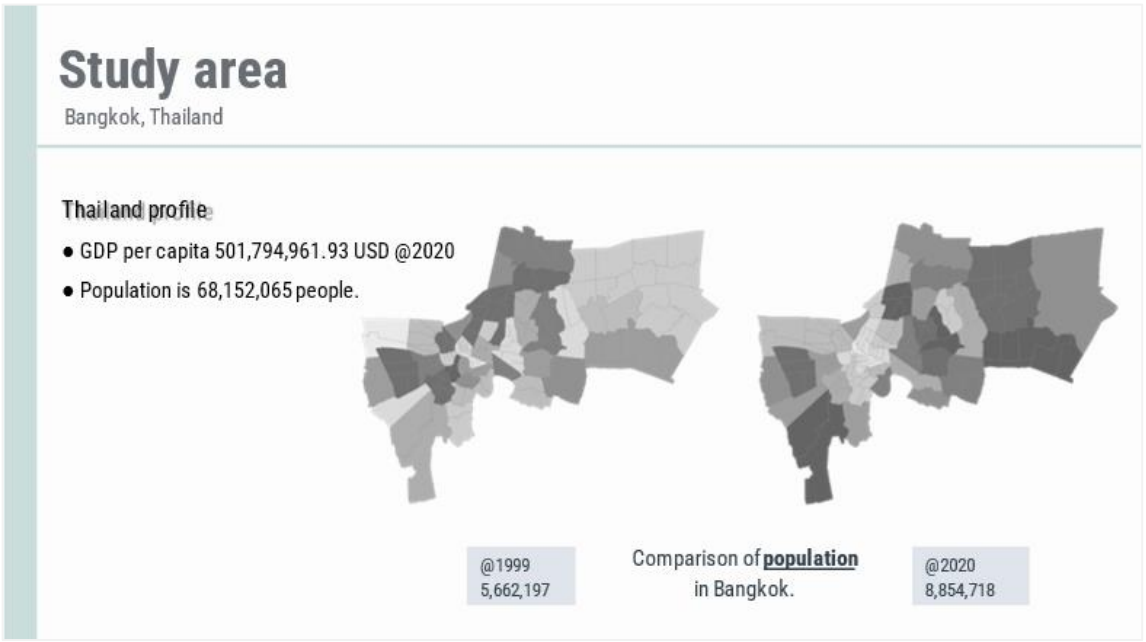
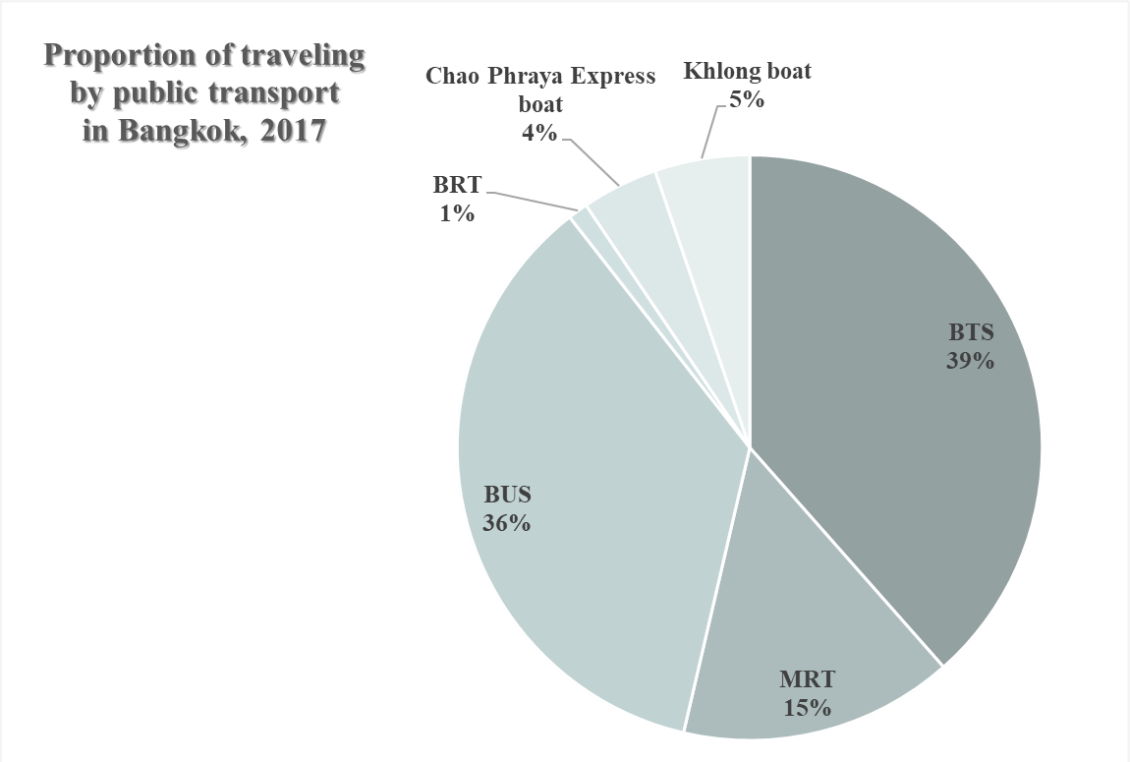


Figure 3-2 Thailand and Bangkok profiles

There are several kinds of transportation available in Bangkok, including a wide variety of public transit options. Furthermore, app-based taxi services Grab (company) is available in Bangkok. In total 15 modes divided into 3 categories as follows:

1) Paratransit, including motorcycle taxi, Tuk-Tuk and private car taxi
2) Feeder transit, including bus, BRT, passenger van, Chao Phraya Express boat, Khlong boat, and local train
3) Mass transit, including BTS dark green line, BTS light green line, MRT blue line, MRT purple line, ARL airport rail link, and monorail gold line.

According to the data from the National Research Council of Thailand report, the proportion of people traveling by public transport in Bangkok in 2017 was BTS, bus, and MRT, respectively (see Figure 3-3). In addition, the number of passengers on BTS and MRT is trending to increase, while bus passengers have declined steadily over the past 20 years, suggesting that some bus passengers are shifting to using mass transit. This indicates that more people are moving to middle and suburban area [89].



Source: National Research Council of Thailand [89]

Figure 3-3 The proportion of people traveling by public transport in Bangkok in 2017

Table 3-1 Forecast of travel volume in Bangkok metropolitan area, 2017 – 2042

Travel mode	Traffic volume (million trips/day)					
	2017	2022	2027	2032	2580	2585
Private car	**22.44 (68.7%)**	**23.30 (66.0%)**	**24.43 (64.8%)**	**24.99 (64.5%)**	**25.00 (63.6%)**	**24.29 (60.8%)**
Personal car	14.12 (43.2%)	15.60 (44.2%)	17.22 (45.7%)	18.31 (47.3%)	18.98 (48.3%)	19.11 (47.9%)
Motorcycle	8.32 (25.5%)	7.70 (21.8%)	7.21 (19.1%)	6.68 (17.2%)	6.02 (15.3%)	5.18 (13.0%)
Public transport	**10.21 (31.3%)**	**11.99 (34.0%)**	**13.25 (35.2%)**	**13.77 (35.5%)**	**14.31 (36.4%)**	**15.64 (39.2%)**
Taxi	1.36 (4.2%)	1.59 (4.5%)	1.87 (5.0%)	2.02 (5.2%)	2.19 (5.6%)	2.44 (6.1%)
Public transport	6.60 (20.2%)	7.82 (22.2%)	8.62 (22.9%)	8.85 (22.8%)	9.09 (23.1%)	9.94 (24.9%)
Shuttle bus	0.62 (1.9%)	0.81 (2.3%)	0.88 (2.3%)	0.96 (2.5%)	1.06 (2.7%)	1.26 (3.2%)
Walk	1.62 (5.0%)	1.76 (5.0%)	1.88 (5.0%)	1.94 (5.0%)	1.97 (5.0%)	2.00 (5.0%)
Total	**32.65**	**35.29**	**37.69**	**38.75**	**39.31**	**39.93**

Source: National Research Council of Thailand [89]

In the Bangkok metropolitan area, traffic volume in 2017 was at 32.65 million trips per day, mostly travelling within Bangkok, at 54.2%. Whereas data on traffic demand forecasting from 2017 to 2042 discovered that the majority of travel modes in the Bangkok metropolitan area are private cars, decreasing from 69% in 2017 to 61% in 2042 and increasing in public transportation modes as show in Table 3-1.

Since the 1990s, the urban railway master plan for the Bangkok metropolitan region (BMA) has been developed. The Thai government, with the cooperation of the Japan International Cooperation Agency (JICA) and the Office of Transport and Traffic, Policy and Planning (OTP) under the Ministry of Transport (MOT), formulated the Mass Rapid Transit Master Plan for the Bangkok Metropolitan Region (M-MAP) in 2010, and a new master plan (M-MAP2) is currently being developed [90]. The history of mass rapid transit plans for development is shown in Table 3-2.

Table 3-2 Development of mass transit plan in Bangkok

Year	Study/Plan	Summary
1972	The Bangkok Transport Study	Highway and rail transit development.
1994	The Mass Rapid Transit System Master Plan (MTMP)	Rail transit development during 1995–2011 (135 km).
1996	The Conceptual Mass Rapid Transit Implementation Plan (CTMP)	MTMP adapted version (179 km).
1998	The Feeder Transit System Study	Additional 11 LRT and monorail projects (206 km).
2000	The Urban Rail Transportation Master Plan (URMAP)	Rail transit network development in BMR in 20 years (375 km).
2004	The Bangkok Mass Transit Implementation Plan (BMT)	The 1st phase development of 7 lines (291 km), expected to complete by 2009
2006	10 Lines of Mass Transit Network	BMT adapted version, 10 lines (365.5 km).
2007	5 Urgent Mass Transit Lines	High priority urban railway lines, 5 lines (135 km).
2008	Concept of Mass Transit Network	Extension to the suburbs, 9 lines (311 km).
2010	Mass Rapid Transit Master Plan (M-Map)	Urban railway development during 2010 to 2029, 12 lines (509 km).
Ongoing	The Second Mass Rapid Transit Master Plan (M-Map2)	A study being carried out in cooperation with JICA.

Source: Yang et al., 2016

Bangkok's first rail system, known as BTS, began operating in December 1999. BTS Skytrain operates on 2 lines, serving 23 stations in total [91]. However, six mass transit lines were operational in 2020, including the BTS light green (54.3 km), BTS dark green (14 km), MRT blue line (47 km), MRT purple line (23 km), airport rail link (28.5 km) [92], and gold line (1.74 km) [93], for a total of 168.54 km and 125 stations. Figure 3-1 shows the development plan for mass transit and existing mass transit in the study area. The mass rapid transit system has become a priority for the travel of Bangkok residents. The ridership of mass rapid transit users increased by 29% between 2014 and 2018 [94]. The increase in ridership comes from the development of public transit systems to promote the reduction of personal cars. Nevertheless, 77% of people in Bangkok have shifted to using mass transit instead of private cars [95]. As seen in Figures 3-4, the current state of mass transport in 2020 and the complete future development plan for mass transit in 2029.

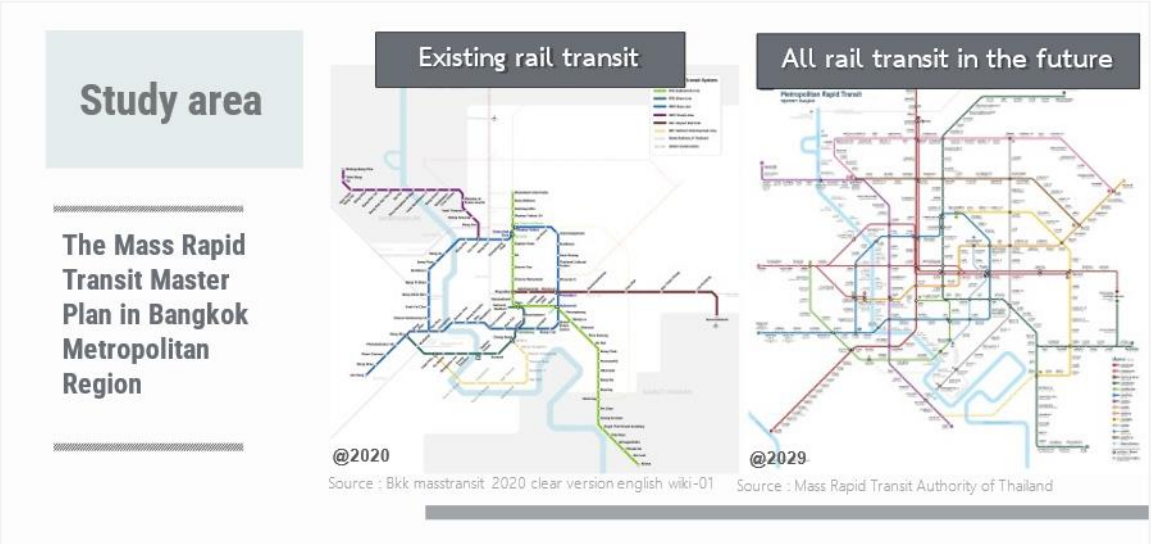
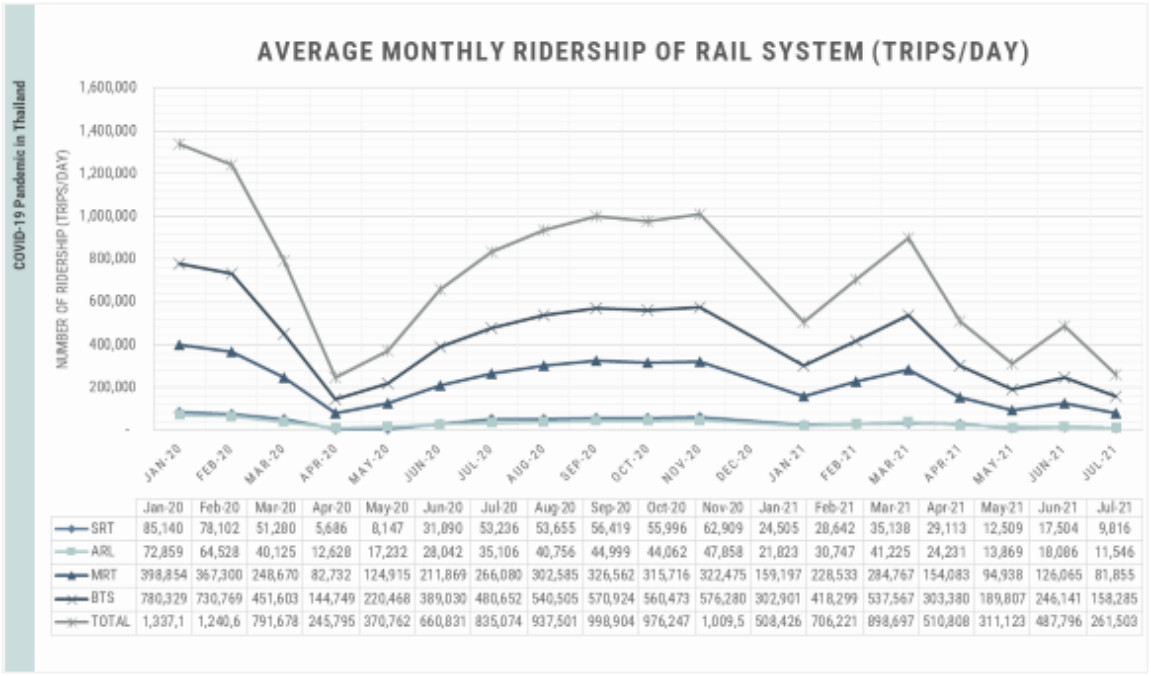


Figure 3-4 The development plan for mass transit and existing mass transit in the study area.

As a consequence, the use of public transportation and non-motorized modes of transportation is becoming increasingly popular in areas near mass transit lines. The average rate of condominium sales grew by 14% when compared to the previous five years (2012–2016) [96]. A further finding was that households with fewer cars were more likely to live in high-density areas in the central business district (CBD) [97]. In terms of residential property price, listed land price, or assessed land values, urban rail transit lines have a considerable impact on the growth in property value along rail corridors, whereas walkability had a significant impact on property price in the central city [98].

A pandemic of the COVID-19 epidemic occurred in Thailand in early January 2020, which had an impact on the behavior of the people. To prevent the spread of the virus, numerous measures such as wearing masks, reducing work, decreasing activities to meet people, quarantine, working at home, and social distancing were used as the new normal of daily life. Thailand reported the highest number of cases on March 22 [99]. The Declaration of a State of Emergency became effective on March 26. In April, lockdown measures and curfews were implemented to control the pandemic. The Thai government locked down all cities and returned to normal in May 2020. This affected the daily travel of citizens directly. Nevertheless, the volume of traffic on road trips changed from March to May 2020, as well as with mass transit, and that the volume returned to near-normal levels in June. During the COVID-19 pandemic, Thailand's Department of Rail Transport disclosed that the ridership of mass transit decreased by approximately 80 % in April (the first wave of COVID-19) compared with January 2020 [100] as shown in Figure 3-5.



	Jan-20	Feb-20	Mar-20	Apr-20	May-20	Jun-20	Jul-20	Aug-20	Sep-20	Oct-20	Nov-20	Jan-21	Feb-21	Mar-21	Apr-21	May-21	Jun-21	Jul-21
SRT	85,140	78,102	51,280	5,686	8,147	31,890	53,236	53,655	56,419	55,996	62,909	24,505	28,642	35,138	29,113	12,509	17,504	9,816
ARL	72,859	64,528	40,125	12,628	17,232	28,042	35,106	40,756	44,999	44,062	47,858	21,823	30,747	41,225	24,231	13,869	18,086	11,546
MRT	398,854	367,300	248,670	82,732	124,915	211,869	266,080	302,585	326,562	315,716	322,475	159,197	228,533	284,767	154,083	94,938	126,065	81,855
BTS	780,329	730,769	451,603	144,749	220,468	389,030	480,652	540,505	570,924	560,473	576,280	302,901	418,299	537,567	303,380	189,807	246,141	158,285
TOTAL	1,337,1	1,240,6	791,678	245,795	370,762	660,831	835,074	937,501	998,904	976,247	1,009,5	508,426	706,221	898,697	510,808	311,123	487,796	261,503

Source: Department of Rail Transport, Thailand (2021) [100]
Note: December 2020 data not available.

Figure 3-5 Average monthly ridership of rail system

3.1.2 Survey Instrument

This study focused on mass transit station areas of Bangkok, Thailand. The target population of this study included residents of the current mass transit station and travelers near the mass transit station in the Bangkok metropolitan area. The survey designated an area within 1 km of the station to control the target respondents. The population in this study represents people around stations, mainly in the Bangkok area. A map of the survey area with the existing mass transit stations is shown in Figure 3-6. To considering or focus area at station, According to a previous study conducted in Bangkok [101], the proportion of people walking to the stations decreased when the distance to the station was more than 400 meters, while less than 10% of people walked more than 1 km to the station, because long distance is associated with a lower probability of walking to public transportation [102].

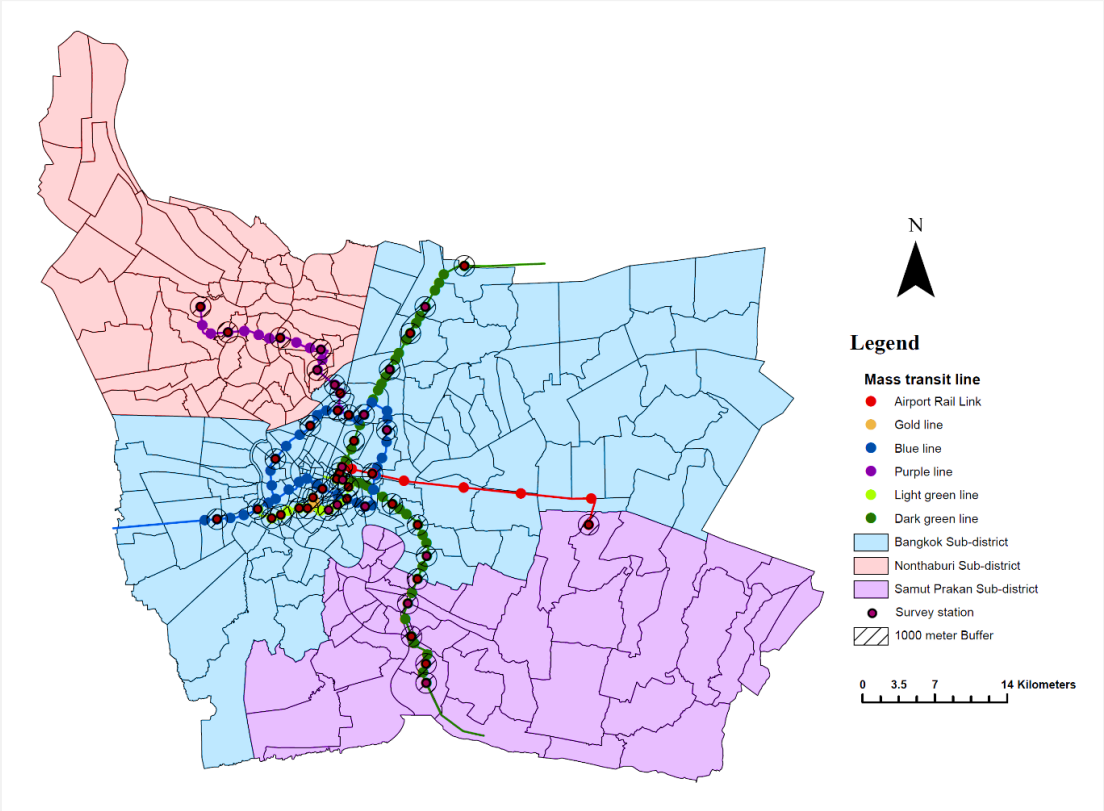


Figure 3-6 Study area of existing mass transit station and survey area

The participants represented in this study were randomly selected from existing stations in three provinces, including Bangkok, Nonthaburi, and Samut Prakan. However, the pre-survey conducted online received a relatively low response rate and could lead to selection bias for young people, those who can access the Internet and people who are familiar with the online survey. Consequently, data was collected using questionnaires and face-to-face paper-based interviews while observing social distancing. At the time of the survey, during COVID-19 situation, there were no lockdown restrictions, but state of emergency was maintained.

3.1.3 Questionnaire Design

The questionnaire has the purpose of collecting data for studying the characteristics of residents and travelers along existing mass transit stations in the Bangkok Metropolitan Region, Thailand. The survey was designed into five sections, including:

1. Personal Data: 12 questions
2. Travel Behavior: 8x2 questions (before and during COVID-19)
3. Travel pattern: 2 forms before and during COVID-19
4. Traveler and Residential attitude: 18x2 questions for travel attitude and 23x2 questions for residential attitudes (before and during COVID-19)
5. State preference for travel and residential choice

In sections 2 to 4 of the questionnaire, all questions were divided into two categories: before COVID-19 and during COVID-19. Questions in Section 1 cover socio-demographic information, residential characteristics, and traveler characteristics. Section 2 of travel behavior consists of questions about changes in socio-demographic and travel behavior before and during COVID-19. The travel pattern will be discussed in Section 3. In this section, the respondent will describe the travel pattern on a weekday or normal trip from the start origin (home) to the end destination (home). Section 4 of travel attitude and residential attitude questions includes 42 statements with 18 statements of four main effects on travel attitude and 23 statements of four main effects on residential attitudes. All attitudes are considered using a 5-point Likert scale (5 = strongly agree to 1 = strongly disagree). Lastly, section 5 states preference for consideration of residential self-selection by four mode of travel choices and two residential choices. The details of the questionnaire are demonstrated in APPENDIX 8.1.1

Based on the states' preference in Section 5, the experimental design of the choice set produced a total of nine situations for each mode (Details are provided in APPENDIX 8.1.2) However, all the questions of the 9 choices set for each respondent lead to confusion easily and take a long time to answer. To avoid these issues, the questionnaire will be divided into six choice sets for each respondent. As a result, questionnaire number 1 was represented in choice sets 1-6, number 2 was represented in choice sets 4–9, and number 3 was represented in choice sets 1-3 and 7-9 as shown in Figure 3-7.

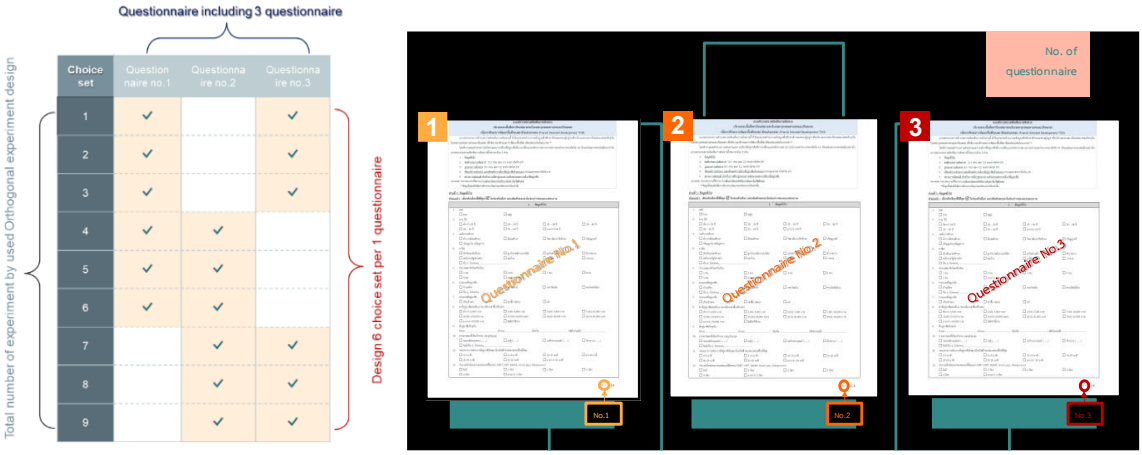


Figure 3-7 Three types of questionnaires for distribution

3.1.4 Sampling Design and Distribution Plan

Sampling sizes represent the population in the Bangkok Metropolitan Area that covers all existing mass transit in 2020. Nevertheless, the target group had been focusing on residents and travelers around the station area. In determining the sample size, the formula of Cochran, 1963 [103] is applied in the case of a large population. The sample size (n_0) can be found using equation as follow.

$$n_0 = \frac{Z^2 p(1-p)}{e^2}$$

Where n_0 = Sample size

Z = Z value from Standard Normal Distribution

p = The estimated proportion of an attribute that is present in the population

e = the acceptable sampling errors

Assumption Z =1.96 (Confidence level at 0.95)

p = 0.5

e = 0.05 (margin of error at ±5%)

The total minimum sample size = (1.96^2 * .5 * (1-.5)) / (.05^2) = 384.16 ≈ 385 samples.

Consideration of the sample defined by the population size of 3 provinces (Bangkok, Samut Prakhan, and Nonthaburi) follows the existing mass transit cover area in December 2020.The minimum of sample for Bangkok province 264 samples, Samut Prakhan province 63 samples, and Nonthaburi province 59 samples. Therefore, since the survey target is residents and travelers around mass transit stations, The minimum sample size considered by the number station of the province is shown in the Table 3-3.

Table 3-3 Comparing the sample size by the target

By population target				**By station target**			
Province	Population @2019	Prop-ortion	Sample size	***Province***	Number of stations	Prop-ortion	Sample size
Bangkok	5,666,264	68%	264	***Bangkok***	100	82%	316
Samut Prakhan	1,344,875	16%	63	***Samut Prakhan***	9	7%	29
Nonthaburi	1,265,387	15%	59	***Nonthaburi***	13	11%	42
Total	8,276,526	100%	386	***Total***	122	100%	387

However, the minimum number of samples has been considered in case the questionnaire is incomplete. The survey plan for questionnaire distribution was setting target of 200 samples for each number of questionnaires as shown in Table 3-4.

Table 3-4 Number of questionnaire distribution

Survey area	Total sample	Questionnaire No.1	Questionnaire No.2	Questionnaire No.3
Bangkok	400	134	133	133
Nonthaburi	100	33	34	33
Samut Prakhan	100	33	33	34
Total sample		**200**	**200**	**200**

Since the average interview time for a questionnaire is 20–30 minutes, and the total survey time each day is 7 hours, a single day could survey 14 questionnaires per day, per questionnaire. Also, because the total number of respondents is 600 samples, 43 questioners or 15 questioners for each day of the survey on the 16th through 18th of December 2020 were required to accomplish the target of 600 samples. Table 3-5 includes the details of the survey plan, including the date of the survey, the target sample size, and the name of the survey station. Figure 3-8 to 3-10 shows the map of survey distribution by station on 16-18 December 2020.

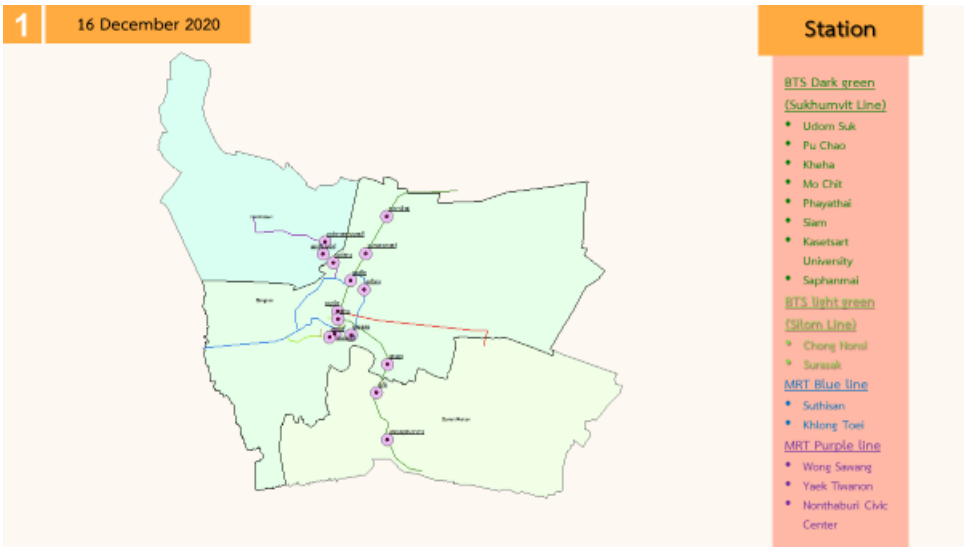


Figure 3-8 A map of survey distribution by station on December 16, 2020

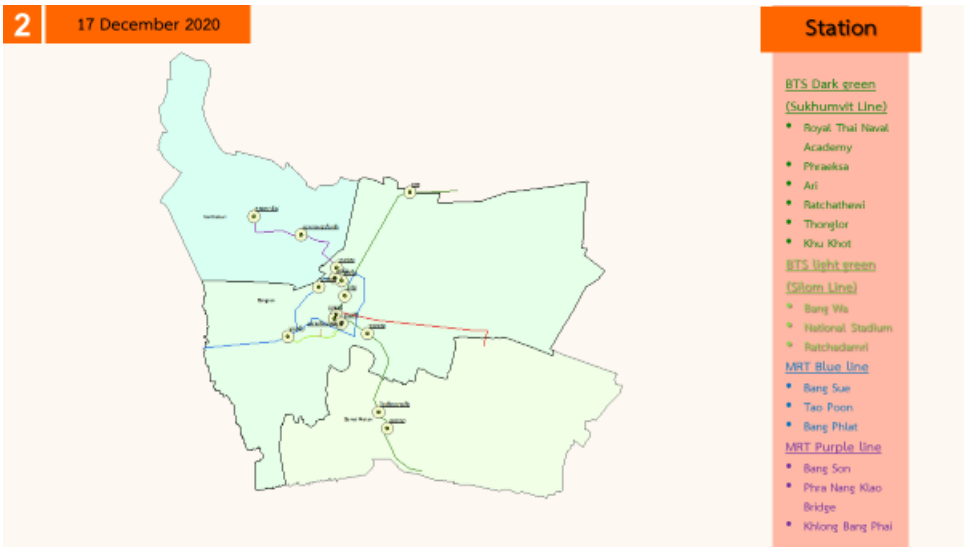


Figure 3-9 A map of survey distribution by station on December 17, 2020

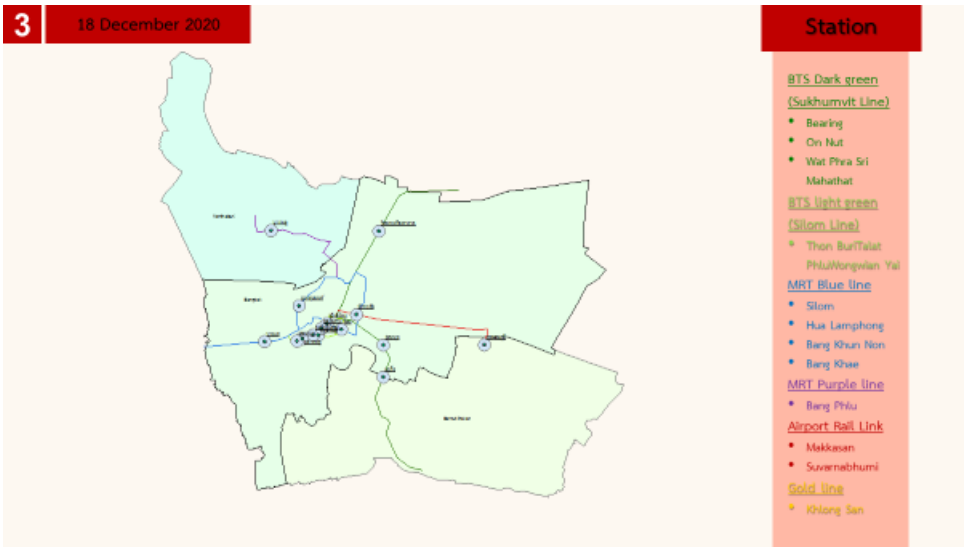


Figure 3-10 A map of survey distribution by station on December 18, 2020

Table 3-5 Details of survey plan by station

Province	Survey date	Sample size	Station	
Bangkok	16 December 2020	134	• Chong Nonsi (LG) • Morchit (DG-B) • Phayathai (DG-A) • Wong Sawang (P) • Udomsuk (DG) • Kasetsart University (DG)	• Saphanmai (DG) • Siam (LG) • Surasak (LG) • Sutthisan (B) • Khlong Toei (B)
	17 December 2020	133	• Ratchathewi (DG) • Tao Poon (B-P) • Bang Wa (LG-B) • Bang Son (P) • Khu Khot (DG) • Ari (DG)	• Thonglor (DG) • Ratchadamri (LG) • National Stadium (LG) • Bang Sue (B) • Bang Phlat (B)
	18 December 2020	133	• Krungthonburi (LG) • Makkasan (A-B) • Silom (B-LG) • Wutthakat (LG) • Bang Khun Non (B) • Wat Phra Sri Mahathat (DG)	• On Nut (DG) • Talat Phlu (LG) • Wong Wian Yai (LG) • Hua Lamphong (B) • Bang Khae (B)
Nonthaburi	16 December 2020	33	• Yaek Tiwanon (P)	• Nonthaburi Civic Ceter (P)
	17 December 2020	34	• Khlong Bang Phai (P)	• Phra Nang Klao Bridge (P)
	18 December 2020	33	• Bang Phlu (P)	• Khlong San (Gd)
Samut Prakhan	16 December 2020	33	• Kheha (DG)	• Pu Chao (DG)
	17 December 2020	33	• Phraeksa (DG)	• Royal Thai Naval Academy (DG)
	18 December 2020	34	• Bearing (DG)	• Suvarnabhumi (A)

Note: LG=Light Green line, DG=Dark Green line, B=Blue line, P=Purple line, A=Airport rail link, Gd=Gold line, and "-"=transfer station.

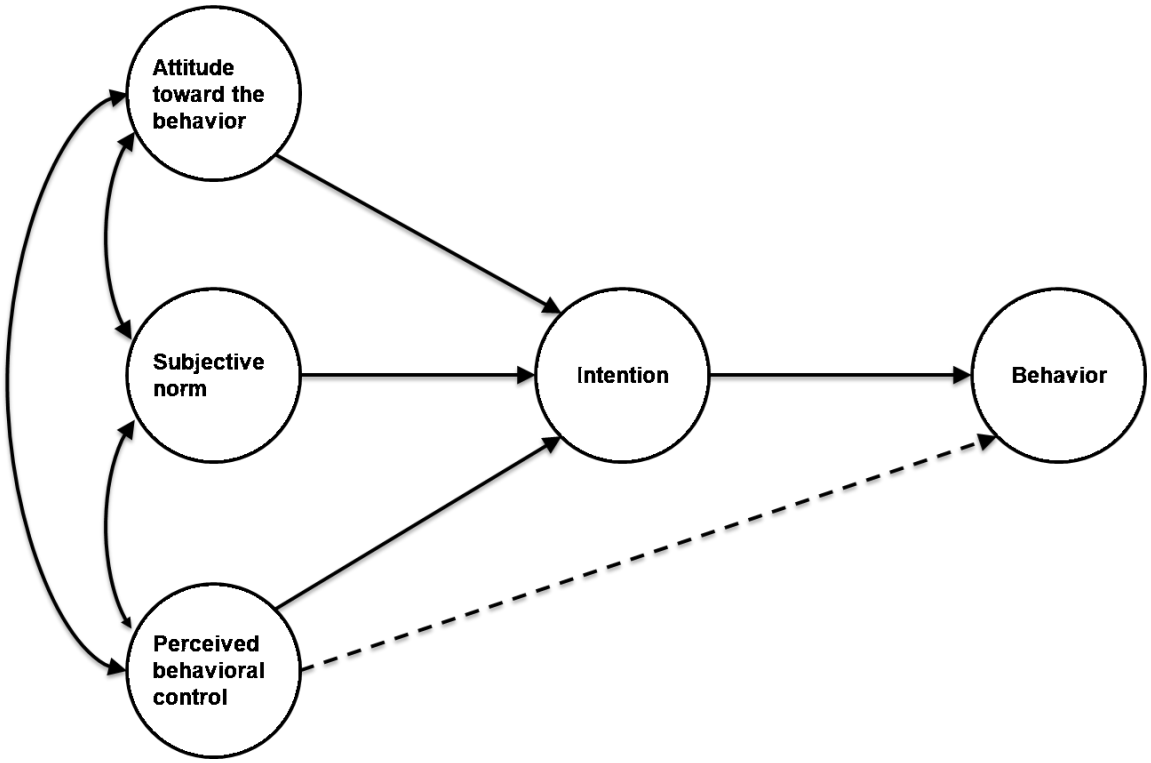
Note that, on December 16, 2020, there have been 4,261 confirmed cases of COVID-19, with 60 deaths. 2,463 of these cases were spread by people living in the same area, and there have been 0 new cases of infection in Thailand [104]. The picture taken onsite during the survey time is shown in APPENDIX 8.1.4.

3.2 Travel Behavior

The effect of social–psychological attitude–behavior theory on the direction of residential self-selection is crucial for analyzing travel-related attitudes in the relationship between the built environment and travel behavior as shown by the literature review. in Chapter 2, which can be summarized into two theories of behavior change have been considered: 1) the theory of planned behavior and 2) the cognitive dissonance theory.

3.2.1 Travel Behavior Change

The theory of planned behavior is a theory for understanding how changes in people's behavior is made. Figure 3-11 shows the theory of planned behavior structural diagram, which can be expressed by attitudes toward the behavior, subjective norms about the behavior, and perceived control over the behavior, and is frequently found to accurately predict behavioral intentions [105] .



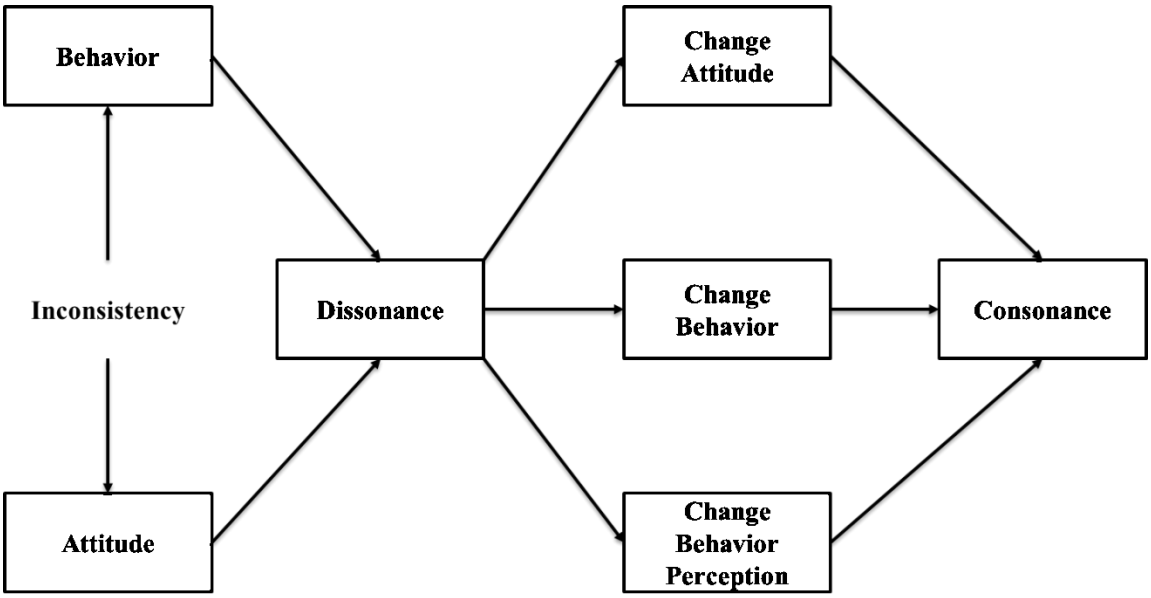
Source: Ajzen (1991) [105]

Figure 3-11 Theory of planned behavior structural diagram

The assumption behind intention prediction is that the relative significance of attitudes, subjective norms, and perceived behavioral control varies between activities and circumstances. It is conceivable that only attitudes have a significant impact on intentions in particular applications. In others, attitudes and perceived behavioral control are adequate predictors of intentions, while in others, all three predictors create independent contributions. However, this research is specific to attitude behavior because attitudes have an important influence on travel behavior [6] and It is to determine respondents' intentions

based on their attitudes rather than their wants, which are a more accurate predictor of conduct [106].

In dimension of residential self-selection hypothesis, assumed that ‘‘the tendency of people to choose locations based on their travel abilities, needs, and preferences’’ [1] [49]. People's attitudes toward travel and the dissonance between attitudes as well as the characteristics of the residential built environment are believed to play an important role in the effectiveness of land use policies. Furthermore, people adjust their built environments along with their attitudes over time, and these processes are interrelated. [107]. This phenomena is call tension of dissonance based on theory of cognitive dissonance (Festiger, 1957) [53] as shown in Figure 3-12.



Source: Wiafe (2012) [108]

Figure 3-12 Cognitive dissonance theory from Festiger (1957)

People can modify their attitudes about their present residential area in order to reduce residential dissonance. This is in addition to relocation, which is an example of residential self-selection. The cognitive dissonance theory can contribute to the explanation of changes in travel-related attitudes as well as choices of residence location and travel mode, in terms of providing important insights into the levels of satisfaction with travel and the place of residence [109]. The dissonance of attitudes and behavior leads to a change in decision process of attitude, in the case of this study COVID-19.

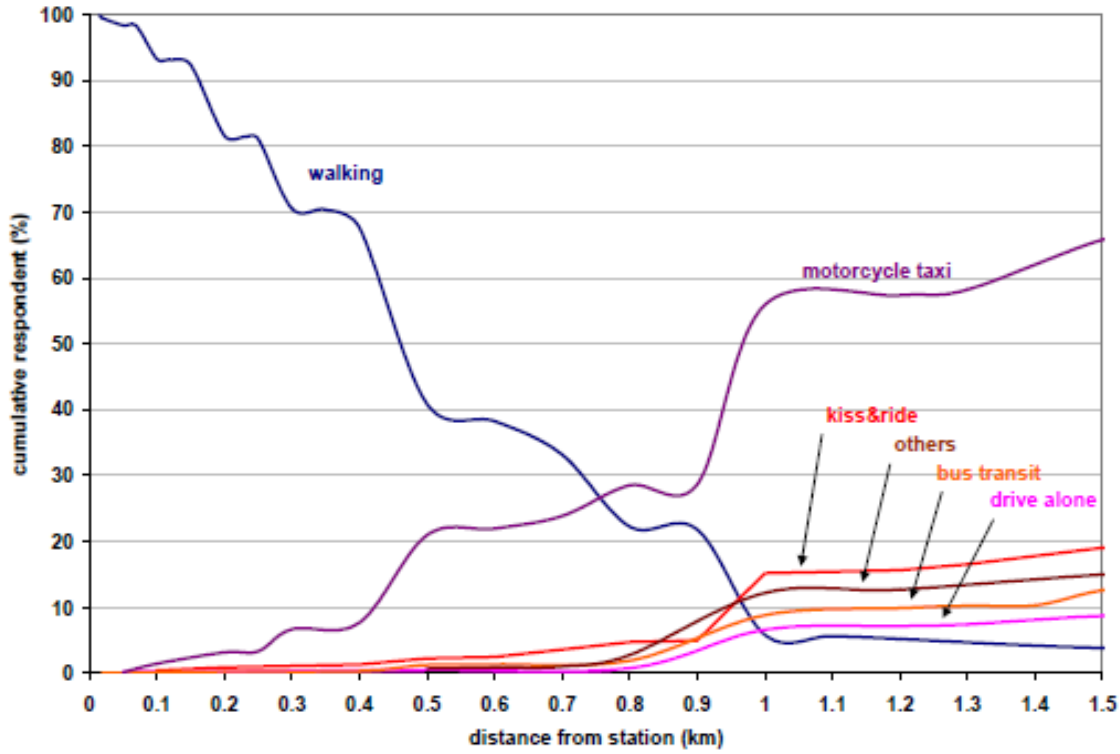
3.2.2 Travel Mode Accessibility

According to various studies, the built environment has a significant effect on residential choice, travel mode, and travel behavior. Studies on residential self-selection frequently emphasize the importance of the built environment on travel behavior due to the impact of the built environment on travel behavior. Because of the residential built environment, walkability, and regional accessibility, all these things have an effect on the types of active transportation that are available and the distance traveled [46].

Mass transit is the most convenient and accessible mode of transportation in urban areas. Subway ridership is positively influenced by subway catchment areas, population and employment density, land-use mix diversity, and intermodal connection [12]. The area around the mass transit station has been characterized differently from other areas by the surrounding infrastructure and the high accessibility it provides to commuters and residents near the stations. Urban travel characteristics indicate that the vast majority of inner-city residents 1) travel shorter distances than suburban residents [15], and 2) prefer traveling by train, indicating that people who moved closer to the stations became regular passengers [13]. The quality of services in public transportation is frequently determined more by the time of day and the location of the destination If the station is within walking distance but the trip frequency is low, it means public transit connectivity is rendered ineffective [10].

However, walkability has been associated with physical activity. For example, residential density mediated the relationship between walking and the amount of time spent walking [110]. Nevertheless, none of the correlations between walkability parameters and physical activity outcomes were moderated by car ownership [111]. Walkability strongly affects the property price at the city center [98]. Among the key variables of access mode choice and density are the distance to the station, gender, ethnicity, age of passengers, and car availability. In addition to the availability of parking spaces at the station, income and educational levels of residents were found to be important factors influencing the decision to walk [112].

In the case of Bangkok, the results of comparing the utility of private vehicles and mass transit modes indicated that the distance from home to the mass transit station influenced the travelers' mode choice behavior [24]. A previous study determining the association between the distance to a transit stop and transit access mode found that a longer distance is correlated with a lower probability of walking to public transit [102]. The access distance was used as the catchment area or walkability distance to access transit and activities. However, due to the intense competitiveness of motorcycle taxis, the proportion of people walking is lower in Bangkok than in other major cities [101]. Chalermpong and Wibowo (2007) discovered that the proportion of pedestrians decreases with distance and drops dramatically beyond 400 meters, with less than 10 percent of travelers walking from a distance greater than 1 kilometer (as shown in Figure 3-13). Consequently to a previous study conducted in Bangkok [101], the proportion of people walking to the stations decreased when the distance to the station was more than 400 meters, while less than 10 % of people walked more than 1 km to the station, because long distance is associated with a lower probability of walking to public transportation [102]. Therefore, this study defined the importance of the built environment variable of walking distance from residence to the nearest mass transit station by assigning a maximum walking distance of 400 meters and feeder transit access of 1000 meters in the Bangkok area.



Source: Chalermpong and Wibowo (2007) [101].

Figure 3-13 Relationship between access mode share and distance from station

Generally, the walking distance to access rail transit mode for commuting trips was 1 km or less, and 1–1.6 km for bus transit [113]. In the San Francisco Bay Area, researchers discovered that pedestrians walked an average of 548 m and as far as 1100 m [114]. However, in the United States, the average distance between train stations is half a mile [115].

3.2.3 Latent Variables

This study will provide an insight into attitudes, which are a subjective assessment of the decision-making process and the intention to participate in a particular action or behavior. The latent variables investigated in this research are travel attitude and residential attitude, which are related to the dimensions of travel behavior and residential choice. According to previous studies, most studies emphasize attitudes toward travel, attitudes toward modes of travel, attitudes toward travel-related locations, and attitudes toward travel-related neighborhoods. Thus, in terms of residential self-selection, residential attitudes will separate resident attitudes from travel attitudes, which allows for a more in-depth study of the relationship between travel attitudes and travel behaviors.

Travel attitude

Accordingly, this study focuses on attitudes toward travel and travel modes, which might affect decision-making and actual behavior in the future. The attitude was applied to test hypotheses considered from the perspectives of a variety of attitudes, such as accessibility of mode of transport [116], comfort of transport mode [117], environment [29], [118], and safety [49], [119] of travel, that are most considered in travel attitude.

Residential attitude

However, residence-associated attributes could be split into two categories: housing attributes and others that are related to the location and neighborhood [120]. In addition, travel behavior was influenced by these attitudes and preferences for particular modes of travel or neighborhood characteristics [121]. Furthermore, residents prefer walkable neighborhoods [122] and public transportation [123]. However, many residents preferred suburban or small-town locales [124]

The availability of public transit is the most important factor influencing current residential location choices, followed by living in a good neighborhood and housing affordability [33]. Nevertheless, the type of residential location had little effect on travel behavior, whereas attitude and lifestyle variables had an outstanding impact on travel demand [36]. Moreover, car ownership, additional car purchase, income, particular housing type and size, relocation type, accessibility of subway/bus for commuting, change in commuting distance, and distance to subway station were significant when considering to change from private car to public transportation [35]. Note that, during COVID-19, people's preferences for housing types may change as a result of COVID-19 effects, and the quality of living environments will likely become more important [82].

3.3 Structural Equation Model

3.3.1 Structural Equation Model Technique

This study is designed to test a theoretical hypothesis and explore the path of the relationship. The methodology widely used to prove hypotheses is structural equation modeling (SEM). SEM is a statistical modeling technique that can handle a large number of endogenous and exogenous variables, in addition to latent (unobserved) variables described as linear combinations (weighted averages) of the observed variables. SEM is a sort of regression that combines simultaneous equations (both with and without error term correlations), path analysis, and variations with factor analysis and canonical correlation analysis. Thus, a summary of the structural equation model is presented. This is the outcome of the synthesis of three major data analysis techniques: factor analysis, path analysis, and regression analysis [125]. The analysis of path analysis and factor analysis is the initial concept and the origin of analyzing structural equation models. Path analysis was originally used to address the problem of estimating size components from bone measurements in 1918 by Wright (1918). This first application of path analysis was statistically equivalent to factor analysis [126]. In the 1970s, Joreskog [127] structures governing matrices of covariances among observed variables that integrated the measurement of factor analysis with the regression modeling of path analysis to provide a

powerful combination of measurement and regression modeling capabilities. Known as the LISREL (Linear Structural Relations) Model and the SEM (Structural Equation Model) in recent years.

The element of structural equation modeling could be explained as follow:

- Latent variable (Unobserved variables)

  Latent variables represent unobserved variables that are related to measurement variables. Typically, latent variables are set for theoretical concepts or phenomena that cannot be measured directly. However, latent variables must always be continuous variable in structural equation modeling only continuous variables can be analyzed [128]

- Measurement variable (Observed variables)

  Measurement variable is the data collect from responses, that can be categorical discrete or continuous type. Likert-type ordinal scales are commonly employed in research surveys. Integer values are being used in the scale type and are sorted by importance. In a structural model, a measurement variable is also known as an indicator.

- Exogenous variables

  Exogenous latent variables are the same as independent variables. They "cause" other latent variables in the model to have variations in values. [129].

- Endogenous variables

  Endogenous latent variables are synonymous with dependent variables and are influenced by the exogenous variable in either direct or indirect relationships.

- Factor analytic model

  Factor analysis mainly divided into 2 basic types 1) exploratory factor analysis (EFA) and 2) confirmatory factor analysis (CFA). Whereas EFA uses to extract measurement variables and/or identify latent variable based on covariance of measurement variables. In contrast, CFA uses for latent constructs based on hypothesis group underlying measurement variables. Table 3-6 shown the difference of factor analysis type.

- Full latent variable model

  The full latent variable model is a systematic model of the structural equation model in which all path relationships are defined by the regression structure to connect with latent variables. This model is called the structural equation model.

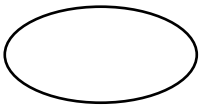
Table 3-6 Difference of factor analysis type

Explanatory	Confirmatory
• Multidimensional Scaling • Cluster Analysis • Explanatory Factor Analysis • Partial Least Squares Structural Equation Modeling (PLS-SEM)	• Analysis of Variance • Logistic Regression, Multiple Regression • Confirmatory Factor Analysis • Covariance Based Structural Equation Modeling (CB-SEM)

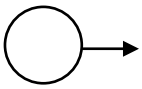
Source: Hair, J. F., Hult, G. T. M., Ringle, C. M., & Sarstedt, (2017) [130]

Relationships to analyzed and evaluated in the SEM model are represented by diagrams. Diagram symbols used in SEM can be expressed by:

Observed variables/ Indicator



Latent variables/Construct

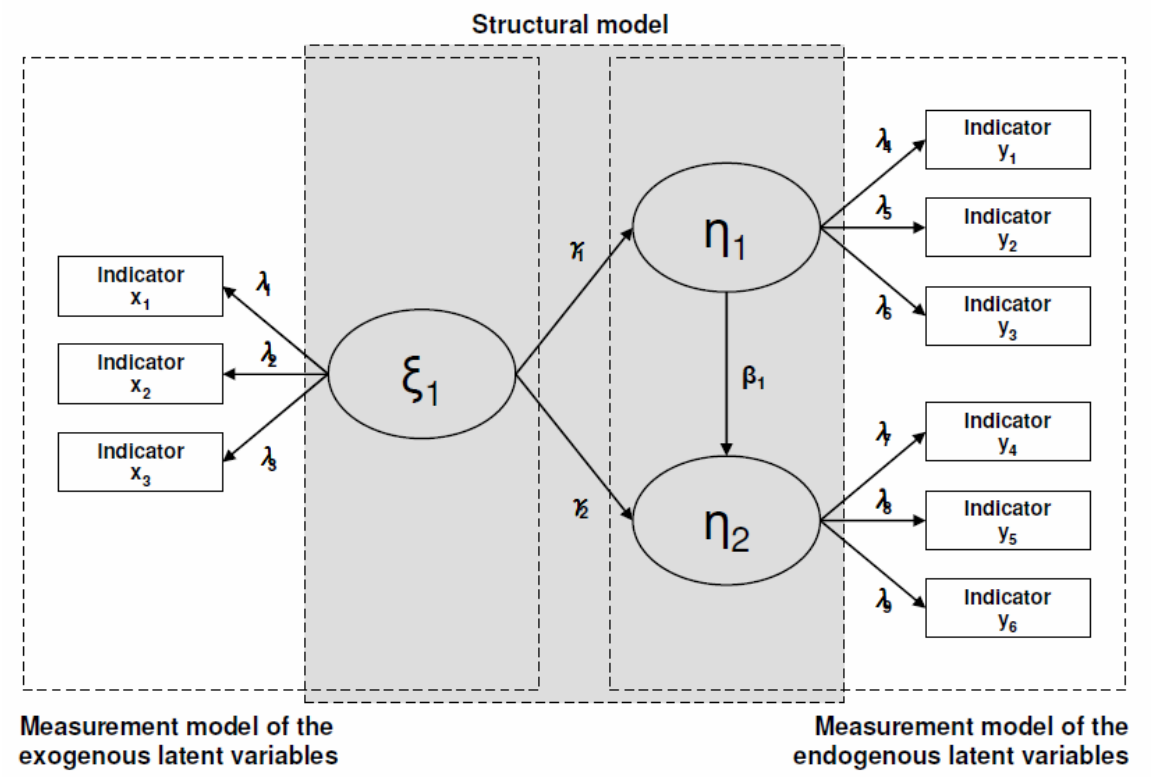


Measurement error of observed variable /Residual error of latent variable

Variance/Covariance

Regression path/Loading

The general structural equation modeling (as shown in Figure 3-14) includes a structural model and measurement model, whereas the measurement model is a relationship of latent variables and indicator variables (x_i). The structural model is the model between latent variables of exogenous latent variables (ξ_i) or independent variables and endogenous latent variables (η_i) or dependent variables and represents the theoretical considerations. The relationship between variables is quantified by path coefficients, and path coefficients within the measurement model (λ_i) are determined by weight or loading. The path coefficients between latent variables between endogenous β_i and exogenous (γ_i) are defined. Note that ζ_{I} represent residuals or error terms of endogenous variables. Moreover, in the measurement model, each indicators including e_i error terms for each variable.



Source: Urbach & Ahlemann, (2010) [131]

Figure 3-14 A general structural equation modeling

From Figure 3-14, which can be expressed by

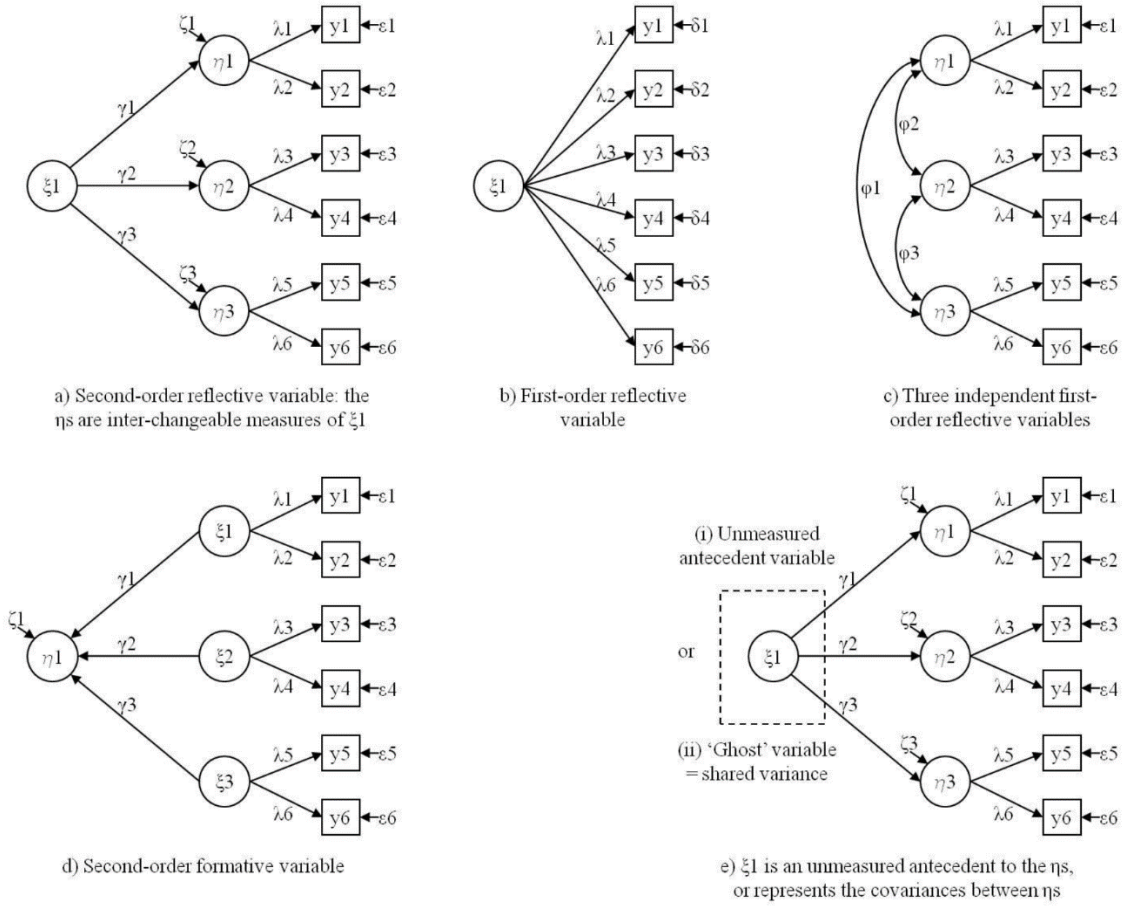
Structural equation

$$\eta_1 = \gamma_1 \xi_1$$
$$\eta_2 = \gamma_2 \xi_1 + \beta_1 \eta_1$$

Measurement equation:

$$\eta_1 = \lambda_4 y_1 + \lambda_5 y_2 + \lambda_6 y_3 + \zeta_2$$
$$\eta_2 = \lambda_7 y_4 + \lambda_8 y_5 + \lambda_9 y_6 + \zeta_2$$
$$\xi_1 = \lambda_1 x_1 + \lambda_2 x_2 + \lambda_3 x_3$$

The method of structural equation modeling combines factor analysis and regression analysis. The models studied in SEM are often based on probabilistic causality rather than deterministic causality. SEM is generally considered a confirmatory procedure rather than an exploratory one [132]. However, the measurement model is constructed by confirmatory factor analysis to develop a model based on theory. To construct the latent variable, confirmatory factor analysis employs to analyze based on structural model order for example as shown in Figure 3-15



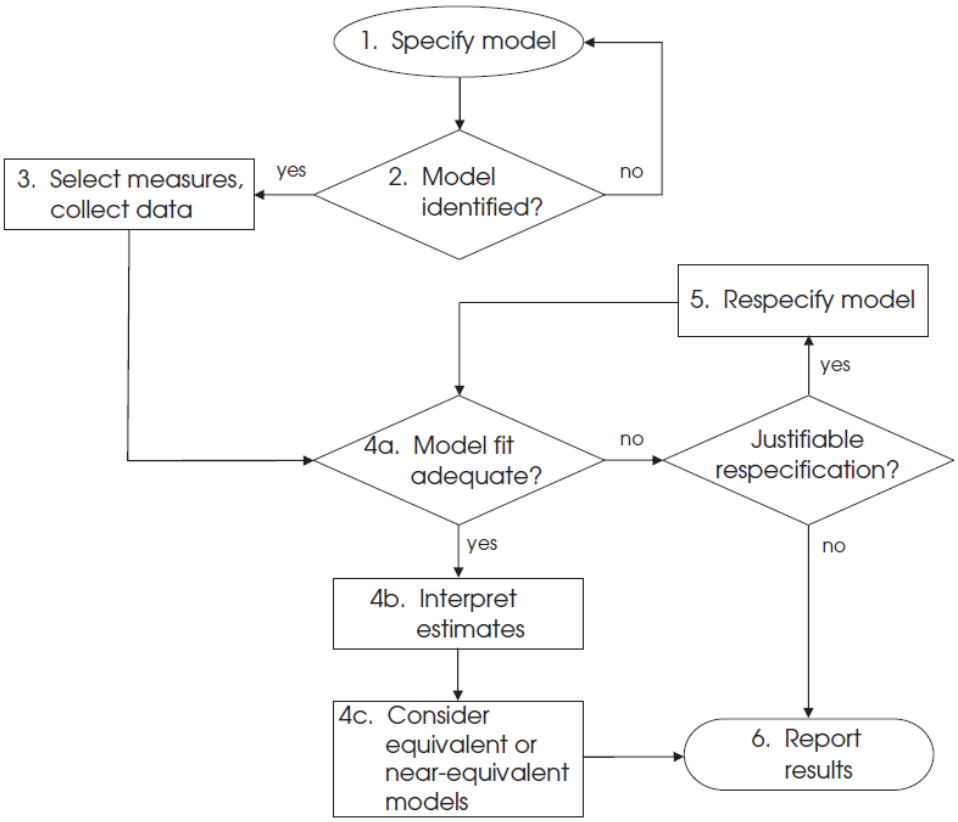
Source: Lee & Cadogan (2013)

Figure 3-15 Measurement model order type and model alternative

Nonetheless, it is suggested to identify a prior the weight of each sub-dimension to be constructed in the case of a second-order construct; conversely, higher-order reflective constructs are invalid and draw attention to the damage inflicted on theory development through higher-order constructs [133].

In the field of behavioral sciences, researchers typically have an interest in investigating theoretical structures that cannot be seen directly. These non-tangible phenomena are referred to as latent variables or factors [129]. Latent variables are unobserved variables that cannot be measured directly and represent the link between observed variables, also known as measurement variables.

Structural equation modeling analysis is divided into six primary processes, which are depicted in Figure 3-16. First, identify the theory's model, and then, following ensuring that the model has been identified, select a sample from which measurements could be obtained. Next, model estimation of the parameters from the measurement model and the structural model (or simultaneous estimate) will be estimated. The procedure of the model is adequate if the goodness of fit of the model is modified until fit. Interpret the parameter estimates or consider the equivalent model to report the result.



Source: Klein, 2016 [128]

Figure 3-16 Flowchart of the basic steps of structural equation modeling

3.3.2 Conditional Process Model

Conditional process modeling is a method of data analysis that combines statistical mediation with moderation analysis. Conditional process modeling is also known as moderated mediation models or mediated moderation models [134]. The conditional process model analyzes hypotheses about effects that are dependent on other variables by analyzing the conditional aspect of the mechanism or processes by which one variable exerts its influence on another variable [135]. When it refers to moderating and mediating, the most fundamental point to note is that a third variable plays a key role in influencing the relationship between the two other variables [136]. The mediate relationship is a variable that mediates or interacts with the causal relationship between independent and dependent variables, which is examined through direct and indirect pathways (as shown in Figure 3-17). A moderation relationship is a variable that moderates or interevent between dependent and independent variables and refers to the change level function of a moderator. Figure 3-18 illustrates the difference between the effects of moderation, mediation, and one example of moderated mediation in diagram form.

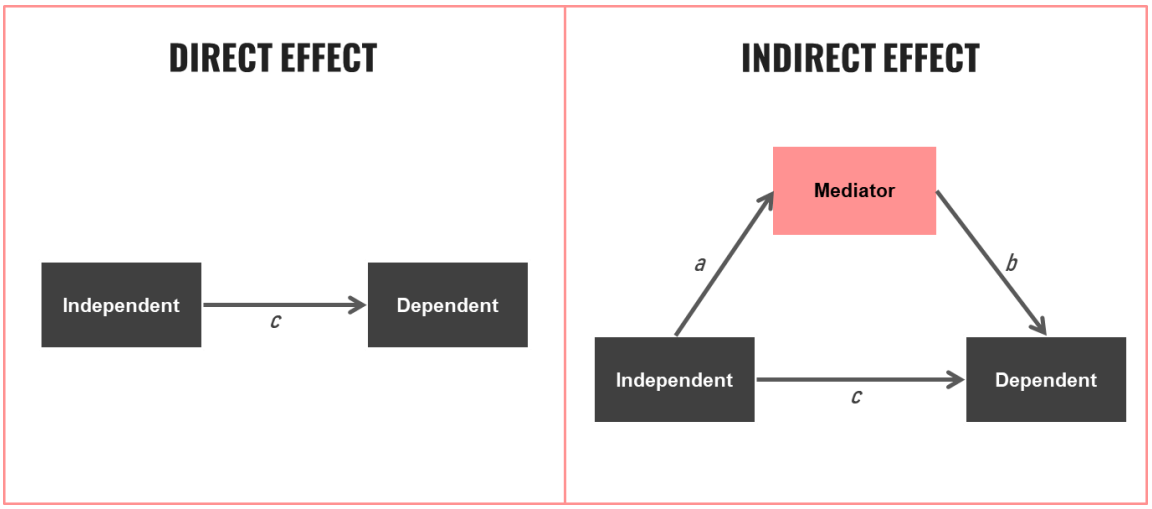


Figure 3-17 Diagram of direct and indirect effects

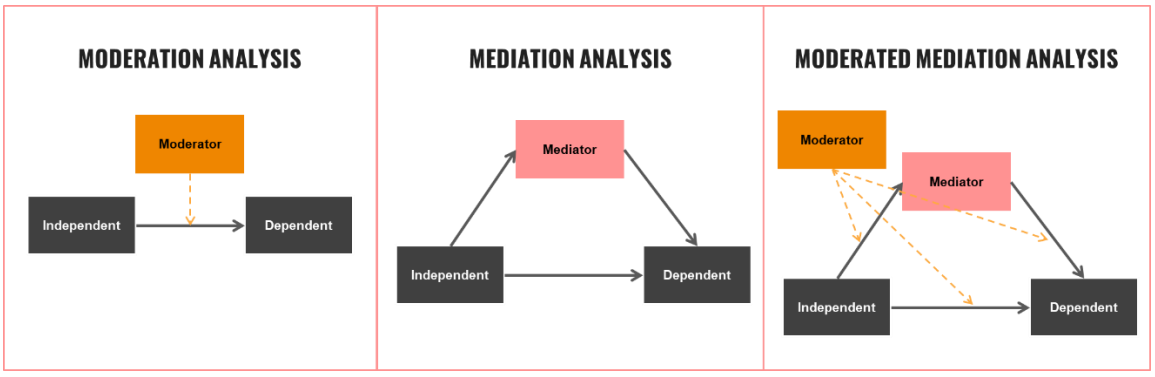


Figure 3-18 Comparison of moderation, mediation, and moderated mediation diagrams

In the social, behavioral, and health sciences, as well as in business, medicine, and a variety of other fields, mediation and moderation analysis are two of the statistical approaches that are widely applied [135]. The mediation moderation model, or conditional process model, integrates mediation and moderation analysis to estimate and test a variety of hypotheses involving conditional indirect effects [137]. An indirect effect of mediation was defined as a relationship that flowed from an independent variable to a mediator and then to a dependent variable. Besides, a third variable can affect or change the direct influence of an independent variable on a dependent variable, which is referred to as moderation (moderator) [138]. Figure 3-19 represents the statistical diagram of the moderated mediation model based on Figure 3-19, including the indirect effect of independent (X) on dependent (Y) variables through mediator (M) variables and one moderator variable (W) moderated between X→Y, X→M and M→Y. In this diagram, provide moderator defined by levels.

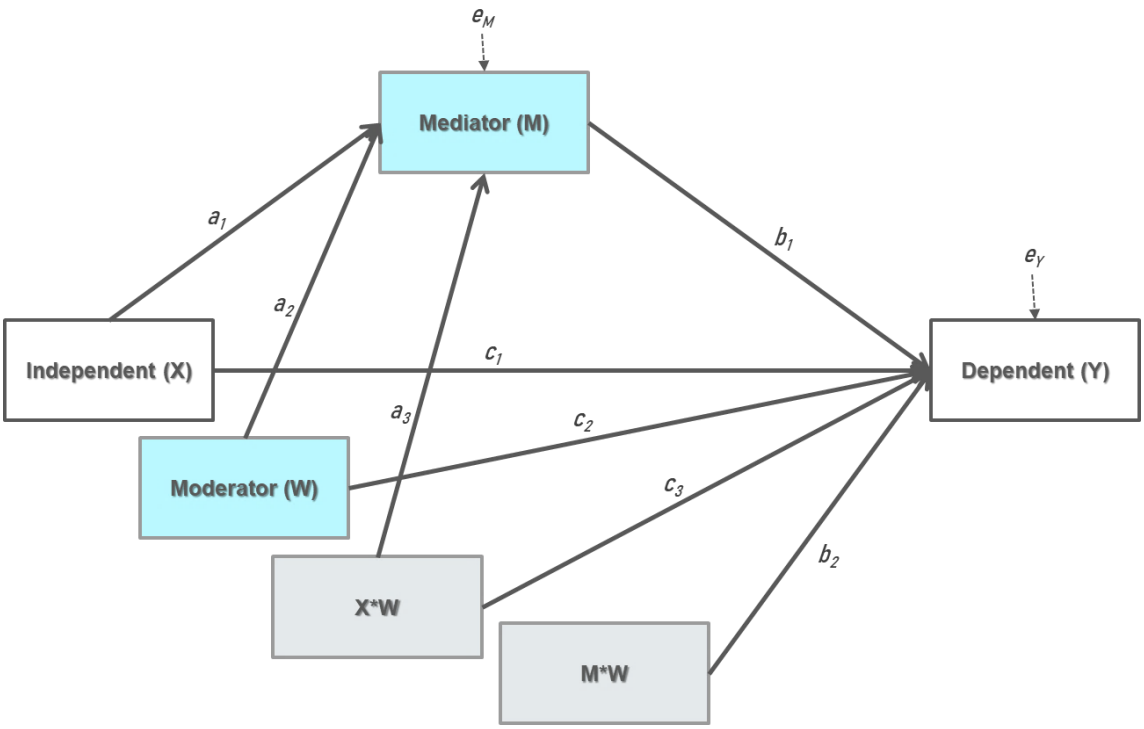


Figure 3-19 Statistical diagram of the regression-based conditional process model Adapted from Hayes (2017)

From Figure 3-19, which can be expressed in formulars by

Statistical diagram

$$M = i_M + a_1X + a_2\mathrm{W} + a_3XW + e_M$$

$$Y = i_Y + c_1X + c_2\mathrm{W} + c_3XW + b_1\mathrm{M} + b_2MW + e_Y$$

Indirect Effect of X→M

$$\theta_{X\to M} = a_1 + a_3W$$

Indirect Effect of M→Y

$$\theta_{M\to Y} = b_1 + b_2 W$$

Indirect Effect of X on Y through M

$$\theta_{X\to M}\theta_{M\to Y} = (a_1 + a_3 W)(b_1 + b_2 W)$$

Direct Effect of X→Y

$$\theta_{X\to Y} = c_1 + c_3 W$$

The relationship between the two constructs may indeed be mediated by a third variable referred to as a mediator. In these cases, the third variable can intervene in the influence of the two independent and dependent variables [139]. The indirect effect is involved with the various forms of mediation effects that might occur in different circumstances of analysis, as shown in Figure 3-20.

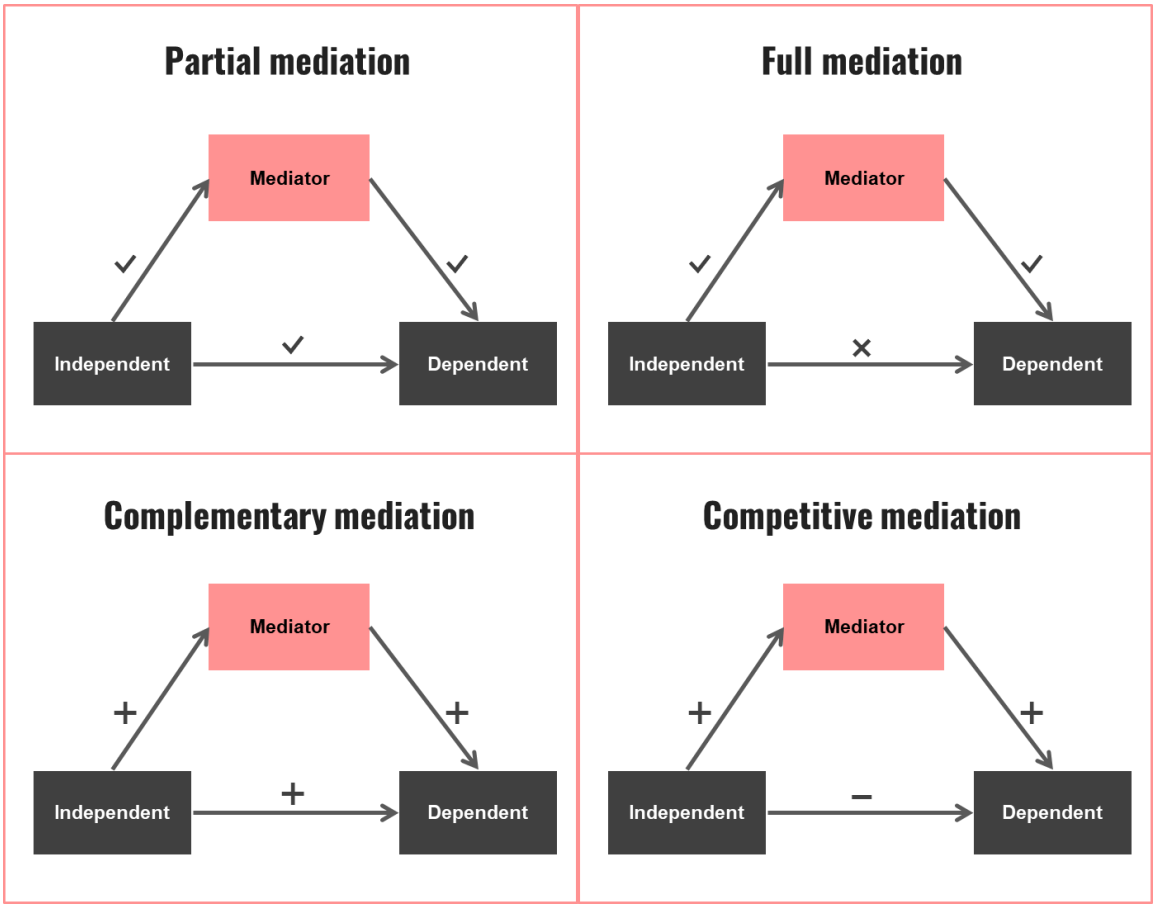


Figure 3-20 The different form of indirect effect on mediation
Adapted from Collier, (2020)

3.3.3 Pre-test and Post-test Experiment Design

Pre-test and post-test designs are commonly used in behavioral research, particularly for comparing groups and/or assessing the change of experimental treatments [140]. Whereas the first measurement is referred to as the pre-test, or baseline measurement, the second measurement is referred to as the post-test measurement [141]. The purpose of the post-test measurement is to determine whether there is a difference between the first and second measurements or whether the subject is receiving treatment intervention to measure the difference between the pre-test and post-test.

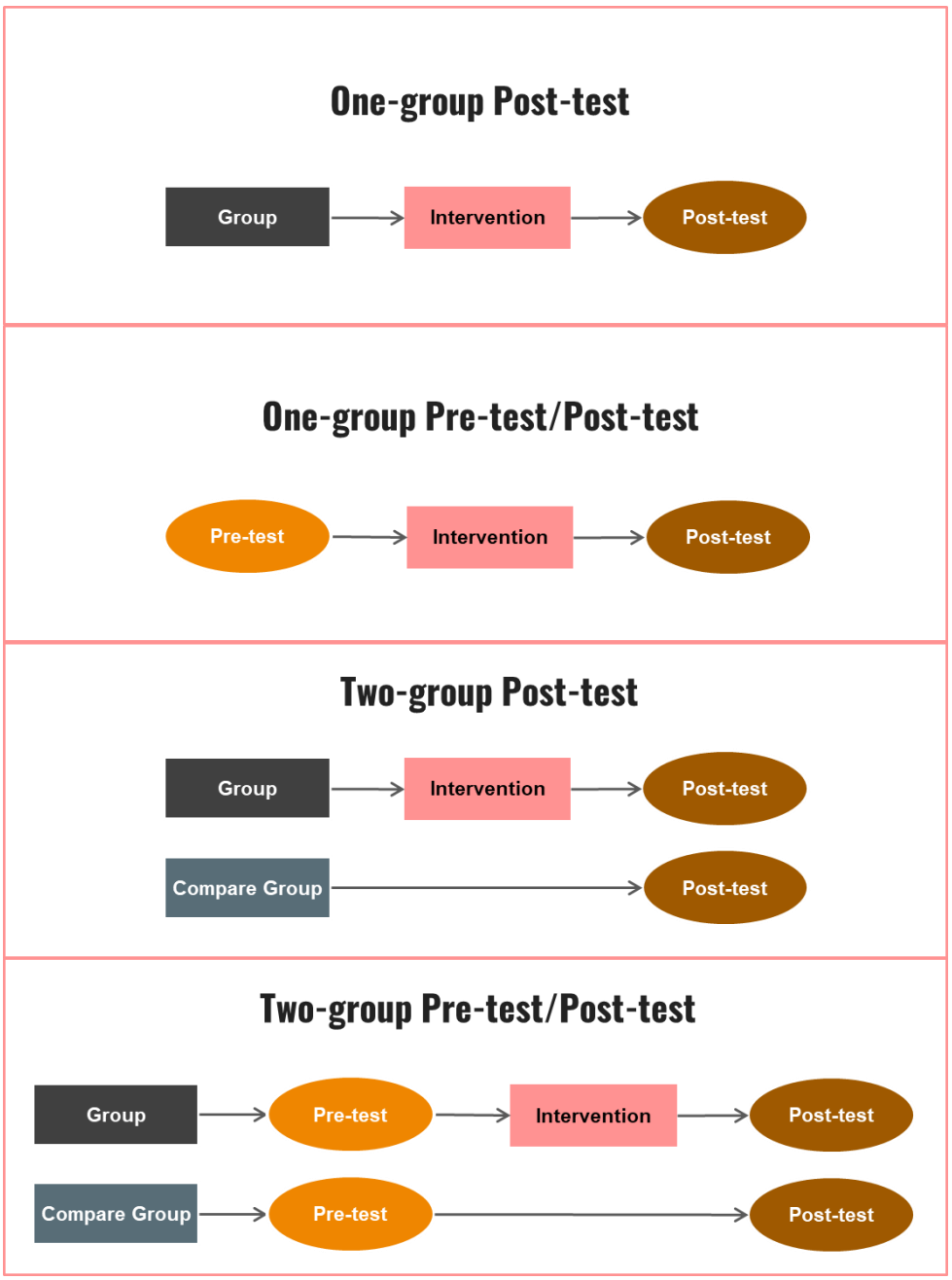


Figure 3-21 The conceptual of pre-test and post-test experiment design
Adapt from University of Minnesota (2022) [142]

Figure 3-21 represent the conceptual of pre-test and post-test experiment design, intervention represents the treatment between pre and post. However, the experiment design could consider one group (test with treatment) and two groups (test with and without treatment) for the experiment. In addition, the analysis experiment design can be performed using a posttest design or a pretest/posttest design. Therefore, two designs can be used for a single group or a combined group to perform a comparison [142]. In transportation research, pre-test and post-test designs were used to measure the relationship between density and travel behavior in the United States and Europe, and post-test analysis indicated that the rigor of study designs and statistical methodologies influenced the variance [143].

3.4 Decision Tree

3.4.1 Decision Tree for Classification and Regression

The model-based segmentation approach is used to identify groups of people that have similar behavioral and attitude characteristics. A decision tree is an intuitive, easy-to-implement, and productive modeling technique that can be depicted as a tree for classifying customers [144]. Recently, decision trees have been used in decision-making processes, and have been demonstrated to be an effective approach for making decisions. The decision tree for classification has four algorithms: Classification and Regression Trees (CART), exhaustive CHAID, CHAID, and Quick, Unbiased, Efficient, and Statistical tree (QUEST) [145]. This study addresses CART and CHAID, which represent classification and regression trees and use nonparametric statistical techniques that can be used for categorical and continuous data. Moreover, the accuracy of the decision-tree model using the CHAID algorithm was found to be higher than other models [146].

The CART, first presented by Gordon et al. (1984), use a binary tree technique based on the sum of squared estimates of errors between the observation and the mean value of the node, and the Gini diversity index as a measure of impurity when deciding splitting. However, the CART always produces binary trees, and the binary tree is not an efficient representation and can be difficult to interpret [147]. CHAID proposed by Kass (1975) [148], is a decision tree technique, based on the chi-squared test when determining the best splitting pattern for tree classifiers. CHAID has been used for the prediction, classification, and detection and establishment of relationships between variables. CHAID decision trees use nonparametric techniques that make no assumptions about data and are most used in market research for segmentation.

3.4.2 CHAID Algorithm

The CHAID algorithm is divided into two types of analysis: classification problems and regression problems. For classification problems, the chi-square test is used to find the appropriate split at each level (for a category target variable), as well as the F-test, which is used for regression problems (for a continuous target variable) [149]. However, the focus of this research is on the classification problem, which will be considered in the segmentation stage.

The CHAID algorithm association with of dependent variables are categorical data and multiple categorical or continuous dependent variables, the Pearson's chi-squared (X^2) test is performed [150] and corresponding P-value (P) [151] using the following formula:

$$X^2 = \sum_{j=1}^{J} \sum_{i=1}^{I} \frac{\left(n_{ij} - m_{ij}\right)^2}{m_{ij}}$$

$$n_{ij} = \sum_{n \in D} f_n I(x_n = i \cap y_n = j)$$

$$P = Pr(x_d^e > x^2)$$

Whereas

n_{ij} = the observed frequency

m_{ij}= the estimated expected frequency for $x_n = i$, $y_n = j$

x_n and y_n = whole sample

f_n = the frequency weight associated with case

I = degrees of freedoms

D = the relevant data

The CHAID algorithm, according to employs a sequence of merging, splitting, and stopping stages. The whole algorithm is as follow [152]:

1. Perform a cross-tabulation of the categories of the predictor variables with the categories of the dependent variables, and then proceed to steps 2 and 3 of the procedure.
2. Finding the least considerably different 2xd sub-table of the predictors (only considering allowable pairings as determined by the type of predictor). If the significance does not meet a critical value, merge the two categories, and consider the resulting composite category as a single compound category.
3. For each compound category comprised of three or more original categories, find the most significant binary split (which must be confined by the kind of predictor) by which the merger might be resolved. If the significance exceeds a threshold value, it is required to apply the split and return to step 2.
4. Identify and isolate the most important predictor among each of the optimally merged predictors by calculating its significance. If the significance of the chosen predictor is greater than the criterion value, divide the data into the (merged) categories of the chosen predictor.
5. Repeat steps 1 through 5 for each partition of the data that has not yet been evaluated. In order to modify this phase, partitions with a small number of observations might be excluded.

However, the CHAID technique tests hypotheses about the (in)dependence of two variables at each stage of the algorithm's implementation. The logic used to conduct the tests and formulate the findings is identical to that of classic statistical hypothesis testing [153].

3.5 Model Development

3.5.1 The Conceptual Model

The various relationships of residential self-selection based on literature review synthesize the involved factors of residential self-selection, including attitude related to travel and neighborhood characteristics of residential life. In particular, in urban areas, public transport, accessibility of mode and catchment influence travel behavior and residential location. Furthermore, some socio-demographic also impact travel behavior decisions. The primary focus of this research addresses the psychological aspects of attitude. Most of the research found that attitude has the most significant influence on travel behavior and influences residential self-selection. However, attitude in the study considers 2 different dimensions of travel attitude and residential attitude to get an in-depth understanding of the effects and relationship between travel behavior and residential choice. The phenomena might also affect people's short-term behavior and decision-making processes that might lead to relocation in the future. Figure 3-22 demonstrated the conceptual model of research on the normal situation to consider relationships between travel behavior, attitude toward travel, and attitude toward residential areas, and how COVID-19 phenomena affect short-term and long-term travel behavior and attitude. Due to the situation of COVID making it impossible to collect longitudinal data on residential choice, the focus point is attitude effects and current behavior only.

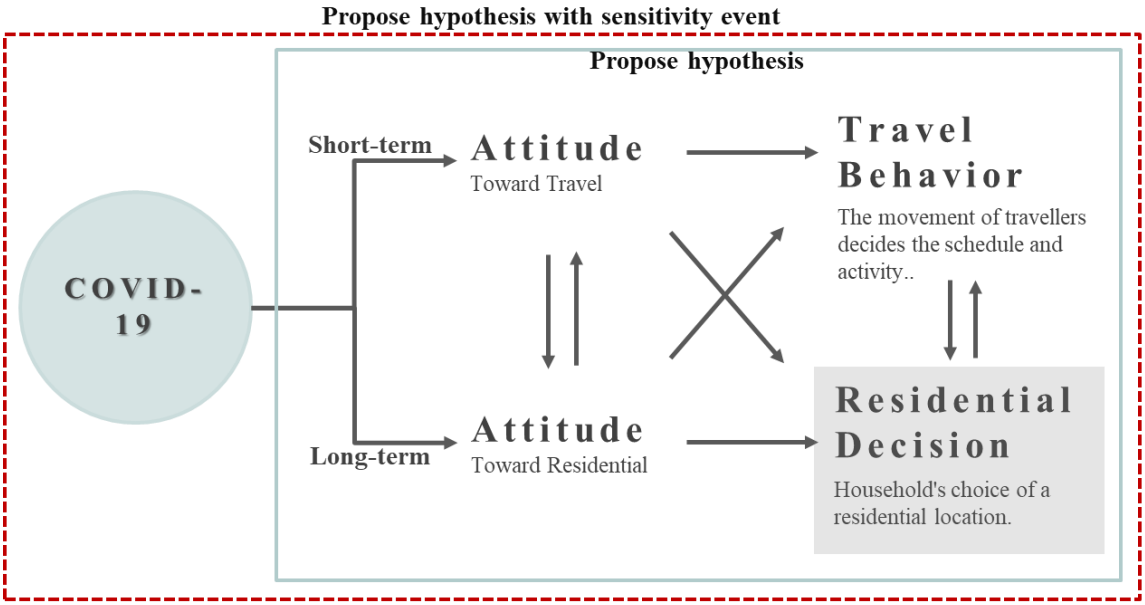


Figure 3-22 Conceptual model of research

3.5.2 Model Design

The majority of this research surrounds residential self-selection or relocation related to travel behavior and attitude. The study area has been focused on the catchment areas of mass transit stations, as this is the easiest mode of transport to access in urban areas, and people tend to live along mass transit routes. This research highlights the sensitivity of the COVID-19 pandemic to add a level of depth to understanding the effect and change in significant variables. The hypothesis of this research is divided into 3 stages sequentially:

In the first stage, residential self-selection was used to identify the relationship between exploratory variables and latent variables. The latent variables were focused on two dimensions: travel attitude and residential attitude. Most of the research emphasizes travel-related attitudes, so in terms of residential self-selection, residential attitudes should be taken into more consideration. Separating resident attitudes from travel attitudes allows for a more in-depth study of the relationship between travel attitudes and travel behaviors. The study details of the first stage are shown in Chapter 4.

According to the results of stage 1, the relationship among the variables affecting residential self-selection was identified. The results show that among the variables of travel behavior, travel mode is the most significant in the relationship. In the second stage, to explore the in-depth relationship between direct and indirect effects, were considered and interacted with for the group analysis. The study details of the second stage are shown in Chapter 5.

In the first and second stages, the analysis was separated by the sensitivity case of COVID-19 to understand the difference in the relationship. The third stage investigated the relationship effects of pre and post sensitivity cases as well as the interrupt variables, which demonstrated relationship effects on casual relationships. The study details of the second stage are shown in Chapter 6.

The hypothesis testing in this research provided insight into the relationships between residential self-selection, built environment, socio-demographics, residence characteristics, traveler characteristics, travel behavior, measurement, and latent variables were employed to explore the decision-making of attitude-based hypothesis. The overall hypothesis of the study is shown in Figure 3-23.

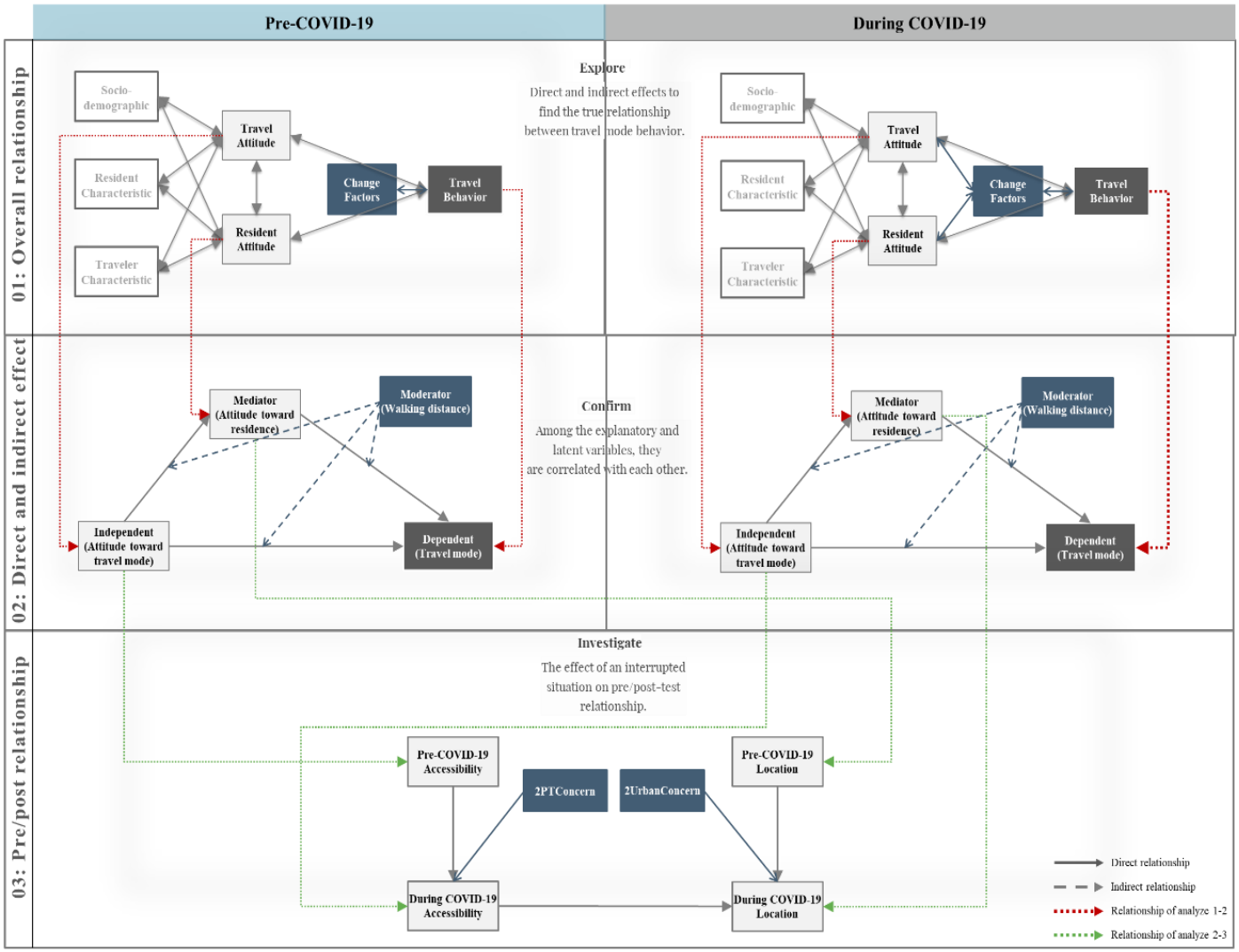


Figure 3-23 Conceptual model of study

4 IMPACT OF COVID-19 ON RESIDENTIAL SELF-SELECTION AND TRAVEL BEHAVIOR CHANGE

Resident location choices have been influenced by the mass transit network, such as in Bangkok, where residential areas have expanded along with the mass transit network. This trend might be changed due to the COVID-19 pandemic. This chapter investigates the change of travel behavior, reflecting the residential self-selection based on an assumption of travel attitude and resident attitude during the pandemic. Structural Equation Modelling (SEM) was utilized to confirm the relationship between travel behavior and other indicators. Hypothesis testing of the model was examined that the travel behavior had a strong relationship with mode choice and number of transfers. Travel attitude and resident attitude was a very strong relationship with each other. Furthermore, the resident attitude had influenced accessibility strongly in both cases. However, before the pandemic, neighborhoods were important for residential self-selection. In contrast, during the pandemic safety was more concerned.

4.1 Introduction

Generally, residential self-selection adjustments due to travel behavior, socioeconomic, and built environment. Residential self-selection was found to be a significant predictor of daily travel, considering it together with the built environment, and can be true in some other long-term choices [2]. Attitudes and socio-demographic characteristics contribute to residential self-selection [25]. Therefore, self-selection in this context refers to ‘‘the tendency of people to choose locations based on their travel abilities, needs, and preferences’’ [1]. In addition, the hypothesis of residential self-selection is influenced by their travel preferences and travel attitudes. And attitudes could be associated with the use of travel modes [5], [6]. In North-California, attitudes toward travel modes by using a dominant role to explain the differences in travel behavior that affected residential self-selection [49].

According to the INRIX Global Traffic Scorecard rated 2019 data, marginal time in Bangkok spend around 90 hours per year from the traffic congestion [87]. Moreover, public transport travels in the same flow as a private car, in which traveling by using public transportation to reduce traveling time is impossible. The accumulated number of cars is not suitable for the currently available road capacity and the physical characteristics of the area that cannot expand the capacity of the roads to keep up with the growth of the city. The mass rapid transit system has become more priority for the traveling of Bangkok residents. According to statistics of ridership of mass rapid transit users increased by 29% compared from 2014 to 2018 [94]. The increase in ridership comes from the development of public transit systems to promote the reduction in the use of personal cars. Nevertheless, 77% of people in Bangkok have shifted to using mass transit instead of private cars [95].

Settlement in the city to reducing travel times in workday trips can be a good alternative. As a concept of Transit Oriented Development (TOD), which develops areas around mass transit stations by the focus on the development of public transportation systems and increase traveling of non-motorized mode, as well as developing the commercial area around the station. Furthermore, the residential location choices of people will be chosen by their travel preference at a high-level degree. Due to the residents' preference for commuting by train, they moved closer to the stations in order to be able to more easily use the train and became frequent passengers [13]. However, development consumes time to develop all the mass transit network systems for access to all areas in Bangkok and the surrounding areas. Currently, the mass transit network has developed 31% as of 2019, compared to the overall development plan of The Mass Rapid Transit Master Plan in the Bangkok Metropolitan Region.

Consequently, the increasing trend in resident locations along mass transit lines involves using mass transit and non-motorized travel. By the number of condominium sales in Bangkok, according to NEXUS Research in 2017, found that the average sales rate increased in 2017 by 14% compared to the last 5 years (2012-2016) [96]. Furthermore, households with fewer cars tended to live in high-density areas and close to the central business district (CBD) area [97]. Significantly, the importance of residential self-selection is related to travel behavior and access mode.

In early January 2020, there was a pandemic of the COVID-19 outbreak in Thailand, that has been affected people's behavior. To prevent the spread of the virus different measures such as wearing masks, reducing work, reducing activities to meet people, quarantine, work at home, social distancing was applied as the new normal of daily life. Thailand reported the highest number of cases on 22 March [99]. The Declaration of a State of Emergency has been effective on 26 March. In April, lockdown measures and curfews were implemented to control the pandemic. The Thai government had locked down all cities and returned to normal in May 2020. This affected directly to the daily travel of citizens.

Such a situation has caused a change in travel behavior, as in the case of an economic crisis. In Athens, Greece, stated during periods of an economic crisis that there are changes in users' travel patterns, especially in urban areas [21]. It was discovered that the overall cost of transportation led to a drop in the number of trips made by one in five citizens and a reduction in the number of private cars traveled by one in two. However, the previous MERS pandemic was studied in South Korea. MERS decreased the number of passengers on public transport services by more than 10 percent. 14 percent and 9 percent declines in trips were recorded in affected and other areas, respectively [22]. That means travel during the pandemic and crisis has decreased significantly.

In the past, travel has affected the spread of infectious diseases; for emerging infections, travelers have been seen as an important determinant in the surveillance process [16]. Restricted measures have been put to Thailand's public transport service to prevent the pandemic of COVID-19. This could lead to more switching to more use private car. As a result of COVID-19, people will travel less and choose active modes or cars over public transportation [17]. In the short term, the change of workdays travels behavior will gradually change because of the control of pandemic and various measures as well as limitation of the service of public transport.

The new suburbanism is a concept for creating better suburban communities, considering a better environment, urban conveniences, relaxed living, and total to be a better quality of life since the epidemic of COVID-19 might be caused by people's behavior change. Besides, housing considerations could be considered for the suburban area in the future. Due to such a case of COVID-19 pandemic is not under control situation and the future might chance of further spreading of another disease as well in the future.

The objective of the research focuses on travel behavior, residential self-selection and examines the relationship between commuting trips as follows:

1) Study socio-demographic and travelers' and residents' characteristics to corroborate a short-term decision on travel attitude and long-term decision on residential attitude and could be effective for travel behavior.

2) Evaluate the impact of COVID-19 influence on attitudes and travel behavior due to the factors that were affected by COVID-19.

3) Investigate relationships between factors by using structural equation modeling (SEM) to test empirical models of hypothesis research. Mass transit station in Bangkok area was selected in this study. An important aspect of the study to understand residential

self-selection of long-term decisions tends to challenge the point of view of the pandemic concerns that will affect land use policy and the accessibility of suburban areas as well.

The remainder of this paper is organized as follow: related literature reviewed and the pandemic of COVID-19 in Section 2, hypothesis and framework design of the study in Section 3, data collection and data analysis including in Section 4, results of hypothesis testing model showed in Section 5 and the last section, Section 6 concludes and limitation of this research.

4.2 Literature Review

4.2.1 Relationship of Residential Self-selection on Travel Behavior

In earlier studies of transportation that were characterized by a divide between the objective and the subjective in attempting to explain travel behavior, there was the debate on residential self-selection [26], [48]. Hard variables, such as urban structure and socioeconomic factors, are considered to be influential factors in a variety of characteristics of travel behavior [8]. Soft variables [6] are included in the travel behavior study because of their tendency to have an effect on travel behavior. These soft factors might include attitudes and preferences regarding particular modes of transport or neighborhood characteristics.

Empirical studies showed that travel-related attitudes have influenced travel behavior directly and also through residential choice, although the variety of housing and neighborhood attributes is of more importance [10]. In various research, residents preferred more walkable neighborhoods [122] and transit [123]. However, many residents preferred suburban or small-town locales [124]

Accordingly, the importance to understand the relationship of resident self-selection on travel behavior has been more considered. Moreover, in the past, most studies have focused on travel behavior and mode choice according to preferred behavior. However, long-term consideration has been mentioned in terms of the impact of the current situation rarely changes. Resident self-selection in the long-term is appropriate to predict trends in travel behavior, land use, transportation policies, and urban development approaches have been important.

4.2.2 Travel and Resident Attitude on Travel Behavior Change

Various research indicates that personal lifestyles and attitudes have a significant influence on travel behavior [6]. In order to accurately forecast people's behavior, it is important to apply attitudes and additional data to evaluate respondents' intentions rather than their desires [106].

According to research on travel attitudes and relocation motives, the reasons for moving are travel-related [7]. When determining where to live, it found that travel preferences were less important than concerns about safety and the price of housing [122], [154]. Travel attitudes are more subject to changing travel behavior, and some studies have found significant relationships between attitudes towards characteristics of travel modes and travel behavior [155], [156].

Not only in travel attitude, but also in resident attitude, has been mentioned in the tourism research. The useful predictors of residents' attitudes toward tourism development, explaining residents' attitudes toward tourism and corresponding development [157]. Therefore, the hypothesis of the relationship attitude on residential self-selection that focusing on the environment of residential selection might be affected to relocation in long term.

4.2.3 Structural Equation Modelling (SEM) in Transport Studies Research

SEM is one technique for testing and estimate of causal relationships in statistics. The objective of SEM is theory testing or theory building. In contrast, according to Garson (2009), SEM is typically regarded as a confirming rather than an exploratory approach. The analysis of path analysis and factor analysis is the initial concept and the origin of analyzing structural equation models. The structural equation models are a combination of three fundamental data analysis techniques: factor analysis, path analysis, and regression analysis parameter estimation [125].

In the study of travel behavior, SEM is used in the correlation analysis and the impact of travel behavior. For example, the relationship between land use that affects weekend travel compared to workday travel, using SEM to confirm the opposing role of land use in travel mode choice and trip frequency on weekdays and weekends [54]. The association between the built environment and travel attitude in travel behavior is estimated by using SEM to estimate the residential self-selection framework and environmental determination framework [55]. SEM were used to analyze sensitivity to changes in the travel utility of mode choice behavior [56]. SEM has been applying to many research that can evaluate relationships and very useful for the transportation field especially for human behavior of subjective norm.

4.2.4 COVID-19 Pandemic

The COVID-19 pandemic has begun to become a major factor that affects people's lives around the world. In overseas cases, the majority of confirmed COVID-19 cases were reported by the European Region with 423,946 cases (56.45%), followed by the American Region with 163,014 cases (21.70%), and the remaining were in other regions [158]. The COVID-19 pandemic has affected people in various sectors. The department of disease control reported Thailand's situation updated on 16 December 2020 that there have been 4,261 confirmed COVID-19 cases with 60 deaths; 2,463 cases were from the local transmission and 0 new cases of infected in Thailand.

Furthermore, the transport sector was impacted by COVID-19. The aviation industry and the International Air Transport Association (IATA) have estimated the percentage change in passenger demand in 2020 to decreased by 52% compared with 2019. In the case of traveling on road trips found that the traffic volume changed significantly from March to May 2020. In June, traffic volume trends were close to normal as well as with mass transit. An example of the traffic volume information from the Chalong Rat expressway and mass transit system from the data on ridership on the purple line is shown in Table 4-1.

Table 4-1 Traffic volume on expressway and ridership on mass transit, 2020

Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Expressway (Chalong Rat)											
232,710	235,467	188,455	119,960	159,559	202,202	214,377	223,369	229,498	223,023	228,963	215,172
Mass transit (Purple line)											
67,781	68,406	47,436	18,001	28,009	41,688	57,068	63,799	70,104	69,885	68,739	60,659

Note: Unit: vehicles per day and trips per day
Source: Data support from the Expressway Authority of Thailand and Mass Rapid Transit Authority of Thailand, 2021

4.3 Hypothesis of Study and Framework

4.3.1 Conceptual Framework

In the context of developing countries such as Bangkok, people tend to stay in the center of the city as long as they can [159]. Concern on housing price more than travel related. The research of residential self-selection on mode choice behavior in Bangkok indicated that station residents of areas with a high degree of rail preference had a higher probability of commuting by transit than people without this preference [13].

Recently, the mass transit system in Bangkok has developed a circular route, and more routes are being expanded. The increase in resident locations tends to follow the development around the mass transit network. During the COVID-19 pandemic, travel demand may be reduced due to disease control that was measured in short-term concerns. It might affect the consideration of changing resident locations as an effect of COVID-19 in the long term. Accordingly, the main study considers the behavior changes of residents and travelers who access mass transit and the dense areas of Bangkok. The purpose of this study is to evaluate the impact of travel behavior change on COVID-19, considering attitude before and during COVID-19 divided to travel attitude and resident attitude differently point view, and to identify the relationship between travel behavior (short term decision) and residential self-selection (long term decision) through factor analysis. SEM was used to confirm the relationship with the sensitivity of the COVID-19 situation.

4.3.2 Hypothesis of Study

The hypothesis focuses on the travel attitude and resident attitude that have a relationship to travel behavior. However, the attitude is divided into two groups. First, the attitude on travel preference, and second, the resident preference. Travel attitude deals with the accessibility of mode choice, comfortable of ease and relaxation on mode, surroundings and weather conditions by mode define to the environment and safety factor to the concern of safety life effect by mode choice. Resident attitudes considered residential self-selection, including neighborhood qualities, addressing accessibility transport, surrounding of the residential area, and safety for choosing the residential area as show in Figure 4-1.

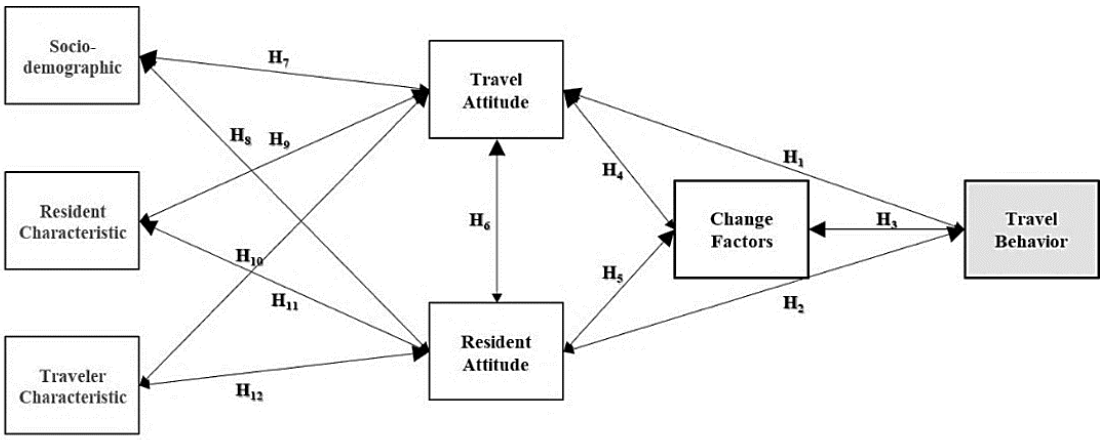


Figure 4-1 The framework and hypothesis of the study

The hypothesis of study was to deal with the personal information (socio-demographic, resident characteristic, and traveler characteristic) related to attitude (travel attitude and resident attitude) that affected travel behavior. However, COVID-19 is an important part that will affect attitudes and travel behavior. The change factor is factors that is affected COVID-19, which was defined as personal information (income and place of work) and travel information (frequency of traveling and vehicle often use). However, the null hypothesis assigns factors that do not affect each other.

4.4 Data Collection

4.4.1 Data Collection

In this research, the data considered residents around the current mass transit station and travelers near the mass transit station in Bangkok. However, the current mass rapid transit routes have 125 stations (updated on December 16, 2020) and cover 4 provinces, including Bangkok, Nonthaburi, Samut Prakan, and Pathum Thani. The sample group was random from the people who had traveled and living around the station. Questionnaires were used through face-to-face interviews with social distancing to collect the data.

The access distance was used as the catchment area or walkability distance to access transit and activities. Nevertheless, due mainly to competition from motorcycle taxis, the proportion of people walking in Bangkok is lower than in other big cities. Furthermore, the percentage of people walking decreases with distance, and it drops dramatically after 400 meters, with less than 10% of travelers walking from a distance greater than one kilometer [101]. Therefore, the survey area assigned around the mass transit station for a survey is 1000 meters from the station due to the maximum walking distance (400 meters) and feeder transit access (1000 meters) in the Bangkok area. The survey area covered all provinces that have mass rapid transit. Questionnaire distribution was conducted on the weekday of December 2020. There was no lockdown of the area due to the spread of COVID-19 on the survey date.

The questionnaire consisted of 4 sections: 1) personal information, 2) travel behavior, 3) travel patterns of weekdays, and 4) travel attitude and resident attitude. Therefore, the questionnaire sections 2, 3, and 4 are divided into before COVID-19 and during the COVID-19 pandemic. Section 1 and 2 are choice questions. Section 3 identifies the travel patterns on weekdays (travel daily), including travel purpose, travel time, and transfer. Section 4 is questions about attitudes to travel behavior and residential self-selection. The survey also includes increased spreading concerns.

4.5 Data Analysis

4.5.1 Sample Description

682 questionnaires were completed in the interview survey. The socio-demographic of the respondents was summarized in Table 4-2. Residents' characteristics were summarized in Table 4-3, and travelers' characteristics were summarized in Table 4-4. The gender of respondents was mainly women (63%). Most of the sample ages were in the 18– 24 years old (25%) and 25– 34 years old (26%) ranges, with a bachelor's degree at 42%. While the main occupation of respondents was company employee (51%).

Table 4-2 Descriptive statistics of socio-demographic characteristics

Factors	Description	Mean	SD.	Median
Socio-demographic				
Gender	Male (37%), Female (63%)	1.64	0.48	2
Age	Less than 18 years old (2%), 18 – 24 years old (25%), 25 – 34 years old (26%), 35 – 44 years old (18%), 45 – 54 years old (14%), 55 – 64 years old (11%), > 64 years old (4%)	3.64	1.51	3
Education	Less than High school (6%), High school (32%), College (17%), Bachelor's degree (42%), Master's degree or higher (3%)	3.04	1.04	3
Occupation	Student (17%), Company employee (51%), Personal business (14%), Government officer (4%), State Enterprise Employee (3%), Housewife (6%), Retire (3%), Unemployed (1%), Others (1%)	2.65	1.73	2

Characteristics of residents found that the number of household members was small, 2-3 people (30% and 26%), with most of them living in single homes (38%). Ownership of residential was owner status. The survey result shows the place of residence of the respondents around the mass transit station. Most of the sample live in Bangkok (72%) and are spread out along the route of the mass transit system (Figure 4-3.).

Table 4-3 Descriptive statistics of residents' characteristics

Factors	Description	Mean	SD.	Median
Resident Characteristic				
No. of household members	1 Person (12%), 2 Persons (30%), 3 Persons (26%), 4 Persons (17%), 5 Persons (8%), >5 Persons (7%)	3.01	1.39	3
Type of residential	Single home (38%), Townhouse (14%), Apartment (34%), Condominium (8%), Other (6%)	2.31	1.24	2
Type of property ownership	Owner (46%), Hire purchase (7%), Renting (47%)	2.02	0.96	2
Housing cost per month	< 3,500 THB (10%), 3,501-5,000 THB (27%), 5,001-7,500 THB (11%), 7,501-10,000 THB (3%), 10,001-15,000 THB (2%), 15,001-20,000 THB (1%), 20,01-30,000 THB (0%), 30,01-50,000 THB (0%), >50,000 THB (0%), No pay (46%)	5.81	3.88	4

Travelers' characteristics from the sample found that most of the population traveled without vehicles (48%) and the private car is more important than other vehicles. The survey found that most residents of the respondents were able to access the nearest station by walking within 5 minutes (30%). As 60.9% of people have no transport cards. The most popular travel card was the Rabbit card that can be used for BTS service routes, which covered most of Bangkok's central areas compared to the other lines.

Table 4-4 Descriptive statistics of travelers' characteristics

Factors	Description	Mean	SD.	Median
Traveler Characteristic				
Vehicle ownership	Private car (19%), Motorcycle (14%), Bicycle (2%), Other (1%), No (48%), Private car+Motorcycle (12%), Private car+Motorcycle+Bicycle (2%), Private car+Bicycle (1%), Motorcycle+Bicycle (1%)	4.84	2.26	6
Total no. of car ownership	No car (49%), 1 car (34%), 2 cars (14%), 3 cars (2%) 4 cars (1%)	0.75	0.95	1
Walking distance to the nearest mass transit station.	0-5 min. (30%), 5-10 min. (27%), 10-15 min. (16%), 15-20 min. (8%), 20-25 min. (4%), 25-30 min. (6%), > 30 minutes (9%)	2.83	1.91	2
Transport card ownership.	MRT (6.6%), MRT Plus (1.5%), Rabbit (21.7%), Smart pass (0.7%), Mangmoom (0.5%), No. (60.9%), MRT+Rabbit (4.8%), MRT+Smart Pass (0.2%), MRT Plus, Rabbit (2.4%), Rabbit+Smart Pass (0.5%) MRT+MRT Plus+Rabbit (0.3%), MRT+Rabbit+Mangmoom (0.1%)	5.09	1.89	6
Total no. of transport card ownership	No card (61%), 1 card (31%), 2 cards (7%), 3 cards (1%)	0.48	0.66	0

According to the normality tested by the Shapiro-Wilk test (n<2000), the result showed all variables rejected the null hypothesis. The research hypothesis states have not resembled a normal distribution, processing of data has been used nonparametric measures to analyze.

4.5.2 Impact of COVID-19 on Change in Travel Behavior

During survey time, the average number of infected due to the spread of COVID-19 in the country was zero. Nonparametric statistics analysis has been used for analysis to be paired before and during COVID-19 data. The paired test was examined by the Wilcoxon signed ranks test. According to before COVID-19 and during the COVID-19 situation, there were significant in the case of income, place of work, travel frequency of work/school trip, travel frequency of personal business trips, and the frequency of vehicle usage. However, in the case of travel frequency of shopping/eating trips did not differ at a significant level of 0.05 as shown in Table 4-5.

Table 4-5 Wilcoxon signed rank test before & during COVID-19

Factors	**N (682)**		**Z**	**p value***
Before & During COVID-19	**Negative**	**Positive**		
Income (per month)	50	6	-5.519	0.000
Place of work	4	27	-2.828	0.005
Travel frequency of work/school trip (times/week)	49	4	-5.652	0.000
Travel frequency of shopping/eating trip (times/week)	19	16	-1.531	0.126
Travel frequency of personal business trip (times/week)	23	12	-2.875	0.004
Vehicle often use	56	11	-5.566	0.000

* Significant at the 0.05 significance level.

The impact of the change factors showed a proportional change on the decimal point scale to compare differences value of before and during the COVID-19 case as show in Figure 4-2. The COVID-19 situation is affecting the middle and high-income range, as the range 0-18000 THB increased by 2.9 % (Figure 4-2A) which shows an overview of the income affected by COVID-19. Nevertheless, working from home has seen a significant increase of 3.8% (Figure 4-2B) during COVID-19. The change from the frequency of trips divided by the number of times/week and mode use compared with before and during the COVID-19 case, as shown in Figure 4-2C. The result of travel found the change on work/school trips during COVID-19 by the proportion of travel 7-9 time/week decreased by 0.6%, on shopping trips increased by 7.1% and personal business trips increased by 5.5% from total trips.

*Value (before, during)

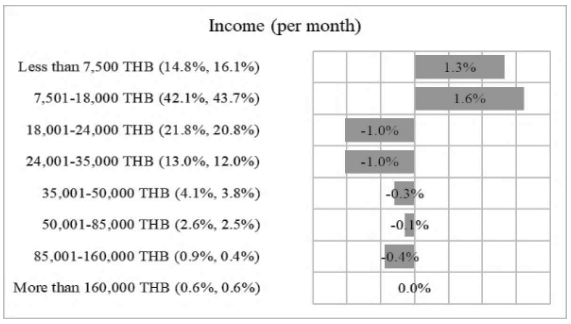


Figure A Change of income

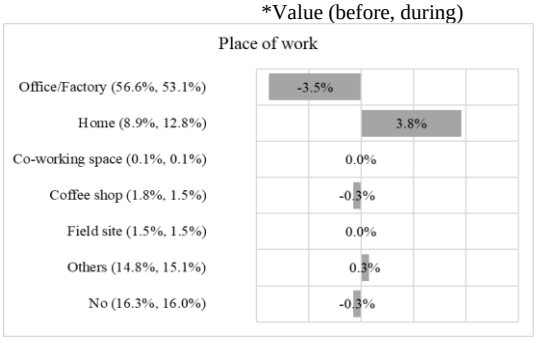


Figure B Change of place of work

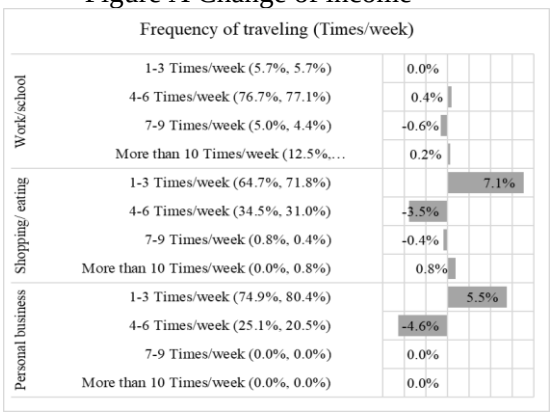


Figure C. Change of frequency of traveling by times/week

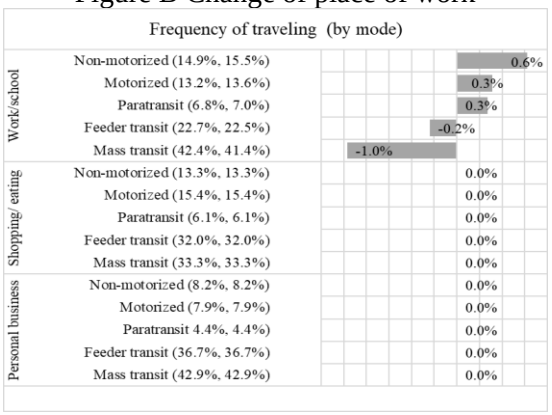
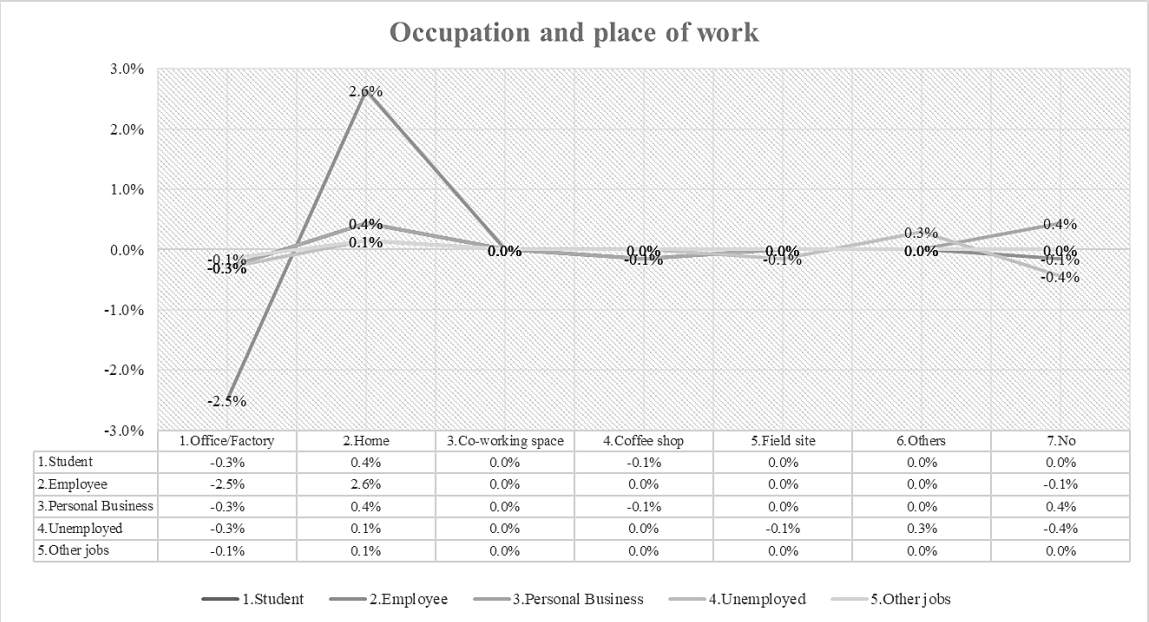


Figure D Change of frequency of traveling by mode choice

Figure 4-2 Change of travel behavior

However, the mode of travel of shopping trips and personal business trips, travelers have been using the same mode of travel as before the COVID-19 case. Remarkable that the frequency used mode on work/school trips was reduced for mass transit by 1% and feeder transit by 0.2%, which reflected another mode was increased to non-motorized mode by 0.6%, motorized mode by 0.3%, and paratransit 0.3% from total trips as shown in Figure 4-2D.

During the COVID-19 pandemic, there has been an apparent increase in the number of people working from home, as compared to before the COVID-19 situation. During the period covered by the COVID-19 survey, working from home increased by 2.6 percent of employees and 0.4 percent of personal business owners (as shown in Figure 4.3).



	1.Office/Factory	2.Home	3.Co-working space	4.Coffee shop	5.Field site	6.Others	7.No
1.Student	-0.3%	0.4%	0.0%	-0.1%	0.0%	0.0%	0.0%
2.Employee	-2.5%	2.6%	0.0%	0.0%	0.0%	0.0%	-0.1%
3.Personal Business	-0.3%	0.4%	0.0%	-0.1%	0.0%	0.0%	0.4%
4.Unemployed	-0.3%	0.1%	0.0%	0.0%	-0.1%	0.3%	-0.4%
5.Other jobs	-0.1%	0.1%	0.0%	0.0%	0.0%	0.0%	0.0%

Figure 4-3 Occupation and place of work before and during COVID-19

According to the income during COVID-19 with socio-demographic, residents' characteristics, and travelers' characteristics as shown in Figure 4-4, it was found that income declined in the range of 18,001–160,000 THB and increased to a range of 0–18,000 THB. Moreover, the change in the 0–18,000 THB range is mostly driven by women, accounting for 2.4%. The income difference increased by 12% and 9% for those aged 25–34 and 45–54 years old in the 0–18,000 THB range, respectively. In addition, people with high school education and those with a college education have seen a difference of 9 percent and 14 percent, respectively, in the income range of 0–18,000 THB. The majority of the changes in income were company employees and personal businesses, by 1.5 and 1.3 percent. The difference before and during COVID-19 effect of COVID-19 on residential characteristics was found to be most significant in households with 2 and 3 people, with a 0.9 and 0.7%, and with people who live in apartments by 1.2%, rent by 1.8% and who did not to pay for housing cost by 1.1% in the income range of 0–18,000 THB. The majority difference increases income between 0-18,000 THB by 2.5 percent and decreases income between 18,001 to 35,000 THB by 18 percent for Bangkok residents. The people who did not have a vehicle group had an increase in income between 0–18,000 THB by 0.9% and reflected the difference in income by a decrease in the 18,001–160,000 THB range by 11%. In addition, the impact of COVID-19 on the incomes of persons who walk 0-5 minutes from their residences to the station revealed an increase of 0.8% in the range of 0-18,000 THB and a decrease of 1.7% in the range of 18,001-160,000 THB. Those without a transit card had an increase of 2.2 percent in the 0-18,000 THB income range and 2.1 percent in the 18,001-160,000 THB income range.

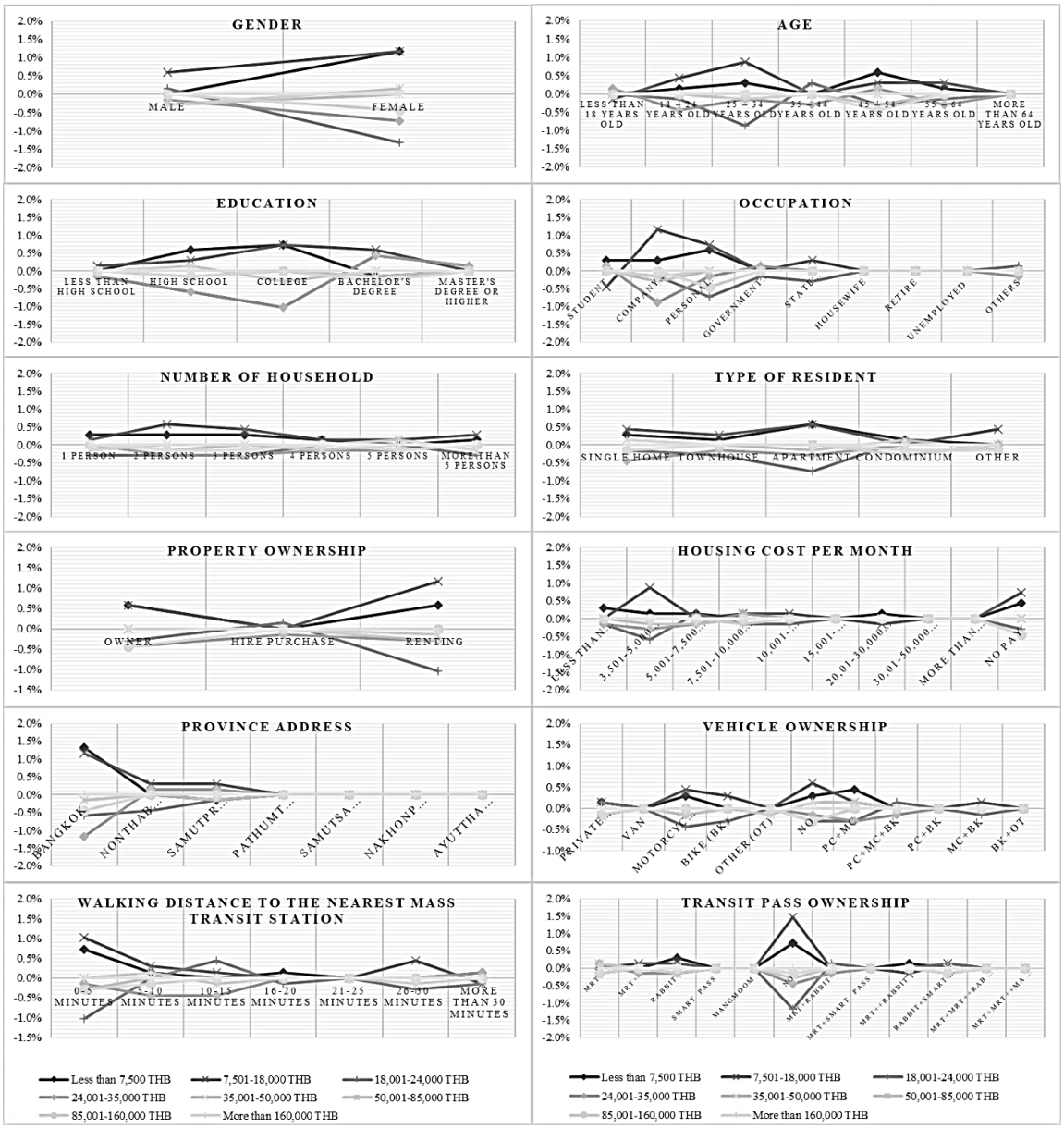


Figure 4-4 Different of income before and during COVID-19

4.5.3 Impact of COVID-19 on Commuting Trips

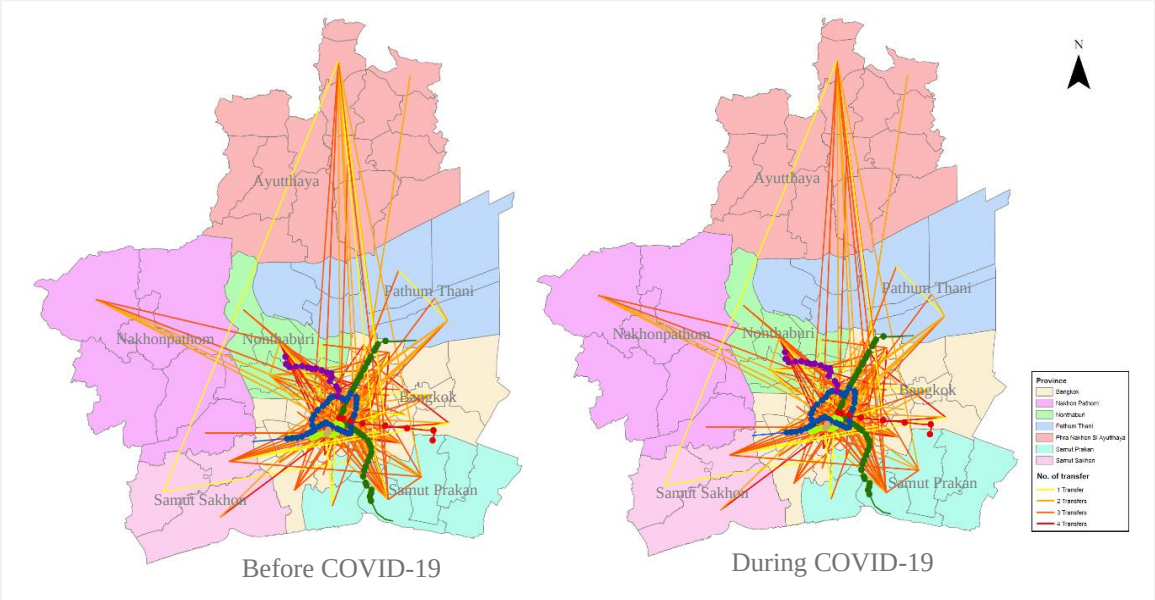


Figure 4-5 Origin-Destination before and during COVID-19 of commuting trips

Travel characteristics of the commuting trip. Most trips go forward to the CBD area of Bangkok. Only a small percentage of travel came from other provinces around Bangkok. When divided into trips, around 72%, 14%, 12%, and 2% were from Bangkok, Nonthaburi, Samut Prakan, and Pathum Thani respectively. Nevertheless, Ayutthaya, Samut Sakhon, and Nakhonpathom provinces were slightly away from their area. Figure 4-5 shows the origin and destination of travelers before and during COVID-19 compared with the number of transfers for each trip.

Comparing 2 scenarios cases of before and during COVID-19, the Wilcoxon Signed Ranks Test was tested for a difference of pair. The result showed that all variables difference in the distribution of the two samples as shown in Table 4-6. Two majorities of factors most importance are mode choice and number of transfers.

Table 4-6 Wilcoxon signed rank test before & during COVID-19 on commuting trips

Factors	N (682)		Z	p value*
Before & During COVID-19	**Negative**	**Positive**		
Mode choice	32	10	-4.002	0.000
No. of trips (trips/day)	8	0	-2.828	0.005
Total travel time (hr:mm)	40	15	-3.630	0.000
No. of transfers (times/day)	34	7	-4.263	0.000
Total cost (THB/day)	24	4	-3.778	0.000
Total travel distance (km./day)	24	17	-2.132	0.033

* Significant at the 0.05 significance level.

Mode choices were divided into 18 categories from the questionnaire survey, covering all transport modes in Bangkok and surrounding areas. The proportion of travel by bus was 24.3% before the COVID-19 case and 22.9% during the COVID-19. Meanwhile, people avoid using buses that decreased 1.5%. However, walk and motorcycle taxi usage were increased by 1.3% and 1.2% during COVID-19 case. Most respondents avoid using public transport (mode 8-12) by 2.8% reduced during COVID-19. Therefore, mass transit (mode 13-15) usage was reduced but increase in paratransit as shown in Figure 4-6. Overall, commuting trips showed the bus mode was most used in Bangkok. Nonthaburi province was highly used in boat mode, and taxi mode was used at a high rate in Samutprakran province.

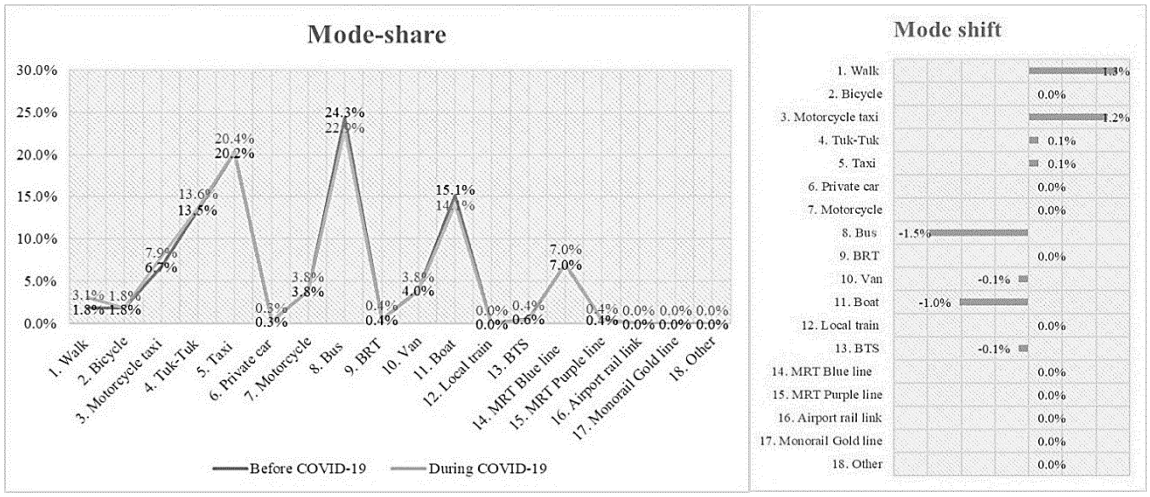
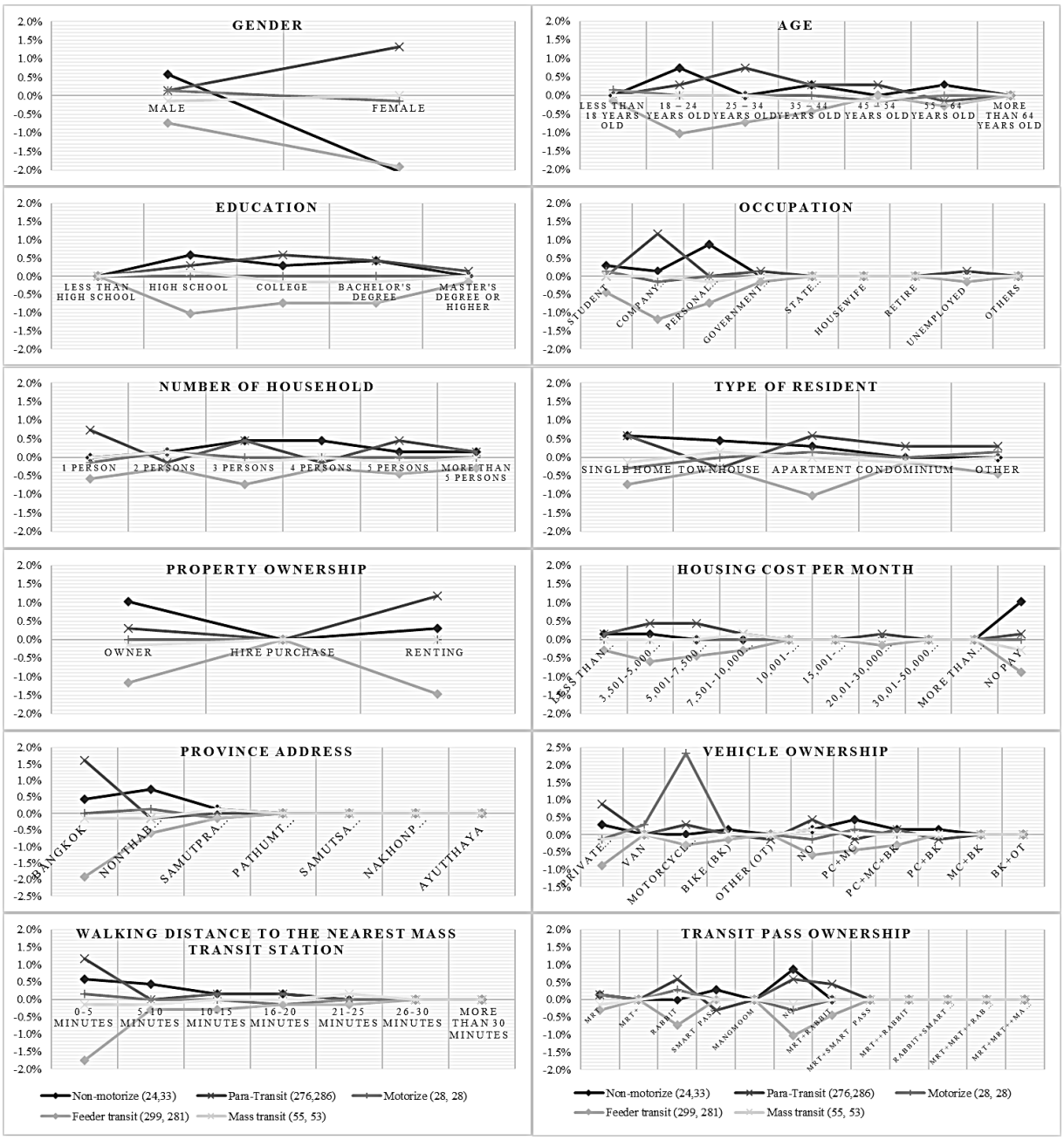


Figure 4-6 Mode share and shift on commuting trips

Travel mode shares commuting trips divided by 5 groups (non-motorized, paratransit, motorized, feeder transit, and mass transit) with socio-demographic, residents' characteristics, and travelers' characteristics. The difference percentage of mode share before and during COVID-19 was shown in Figure 4-7. Feeder transit and mass transit trend to decline and more use of non-motorized, paratransit, and motorized. The difference in mode shift with gender found that females reduced use of non-motorized (2.1%) and feeder transit (1.9%) but increased use of paratransit (1.3%). However, males increased use of non-motorized (0.6%) and reduced use of feeder transit (0.7%). The age range of 18-24 years old increased 0.7% of using non-motorized and reduced use of feeder transit (1.0%). 25-34 years old increased use of paratransit (0.7%) and reduced use of feeder transit (0.7%). High school, college, and bachelor's degree education was most reduced to using feeder transit (1.0%, 0.7%, and 0.7%). The number of travelers was increased to use non-motorized (0.9%), that was personal business occupation and paratransit (1.2%) was company employee, also reduced use of feeder transit by 0.7% and 1.2%. Proportions have changed with reduced use of feeder transit (0.6%) and increased use of paratransit (0.7%) most live alone. Furthermore, travelers who are sensitive to change mode choice live in single homes and apartments. Hire purchasing of property not sensitive to change of mode choice during COVID-19. Travelers without monthly housing costs changed to using non-motorized (1.0%) more and reduced feeder transit (0.9%).



*n of sample (before, during)

Figure 4-7 Difference of mode shift on commuting trips

Only Bangkok and Nonthaburi provinces that were showed evidence of change in mode choice. However, travelers who have a private car use paratransit increasingly (0.9%) and decreased feeder transit use (0.9%). Motorcycle ownership uses their car more during COVID-19 (2.3%). The majority of travelers that changed mode during COVID-19 lived near mass transit stations (0-5 min.) without holding a transit card.

Summarizes the results of travel behavior change compared before and during the COVID-19 situation (Figure 4-8) that showed the number of 2 trips/day was traveled 93% in the case of before COVID-19. The trips differ 1% for increased 2 trips/day and 3 trips/day decreased, meaning that total trips per day were reduced significantly. Compared to during the COVID-19, total travel time was increased by 3% in the 0-1 hour range and long trips (61-360 minutes) were decreased by 3%. However, total travel cost was found to 2% decrease in the 51-100 THB range and an increase of 2% in the 0-50 THB range. The number of transfers per day (including between mode and out-of-mode transfers) showed travelers reduced range of 6-9 times/day by 2% and increased 2-3 times/day by 2%.

*Value (before, during)

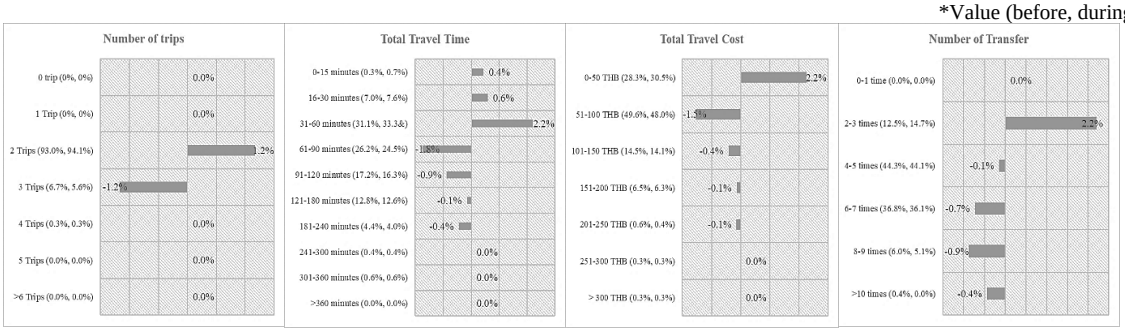


Figure 4-8 Travel behavior data, before & during COVID-19 case.

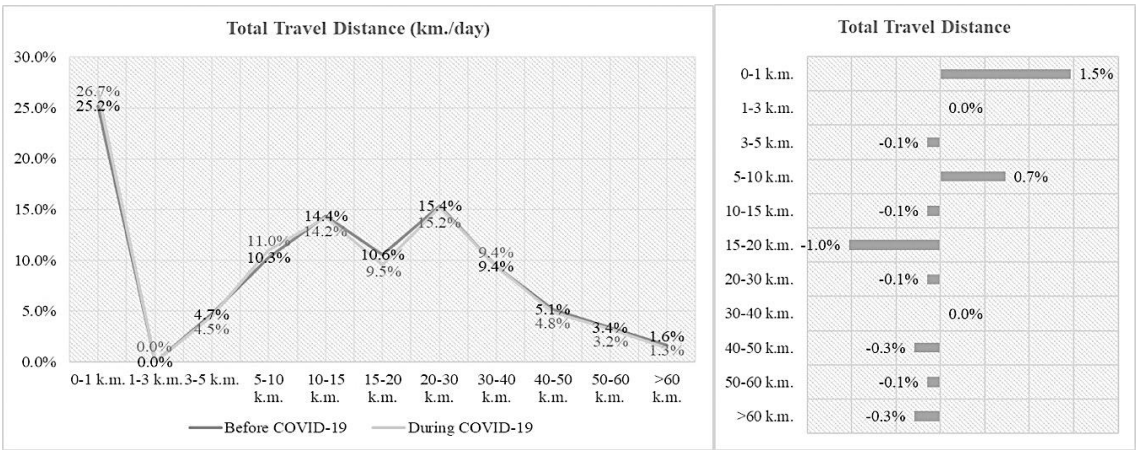


Figure 4-9 Total travel distance on commuting trips

However, most of the travel distance per day was short distance (0-10 km.) to medium distance (10-30 km.) as shown in Figure 4-9. Nevertheless, comparing the before and during the covid-19 case, we found the number of trips, the number of transfers, travel time, and travel cost overall were reduced.

This shows people reduce the traveling evidently. However, the period time of travel during the morning rush hour from Figure 4-10 showed the change in travel period that has changed during COVID decreasing 1.4% (5-9 a.m.). There is the possibility of traveler concern spreading the virus and avoiding congestion from the transport system. Therefore, most travelers change to traveling during non-peak hours from 9 a.m. to 4 p.m. showed an evidently increase overall of 1.7%.

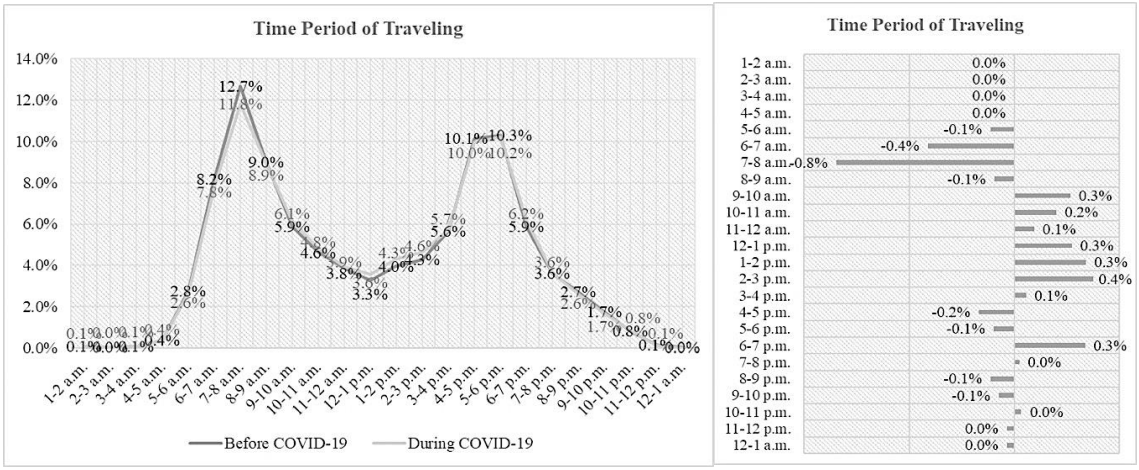


Figure 4-10 Time period of travel on commuting trips

4.5.4 Impact of COVID-19 on Travel Attitudes and Resident Attitudes

The data on travel attitudes and resident attitudes was collected, including 42 statements with 18 statements of 4 main effects on travel attitude and 23 statements of 4 main effects on residential self-selection attitudes. All attitudes are considered by a used ranking score (5 = Strong agree to 1 = Strong disagree). Reliability evaluation for the travel and resident attitude of the main factor in both cases was 0.57 to 0.90. Therefore, Cronbach's alpha value of 0.5–0.7 is generally accepted on a moderately reliable scale.

The result from the questionnaire is shown in Table 4-7. The difference in the main factors was accessibility, environment, and safe travel attitude. During COVID-19, people showed less preference for walking/biking than before COVID-19. However, the respondents were worried about infection concerns to using public transport and more concerned about safety in the state of criminal risk during COVID-19. Therefore, for resident attitude, the result shows a difference all main effects. The urban area was more preferred to live in during COVID-19. Constantly they less care about social image and social environment in the urban area. However, respondents considered accessibility around the residential area near the bus stop more, while concerned more about pollution and land prices if living in an urban area. Also, noteworthy is that they are not choosing to live in an urban area due to concern about the infection that is more concern than before COVID-19.

Table 4-7 Travel and resident attitude before and during COVID-19

	TRAVEL ATTITUDE	Before Covid-19		During Covid-19	
		SD	Median	Median	SD
ACCESSIBILITY	Prefer to use mass transit (BTS, MRT, ARL).	0.86	4	4	0.92
	Prefer to use public transport (Bus, Boat).	0.86	4	4	0.93
	Prefer to use bike/walk.	0.97	4	3	0.97
	Prefer to use private car.	0.99	3	3	1.01
	Prefer to use para transit (Taxi, bike-taxi, Tuk-Tuk).	0.95	3	3	0.96
COMFORTABLE	Accept more travel cost for use private car.	1.08	3	3	1.04
	Choose travel mode by saving time first.	0.91	4	4	0.96
	Choose private car because social image.	1.13	3	3	1.12
	Mass transit easy to travel more.	0.90	4	4	0.93
	If online pre-paid fare system are available, public transport will be prefer.	0.96	4	4	0.99
	If station ready for the good facility (clean, toilet, etc.), mass transit will be prefer.	0.97	4	4	0.99
ENVIRON-MENT	Avoid pollution by use private car.	0.95	3	3	0.94
	Prefer private car because of weather condition.	0.99	3	3	0.99
	Worried about infection concerns to use public transport.	0.88	3	4	0.96
	Prefer to use public transport because concern global warming.	0.88	4	4	0.91
SAFE	Will use public transport if passengers wearing face masks.	0.87	4	4	0.93
	Prefer to use private car or public transport to avoid crime of taxi / unfair price	0.90	3	4	0.90
	Prefer to use private car to avoid criminal risk.	0.88	3	4	0.90
	RESIDENTIAL ATTITUDE	Before Covid-19		During Covid-19	
		SD	Median	Median	SD
NEIGHBORHOOD	Prefer to live in urban area.	0.78	3	4	0.80
	Prefer to live near community/shopping/office/school/hospital.	0.86	4	4	0.88
	Prefer social image and social environment in urban area.	0.93	4	3	0.94
	Prefer to live in residential areas.	0.80	4	4	0.86
	Do not like crowded but not too far from urban area.	0.87	4	4	0.91
	Prefer to live in rural area.	0.91	4	4	0.94
ACCESSIBILITY	Prefer residential area near mass transit station.	0.80	4	4	0.87
	Prefer residential area near bus stop..	0.84	3	4	0.90
	Prefer residential area near highways or main roads.	0.95	4	4	0.93
	Prefer residential area near park and ride building.	0.96	4	3	0.94
	Residential areas are easy to use by taxi.	0.86	4	4	0.88
	Activity place can walk from home.	0.88	4	4	0.91
	Residential area is a friendly environment for pedestrian.	0.90	4	4	0.94
	Residential area is a friendly environment for cycling.	0.92	4	4	0.93
SUR-ROUNDING	Do not like pollution in urban area.	0.90	3	4	0.92
	Prefer natural environment of rural area more.	0.88	4	4	0.92
	Prefer green space/ park nearby home.	0.87	4	4	0.93
	If choosing to live in an urban area, can accept the pollution.	1.00	4	3	0.99
	If choosing to live in an urban area, can accept land prices.	0.98	4	3	0.99
SAFE	Choose a residential area from no crime or less.	0.82	4	4	0.91
	Choose a residential area from the facility lighting around.	0.80	4	4	0.87
	Choose a residential area near the police station.	0.81	4	4	0.90
	Not choosing to live in an urban area due to concern about infection.	0.85	3	4	0.91

4.6 Hypothesis Testing

4.6.1 Goodness-of-fit

Firstly, reliability analysis was used to check the stability and consistency of the variable. In the case of the value of Cronbach's Alpha, all variables have reliability at 0.713. As referring to Cronbach alpha value, more than 0.7 is acceptable (Guilford, 1965: Cronbach, 2003). The hypothesis testing of this research used the AMOS 23.0 software package to analyze Structural Equation Modeling (SEM). Two models were developed in this study. The first model is the situation before COVID-19 and the second model is the situation during COVID-19. Second-order single factor models were used to construct the model. The result from AMOS shown in APPENDIX 8.2.1.

Therefore, structural equation modeling was used to covariance and mean structures of normal distribution for analysis. The technique that can handle non-normal data is using an approach known as "the bootstrap". The bootstrapping approach is a resample in which the original sample is used to determine a representative of the population [160]. Maximum likelihood was used to be estimator and performed at 5000 samples of bootstrap to provide bias-corrected confidence intervals for each parameter. The initial model was considered in low correlation and deleting all paths with p-value more than 0.05($p>0.05$). The goodness of fit in this testing was indicated based on how to fit the index from [56]. The result of the model test showed a good fit for the data as in Table 4-8.

Table 4-8 The fitness test result of model

Fitness Index	Ideal Standard	Acceptable Standard	Before COVID-19	During COVID-19
Likelihood-ratio Chi-square/degrees of freedom (χ 2/d f)	1~3		3.011	2.528
Goodness-of-fit index (GFI)	>0.90	>0.80	0.942	0.948
Adjusted goodness-of-fit index (AGFI)	>0.90	>0.80	0.920	0.928
Root mean square residual (RMR)	<0.05	<0.06	0.052	0.054
Root mean square error of approximation (RMSEA)	<0.08	<0.09	0.054	0.047
Normed fit index (NFI)	>0.90	>0.80	0.925	0.939
Incremental fit index (IFI)	>0.90	>0.80	0.948	0.962
Comparative fit index (CFI)	>0.90	>0.80	0.948	0.962

4.6.2 SEM Model Result and Evaluation

To modify the model efficiently to approach the criteria of goodness of fit, the structural model presented the relationship of path coefficients as shown in Figure 4-11 and Figure 4-12. The path diagram for structural equation model in the case of before COVID-19 and during COVID-19 shows that most of the parameters are significant at $p<0.05$. Furthermore, the result found that socio-demographic, residents' characteristics, and travelers' characteristics have a relationship in the model. In the case of during COVID-19, the change factor had a relationship with resident attitude, travel attitude, and travel behavior.

Final structural equation modeling in the case of before COVID-19, there were 3 covariances between latent variables and 18 factors loading. During COVID-19, there were 4 covariances between latent variables and 19 factors loading. Travel behavior has a correlation with resident attitude and travel attitude in both cases.

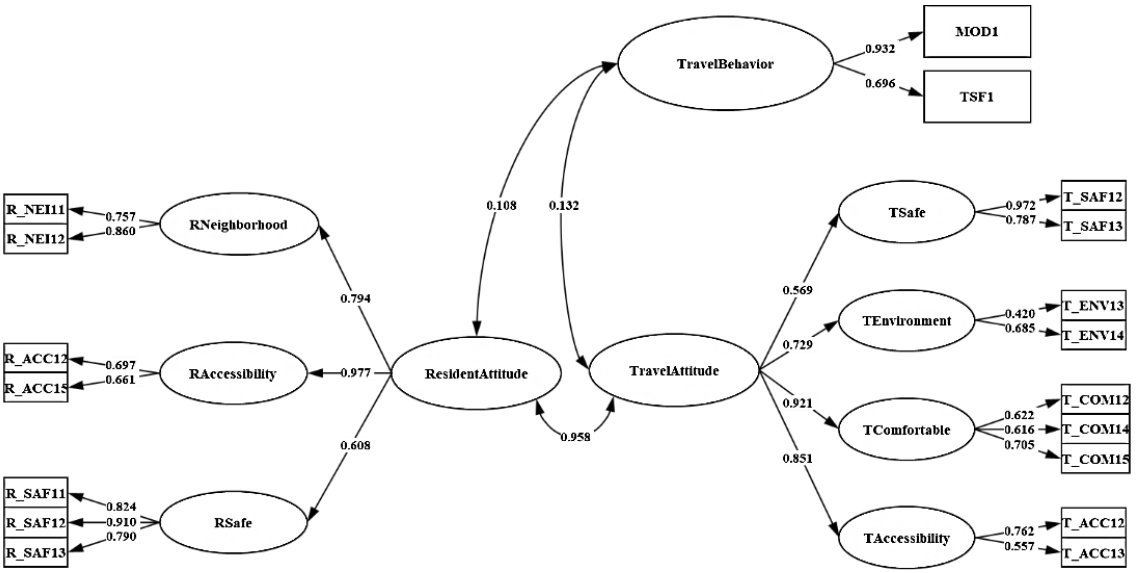


Figure 4-11 Final structural equation modeling of before COVID-19 case

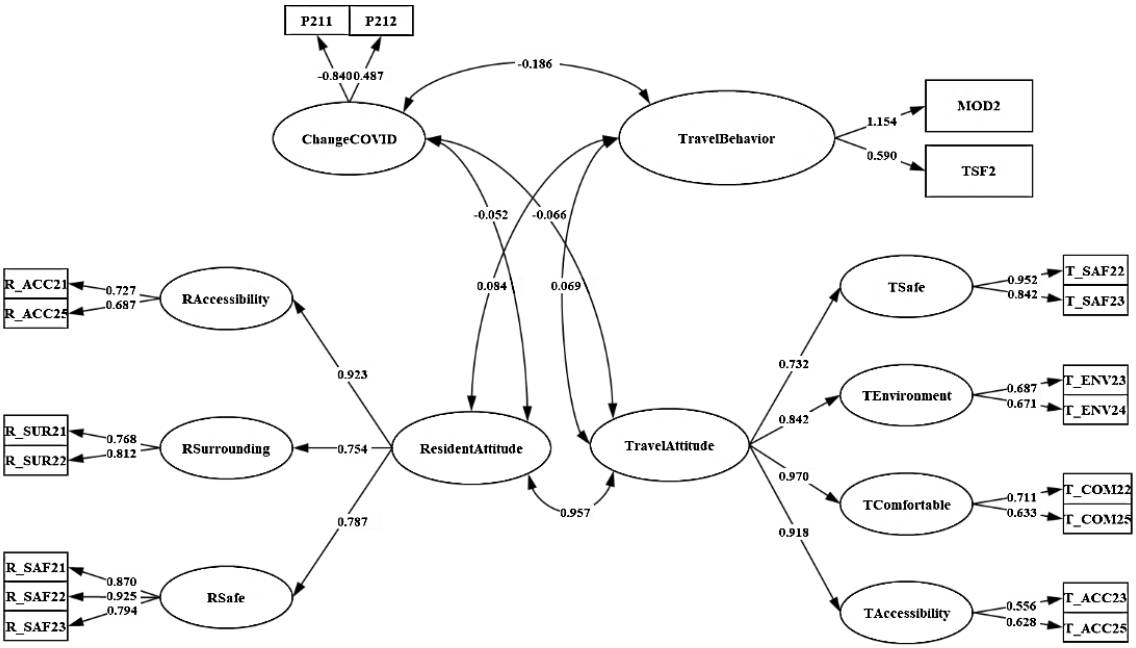


Figure 4-12 Final structural equation modeling of during COVID-19 case

Considered before the COVID-19 case, the relationship between travel behavior to resident attitude and travel behavior to travel attitude correlated as values of 0.108 and 0.132. During the COVID-19 case, correlated as values 0.084 and 0.069. However, it is even more noteworthy that the change factor was a strongly negative relationship with income (P211) as correlation value of 0.840 and a positive relationship with place of work (P212) as 0.487 during the COVID-19 case. The model has proposed mode choice and number of transfers as the strong indicator of travel behavior in both cases (before COVID-19 and during COVID-19). Besides, the number of transfers represents the characteristic of travel in Bangkok. Therefore, the relation of change factor to travel behavior was a negative relation at 0.186. Nevertheless, during the COVID-19 case, it was found travel attitude not significant to travel behavior, and the change factor was not significant to travel attitude and resident attitude as shown in Table 4-9.

Table 4-9 Parameter estimation of model

Before COVID-19					During COVID-19				
Regression paths			Std. coef.	p	Regression paths			Std. coef.	p
RAccessibility	<---	ResidentAttitude	0.977	***	RAccessibility	<---	ResidentAttitude	0.923	***
RSafe	<---	ResidentAttitude	0.608	***	RSafe	<---	ResidentAttitude	0.787	***
RNeighborhood	<---	ResidentAttitude	0.794		RSurrounding	<---	ResidentAttitude	0.754	
TAccessibility	<---	TravelAttitude	0.851	***	TAccessibility	<---	TravelAttitude	0.918	***
TComfortable	<---	TravelAttitude	0.921		TComfortable	<---	TravelAttitude	0.970	
TEnvironment	<---	TravelAttitude	0.725	***	TEnvironment	<---	TravelAttitude	0.842	***
TSafe	<---	TravelAttitude	0.569	***	TSafe	<---	TravelAttitude	0.732	***
MOD1	<---	TravelBehavior	0.932		MOD2	<---	TravelBehavior	1.154	
TSF1	<---	TravelBehavior	0.696	0.007	TSF2	<---	TravelBehavior	0.590	***
R_NEI12	<---	RNeighborhood	0.860		R_SUR21	<---	RSurrounding	0.768	***
R_NEI11	<---	RNeighborhood	0.757	***	R_SUR22	<---	RSurrounding	0.812	
R_ACC15	<---	RAccessibility	0.661		R_ACC25	<---	RAccessibility	0.687	***
R_ACC12	<---	RAccessibility	0.697	***	R_ACC21	<---	RAccessibility	0.727	
R_SAF13	<---	RSafe	0.790	***	R_SAF23	<---	RSafe	0.794	***
R_SAF12	<---	RSafe	0.910		R_SAF22	<---	RSafe	0.925	
R_SAF11	<---	RSafe	0.824	***	R_SAF21	<---	RSafe	0.870	***
T_ACC13	<---	TAccessibility	0.557	***	T_ACC23	<---	TAccessibility	0.556	***
T_ACC12	<---	TAccessibility	0.762		T_ACC25	<---	TAccessibility	0.628	
T_ENV14	<---	TEnvironment	0.685		T_ENV24	<---	TEnvironment	0.671	***
T_ENV13	<---	TEnvironment	0.420	***	T_ENV23	<---	TEnvironment	0.687	
T_SAF12	<---	TSafe	0.973		T_SAF22	<---	TSafe	0.952	
T_SAF13	<---	TSafe	0.787	***	T_SAF23	<---	TSafe	0.842	***
T_COM15	<---	TComfortable	0.705	***	T_COM25	<---	TComfortable	0.633	***
T_COM14	<---	TComfortable	0.616	***	T_COM22	<---	TComfortable	0.711	
T_COM12	<---	TComfortable	0.622		P212	<---	ChangeCOVID	0.487	
					P211	<---	ChangeCOVID	-0.840	0.014
Correlation paths			Std. coef.	p	Correlation paths			Std. coef.	p
ResidentAttitude	<-->	TravelAttitude	0.958	***	ResidentAttitude	<-->	TravelAttitude	0.957	***
TravelBehavior	<-->	ResidentAttitude	0.108	0.023	TravelBehavior	<-->	ResidentAttitude	0.084	0.030
TravelBehavior	<-->	TravelAttitude	0.132	0.006	TravelBehavior	<-->	TravelAttitude	0.069	0.061
*** Significant at the 0.001					ChangeCOVID	<-->	ResidentAttitude	-0.052	0.362
					ChangeCOVID	<-->	TravelAttitude	-0.066	0.193
					ChangeCOVID	<-->	TravelBehavior	-0.186	0.023

The result of the research hypothesis study found that the relationship of Travel Attitude ↔ Resident Attitude has a highly strong relationship with each other for both cases, which showed the significance of the factor. The models were able to significantly answer the hypothesis of the study that attitude has an important effect when considered traveling, especially the assumption of the study was resident attitude separated from travel attitude. The attitudes of travel are directly related to the resident attitude to different considerations.

From the study relationship of travel behavior and residential self-selection on commuting trips, it was found that socio-demographic and travelers' and residents' characteristics were not significant in the relationship between travel attitude, residential attitude, and travel behavior (H_7-H_{12}) as shown in Table 4-10. The assumption of travel attitude has a causal relation to travel behavior during COVID-19 was rejected (H_1). Furthermore, the relation of travel and resident attitude to the change factor was rejected (H_4, H_5). This shows that factors affected by COVID-19 were directly affected by travel behavior (H_3). The resident attitude indicated the correlation to travel behavior (H_2) and travel attitude (H_6).

Table 4-10 Hypothesis testing result of significance parameter

	Hypothesis of study	Coef.	p value	Result
H_1	Travel Attitude ↔ Travel Behavior	0.069	0.061	Not accept
H_2	Resident Attitude ↔ Travel Behavior	0.084	0.030	Accept
H_3	Change Factor ↔ Travel Behavior	-0.186	0.023	Accept
H_4	Travel Attitude ↔ Change Factor	-0.066	0.193	Not accept
H_5	Resident Attitude ↔ Change Factor	-0.052	0.362	Not accept
H_6	Travel Attitude ↔ Resident Attitude	0.957	<0.001	Accept
H_7	Socio-demographic ↔ Travel Attitude	-	-	Not accept
H_8	Socio-demographic ↔ Resident Attitude	-	-	Not accept
H_9	Resident Characteristic ↔ Travel Attitude	-	-	Not accept
H_{10}	Resident Characteristic ↔ Resident Attitude	-	-	Not accept
H_{11}	Travel Characteristic ↔ Travel Attitude	-	-	Not accept
H_{12}	Travel Characteristic ↔ Resident Attitude	-	-	Not accept

* Significant at the 0.05 significance level.

4.7 Conclusion

The finding of the study elucidated that the traveler's sensitive to travel mode shift were employees that stay alone. Residents of single homes and apartments, both for rent and owner, showed the change in travel daily from this study. Most of them have vehicles and do not have transit cards. Travel modes that are extremely important in Bangkok consist of non-motorized, paratransit, and feeder transit. The study found that using active mode (non-motorized) increased by 1.3% and 1.4% of paratransit. The impact of COVID-19 demonstrated a reduction in the use of public transport significantly. Private car usage was no change in the study area.

Results of the study showed evidence of attitude'' significant importance for travel behavior. Therefore, the change of travel attitude before and during COVID-19, the differences are as follows: 1) Travel accessibility of before COVID-19 considered on public transport, meanwhile paratransit become important more During COVID-19. However, during COVID-19 walk and bike access received less attention. 2) Comfortable travel on mass transit the most but need to improve the payment system and timesaving of

travel that is importance for travel in both cases. 3) Environment of public transport usage, more concerned about infection but willing to use mass transit because of sustainability mode. 4) Safety of traveling more concerned about crimes and criminals during COVID-19. The differences in residential attitude before and during COVID-19 are as follows: 1) Before COVID-19, residential neighborhoods preferred an urban area with near community and activity places. 2) Accessibility of residential areas preferred to live near the bus stop. In contrast, during COVID-19, people prefer to live near mass transit stations. Therefore, they prefer residential areas that are able to access taxis for both cases. 3) Surrounding of the residential areas, prefer rural areas and avoid pollution in the urban areas during COVID-19. 4) Safety of the residential areas has no difference in both cases. People prefer to choose the area near the police station, lighting around and low risk of crime.

The overall examined of residential self-selection relationship, the result shown in before COVID-19 pandemic were found relationship between travel attitude to travel behavior (H_1), resident attitude to travel behavior (H_2), and travel attitude and resident attitude (H_6) all significant relationship. The latent variable and variables included on the relationship as follow:

Before COVID-19

- Travel behavior: 1) travel mode, 2) number of transfers
- Residential attitude: 1) neighborhood, 2) accessibility, 3) safe
- Travel attitude: 1) accessibility, 2) comfortable, 3) environment, 4) safe

While the COVID-19 case showed different impacts on relationships, among which relationships of resident attitude to travel behavior (H_2), travel attitude and resident attitude (H_6), and change factors and travel behavior were found to have significant relationships. However, travel attitude to travel behavior (H_1) wasn't significant in the COVID-19 case. The latent variable and variables included in the relationship are as follows:

During COVID-19

- Travel behavior: 1) travel mode, 2) number of transfers
- Residential attitude: 1) accessibility, 2) safe, 3) surrounding
- Travel attitude: 1) accessibility, 2) comfortable, 3) environment, 4) safe
- Change COVID: 1) income, 2) place of work

Table 4-11 Summary hypothesis result of overall residential self-selection

Hypothesis	Path	Results	
		Before COVID-19	During COVID-19
H_1	TA↔ TB	Support	Not support
H_2	RA↔ TB	Support	Support
H_3	CF↔ TB	Not support	Support
H_4	TA↔ CF	Not support	Not support
H_5	RA↔ CF	Not support	Not support
H_6	TA↔ RA	Support	Support
H_7	SO↔ TA	Not support	Not support
H_8	SO↔ RA	Not support	Not support
H_9	RC↔ TA	Not support	Not support
H_{10}	RC↔ RA	Not support	Not support
H_{11}	TC↔ TA	Not support	Not support
H_{12}	TC↔ RA	Not support	Not support

Note: SO= Socio-demographic characteristic, RC= resident characteristic, TC= travel characteristic, RA= resident attitude, TA= travel attitude, TB= travel behavior, CF= change factor

The findings also indicate that the relationship between socio-demographic, resident, and traveler characteristics does not have a significant impact in all cases. This demonstrated that the relationship between attitude has a stronger impact on travel behavior than any of the other variables. Besides, among the travel behavior variables found, travel mode has the strongest significant impact on travel behavior. Based on these findings, the next stage of travel mode has been to consider an in-depth relationship in Chapter 5. The summary of study shown in Figure 4-13 and Table 4-11

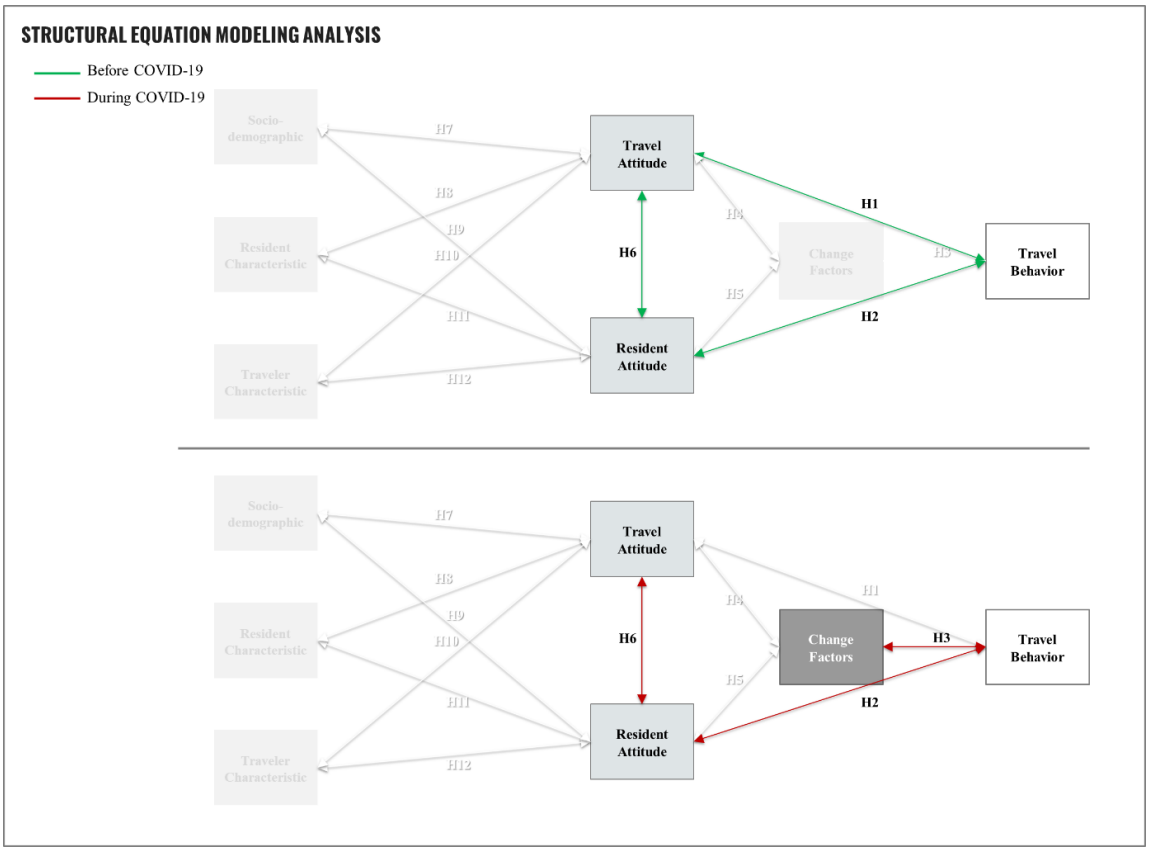


Figure 4-13 Summary hypothesis result of overall residential self-selection

In considering the residential self-selection, the key indicators of this study area are travel mode and number of transfers based on income and workplaces that affect location choice. However, the results of the study associated land development with residential self-selection for the urban planning of Bangkok and surrounding areas that would expand systematically. The overall study found that improving sidewalk facilities, connectivity of mode, quality of paratransit service, improving mass transit, and the sprawl of feeder transit are crucial to support the demand for stay in the rural or suburban areas that tends to increase.

Therefore, under the limitation of the research, there was no lockdown in the study area. While at survey time, the people who lost their jobs mostly choose to return to their hometown. The information received is from people who are still employed but may have some behavioral changes. Depending on a variety of conditions, the outcomes in each area might be different. When determining where to live, it seems to be that concerns about safety and housing costs are more relevant than travel-related preferences for travel [122], [154]. That means only safety consistent with this study. Recommendation of study to understand residential self-selection more. The built environment factors are another important factor to consider with residential self-selection [2], [161] and that was a limitation of this study. The finding of the research was an analysis of the current situation and understanding residential self-selection of long-term decisions to variables related. Nevertheless, more research of residential self-selection or relocation forecast on travel mode choice needs to be addressed in future studies.

5 EFFECT OF COVID-19 BASED ON WALKING DISTANCE AND TRAVEL MODE – USING MODERATED MEDIATION MODEL

This chapter examines the relationship between travel modes and the attitudes of residents and travelers around mass transit stations. The importance of this study was emphasized by considering that the attitudes toward residence could affect future travel and relocation considerations. In particular, the outbreak of COVID-19 may have a significant effect on their relationship. To investigate the direct and indirect effects before and during the COVID-19 pandemic, a moderated mediation model was used to test the hypothesis of this study by three-step approach analysis. The attitude toward residence was defined to test the hypothesis of the mediator, and the walking distance to the nearest mass transit station was employed to identify the level of the moderator. The results indicated that the attitude toward residence mediated the relationship between the attitude toward travel mode and travel mode behavior. The sensitivity of COVID-19 accurately reflects the various effects on travel mode. Moreover, multi-group analyses show that walking distance moderators have a direct effect on attitudes toward travel mode and travel mode behavior as well as the attitude toward residence.

5.1 Introduction

The current impact of COVID-19 has illustrated a significant change in behavior and government management in the various disease control sectors, all of which have economic and social impacts. In addition, the effects on the economy, epidemic control policies, and concerns about the pandemic have directly affected people's daily travel. The outbreak and spread of infectious diseases have been impacted by travel. Travelers have been seen as an important element of surveillance for new infections [16]. In the short term, changes in workday travel behavior will gradually occur as a consequence of the pandemic control measures, as well as restrictions on the use of public transportation services. Restricted measures of public transportation services have been implemented in order to avoid or minimize the COVID-19 pandemic. This might result in an increase in the number of people shifting to more frequent private car use and preferring active modes over public transport services [17]. COVID-19's first wave in Switzerland reportedly led to a reduction in the average daily distance traveled by more than 60% and public transport by more than 90% [79]. Passenger numbers on Hong Kong's subway declined by 42 percent, 86 percent, 73 percent, and 48 percent for adults, children, students, and senior citizens, respectively [20].

Nonetheless, the characteristics of each area led to different travel patterns. A study that classified the differences in travel behavior across the United States based on demographic characteristics found that people who live in urban areas and those with low incomes were more likely to be public transit riders [14], while the large majority of inner-city residents travel shorter distances than suburban residents [15]. Moreover, the residents' who preferred traveling by train moved nearer to the stations and became regular passengers [13].

Furthermore, the assumption regarding the impact of COVID-19 on travel modes has not been confirmed in the case of those who live near mass transit stations and who have easy access to the stations as well as a variety of modes of transportation. As specified by the accessibility of mass transit stations, access significantly influences mode choice, and the distance from home to a mass transit station has an influence on the travelers' mode of choice behavior [24]. In Bangkok, 77% of the population switched to public transport instead of private cars [95]. In contrast, during the COVID-19 pandemic, Thailand's Department of Rail Transport disclosed that the ridership of mass transit decreased by approximately 80% in April compared to January 2020 [100]. Changes in travel behavior might be a result of socio-economic and psychological changes. Various studies have shown evidence of the psychological impact of travel behavior, such as personal lifestyles and attitudes [6]. Specifically, by evaluating travel attitudes and relocation motives, it was discovered that the reasons for moving were travel-related [7]. These studies show that travel attitudes are more subject to changes in travel behavior.

Previous studies have demonstrated that travel behavior and mode choice may be differentiated in terms of the difference between walking distance access and mode choice [101]. Consequently, the purpose of this study is to explore the causal relationships between travel mode behavior and attitudes about travel modes based on the relocation hypothesis that attitudes toward various transport modes are an important factor in location choice [39]. The intervention variable of attitude toward residence and the interaction variables of walking distance to the nearest mass transit station examine the direct and indirect effects before and during the COVID-19 pandemic. Moderated mediation models were used in a case study of the Bangkok Metropolitan Areas in Thailand.

5.2 Theoretical Framework and Hypothesis Development

5.2.1 Mediation and Moderation Analysis

Mediation and moderation analysis are two of the most often used statistical approaches in the social, behavioral, and health sciences, as well as in business, medicine, and other areas [135]. The mediation moderation model, or conditional process model, integrates mediation and moderation analysis to estimate and test a variety of hypotheses involving conditional indirect effects [137]. An indirect effect of mediation was defined as a relationship that flowed from an independent variable to a mediator and then to a dependent variable. In addition, a third variable can affect or change the direct influence of an independent on a dependent variable, which is referred to as moderation (moderator) [138].

In studies on travel behavior, the mediating effects of perception were used to evaluate the relationship between the built environment and travel behavior, as well as the moderating influence of travel attitudes on the relationship [162], as well as to compare mediation and moderation models to test the causal relationship between capability influencing population density and travel time [163]. One study explains the role of the moderate-based and mediation-based models on the willingness to adopt different environmentally friendly sources of sustainable transportation in order to comprehend the acceptability of sustainable transportation behavior [164]. The moderated mediation model was used to study the behavior of tourists to gain insight into social norms of social distancing during the COVID-19 pandemic [165].

By determining the indirect correlation between the interaction factors and intervention effects, the moderated mediation model is appropriate for determining the relationship between factors and testing hypotheses based on latent variables of attitudes. In addition, the model could provide an inside view of various factors and relationships.

5.2.2 COVID-19 Effect on Travel Behavior

COVID-19 has had a widespread impact on various sectors, including everyday life and travel. A previous study on the relationship between the COVID-19 pandemic and changes in travel behavior found that travel demand was significantly reduced, with only shopping-related travel being undertaken [4]. According to a study of changes in travel behavior caused by the COVID-19 pandemic throughout the world, there was a major shift from public transportation to private cars and non-motorized modes [17]. In the short term,

changes in workday travel behavior will gradually occur because of the pandemic control measures, as well as restrictions on the use of public transportation services. Restricted measures of public transportation services have been implemented to avoid or minimize the COVID-19 pandemic. Moreover, during COVID-19, passengers were more concerned about public transportation usage than they were before COVID-19 [78]. Additionally, because public transportation may not fully recover to pre-pandemic levels in terms of daily travel modes, many people will resort to more biking and walking than before [166].

COVID-19 change effects have the potential to influence people's decision-making on attitudes and behavior. To emphasize the difference between effects before and during COVID-19, it is important to evaluate the influence of COVID-19 on the relationship between travel mode behavior and attitude change before and during COVID-19.

5.2.3 Relationship of Travel Attitude and Travel Behavior

Ajzen (1985) introduced the theory of planned behavior and suggested that behavior is determined by intents, attitudes, and subjective norms between perceived behavioral control and behavior in order to comprehend human behavior [47]. Moreover, in travel behavior research, the importance of perceptions and attitudes has been more considered. Perceived behavioral control is hypothesized to influence intention and behavior, whereas attitude is defined as an individual's overall evaluation of their behavior. According to various studies, psychological factors have been studied to determine people's decision-making in travel behavior and travel demand to improve the accuracy of forecasting data. Considering their influence on travel behavior, soft factors [6] are implemented in travel behavior research, such as attitudes and preferences for particular modes of travel or neighborhood characteristics [121]. Previous research suggests that attitudes and preferences toward travel, as well as residential neighborhoods, are the true predictors of travel patterns [25]. Furthermore, travel attitudes have been shown to significantly moderate the effects of perceptions on travel behavior [162] and may be related to the mode of transportation they use [11], [29], while travel mode and attitude toward using that mode both have an impact [167].

Accordingly, this study focuses on attitudes by considering the relationship between attitudes toward travel mode and travel mode behavior, which might affect decision-making and actual behavior in the future. The attitude was applied to test hypotheses considered from the perspectives of accessibility [116], comfort [117], environment [118], and safety [119] of travel. The proposed hypotheses are as follows:

Hypothesis 1 (H1): Attitude toward travel mode positively impacts travel mode behavior.

5.2.4 Mediating Influence of Attitude Toward Residence

The relationship between travel behavior and household decisions about location or residential choice is called "residential self-selection." Studies on residential self-selection frequently emphasize the importance of the built environment on travel behavior. Moreover, many previous studies have examined preferences for travel modes and residential choices. The results show that mode preference seems to be strongly associated with both travel behavior and residential choice [38]. According to a recent study, travel attitudes affect travel behavior and resident location choice. In addition, the residential environment affects attitudes toward specific modes of travel [39]. Residential self-selection, or the decision to live in a certain neighborhood, has an indirect effect on travel attitudes and satisfaction [3], [4]. Residential choices are determined by travel attitude. Some research suggests that the type of residential neighborhood affects the choice of commuting mode [40].

However, residence-associated attributes could be split into two categories: housing attributes and others that are related to the location and neighborhood [120]. In addition, travel behavior was impacted by attitudes and preferences regarding specific modes of travel or neighborhood characteristics [121]. Furthermore, residents prefer walkable neighborhoods [122] and public transportation [123]. During COVID-19, people's preferences for housing types may change as a result of COVID-19 effects, and the quality of living environments will likely become more important [82]. Most of the research has demonstrated a correlation between residence choice and travel patterns, as well as attitudes toward travel itself. Neighborhood attitudes that are related to residential location are often considered in travel attitudes. In terms of residential self-selection or relocation, residential attitudes should be taken into more consideration. Separating resident attitudes from travel attitudes allows for a more in-depth study of the relationship between travel attitudes and travel behaviors.

To emphasize attitudes related to residential and travel behavior, this study proposes the attitude toward residence as a mediator to produce interventions on the relationship between the attitude toward travel mode and travel mode behavior. The attitude was applied to test hypotheses from the perspective of neighborhood, accessibility, the environment, and safety of residence. The proposed hypotheses are as follows:

Hypothesis 2 (H2): Attitude toward residence mediates the relationship between attitude toward travel mode and travel mode behavior.

5.2.5 Moderating Influence of Walking Distance to Access Station

According to various studies, the built environment has a significant impact on residential choice, travel mode, and travel behavior. Studies on residential self-selection frequently emphasize the importance of the built environment on travel behavior due to the impact of the built environment on travel behavior. Residents who prefer to walk may consciously choose to live in walking-friendly neighborhoods, resulting in more walking [3]. Furthermore, the built environment has a direct and indirect effect on travel mode choice [45]. Because of the residential built environment, walkability, and regional

accessibility, all of these things have an effect on the types of active transportation that are available and the distance traveled [46].

Walkability has been associated with physical activity. For example, residential density mediated the relationship between walking and the amount of time spent walking [110]. Nevertheless, none of the correlations between walkability parameters and physical activity outcomes were moderated by car ownership [111]. This demonstrates that the majority of relationships are formed as a result of other modes of travel, such as public transportation, instead of private cars. In Bangkok, the results of a comparative study of the utility of private vehicles and mass transit modes revealed that the distance from the traveler's residence to the mass transit station impacted individual mode choice behavior [24]. A previous study determining the association between the distance to a transit stop and transit access mode found that a longer distance is correlated with a lower probability of walking to public transit [102].

Generally, the walking distance to access rail transit mode for commuting trips was 1 km or less, and 1–1.6 km for bus transit [113]. In the San Francisco Bay Area, researchers discovered that pedestrians walked an average of 548 m and as far as 1100 m [114]. However, in the United States, the average distance between train stations is half a mile [115]. In Bangkok, the percentage of people who walked less than 400 m dropped after that, and less than 10% of people walked more than 1 km [101].

According to a previous study, the walking distance from a residential area to the nearest mass transit station was classified as less than 400 m, less than 1000 m, and more than 1000 m, which represents the accessibility of mass transit. Furthermore, walking distance variables (i.e., distance from the residence to the nearest mass transit station) are moderators that interact with all relationships, as shown in Figure 5-1. The proposed hypotheses are as follows:

Hypothesis 3 (H3): Walking distance moderates the mediation effects of paths of the model on three levels of the moderator.

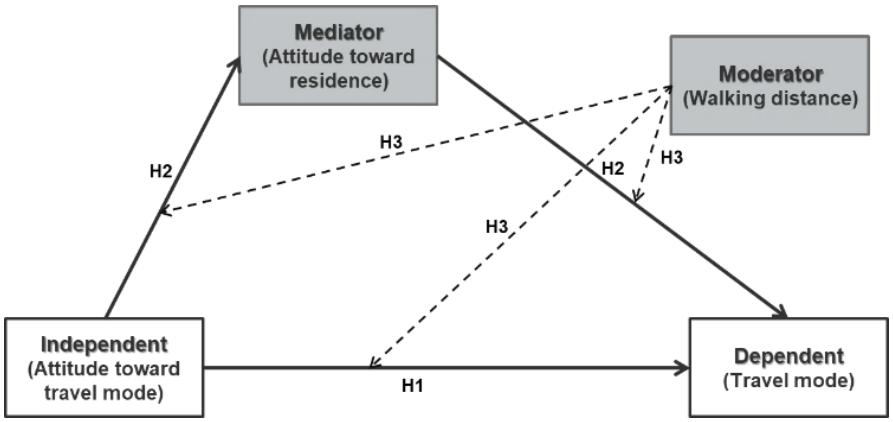


Figure 5-1 The conceptual moderated mediation model

5.3 Data Collection

5.3.1 Survey Instrument

The target population of this study included residents of the current mass transit station and travelers near the mass transit station in the Bangkok metropolitan area. The survey designated an area within 1 km of the station to control the target respondents. The population in this study represents people around stations, mainly in the Bangkok area.

The survey was conducted in the Bangkok metropolitan area, which covers all existing mass transit stations in the area (as shown in Figure 5-2). In December 2020, the existing mass transit stations had six lines and 125 stations. The participants represented in this study were randomly selected from existing stations in three provinces, including Bangkok, Nonthaburi, and Samut Prakan. However, the pre-survey conducted online received a relatively low response rate. Consequently, data were collected using questionnaires and face-to-face interviews while observing social distancing. In this study, attitudes were divided into two categories: before COVID-19 and during COVID-19, to explore attitudes that may contribute to changes in travel behavior. As of 16 December 2020, there have been 4261 confirmed cases of COVID-19, with 60 deaths. In total, 2463 of these cases were spread by people living in the same area, and there have been 0 new cases of infection in Thailand [104].

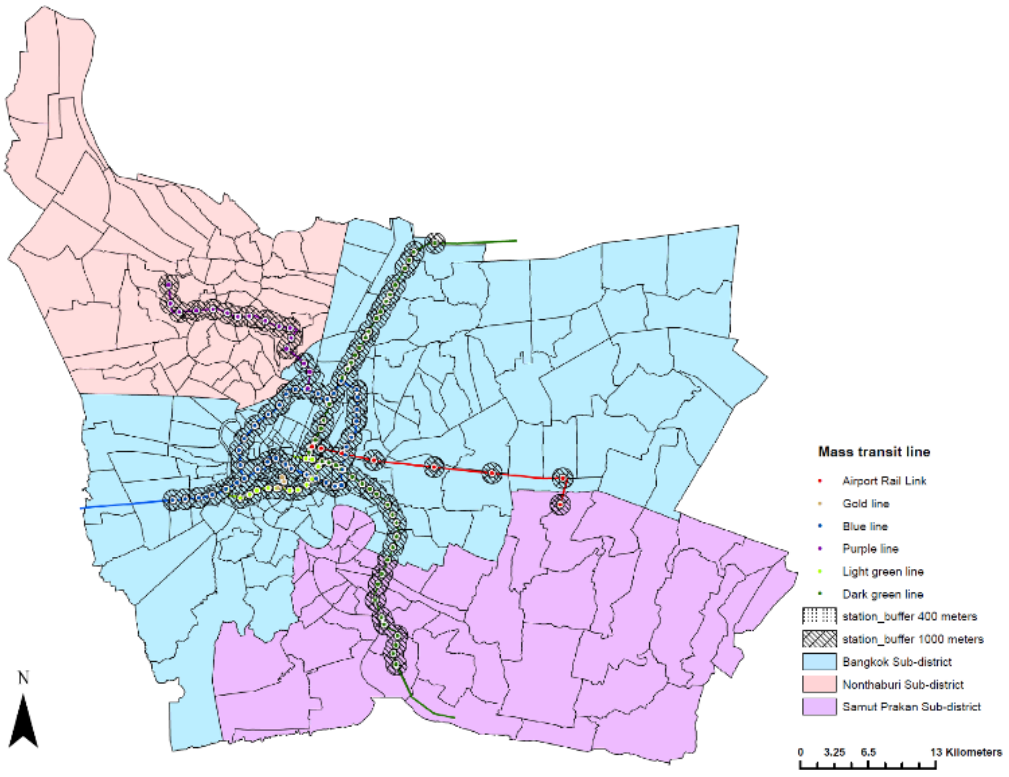


Figure 5-2 Map of the study area with buffer zones at 400 and 1000 m

5.3.2 Sample Characteristic

The distribution of questionnaires was conducted on a weekday in December 2020 to explore commuting trips. There was no lockdown on the day of the survey, which was carried out after the first wave of the outbreak. A total of 682 valid questionnaires were obtained. According to the participants' residence locations, around 72 percent, 14 percent, 12 percent, and 2 percent of those that participated were from Bangkok, Nonthaburi, Samut Prakan, and Pathum Thani, respectively.

The socio-demographic characteristics of the participants are summarized in Table 5-1. The majority of the respondents were women (63%). Most of the participants were 18–24 years old (25%) and 25–34 years old (26%). In addition, 42% of the respondents had a bachelor's degree, and 58% were employed. The majority of the households had two (30%) or three (26%) members. Approximately 50% of the respondents did not own a vehicle, and 61% did not have a transport card (e.g., Rabbit, MRT, MRT+, Smart pass, and Mangmoom). Respondents had residences near the mass transit station within 1 km (44%) and 400 m (29%).

According to the population of Bangkok in 2020, the total population was 8,854,718 people, and 52% were women [88]. However, the population in this study represents residents and travelers near the mass transit station area. In comparison to the general population of Bangkok, this may be a different circumstance. Referring to the previous study on data of station-area residents, it found that the respondent characteristics were female, 62.8%, and car ownership, at 58.7% [168]. This research found that the population of residents and travelers around a mass transit station were found to have similar characteristics. (see APPENDIX 8.3.2)

The survey was conducted during the COVID-19 outbreak, and respondents were asked questions concerning their income before and during the pandemic. The COVID-19 pandemic affected the middle and high-income groups, with the range of 0–18,000 THB increasing by 2.9% (see Table 5-2). The travel mode was divided into four modes based on the main mode of the usual trip. Travel by mass transit was reduced from 72% to 69% during COVID-19. The total travel time increased by 3% in the 0–60 min range, and long trips (> 61 min) decreased by 3%. However, the total travel costs decreased by 2% in the 51–100 THB range and increased by 2% in the 0–50 THB range.

Table 5-1 Demographic characteristics of participants

Variable	Frequency	Percent
Gender		
Male	249	37%
Female	433	63%
Age (years)		
<18	17	2%
18-24	172	25%
24-34	176	26%
35-44	120	18%
45-54	99	15%
55-64	71	10%
>64	27	4%
Education		
< High school	39	6%
High school	220	32%
College	117	17%
Bachelor's degree	288	42%
≥Master's degree	18	3%
Occupation		
Student	120	17%
Employee	393	58%
Personal Business	93	14%
Unemployed	66	10%
Other jobs	10	1%
Number of households		
1	81	12%
2	205	30%
3	176	26%
4	115	17%
≥5	105	15%
Total vehicle ownership		
No vehicle	339	50%
1	220	32%
2	93	13%
3	18	3%
≥4	12	2%
Total transport card ownership		
No card	414	61%
1	212	31%
≥2	56	8%
Walking distance from residence to nearest station (m)		
<400	202	29%
<1000	298	44%
≥1000	182	27%

Table 5-2 Demographic and travel behavior change of participants

Variable	Before COVID-19		During COVID-19	
	Frequency	Percent	Frequency	Percent
Income				
<7,500THB	102	15%	110	16%
7,501-18,000 THB	286	42%	298	44%
18,001-24,000 THB	150	22%	142	21%
24,001-35,000 THB	88	13%	82	12%
>35,000 THB	56	8%	50	7%
Travel mode				
Walking/biking	12	2%	21	3%
Mass transit	489	72%	471	69%
Public transport	167	24%	176	26%
Private car	14	2%	14	2%
Travel time (min/day)				
0-30	50	7%	57	8%
31-60	212	31%	227	33%
61-90	179	26%	167	25%
91-120	117	17%	111	16%
121-180	87	13%	86	13%
>180	37	6%	34	5%
Travel cost (THB/day)				
0-50	193	27%	208	31%
51-100	338	50%	327	48%
101-150	99	15%	96	14%
>150	52	8%	50	7%

5.4 Data Analysis and Results

To test the hypothesis, this research examined the measurement items to construct latent variables of attitude toward travel mode and attitude toward residence. A five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used to evaluate the attitude questions (strongly agree). In this study, attitudes toward travel modes were measured using a total of 18 items, and attitudes toward residence were measured using a total of 23 items. The SPSS statistical program and the AMOS software package were used to perform exploratory factor analysis (EFA), confirmatory factor analysis (CFA), and structural equation modeling (SEM).

5.4.1 Exploratory Factor Analysis (EFA)

EFA was used to extract measurement variables and to consider the latent variables of the measurement variables. The Kaiser–Mayer–Olkin (KMO) test of sampling adequacy was 0.902 and 0.928 before and during COVID-19, respectively. Nonetheless, the Cronbach's alpha of each latent factor is higher than 0.7 (the cut-off value of the reliability test) [169]. The maximum likelihood estimate was used to determine the variance and correlation between factors. In the final analysis with Promax rotation, five groups were obtained before and during COVID-19 (see Table 5-3). According to the results of the factor analysis, the dimension factors of attitude toward travel modes, including attitude toward private cars and attitude toward public transportation, have an

impact on this study. In addition, attitudes toward residential neighborhoods, attitudes toward urban areas, and attitudes toward residential locations were determined as the results for attitudes toward residence.

Table 5-3 Exploratory factor analysis results

Factor	Before COVID-19		During COVID-19	
	Item	**Factor loading**	**Item**	**Factor loading**
Attitude toward private car (PC)	**α = 0.774**		**α = 0.841**	
Prefer to use private car.	1PC1	0.448	-	-
Accept more travel cost to use private car.	1PC2	0.485	2PC2	0.479
Choose private car because of social image	1PC3	0.433	2PC3	0.431
Prefer private car because of weather condition	1PC4	0.597	2PC4	0.625
Prefer to use private car or public transport to avoid crime of taxi / unfair price	1PC5	0.778	2PC5	0.777
Prefer to use private car to avoid criminal risk.	1PC6	0.887	2PC6	0.896
Avoid pollution by using private car	-	-	2PC7	0.502
Attitude toward public transport (PT)	**α = 0.788**		**α = 0.848**	
Prefer to use public transport (Mass transit, Bus, Boat).	1PT1	0.426	2PT1	0.402
Mass transit easy to travel more	1PT2	0.492	2PT2	0.574
If they have online pre-paid fare system, public transport will be preferred	1PT3	0.828	2PT3	0.839
If they have good facility of station (clean, toilet, etc.), mass transit will be preferred	1PT4	0.839	2PT4	0.899
Prefer residential area near bus stop.	-	-	2PT5	0.353
Attitude towards neighborhood of residential area (NB)	**α = 0.874**		**α = 0.897**	
Prefer residential area with no crime or less.	1NB1	0.831	2NB1	0.888
Prefer residential area with lighting around.	1NB2	0.939	2NB2	0.998
Prefer residential area near the police station	1NB3	0.772	2NB3	0.738
Not choosing to live in an urban area due to concern about infection.	1NB4	0.643	2NB4	0.690
Attitude toward urban area (UB)	**α = 0.826**		**α = 0.838**	
Prefer to live in urban area.	1UB2	0.654	2UB2	0.686
Prefer to live near community/shopping/office/school/hospital	1UB3	0.671	2UB3	0.688
Prefer social image and social environment in urban.	1UB4	0.739	2UB4	0.807
Attitude towards residential location (RL)	**α = 0.886**		**α = 0.878**	
Residential areas are easy to use by taxi	-	-	2RL1	0.362
Activity place can walk from home	1RL2	0.787	2RL2	0.829
Residential area is a friendly environment for pedestrians.	1RL3	0.960	2RL3	1.012
Residential area is a friendly environment for cycling	1RL4	0.784	2RL4	0.829
Kaiser-Meyer-Olkin	**0.882**		**0.928**	
Bartlet''s Test	**7120.652**		**9618.719**	
Significance	**0.000**		**0.000**	

5.4.2 Confirmatory Factor Analysis (CFA)

After EFA was used to examine all factors, CFA was used to evaluate and confirm the structure of the corresponding factors. Before evaluating the structural model, the validity of the entire dataset of the measurement model must be validated. [160].

The results indicate that all standardized factor loadings of CFA before and during the COVID-19 model (see Figure 5-3) were significant, and the goodness of fit indicated an adequate fit of the measurement model in CFA, as shown in Table 5-4. According to the recommended index, the chi-square/degree of freedom (Chisq/df) is in the range of 1–4 [170], the root mean square of error approximation (RMSEA) is lower than 0.07 [171], the goodness of fit index (GFI) is greater than or equal to 0.09 [172], and the comparative fit index (CFI) and Tucker–Lewis Index (TLI) are greater than or equal to 0.09 [173].

Table 5-4 Fitness index and results of CFA and SEM

Index	Level of Acceptance	CFA		SEM	
		Before model	During model	Before model	During model
Chisq/df	1-4	3.304	3.808	2.015	2.052
RMSEA	< 0.07	0.058	0.064	0.039	0.039
GFI	≥ 0.90	0.941	0.920	0.908	0.917
CFI	≥0.90	0.959	0.951	0.946	0.959
TLI	≥ 0.90	0.949	0.941	0.930	0.945
p-value	<0.05	0.000	0.000	0.000	0.000

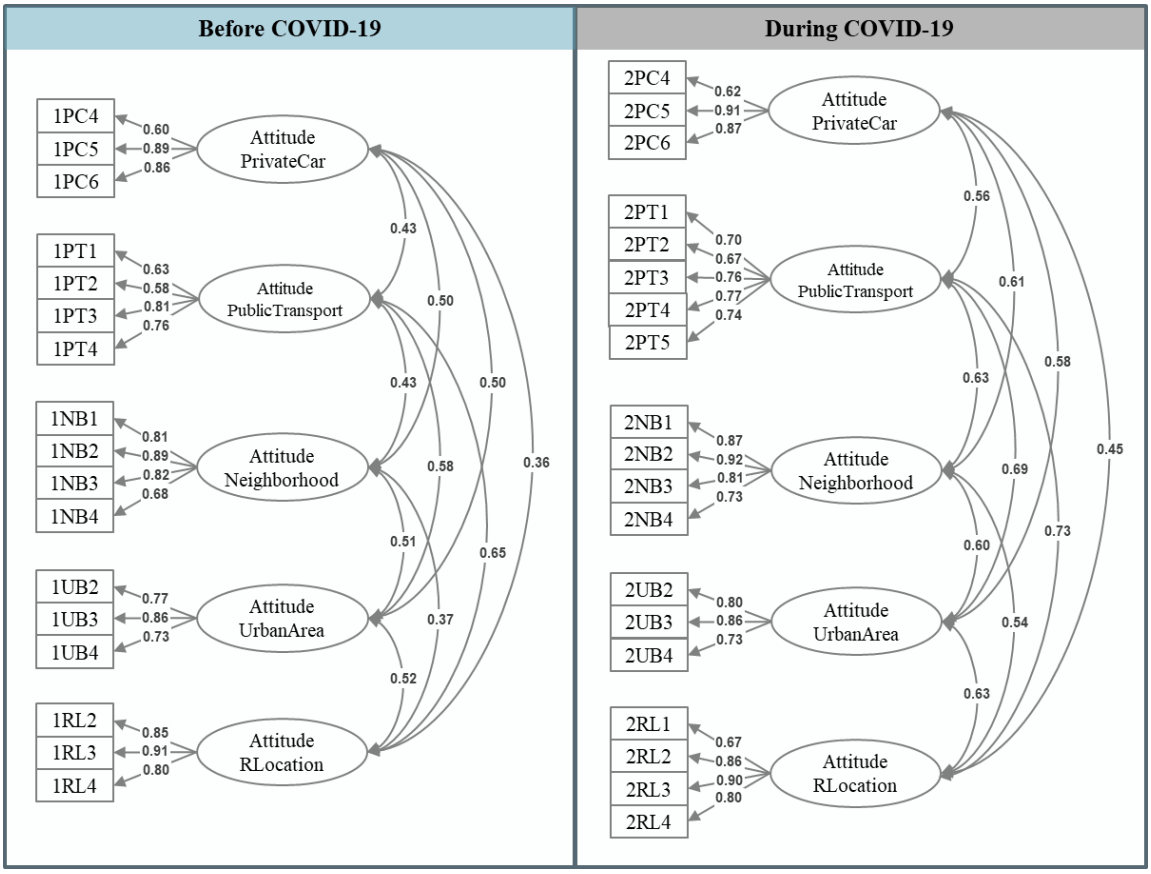


Figure 5-3 Confirmatory factor analysis results

5.4.3 Structural Model

The structural model was going to be evaluated before hypotheses testing. In order to minimize the structural model's complexity, second-order factor models were applied to construct it. The proposed structural model is demonstrated in Figure 5-4. The results of the structural model on path analysis are shown in Table 5-5, along with the models obtained before and during the COVID-19 model. The SEM results indicated the good fit of the model (as shown in Table 5-4) before and during the COVID-19 model were significant. The result from AMOS shown in APPENDIX 8.2.2.

The structural model demonstrated the causal relationship effect of Hypothesis 1 (H1). The results indicate that the attitude toward private cars significantly impacts travel mode behavior, and the outcome supports Hypothesis 1a (H1a) at values of $\beta = 0.109$ and 0.089 before and during COVID-19, respectively. However, attitudes toward public transport have an insignificant impact on travel modes and do not support Hypothesis 1b (H1b).

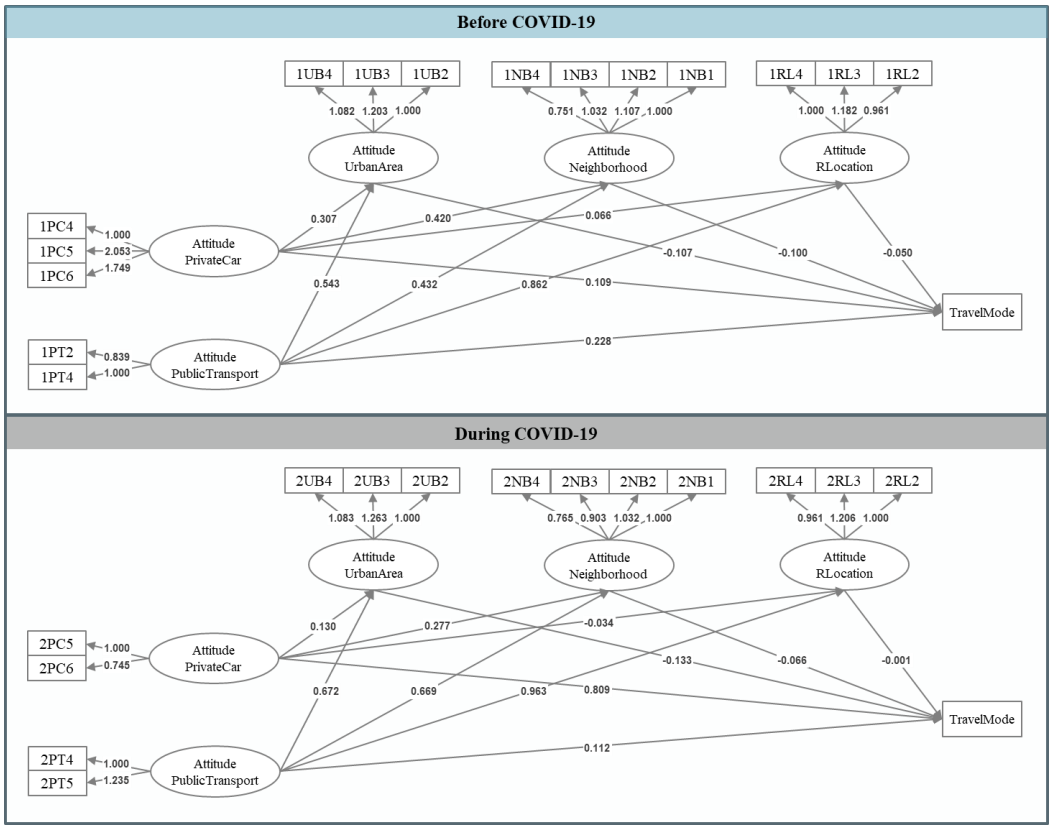


Figure 5-4 Structural model of study

Table 5-5 Direct path of structural model

Paths	Before COVID-19		During COVID-19	
	β	SE	β	SE
PC → Travel mode	0.109*	0.057	0.089*	0.089
PT → Travel mode	0.228ns	0.128	0.112ns	0.112
PC →UB	0.307*	0.063	0.130*	0.036
PC →NB	0.420*	0.067	0.277*	0.045
PC →RL	0.066ns	0.084	-0.034ns	0.045
PT →UB	0.543*	0.075	0.672*	0.064
PT →NB	0.432*	0.071	0.669*	0.070
PT →RL	0.862*	0.106	0.963*	0.083
UB → Travel mode	-0.107ns	0.069	-0.133ns	0.072
NB→ Travel mode	-0.100*	0.047	-0.066ns	0.048
RL → Travel mode	-0.050ns	0.060	-0.001ns	0.059

Note: ns Not significant, * $p < 0.05$

5.4.4 Mediation Analysis

The bias-corrected bootstrap approach was used to test the significance of the mediation effect, and a significance level of 0.05 was employed to indicate 95% confidence. Finally, the mediation model was tested using 5000 bootstraps.

The result of the mediation effect in Hypothesis 2 (H2) was that attitudes toward urban areas, neighborhoods, and residential locations mediated the relationship between the attitudes toward travel modes (attitudes toward public transportation and attitudes toward private cars) and travel mode behavior. The mediated effect is shown in Table 5-6.

The mediated effect obtained was partially mediated between attitudes toward urban areas and attitudes toward private cars and travel mode behavior (H2a) during COVID-19 with a significant value of $\beta = -0.017$. Additionally, the attitude toward neighborhood to attitude toward private cars and travel mode behavior (H2b) was partially mediated at the significant value of $\beta = -0.042$ before COVID-19.

According to the causal relationship, the attitude toward public transport does not have a significant impact on travel mode and does support Hypothesis 1b (H1b). The outcome of the mediation effects shows that the relationship between the attitudes toward public transport and travel mode behavior (H2e) was fully mediated by attitudes toward neighborhood before COVID-19, with a significant value of $\beta = -0.043$.

Table 5-6 Results of mediation analyses

Paths	Before COVID-19				During COVID-19			
	β	Lower	Upper	Result	β	Lower	Upper	Result
Direct effect								
PC → Travel mode (H1a)	0.109*	-0.020	0.234	Support	0.089*	0.019	0.173	Support
Indirect effect								
PC → UB → Travel mode (H2a)	-0.033ns	-0.086	0.001	No mediation	-0.017*	-0.047	0.000	Partial mediation
PC → NB → Travel mode (H2b)	-0.042*	-0.090	-0.008	Partial mediation	-0.018ns	-0.048	0.006	No mediation
PC → RL → Travel mode (H2c)	-0.003ns	-0.041	0.009	No mediation	0.000ns	-0.010	0.011	No mediation
Direct effect								
PT → Travel mode (H1b)	0.228ns	0.003	0.590	Not support	0.112ns	-0.166	0.428	Not support
Indirect effect								
PT → UB → Travel mode (H2d)	-0.058ns	-0.190	0.004	Not support	-0.089ns	-0.209	0.006	Not support
PT → NB → Travel mode (H2e)	-0.043*	-0.111	-0.007	Full mediation	-0.044ns	-0.113	0.017	Not support
PT → RL → Travel mode (H2f)	-0.043ns	-0.222	0.060	Not support	-0.001ns	-0.144	0.122	Not support

Note: ns Not significant, * $p < 0.05$

5.4.5 Moderated Mediation Analysis

The moderating effect was evaluated using a multi-group moderation technique, which was divided into three groups: 1. walking distance of less than 400 m; 2. walking distance of less than 1000 m; and 3. walking distance of more than 1000 m from the residence to the nearest mass transit station. The model comparison of df (24) and $\chi 2$ (59.76) was significant at $p = 0.000$. This result revealed the moderating effect of various walking distances. Table 5-7 shows the standardized factor loading before and during COVID-19, regrading Hypothesis 3 (H3) as the walking distances interacting with all relationships.

Walking distance had a significant moderating effect on attitude toward travel mode and travel mode behavior for the relationship of attitude toward private cars and travel mode behavior (H3a), in which the moderator discovered a positive effect (= 0.231 and = 0.209 before and during COVID-19, respectively). People who walked a lot before and during COVID-19 didn't see a connection between how they felt about public transportation and how they used public transportation (H3b).

Before and during COVID-19, all moderator groups had a significant direct effect on attitudes toward private cars and attitudes toward neighborhoods (H3d), attitudes toward public transportation and attitudes toward urban areas (H3f), and attitudes toward public transportation and attitudes toward residential locations (H3h). The direct effect of attitudes toward private cars on attitudes toward urban areas (H3c) was significant before and during COVID-19 at walking distances of less than 1000 m and more than 1000 m groups. Furthermore, the relationship between attitudes toward private cars and attitudes toward residential locations (H3e) was significant for both cases (before and during COVID-19) at walking distances of less than 400 m and more than 1000 m. The relationship between attitudes toward public transport and attitudes toward the neighborhood (H3g) was significant at a walking distance of less than 400 m and less than 100 m for both cases. Therefore, for a walking distance of more than 1000 m moderators, the relationship became significant during COVID-19 ($\beta = 0.356$).

The results of moderated mediation analysis indicate that the moderator of walking distance was not significant in the relationship between attitudes toward urban areas and travel mode behavior (H3i), attitudes toward the neighborhood of residence and travel mode behavior (H3j), and attitudes toward residence location and travel mode behavior (H3k) before and during COVID-19. The results showed that the indirect effect was insignificant in the moderated mediation analysis.

Table 5-7 Results of moderated mediation analyses

Paths	Before COVID-19						During COVID-19					
	< 400 m		< 1000 m		≥ 1000 m		< 400 m		< 1000 m		≥ 1000 m	
	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect	Direct	Indirect
PC → Travel mode (H3a)	0.231^{*}	-0.100^{ns}	0.009^{ns}	-0.059^{ns}	0.288^{ns}	-0.148^{ns}	0.209^{*}	-0.101^{ns}	0.049^{ns}	-0.019^{ns}	0.225^{ns}	-0.116^{ns}
PT → Travel mode (H3b)	-0.540^{ns}	0.266^{ns}	0.177^{ns}	-0.141^{ns}	0.213^{ns}	-0.033^{ns}	0.021^{ns}	-0.140^{ns}	-0.054^{ns}	-0.055^{ns}	0.271^{ns}	-0.110^{ns}
PC →UB (H3c)	0.092^{ns}	-	0.269^{*}	-	0.579^{*}	-	0.123^{ns}	-	0.239^{*}	-	0.390^{*}	-
PC →NB (H3d)	0.239^{*}	-	0.264^{*}	-	0.724^{*}	-	0.293^{*}	-	0.313^{*}	-	0.510^{*}	-
PC →RL (H3e)	-0.237^{*}	-	0.071^{ns}	-	0.367^{*}	-	-0.231^{*}	-	0.066^{ns}	-	0.405^{*}	-
PT →UB (H3f)	0.614^{*}	-	0.509^{*}	-	0.308*	-	0.720^{*}	-	0.581^{*}	-	0.511^{*}	-
PT →NB (H3g)	0.424^{*}	-	0.449^{*}	-	0.010^{ns}	-	0.519^{*}	-	0.517^{*}	-	0.356^{*}	-
PT →RL (H3h)	0.805^{*}	-	0.574^{*}	-	0.483^{*}	-	0.771^{*}	-	0.677^{*}	-	0.482^{*}	-
UB → Travel mode (H3i)	-0.021^{ns}	-	-0.046^{ns}	-	-0.101^{ns}	-	-0.207^{ns}	-	-0.115^{ns}	-	-0.092^{ns}	-
NB→ Travel mode (H3j)	-0.045^{ns}	-	-0.152^{ns}	-	-0.124^{ns}	-	-0.161^{ns}	-	0.028^{ns}	-	-0.128^{ns}	-
RL → Travel mode (H3k)	0.370^{ns}	-	-0.085^{ns}	-	-0.001^{ns}	-	0.121^{ns}	-	-0.004^{ns}	-	-0.037^{ns}	-

Note: ^{ns} Not significant, * $p < 0.05$

5.5 Discussion and Conclusions

This study investigates the hypothesis of the decision on travel mode behavior by considering the psychological factors of attitude. We focused on the main attitude factor based on residential location to determine the effect of walking distance and attitude toward travel mode. According to a research on residential relocation and travel satisfaction, residential relocation may provide an opportunity to improve travel satisfaction [174]. To explore the difference in travel mode behavior based on attitude toward travel modes, the walking distance from the residence to the nearest mass transit station was designed to be a moderator. This study was divided into two categories: before and during COVID-19.

An in-depth study on relationships between residential self-selection, which is mediation, and moderated mediation analysis was used to consider direct and indirect effects. In this study, the hypothesis focuses on the mediation of attitude toward residence (the same dimension of resident attitude as in the previous chapter) to explore the type (direct and indirect) and form of indirect effect.

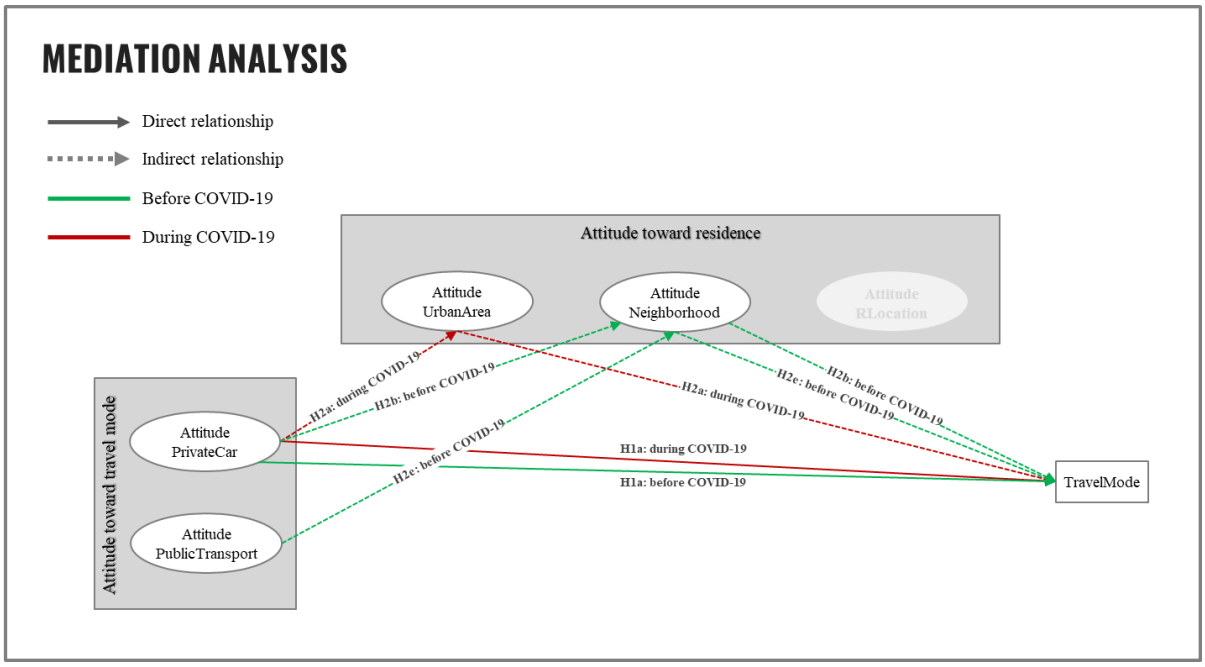


Figure 5-5 Summary hypothesis result of mediation effect

Based on the mediator of attitude toward residence, the result indicated a direct effect on attitude toward private car to travel mode in both cases (before and during COVID-19). Before COVID-19 found 2 indirect effects on the relationship: 1) attitude toward private cars to attitude toward neighborhood and travel mode, and 2) attitude toward public transport to attitude toward neighborhood and travel mode. However, there was full mediation on the relationship, particularly in terms of attitudes toward public transport. In the case of during COVID-19, indirect effect was found in the relationship of attitudes toward private cars to attitudes toward neighborhood and travel modes, and there was a partial mediation relationship. The summary of result shown in Figure 5-5.

According to the hypothesis of this study, focus is on the mass transit station area and the built environment of walking distance, which represents the accessibility level to mass transit of residential. A walking distance moderator is identified on all relationship paths to test direct and indirect effects. The findings indicated that moderated mediation analysis has an indirect effect. Overall, there was a relationship between attitude toward travel mode and attitude toward residence, as well as a relationship between attitude toward travel mode and travel mode behavior, indicating that there was no relationship between attitude toward residence and travel mode.

Thus, the moderator is divided into 3 levels: less than 400 m, 400 to 1000 m, and more than 1000 m from the residence to the nearest mass transit station. Moderated mediation analysis reveals a difference in the effect of moderator level. Furthermore, the relationship between attitude toward public transportation and attitude toward neighborhood before the COVID-19 case was significant by less than 400 m and 400 to 1000 m moderators, but it was significant by all moderator levels during the COVID-19 case. The result shown in Figure 5-6. Thus, overall result of this stage study shown in Table 5-8.

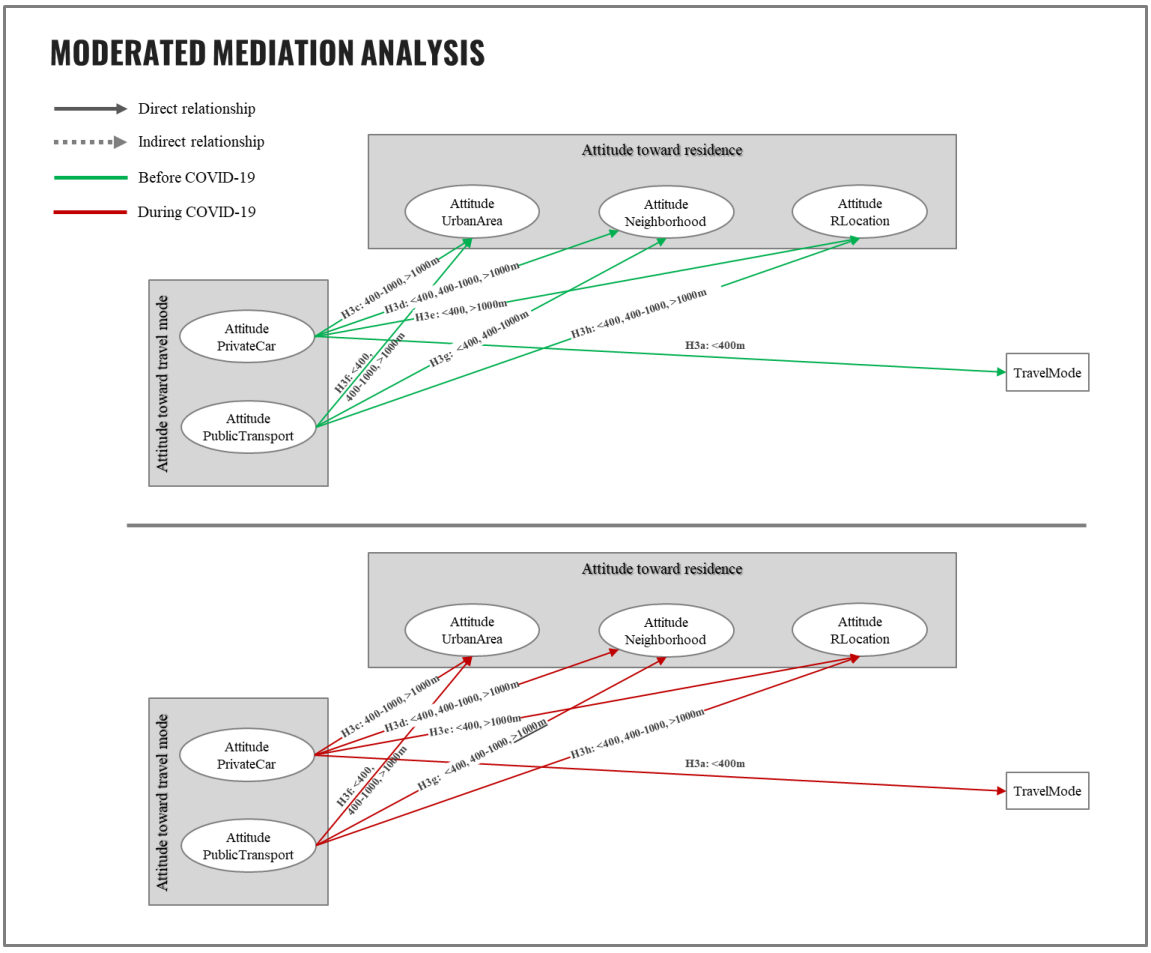


Figure 5-6 Summary hypothesis result of moderated mediation effect

Table 5-8 Summary hypothesis result of direct and indirect effect

Hypothesis	Path	Effect	Results	
			Before COVID-19	During COVID-19
H1a	PC → Travel mode	Direct	Support	Support
H1b	PT → Travel mode	Direct	Not support	Not support
H2a	PC → UB → Travel mode	Indirect	Not support	Partial mediation
H2b	PC → NB → Travel mode	Indirect	Partial mediation	Not support
H2c	PC → RL → Travel mode	Indirect	Not support	Not support
H2d	PT → UB → Travel mode	Indirect	Not support	Not support
H2e	PT → NB → Travel mode	Indirect	Full mediation	Not support
H2f	PT → RL → Travel mode	Indirect	Not support	Not support
H3a	PC → Travel mode	Direct	<400m	<400m
H3b	PT → Travel mode	Direct	Not support	Not support
H3c	PC →UB	Direct	400-1000,>1000m	400-1000, >1000m
H3d	PC →NB	Direct	<400, 400-1000, >1000m	<400, 400-1000, >1000m
H3e	PC →RL	Direct	<400, >1000m	<400, >1000m
H3f	PT →UB	Direct	<400, 400-1000, >1000m	<400, 400-1000, >1000m
H3g	PT →NB	Direct	<400, 400-1000m	<400, 400-1000, >1000m
H3h	PT →RL	Direct	<400, 400-1000, >1000m	<400, 400-1000, >1000m
H3i	UB → Travel mode	Direct	Not support	Not support
H3j	NB→ Travel mode	Direct	Not support	Not support
H3k	RL → Travel mode	Direct	Not support	Not support

Note: PC= private car, PT= public transport, UB= urban area, NB= neighborhood, RL= residential location.

The findings of this research were based on three main hypotheses. First, the causal relationship between attitude toward travel mode and travel mode behavior was found to have a positive impact on attitude toward private cars on travel mode behavior, whereas it was not significant for attitudes toward public transport relationships. This can be explained by how attitude toward travel mode may impact on travel mode depending on the mode considered. Second, according to the findings of the attitude toward residence mediator, attitude toward residence produced a negative indirect effect on travel mode behavior. Moreover, attitudes toward neighborhoods and urban areas were partially mediated by attitudes toward private cars and travel mode behavior before and during COVID-19, respectively. In addition, attitudes toward neighborhoods were significantly mediated by attitudes toward public transport and travel mode behavior before COVID-19. This result confirmed that the attitude toward residence mediated the relationship between the attitude toward travel mode and travel mode behavior. In particular, the indirect effect of the attitude toward neighborhood was of importance before COVID-19. During COVID-19, attitudes toward urban areas were more important than neighborhoods, implying that people were more concerned about living in urban areas.

Lastly, the moderated mediation analysis is given inside all relationship paths as moderated by the walking distance from the residence to the nearest mass transit station. The result proved that walking distance moderated the relationship between attitude toward travel mode and attitude toward residence all along the path by various moderators. During COVID-19, the relationship between attitude toward public transport and attitude toward neighborhood became significant at a walking distance of more than 1000 m, which means people who live more than 1000 m from the station and have a positive attitude toward public transport will more likely consider their attitude toward neighborhood. However, the relationship between the attitude toward private cars and travel mode behavior was moderated by a walking distance of less than 400 m before and during COVID-19. It means that people who drive and live less than 400 m from the station are likely to use the park and ride service to transfer to other modes of transport. The further difference in the moderation effect is defined by an insignificant relationship between attitude toward residence and travel mode behavior.

This research investigated the moderated mediation effect of the causal relationships between travel mode behavior and attitudes toward travel modes based on the relocation hypothesis by defining the intervention variable of attitude toward residence and the interaction variables of walking distance to the nearest mass transit station. The overall result was able to demonstrate significant differences in relationships, and the mediation effect found that during COVID-19, private cars influenced attitudes toward urban areas. Before COVID-19, public transportation seemed to be more important. However, during COVID-19, private cars became the first mode of travel choice. This research provides evidence for an attitude toward resident mediator and a walking distance moderator that the attitude toward residence was influenced by the attitude toward travel mode. The findings of this study indicate attitudes and preferences for specific modes of transport or neighborhood characteristics that affect travel behavior [121]. However, attitudes toward residents do not directly impact travel mode behavior. Attitudes toward urban areas and attitudes toward the neighborhood of residence were the main players in the indirect effect of attitudes toward travel mode that influenced the choice of travel mode. As attitude toward the neighborhood residence area confirms, the type of residential neighborhood affects the choice of commuting mode [40]. The hypothesis of the COVID-19 pandemic is effective for attitude and behavior.

However, the influence of COVID-19 on public transportation is not significant. This might be related to the reason cited in the survey that most representative commuters are already regular commuters, even in the case of a pandemic. The outbreak may not have a considerable impact on travel patterns. Second, because public transport is the primary mode of transportation in Bangkok and most people do not own a vehicle, they do not have many options in terms of transport modes. Nonetheless, there is a limitation to this study. The survey did not include the question about residential choice decisions, and the results provided only a travel mode choice and did not offer future residential location choices in the study hypothesis.

The study's findings implicate critical policies on mode accessibility improvement. According to the study's findings, public transportation has a strongly significant attitude toward residents and a more negative indirect impact on public transport compared to private cars. Public transport is important in Bangkok, but not efficient. The people who live within 1000 m of the station are the main users. Thus, problems with car use in Bangkok are driven by the insufficient availability of alternative modes of travel and service routes. As a result, public transportation may not fully recover to pre-pandemic levels in terms of daily travel modes [166]. The service provider's management is key. The strategic planning of the service provider to manage the availability of up-to-date schedules and service frequencies and make available up-to-date information for customers could reduce crowds at the station and in service. A survey of current customer needs and their satisfaction level should be done more often, to make sure that an operation plan is being properly implemented.

The relationship analysis in this study can be utilized in analyzing behavior and making long-term change predictions. In the current situation, there is a tendency for people to stay longer in their homes. Their residences and environment are more important. This study considered only attitude-based, longitudinal data on residential location change, and the model forecast of the integrated discrete choice model should be considered in future research to predict and help with urban policy, working with land use planning to get more accurate forecasts for the future.

6 ATTITUDE-BASED SEGMENTATION OF RESIDENTIAL SELF-SELECTION AND TRAVEL BEHAVIOR CHANGES AFFECTED BY COVID-19

This chapter evaluated the effects of COVID-19 on attitudes toward residential associated with travel behavior on decisions regarding future relocation. Chi-square automatic interaction detection was used to generate tree and classification segments to investigate the various segmentations of travelers and residents around mass transit stations. The decision tree revealed that the most influential variables were the number of transport card ownerships, walking distance to the nearest mass station, number of households, type of resident, property ownership, travel cost, and trip frequency. During the COVID-19 pandemic, people have concentrated on reducing travel time, reducing the number of transfers, and decreasing unnecessary trips. Consequently, people who live near mass transit stations less than 400 and 400-1000 meters away more prefer to live in residential and rural areas in the future. Structural Equation Modeling was used to confirm the relationship between attitudes in normal and pandemic situations. According to the findings, attitudes toward residential accessibility of travel modes were a significant determinant of attitudes toward residential location areas. This research demonstrates travelers' and residents' uncertain decision-making regarding relocation, allowing policymakers and transport authorities to better understand their behavior to improve transportation services.

6.1 Introduction

The COVID-19 pandemic affected several changes and occurred in a variety of fields such as economy, society, politics, government, population, disease control management, etc. The COVID-19 has been found all over the world for more than two years. People's lifestyles, behavior, and attitudes are changing as a result of the changes in the globe to avoid the spread of pandemics, and people are becoming more aware and concerned about pandemics.

In addition, the pandemic has a significant long-term impact on behavior and attitude. Most of the travel behavior studies showed a significant decrease in travel, including avoiding the use of public transport and using private cars more. According to the study of changes in travel behavior due to the COVID-19 pandemic around the world, there was a significant shift from public transport (before by 36% and during by 13%) to private transport (before by 32% and during by 39%) and non-motorized modes (before by 12% and during by 20%) during the pandemic [17]. The first wave of COVID-19 in Switzerland [18] found that it lowered the average daily distance by over 60% and public transportation by more than 90%.

Furthermore, the effects were evident in the short-term on travel behavior that has changed during the COVID-19 pandemic, and concentrating on residential location analyses, transportation system resiliency and longer-term considerations in pandemic situations should be considered in policy implementations and future insight [23]. Nevertheless, psychological factors have been demonstrated to be crucial in describing behavioral decisions more accurately in travel behavior studies. The attitudes might be related to the use of travel modes [4], [5]. Consequently, travel attitudes and motives for relocation were examined and it was discovered that the reasons for moving were related to travel [7]. However, housing and neighborhood characteristics are more important than travel-related attitudes, which have influenced travel behavior and also through residential choice [10].

However, in urban areas, mass transit is the most convenient and highly accessible transport mode. According to subway catchment areas, It was discovered that population and employment density, land use mix diversity, and intermodal connection all positively affect subway ridership [12]. The area around the mass transit station has been differently characterized from other areas by the built environment and the high accessibility it provides to commuters and residents nearby the stations. Nevertheless, urban travel characteristics indicate that the vast majority of inner-city residents travel shorter distances than suburban residents [15], as well as residents' preferences for traveling by train, finding that people who moved closer to the stations have become regular passengers [13].

The process of identifying groups or segments of the market that share characteristics of their characteristics or needs is referred to as market segmentation [58]. Market segmentation in travel behavior has been used to increase ridership, implement strategies/policy, improve service, etc. Segmentation of traveler can be based on multi-dimensions such as identify segment by different types of workers based on the predictability of their travel behavior over multiple days to understand changes in working

patterns [59] and identity segment by commuting pattern to provide effective support for the planning and operation of public transport systems [60]. Moreover, recently attitude-based market segmentation has been significantly increased in transportation research to understand the inside from the psychological perspective. According to a research attitude-based target group approach in forecasting the ecological effect of mobility behavior, the findings showed that attitude-based segmentation performed better than socio-demographic and geographic segmentation [64].

This study examines the relationship between residential location and travel mode behavior as impacted by attitudes toward relocation, as well as the impact of the COVID-19 scenario to understand the tendency of behavior in the future. To specific the objective of this study including:

1. To investigate the impact of COVID-19 on behavior and attitude by attitude toward relocation of attitude toward residential location area, and attitude toward residential accessibility on the travel mode associated with travel behavior which leads to future relocation decisions.
2. To identify and categorize the segmentation of travelers and residents around mass transit station area characteristics based on attitude change in the dimensions of the short-term decision of attitude toward residential accessibility of the travel mode and concern for using public transportation, and the long-term decision of attitude toward residential location area and concern for living in an urban area.
3. To confirm the relationship between the effect of attitude toward residential accessibility and the attitude toward residential location areas, pre-test and post-test designs were applied to investigate the relationship of intervention variables from the COVID-19 pandemic.

In this research, Chi-square Automatic Interaction Detection (CHAID) algorithm was applied to classification split into segment groups based on the multi-way splits algorithm for building a decision tree and separate characteristics of travelers and residents into groups under attitude toward relocation and provide a more in-depth understanding of the COVID-19 phenomenon that was affected in the case study. Structural Equation Modeling (SEM) was used to confirm the relationship between attitudes that were affected pre and during the COVID-19 period, and the consequent model (pre-test and post-test) illustrates the phenomenal effected by COVID-19.

6.2 Literature Review

6.2.1 Residential Self-selection and Attitude

There was a debate regarding considering residential self-selection or relocation in past transportation research, which was marked by an objective-subjective division in understanding travel behavior [15], [16]. Hard factors such as urban form and socioeconomic factors are recognized as having an impact on various aspects of travel behavior. Soft factors [15] are used in travel behavior research to consider the impact on travel behavior, such as attitudes and preferences for various modes of transportation or neighborhood characteristics [8]. Additional, personal characteristics and travel-related attitude were found to be significant predictors of how people evaluate their travel [9].

In considering the factors of residential location related to travel behavior, the availability of public transit is demonstrated to be the most important factor influencing current residential location choices, followed by living in a good neighborhood and housing affordability [33]. Nevertheless, the type of residential location had little effect on travel behavior, while attitude and lifestyle variables had an outstanding impact on travel demand [36]. In addition, the relationship between changes in the built environment, changes in car ownership, and changes in travel behavior revealed that relocating to neighborhoods closer to destinations or with alternative travel mode choices may lead to less driving and more walking [37]. This is evident in residential self-selection, which includes neighborhood preferences and/or travel-related attitudes, as well as the built environment and socio-demographic characteristics, all of which have a significant impact on travel behavior.

In addition, relocations and related changes in the built environment produce significant changes in car ownership and travel mode use, as well as changes in household structure, which have important effects [34]. Moreover, the mode of travel was shown to be associated with residential relocation, with statistically significant relationships between modal shift and selected explanatory factors. Car ownership, additional car purchase, income, particular housing type and size, kind of relocation, convenience of subway/bus for commuting, change in commute distance, and distance to subway station variables were significant when deciding to change from a private car to public transport [35].

6.2.2 Decision Tree on Travel Behavior Research

A decision tree is a very intuitive, easy-to-implement and productive modeling technique that can be depicted as a tree for classifying customers [144]. Recently, decision tree has been used in decision-making process, and they have been demonstrated to be an effective approach for making decisions. The decision tree of classification has four algorithms, including Classification and Regression Trees (CART), exhaustive CHAID, Chi-square Automatic Interaction Detection (CHAID) and Quick, Unbiased, Efficient, and Statistical tree (QUEST) [145]. This study will address CART and CHAID, which stand for classification and regression trees, nonparametric statistical techniques that can be used for categorical and continuous data.

The Classification and Regression Trees (CART) was presented by Gordon et al. (1984) CART is a binary tree technique based on the sum of squared estimates of errors between the observation and the mean value of the node, and the Gini diversity index as a measure of impurity when deciding splitting. However, CART will always produce binary trees. In this case, a binary tree is not an efficient representation and can be hard to interpret [147]. The Chi-square Automatic Interaction Detection (CHAID) was presented by Kass (1975) [148]. CHAID is a decision tree technique based on the Chi-squared test when deciding on the best spitting pattern for tree classifiers.

CHAID has been used for prediction, classification, detection of relationship between variables and establishing relationships between variables. CHAID decision trees are nonparametric techniques that make no assumptions about data and are most commonly used in market research for segmentation.

In transportation research, some studies used CART and CHAID in association with logistic regression to classify attribute variables more precisely, such as applying CART analysis to propose to obtain the attribute levels of comfort, speed, and travel cost, and proved that to be efficient for later applications [70]. Jang and Ko (2019) employed CHAID analysis to identify commute time ranges with a significantly variable composition of satisfied and dissatisfied commuters by separating the sample by travel time range [71]. Levin and Zahavi (2001) studied CHAID using the logistic regression model as a benchmark and found that automatic segmentation methods may very well substitute the judgmentally based segmentation methods for response analysis [72]. In the study of travel behavior models, CHAID was also investigated by using segmentation analysis and was used to examine the rates of household trip generation. The predictive ability of the model was validated, and the findings show that CHAID can be utilized as an exploratory tool to enhance model development or as a model on its own [74]. As well as the trip distribution model, CHAID applied traditional gravity models to estimate destination choices and compared them to decision tree (CHAID and CART) approaches. The results showed that the CHAID algorithm produced the best fit for real destination choices. By including the impacts of disaggregated variables, they propose that decision tree algorithms can be utilized to improve traditional trip distribution models by incorporating the effects of decision tree algorithms [75].

Therefore, in determining the most effective and efficient ways to investigate how different segments affect attitudes toward relocation and COVID-19 concerns of traveler and resident decision-making, the Chi-square Automatic Interaction Detection (CHAID) method is one of the most effective segmentation approaches. In this research, the CHAID algorithm was applied for this study due to the algorithm allows multi-way splits for nodes and is more flexible when used with category variables that are suited for the study segmentation of characteristics under consideration of attitude dependent variables.

6.2.3 Structural Equation Modelling on Residential Self-selection

The Structural Equation Modeling (SEM) approach is a statistical method for testing and evaluating causal relationships. The purpose of SEM is to test or develop theories. SEM is generally considered as a confirmatory rather than an exploratory procedure [132]. The analysis of paths and factors is the basic concept and origin of structural equation modeling. Conclusively, the summary of the structural equation model. It is the outcome of a synthesis of three major data analysis techniques: factor analysis, path analysis, and regression analysis [125].

In the study of transportation research and residential self-selection, SEM is used in the correlation analysis and the impact of travel behavior and residential relocation. For example, SEM was used to utilize the relationship between land use and travel patterns that influence weekend travel relative to weekday travel. It showed that land use has an

opposing effect on travel mode choice and trip frequency on weekdays compared to weekend travel [54]. Nonetheless, the changes in neighborhood characteristics lead to changes in travel choices, and neighborhood characteristics influence travel behavior and have an impact on travel behavior through their influence on automobile ownership [57]. In addition, the relationship between the built environment and travel attitude in travel behavior was used to evaluate residential self-selection as well as environmental determination frameworks using structural equation modeling (SEM). The result argues that both residential self-selection and residential determination are defined by the complex relationships between the built environment, travel attitude, and travel behavior [55].

6.2.4 COVID-19 on Travel Behavior Change

The COVID-19 epidemic has begun to have a significant impact on people's lives all around the world, affecting people's behavior in both the short and long term, including physical and mental impacts. Due to COVID-19, people will reduce their travel and choose active modes and cars over public transit [17]. In the short term, due to pandemic control and various measures, as well as the limitation of public transport service, workday travel behavior will gradually change in commuter'' decision-making regarding their travel behavior because of COVID-1''s physical distancing. In India, 41.65% of people stopped traveling during the transition to lockdown period, while 51.31 % continued to use the same mode of transportation as previous [175].

The pandemic has had a major impact on public transport due to concerns about being in contact with or being close to people at risk of infection and policy responses of disease control. While the level of hygiene on public transportation found that 58% of a passenger has been extremely concerned than pre-COVID-19 [78]. Evidently, people are concerned about using the public transport system and having their travel intentions disturbed. As the first wave of COVID-19 in Switzerland reduced the average daily distance by approximately 60% and public transport by over 90% [79]. Additionally, the huge average decreases in travel and public transport use as a result of the pandemic and associated policy responses mask major differences across socioeconomic groups, with travel decreasing less among the less educated and lower-income groups [81]. According to a study of public transport use in the United States, lower-income transit passengers reduced their travel lower than others and were unwilling to use transit because to the risk of infection. However, reducing crowding and requiring mask usage may enhance transport user' willingness to utilize it [14]. People's preferences for housing types may change as a consequence of COVID-19 impacts, and the quality of living environments will almost certainly become more significant [82].

6.3 Descriptive Statistics

6.3.1 Data Collection

This research proposes to focus on the mass transit station areas. Bangkok, Thailand was selected in this study. Note that, after the mass transport system was implemented in Bangkok, 77 percent of the citizens changed from private cars to mass transit [95]. The study area was considered around the existing mass transit station area to focus on the target group of travelers and residents around the station, which represents the highest access to mass transit. The spatial sample distribution survey over the existing mass transit station is demonstrated in Figure 6-1. The survey's catchment area was investigated by measuring the walking distance within 1,000 meters. According to a previous study conducted in Bangkok [101] the proportion of people walking distance decreased after 400 meters, and less than 10% of people traveled more than 1 km, because the long distance is associated with a lower probability of walking to public transportation [102]. According to the study area, existing mass transit stations are mainly in the Bangkok area, and some stations are in Nonthaburi and Samut Prakan.

The survey was conducted in the Bangkok metropolitan area in December 2020, which covers all existing mass transit stations in the area. At the time, there were six lines of mass transit in operation, including BTS light green (54.3 km), BTS dark green (14 km), MRT blue line (47 km), MRT purple line (23 km), Airport Rail Link (28.5 km) [92], and gold line (1.74 km), for a total of 168.54 km and 125 stations. Nevertheless, during the COVID-19 pandemic, Thailand's Department of Rail Transport disclosed that the ridership of mass transit decreased by approximately 80% in April (first wave of COVID-19) compared to January 2020 [100].

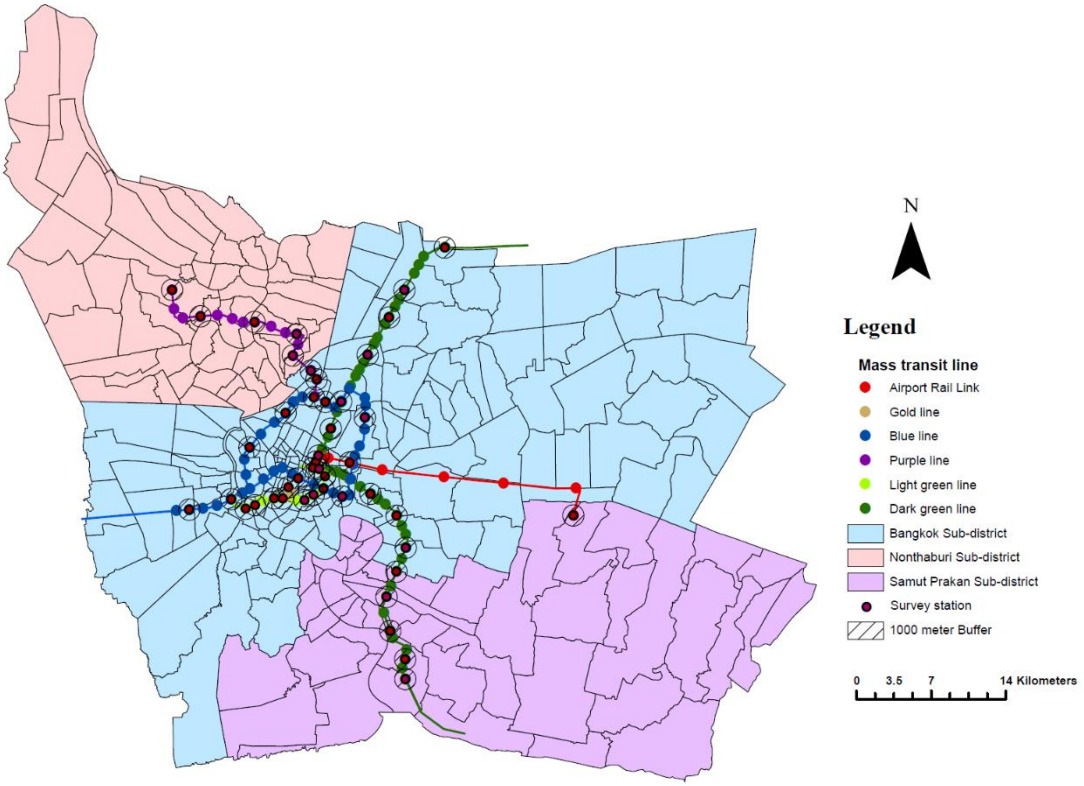


Figure 6-1 Study area of existing mass transit station and survey area

At the time of the survey, COVID-19 situation, there was no lockdown restriction. A state of emergency has been retained. However, the questionnaire survey was used face-to-face with social distancing interviews. Due to the context of the country, the online questionnaire had a low response rate and could lead to selection bias of young people or those who can access the internet and people who are familiar with the online survey. The questionnaire has four major sections; 1) personal characteristics, 2) changes in socio-demographic and travel behavior, 3) trip characteristics, and 4) attitudes toward relocation of 6 statements (attitude toward residential location area: 3 statements; attitude toward residential accessibility: 3 statements) and attitude toward concern of COVID-19 2 statements. Respondents were asked in situations pre and during COVID-19 on sections 2-4. In addition, attitude factors were collected by using a 5 likely scale (5 = strongly agree to 1 = strongly disagree).

6.3.2 Sample Characteristics

This study was conducted on commuting trips on weekdays. Finally, a total of 682 complete respondents were collected for analysis in this study. Table 6-1 and 6-2 contains statistical information about respondents, including socio-demographic characteristics, residential characteristics, and traveler characteristics.

Table 6-1 Characteristic of respondents

Description	Variable	Categorical	Percentage (n)
Socio-demographic characteristics			
Gender	S01	Male	37% (249)
		Female	63% (433)
Age	S02	<18 years	2% (17)
		18-24 years	25% (172)
		25-34 years	26% (176)
		35-44 years	18% (120)
		45-54 years	15% (99)
		55-64 years	10% (71)
		>64 years	4% (27)
Education	S03	<High school	6% (39)
		High school	32% (220)
		College	17% (117)
		Bachelor's degree	42% (288)
		≥Master's degree	3% (18)
Occupation	S04	Student	17% (120)
		Employee	58% (393)
		Personal Business	14% (93)
		Unemployed	10% (66)
		Other jobs	1% (10)
Residential characteristics			
No. of people in a household	R01	1 person	12% (81)
		2 peoples	30% (205)
		3 peoples	26% (176)
		4 peoples	17% (115)
		≥5 peoples	15% (105)
Type of residential	R02	Apartment	33% (228)
		Condominium	8% (55)
		Single house	38% (261)
		Townhouse	14% (94)
		Other	7% (44)
Property ownership	R03	Hire purchase	8% (50)
		Owner	45% (310)
		Rent	47% (322)
Housing cost/month	R04	<3500 THB	10% (67)
		3501-5000 THB	27% (183)
		5001-7500 THB	11% (75)
		7501-10000 THB	4% (25)
		10001-15000 THB	2% (17)
		15001-20000 THB	1% (6)
		20001-30000 THB	0% (2)
		30001-50000 THB	0% (0)
		>50000 THB	0% (1)
		No pay	45% (306)

Table 6-2 Characteristic of respondents (Cont.)

Description	Variable	Categorical	Percentage (n)
Traveler characteristics			
No. of vehicle ownership	T01	No vehicle	50% (339)
		1 car	32% (220)
		2 cars	13% (93)
		3 cars	3% (18)
		≥4 cars	2% (12)
No. of Transport card ownership	T02	No card	60% (414)
		1 card	31% (211)
		2 cards	8% (53)
		≥3 cards	1% (4)
Walking distance to nearest station	T03	<400 meter	29% (202)
		400-1000 meter	44% (298)
		>1000 meter	27% (182)

According to the socio-demographic characteristics of the responses, the majority were women (63%) and men (37%). The majority of respondents were between the ages of 18-24 and 25-26 years old (25% and 26%, respectively), with 42% having bachelor's degrees and 32% having high school education. Most of them were employed (58%), including government officials, state enterprise employees, and private company employees. In terms of Bangkok's population in 2020, the total population was 8,854,718, of which women made up 52 percent [88]. However, the population represented in this research consists of residents and travelers in the area of the mass transit station. This may be a different circumstance in relation to Bangkok's general population. In the previous research on the demographics of people residing in the station area, respondents with comparable characteristics were also uncovered. It was discovered that the majority of the respondents were female (62.8 percent), with 58.7 percent of car ownership [168].

The residential characteristics of the respondents were found that the majority lived in 2-3 people (30% and 26%, respectively), apartments (33%), and single houses (38%) preferred to live the most. Most are rented by 47% and owned by 45%. Consequently, 45% are not pay for housing costs per month. In terms of travel characteristics, 50% of respondents had no vehicle, 32% had one vehicle, 60% had no transport card, and only 31% had one transport card. Transport cards have been operated independently by operators in mass transit systems due to the mass transit system's non-success in integrating transport card systems in 2020. I''s possible for the respondent to carry more than one card in case the system has to be transferred. All the card types were available, including the MRT and MRT Plus, Rabbit, Smart Pass, and Mangmoom cards.

6.3.3 Behavior Change

From the survey, it was found that the COVID-19 pandemic has resulted in changes in socio-demographic and travel behavior. As seen in Table 6-2, the change in socio-demographic income pre and during COVID-19 showed the income range of 0–18000 THB (0–600 USD) per month increased by 3%, which shows an overall income affected by COVID-19. Nonetheless, the middle and high-income range of more than 18000 THB (> 600 USD) per month was decreased from pre-COVID-19 in total by 3%. Note that the average household income per month in the Bangkok Metropolitan Region in 2019 (pre-

COVID-19) was 37,751 THB (1256.48 USD) [176]. When compared to the pre-COVID-19 pandemic period, it was discovered that commuting to work at the office or factory was reduced by 2% and overall work outside was reduced by 4%, which consequently work from home increased by 4%. Other places/workplaces weren't different from pre-COVID-19.

Table 6-3 Behavior changes characteristic of respondents

Description	Categorical	Pre-COVID-19		During COVID-19	
		Variable	Percentage (n)	Variable	Percentage (n)
Change in socio-demographic					
Income/month	<7500 THB	S15	15% (102)	S25	16% (110)
	7501-18000 THB		42% (286)		44% (298)
	18001-24000 THB		22% (150)		21% (142)
	24001-35000 THB		13% (88)		12% (82)
	35001-50000 THB		4% (28)		4% (26)
	50001-85000 THB		2% (18)		2% (17)
	85001-160000 THB		1% (6)		0% (3)
	>160000 THB		1% (4)		1% (4)
Place of work	Office/Factory	S16	56% (387)	S26	54% (363)
	Home		9% (61)		13% (87)
	Coffee shop		2% (12)		1% (10)
	Field site		2% (11)		1% (10)
	Co-working space		0% (1)		0% (1)
	Other/no		31% (210)		31% (211)

6.3.4 Travel Behavior Change

The survey is divided into two parts: travel characteristics before the pandemic (pre-COVID-19) and travel characteristics during the pandemic (during-COVID-19). Change in travel behavior from the sample was collected by trip characteristics to explain daily trips (one-way trip) on the weekday or usual trip. It was shown that most people travel 4-6 trips per week (65%) and 0-3 trips per week (20%). However, people reduced overall weekly trip frequency more during the COVID-19 pandemic, resulting in a 5% increase in 0–3 trips per week compared to before the outbreak. It was shown that most people travel 4-6 times per week (65%) and 0-3 times per week (20%). Furthermore, people reduced overall weekly trip frequency more during the COVID-19 pandemic, resulting in a 5% increase in 0–3 trips per week compared to before the outbreak. As a result of the number of trips per day, it was found that 93% traveled 0–2 trips per day during the pre-COVID-19 and 94.6% during the COVID-19 pandemic, with the number of trips per day decreasing from 7% to 6% (see Table 6-4).

Table 6-4 Behavior changes characteristic of respondents (Cont.)

Description	Categorical	Pre-COVID-19		During COVID-19	
		Variable	Percentage (n)	Variable	Percentage (n)
Change in travel behavior					
Trip frequency	0-3 trips/week	T14	20% (139)	T24	25% (171)
	4-6 trips/week		65% (442)		61% (418)
	7-9 trips/week		4% (29)		4% (24)
	≥10 trips/week		11% (72)		10% (69)
Number of trips	0-2 trips/day	T15	93% (634)	T25	94% (642)
	3-4 trips/day		7% (46)		6% (38)
	≥5 trips/day		0% (2)		0% (2)
Number of transfers	0-1 times/day	T16	0% (0)	T26	0% (0)
	2-3 times/day		13% (85)		15% (100)
	4-5 times/day		44% (302)		44% (301)
	6-7 times/day		37% (251)		36% (246)
	8-9 times/day		6% (41)		5% (35)
	≥10 times/day		0% (3)		0% (0)
Travel time	0-30 min/day	T17	7% (50)	T27	8% (57)
	31-60 min/day		31% (212)		33% (227)
	61-90 min/day		26% (179)		25% (167)
	91-120 min/day		17% (117)		16% (111)
	121-180 min/day		13% (87)		13% (86)
	>180 min/day		6% (37)		5% (34)
Travel cost	0-50 THB/day	T18	28% (193)	T28	31% (209)
	51-100 THB/day		50% (338)		48% (327)
	101-150 THB/day		15% (99)		14% (96)
	>150 THB/day		7% (52)		7% (50)

Respondent'' commute trips generally necessitate transfers within mode and multi-mode for access to the main mode of travel per trip. According to the results of the survey, 44% of the trips in one day were transferred between 4-5 times per day and 6-7 times per day by 37% in the pre-COVID-19 period. During the pandemic, people tried to reduce travel and mode transfer by 2-3 transfer times per day by increasing 2%. Respondents who spent 31–60 minutes on all commuting trips per day were 31%, while those who spent 61–90 minutes on all commuting trips per day were 26% in the pre-COVID-19 period. During the COVID-19 period, people who spent time travelling more than 60 minutes on all commuting trips per day reduced their time by 3%. Hence, people who travel less than 60 minutes on all commuting trips per day increased by 3%. As a consequence of overall travel time, respondents who were spending 51–100 THB (1.67-3.33 USD) per day were 50 % and those spending 0–50 THB (0-1.67 USD) per day were 28%. However, during the COVID-19 period, people who spend more than 50 THB (>1.67 USD) per day on travel reduced by 3%, whereas those who spent 0–50 THB (0-1.67 USD) per day on travel increased by 3%.

On the commuting or usual trip, there are possibly being more than 1 purpose during a commuting trip. The main trip purpose of this study is divided into 6 purposes as 1) school/work purpose (SW) 2) shopping/eating/exercise purpose (SH) 3) visit purpose (VS) 4) personal business purpose (PB) 5) home purpose (HM) 6) other purposes (OT). According to the survey results, 94% of the sample was traveling for 1 trip purpose with 74% of respondents commuting mainly for work or school, with approximately 2% reduction in travel during the COVID-19 pandemic. The decrease in travel might be due to work from home increased, as shown in the shopping and recreation trips by 10% of the pre-COVID-19 period and increased to 12% during the pandemic. The traveling for 2 purposes per day (6% of the sample) was slightly changed compared with pre and during COVID-19 periods such as commuting to work/school with shopping/eating/exercise purposes (SW+SH+HM), work/school with a personal business purpose (SW+PB+HM), and other with shopping/eating/exercise purposes (OT+SH+HM). However, there is no difference in percentage change of traveling for three purposes per day (see Table 6-5 and Figure 6-2).

Table 6-5 Trip purpose characteristic of respondents

Description	**Categorical**	**Pre-COVID-19**		**During COVID-19**	
		Number of samples	**Percentage (%)**	**Number of samples**	**Percentage (%)**
1 purpose	SW+HM	507	74%	489	72%
	SH+HM	66	10%	82	12%
	VS+HM	4	1%	7	1%
	PB+HM	48	7%	52	7%
	OT+HM	14	2%	17	2%
2 purposes	SW+SH+HM	23	3%	19	3%
	SW+VS+HM	1	0%	1	0%
	SW+PB+HM	7	1%	4	1%
	SH+SW+HM	1	0%	1	0%
	SH+SH+HM	3	1%	3	1%
	VS+SH+HM	1	0%	1	0%
	PB+SW+HM	1	0%	1	0%
	PB+SH+HM	3	1%	3	1%
	OT+SH+HM	2	0%	1	0%
3 purposes	PB+HM+SH+HM	1	0%	1	0%

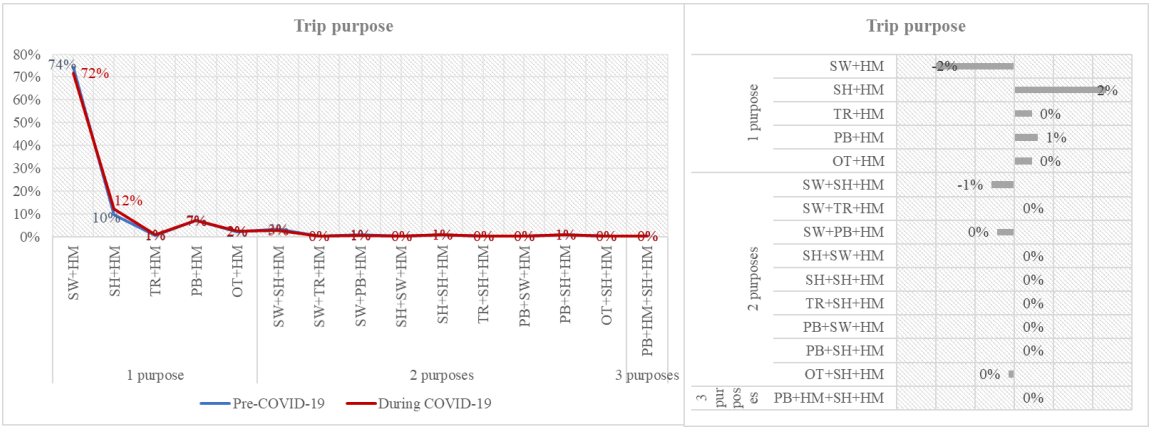


Figure 6-2 Comparison of trip purpose on pre-COVID-19 (TP1) and during COVID-19 period (TP2)

Referring to the study area, available on travel mode was divided into 18 modes from the questionnaire survey that cover all transport modes in Bangkok metropolitan areas. This study focuses on transportation accessibility characteristics. Therefore, shares of traveling mode are divided into five categories as follows:

1) Non-motorized (NM): including walk and bicycle
2) Motorized (MO): including private car and motorcycle
3) Paratransit (PR): including motorcycle taxi and private car taxi
4) Feeder transit (FD): including bus, BRT, passenger van, Chao Phraya Express boat, Khlong boat, and local train
5) Mass transit (MT): including BTS dark green line, BTS light green line, MRT blue line, MRT purple line, ARL airport rail link, and monorail gold line.

In the pre-COVID periods, respondents who used only one mode for travel per day were 45% of respondents and found that 20% used mass transit and 14% used feeder transit. However, during COVID-19 period the number of respondents using non-motorized modes increased from 2% to 3%, and those using paratransit by 1 %. Total 47 % of the respondents use 2 modes for travel per day pre-COVID-19, which decreased to 45 % during COVID-19. This demonstrated that people attempted to minimize their travel and transfer modes as much as possible to minimize meeting people while traveling and reduce their chances of contracting COVID-19. Respondents preferred to travel by personal vehicle (motorized) and mass transit by 24% and 23% of pre and during COVID-19 period respectively. In terms of feeder transit and mass transit, 15% of respondents indicated that there was traveled pre-COVID-19 and 14% traveled during COVID-19. Three modes of trip preference were not changed pre and during the COVID-19 outbreak, 8% of respondents travel 3 modes per day. This would be because the route of travelers does not have many options to travel and found that most of the people travel by motorized, feeder transit and mass transit by 7% of respondents, next was traveled by motorized, paratransit, and mass transit by 1% of respondents The detail of mode share as shown in Table 6-6 and Figure 6-3.

Table 6-6 Travel mode characteristic of respondents

Description	Categorical	Pre-COVID-19		During COVID-19	
		Number of samples	Percentage (%)	Number of samples	Percentage (%)
1 mode	Non-motorized (NM)	12	2%	21	3%
	Motorized (MO)	12	2%	12	2%
	Paratransit (PR)	46	7%	54	8%
	Feeder transit (FT)	92	14%	93	14%
	Mass transit (MT)	138	20%	139	20%
2 modes	MO+PR	2	0%	2	0%
	MO+FT	26	4%	26	4%
	MO+MT	166	24%	156	23%
	PR+FT	3	0%	3	0%
	PR+MT	27	4%	26	4%
	FT+MT	103	15%	96	14%
3 modes	MO+PR+FT	0	0%	0	0%
	MO+PR+MT	4	1%	3	1%
	MO+FT+MT	48	7%	48	7%
	PR+FT+MT	3	0%	3	0%

Note: *NM=non-motorized, MO=motorized, PR=paratransit, FT=feeder transit, MT=mass transit

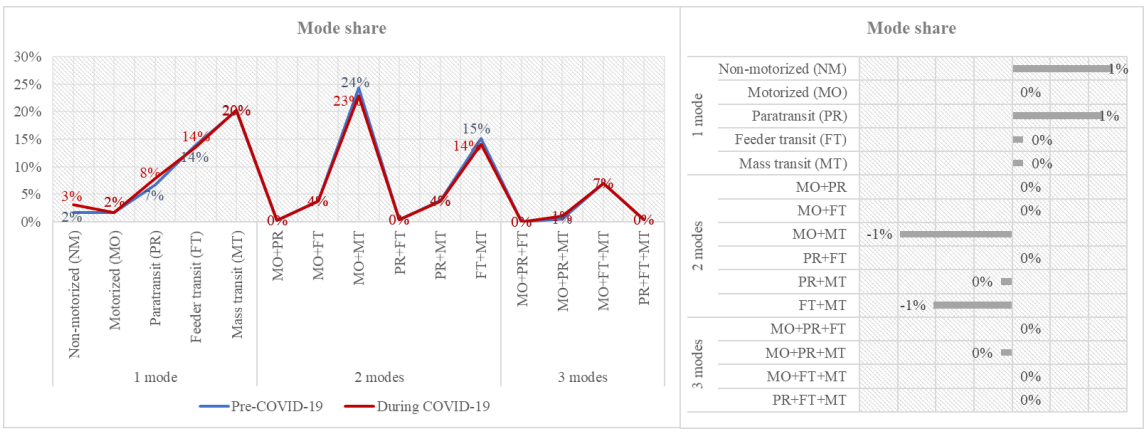


Figure 6-3 Comparison of mode share on pre-COVID-19 (TM1) and during COVID-19 period (TM2)

6.3.5 Attitude Change

This study considered attitude questions to quantify the attitude related to relocation and travel behavior effects on residents and traveler near mass transit stations. The attitude change factor affected by COVID-19 has been collected, including 8 statements: attitude toward residential location area (3 statements), attitude toward residential accessibility (3 statements), and attitude toward concern of COVID-19 (2 statements), divided into pre and during COVID-19 questions. All attitudes are considered using a 5-point Likert scale (5 = Strongly agree to 1 = Strongly disagree). Reliability analysis for attitude was between 0.78 and 0.96, as shown in Table 6-7. However, Cronbach's alpha value of more than 0.7 is generally accepted on a moderately to excellently reliable scale.

The result of the attitude toward residential location areas found that attitude of prefer to live in an urban area more prefer in during COVID-19 period, residential area and rural area not differed of pre and during the COVID-19 period. Considering that during pandemic situations it is difficult to access hospitals due to hospital congestion and limited medical personnel, there is a possibility that people prefer to live in an urban area with more accessible neighborhood access, such as near a hospital and grocery store. Conversely, attitude toward residential accessibility of attitude prefers residential area near bus stops, which respondents more preferred. However, there was no change in preferred residential areas near mass transit stations, and highways or main roads before and after COVID-19. Nevertheless, the attitude toward concern of COVID-19 was found to be more concerning in terms of the respondent'' choice to not choose to live in an urban area due to concerns about infection and about infection concerns when using public transport.

Table 6-7 Attitude change on pre-COVID-19 and during COVID-19 period

Factor	Pre-COVID-19				During COVID-19			
	Variables	α[1]	Median	SD	Variables	α[1]	Median	SD
Attitude toward residential location area								
Prefer to live in urban area.	1UrbanArea	0.798	3	0.78	2UrbanArea	0.790	4	0.80
Prefer to live in residential areas.	1ResidentialArea	0.797	4	0.80	2ResidentialArea	0.791	4	0.86
Prefer to live in rural area.	1RuralArea	0.810	4	0.91	2RuralArea	0.806	4	0.94
Attitude toward residential accessibility								
Prefer residential area near mass transit station.	1MassTransit	0.793	4	0.80	2MassTransit	0.789	4	0.87
Prefer residential area near bus stop.	1BusStop	0.792	3	0.84	2BusStop	0.789	4	0.90
Prefer residential area near highways or main roads.	1Highway	0.795	4	0.95	2Highway	0.791	4	0.93
Attitude toward concern of COVID-19								
Not choosing to live in an urban area due to concern about infection.	1UrbanConcern	0.802	3	0.85	2UrbanConcern	0.797	4	0.91
Worried about infection concerns to use public transport.	1pTconcern	0.808	3	0.88	2pTconcern	0.802	4	0.96

Note: [1] Cronbach's Alpha

6.4 Decision Tree Analysis

In this study, the decision on attitude change was analyzed by using decision trees of the CHAID algorithm to identify the segmentation of traveler and resident characteristics near the mass transit station. The CHAID algorithm was analyzed using IBM SPSS version 26 to develop a decision tree. CHAID's algorithm performs a sequence of merging, splitting, and stopping processes based on user-defined criteria such as chi-square test significance level, minimum node or segment size, and maximum tree depth level [71]. The CHAID in this study specification for developing a tree used user-specified split model criteria, including: 1) the significant level for splitting nodes and merging is set at 0.05, 2) the number of cases for parent nodes is limited to 50, and 3) the minimum number of instances for a child node is set at ten. Meanwhile, the maximum tree depth level is controlled by the minimum segment size. A 10-fold cross-validation approach was applied to estimate the model's misclassification risk. Nevertheless, the accuracy and detection of CHAID were represented as a percentage.

The research hypothesis was to explore the characteristics of travelers and residents around mass transit stations under the attitude affected by COVID-19 and what the relationship between the independent variables is at each level of the dependent variable. Dependent variables were determined by attitude factor. Eight factors were applied by one factor for each model. However, to consider attitude in a positive and negative way due to the under consideration of segment analysis, the dichotomous choice was applied. This scale allows determining the level of agreement or disagreement of respondents. From 5 likely scales (5=Strongly agree to 1=Strongly disagree) was transferred to positive (scale 5 and 4) and negative scale (scale 3, 2, and 1). The model divided the pre-COVID and during COVID-19 using a single decision tree with a total of 20 independent variables and 1 dependent variable.

6.4.1 Segmentation by Attitude Toward Residential Location Area

The CHAID tree of attitude toward residential location areas is divided into 3 models. 1) Prefer to live in urban area, 2) Prefer to live in residential areas, and 3) Prefer to live in rural area. The tree analysis results in Figure 6-4 and Table 6-8 shows relevant segmentation of attitude toward residential location area and decision rule for terminal node. The result from CHAID model shown in APPENDIX 8.3.1.

Prefer to live in urban area

Attitude toward prefer to live in urban area in pre-COVID-19 consists of 8 nodes, 3 levels, 5 terminal nodes, and 2 branches classified by the number of transport card ownership (T02) as the most important variables. The importance segment is terminal 3 by the segment of level 1 by variable T02 (0, 2, and ≥3 cards) and level 2 by variable R03 (Rent and Owner) by 65.2 percent of respondents with the highest proportion of 51.5 percent prefer to live in urban area. During COVID-19 consist of 14 nodes, 5 levels, 8 terminal nodes, and 2 branches classified by the number of transport card ownership (T02). The terminal 7 presented the most important segment of level 1 by variables T02 (1 card) and level 2 by variable S16 (Home and Office/Factory) by 22.9 percent of respondents with the highest proportion of 72.4 percent prefer to live in urban area.

Prefer to live in residential areas

Attitude toward prefer to live in residential areas in pre-COVID-19 consists of 16 nodes, 4 levels, 9 terminal nodes, and 3 branches classified by travel cost/ day (T18) as the most important variables. The importance segment is terminal 8 by the segment of level 1 by variable T18 (101-150 and >150 THB) and level 2 by variable R03 (Rent and Owner) by 19.1 percent of respondents with the highest proportion of 70 percent prefer to live in residential area. During COVID-19 consist of 11 nodes, 4 levels, 6 terminal nodes, and 2 branches classified by the number of transport card ownership (T02). The terminal 7 presented the most important segment of level 1 by variables T02 (0 and 2 cards), level 2 by variable T03 (<400 and 400-1000 meter) and level 3 by variable R02 (Apartment and Single home) by 37.1 percent of respondents with the highest proportion of 43.1 percent prefer to live in residential area.

Prefer to live in rural area

Attitude toward prefer to live in rural area in pre-COVID-19 consists of 7 nodes, 2 levels, 4 terminal nodes, and 2 branches classified by travel time/day (T14) as the most important variables. The importance segment is terminal 3 by the segment of level 1 by variable T14 (0-3, 4-6 and 7-9 times/week) and level 2 by variable R02 (Apartment, Single home, and Condominium) by 70.7 percent of respondents with the highest proportion of 70 percent prefer to live in rural area. During COVID-19 consist of 11 nodes, 4 levels, 6 terminal nodes, and 2 branches classified by type of residential (R02). The terminal 6 represented the most important segment of level 1 by variables R02 (Apartment, Single home, and Condominium) level 2 by variable T03 (<400 and 400-1000 meter) and level 3 by variable T24 (4-6 and ≥10 times/week) by 41.2 percent of respondents with the highest proportion of 48.4 percent prefer to live in rural area.

The results of attitude toward residential location areas demonstrate that the number of transport card ownership was the most important variable in splitting segments in attitude toward prefer to live in urban area on pre-COVID and during COVID-19 period. However, attitude toward prefer to live in urban area in the pre-COVID-19 period found that travel cost and property ownership were given more priority than during COVID-19. Conversely, during COVID-19, it was found that walking distance to the nearest station, place of work, and trip frequency were more important than pre-COVID-19. For attitude toward prefer to live in residential area were found travel cost/day and the number of transport card ownership are most important variable to splitting segment on pre-COVID-19 and during COVID-19 respectively. The variable difference between attitude toward prefer to live in urban and residential areas is education and the type of residential that is related to those who prefer to live in residential area. Additionally, attitude toward prefer to live in rural area in the pre-COVID-19 period found trip frequency more important variable. Meanwhile, during the COVID-19 period, the type of residential was more important to consider.

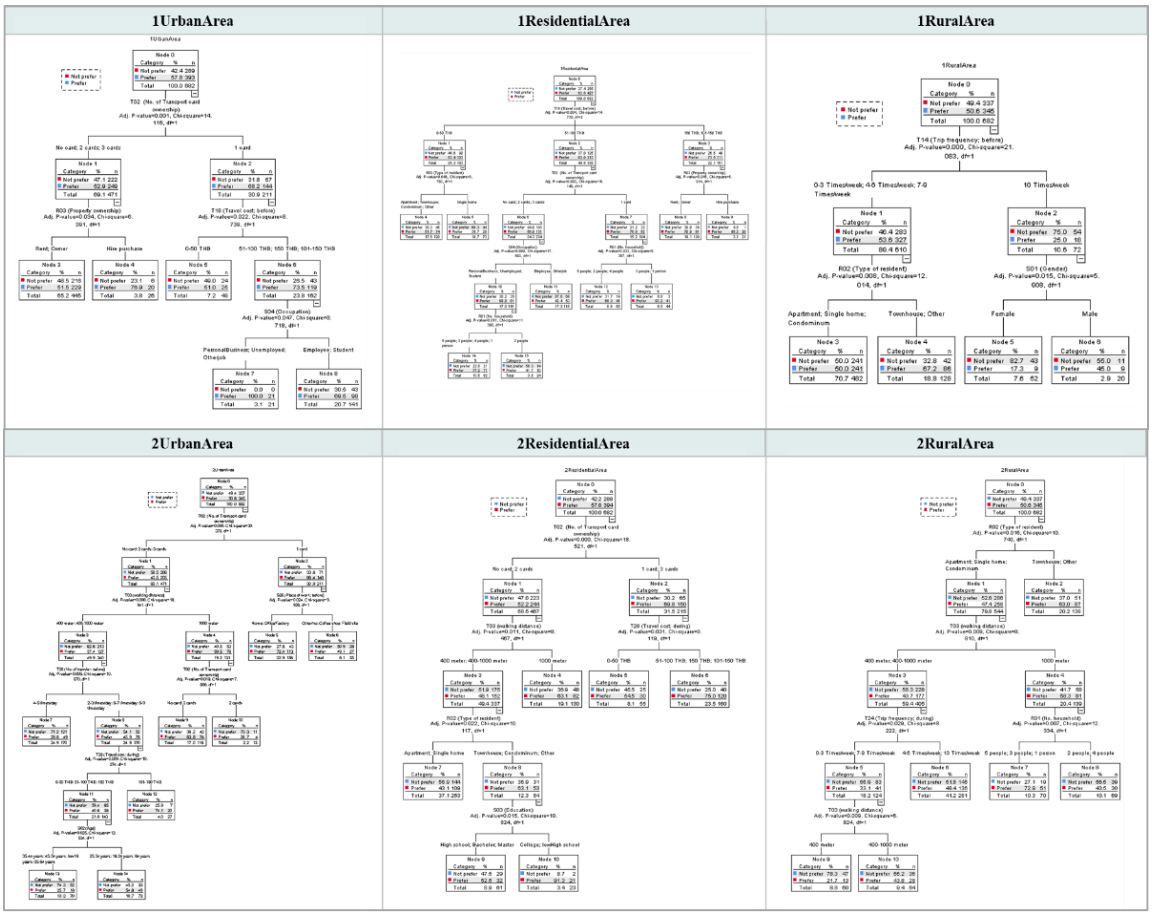


Figure 6-4 Decision tree map of attitude toward residential location areas pre-COVID-19 and during COVID-19

Table 6-8 Relevant segmentation of attitude toward residential location area and decision rule for terminal node

Factor	Node	Level 1	Level 2	Level 3	Level 4	Level 5	% N (n)	% Prefer (n)
1UrbanArea	3	T02; 0, 2, ≥3 cards	R03; Rent, Owner				65.2 (445)	51.5 (229)
	4	T02; 0, 2, ≥3 cards	R03; Hire purchase				3.8 (26)	76.9 (20)
	5	T02; 1 card	T18; 0-50 THB				7.2 (49)	51.0 (25)
	7	T02; 1 card	T18; 51-100, 101-150, >150 THB	S04; Personal Business, Unemployed, Other job			3.1 (21)	100 (21)
	8	T02; 1 card	T18; 51-100, 101-150, >150 THB	S04; Student			20.7 (141)	69.5 (98)
2UrbanArea	5	T02; 1 card	S16; Home, Office/Factory				22.9 (156)	72.4 (113)
	6	T02; 1 card	S16; Coffee shop, Other/no, Field site				8.1 (55)	49.1 (27)
	9	T02; 0, 2, ≥3 cards	T03; >1000 meter	T02; 0, ≥3 cards			17.0 (116)	60.8 (74)
	10	T02; 0, 2, ≥3 cards	T03; >1000 meter	T02; 2 cards			2.2 (15)	26.7 (4)
	7	T02; 0, 2, ≥3 cards	T03; <400, 400-1000 meter	T26; 4-5 times/day			24.9 (170)	28.8 (49)
	12	T02; 0, 2, ≥3 cards	T03; <400, 400-1000 meter	T26; 2-3, 6-7, 8-9 times/day	T28; 101-150 THB		4.0 (27)	74.1 (20)
	13	T02; 0, 2, ≥3 cards	T03; <400, 400-1000 meter	T26; 2-3, 6-7, 8-9 times/day	T28; 0-50, 51-100, >150 THB	S02; <18, 35-44, 45-54, 55-64 years	10.2 (70)	25.7 (18)
	14	T02; 0, 2, ≥3 cards	T03; <400, 400-1000 meter	T26; 2-3, 6-7, 8-9 times/day	T28; 0-50, 51-100, >150 THB	S02; 18-24, 25-34, >64 years	10.7 (73	54.8 (40)
1ResidentialArea	4	T18; 0-50 THB	R02; Apartment, Townhouse, Condominium, Other				17.6 (120)	61.7 (74)
	5	T18; 0-50 THB	R02; Single home				10.7 (73)	39.7 (29)
	8	T18; 101-150, >150 THB	R03; Rent, Owner				19.1 (130)	70.0 (91)
	9	T18; 101-150, >150 THB	R03; Hire purchase				3.1 (21)	95.2 (20)
	12	T18; 51-100 THB	T02; 1 card	R01; 2, 4, ≥5 peoples			8.8 (60)	68.3 (41)
	13	T18; 51-100 THB	T02; 1 card	R01; 1, 3 peoples			6.5 (44)	93.2 (41)
	11	T18; 51-100 THB	T02; 0, 2, ≥3 cards	S04; Employee, Other job			17.3 (118)	42.4 (50)
	14	T18; 51-100 THB	T02; 0, 2, ≥3 cards	S04; Personal Business, Unemployed, Student	R01; 1, 3, 4, ≥5 peoples		13.5 (92)	77.2 (71)
	15	T18; 51-100 THB	T02; 0, 2, ≥3 cards	S04; Personal Business, Unemployed, Student	R01; 2 peoples		3.4 (24)	41.7 (10)
2ResidentialArea	5	T02; 1, ≥3 cards	T28; 0-50 THB				8.1 (55)	54.5 (30)
	6	T02; 1, ≥3 cards	T28; 51-100, 101-150, >150 THB				23.5 (160)	75 (120)
	4	T02; 0, 2 cards	T03; >1000 meter				19.1 (130)	63.1 (82)
	7	T02; 0, 2 cards	T03; <400, 400-1000 meter	R02; Apartment, Single home			37.1 (253)	43.1 (109)
	9	T02; 0, 2 cards	T03; <400, 400-1000 meter	R02; Townhouse, Condominium, Other	S03; High school, Bachelor, ≥Master		8.8 (61)	52.5 (32)
	10	T02; 0, 2 cards	T03; <400, 400-1000 meter	R02; Townhouse, Condominium, Other	S03; >High school		3.4 (23)	91.3 (21)
1RuralArea	3	T14; 0-3, 4-6, 7-9 times/week	R02; Apartment, Single home, Condominium				70.7 (482)	50.0 (241)
	4	T14; 0-3, 4-6, 7-9 times/week	R02; Townhouse, Other				18.8 (128)	67.2 (86)
	5	T14; ≥10 times/week	S01; Female				7.6 (52)	17.3 (9)
	6	T14; ≥10 times/week	S01; Male				2.9 (20)	45.0 (9)
2RuralArea	2	R02; Townhouse, Other					20.2 (138)	63.0 (87)
	7	R02; Apartment, Single home, Condominium	T03; >1000 meter	R01; 1, 3, ≥5 peoples			10.3 (70)	72.9 (51)
	8	R02; Apartment, Single home, Condominium	T03; >1000 meter	R01; 2, 4 peoples			10.1 (69)	43.5 (30)
	6	R02; Apartment, Single home, Condominium	T03; <400, 400-1000 meter	T24; 4-6, ≥10 times/week			41.2 (281)	48.4 (136)
	9	R02; Apartment, Single home, Condominium	T03; <400, 400-1000 meter	T24; 0-3, 7-9 times/week	T03; <400 meter		8.8 (60)	21.7 (13)
	10	R02; Apartment, Single home, Condominium	T03; <400, 400-1000 meter	T24; 0-3, 7-9 times/week	T03; 400-1000 meter		9.4 (64)	43.8 (28)

6.4.2 Segmentation by Attitude Toward Residential Accessibility

The CHAID tree of attitude toward residential accessibility is divided into 3 models: 1) prefer residential areas near mass transit stations; 2) prefer residential areas near bus stops; and 3) prefer residential areas near highways or main roads. The tree analysis results in Figure 6-5 and Table 6-9 present relevant segmentation of attitude toward residential accessibility and decision rule for terminal node. The result from CHAID model shown in APPENDIX 8.3.2.

Prefer residential area near mass transit station

Attitude toward prefer residential area near mass transit station in pre-COVID-19 consists of 7 nodes, 3 levels, 4 terminal nodes, and 2 branches classified by trip frequency (T14) as the most important variables. The importance segment is terminal 3 by the segment of level 1 by variable T14 (0-3 and 4-6 times/week) and level 2 by variable T02 (0 and 3 cards) by 53.5 percent of respondents with the highest proportion of 67.1 prefer residential area near mass transit station. During COVID-19 consist of 17 nodes, 6 levels, 9 terminal nodes, and 2 branches classified by the number of transport card ownership (T02). The terminal 9 presented the most important segment of level 1 by variables T02 (1 and 2 cards), level 2 by variable T24 (0-3 and 4-6 times/week), and level 3 by variables R02 (Apartment, Townhouse, and Other) by 16.7 percent of respondents with the highest proportion of 92.1 percent prefer residential area near mass transit station.

Prefer residential area near bus stop

Attitude toward prefer residential area near bus stop in pre-COVID-19 consists of 9 nodes, 4 levels, 5 terminal nodes, and 2 branches classified by type of residential (R02) as the most important variables. The importance segment is terminal 2 by the segment of level 1 by variable R02 (Single home and Other) by 44.7 percent of respondents with the highest proportion of 60.0 prefer residential area near bus stop. During COVID-19 consist of 21 nodes, 6 levels, 11 terminal nodes, and 2 branches classified by walking distance to nearest station (T03). The terminal 5 presented the most important segment of level 1 by variables T03 (>1000 meter) and level 2 by variable R01 (1, 2, 3, and ≥5 peoples) by 22.0 percent of respondents with the highest proportion of 81.3 percent prefer residential area near bus stop.

Prefer residential area near highways or main roads.

Attitude toward prefer residential area near highways or main roads in pre-COVID-19 consists of 7 nodes, 3 levels, 4 terminal nodes, and 2 branches classified by trip frequency (T14) as the most important variables. The importance segment is terminal 3 by the segment of level 1 by variable T14 (4-6 times/week) and level 2 by variable T02 (0 and 2 cards) by 41.60 percent of respondents with the highest proportion of 52.8 prefer residential area near highways or main roads. During COVID-19 consist of 13 nodes, 4 levels, 7 terminal nodes, and 2 branches classified by property ownership (R03). The terminal 3 presented the most important segment of level 1 by variables R03 (Rent and Owner) and level 2 by variable T24 (0-3, 7-9, and ≥10 times/week) by 37.5 percent of respondents with the highest proportion of 42.4 prefer residential area near highways or main roads.

Overall, trip frequency and the number of transport card ownership were the most important variables in the split segment in attitude toward residential areas near mass transit during the pre-COVID and COVID-19 periods, respectively. Nonetheless, during COVID-19 it was shown that walking distance to the nearest station, the type of residential, the number of car ownership, and travel time all became significant variables. Interestingly, the attitude toward prefers residential area near bus stop pre-COVID-19, the number of households was not important. Furthermore, during COVID-19, it showed that the number of households, education, gender, and the number of transfers were significantly different from pre-COVID-19. Although attitudes toward prefer residential area near highways or main roads were explored, the walking distance to the nearest station was not related to the relationship pre and during COVID-19. However, trip frequency and property ownership are the most important variables in splitting segments in pre-COVID-19 and during COVID-19, respectively. Furthermore, the type of residential and trip purpose was crucial during the COVID-19 period.

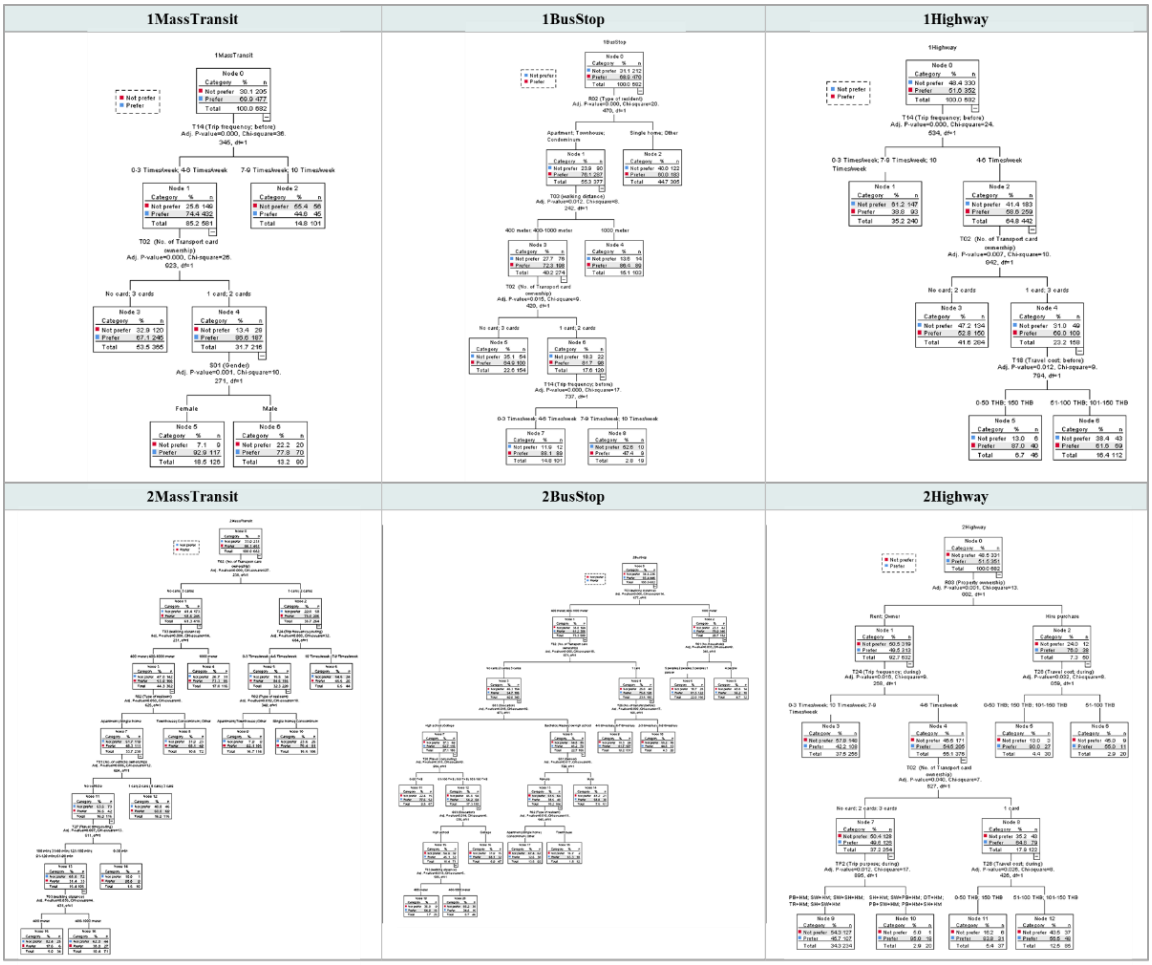


Figure 6-5 Decision tree map of attitude toward residential accessibility pre-COVID-19 and during COVID-19

Table 6-9 Relevant segmentation of attitude toward residential accessibility and decision rule for terminal node

Factor	Node	Level 1	Level 2	Level 3	Level 4	Level 5	Level 6	% N (n)	% Prefer (n)
1MassTransit	2	T14; 7-9, ≥10 times/week						14.8 (101)	44.6 (45)
	3	T14; 0-3, 4-6 times/week	T02; 0, 3 cards					53.5 (365)	67.1 (245)
	5	T14; 0-3, 4-6 times/week	T02; 1, 2 cards	S01; Female				18.5 (126)	92.6 (117)
	6	T14; 0-3, 4-6 times/week	T02; 1, 2 cards	S01; Male				13.2 (90)	77.8 (70)
2MassTransit	6	T02; 1, 2 cards	T24; 7-9, ≥10 times/week					6.5 (44)	45.5 (20)
	9	T02; 1, 2 cards	T24; 0-3, 4-6 times/week	R02; Apartment, Townhouse, Other				16.7 (114)	92.1 (105)
	10	T02; 1, 2 cards	T24; 0-3, 4-6 times/week	R02; Single home, Condominium				15.5 (106)	76.4 (81)
	4	T02; 0, ≥3 cards	T03; >1000 meter					17.0 (116)	73.3 (85)
	8	T02; 0, ≥3 cards	T03; <400, 400-1000 meter	R02; Townhouse, Condominium, Other				10.6 (72)	68.1 (49)
	12	T02; 0, ≥3 cards	T03; <400, 400-1000 meter	R02; Single home	T01; 1, 2, 3, 4 cars			16.9 (115)	60.0 (69)
	14	T02; 0, ≥3 cards	T03; <400, 400-1000 meter	R02; Single home	T01; 0 car	T27; 0-30 min		1.5 (10)	90.0 (9)
	15	T02; 0, ≥3 cards	T03; <400, 400-1000 meter	R02; Single home	T01; 0 car	T27; 31-60, 61-90, 91-120, 121-180, ≥180 min	T03; <400 meter	5.0 (34)	17.6 (6)
	16	T02; 0, ≥3 cards	T03; <400, 400-1000 meter	R02; Single home	T01; 0 car	T27; 31-60, 61-90, 91-120, 121-180, ≥180 min	T03; 400-1000 meter	10.3 (71)	38.0 (27)
1BusStop	2	R02; Single home, Other						44.7 (305)	60.0 (183)
	4	R02; Apartment, Townhouse, Condominium	T03; >1000 meter					15.1 (103)	86.4 (89)
	5	R02; Apartment, Townhouse, Condominium	T03; <400, 400-1000 meter	T02; 0, ≥3 cards				22.6 (154)	64.9 (100)
	7	R02; Apartment, Townhouse, Condominium	T03; <400, 400-1000 meter	T02; 1, 2 cards	T14; 0-3, 4-6 times/week			14.8 (101)	88.1 (89)
	8	R02; Apartment, Townhouse, Condominium	T03; <400, 400-1000 meter	T02; 1, 2 cards	T14; 7-9, ≥10 times/week			2.8 (19)	47.4 (9)
2BusStop	5	T03; >1000 meter	R01; 1, 2, 3, ≥5 peoples					22.0 (150)	81.3 (122)
	6	T03; >1000 meter	R01; 4 peoples					4.7 (32)	56.2 (18)
	9	T03; <400, 400-1000 meter	T02; 1 card	T26; 4-5, 6-7 times/day				19.2 (131)	81.7 (107)
	10	T03; <400, 400-1000 meter	T02; 1 card	T26; 2-3, 8-9 times/day				4.3 (29)	44.8 (13)
	11	T03; <400, 400-1000 meter	T02; 0, 2, ≥3 cards	S03; High school, College	T28; 0-50 THB			9.8 (67)	77.6 (52)
	14	T03; <400, 400-1000 meter	T02; 0, 2, ≥3 cards	S03; <High school, Bachelor, ≥Master	S01; Male			7.5 (51)	58.8 (30)
	16	T03; <400, 400-1000 meter	T02; 0, 2, ≥3 cards	S03; High school, College	T28; 51-100, 101-150, >150 THB	S03; College		6.9 (47)	68.1 (32)
	17	T03; <400, 400-1000 meter	T02; 0, 2, ≥3 cards	S03; <High school, Bachelor, ≥Master	S01; Female	R02; Apartment, Single home, Condominium, Other		13.4 (92)	32.6 (30)
	18	T03; <400, 400-1000 meter	T02; 0, 2, ≥3 cards	S03; <High school, Bachelor, ≥Master	S01; Female	R02; Townhouse		1.8 (12)	83.3 (10)
	19	T03; <400, 400-1000 meter	T02; 0, 2, ≥3 cards	S03; High school, College	T28; 51-100, 101-150, >150 THB	S03; High school	T03; 400 meters	3.7 (25)	64.0 (16)
	20	T03; <400, 400-1000 meter	T02; 0, 2, ≥3 cards	S03; High school, College	T28; 51-100, 101-150, >150 THB	S03; High school	T03; 400-1000 meter	6.7 (46)	34.8 (16)
1Highway	1	T14; 0-3, 7-9, ≥10 times/week						35.2 (240)	38.8 (93)
	3	T14; 4-6 times/week	T02; 0, 2 cards					41.60 (284)	52.8 (150)
	5	T14; 4-6 times/week	T02; 1, ≥3 cards	T18; 0-50, >150 THB				6.7 (46)	87.0 (40)
	6	T14; 4-6 times/week	T02; 1, ≥3 cards	T18; 51-100, 101-150 THB				16.5 (112)	61.6 (69)
2Highway	3	R03; Rent, Owner	T24; 0-3, 7-9, ≥10 times/week					37.5 (256)	42.4 (108)
	5	R03; Hire purchase	T28; 0-50, 101-150, >150 THB					4.4 (30)	90.0 (27)
	6	R03; Hire purchase	T28; 51-100 THB					2.9 (20)	55.0 (11)
	9	R03; Rent, Owner	T24; 4-6 times/week	T02; 0, 2, ≥3 cards	TP2; SW+HM, PB+HM, VS+HM, SW+SH+HM, SH+SW+HM			34.3 (234)	45.7 (107)
	10	R03; Rent, Owner	T24; 4-6 times/week	T02; 0, 2, ≥3 cards	TP2; SH+HM, OT+HM, SW+PB+HM, PB+SW+HM, PB+HM+SH+HM			2.9 (20)	95.0 (19)
	11	R03; Rent, Owner	T24; 4-6 times/week	T02; 1 card	T28; 0-50, >150 THB			5.5 (37)	83.8 (31)
	12	R03; Rent, Owner	T24; 4-6 times/week	T02; 1 card	T28; 51-100, 101-150 THB			12.5 (85)	56.5 (48)

6.4.3 Segmentation by Attitude Toward Concern of COVID-19

The attitude tree of attitude toward concern of COVID-19 was constructed for attitude toward not choosing to live in an urban area due to concern about infection and attitude toward worried about infection concerns to use public transport. The overall result from CHAID model shown in APPENDIX 8.3.3. The result of each attitude decision tree is described as follows:

The CHAID analysis results of attitude toward not choosing to live in an urban area due to concern about infection by pre-COVID-19 consists of 9 nodes, 3 levels, 5 terminal nodes, and 2 branches classified by the number of transport cards owned (T02) represented the most important variables. Terminal 3 is the highest proportion of agreeing to prefer not choosing to live in an urban area due to concern about infection by 49.4 percent of respondents and agree with percent 49.3 of attitude. The segment decision rule is sorted by level 1 by variable T02 (0 and 2 cards) and level 2 by variable T03 (<400 and 400-1000 meters). During the COVID-19 period, the tree result consisted of 7 nodes, 3 levels, 4 terminal nodes, and 2 branches classified by walking distance to the nearest station (T03), the most important variable in the decision tree. The highest proportion was demonstrated by 73.3 percent of respondents in terminal 1 of level 1 by variable T03 (<400 and 400-1000 meters), who agreed with 57.2 percent of the attitude. Nevertheless, the difference in the decision tree showed that the type of residential in pre-COVID-19 was an important variable, whereas travel time demonstrated an important variable during COVID-19, as shown in Table 6-10 and Figure 6-6. Based on the validation sample of the decision tree technique, the CHAID algorithm has an accuracy of 59.1 percent before and 62.0 percent during COVID-19, respectively.

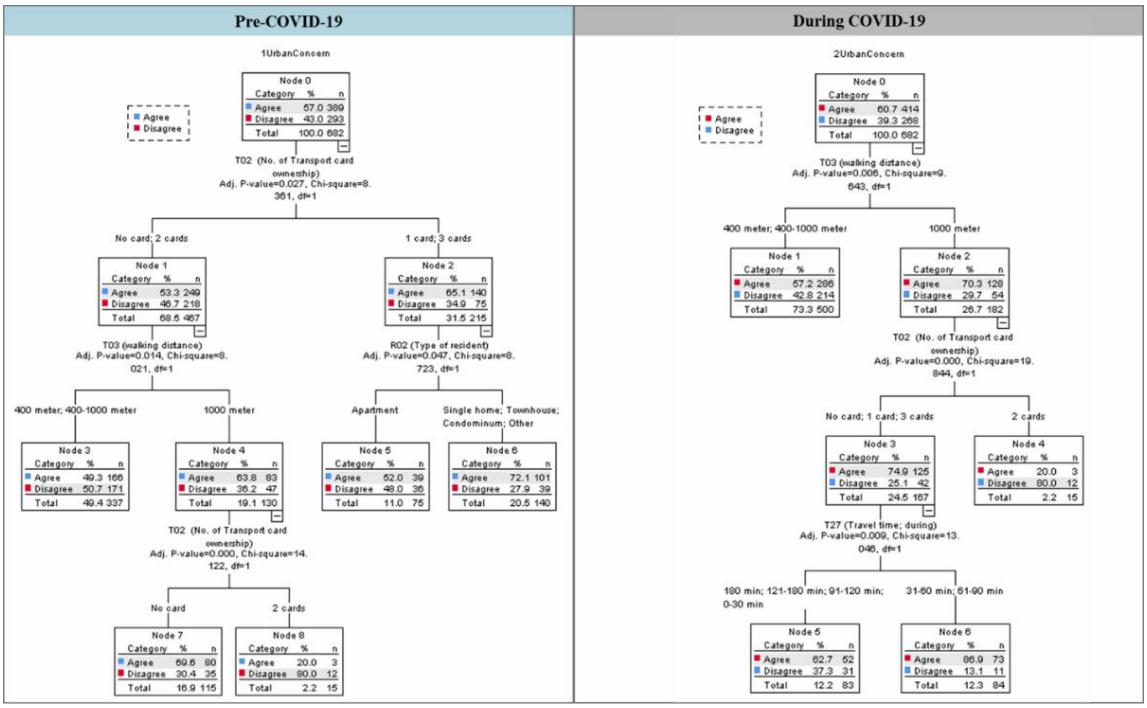


Figure 6-6 Decision tree map of attitude toward not choosing to live in an urban area due to concern about infection

The CHAID analysis results of attitude toward worried about infection concerns to use public transport pre-COVID-19 consisted of 11 nodes, 4 levels, 6 terminal nodes, and 2 branches classified by trip frequency (T14) were the most important variables. The highest proportion is illustrated on terminal 8 on the segment decision rule of level 1 by variable T14 (0-3 and 4-6 times/week), level 2 by variable R03 (Rent and Owner), level 3 by variable S16 (Home, Office/Factory, Coffee Shop, and Co-working space), and level 4 by variable R03 (Owner), as represented by 26.0 percent of respondents and agreeing with 62.7 percent of the attitude toward worried about infection concerns to use public transport. The tree result during the COVID-19 period consists of 9 nodes, 4 levels, 5 terminal nodes, and 2 branches classified by type of residential (R02), which was the most important variable. The segment of terminal 3 had the highest proportion of 59.4 percent of respondents and agreed with the percent 54.6 attitude and segment decision rule shown on level 1 by variable R02 (Apartment, Single home, and Condominium) and level 2 by variable T03 (<400 and 400-1000 meters). Nevertheless, the difference in the decision tree showed that property ownership, place of work, and gender in pre-COVID-19 became important variables, whereas type of residential, walking distance to the nearest station, and number of transport card ownership were important variables during COVID-19, as shown in Table 6-10 and Figure 6-7. The CHAID algorithm of attitude toward worried about infection concerns toward using public transport has an accuracy of 62.3 and 63.9 percent before and after COVID-19, respectively.

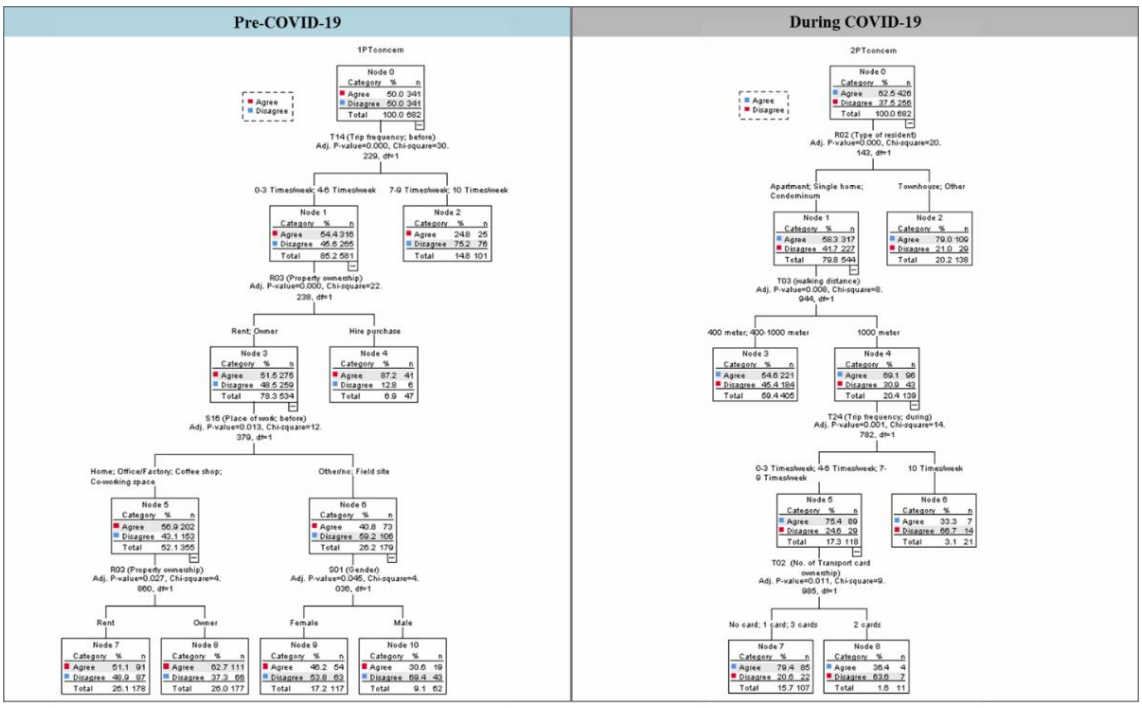


Figure 6-7 Decision tree map of attitude toward worried about infection concerns to use public transport

Table 6-10 Relevant segmentation of attitude toward not choosing to live in an urban area due to concern about infection and attitude toward worried about infection concerns to use public transport with decision rule for terminal node

Factor	Node	Level 1	Level 2	Level 3	Level 4	% N (n)	% Agree (n)
Attitude toward not choosing to live in an urban area due to concern about infection							
1UrbanConcern	3	T02; 0, 2 cards	T03; < 400, 400-1000 m			49.4 (337)	49.3 (166)
	5	T02; 1, ≥3 cards	R02; Apartment			11.0 (75)	52.0 (39)
	6	T02; 1, ≥3 cards	R02; Single home, Townhouse, Condominium, Other			20.5 (140)	72.1 (101)
	7	T02; 0, 2 cards	T03; >1000 m	T02; 0 card		16.9 (115)	69.6 (80)
	8	T02; 0, 2 cards	T03; >1000 m	T02; 2 cards		2.2 (15)	80.0 (12)
2UrbanConcern	1	T03; < 400, 400-1000 m				73.3 (500)	57.2 (286)
	4	T03; >1000 m	T02; 2 cards			2.2 (15)	20.0 (3)
	5	T03; >1000 m	T02; 0, 1, ≥3 cards	T27; 0-30, 91-120, 121-180, ≥180 min		12.2 (83)	62.7 (52)
	6	T03; >1000 m	T02; 0, 1, ≥3 cards	T27; 31-60, 61-90 min		12.3 (84)	86.9 (73)
Attitude toward worried about infection concerns to use public transport							
1pTconcern	2	T14; 7-9, ≥10 times/week				14.8 (101)	24.8 (25)
	4	T14; 0-3, 4-6 times/week	R03; Hire purchase			6.9 (47)	87.2 (41)
	7	T14; 0-3, 4-6 times/week	R03; Rent, Owner	S16; Home, Office/Factory, Coffee shop, Co-working space	R03; Rent	26.1 (178)	51.1 (91)
	8	T14; 0-3, 4-6 times/week	R03; Rent, Owner	S16; Home, Office/Factory, Coffee shop, Co-working space	R03; Owner	26.0 (177)	62.7 (111)
	9	T14; 0-3, 4-6 times/week	R03; Rent, Owner	S16; Other/no, Field site	S01; Female	17.2 (117)	46.2 (54)
	10	T14; 0-3, 4-6 times/week	R03; Rent, Owner	S16; Other/no, Field site	S01; Male	9.1 (62)	30.6 (19)
2pTconcern	2	R02; Townhouse, Other				20.2 (138)	79.0 (109)
	3	R02; Apartment, Single home, Condominium	T03; <400, 400-1000 m			59.4 (405)	54.6 (221)
	6	R02; Apartment, Single home, Condominium	T03; >1000 m	T24; ≥10 times/week		3.1 (21)	33.3 (7)
	7	R02; Apartment, Single home, Condominium	T03; >1000 m	T24; 0-3, 4-6, 7-9 times/week	T02; 0, 1, ≥3 cards	15.7 (107)	79.4 (85)
	8	R02; Apartment, Single home, Condominium	T03; >1000 m	T24; 0-3, 4-6, 7-9 times/week	T02; 2 cards	1.6 (11)	36.4 (4)

The CHAID decision tree was used to determine the segmentation characteristics profile of travelers and residences in the surrounding of mass transit stations with the highest accessibility of travel modes. The CHAID modeling developed provided segmentation of the relationship between the independent variable and the attitude dependent variable. Gender, place of work, number of transport card ownership, walking distance to the nearest station, type of residential, property ownership, trip frequency, and travel cost are among the variables having the same correlation in all models of the pre-COVID-19 and COVID-19 periods.

Furthermore, prior to COVID-19, occupation variables were found to have an effect on attitudes toward preferring to live in urban areas and prefer to live in residential areas. However, during COVID-19 period revealed that other variables related to attitude as follow, age on prefer to live in urban area attitude, education on prefer to live in residential areas and prefer residential area near bus stop attitude, number of vehicle ownership on prefer residential area near mass transit station attitude, number of transfers on prefer to live in urban area and prefer residential area near bus stop attitude, travel time on prefer residential area near mass transit station and not choosing to live in an urban area due to concern about infection attitude, and trip purpose on prefer residential area near highways or main roads. Table 6-11 provided a summary of the model, describing the important variables by segment for all decision trees pre and during COVID-19, as well as the accuracy demonstrated by the model's overall percent correct.

Table 6-11 Summary of the node level and p-value of relevant variables of decision tree pre and during COVID-19 period

Independent variables	Attitude toward residential location area			Attitude toward residential accessibility			Attitude toward concern of COVID-19	
Pre-COVID-19	**1Urban Area**	**1ResidentialArea**	**1Rural Area**	**1Mass Transit**	**1Bus Stop**	**1Highway**	**1Urban Concern**	**1PT concern**
S01			2 (0.015)	3 (0.001)				4 (0.045)
S04	3 (0.047)	3 (0.000)						
S16								3 (0.013)
T02	1 (0.001)	2 (0.000)		2 (0.000)	3 (0.015)	2 (0.007)	1 (0.027), 3 (0.000)	
T03					2 (0.012)		2 (0.014)	
R01		3 (0.033), 4 (0.011)						
R02		2 (0.046)	2 (0.008)		1 (0.000)		2 (0.047)	
R03	2 (0.034)	2 (0.045)						2 (0.000), 4 (0.027)
T14			1 (0.000)	1 (0.000)	4 (0.000)	1 (0.000)		1 (0.000)
T18	2 (0.022)	1 (0.004)				3 (0.012)		
Overall correct	**57.6%**	**68.0%**	**55.9%**	**71.6%**	**69.1%**	**59.5%**	**59.1%**	**62.3%**
Number of nodes	**9**	**16**	**7**	**7**	**9**	**7**	**9**	**11**
Number of terminals	**5**	**9**	**4**	**4**	**5**	**4**	**5**	**6**
During COVID-19	**2Urban Area**	**2ResidentialArea**	**2Rural Area**	**2Mass Transit**	**2Bus Stop**	**2Highway**	**2Urban Concern**	**2PT concern**
S01					4 (0.017)			
S02	5 (0.025)							
S03		4 (0.015)			3 (0.018), 5 (0.018)			
S26	2 (0.024)							
T01				4 (0.006)				
T02	1 (0.000), 3 (0.018)	1 (0.000)		1 (0.000)	2 (0.000)	3 (0.040)	2 (0.000)	4 (0.011)
T03	2 (0.000)	2 (0.011)	2 (0.009), 4 (0.009)	2 (0.000), 6 (0.035)	1 (0.000), 6 (0.018)		1 (0.006)	2 (0.008)
R01			3 (0.007)		2 (0.033)			
R02		3 (0.022)	1 (0.016)	3 (0.050), 3 (0.019)	5 (0.010)			1 (0.000)
R03						1 (0.001)		
T24			3 (0.029)	2 (0.000)		2 (0.024)		3 (0.001)
T26	3 (0.008)				3 (0.000)			
T27				5 (0.007)			3 (0.009)	
T28	4 (0.009)	2 (0.031)			4 (0.011)	2 (0.032), 4 (0.026)		
TP2						4 (0.012)		
Overall correct	**67.3%**	**62.9%**	**59.4%**	**72.4%**	**72.6**	**60.3%**	**62.0%**	**63.9%**
Number of nodes	**15**	**11**	**11**	**17**	**21**	**13**	**7**	**9**
Number of terminals	**8**	**6**	**6**	**9**	**11**	**7**	**4**	**5**

Note: ( ) = p-value

6.5 Hypothesis Testing

Structural Equation Modeling (SEM) was applied in this study to confirm the relationship between attitudes affected pre and during COVID-19. A Structural Equation Modeling (SEM) approach is used to investigate the determinants of change in attitudes toward residential location areas and attitudes toward residential accessibility that are impacted by attitudes toward COVID-19 concern. The pre-test and post-test designs and first order factor model were applied to the test model in order to hypothesize the relationship that was influenced by COVID-19.

The intervention factors are defined by the COVID-19 concern attitude change, with the model divided into two models along the dimensions of 1) attitude toward residential location area and 2) attitude toward residential accessibility. For each model, four latent variables representing the pre-COVID-19 and during COVID-19 were defined. Therefore, the study's hypotheses based on the attitude towards residential accessibility related to travel mode will influence attitudes toward residential location areas due to the type of residential location had an effect on travel behavior [36].

6.5.1 Goodness-of-fit

The AMOS 23.0 software package was implemented for Structural Equation Modeling (SEM) analysis A maximum likelihood estimator was utilized, and 5000 bootstrap samples were used to give bias-corrected confidence intervals for each parameter. Due to the bootstrapping technique, which is a method of resampling in which the original sample is considered to be representative of the population [129]. The result from AMOS shown in APPENDIX 8.2.3.

The model result was indicated based on the goodness of fit recommended as shown in Table 6-12. At the 0.000 significance levels, the chi square value was significant. The chi-square divided by the number of degrees of freedom was higher than the acceptance value of 4, suggesting an acceptable fit. The Root Mean Square Error of Approximation (RMSEA) value was greater than the expected value of acceptable fit (0.07), and the Comparative Fit Index (CFI), the Goodness of Fit Index (GFI), and the Tucker-Lewis Index (TLI) values were greater than the acceptable goodness-of-fit cut-off score of 0.90. The goodness of fit test shows that all models fit adequately and are statistically significant.

Table 6-12 Recommended fitness index and results of model

Index	Level of Acceptance	Model result
Chi-square/df [170]	1-4	3.289
p-value	<0.05	0.000
RMSEA [171]	< 0.07	0.058
GFI [172]	≥ 0.90	0.960
CFI [173]	≥0.90	0.961
TLI [173]	≥ 0.90	0.943

6.5.2 SEM Model Results

The model was evaluated for attitudes toward residential location areas and residential accessibility, as well as their relationship, to identify whether the model was affected by the COVID-19 pandemic. The results of structural equation modeling revealed a significant influence of attitudes toward residential accessibility, with a relationship of 0.794 between pre-COVID-19 (PreCOVIDAccessibility) and during COVID-19 (DuringCOVIDAccessibility). The intervention variables of 2PTconcern were affected by DuringCOVIDAccessibility as a value of 0.075. The variance of the dependent variables or squared multiple correlation (R^2) of DuringCOVIDAccessibility affected by PreCOVIDAccessibility and the intervention variable of 2PTconcern explained is 65% of DuringCOVIDAccessibility as shown in Figure 6. The relationship of attitudes toward residential location areas shows that pre-COVID-19 (PreCOVIDLocation) to during COVID-19 (DuringCOVIDLocation) has a positive value of 0.464. The intervention variables of 2UrbanConcern were affected by DuringCOVIDLocation as a value of 0.075. PreCOVIDLocation and 2UrbanConcern explained 82 percent of the effect of DuringCOVIDLocation. The results of the research hypothesis study found that the relationship between DuringCOVID-19Accessibility and DuringCOVID-19Location indicated a significant positive relationship and had direct significant influences on the DuringCOVID-19Location with a value of 0.514. Table 6-13 and Figure 6-8 show the standardized path coefficients of the structural model.

Table 6-13 Parameter estimates of regression weight and correlation of model result

Regression paths	***β***	**p**
PreCOVIDLocation		
1UrbanArea	0.495	***
1ResidentialArea	0.475	***
1RuralArea	0.231	***
DuringCOVIDLocation	0.464	
DuringCOVIDLocation		
2UrbanArea	0.533	***
2ResidentialArea	0.510	***
2RuralArea	0.291	***
2UrbanConcern		
DuringCOVIDLocation	0.249	***
PreCOVIDAccessibility		
1MassTransit	0.521	***
1BusStop	0.683	***
1Highway	0.503	***
DuringCOVIDAccessibility	0.794	***
DuringCOVIDAccessibility		
2MassTransit	0.607	***
2BusStop	0.723	***
2Highway	0.549	***
DuringCOVIDLocation	0.514	***
2PTConcern		
DuringCOVIDAccessibility	0.075	0.021
Correlation paths	***β***	**p**
PreCOVIDLocation		
2UrbanConcern	0.076	0.045
PreCOVIDAccessibility	0.673	***
PreCOVIDAccessibility		
2PTconcern	0.093	0.035
2PTConcern		
2UrbanConcern	0.278	***

Note: *** Significant at the 0.001

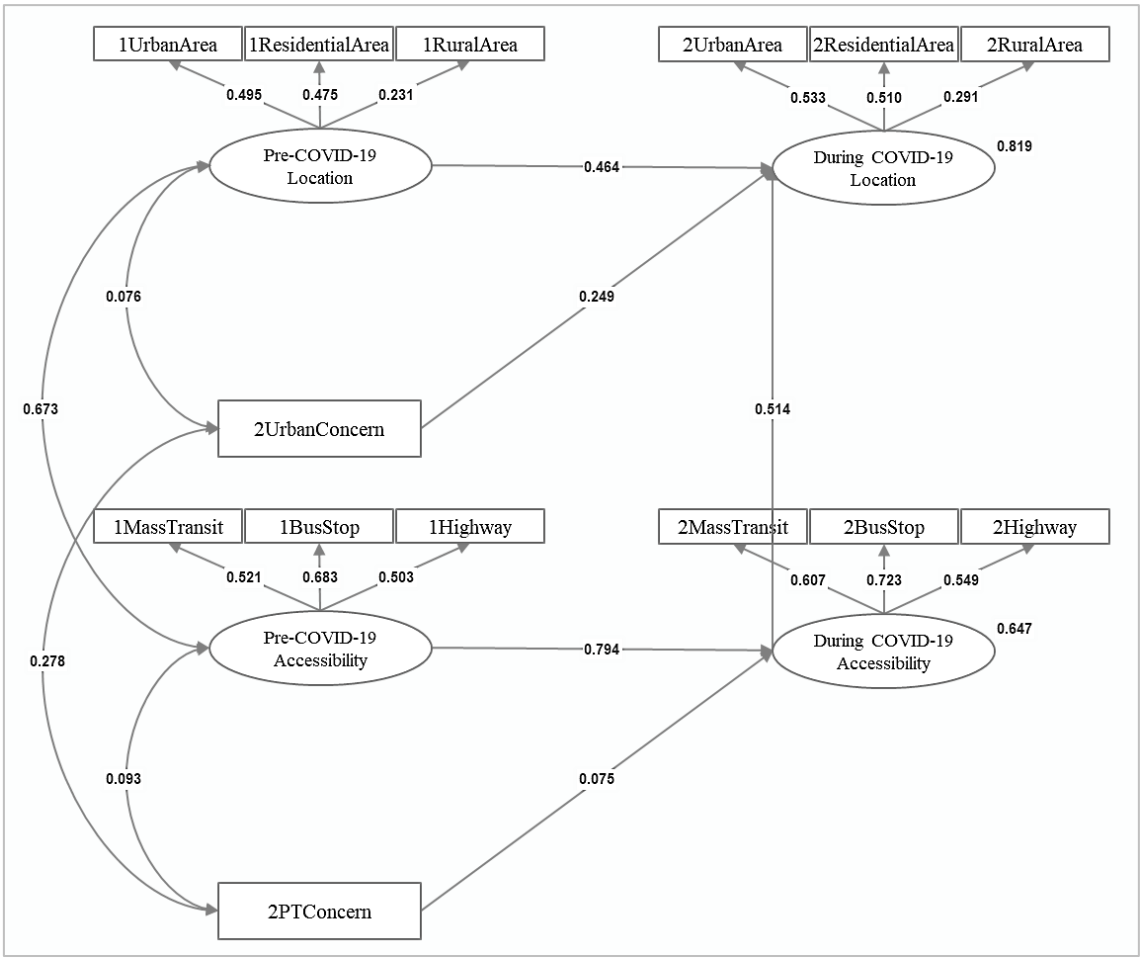


Figure 6-8 Pre-test and post-test model specification and standardized estimates

6.6 Discussion

Residential self-selection could lead to relocation related to travel behavior and various variables (such as socio-demographic characteristics, residential characteristics, and travel characteristics). Furthermore, to understand future effects, travel-related attitudes were significant predictors of their travel evaluation [9] and motivations for relocation and discovered that the reasons for relocation were travel-related [7]. However, the uncertain situation of COVID-19 directly affects behavior and attitude toward relocation under this study. The study area's characteristics showed that mass transit and feeder transit were the main modes of transport used by people to travel. Traveling by non-motorized and paratransit was slightly increased in usage during the COVID-19 pandemic, the same as in the previous research [17]. During COVID-19 passengers were more concerned about public transportation usage than they were before COVID-19 [78] and this may impact housing types of preference [14] as shown by the change in attitude toward residential location area.

The study of the segmentation of travelers and residents around the mass transit station area has qualifying variables in order to understand the characteristics of travelers and residents under consideration for attitude-based relocation related to travel behavior. The decision tree identified variable of age, education, number of car ownership, number of transfers, travel time, and travel cost significant importance to consider than before pre-COVID-19 period. Evidently, during the COVID-19 pandemic, people concentrated on travel time, decreasing the number of transfers, and eliminating unnecessary travel purposes. Consistency with past pandemics, such as MERS, reduced trips during the pandemic [22]. Additionally, the result of segmentation further confirmed that the most significant variables relating to traveler and resident characteristics are the number of transport cards ownership, the walking distance to the nearest mass station, the number of households, the type of resident, property ownership, travel cost, and trip frequency.

As a result, the hypotheses of the study that are based on attitudes toward residential accessibility in relation to travel mode will have an influence on attitudes toward residential location areas. Previous analysis (Chapter 5) of overall residential self-selection and direct and indirect effects found the results of attitude were strongly associated with each other. This stage focuses on the effect of before-interrupted events such as COVID-19 on the impact of the event. The interrupted variables are divided into 2 dimensions based on travel mode and residential location within the context of the mass transit station area.

The result indicated all the hypotheses were significant, including the pre-COVID-19 effect during COVID for both attitudes toward residential accessibility and attitudes toward residential location areas, the attitude toward worrying about infection concerns to using public transport, the effect on attitude toward residential accessibility during COVID-19, the attitude toward not choosing to live in an urban area due to concern about infection effect on attitude toward residential location area during COVID-19, and the attitude toward residential accessibility effect on attitude toward residential location area significantly. The result clearly demonstrated the impact of COVID-19 on both attitudes as shown in Figure 6-9 and Table 6-14.

Table 6-14 Summary hypothesis result of pre/post relationship

Hypothesis	Path	Result
H1	During COVID-19 Accessibility→ During COVID-19 Location	Support
H2a	Pre-COVID-19 Accessibility→ During COVID-19 Accessibility	Support
H2b	Pre-COVID-19 Location→ During COVID-19 Location	Support
H3a	2PTConcern → During COVID-19 Accessibility	Support
H3b	2UrbanCorcern→ During COVID-19 Location	Support

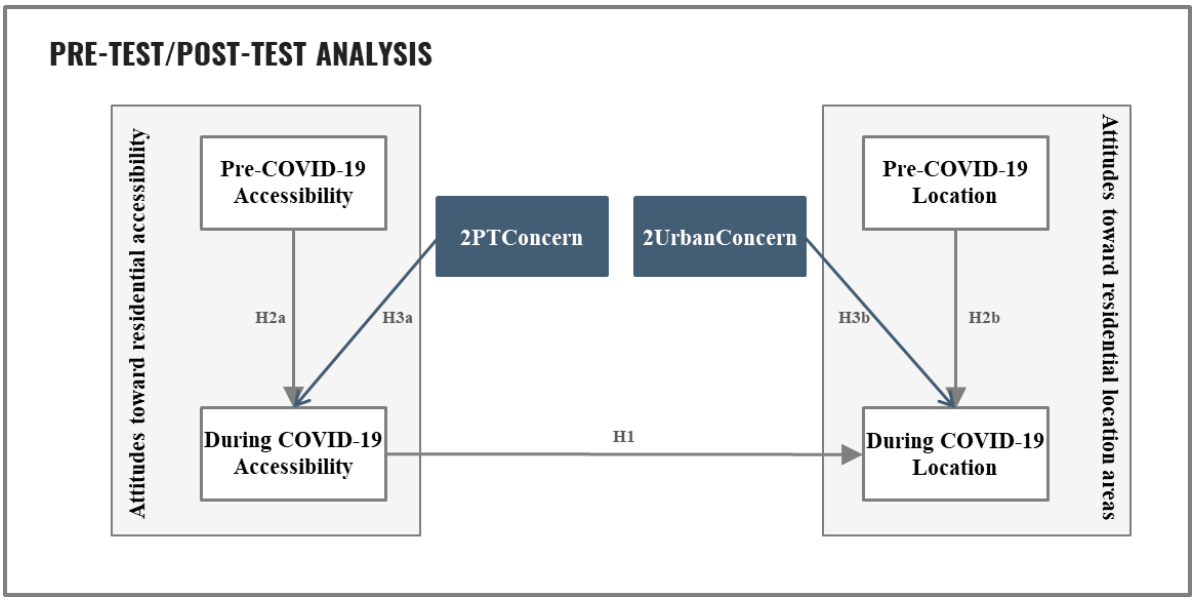


Figure 6-9 Summary hypothesis result of pre/post relationship

SEM results revealed that attitudes toward residential accessibility of travel mode were a significant determinant of attitudes toward residential location areas, thereby supporting residential self-selection or relocation based on the attitude hypothesis for normal situations (pre-COVID) and pandemic situations (during COVID-19). However, it is not surprising that the pre-COVID-19 latent variable had a direct effect on the variables during COVID-19. The intervention variable of concern to using public transport had a slight effect during COVID-19 on accessibility of travel modes, whereas the variable of concern to living in an urban area had a stronger effect during COVID-19 on location area.

6.7 Conclusion

This study examined the impact of COVID-19 on the majority of traveler and resident characteristics groups in the nearby area of a mass transit station, with the objective of understanding the target of the user and providing information to encourage increased use of mass transit and feeder transit service as well as non-motorized transportation under the pandemic situation in the future. However, the allocation of areas, access to mass transit and feeder transit, and neighborhoods that will support the growth of the city, as well as urban development, should improve more appropriately in the future under the trend of considering relocation that has been influenced by changes in attitudes and behaviors.

CHAID has been designed to accommodate a variety of data types, including scale data (also known as continuous data) and categorical data (ordinal or nominal variables). This methodology is also well-suited for examining large, complex data sets since it is effective at identifying relationships between independent and dependent variables. The attitudes of the various segments of travelers and residents' characteristics groups could help to understand and address any potential differences in pandemic-related travel impacts. The results of CHAID could explain the fundamentals of travelers' and residents' characteristics clearly. Regarding hypothesis analysis, SEM has been used to determine

the relationship between variables and has confirmed the significant relationship and impact of the pre and during COVID-19 effect.

Considering the significance of the study, policymakers should place additional emphasis on relocation as a consequence of the change in attitudes. It has been demonstrated that the segment of people who live near mass transit stations less than 400 and 400-1000 meters away prefer to live in residential and rural areas by 23% and 25% of respondents, respectively, in the future, compared to prefer to live in urban areas by 18% of the respondents under attitude based. This reflects people who prefer to avoid commuting by public transportation (feeder transit and mass transit), as evidenced by the attitudes toward residential accessibility of travel modes.

However, according to the CHAID analysis, a limited sample size for analysis was a limitation of the study; a large sample size produced a stronger classification [177]. In the future, synthetic data should be thought of in addition to model validation and evaluating the prediction performance of tree classifiers. Therefore, the preferences and attitudes of decision-makers regarding relocation were taken into consideration in this study. However, under the COVID pandemic scenario, a longer forecasting period would be required. Additionally, tracking changes in population relocation and the use of longitudinal data will be advantageous for more accurate forecasting.

7 DISCUSSION AND CONCLUSION

Finally, study results of the hypothesis and related results, which answer research questions, are discussed in this part. It concludes with a more detailed explanation of the conclusion, limitations, and suggestions for future research.

7.1 Discussion

7.1.1 Summary of Results

Residential self-selection of this research is illustrated in the case study by applying SEM methodology to identify the relationship based on hypothesis setting. The results on the impact of COVID-19 on travel behavior and attitude on residential and travel were found to be overall people reducing all mobility and meeting people that travel daily. In particular, infection by COVID-19 has decreased usage of public transport. Furthermore, the effect of COVID-19 has affected travel attitudes by less preference for walking or biking than before because people are worried about infection concerns when using public transport and more concerned about safety in the state of criminal risk during COVID-19. Residential attitudes were changed by the urban areas being preferred to live in during COVID-19. However, respondents considered accessibility around the residential area near the bus stop more. Noteworthy is that they are not choosing to live in an urban area due to concern about infection, which is more concerning than before COVID-19. Socio-demographic, resident, and traveler characteristics have less influence on relationships, according to the findings of SEM analysis. Travel mode and number of transfers were found has the strong significant impact on travel behavior. Attitudes towards residential and travel have a strong effect on each other, and travel attitudes directly impact travel behavior.

However, factor analysis of measurement variables to identify the structure model used in this study, including 2 types of setting: 1) hypothesis setting of latent variables by CFA (Chapters 4 and 6) and 2) hypothesis setting of latent variables by EFA (Chapter 5). CFA could describe conceptual hypotheses clearly. However, EFA was separated into groups that differed from the CFA hypothesis groups. For example, attitudes toward residences were separated into the characteristics of residences rather than into considerations of elements such as safety or the environment. As a result, the choice of the factor analysis method was based on the questions and hypotheses set for the measurement variables. Intervention by attitude toward residence provided an indirect effect on travel attitude via travel behavior of travel mode, which presented the same as previous research that found the decision to live in a certain neighborhood has an indirect effect on travel attitudes and satisfaction [3], [4]. The built environment of this study was considered based on the walking distance for residential areas to the nearest mass transit station being the interaction variable. The results show only a direct effect on travel mode, which contrasts with previous research that suggests the built environment has a direct and indirect effect on travel mode choice [45]. However, the built environment was one variable in this study, and it could have had different results. Figure 7-1 illustrates the result of the conceptual model of this research. However, the effect of COVID-19 demonstrated the indirect effect was found in the relationship of attitudes toward private cars to attitudes toward neighborhood and travel modes. In particular during COVID-19, private cars became the first mode of travel choice.

The uncertain situation of COVID-19 directly affects behavior and attitude toward relocation and the study area's characteristics showed that mass transit and feeder transit were the main modes of transport used by people to travel. Traveling by non-motorized and paratransit was slightly increased in usage during the COVID-19 pandemic. Passengers were more concerned about public transportation usage than they were before COVID-19 and may impact housing types of preference as shown by the change in attitude toward residential location area. COVID is a current phenomenon that shows how attitude pre-test and post-test can affect how people make decisions. For example, the interruption of the COVID-19 pandemic shows how this affects how people make decisions. accessibility of travel modes influences residential location decisions as well. Overall, the study suggests the same as previous research by suggesting travel attitudes have a significant impact in determining travel mode [36] and residential neighborhoods [25] A variety of housing and neighborhood attributes are of importance [10].

The CHAID methodology was applied to identify the characteristics of travelers and residents around mass transit station areas by segment of an attitude-based application. In urban areas, mass transit and feeder transit are crucial transport modes. It was found that the segment of people who live near mass transit stations less than 400 and 400–1000 meters away prefer to live in residential and rural areas more than before COVID-19. Further CHAID analysis revealed that the most important variables for the divided segment are the number of transport cards and the walking distance to the nearest station, which represent the case study area's characteristics, as well as the type of residence importance variable. This examines the same trend of how the type of residential neighborhood affects the choice of commuting mode [40].

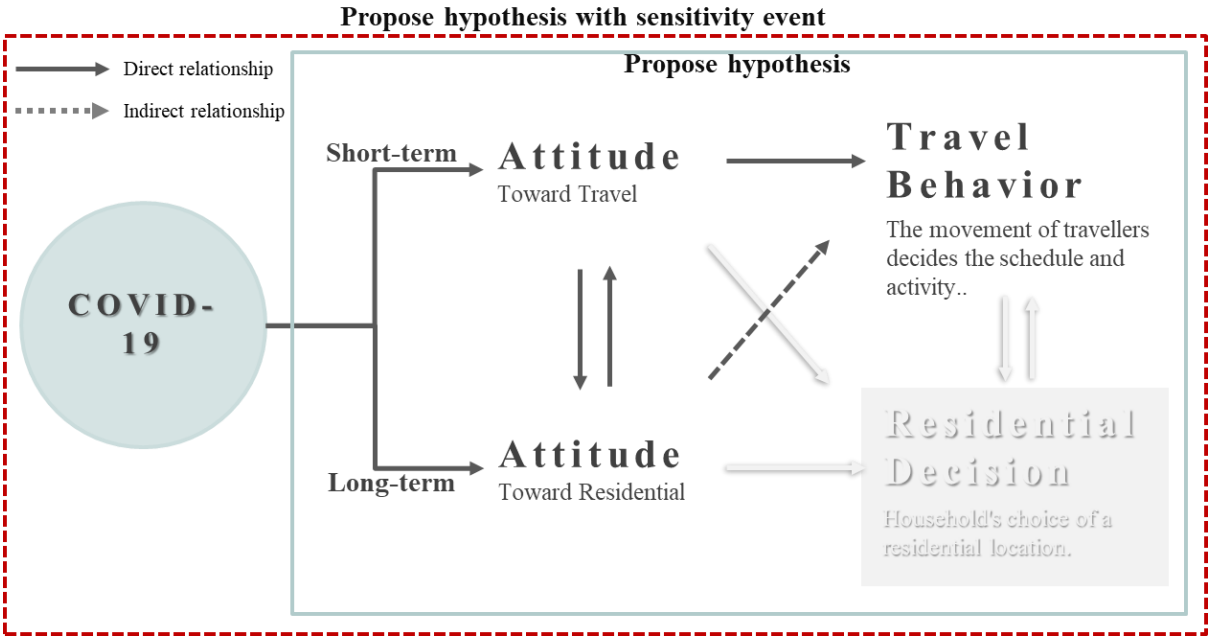


Figure 7-1 Summary of conceptual model results

7.1.2 Answer the Research Questions

The following is an explanation of the answer to the research question provided in Chapter 1:

1. Is it possible that changes in travel behavior will have a long-term effect on the attitude toward residential decision-making?

The results of the attitude-based analysis were found to have a long-term impact on residential attitudes and an indirect effect on travel behavior, especially in travel mode. Moreover, the relationship between travel attitude and residential attitude is strong. As demonstrated in this study, this demonstrated decision-making clearly changes attitudes, particularly that of the interrupted phenomenon.

2. What is the relationship between attitudes and travel behavior for future relocation intentions?

It was discovered that the travel mode and the number of transfers have an effect on travel attitude and residential attitude. Additionally, for residential attitudes, people change their attitudes towards urban areas and live in urban areas more in study areas. That could reflect the problems in accessing treatment and hospitals during the COVID-19 outbreak. Conversely, due to people's avoidance of using mass transit, it was found that people intend to live near bus stops in the future. Based on the results of the attitude survey, we conclude that it is possible that people will become more aware of residential relocation and that this will lead to relocation in the future.

3. What is the interaction and intervention between the relationship of attitudes and travel behavior in decision-making?

The hypothesis setting of this research is defined by the relationship between travel attitude and travel mode behavior. There has been interaction by residential attitude and intervention by walking distance from the residence to the nearest mass transit station. They were significant for various effects on different latent variables. Furthermore, the walking distance moderator confirmed that the effect was demonstrated at different distances and in different situations (before and during COVID-19).

4. What are the characteristics of travelers and residents around mass transit station areas affected by COVID-19?

Characteristics of travelers and residents around mass transit station areas found that mass transit and feeder transit provide the biggest segment of the study. In particular, the number of transport cards, walking distance to the nearest station, type of residential, property ownership, place of work, gender, trip frequency, and travel cost are significantly important to identify. Before COVID-19, occupation and vehicle ownership were also considered to be a segment of the characteristics of travelers and residents around mass transit station areas. However, during the

COVID-19, age, education, number of transfers, travel time and trip purposes become important to the divided segment of characteristics.

7.2 Conclusion

7.2.1 Policy Implementation

The importance of this study is to reach planners and policymakers with the awareness that they should place additional emphasis on relocation as a consequence of the change in attitudes. This research clearly shows that the tendency of decision-making in people might change differently when COVID-19 is triggered. Providing more options on the allocation of areas, access to mass transit and feeder transit, and neighborhoods that will support the growth of the city, as well as urban development, should improve the appropriateness and sustainability of residential neighborhoods and travel modes in the future under the trend of considering relocation that has been influenced by changes in attitudes and behaviors.

Under the circumstances of COVID-19, the disease's impacts on human activities, social life, and the tourism industry were dramatically reduced. Bangkok's tourism was directly affected by the transportation industry. The recommendation would suggest that considering the crisis management of the past lessons in order to prepare for the next crisis is crucially necessary for every sector and possibly to deliver prepared management with the improvement and development of the transportation system in Bangkok, the strengthening of the building of infrastructure, and the improvement of Bangkok's image both domestically and internationally to create a welcoming environment, promote the expansion of tourism, and boost Bangkok to a position of leading change.

In particular, in the study area, it was found that the majority of public transit passengers are those who live within a 1000-meter radius of the station. The findings of the study suggest that critical policies to improve mode accessibility should be implemented. According to the findings of the study, public transport has a statistically significant attitude toward residents and has a more negative indirect effect on public transport as compared to private cars. However, Bangkok's public transportation system is important to residents and travelers in urban areas but is currently inefficient. In terms of residential self-selection, residential attitudes highly recommend separating resident attitudes from travel attitudes, which allows for a more in-depth study of the relationship between travel attitudes and travel behaviors. The majority of the research focuses on travel-related locations or neighborhoods.

The findings of this study have implications for policies of governments and policymakers should procure more transport infrastructure projects to improve transport systems in coordination with transport planners, as well as public housing, health and well-being to support and promote the quality of life in terms of housing and neighborhood related travel and residential attitude. Encourage people to effectively relocate under the policy support of urban sprawl and crowd management in the urban area so that the expansion of the city implies a residential self-selection policy into a neighborhood-friendly of the built environment and public transport more efficiently. In addition, in order to improve public transport service in urban areas and reduce the use of personal cars,

service providers and operators should be able to consider increasing ridership by providing strategic plan management based on the characteristics of urban users in order to improve the connectivity of feeder and mass transit systems.

7.2.2 Future Research Recommendations

However, in the case of considering the model forecast, the integrated discrete choice model (location choice and mode choice) would be more obvious in the impact of various variables. Attitude-based variables were the main variables taken into consideration in this study. The integrated discrete choice model prediction of demand and longitudinal data on travel behavior studied and residential location change, involved with other variables of the built environment, should be explored in future studies to predict and contribute to urban policy, cooperating with land use planning to obtain more accurate predictions of the future.

The attitudes of the various segments of travelers and resident characteristic groups could be used to better understand and address any possible differences in pandemic-related travel impacts among the various segments of travelers and residents. The findings of CHAID were able to describe the underlying features of travelers and residents in a clear manner. Additionally, the most important characteristic of understand characteristics of travelers and residents around mass transit station areas is the target customer of each travel mode, particularly of public transport. This will be beneficial to the development of services and policy formulation to increase the number of passengers in the future. Figure 7-2 summarizes the summary of policy implementation and future research recommendations.

Figure 7-2 Summary of policy implementation and future research recommendations

As with all the analysis in this research, the assumption of data is based on nonparametric data because nonparametric methods are available to treat data that are simply classificatory or categorical. In SEM analysis used the bootstrapping technique to resample the original sample and the result with no difference in parametric assumption (see APPENDIX 8.3.1). Besides, for CHAID analysis, nonparametric statistical techniques can be used for categorical and continuous data. The limitation of this study's sample size to analyze CHAID suggests that a large sample size produced a stronger classification. Furthermore, the survey did not include the question about residential choice decisions, and the results provided only a travel mode choice and did not offer future residential location choices in the study.

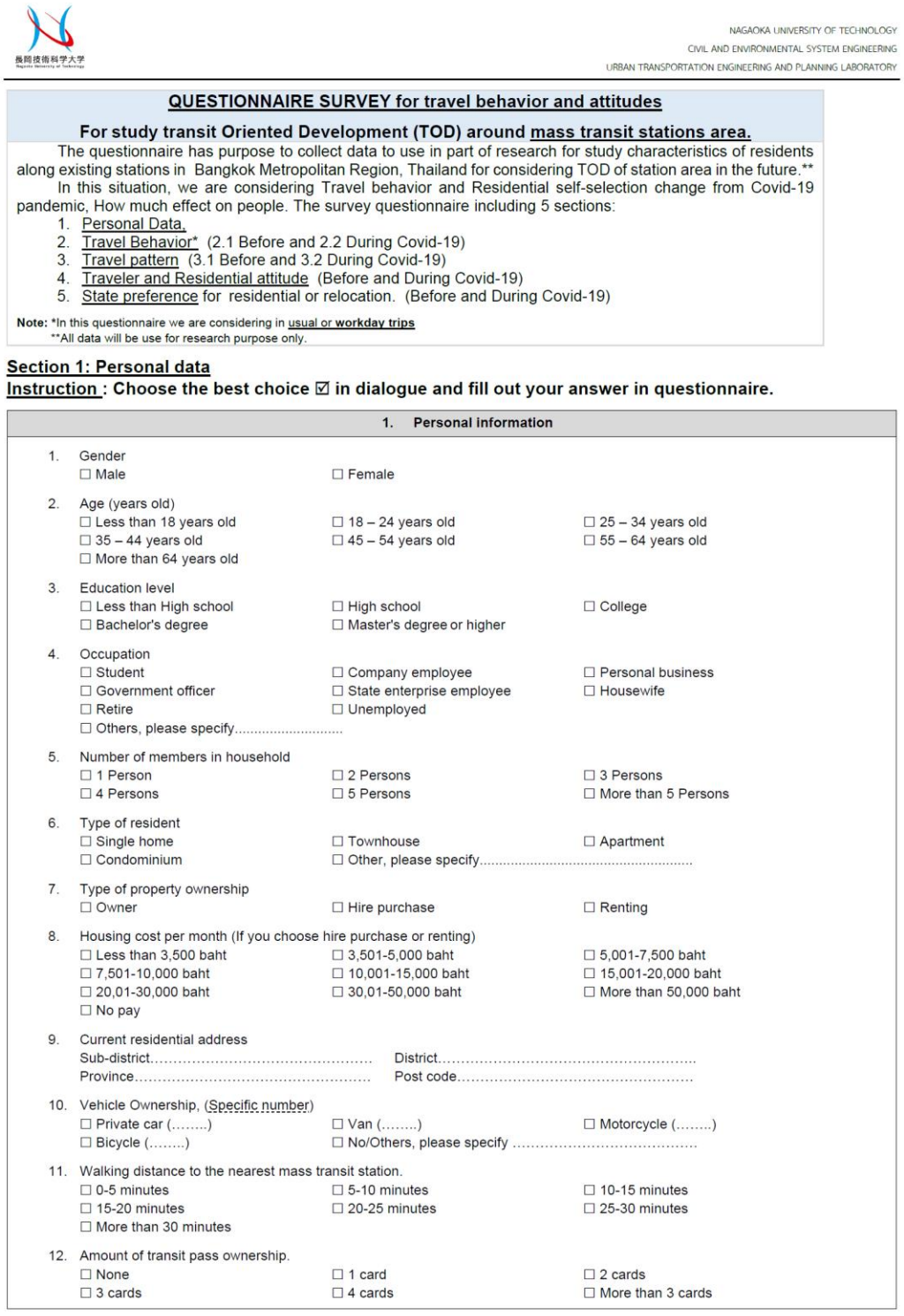
8 APPENDIX

This chapter includes further documents and results that are related to the study.

8.1 Questionnaire

8.1.1 Questionnaire Form

Questionnaire survey by paper based, including 10 pages. The questionnaire was distribute in the Thai language version



NAGAOKA UNIVERSITY OF TECHNOLOGY
CIVIL AND ENVIRONMENTAL SYSTEM ENGINEERING
URBAN TRANSPORTATION ENGINEERING AND PLANNING LABORATORY

QUESTIONNAIRE SURVEY for travel behavior and attitudes

For study transit Oriented Development (TOD) around mass transit stations area.

The questionnaire has purpose to collect data to use in part of research for study characteristics of residents along existing stations in Bangkok Metropolitan Region, Thailand for considering TOD of station area in the future.**
In this situation, we are considering Travel behavior and Residential self-selection change from Covid-19 pandemic, How much effect on people. The survey questionnaire including 5 sections:

1. Personal Data,
2. Travel Behavior* (2.1 Before and 2.2 During Covid-19)
3. Travel pattern (3.1 Before and 3.2 During Covid-19)
4. Traveler and Residential attitude (Before and During Covid-19)
5. State preference for residential or relocation. (Before and During Covid-19)

Note: *In this questionnaire we are considering in usual or **workday trips**
**All data will be use for research purpose only.

Section 1: Personal data
Instruction : Choose the best choice ☑ in dialogue and fill out your answer in questionnaire.

1. Personal Information

1. Gender
☐ Male ☐ Female

2. Age (years old)
☐ Less than 18 years old ☐ 18 – 24 years old ☐ 25 – 34 years old
☐ 35 – 44 years old ☐ 45 – 54 years old ☐ 55 – 64 years old
☐ More than 64 years old

3. Education level
☐ Less than High school ☐ High school ☐ College
☐ Bachelor's degree ☐ Master's degree or higher

4. Occupation
☐ Student ☐ Company employee ☐ Personal business
☐ Government officer ☐ State enterprise employee ☐ Housewife
☐ Retire ☐ Unemployed
☐ Others, please specify.....

5. Number of members in household
☐ 1 Person ☐ 2 Persons ☐ 3 Persons
☐ 4 Persons ☐ 5 Persons ☐ More than 5 Persons

6. Type of resident
☐ Single home ☐ Townhouse ☐ Apartment
☐ Condominium ☐ Other, please specify.....

7. Type of property ownership
☐ Owner ☐ Hire purchase ☐ Renting

8. Housing cost per month (If you choose hire purchase or renting)
☐ Less than 3,500 baht ☐ 3,501-5,000 baht ☐ 5,001-7,500 baht
☐ 7,501-10,000 baht ☐ 10,001-15,000 baht ☐ 15,001-20,000 baht
☐ 20,01-30,000 baht ☐ 30,01-50,000 baht ☐ More than 50,000 baht
☐ No pay

9. Current residential address
Sub-district..... District.....
Province..... Post code.....

10. Vehicle Ownership, (Specific number)
☐ Private car (.....) ☐ Van (.....) ☐ Motorcycle (.....)
☐ Bicycle (.....) ☐ No/Others, please specify .....

11. Walking distance to the nearest mass transit station.
☐ 0-5 minutes ☐ 5-10 minutes ☐ 10-15 minutes
☐ 15-20 minutes ☐ 20-25 minutes ☐ 25-30 minutes
☐ More than 30 minutes

12. Amount of transit pass ownership.
☐ None ☐ 1 card ☐ 2 cards
☐ 3 cards ☐ 4 cards ☐ More than 3 cards

No.1, **1 | 6**

Section 2: Travel behavior

Instruction : Choose the best choice ☑ in dialogue and fill out your answer in questionnaire.

*Note: *In this questionnaire we are considering **usual or workday trips** (typical weekday including all activity usually do in the day start at home and after work until arrived home.)*

In Covid-19 situation Is it effect to you? → If "Yes" ☑ please answer 2.1 and 2.2
"No" ☑ please answer only 2.1

2.1 Before Covid-19

1. Income (per month)
   ☐ Less than 7,500 baht ☐ 7,501-18,000 baht
   ☐ 18,001-24,000 baht ☐ 24,001-35,000 baht
   ☐ 35,001-50,000 baht ☐ 50,001-85,000 baht
   ☐ 85,001-160,000 baht ☐ More than 160,000 baht

2. Place of work
   ☐ Office/Factory ☐ Home
   ☐ Co-working space ☐ Coffee shop
   ☐ Field site ☐ Others

3. Frequency of traveling.(By purpose)
   Work/school ……..Times/week by Mode……
   Shopping/eating……..Times/week by Mode……
   Personal business…….Times/week by Mode……
   Others……..……Times/week by Mode……
   Mode choice define No.1-16 as question 4

4. Vehicle often use for traveling (per one trip).
   (More than one selection is possible).
   ☐ Walk (1) ☐ Bicycle (2)
   ☐ Motorcycle taxi (3) ☐ Tuk-Tuk (4)
   ☐ Taxi (5) ☐ Private car (6)
   ☐ Private Motorcycle(7) ☐ Bus (8)
   ☐ BRT (9) ☐ Van (10)
   ☐ Boat (11) ☐ Local train (12)
   ☐ BTS (13) ☐ MRT Blue line (14)
   ☐ MRT Purple line (15) ☐ Airport rail link (16)

5. How to access mass transit station.
   (More than one selection is possible).
   ☐ Walk ☐ Bicycle
   ☐ Motorcycle taxi ☐ Tuk-Tuk
   ☐ Taxi ☐ Private car
   ☐ Private Motorcycle ☐ Bus
   ☐ BRT ☐ Van
   ☐ Boat ☐ Local train
   ☐ None

6. Frequency of public transport usage.
   ☐ 5 days per week or more
   ☐ 1 to 4 day(s) per week
   ☐ 1 to 3 day(s) per month
   ☐ Rarely
   ☐ Never

7. Expense on traveling (per day)
   ☐ 0-50 baht ☐ 51-100 baht
   ☐ 101-150 baht ☐ 151-200 baht
   ☐ 201-250 baht ☐ 251-300 baht
   ☐ More than 300 baht

8. Parking fee (per day if you use private car)
   ☐ Free parking ☐ 1-20 baht
   ☐ 21-50 baht ☐ 51-100 baht
   ☐ 101-150 baht ☐ More than 150 baht

2.2 During Covid-19

9. Income (per month)
   ☐ Less than 7,500 baht ☐ 7,501-18,000 baht
   ☐ 18,001-24,000 baht ☐ 24,001-35,000 baht
   ☐ 35,001-50,000 baht ☐ 50,001-85,000 baht
   ☐ 85,001-160,000 baht ☐ More than 160,000 baht

10. Place of work
    ☐ Office/Factory ☐ Home
    ☐ Co-working space ☐ Coffee shop
    ☐ Field site ☐ Others

11. Frequency of traveling.
    Work/school ……..Times/week by Mode……
    Shopping/eating……..Times/week by Mode……
    Personal business…….Times/week by Mode……
    Others……..……Times/week by Mode……
    Mode choice define No.1-16 as question 12

12. Vehicle often use for traveling (per one trip).
    (More than one selection is possible).
    ☐ Walk (1) ☐ Bicycle (2)
    ☐ Motorcycle taxi (3) ☐ Tuk-Tuk (4)
    ☐ Taxi (5) ☐ Private car (6)
    ☐ Private Motorcycle(7) ☐ Bus (8)
    ☐ BRT (9) ☐ Van (10)
    ☐ Boat (11) ☐ Local train (12)
    ☐ BTS (13) ☐ MRT Blue line (14)
    ☐ MRT Purple line (15) ☐ Airport rail link (16)

13. How to access mass transit station .
    (More than one selection is possible).
    ☐ Walk ☐ Bicycle
    ☐ Motorcycle taxi ☐ Tuk-Tuk
    ☐ Taxi ☐ Private car
    ☐ Private Motorcycle ☐ Bus
    ☐ BRT ☐ Van
    ☐ Boat ☐ Local train
    ☐ None

14. Frequency of public transport usage.
    ☐ 5 days per week or more
    ☐1 to 4 day(s) per week
    ☐ 1 to 3 day(s) per month
    ☐ Rarely
    ☐ Never

15. Expense on traveling (per day)
    ☐ 0-50 baht ☐ 51-100 baht
    ☐ 101-150 baht ☐ 151-200 baht
    ☐ 201-250 baht ☐ 251-300 baht
    ☐ More than 300 baht

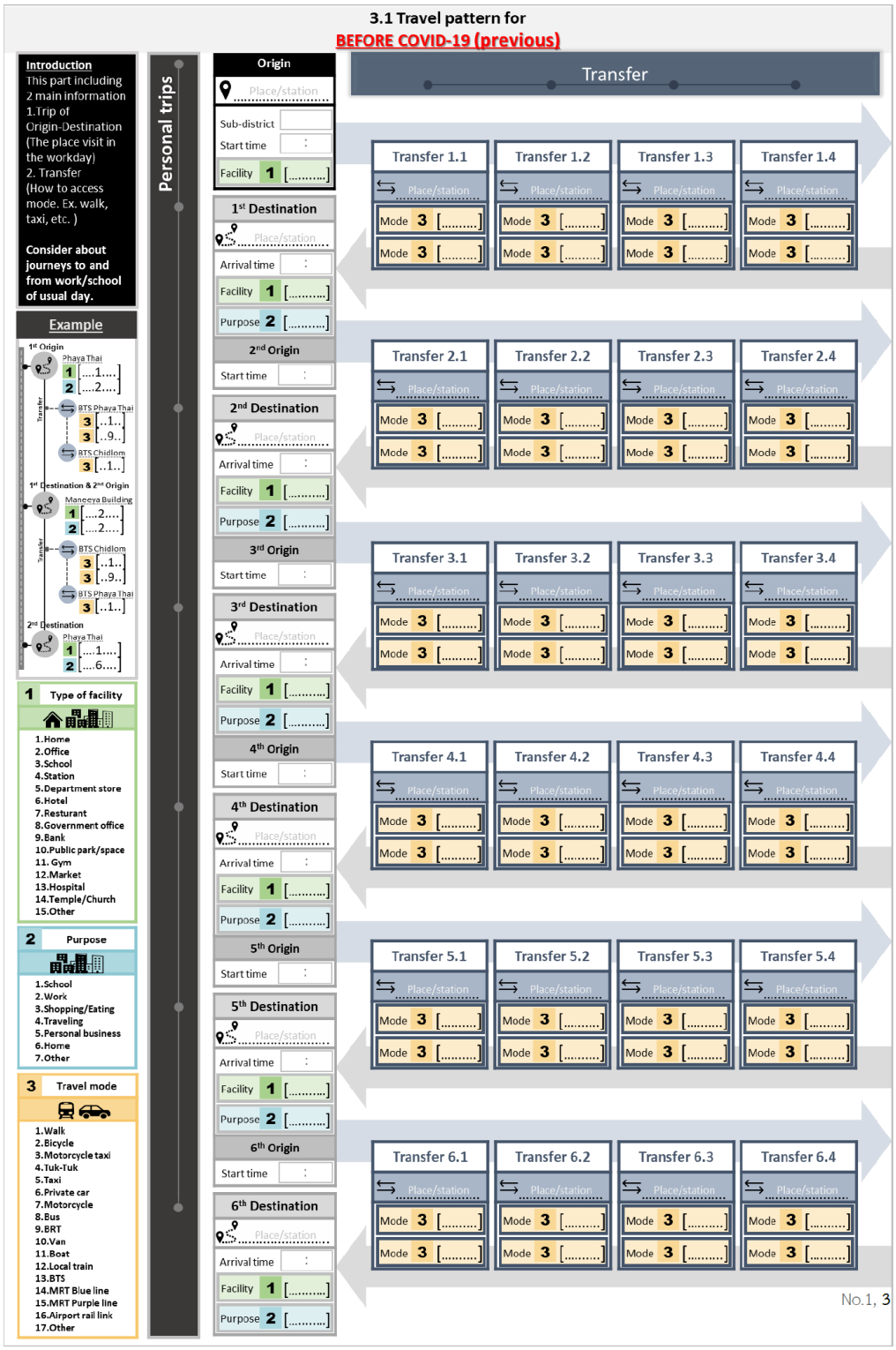
16. Parking fee (per day if you use private car)
    ☐ Free parking ☐ 1-20 baht
    ☐ 21-50 baht ☐ 51-100 baht
    ☐ 101-150 baht ☐ More than 150 baht

Section 3 : Travel pattern (Origin to Destination)

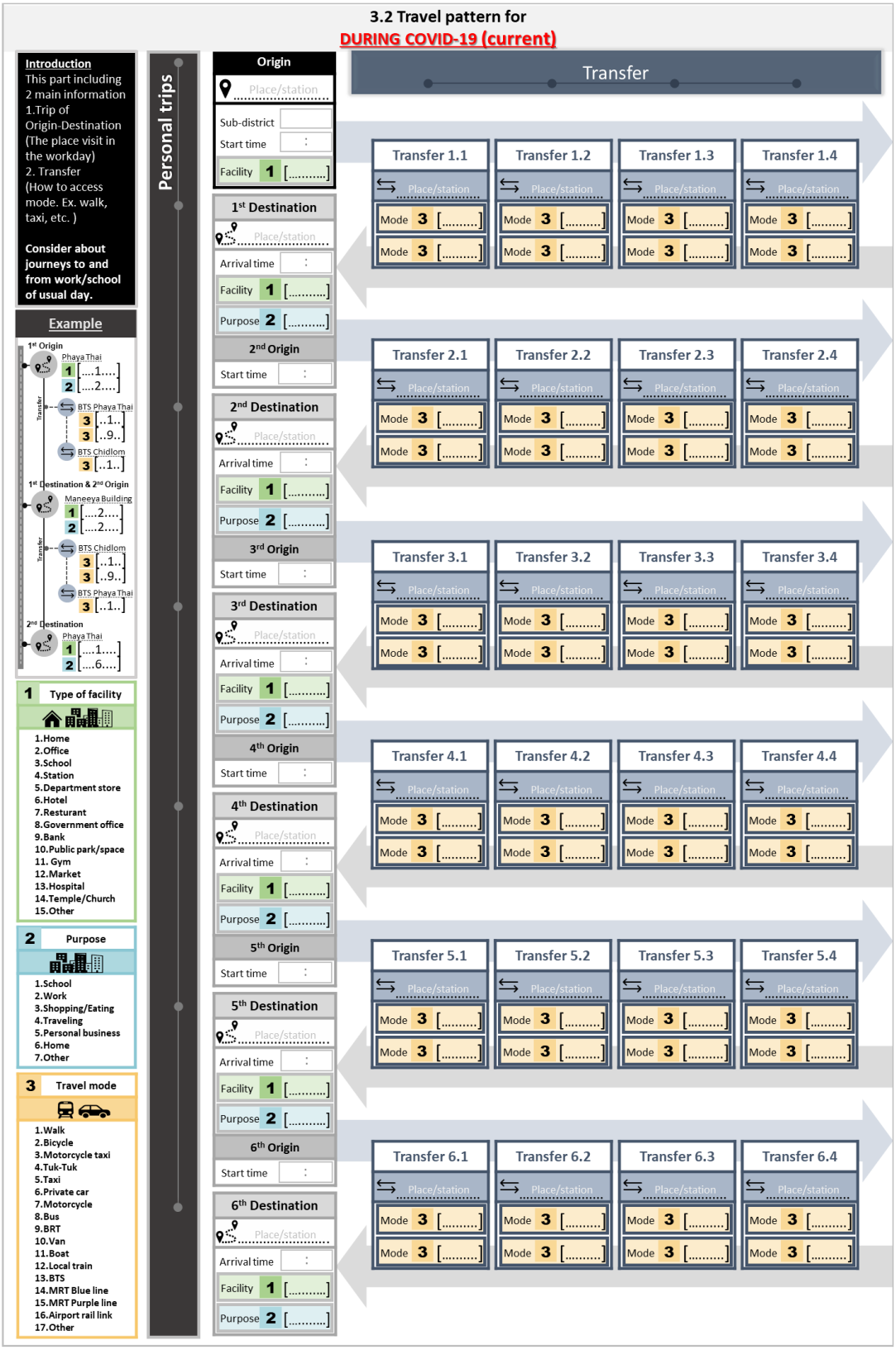
Instruction : Descript your travel pattern in the day

*Note: *In this questionnaire we are considering **usual or workday trips***
(typical weekday including all activity usually do in the day start at home and after work until arrived home.)

In Covid-19 situation Is it effect to you? → If "Yes" ☑ please answer 3.1 and 3.2
"No" ☑ please answer only 3.1



3.2 Travel pattern for DURING COVID-19 (current)



Section 4 : Traveler attitude & Residential self-selection attitude

Instruction : Give the score you agree with by use ✓ in Dialog

Note : Level of score meaning as follow
5 = Strong agree, 4 = Slightly agree, 3 = Neutral, 2 = Slightly disagree and 1 = Strong disagree

	TRAVELER ATTITUDE	OPINION									
		Before Covid-19 (Strong agree ↔ Strong disagree)					During Covid-19 (Strong agree ↔ Strong disagree)				
		5	4	3	2	1	5	4	3	2	1
ACCESSIBILITY	Prefer to use mass transit (BTS, MRT, ARL).										
	Prefer to use public transport (Bus, Boat).										
	Prefer to use bike/walk.										
	Prefer to use private car.										
	Prefer to use para transit (Taxi, bike-taxi, Tuk-Tuk).										
COMFORTABLE	Accept more travel cost to use private car.										
	Choose travel mode by saving time first.										
	Choose private car because social image										
	Mass transit easy to travel more										
	If they have online pre-paid fare system, public transport will be prefer										
	If they have good facility of station (clean, toilet, etc.), mass transit will be prefer										
ENVIRONMENT	Avoid pollution by use private car										
	Prefer private car because of weather condition										
	Worried about infection concerns to use public transport										
	Prefer to use public transport because concern global warming										
SAFE	Will use public transport if passengers wearing face masks										
	Prefer to use private car or public transport to avoid crime of taxi / unfair price										
	Prefer to use private car to avoid criminal risk.										

	RESIDENTIAL ATTITUDE	OPINION									
		Before Covid-19 (Strong agree ↔ Strong disagree)					During Covid-19 (Strong agree ↔ Strong disagree)				
		5	4	3	2	1	5	4	3	2	1
NEIGHBORHOOD	Prefer to live in urban area.										
	Prefer to live near community/shopping/office/school/hospital										
	Prefer social image and social environment in urban.										
	Prefer to live in residential areas.										
	Do not like crowded but not too far from urban.										
	Prefer to live in rural area										
ACCESSIBILITY	Prefer residential area near mass transit station										
	Prefer residential area near bus stop.										
	Prefer residential area near highways or main roads										
	Prefer residential area near park and ride building										
	Residential areas are easy to use by taxi.										
	Activity place can walk from home										
	Residential area is a friendly environment for pedestrian.										
	Residential area is a friendly environment for cycling										
SURROUNDING	Do not like pollution in urban area.										
	Prefer natural environment of rural area more										
	Prefer green space/ park nearby home										
	If choosing to live in an urban area, can accept the pollution.										
	If choosing to live in an urban area, can accept land prices.										
SAFE	Choose from a residential area with no crime or less.										
	Choose from a residential area with lighting around.										
	Choose from a residential area near the police station										
	Not choosing to live in an urban area due to concern about infection.										

Section 5 : Stated preference survey of residential choice

Instruction : Choose the best option ☑ in dialogue in questionnaire.

Example

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	16-30	31-45	31-45	31-45
Travel cost (baht/day)	10 (Bike)	101-150	0-30	0-150
Neighborhood (area)	Residential	Near Mass transit Station	Near Bus Stop	Residential
Rental price (baht)	10,000	10,000	7,000	5,000
Your choice:	☑	☐	☐	☐

In the future, consideration of residential or relocation which option you will prefer to choose? Compare by each situation which mode will prefer to use?

Note : In case of example, prefer to use Walk/Bike mode.

Choice set 1

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	16-30	31-45	31-45	31-45
Travel cost (baht/day)	10 (Bike)	101-150	0-30	0-150
Neighborhood (area)	Residential	Near Mass transit Station	Near Bus Stop	Residential
Rental price (baht)	10,000	10,000	7,000	5,000
Your choice:	☐	☐	☐	☐

Choice set 2

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	16-30	5-15	5-15	10-30
Travel cost (baht/day)	20 (Bike)	51-100	51-100	301-450
Neighborhood (area)	Near Mass transit Station	Residential	Residential	Commercial
Rental price (baht)	15,000	10,000	7,000	5,000
Your choice:	☐	☐	☐	☐

Choice set 3

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	6-15	31-45	31-45	31-45
Travel cost (baht/day)	0	0-50	31-50	151-300
Neighborhood (area)	Residential	Residential	Residential	Commercial
Rental price (baht)	15,000	13,000	9,000	9,000
Your choice:	☐	☐	☐	☐

Choice set 4

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	6-15	16-30	16-30	46-60
Travel cost (baht/day)	20 (Bike)	0-50	31-50	151-300
Neighborhood (area)	Commercial	Commercial	Commercial	Near Bus Stop
Rental price (baht)	10,000	10,000	7,000	5,000
Your choice:	☐	☐	☐	☐

Choice set 5

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	6-15	16-30	16-30	46-60
Travel cost (baht/day)	10 (Bike)	101-150	0-30	0-150
Neighborhood (area)	Near Mass transit Station	Residential	Residential	Commercial
Rental price (baht)	20,000	7,000	5,000	7,000
Your choice:	☐	☐	☐	☐

Choice set 6

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	0-5	5-15	5-15	10-30
Travel cost (baht/day)	20 (Bike)	0-50	31-50	151-300
Neighborhood (area)	Residential	Near Mass transit Station	Near Bus Stop	Residential
Rental price (baht)	20,000	7,000	5,000	7,000
Your choice:	☐	☐	☐	☐

The researcher would like to thank you for your cooperation in answering the questionnaire at this time

You can answer the questionnaire on another channel via an online questionnaire.

No.1, **6** | **6**

แบบสำรวจความคิดเห็นการเดินทาง

บริเวณรอบพื้นที่สถานีขนส่งมวลชนในเขตกรุงเทพมหานครและปริมณฑล

เพื่อการศึกษาการพัฒนาพื้นที่รอบสถานีขนส่งมวลชน (Transit Oriented Development TOD)

แบบสอบถามการสำรวจความคิดเห็นการเดินทางนี้ มีวัตถุประสงค์รวบรวมข้อมูลเพื่อศึกษาลักษณะของผู้อยู่อาศัยบริเวณรอบสถานีขนส่งมวลชนปัจจุบันในเขตกรุงเทพมหานครและปริมณฑล เพื่อพิจารณาลักษณะการพัฒนาพื้นที่สถานีขนส่งมวลชนในอนาคต.**

โดยพิจารณพฤติกรรมการเดินทางและการเลือกที่อยู่อาศัยที่อาจเปลี่ยนแปลงไปจากสถานการณ์การแพร่ระบาดของโควิด 19 .ซึ่งจะส่งผลกระทบต่อผู้คนอย่างไร แบบสอบถามความคิดเห็นการเดินทางนี้ประกอบด้วย 5 ส่วน

1. ข้อมูลทั่วไป
2. พฤติกรรมการเดินทาง* (2.1 ก่อน และ 2.2 ระหว่างโควิท-19)
3. รูปแบบการเดินทาง (3.1 ก่อน และ 3.2 ระหว่างโควิท-19)
4. ทัศนคติการเดินทาง และทัศนคติการเลือกที่อยู่อาศัยด้วยตนเอง (ก่อนและระหว่างโควิท-19)
5. สถานการณ์สมมุติ สำหรับการเลือกรูปแบบการเดินทางและการเลือกที่อยู่อาศัย

หมายเหตุ: *แบบสอบถามนี้พิจารณาการเดินทางโดยปกติหรือการเดินทางในวันทำงาน

**ข้อมูลทั้งหมดใช้เพื่อการศึกษาตามวัตถุประสงค์ของงานวิจัยเท่านั้น

ส่วนที่ 1: ข้อมูลทั่วไป

คำแนะนำ : เลือกตัวเลือกที่ดีที่สุด ☑ ในช่องตัวเลือก และเติมคำตอบลงในช่องว่างของแบบสอบถาม

1. ข้อมูลทั่วไป

1. เพศ
   ☐ ชาย ☐ หญิง
2. อายุ (ปี)
   ☐ ต่ำกว่า 18 ปี ☐ 18 – 24 ปี ☐ 25 – 34 ปี ☐ 35 – 44 ปี
   ☐ 45 – 54 ปี ☐ 55 – 64 ปี ☐ มากกว่า 64 ปี
3. ระดับการศึกษา
   ☐ ต่ำกว่ามัธยมศึกษา ☐ มัธยมศึกษา ☐ วิทยาลัย/อาชีวศึกษา ☐ ปริญญาตรี
   ☐ ปริญญาโท หรือสูงกว่า
4. อาชีพ
   ☐ นักเรียน/นักศึกษา ☐ ลูกจ้าง/พนักงานบริษัท ☐ ธุรกิจส่วนตัว ☐ ข้าราชการ
   ☐ พนักงานรัฐวิสาหกิจ ☐ แม่บ้าน ☐ เกษียณ ☐ ว่างงาน
   ☐ อื่น ๆ, โปรดระบุ.....
5. จำนวนสมาชิกในครัวเรือน
   ☐ 1 คน ☐ 2 คน ☐ 3 คน ☐ 4 คน
   ☐ 5 คน ☐ มากกว่า 5 คน
6. ประเภทที่อยู่อาศัย
   ☐ บ้านเดี่ยว ☐ ทาวน์เฮาส์ ☐ อพาร์ทเม้น ☐ คอนโดมิเนียม
   ☐ อื่น ๆ, โปรดระบุ.....
7. ประเภทที่อยู่อาศัย
   ☐ เป็นเจ้าของ ☐ เช่าซื้อ (ผ่อน) ☐ เช่า
8. ค่าที่อยู่อาศัยต่อเดือน (หากเลือกเช่าซื้อหรือเช่า)
   ☐ ต่ำกว่า 3,500 บาท ☐ 3,501-5,000 บาท ☐ 5,001-7,500 บาท ☐ 7,501-10,000 บาท
   ☐ 10,001-15,000 บาท ☐ 15,001-20,000 baht ☐ 20,01-30,000 บาท ☐ 30,01-50,000 บาท
   ☐ มากกว่า 50,000 บาท ☐ ไม่มีค่าใช้จ่าย
9. ที่อยู่อาศัยปัจจุบัน
   ตำบล.....อำเภอ.....จังหวัด.....รหัสไปรษณีย์.....
10. ยานพาหนะที่เป็นเจ้าของ, (ระบุจำนวน)
    ☐ รถยนต์ส่วนบุคคล (.....) ☐ รถตู้ (.....) ☐ รถจักรยานยนต์ (.....) ☐ จักรยาน (.....)
    ☐ ไม่มี/อื่น ๆ, โปรดระบุ.....
11. ระยะทางการเดินจากที่อยู่อาศัยถึงสถานีรถไฟฟ้าขนส่งมวลชนที่ใกล้ที่สุด
    ☐ 0-5 นาที ☐ 5-10 นาที ☐ 10-15 นาที ☐ 15-20 นาที
    ☐ 20-25 นาที ☐ 25-30 นาที ☐ มากกว่า 30 นาที
12. จำนวนบัตรโดยสารขนส่งมวลที่ถือครอง (MRT, MRT, Rabbit, Smart pass, Mangmoom)
    ☐ ไม่มี ☐ 1 บัตร ☐ 2 บัตร ☐ 3 บัตร
    ☐ 4 บัตร ☐ มากกว่า 3 บัตร

ส่วนที่ 2: พฤติกรรมการเดินทาง

คำแนะนำ : เลือกตัวเลือกที่ดีที่สุด ☑ ในช่องตัวเลือก และเติมคำตอบลงในช่องว่างของแบบสอบถาม.

*หมายเหตุ : "แบบสอบถามนี้พิจารณาการเดินทางโดย**ปกติหรือการเดินทางในวันทำงาน** (วันธรรมดาทั่วไป โดยรวมกิจกรรมที่ดำเนินเป็นประจำของวันธรรมดา เริ่มจากบ้านไปทำงานรวมถึงกิจกรรมอื่น ๆ ระหว่างวันจนกลับถึงบ้าน*

ในสถานการณ์ โควิท-19 ได้มีผลกระทบต่อท่านหรือไม่ → หาก "ใช่" ☑ กรุณาตอบข้อ 2.1 และ 2.2
"ไม่" ☑ กรุณาตอบข้อ 2.1 เท่านั้น

2.1 ก่อน โควิท-19	2.2 ระหว่าง โควิท-19
1. รายได้ (ต่อเดือน) ☐ น้อยกว่า 7,500 บาท ☐ 7,501-18,000 บาท ☐ 18,001-24,000 บาท ☐ 24,001-35,000 บาท ☐ 35,001-50,000 บาท ☐ 50,001-85,000 บาท ☐ 85,001-160,000 บาท ☐ มากกว่า 160,000 บาท	9. รายได้ (ต่อเดือน) ☐ น้อยกว่า 7,500 บาท ☐ 7,501-18,000 บาท ☐ 18,001-24,000 บาท ☐ 24,001-35,000 บาท ☐ 35,001-50,000 บาท ☐ 50,001-85,000 บาท ☐ 85,001-160,000 บาท ☐ มากกว่า 160,000 บาท
2. สถานที่ทำงาน ☐ ออฟฟิต/สำนักงาน /โรงงาน ☐ บ้าน ☐ Co-working space ☐ ร้านกาแฟ ☐ พื้นที่หน้างาน ☐ อื่น ๆ	10. สถานที่ทำงาน ☐ ออฟฟิต/สำนักงาน /โรงงาน ☐ บ้าน ☐ Co-working space ☐ ร้านกาแฟ ☐ พื้นที่หน้างาน ☐ อื่น ๆ
3. ความถี่ในการเดินทาง (ตามวัตถุประสงค์) ทำงาน/โรงเรียน .....ครั้ง/สัปดาห์ เดินทางโดย ..... ข้อปิ้ง/กินข้าว.....ครั้ง/สัปดาห์ เดินทางโดย ..... ธุระส่วนตัว.....ครั้ง/สัปดาห์ เดินทางโดย ..... อื่น ๆ .....ครั้ง/สัปดาห์ เดินทางโดย ..... รูปแบบการเดินทางให้ระบุหมายเลข 1-16 ดังคำถามข้อ 4)	11. ความถี่ในการเดินทาง (ตามวัตถุประสงค์) ทำงาน/โรงเรียน .....ครั้ง/สัปดาห์ เดินทางโดย ..... ข้อปิ้ง/กินข้าว.....ครั้ง/สัปดาห์ เดินทางโดย ..... ธุระส่วนตัว.....ครั้ง/สัปดาห์ เดินทางโดย ..... อื่น ๆ .....ครั้ง/สัปดาห์ เดินทางโดย ..... รูปแบบการเดินทางให้ระบุหมายเลข 1-16 ดังคำถามข้อ 12)
4. ยานพาหนะที่ใช้ในการเดินทางโดยส่วนมาก (ต่อเที่ยวการเดินทาง). (สามารถเลือกได้มากกว่า 1 ข้อ) ☐ เดิน (1) ☐ จักรยาน (2) ☐ มอเตอร์ไซค์รับจ้าง (3) ☐ ตุ๊กตุ๊ก (4) ☐ แท็กซี่ (5) ☐ รถยนต์ส่วนบุคคล (6) ☐ รถจักรยานยนต์ส่วนบุคคล (7) ☐ รถโดยสารประจำทาง (8) ☐ BRT (9) ☐ รถตู้ (10) ☐ เรือโดยสาร (11) ☐ รถไฟ (12) ☐ BTS (13) ☐ MRT สายสีน้ำเงิน (14) ☐ MRT สายสีม่วง (15) ☐ Airport rail link (16)	12. ยานพาหนะที่ใช้ในการเดินทางโดยส่วนมาก (ต่อเที่ยวการเดินทาง). (สามารถเลือกได้มากกว่า 1 ข้อ) ☐ เดิน (1) ☐ จักรยาน (2) ☐ มอเตอร์ไซค์รับจ้าง (3) ☐ ตุ๊กตุ๊ก (4) ☐ แท็กซี่ (5) ☐ รถยนต์ส่วนบุคคล (6) ☐ รถจักรยานยนต์ส่วนบุคคล (7) ☐ รถโดยสารประจำทาง (8) ☐ BRT (9) ☐ รถตู้ (10) ☐ เรือโดยสาร (11) ☐ รถไฟ (12) ☐ BTS (13) ☐ MRT สายสีน้ำเงิน (14) ☐ MRT สายสีม่วง (15) ☐ Airport rail link (16)
5. วิธีการที่สามารถเข้าถึงสถานีรถไฟฟ้า (สามารถเลือกได้มากกว่า 1 ข้อ) ☐ เดิน ☐ จักรยาน ☐ มอเตอร์ไซค์รับจ้าง ☐ ตุ๊กตุ๊ก ☐ แท็กซี่ ☐ รถยนต์ส่วนบุคคล ☐ รถจักรยานยนต์ส่วนบุคคล ☐ รถโดยสารประจำทาง ☐ BRT ☐ รถตู้ ☐ เรือโดยสาร ☐ รถไฟ ☐ ไม่มี	13. วิธีการที่สามารถเข้าถึงสถานีรถไฟฟ้า (สามารถเลือกได้มากกว่า 1 ข้อ) ☐ เดิน ☐ จักรยาน ☐ มอเตอร์ไซค์รับจ้าง ☐ ตุ๊กตุ๊ก ☐ แท็กซี่ ☐ รถยนต์ส่วนบุคคล ☐ รถจักรยานยนต์ส่วนบุคคล ☐ รถโดยสารประจำทาง ☐ BRT ☐ รถตู้ ☐ เรือโดยสาร ☐ รถไฟ ☐ ไม่มี
6. ความถี่ในการใช้ระบบขนส่งสาธารณะ ☐ 5 วันต่อสัปดาห์ หรือมากกว่า ☐ 1 ถึง 4 วันต่อสัปดาห์ ☐ 1 ถึง 3 วันต่อเดือน ☐ ใช้น้อยมาก ☐ ไม่เคยใช้	14. ความถี่ในการใช้ระบบขนส่งสาธารณะ ☐ 5 วันต่อสัปดาห์ หรือมากกว่า ☐ 1 ถึง 4 วันต่อสัปดาห์ ☐ 1 ถึง 3 วันต่อเดือน ☐ ใช้น้อยมาก ☐ ไม่เคยใช้
7. ค่าใช้จ่ายในการเดินทางโดยรวม (ต่อวัน) ☐ 0-50 บาท ☐ 51-100 บาท ☐ 101-150 บาท ☐ 151-200 บาท ☐ 201-250 บาท ☐ 251-300 บาท ☐ มากกว่า 300 บาท	15. ค่าใช้จ่ายในการเดินทางโดยรวม (ต่อวัน) ☐ 0-50 บาท ☐ 51-100 บาท ☐ 101-150 บาท ☐ 151-200 บาท ☐ 201-250 บาท ☐ 251-300 บาท ☐ มากกว่า 300 บาท
8. ค่าจอดรถ (ต่อวัน กรณีที่ใช้รถยนต์ส่วนบุคคล) ☐ ค่าจอดรถฟรี ☐ 1-20 บาท ☐ 21-50 บาท ☐ 51-100 บาท ☐ 101-150 บาท ☐ มากกว่า 150 บาท	16. ค่าจอดรถ (ต่อวัน กรณีที่ใช้รถยนต์ส่วนบุคคล) ☐ ค่าจอดรถฟรี ☐ 1-20 บาท ☐ 21-50 บาท ☐ 51-100 บาท ☐ 101-150 บาท ☐ มากกว่า 150 บาท

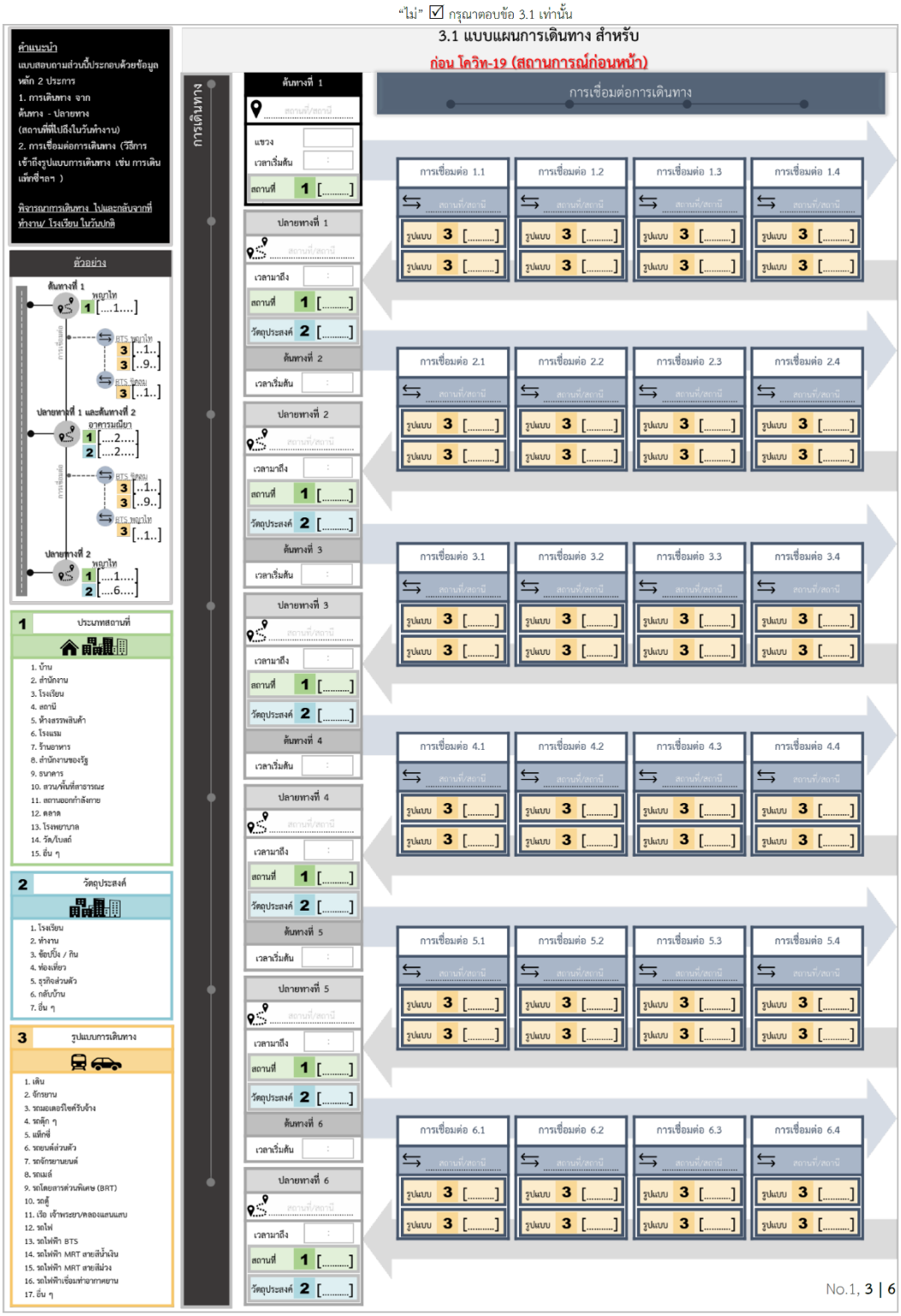
ส่วนที่ 3 : แบบแผนการเดินทาง (จากต้นทาง ถึง ปลายทาง)

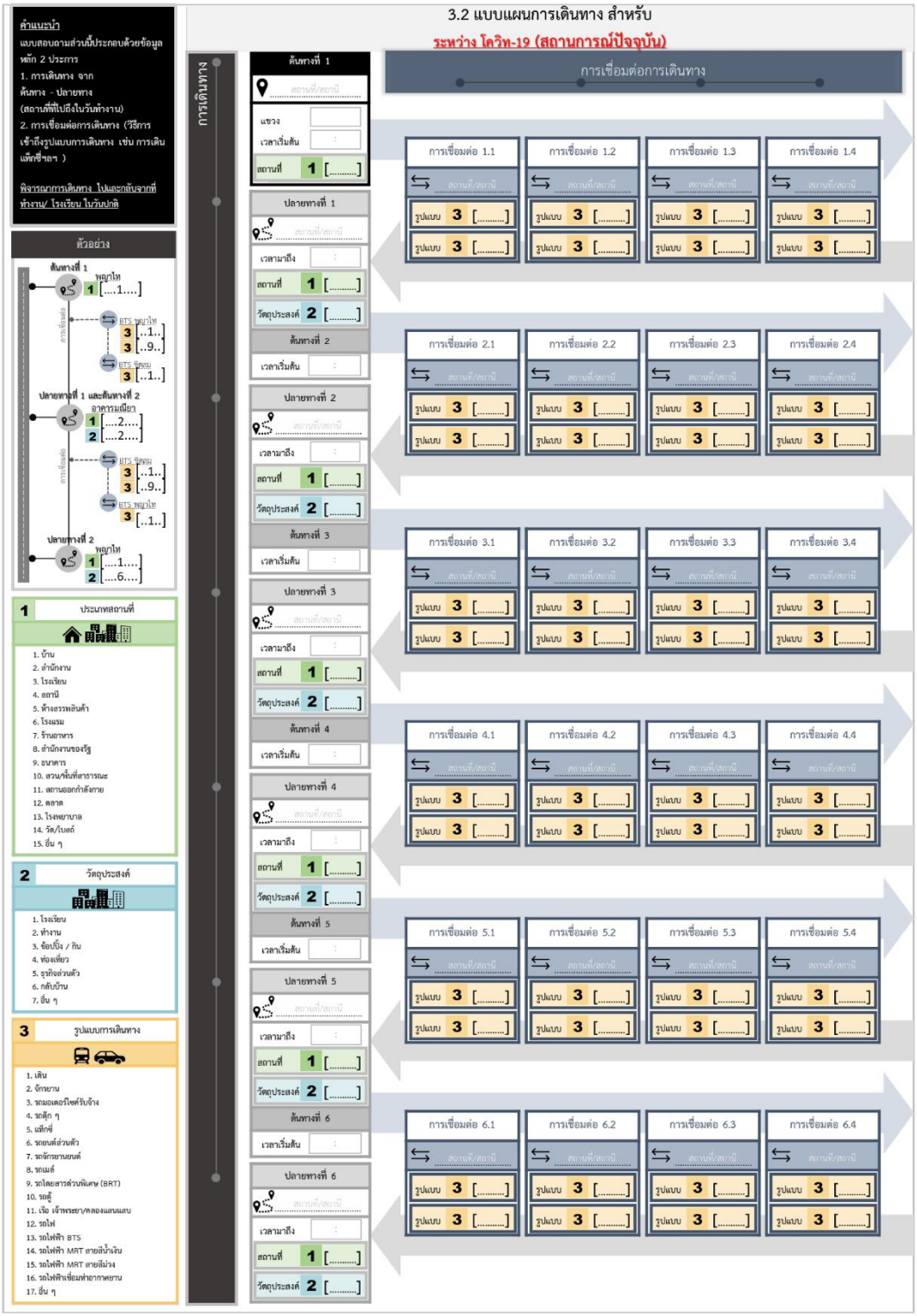
คำแนะนำ : อธิบายแบบแผนการเดินทางของท่านในหนึ่งวัน

*หมายเหตุ : "แบบสอบถามนี้พิจารณาการเดินทางโดย**ปกติหรือการเดินทางในวันทำงาน** (วันธรรมดาทั่วไป โดยรวมกิจกรรมที่ดำเนินเป็นประจำของวันธรรมดา เริ่มจากบ้านไปทำงานรวมถึงกิจกรรมอื่น ๆ ระหว่างวันจนกลับถึงบ้าน*

ในสถานการณ์ โควิท-19 ได้มีผลกระทบต่อท่านหรือไม่ → หาก "ใช่" ☑ กรุณาตอบข้อ 3.1 และ 3.2

"ไม่" ☑ กรุณาตอบข้อ 3.1 เท่านั้น




3.2 แบบแผนการเดินทาง สำหรับ
ระหว่าง โควิท-19 (สถานการณ์ปัจจุบัน)
คำแนะนำ
แบบสอบถามส่วนนี้ประกอบด้วยข้อมูลหลัก 2 ประการ
1. การเดินทาง จาก ต้นทาง - ปลายทาง (สถานที่ที่ไปถึงในวันทำงาน)
2. การเชื่อมต่อการเดินทาง (วิธีการเข้าถึงรูปแบบการเดินทาง เช่น การเดินเท้าซึ่งฯลฯ)
พิจารณาการเดินทาง ไปและกลับจากที่ทำงาน/ โรงเรียน ในวันปกติ
ตัวอย่าง
ต้นทางที่ 1
พญาไท
ปลายทางที่ 1 และต้นทางที่ 2
อาคารมณียา
ปลายทางที่ 2
1 ประเภทสถานที่
1. บ้าน
2. สำนักงาน
3. โรงเรียน
4. สถานี
5. ห้างสรรพสินค้า
6. โรงแรม
7. ร้านอาหาร
8. สำนักงานของรัฐ
9. ธนาคาร
10. สวน/พื้นที่สาธารณะ
11. สถานออกกำลังกาย
12. ตลาด
13. โรงพยาบาล
14. วัด/โบสถ์
15. อื่น ๆ
2 วัตถุประสงค์
1. โรงเรียน
2. ทำงาน
3. ช้อปปิ้ง / กิน
4. ท่องเที่ยว
5. ธุรกิจส่วนตัว
6. กลับบ้าน
7. อื่น ๆ
3 รูปแบบการเดินทาง
1. เดิน
2. จักรยาน
3. รถมอเตอร์ไซค์รับจ้าง
4. รถตู้ ๆ
5. แท็กซี่
6. รถยนต์ส่วนตัว
7. รถจักรยานยนต์
8. รถเมล์
9. รถโดยสารด่วนพิเศษ (BRT)
10. รถตู้
11. เรือ เจ้าพระยา/คลองแสนแสบ
12. รถไฟ
13. รถไฟฟ้า BTS
14. รถไฟฟ้า MRT สายสีน้ำเงิน
15. รถไฟฟ้า MRT สายสีม่วง
16. รถไฟฟ้าเชื่อมท่าอากาศยาน
17. อื่น ๆ
การเดินทาง
ต้นทางที่ 1
แขวง
เวลาเริ่มต้น
สถานที่ 1
ปลายทางที่ 1
เวลามาถึง
สถานที่ 1
วัตถุประสงค์ 2
ต้นทางที่ 2
ปลายทางที่ 2
ต้นทางที่ 3
ปลายทางที่ 3
ต้นทางที่ 4
ปลายทางที่ 4
ต้นทางที่ 5
ปลายทางที่ 5
ต้นทางที่ 6
ปลายทางที่ 6
การเชื่อมต่อการเดินทาง
การเชื่อมต่อ 1.1
การเชื่อมต่อ 1.2
การเชื่อมต่อ 1.3
การเชื่อมต่อ 1.4
การเชื่อมต่อ 2.1
การเชื่อมต่อ 2.2
การเชื่อมต่อ 2.3
การเชื่อมต่อ 2.4
การเชื่อมต่อ 3.1
การเชื่อมต่อ 3.2
การเชื่อมต่อ 3.3
การเชื่อมต่อ 3.4
การเชื่อมต่อ 4.1
การเชื่อมต่อ 4.2
การเชื่อมต่อ 4.3
การเชื่อมต่อ 4.4
การเชื่อมต่อ 5.1
การเชื่อมต่อ 5.2
การเชื่อมต่อ 5.3
การเชื่อมต่อ 5.4
การเชื่อมต่อ 6.1
การเชื่อมต่อ 6.2
การเชื่อมต่อ 6.3
การเชื่อมต่อ 6.4
สถานที่/สถานี
รูปแบบ 3

ส่วนที่ 4 : ทัศนคติการเดินทาง และทัศนคติการเลือกที่อยู่อาศัยด้วยตนเอง

คำแนะนำ : ให้คะแนนที่ตรงกับความคิดเห็น โดยใช้เครื่องหมาย ✓ ลงในช่องว่าง

หมายเหตุ : ระดับคะแนนมีความหมายดังนี้

5 – เห็นด้วยอย่างยิ่ง 4 – เห็นด้วยเล็กน้อย 3 – เป็นกลาง 2 –ไม่เห็นด้วยเล็กน้อย 1 – ไม่เห็นด้วยอย่างยิ่ง

ทัศนคติการเดินทาง		ความคิดเห็น									
		ก่อน โควิท-19 (เห็นด้วยอย่างยิ่ง ↔ ไม่เห็นด้วยอย่างยิ่ง)					ระหว่าง โควิท-19 (เห็นด้วยอย่างยิ่ง ↔ ไม่เห็นด้วยอย่างยิ่ง)				
		5	4	3	2	1	5	4	3	2	1
กลุ่มผู้ใช้ระบบขนส่งมวลชน	ชอบการเดินทางด้วยระบบขนส่งมวลชน (BTS, MRT, ARL).										
	ชอบการเดินทางด้วยระบบขนส่งสาธารณะ (รถโดยสารประจำทาง, เรือโดยสารประจำทาง).										
	ชอบการเดินทางด้วยจักรยาน/การเดินเท้า										
	ชอบการเดินทางด้วยรถยนต์ส่วนบุคคล										
	ชอบการเดินทางด้วยระบบขนส่งกึ่งสาธารณะ (แท็กซี่, มอเตอร์ไซค์รับจ้าง, ตุ๊กตุ๊ก)										
กลุ่มผู้ใช้รถยนต์ส่วนบุคคล	ยอมรับค่าเดินทางที่มากขึ้นเพื่อใช้รถยนต์ส่วนบุคคล										
	เลือกรูปแบบการเดินทางจากการประหยัดเวลาในการเดินทาง										
	เลือกใช้รถยนต์ส่วนบุคคลเนื่องจากภาพลักษณ์ทางสังคม										
	ระบบขนส่งมวลชนง่ายต่อการเดินทางมากกว่ารูปแบบอื่น										
	หากมีระบบชำระค่าโดยสารออนไลน์ จะใช้ระบบขนส่งสาธารณะมากกว่า										
	หากมีสิ่งอำนวยความสะดวกที่ดีที่สถานี (ความสะอาด ห้องน้ำ และอื่น ๆ) จะใช้ระบบขนส่งมวลชน										
กลุ่มผู้ตระหนักถึงสิ่งแวดล้อม	หลีกเลี่ยงมลพิษโดยใช้รถยนต์ส่วนบุคคล										
	ชอบการเดินทางด้วยรถยนต์ส่วนบุคคลเนื่องจากสภาพอากาศ (ร้อน ฝนตก ฯลฯ)										
	กังวลเรื่องการติดเชื้อหากใช้ระบบขนส่งสาธารณะ										
	ชอบการเดินทางด้วยระบบขนส่งมวลชน เนื่องจากมีความกังวลภาวะโลกร้อน										
กลุ่มผู้ชอบความเสี่ยง	จะใช้ระบบขนส่งสาธารณะหากผู้โดยสารสวมหน้ากากอนามัย										
	ชอบใช้รถส่วนบุคคลหรือระบบขนส่งสาธารณะเพื่อหลีกเลี่ยงอาชญากรรม / ราคาที่ไม่เป็นธรรมจากแท็กซี่										
	ชอบใช้รถส่วนบุคคลเพื่อหลีกเลี่ยงความเสี่ยงทางอาชญากรรม										

ทัศนคติการเลือกที่อยู่อาศัยด้วยตนเอง		ความคิดเห็น									
		ก่อน โควิท-19 (เห็นด้วยอย่างยิ่ง ↔ ไม่เห็นด้วยอย่างยิ่ง)					ระหว่าง โควิท-19 (เห็นด้วยอย่างยิ่ง ↔ ไม่เห็นด้วยอย่างยิ่ง)				
		5	4	3	2	1	5	4	3	2	1
กลุ่มผู้ชื่นชอบในเมือง	ชอบอาศัยอยู่พื้นที่เขตเมือง										
	ชอบอยู่ใกล้แหล่งชุมชน / ช้อปปิ้ง / สำนักงาน / โรงเรียน / โรงพยาบาล ฯลฯ										
	ชอบภาพลักษณ์ทางสังคมและสภาพแวดล้อมทางสังคมในเมือง										
	ชอบอาศัยอยู่ในละแวกพื้นที่อยู่อาศัย.										
	ไม่ชอบอาศัยอยู่บริเวณหนาแน่น แต่ไม่ไกลจากตัวเมืองมากเกินไป										
	ชอบอาศัยอยู่ในพื้นที่ชนบท										
กลุ่มผู้ใช้ระบบขนส่งมวลชน	ชอบที่อยู่อาศัยที่ใกล้สถานีขนส่งมวลชน (BTS, MRT, ARL).										
	ชอบที่อยู่อาศัยที่ใกล้ป้ายรถโดยสารประจำทาง										
	ชอบที่อยู่อาศัยที่ใกล้ทางด่วน/ทางพิเศษ หรือถนนสายหลัก										
	ชอบที่อยู่อาศัยที่ใกล้อาคารจอดและจร										
	บริเวณที่อยู่อาศัยง่ายต่อการใช้บริการแท็กซี่										
	สถานที่ทำกิจกรรมต่าง ๆ สามารถเดินเท้าจากบ้านได้										
	บริเวณที่อยู่อาศัยมีสภาพแวดล้อมที่เป็นมิตรสำหรับคนเดินเท้า										
	บริเวณที่อยู่อาศัยมีสภาพแวดล้อมที่เป็นมิตรสำหรับจักรยาน										
กลุ่มผู้ชื่นชอบสภาพแวดล้อม	ไม่ชอบมลพิษในเขตเมือง										
	ชอบสภาพแวดล้อมที่เป็นธรรมชาติของพื้นที่ชนบท										
	ชอบพื้นที่สีเขียว / สวนสาธารณะใกล้บ้าน										
	หากเลือกอาศัยในเขตเมืองสามารถยอมรับมลพิษได้										
	หากเลือกอาศัยในเขตเมืองสามารถยอมรับราคาที่ดินได้										
กลุ่มผู้ตระหนักถึงความปลอดภัย	เลือกที่อยู่อาศัยจากพื้นที่ที่ไม่มีอาชญากรรมหรือมีน้อย										
	เลือกที่อยู่อาศัยจากพื้นที่ที่มีไฟส่องสว่างทั่วบริเวณที่อยู่อาศัย										
	เลือกที่อยู่อาศัยจากพื้นที่ที่มีสถานีตำรวจใกล้ที่อยู่อาศัย										
	ไม่เลือกที่อยู่อาศัยในเขตเมือง เนื่องจากกังวลเกี่ยวกับการติดเชื้อโรค										

<u>ส่วนที่ 5 : สถานการณ์สมมุติ สำหรับการเลือกรูปแบบการเดินทางและการเลือกที่อยู่อาศัย</u>

<u>คำแนะนำ</u> : เลือกตัวเลือกที่ดีที่สุด ☑ ในช่องตัวเลือกของแบบสอบถาม

ตัวอย่าง

คุณลักษณะ	เดิน/จักรยาน	ระบบขนส่งมวลชน	ขนส่งสาธารณะ	รถยนต์/มอเตอร์ไซค์ ส่วนตัว
เวลาเดินทาง (นาที/เที่ยว)	30	45	45	45
ค่าใช้จ่ายในการเดินทาง(บาท/วัน)	10 (จักรยาน)	150	30	150
บริเวณใกล้เคียงที่อยู่อาศัย(พื้นที่)	ย่านที่อยู่อาศัย	ใกล้สถานีรถไฟฟ้า	ใกล้ป้ายรถโดยสาร	ย่านที่อยู่อาศัย
ค่าเช่าที่อยู่อาศัย (บาท)	10,000	10,000	7,000	5,000
	⬇	⬇	⬇	⬇
ตัวเลือกของคุณ	☑	☐	☐	☐

ในสถานการณ์อนาคตที่ต้องพิจารณาการเลือกที่อยู่อาศัยหรือการย้ายที่อยู่อาศัย <u>รูปแบบการเดินทางใดที่ท่านเลือกมากที่สุด?</u> (เปรียบเทียบในแต่ละสถานการณ์ จากปัจจัยต่าง ๆ)

หมายเหตุ : จากตัวอย่าง เลือกรูปแบบการเดินทางคือ <u>เดิน/จักรยาน</u>

ตัวเลือก ชุดที่ 1

คุณลักษณะ	เดิน/จักรยาน	ระบบขนส่งมวลชน	ขนส่งสาธารณะ	รถยนต์/มอเตอร์ไซค์ ส่วนตัว
เวลาเดินทาง (นาที/เที่ยว)	30	45	45	45
ค่าใช้จ่ายในการเดินทาง(บาท/วัน)	10 (จักรยาน)	150	30	150
บริเวณใกล้เคียงที่อยู่อาศัย(พื้นที่)	ย่านที่อยู่อาศัย	ใกล้สถานีรถไฟฟ้า	ใกล้ป้ายรถโดยสาร	ย่านที่อยู่อาศัย
ค่าเช่าที่อยู่อาศัย (บาท)	10,000	10,000	7,000	5,000
	⬇	⬇	⬇	⬇
ตัวเลือกของคุณ	☐	☐	☐	☐

ตัวเลือก ชุดที่ 2

คุณลักษณะ	เดิน/จักรยาน	ระบบขนส่งมวลชน	ขนส่งสาธารณะ	รถยนต์/มอเตอร์ไซค์ ส่วนตัว
เวลาเดินทาง (นาที/เที่ยว)	30	15	15	30
ค่าใช้จ่ายในการเดินทาง(บาท/วัน)	20 (จักรยาน)	100	100	450
บริเวณใกล้เคียงที่อยู่อาศัย(พื้นที่)	ใกล้สถานีรถไฟฟ้า	ย่านที่อยู่อาศัย	ย่านที่อยู่อาศัย	ย่านการค้า
ค่าเช่าที่อยู่อาศัย (บาท)	15,000	10,000	7,000	5,000
	⬇	⬇	⬇	⬇
ตัวเลือกของคุณ	☐	☐	☐	☐

ตัวเลือก ชุดที่ 3

คุณลักษณะ	เดิน/จักรยาน	ระบบขนส่งมวลชน	ขนส่งสาธารณะ	รถยนต์/มอเตอร์ไซค์ ส่วนตัว
เวลาเดินทาง (นาที/เที่ยว)	15	45	45	45
ค่าใช้จ่ายในการเดินทาง(บาท/วัน)	0	50	50	300
บริเวณใกล้เคียงที่อยู่อาศัย(พื้นที่)	ย่านที่อยู่อาศัย	ย่านที่อยู่อาศัย	ย่านที่อยู่อาศัย	ย่านการค้า
ค่าเช่าที่อยู่อาศัย (บาท)	15,000	13,000	9,000	9,000
	⬇	⬇	⬇	⬇
ตัวเลือกของคุณ	☐	☐	☐	☐

ตัวเลือก ชุดที่ 4

คุณลักษณะ	เดิน/จักรยาน	ระบบขนส่งมวลชน	ขนส่งสาธารณะ	รถยนต์/มอเตอร์ไซค์ ส่วนตัว
เวลาเดินทาง (นาที/เที่ยว)	15	30	30	60
ค่าใช้จ่ายในการเดินทาง(บาท/วัน)	20 (จักรยาน)	50	50	300
บริเวณใกล้เคียงที่อยู่อาศัย(พื้นที่)	ย่านการค้า	ย่านการค้า	ย่านการค้า	ใกล้ป้ายรถโดยสาร
ค่าเช่าที่อยู่อาศัย (บาท)	10,000	10,000	7,000	5,000
	⬇	⬇	⬇	⬇
ตัวเลือกของคุณ	☐	☐	☐	☐

ตัวเลือก ชุดที่ 5

คุณลักษณะ	เดิน/จักรยาน	ระบบขนส่งมวลชน	ขนส่งสาธารณะ	รถยนต์/มอเตอร์ไซค์ ส่วนตัว
เวลาเดินทาง (นาที/เที่ยว)	15	30	30	60
ค่าใช้จ่ายในการเดินทาง(บาท/วัน)	10 (จักรยาน)	150	30	150
บริเวณใกล้เคียงที่อยู่อาศัย(พื้นที่)	ใกล้สถานีรถไฟฟ้า	ย่านที่อยู่อาศัย	ย่านที่อยู่อาศัย	ย่านการค้า
ค่าเช่าที่อยู่อาศัย (บาท)	20,000	7,000	5,000	7,000
	⬇	⬇	⬇	⬇
ตัวเลือกของคุณ	☐	☐	☐	☐

ตัวเลือก ชุดที่ 6

คุณลักษณะ	เดิน/จักรยาน	ระบบขนส่งมวลชน	ขนส่งสาธารณะ	รถยนต์/มอเตอร์ไซค์ ส่วนตัว
เวลาเดินทาง (นาที/เที่ยว)	5	15	15	30
ค่าใช้จ่ายในการเดินทาง(บาท/วัน)	20 (จักรยาน)	50	50	300
บริเวณใกล้เคียงที่อยู่อาศัย(พื้นที่)	ย่านที่อยู่อาศัย	ใกล้สถานีรถไฟฟ้า	ใกล้ป้ายรถโดยสาร	ย่านที่อยู่อาศัย
ค่าเช่าที่อยู่อาศัย (บาท)	20,000	7,000	5,000	7,000
	⬇	⬇	⬇	⬇
ตัวเลือกของคุณ	☐	☐	☐	☐

ผู้วิจัยขอขอบคุณท่านที่ให้ความร่วมมือในการตอบแบบสอบถามไว้ ณ โอกาสนี้.

ท่านสามารถตอบแบบสอบถามได้
ทาง<u>แบบสอบถามออนไลน์</u>อีกหนึ่งช่องทาง

8.1.2 Experimental and Choice Set Design

In this study, attributes have been designed for travel mode choice and resident location choice with a separate location choice from the level of the neighborhood after collecting data. Travel mode choice considered 2 attributes: total travel time and total travel cost for 4 mode choices. Resident location choice considered 2 attributes: neighborhood area and rental price for 2 locations. The objective of the stated preference survey is to determine, in consideration of relocation in the future, which mode the respondent will prefer to travel by considering the attributes of each mode.

Each attribute is designed by the average current value of each mode and area. The location choice uses indirect questions to facilitate the answering of questions and to reduce potential respondent confusion. Provided that the neighborhood area represents residential location choice where there is an attribute level of near mass transit and the commercial area represents urban area location choice, Near bus stops and residential areas, which represent suburban area location choices.

Attribute	Walk/bike	Mass transit	Public transport	Private car
Travel time (minute/trip)	5	15	15	30
	15	30	30	45
	30	45	45	60
Travel cost (baht/day)	0	50	30	150
	10	100	50	300
	20	150	100	450
Neighborhood (area)	Near Mass transit Station	Near Mass transit Station	Near Bus Stop	Near Bus Stop
	Commercial	Commercial	Commercial	Commercial
	Residential	Residential	Residential	Residential
Rental price (THB)	10,000	7,000	5,000	5,000
	15,000	10,000	7,000	7,000
	20,000	13,000	9,000	9,000

The experimental design of this research consists of four attributes, three levels of each attribute, and four mode choices. In the case of full factorial experiment design, the number of experiments is 3x3x3x4=81 experiments. In the case of using an orthogonal array to reduce the number of experiments, the experiment was considered by the number of attributes, and the highest number of levels is 3. Finally, the appropriate orthogonal array is L9 (34) with 9 experiments.

Orthogonal array of L_9 [178]

Experiment No.	Column			
	1	2	3	4
1	1	1	1	1
2	1	2	2	2
3	1	3	3	3
4	2	1	2	3
5	2	2	3	1
6	2	3	1	2
7	3	1	3	2
8	3	2	1	3
9	3	3	2	1

For the design choice set, we used a completely randomized experimental design for the random attribute level in the choice set. SPSS software was used to generate the random attributes for the stated preference survey. The results from orthogonal experiment design in a total of 9 experiments and 4 mode choices were shown as follows.

Situation 1 : choice set 1 and 4 mode choices.

Choice set 1

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	30	45	45	45
Travel cost (baht/day)	10 (Bike)	150	30	150
Neighborhood (area)	Residential	Near Mass transit Station	Near Bus Stop	Residential
Rental price (baht)	10,000	10,000	7,000	5,000
	⬇	⬇	⬇	⬇
Your choice:	☐	☐	☐	☐

Situation 2 : choice set 2 and 4 mode choices.

Choice set 2

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	30	15	15	30
Travel cost (baht/day)	20 (Bike)	100	100	450
Neighborhood (area)	Near Mass transit Station	Residential	Residential	Commercial
Rental price (baht)	15,000	10,000	7,000	5,000
	⬇	⬇	⬇	⬇
Your choice:	☐	☐	☐	☐

Situation 3 : choice set 3 and 4 mode choices.

Choice set 3

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	15	45	45	45
Travel cost (baht/day)	0	50	50	300
Neighborhood (area)	Residential	Residential	Residential	Commercial
Rental price (baht)	15,000	13,000	9,000	9,000
	⬇	⬇	⬇	⬇
Your choice:	☐	☐	☐	☐

Situation 4 : choice set 4 and 4 mode choices.

Choice set 4

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	15	30	30	60
Travel cost (baht/day)	20 (Bike)	50	50	300
Neighborhood (area)	Commercial	Commercial	Commercial	Near Bus Stop
Rental price (baht)	10,000	10,000	7,000	5,000
	⬇	⬇	⬇	⬇
Your choice:	☐	☐	☐	☐

Situation 5 : choice set 5 and 4 mode choices.

Choice set 5

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	15	30	30	60
Travel cost (baht/day)	10 (Bike)	150	30	150
Neighborhood (area)	Near Mass transit Station	Residential	Residential	Commercial
Rental price (baht)	20,000	7,000	5,000	7,000
	⬇	⬇	⬇	⬇
Your choice:	☐	☐	☐	☐

Situation 6 : choice set 6 and 4 mode choices.

Choice set 6

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	5	15	15	30
Travel cost (baht/day)	20 (Bike)	50	50	300
Neighborhood (area)	Residential	Near Mass transit Station	Near Bus Stop	Residential
Rental price (baht)	20,000	7,000	5,000	7,000
	⬇	⬇	⬇	⬇
Your choice:	☐	☐	☐	☐

Situation 7 : choice set 7 and 4 mode choices.

Choice set 7

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	5	15	15	30
Travel cost (baht/day)	0	150	30	150
Neighborhood (area)	Near Mass transit Station	Commercial	Commercial	Near Bus Stop
Rental price (baht)	10,000	13,000	9,000	9,000
	⬇	⬇	⬇	⬇
Your choice:	☐	☐	☐	☐

Situation 8 : choice set 8 and 4 mode choices.

Choice set 8

Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	30	30	30	60
Travel cost (baht/day)	0	100	100	450
Neighborhood (area)	Commercial	Near Mass transit Station	Near Bus Stop	Residential
Rental price (baht)	20,000	13,000	9,000	9,000
	⬇	⬇	⬇	⬇
Your choice:	☐	☐	☐	☐

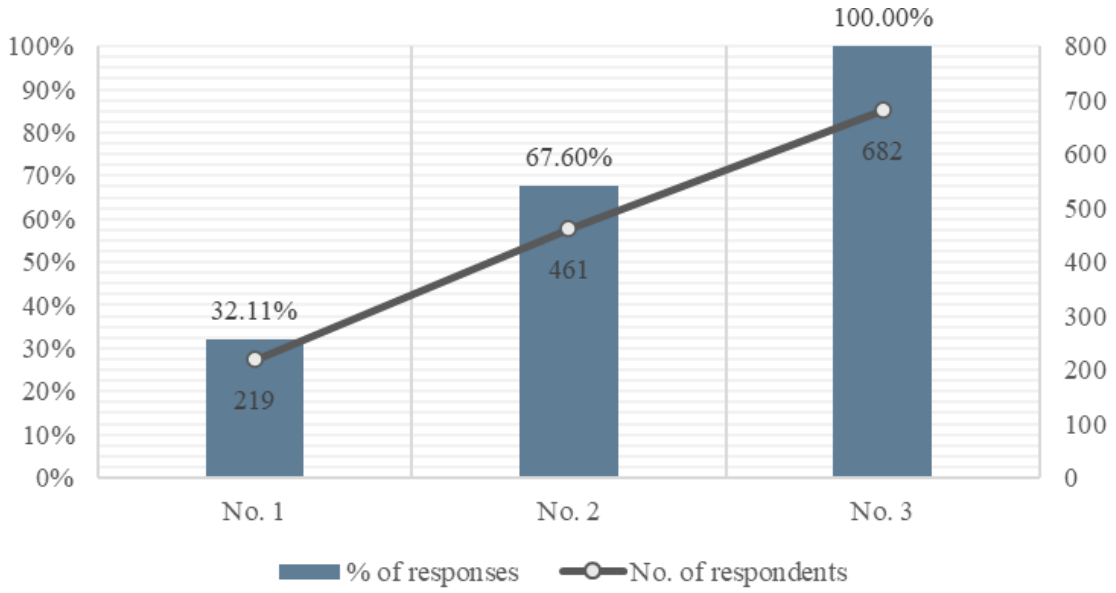
Situation 9 : choice set 9 and 4 mode choices.

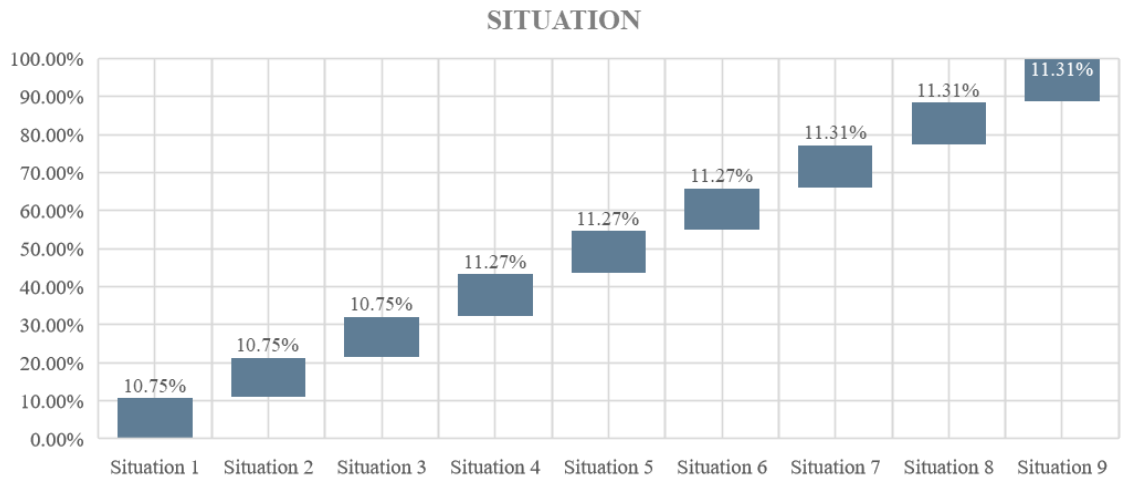
Choice set 9

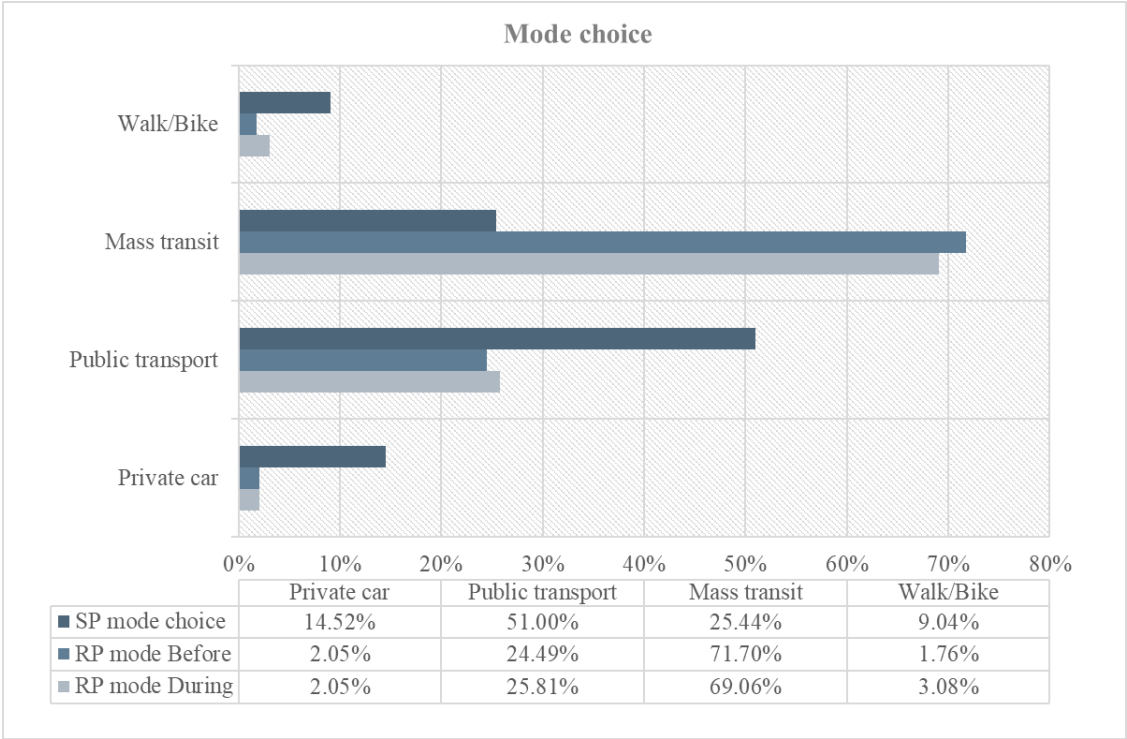
Attributes	Walk/bike	Mass transit	Public transport	Private car/motorbike
Travel time (minute/trip)	5	45	45	45
Travel cost (baht/day)	10 (Bike)	100	100	450
Neighborhood (area)	Commercial	Commercial	Commercial	Near Bus Stop
Rental price (baht)	15,000	7,000	5,000	5,000
	⬇	⬇	⬇	⬇
Your choice:	☐	☐	☐	☐

8.1.3 Summary of Revealed Preference (RP) and State Preference (SP) Data

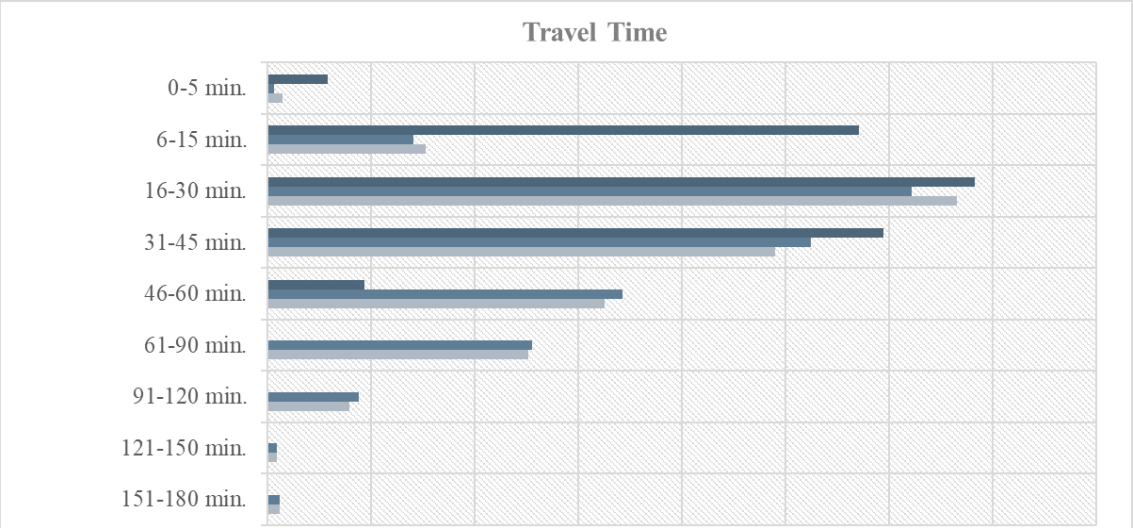
Results of revealed preferences and state preferences were collected by means of a face-to-face questionnaire. The summary of 682 respondents in a total of 4092 scenario observations from 9 situations with 4 mode choices and separated into 6 situations for each questionnaire, the results are shown as follows:



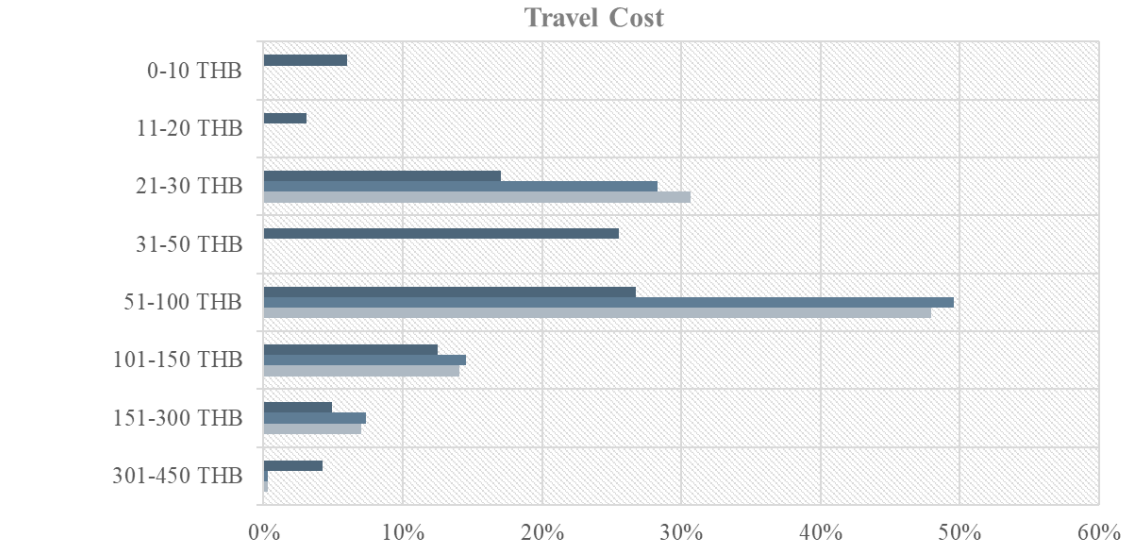




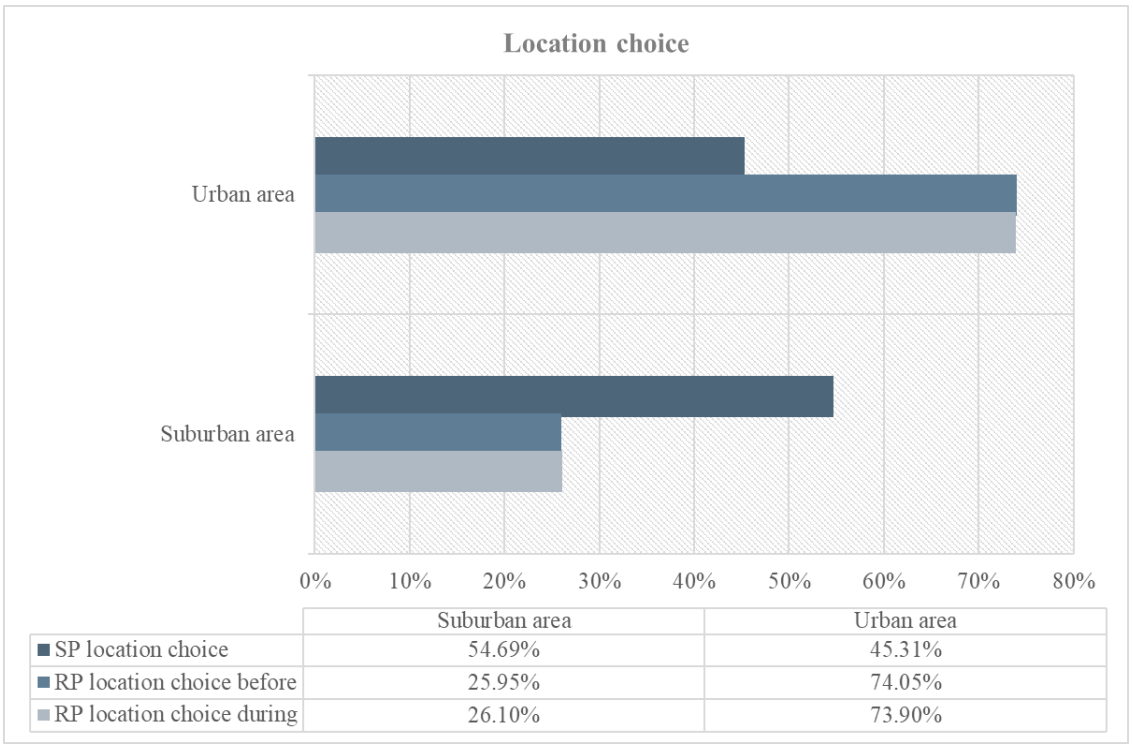
	Private car	Public transport	Mass transit	Walk/Bike
SP mode choice	14.52%	51.00%	25.44%	9.04%
RP mode Before	2.05%	24.49%	71.70%	1.76%
RP mode During	2.05%	25.81%	69.06%	3.08%



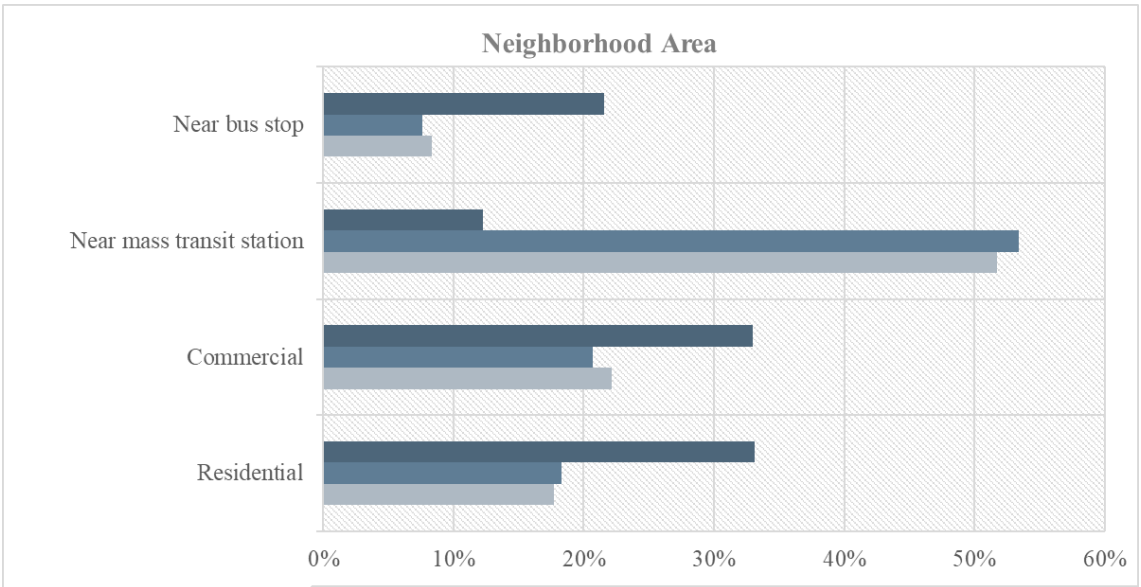
	151-180 min.	121-150 min.	91-120 min.	61-90 min.	46-60 min.	31-45 min.	16-30 min.	6-15 min.	0-5 min.
SP travel time					4.67%	29.72%	34.14%	28.57%	2.91%
RP travel time before	0.59%	0.44%	4.40%	12.76%	17.16%	26.25%	31.09%	7.04%	0.29%
RP travel time during	0.59%	0.44%	3.96%	12.61%	16.28%	24.49%	33.28%	7.62%	0.73%



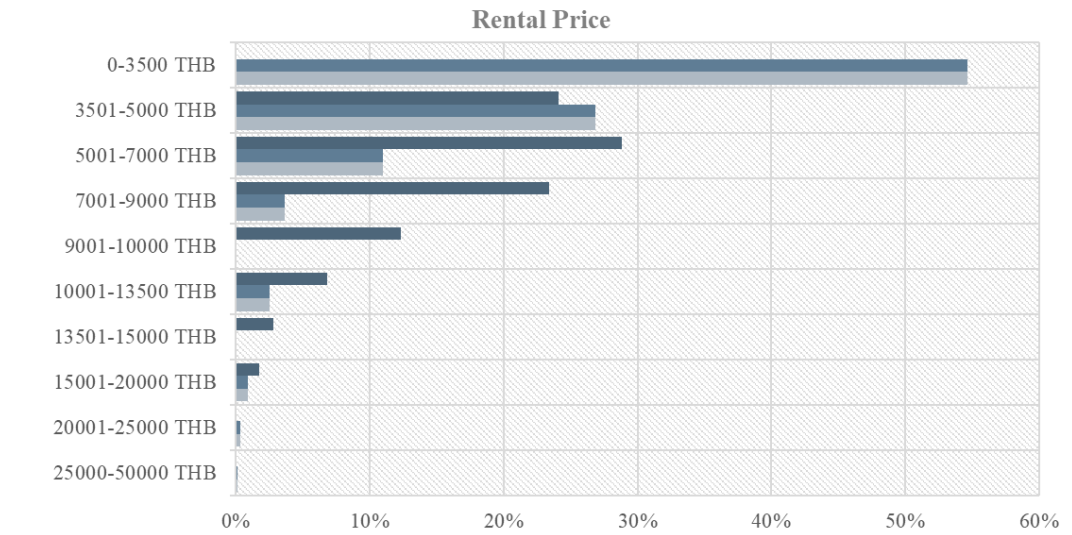
	301-450 THB	151-300 THB	101-150 THB	51-100 THB	31-50 THB	21-30 THB	11-20 THB	0-10 THB
SP travel cost	4.25%	4.89%	12.51%	26.76%	25.51%	17.03%	3.05%	5.99%
RP travel cost before	0.29%	7.33%	14.52%	49.56%	0.00%	28.30%	0.00%	0.00%
RP travel cost during	0.29%	7.04%	14.08%	47.95%	0.00%	30.65%	0.00%	0.00%



	Suburban area	Urban area
SP location choice	54.69%	45.31%
RP location choice before	25.95%	74.05%
RP location choice during	26.10%	73.90%



	Residential	Commercial	Near mass transit station	Near bus stop
SP neighborhood area	33.11%	33.02%	12.29%	21.58%
RP neighborhood area before	18.33%	20.67%	53.37%	7.62%
RP neighborhood area during	17.74%	22.14%	51.76%	8.36%



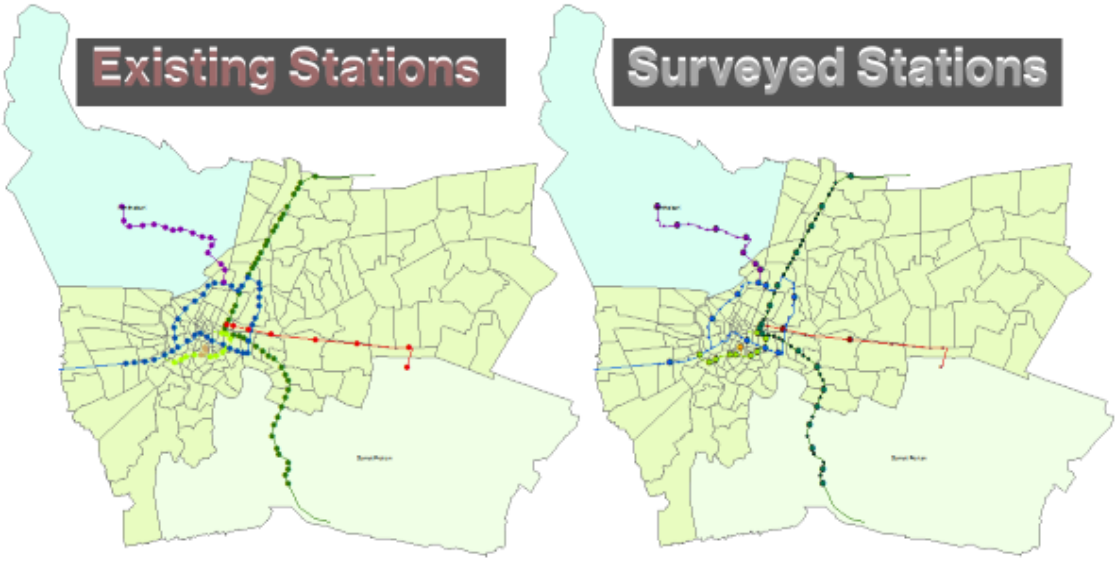
	25000-50000 THB	20001-25000 THB	15001-20000 THB	13501-15000 THB	10001-13500 THB	9001-10000 THB	7001-9000 THB	5001-7000 THB	3501-5000 THB	0-3500 THB
SP rental price	0.00%	0.00%	1.74%	2.76%	6.82%	12.32%	23.44%	28.84%	24.10%	0.00%
RP rental price before	0.15%	0.29%	0.88%	0.00%	2.49%	0.00%	3.67%	11.00%	26.83%	54.69%
RP rental price during	0.15%	0.29%	0.88%	0.00%	2.49%	0.00%	3.67%	11.00%	26.83%	54.69%

8.1.4 Field Survey Images

Survey on December 16-18, 2020

The survey station area totally 45 stations form 125 existing mass transit stations.

All 45 stations from total 125 stations		
	BTS dark green	17 stations
	BTS light green	9 stations
	MRT blue line	9 stations
	MRT purple line	7 stations
	Gold line	1 station
	Airport rail link	2 stations

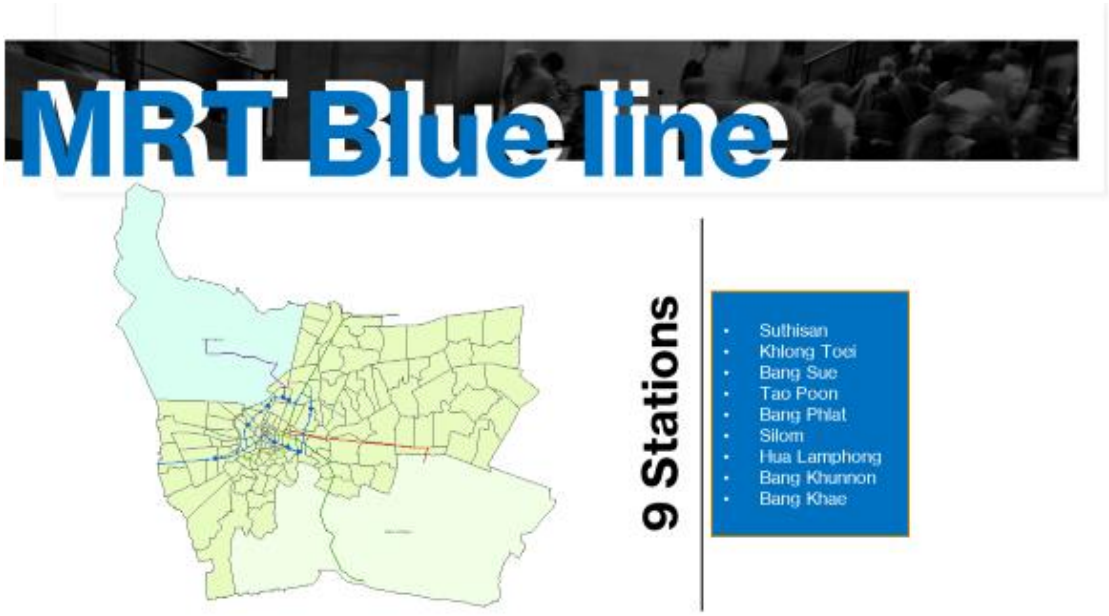



BTS dark green
17 Stations
Udom Suk
Mo Chit
Phayathai
Siam
Kasetsart University
Saphanmai
Ari
Ratchathewi
Thonglor
Khu Khot
Bearing
On Nut
Wat Phra Sri Mahathat
Chao Samingprai
Kheha
Phraeksa
Royal Thai Naval Academy

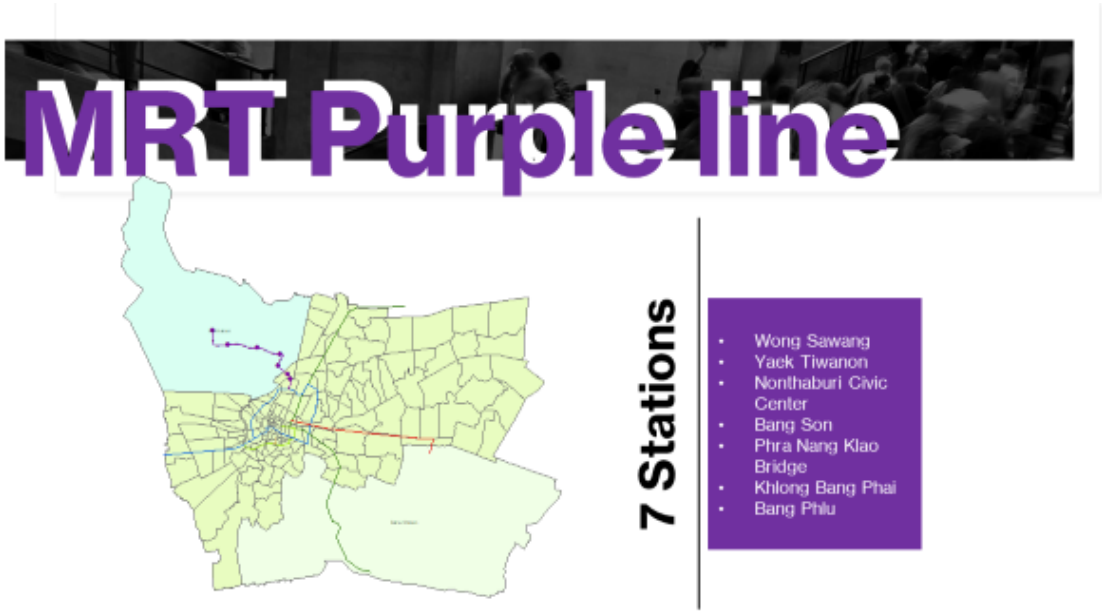

BTS dark green


BTS light green
9 Stations
Chong Nonsi
Surasak
Bang Wa
National Stadium
Ratchadamri
Thon Buri
Wongwian Yai
Talat Phlu
Wutthakat


BTS light green


MRT Blue line
9 Stations
Suthisan
Khlong Toei
Bang Sue
Tao Poon
Bang Phlat
Silom
Hua Lamphong
Bang Khunnon
Bang Khae


MRT Blue line


MRT Purple line
7 Stations
Wong Sawang
Yaek Tiwanon
Nonthaburi Civic Center
Bang Son
Phra Nang Klao Bridge
Khlong Bang Phai
Bang Phlu


MRT Purple line


Airport Rail Link
2 Stations
Makkasan
Suvarnabhumi


Airport Rail Line


Gold line
1 Station
Khlong San

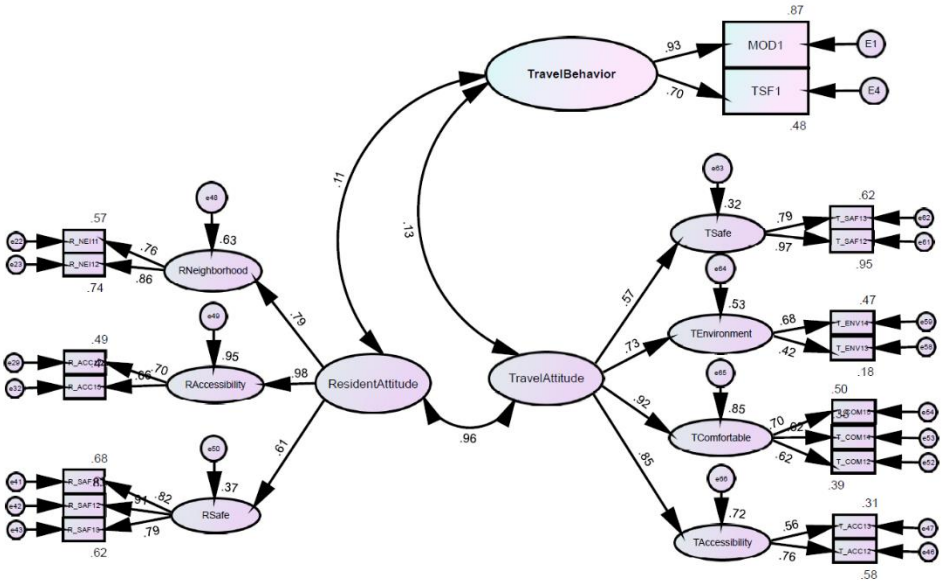

Gold line
G3
G2
G1

8.2 Structural Equation Modelling Result

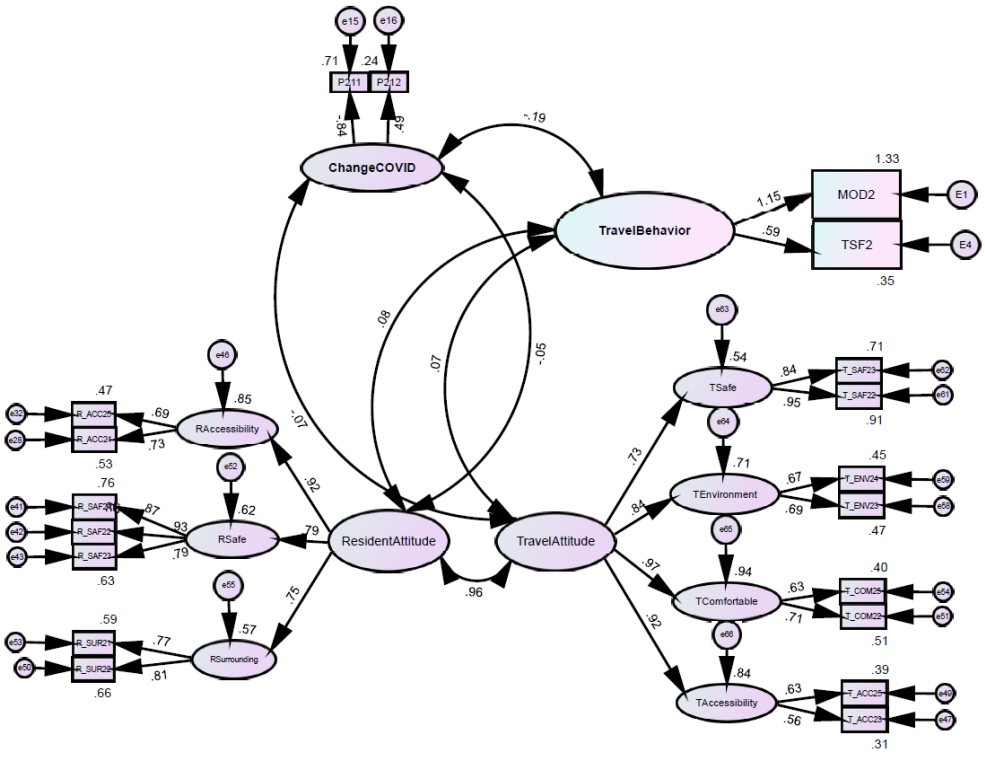
In part of the structural equation modelling (SEM) analysis, the analysis result from AMOS software was divided into 3 results:

8.2.1 Result of SEM (Chapter 4)

Before COVID-19 case

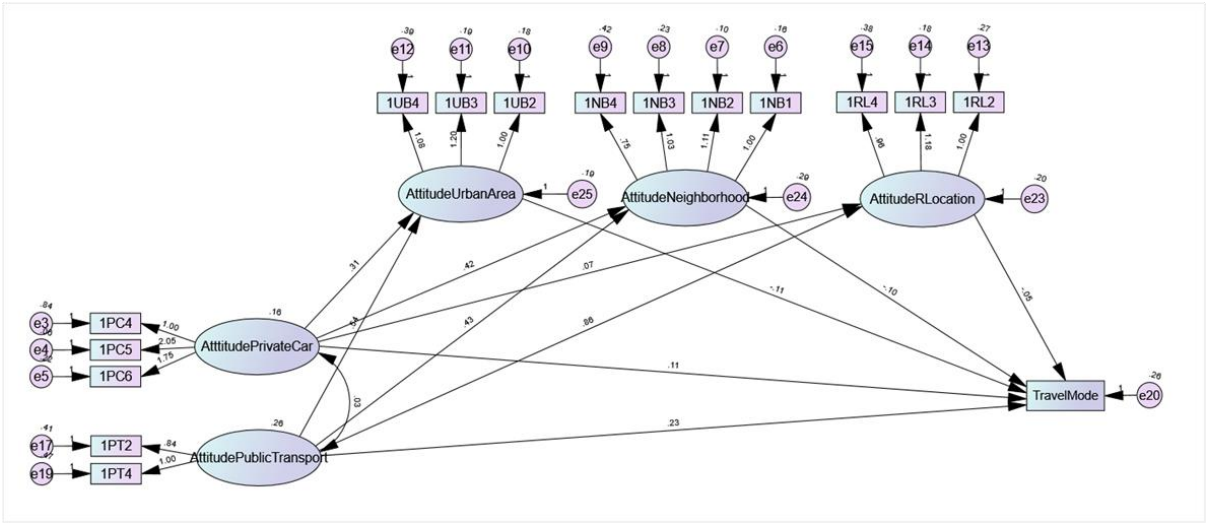


During COVID-19 case

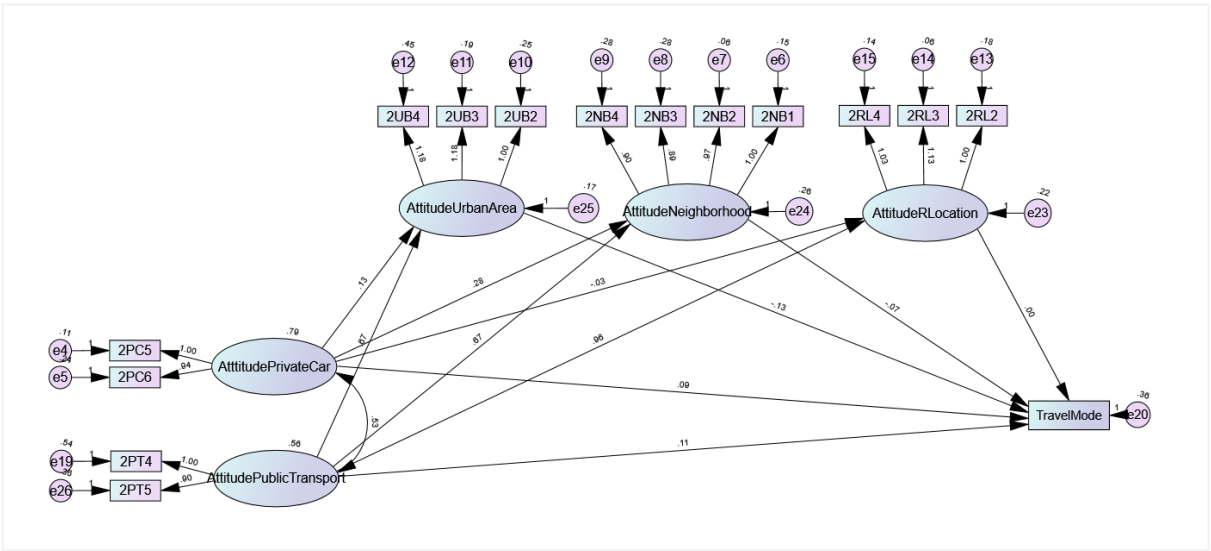


8.2.2 Result of SEM; Moderated Mediation Model (Chapter 5)

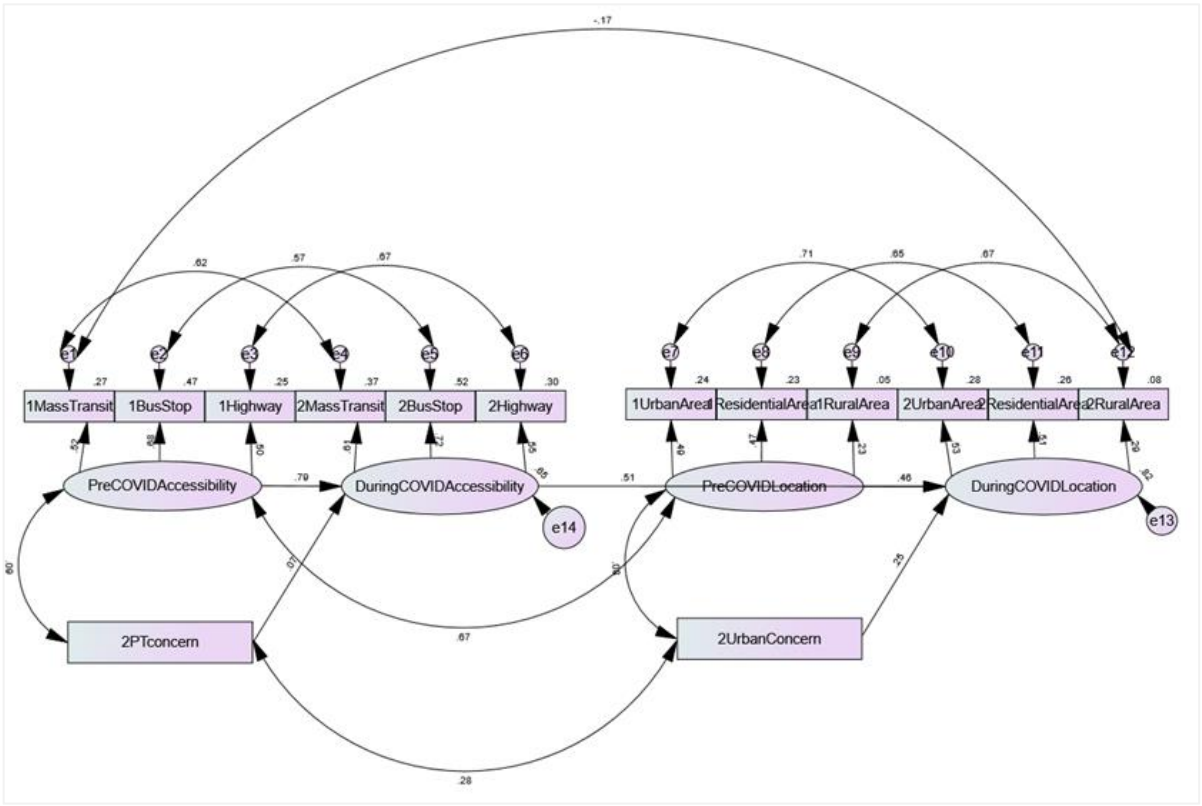
Before COVID-19 case



During COVID-19 case



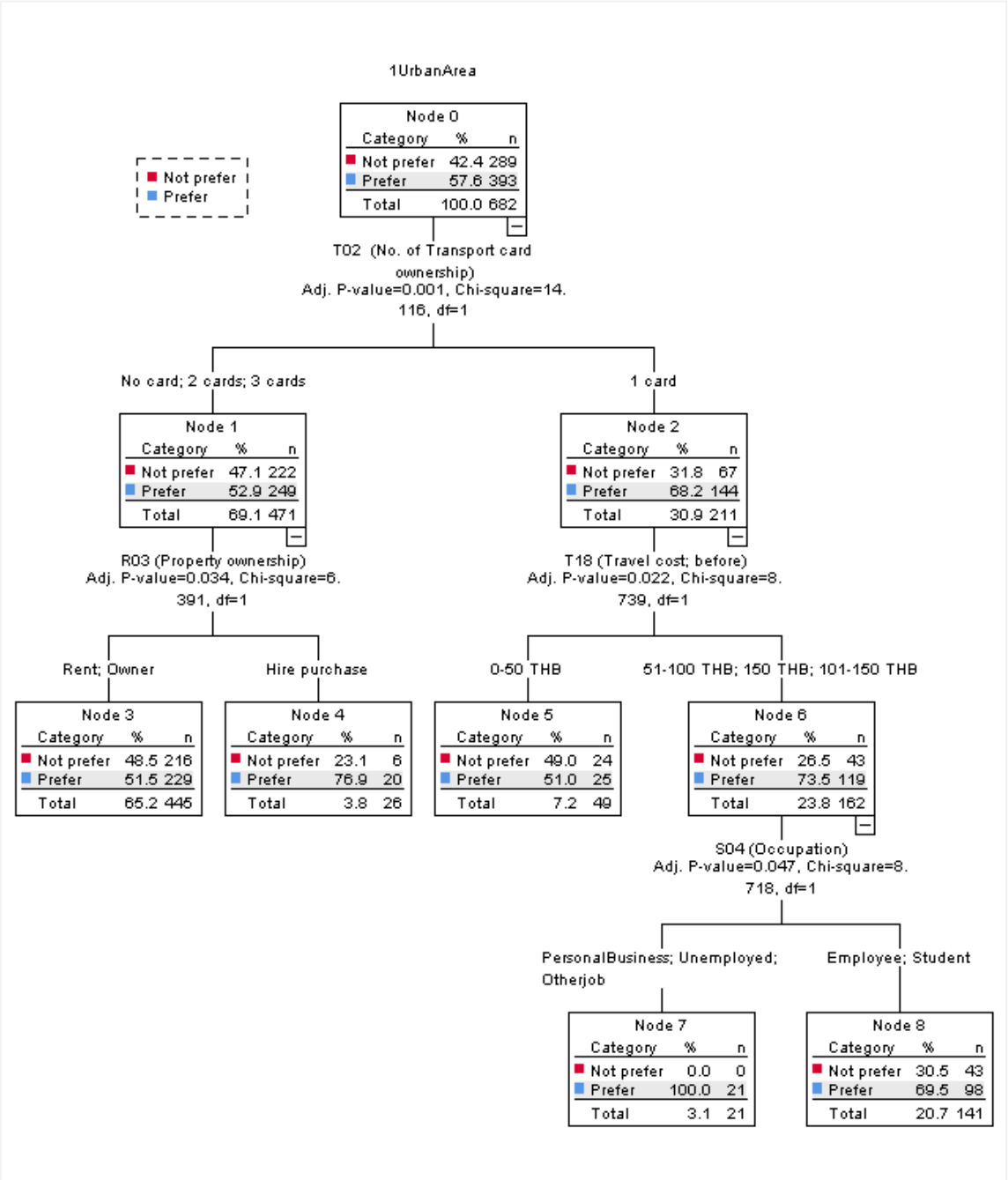
8.2.3 Result of SEM; Pre-test and Post-test Model (Chapter 6)



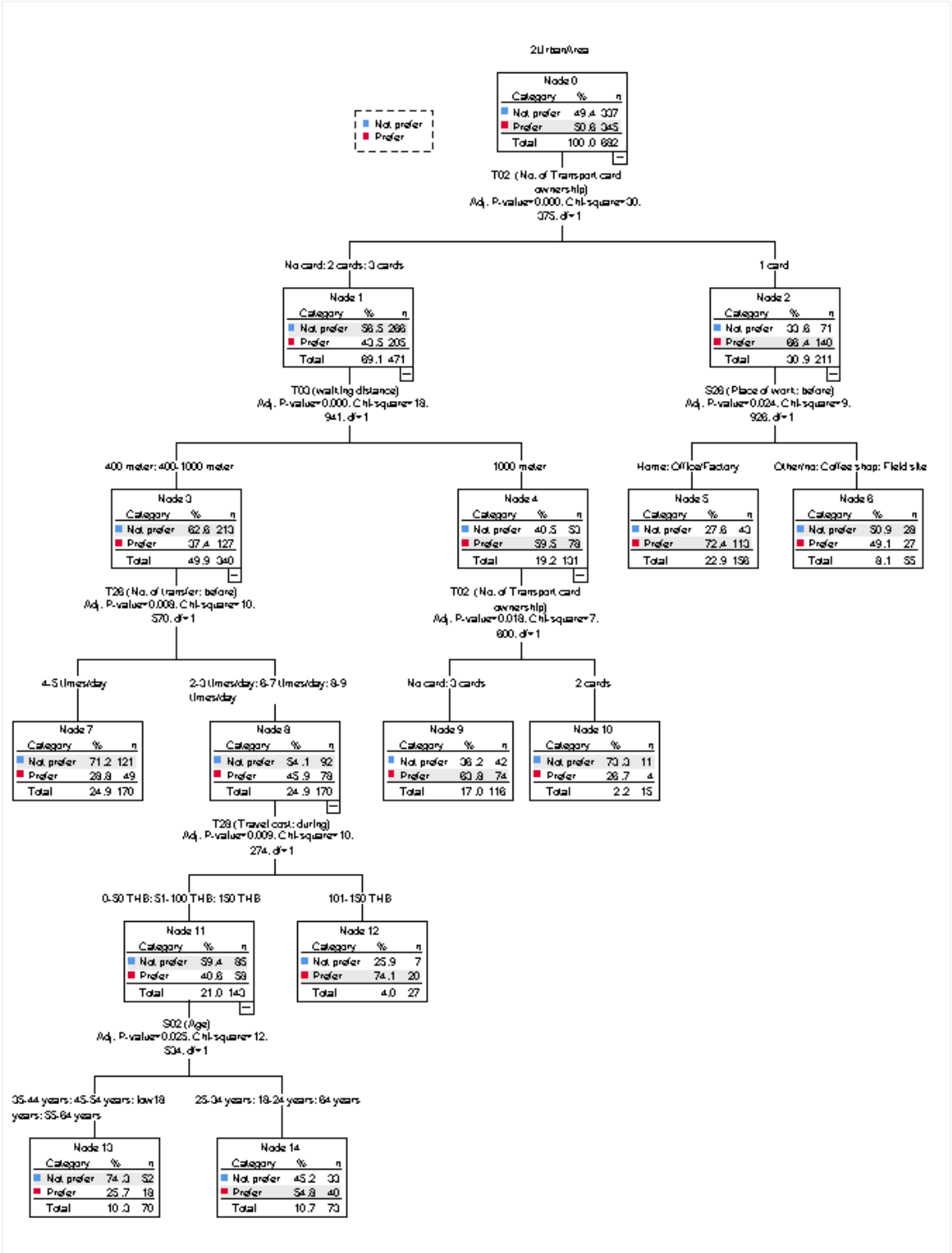
8.3 Chi-Square Automatic Interaction Detection Results

8.3.1 Results of Attitude Toward Residential Location Areas

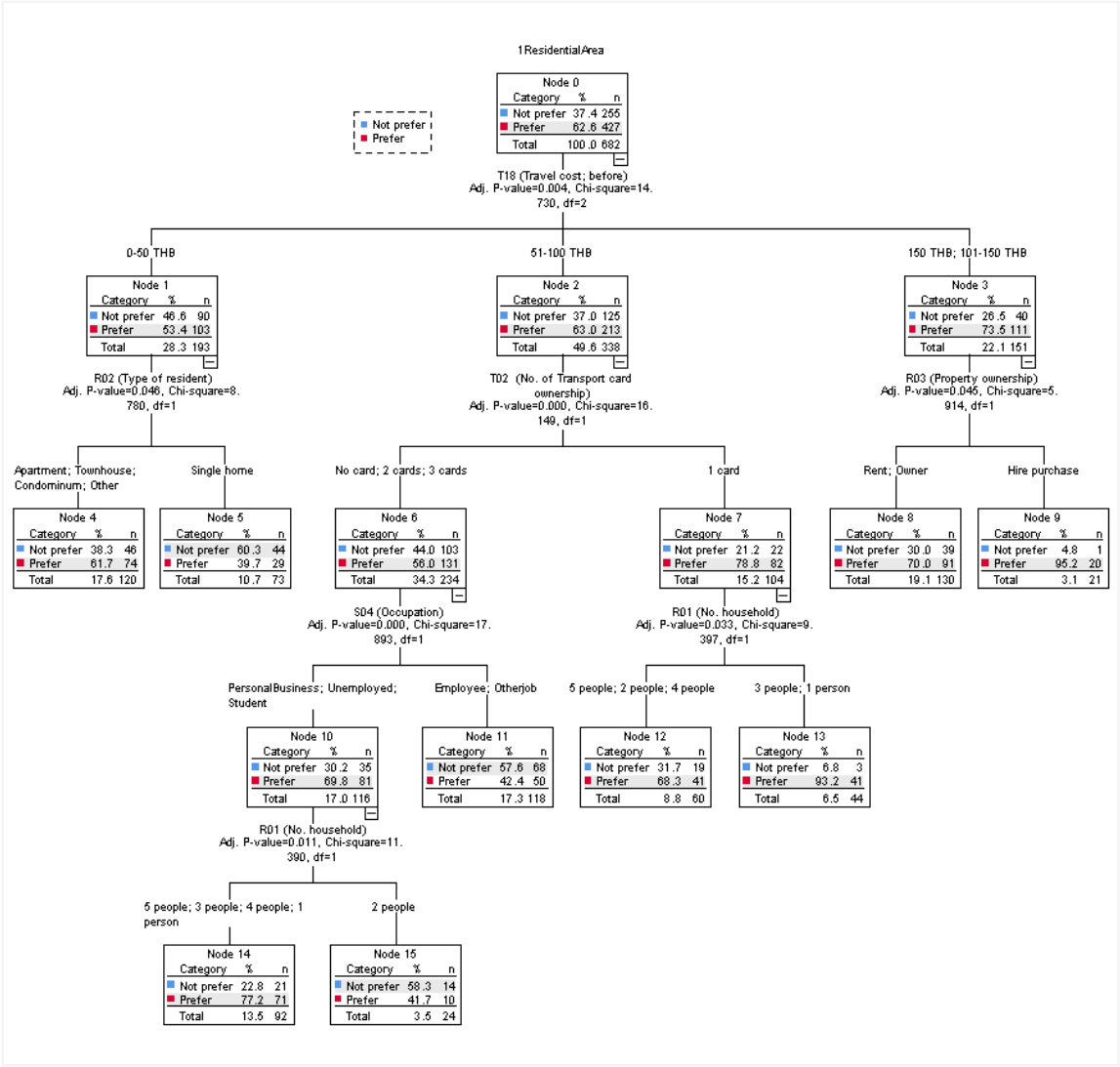
Prefer to live in urban area: pre-COVID-19 case



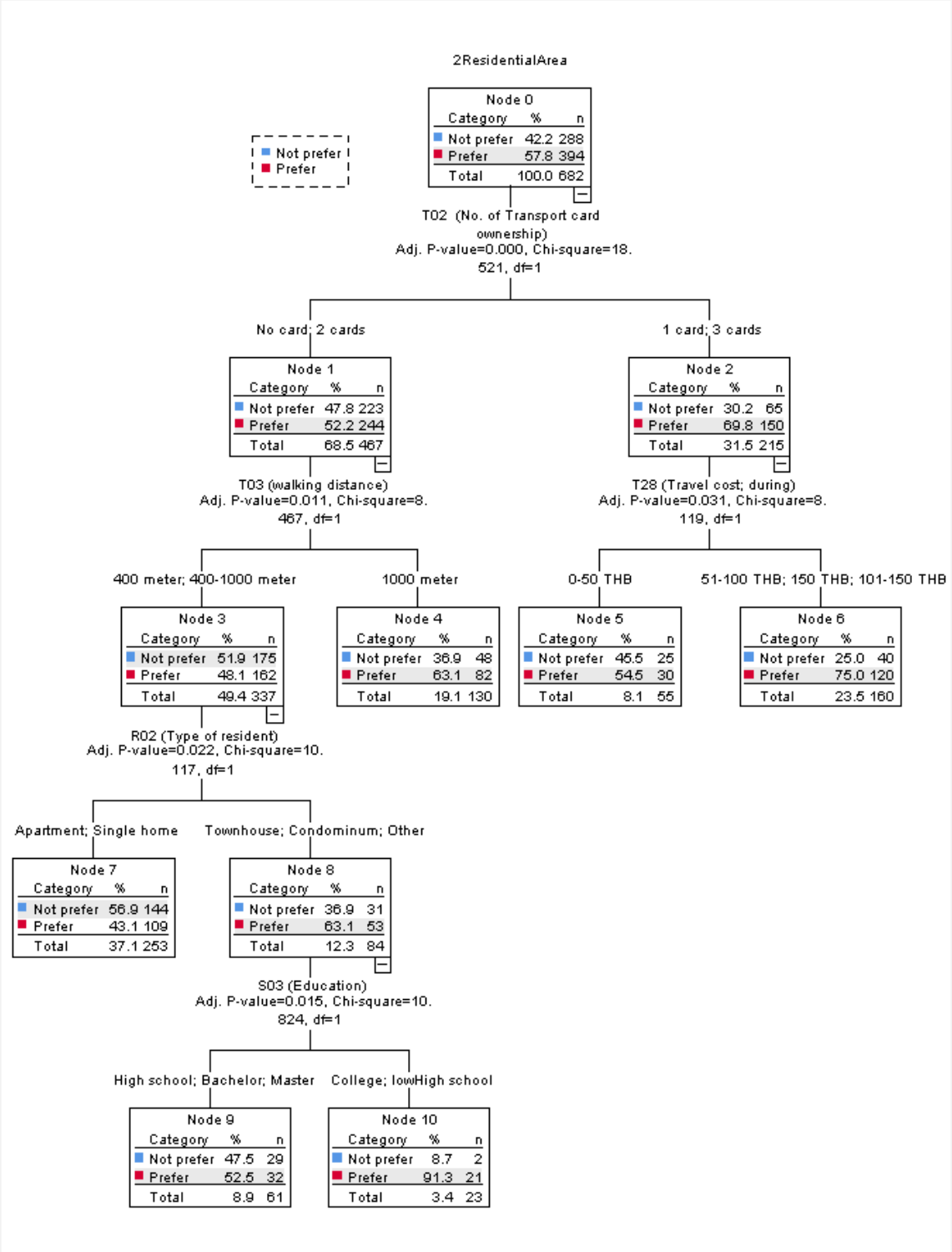
Prefer to live in urban area: during COVID-19 case



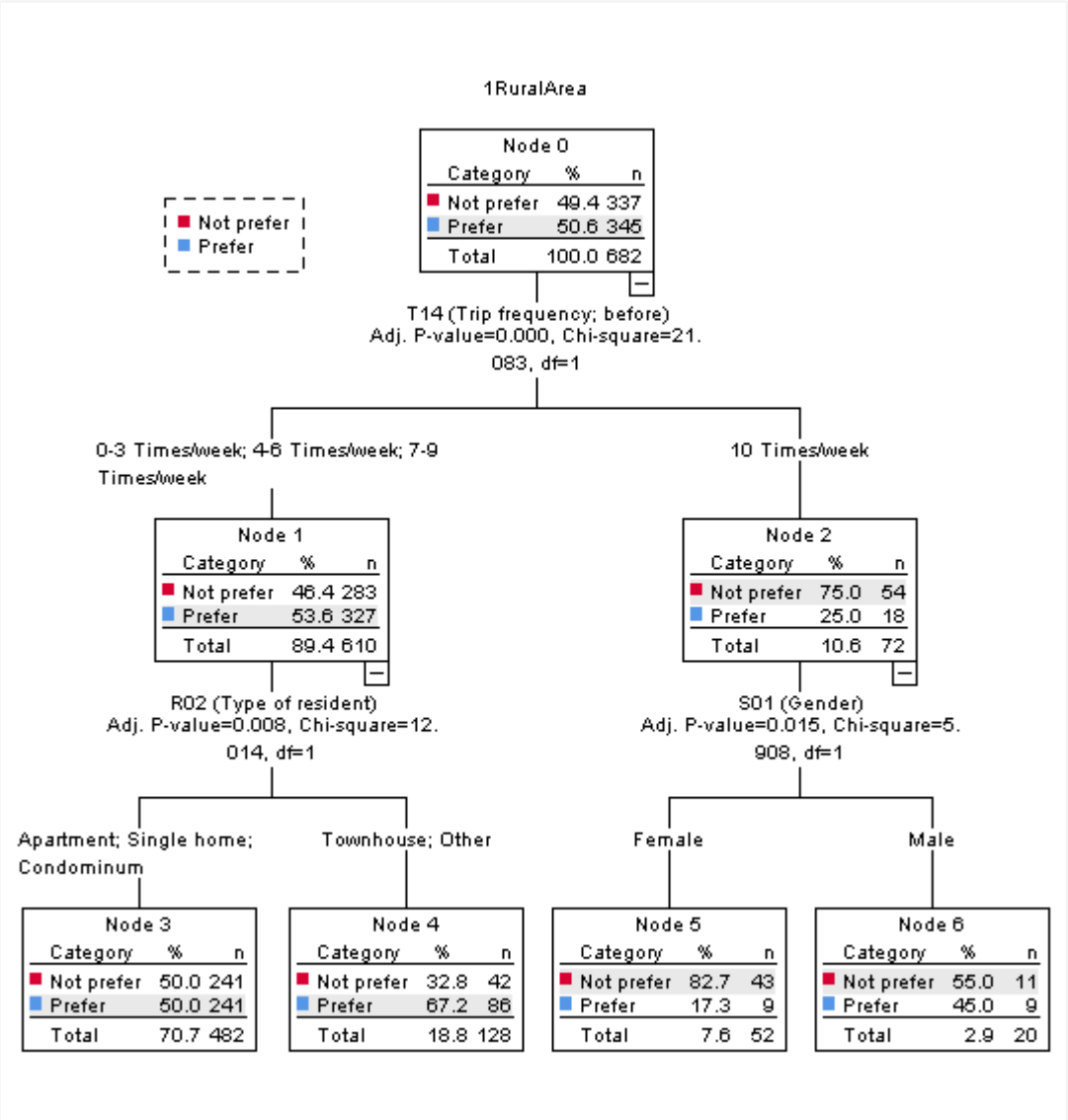
Prefer to live in residential areas: pre-COVID-19 case



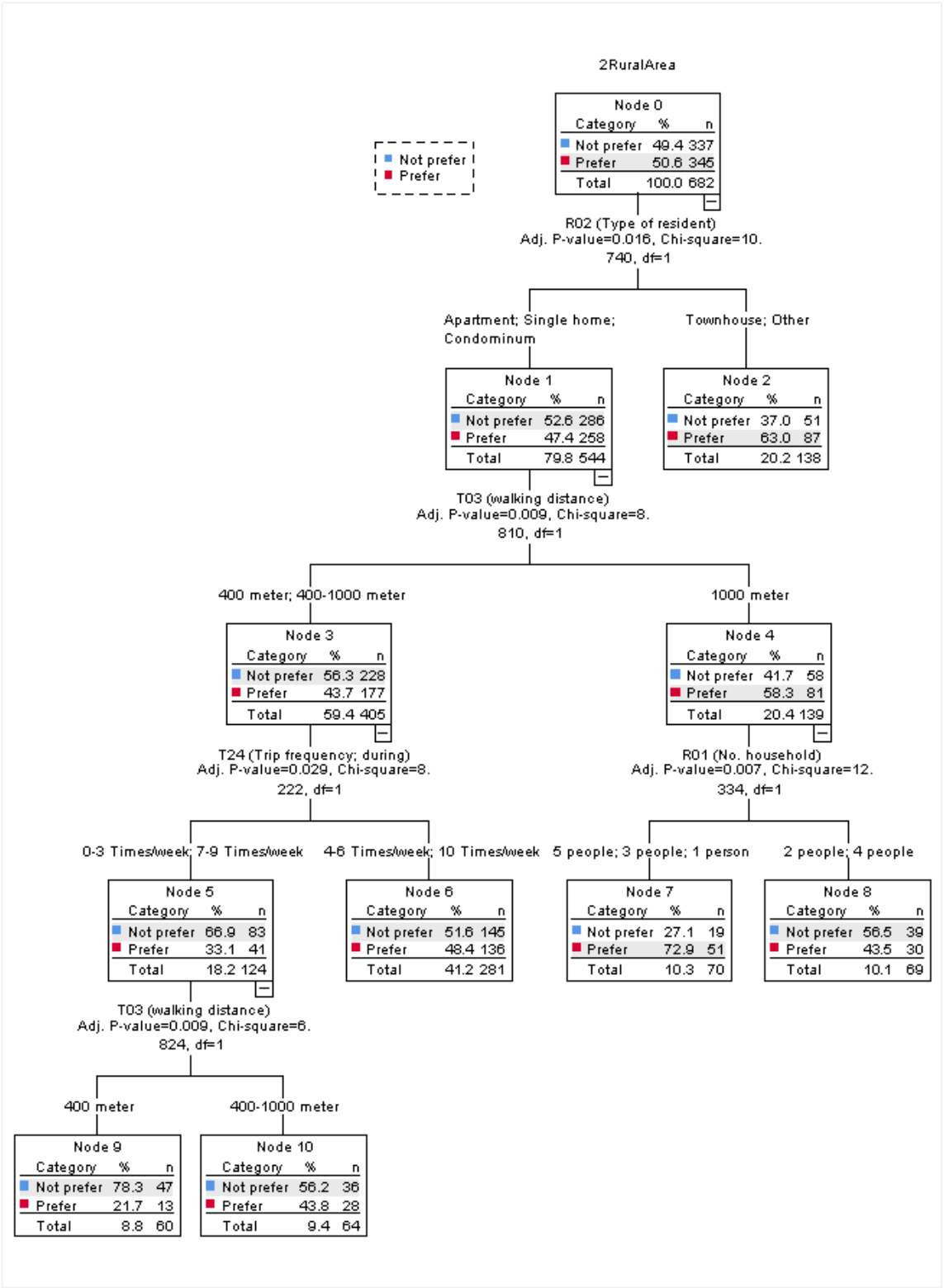
Prefer to live in residential areas: during COVID-19 case



Prefer to live in rural area: pre-COVID-19 case

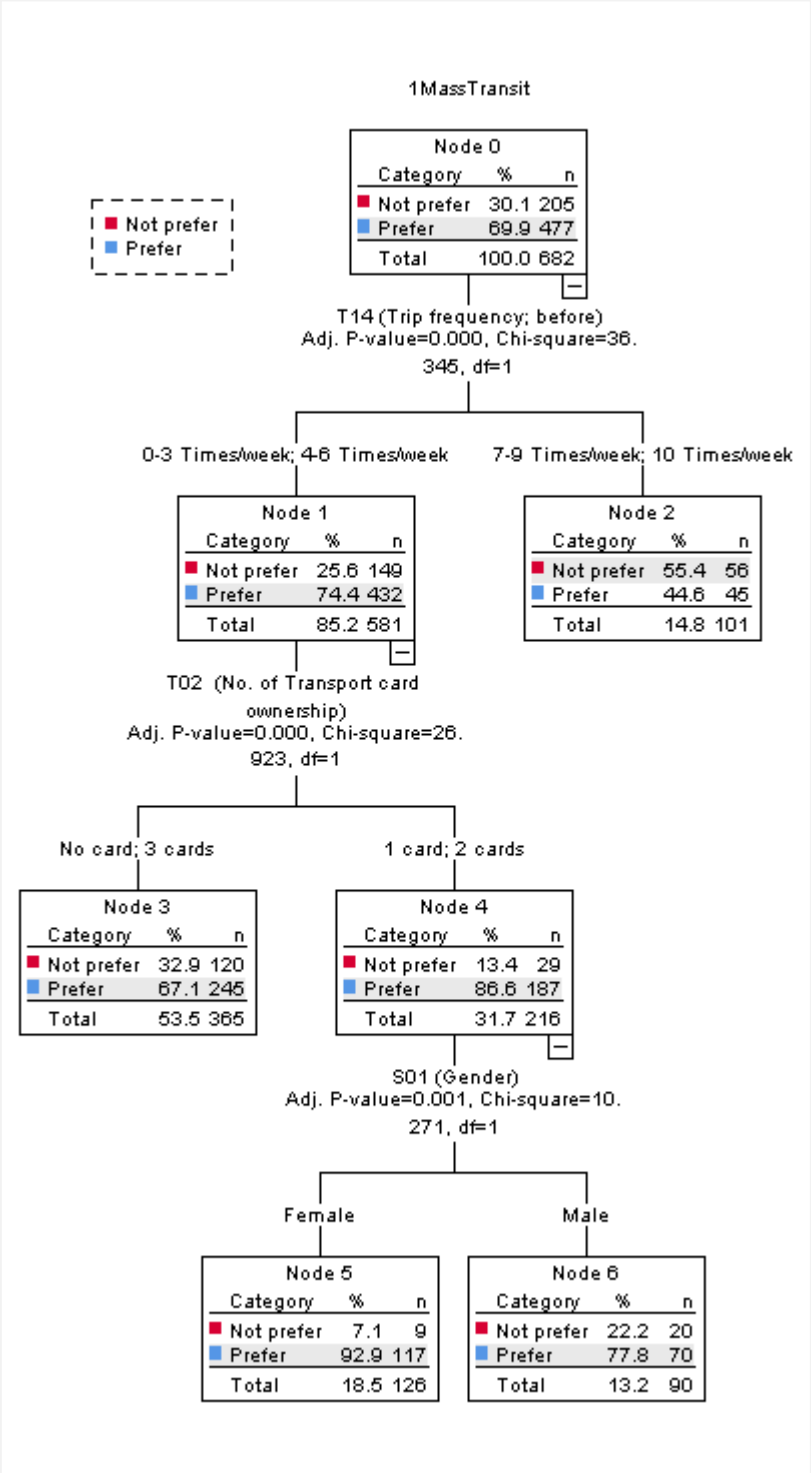


Prefer to live in rural area: during COVID-19 case

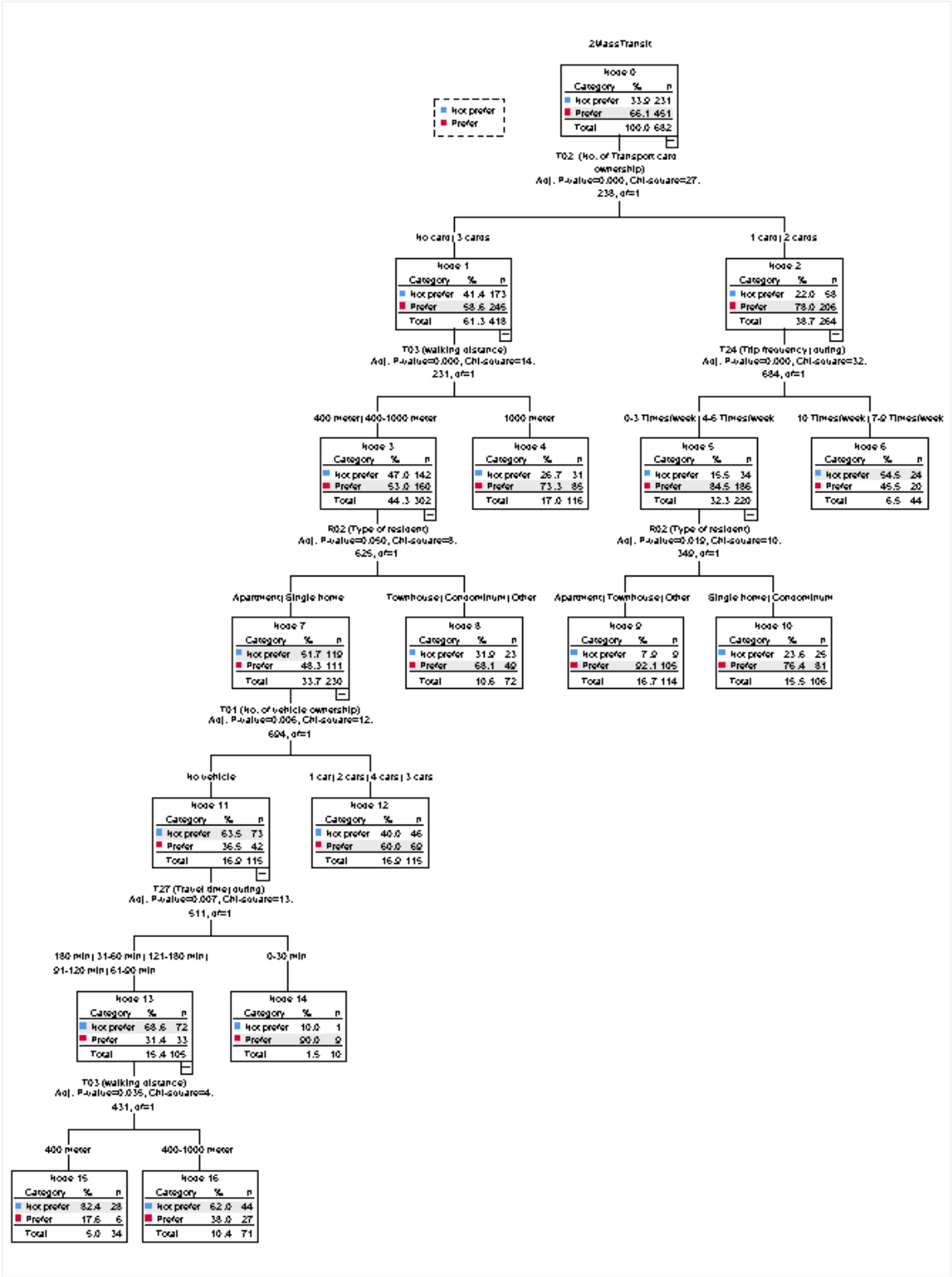


8.3.2 Results of Attitude Toward Residential Accessibility

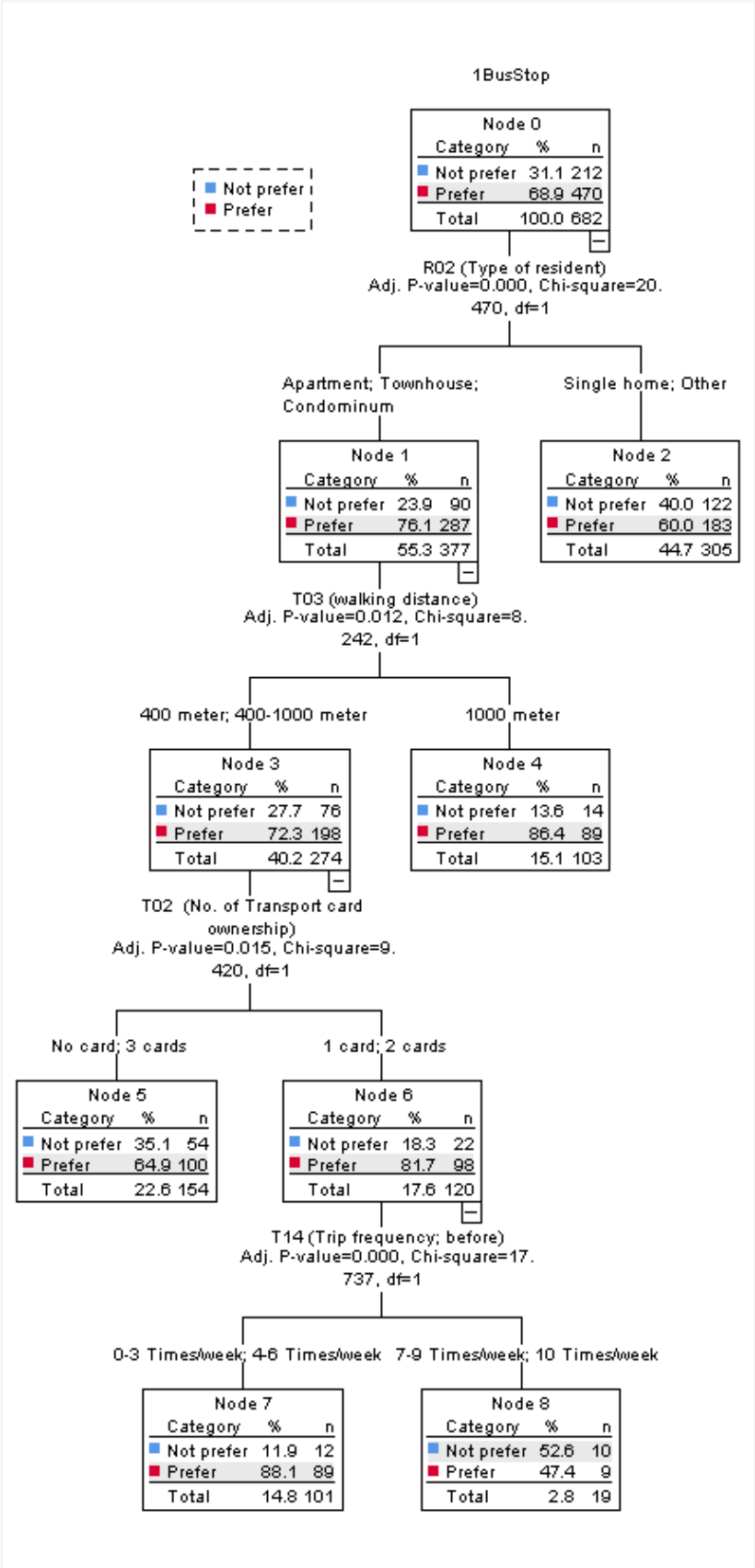
Prefer residential area near mass transit station: pre-COVID-19 case



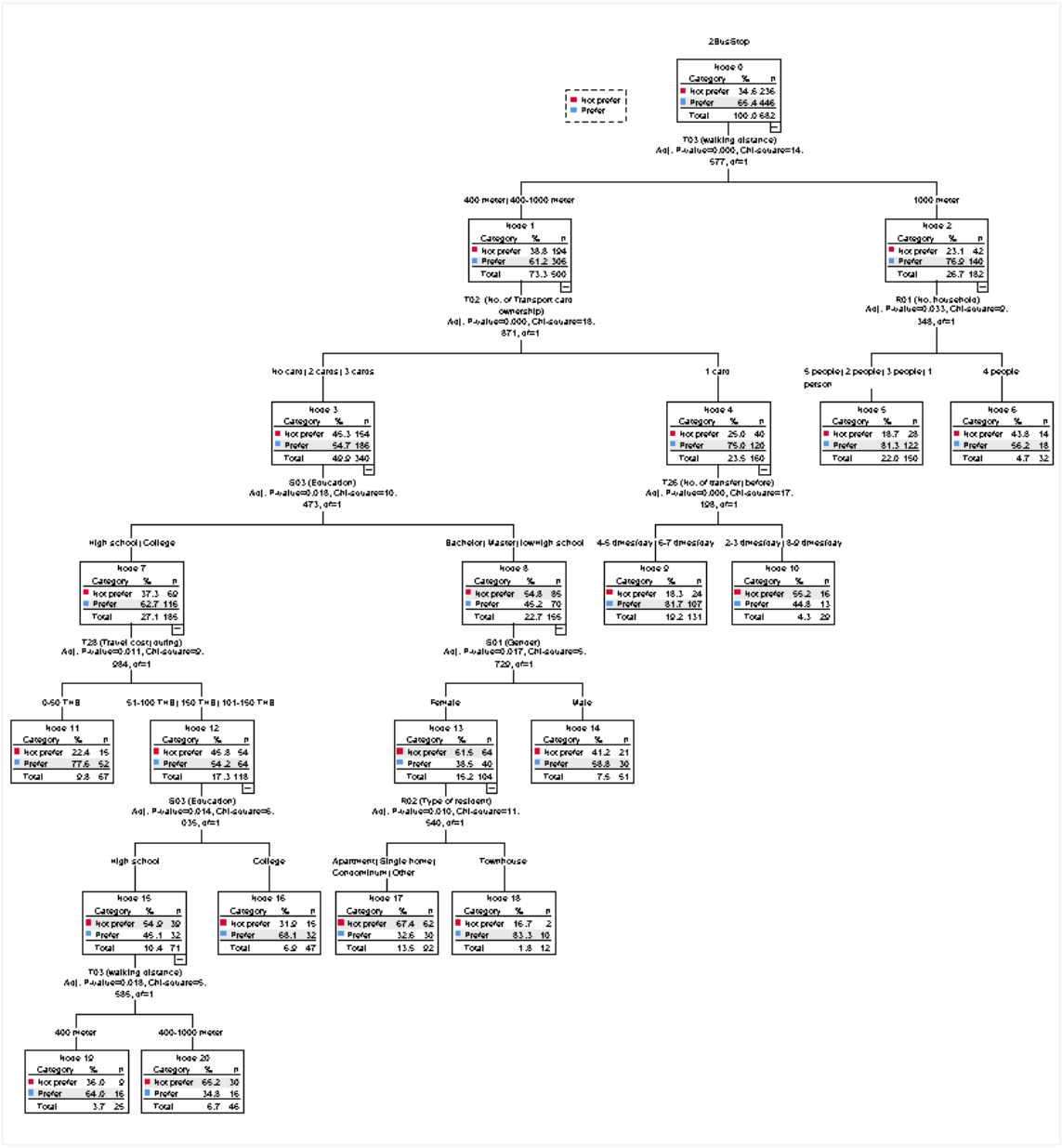
Prefer residential area near mass transit station: during COVID-19 case



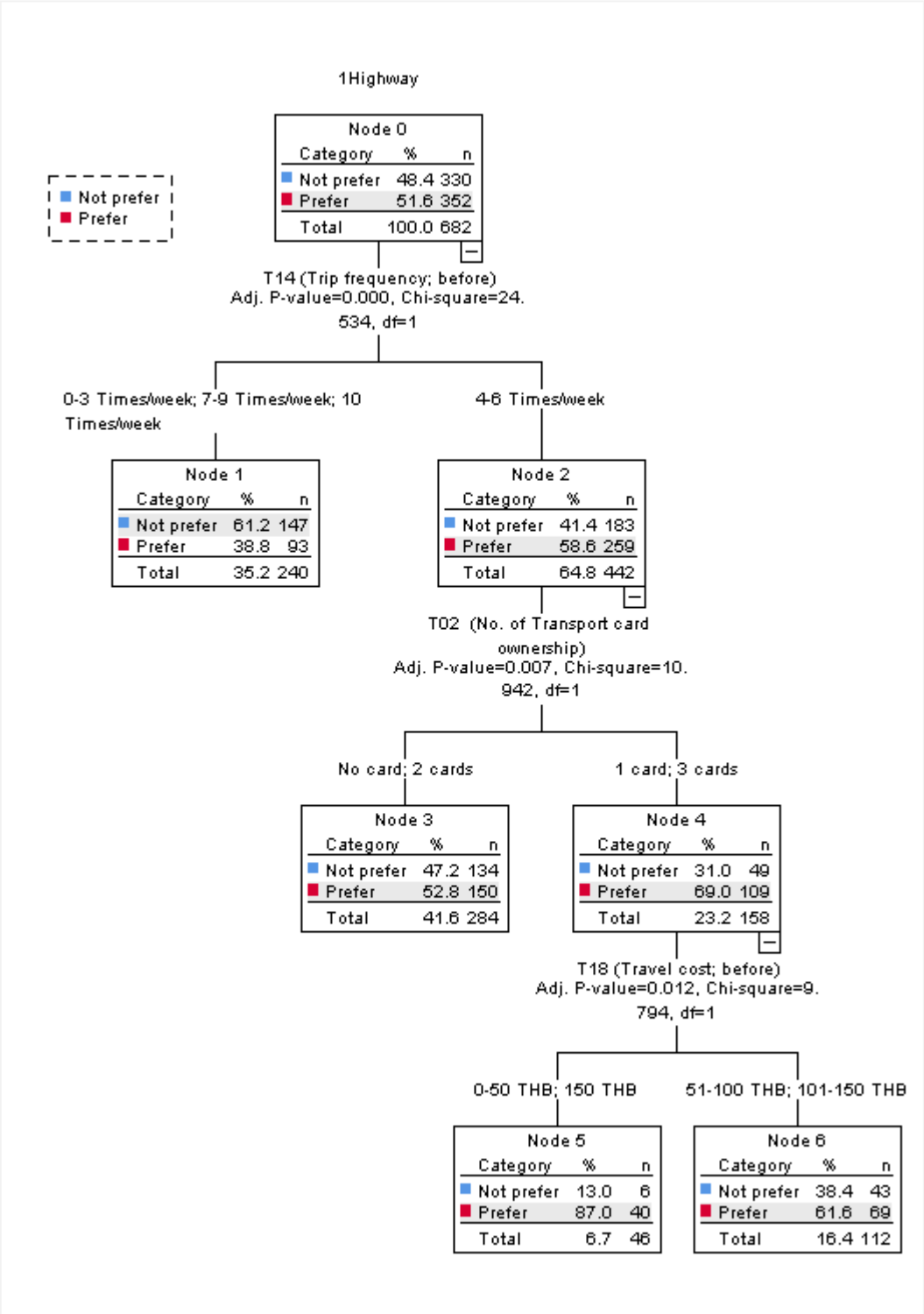
Prefer residential area near bus stop: pre-COVID-19 case



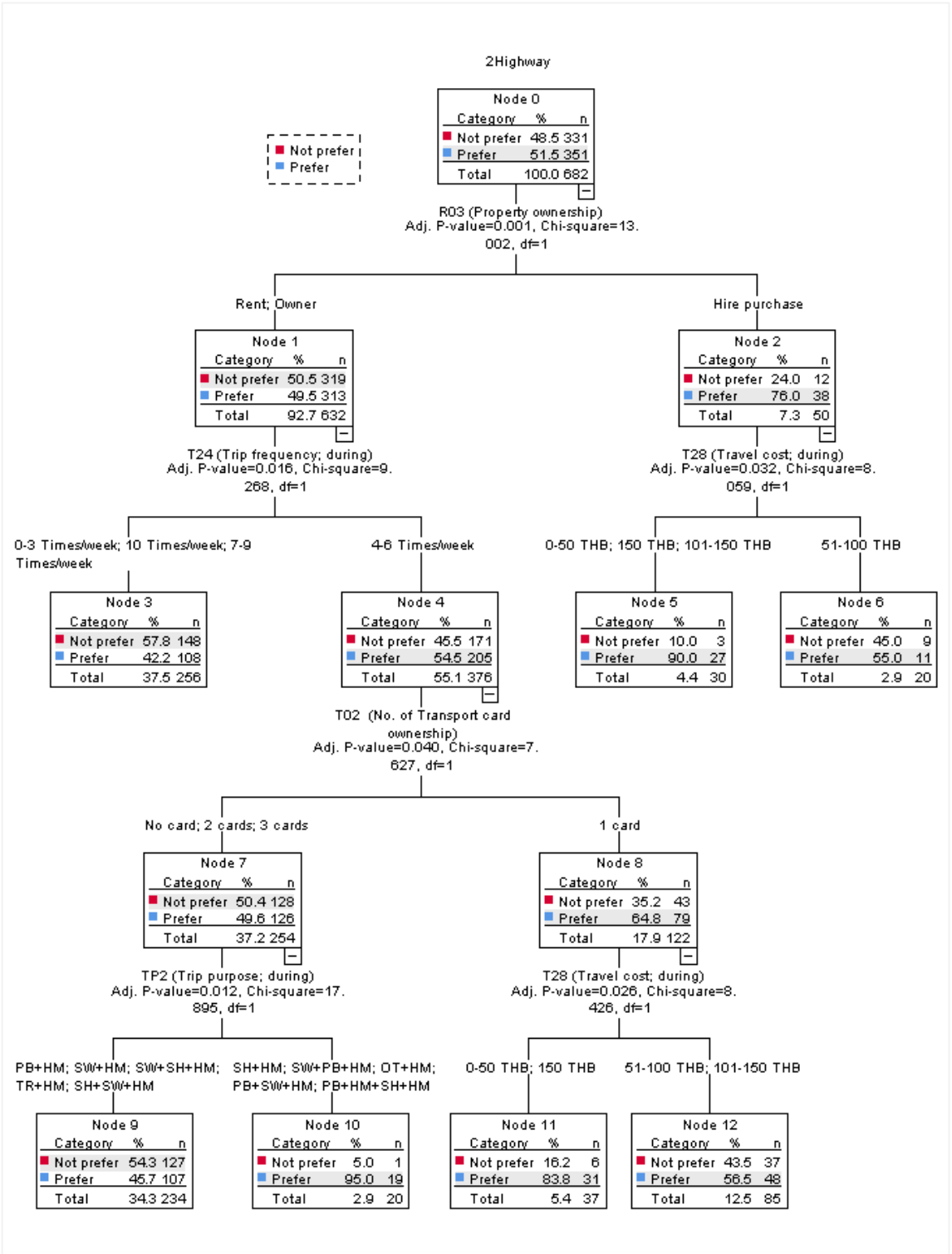
Prefer residential area near bus stop: during COVID-19 case



Prefer residential area near highways or main roads: pre-COVID-19 case

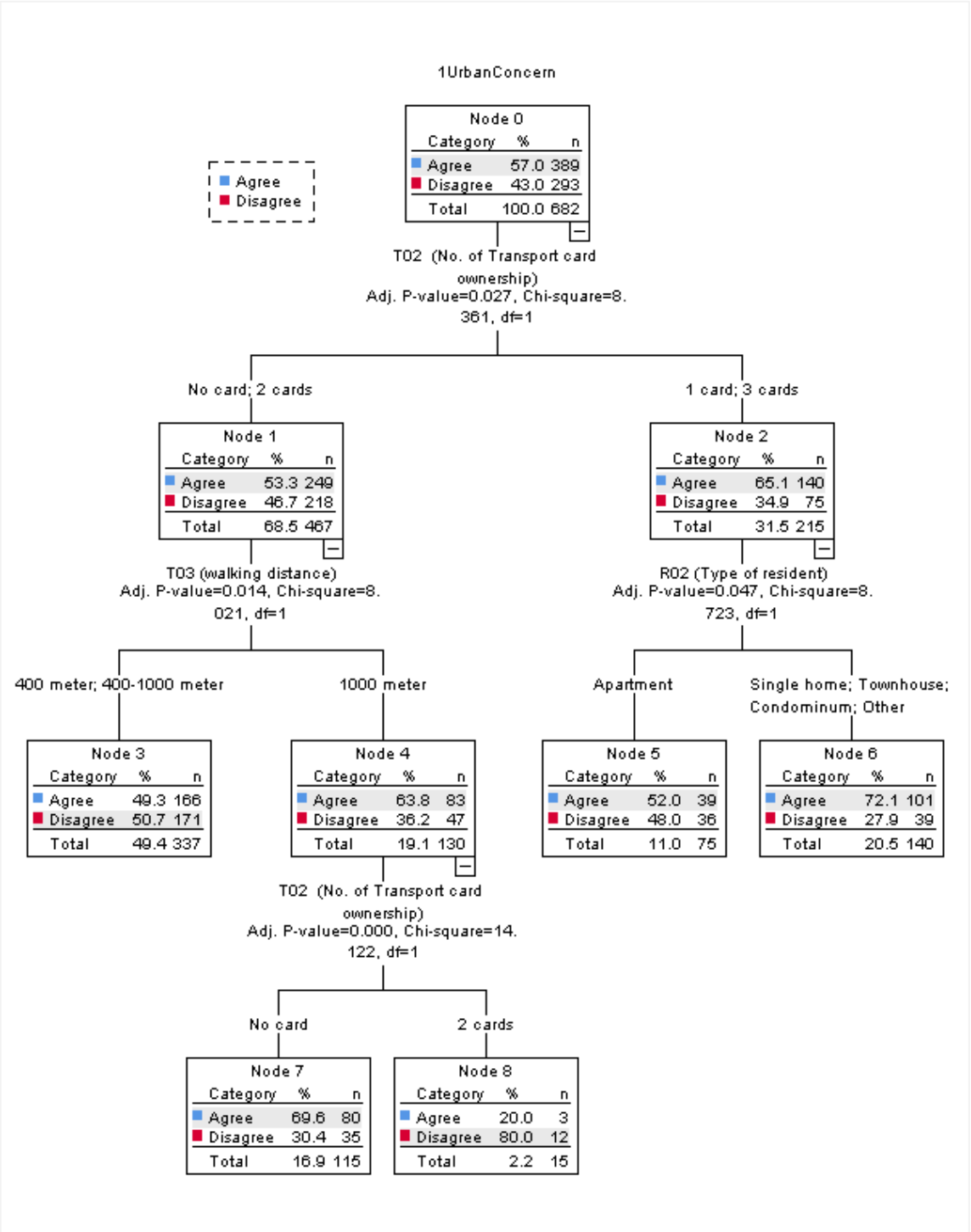


Prefer residential area near highways or main roads: during COVID-19 case

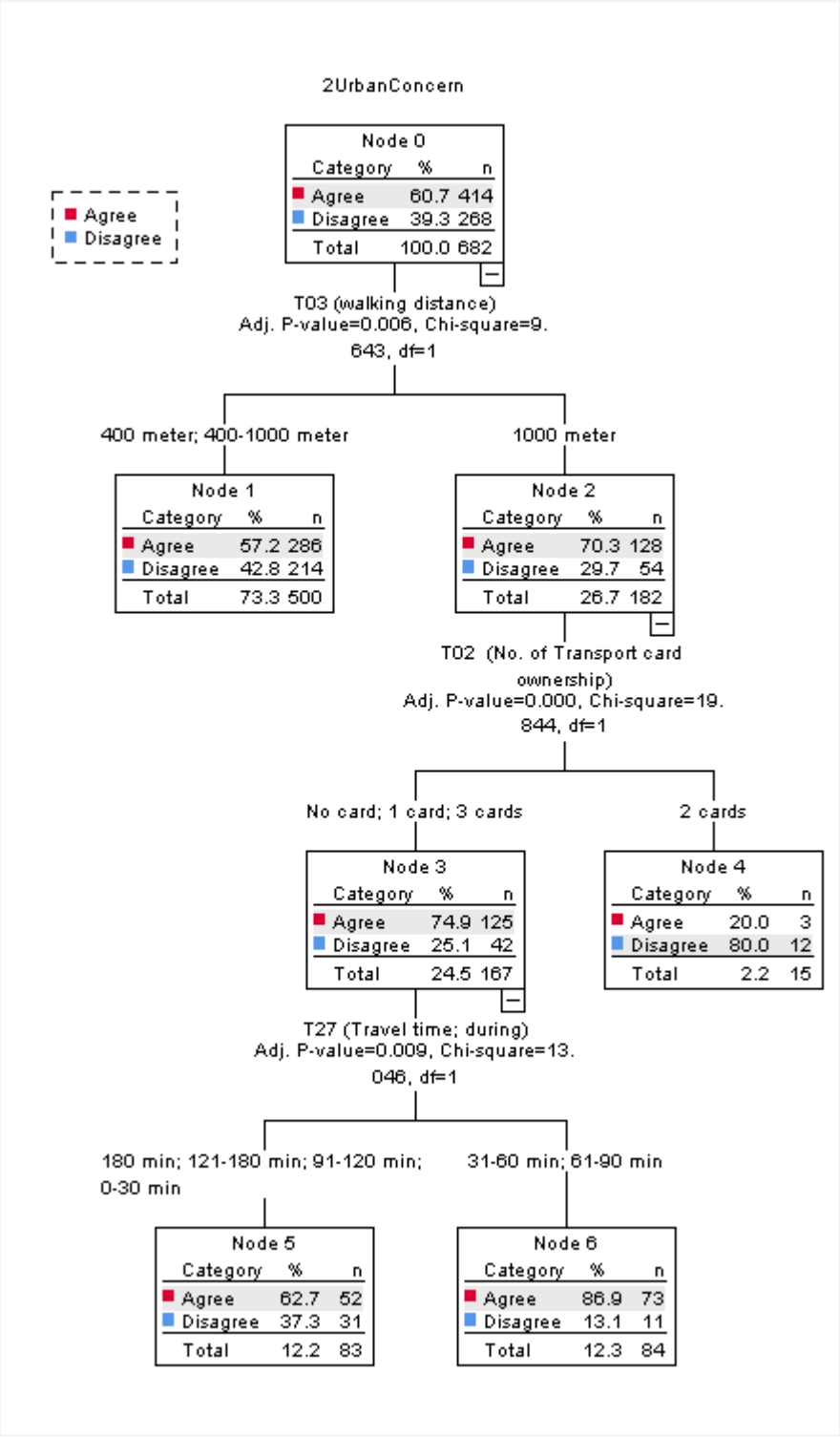


8.3.3 Results of Attitude Toward Concern of COVID-19

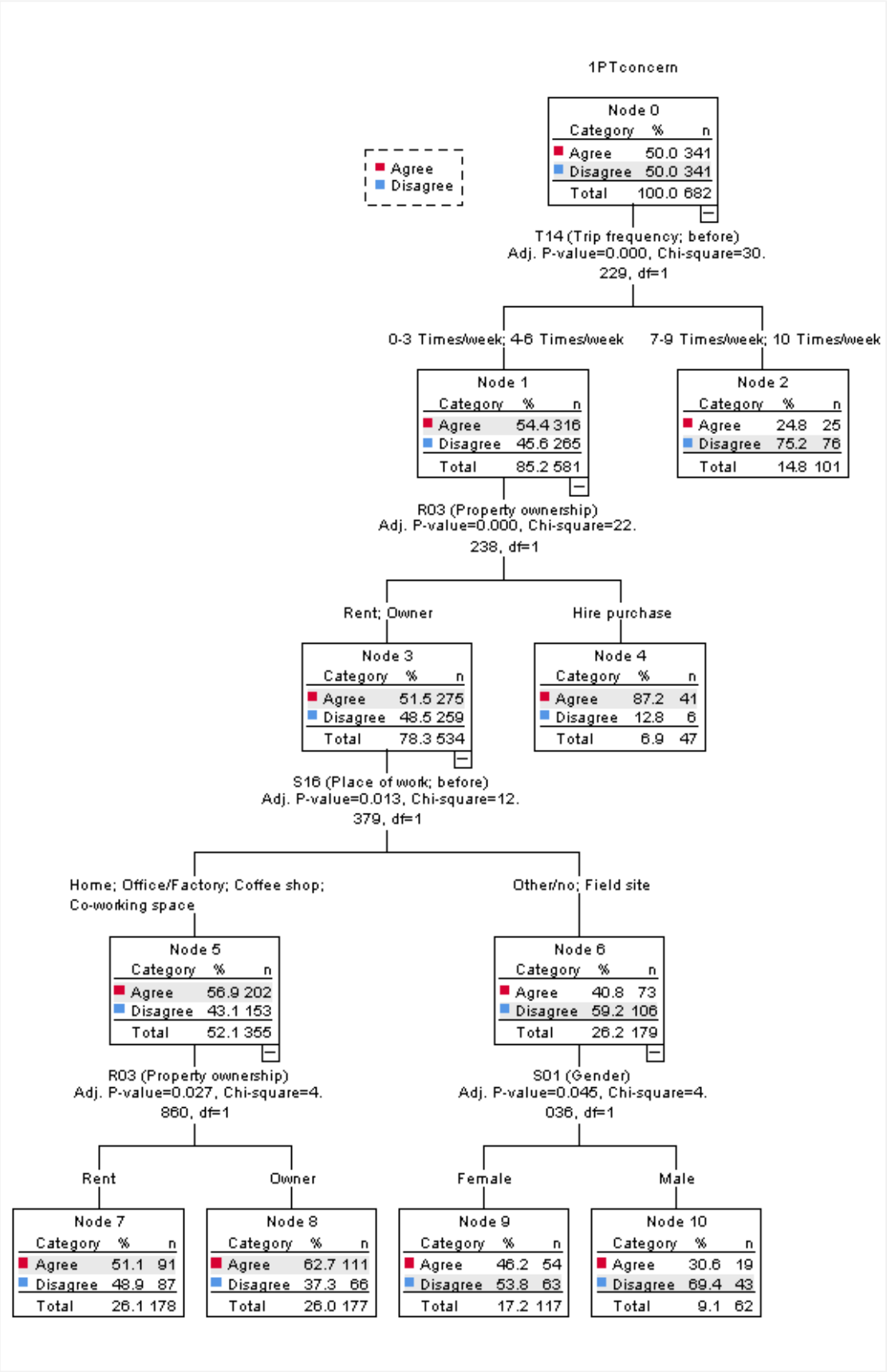
Prefer not to choose to live in an urban area due to concern about infection: pre-COVID-19



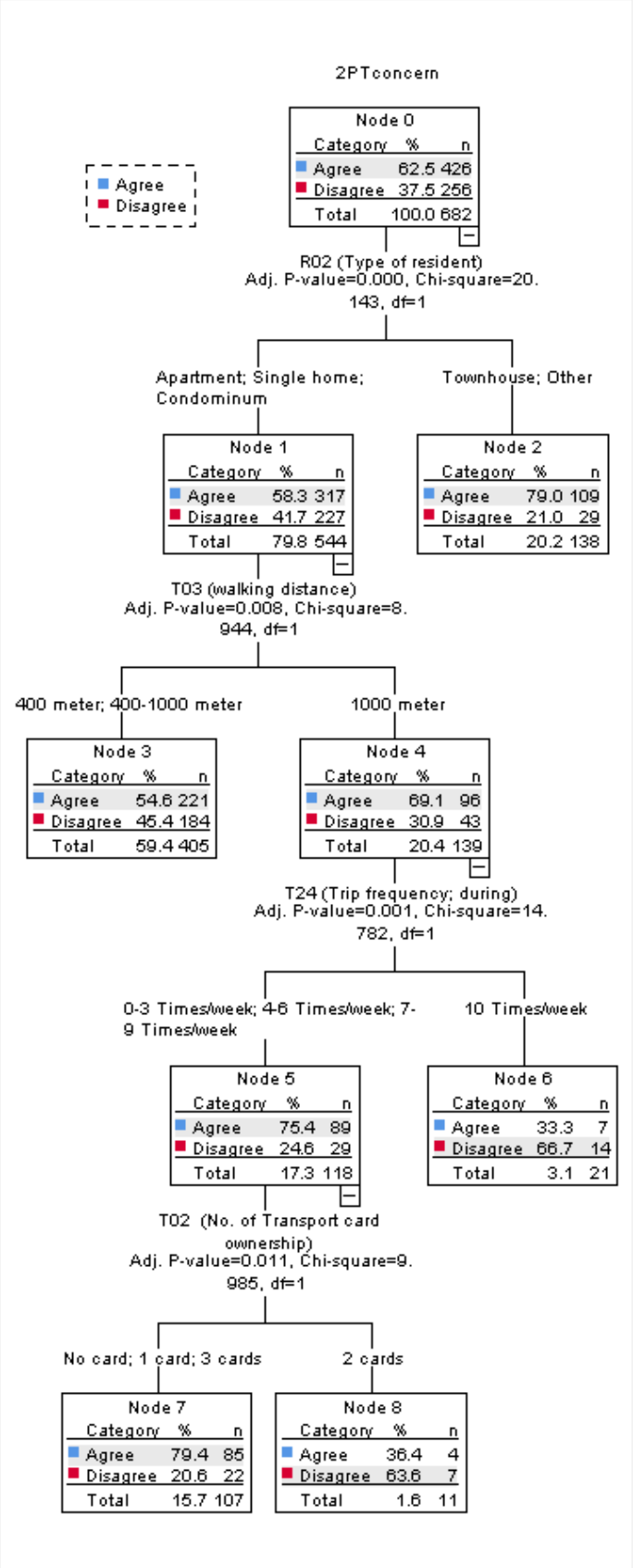
Prefer not to choose to live in an urban area due to concern about infection: during COVID-19



Worried about infection concerns to use public transport: pre-COVID-19



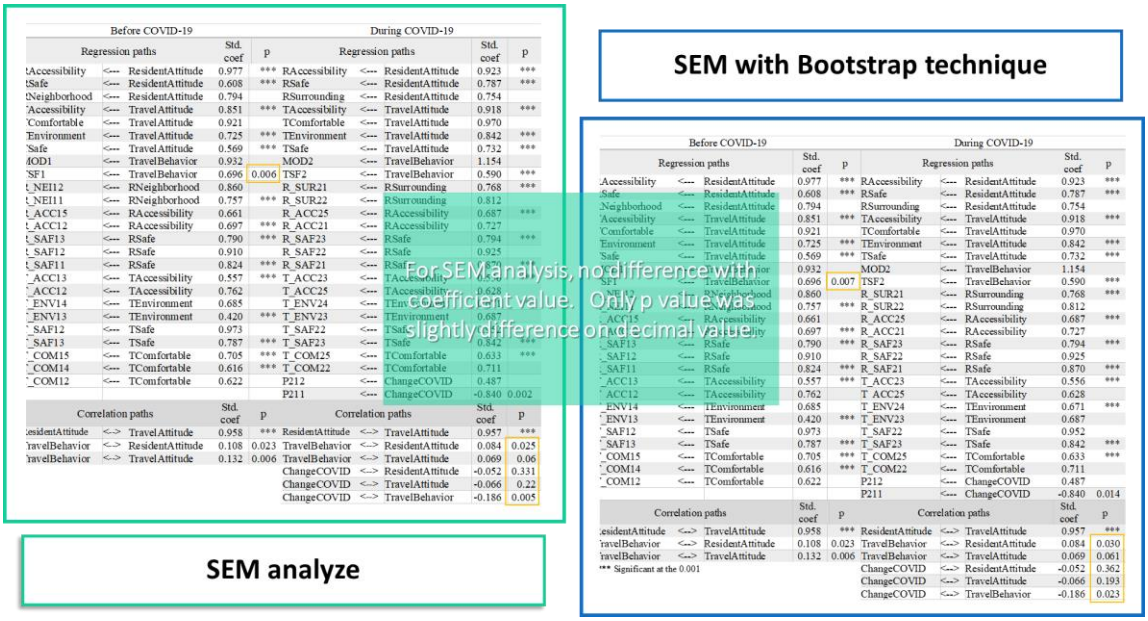
Worried about infection concerns to use public transport: during COVID-19



8.4 Sample of Study

8.4.1 Parametric and Nonparametric

An example results from Chapter 4 demonstrated the comparison result between parametric and nonparametric based assumptions.



Hypothesis of study		Coef.	p value	Result
H_1	Travel Attitude ↔ Travel Behavior	0.069	0.060	Not accept
H_2	Resident Attitude ↔ Travel Behavior	0.084	0.025	Accept
H_3	Change Factor ↔ Travel Behavior	-0.186	0.005	Accept
H_4	Travel Attitude ↔ Change Factor	-0.066	0.220	Not accept
H_5	Resident Attitude ↔ Change Factor	-0.052	0.331	Not accept
H_6	Travel Attitude ↔ Resident Attitude	0.957	<0.001	Accept
H_7	Socio-demographic ↔ Travel Attitude	-	-	Not accept
H_8	Socio-demographic ↔ Resident Attitude	-	-	Not accept
H_9	Resident Characteristic ↔ Travel Attitude	-	-	Not accept
H_{10}	Resident Characteristic ↔ Resident Attitude	-	-	Not accept
H_{11}	Travel Characteristic ↔ Travel Attitude	-	-	Not accept
H_{12}	Travel Characteristic ↔ Resident Attitude	-	-	Not accept

Hypothesis of study		Coef.	p value	Result
H_1	Travel Attitude ↔ Travel Behavior	0.069	0.061	Not accept
H_2	Resident Attitude ↔ Travel Behavior	0.084	0.030	Accept
H_3	Change Factor ↔ Travel Behavior	-0.186	0.023	Accept
H_4	Travel Attitude ↔ Change Factor	-0.066	0.193	Not accept
H_5	Resident Attitude ↔ Change Factor	-0.052	0.362	Not accept
H_6	Travel Attitude ↔ Resident Attitude	0.957	<0.001	Accept
H_7	Socio-demographic ↔ Travel Attitude	-	-	Not accept
H_8	Socio-demographic ↔ Resident Attitude	-	-	Not accept
H_9	Resident Characteristic ↔ Travel Attitude	-	-	Not accept
H_{10}	Resident Characteristic ↔ Resident Attitude	-	-	Not accept
H_{11}	Travel Characteristic ↔ Travel Attitude	-	-	Not accept
H_{12}	Travel Characteristic ↔ Resident Attitude	-	-	Not accept

No different of result

Summary result of SEM model

Assumption of parametric

Summary result of SEM model with bootstrap technique

Assumption of nonparametric

8.4.2 Sample Population Bias

The comparison between the sample used in this study and other samples from the Bangkok area.

Household Travel Survey in Bangkok Metropolitan Region, 2017	Survey of this research 2020	Sanit et al., 2014	Witchayaphong et al., 2020
Vehicle ownership • Private car 0.98 vehicle/household • Motorcycle 0.77 vehicle/household	**All vehicles type** **0.75 vehicle/household** **Private car 19%**	Car ownership 58%	Car ownership 52%
Trip purpose • HBW (Home Base Work) 64.60% • HBE (Home Base Education) 14.20% • HBO (Home Base Other) 13.20% • NHB (Non-Home Base Work) 8.10%	• **Work/school 55%, 53%** • **Shopping/eating 24%, 26%** • **Personal business 21%, 21%** • **Others 0%, 0%** (before,during COVID-19)		
Average travel rate 1.97 people-trip per day			
Mode choice • Private car 39.90% • Motorcycle 23.80% • Public transport 29.50% • School bus/shuttle 2.10% • Taxi/motorcycle hired 4.60% • Other 0.30%	• **Motorize 4%, 4%** • **Non-motorize 4%, 5%** • **Paratransit 40%, 42%** • **Feeder transit 44%, 41%** • **Mass transit 8%, 8%**	• Auto 26% • Non-motorized 6% • Paratransit 4% • Public transport 11% • Train 53%	• Private car 58.23% • Mass transit 41.77%
Average travel distance 12.64 kilometer	**12.76, 12.67 kilometer /day**		<15km. 86%
Average travel time 33 minutes	**90.69, 88.48 minutes/day**		<30min 64%
Average travel cost 32 THB/trip	**76.83, 75.07 THB/day**	111.12 THB (car) 44.22 THB (train)	0-100 THB 91%
Population • Urban 50.8% • Suburban 30.8% • Outer ring of urban 18.4%	• **Urban 74.05%, 73.90%** • **Suburban 25.95%, 26.10%**		
Gender • Woman 52% • Man 48%	**63%** **37%**	62.8% 37.2%	52.07% 47.93%
Average age 34 years old	**37 years old**		34 years old
Household size 2.43 persons/household	**3 persons/household**		2-4 persons/household 92.84%
Average personal income 17,300 THB/month	**20,063, 19,077 THB/month**	<10,000 THB = 4.1% 10,000-20,000 THB = 54.4% >20,000 THB = 41.9%	THB<15,000 = 29.04% THB 15,000–25,000 = 56.35% THB 25,001–35,000 = 10.92% THB 35,001–50,000 = 2.87 THB>50,001 = 0.83%
Sample size 2582 samples @2017	**682 samples @2020**	469 samples @2013	4467 samples @2019

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GLOSSARY

AMOS stands for Analysis of Moment Structures, designed for structural equation modeling software developed by IBM.

Attitude is a psychological construct, a method of thinking that has been established, as well as a feeling about something as an emotional identity that either defines a person or is shown by a person.

Attitude-based is the attitude toward something or alternative based on the principle of attitude and affective.

Attitude toward travel mode is travel attitude related to travel behavior and that is used to define travel attitude in Chapter 5.

Attitude toward residence is a residential attitude related to the residential area that is used to define residential attitude in Chapter 5.

Attitude toward accessibility is an attitude toward travel attitude related to access of travel to residential areas and is used to define travel attitude in Chapter 6.

Attitude toward residence location is an attitude toward residential attitude related to travel behavior and residential location and is used to define travel attitude in Chapter 6.

ARL is The Airport Rail Link, ARL is an express and commuter rail line linking Suvarnabhumi Airport and Phaya Thai station in Bangkok's central business district.

Bangkok metropolitan area is the massive conglomeration province of Bangkok, Thailand, which includes contiguous 5 provinces of Nakhon Pathom, Pathum Thani, Nonthaburi, Samut Prakan, and Samut Sakhon.

Before COVID-19 is the situation of no spread of COVID-19 or normal situation of daily life without COVID-19.

Behavior is a dynamic interaction between three elements: actions, cognition, and emotions.

Binary tree is a tree data structure where each node has a maximum of two child nodes for each parent node.

Bootstrap is a statistical technique for assessing quantities about the original sample by resampling to represent the population.

BTS is the Bangkok Mass Transit System, also known as the BTS Sky Train, is a public transportation system in Bangkok, Thailand, operated by Bangkok Mass Transit System Public Company Limited.

Built environment all physical man-made structures for living, recreation, and work, including structures, furniture, open and public spaces, roads, utilities, and other infrastructure.

Catchment area for public transportation is the area around a stop or station along a public transportation network.

Causal relationship is a relationship between two or more variables is one in which one variable causes the other variable(s) to change or fluctuate, also known as a cause-and-effect relationship.

CBD is central business district which is the section of the city that is part to the city's most important public buildings and commercial areas.

CFA is confirmatory factor analysis, which is a statistical approach used to confirm the factor structure of a group of observed variables.

CHAID is Chi-Square Automatic Interaction Detection, is a classification approach for constructing decision trees by identifying optimum splits of a categorical variable using chi-square statistics.

Categorical data is a type of data or information that consists of categories that may be identified based on their names or labels.

Classification is the process of identifying and organizing things or concepts into distinct groups according to certain criteria.

Cognitive dissonance is a theory of social psychology that attempts to explain the mental discomfort that can occur from maintaining two conflicting beliefs, values, or attitudes.

Commuting trip is a trip that is made on a regular basis between a person's place of living and their place of work or study.

Continuous data is data that can be measured, as opposed to being data that can be counted on an endless scale.

Correlation is a statistical measure expresses the perfect linear relationship (standardized) that exists between two variables.

Covariance is a statistical measure the linear relationship (unstandardized) between two random variables.

COVID-19 is the SARS-CoV-2 virus that the infection caused that led to the illness.

Decision-making is the process of choosing choices by identifying a decision, collecting relevant information, and analyzing alternative solutions.

Decision tree is a non-parametric supervised learning approach that employs a tree-like model of decisions and their possible consequences as a decision support tool.

Dependent variable is variable whose value will change depending on the value of another variable or was influence by independent variables.

Direct effect is a directional relationship between two variables that are dependent on independent variables.

During COVID-19 is the present scenario with COVID-19 infection.

EFA is exploratory factor analysis, which is a statistical method used to uncover the underlying structure by correlation among the variables in a dataset.

Endogenous variable is a variable that depends on other variables.

Exogenous variable is a variable that is not influenced by any other factors.

Factor is an element of circumstance, event, or other influence that plays a role in the contributes of a result.

Feeder transit is a transportation mode providing transportation service between travel destinations or origins and hub stations for the connection of local areas.

Full mediation is relationship between the independent and dependent variables is through a 100% mediated effect by the mediator, or it is presented that there is no direct effect.

Household decision is the process of making a decision that involves participation from more than one member of the household.

Hypothesis is an assumption, also known as a concept, that is given forward for the purpose of argument and examined to see whether or not it might be true.

Kiss and ride are a situation in which they are dropped off at a transportation facility that only allows vehicles to pick up or drop off passengers.

Latent variables is a variable that cannot be directly observed but is instead influenced by one or more indicator variables.

Land-use is the categorization of land based on the types of structures that may be constructed on it and its purposes.

Long-term is a period of time that extends beyond the beginning of something that occurs over a considerable amount of time.

Longitudinal data is an observational research approach and a type of correlational research study in which variables are examined over an extended time period and data is collected repeatedly over a period of time.

Indicator variables is the data collect from responses, that can be categorical discrete or continuous type.

Indirect effect is the effects that are not caused immediately but occur by being mediated or transmitted by a third variable.

Independent variable is a variable whose value is unaffected by other variables and is controlled during the experiment.

Inner-city is the area surrounding the central business district and the city center.

Intention is an important determinant of action and the plan to do or achieve something based on passion, values, or purpose.

Mass transit is a system of large-scale public transportation that transports a large number of people in a single vehicle or combination of vehicles. (Here it means a rapid transit system).

Measurement variables is the data collect from responses, that can be categorical discrete or continuous type.

Mixed-use is one area that has more than one function or purpose, and it generally combines residential, corporate, and social spaces within a single structure that is located in a central location.

Mode share is the proportion of travelers using a particular type of transportation within each mode.

Mediation effect is a circumstance in which two important variables, one independent and one dependent, are related to a third variable.

Moderation effect is the interaction impact of a variable on the connection between two other variables, the independent and the dependent variables.

Moderated mediation is an analytical approach used to determine whether an indirect impact is dependent on the values of a moderating variable.

MRT is the Metropolitan Rapid Transport, is a mass rapid transit system that serves the Bangkok Metropolitan Region in the country of Thailand.

Neighborhood is characteristics that make them different from people who live in a particular area or geographically localized community within a larger city, town, suburb, or rural area.

Non-motorized is a kind of transportation in which the means of transportation does not rely on an engine or motor to move.

Nonparametric is branch of probability and statistics that does not primarily rely on parametrized families of probability distributions.

Null hypothesis is the hypothesis that there is no statistically significant relationship between the two variables under analysis.

Number of transfers a number of interchanges within travel mode or between other modes of travel.

Observed variables are variables that can be measured directly in a dataset.

Park and ride is a form of integrated transport that allows private transport passengers to park their cars at a car park and take the bus or train into the city.

Partial mediation is a significant relationship between the mediator and dependent variable as well as a direct relationship between the independent and dependent variable.

Perceived is the recognition and interpretation of sensory information for the purposes of representing and understanding the presented information or environment.

Planned behavior is a psychological theory that links beliefs to behavior and has three fundamental components, namely attitude, subjective norms, and perceived behavioral control.

Pre-COVID-19 is the previous scenario without a COVID-19 infection.

Pre-test and post-test design is an experiment design in which measurements difference between the first and second measurements or the subject is receiving treatment intervention to measure the difference between the pre-test and post-test.

Phenomenon is an extraordinary occurrence or circumstance that is observed to exist or happen.

Preference is the act of selecting one option above another based on some facet of one's experience in the past.

Psychological is the scientific study of behavior of a mental or emotional character that affects or arises in the mind is related to the mental and emotional status of the person.

Public Transport is a system of transport to move groups of people between two places, including a variety of transit options such as buses, light rail, subways, ferries, and other services.

Relocation is the action of moving to or changing a new place or residence and settling into another.

Resident is someone who resides in a particular building or location on a permanent or long-term basis.

Residence is a place of building, used as a house or other kind of housing where people reside.

Residential is a place of building, used as a house or other kind of housing where people reside.

Residential area is a part of a city or a place inside a city where the majority of the properties located on its property are used for residential purposes and where people live.

Residential attitude is a residential attitude related to a residential area and is used to define residential attitude in Chapter 4.

Residential self-selection is the process by which households select their residential location in accordance with their desired and expected travel behavior.

Ridership is the number of passengers who use a public transportation system.

Rural area is an area of land that has few homes or other buildings and low population density.

TOD is Transit Oriented Development, which is a type of urban development that emphasizes a mixture of commercial, residential, office, and entertainment that is located near a transit station.

Travel attitude is a travel attitude related to travel behavior and used to define travel attitude in Chapter 4.

Travel daily/pattern is information on how people travel daily or most often, which is related to work status, family structure, and other factors.

Transport card is a rechargeable (prepaid) card that can be used to conveniently pay for commuter passes between two set stations on public transportation and to make payments at any vending machine.

Travel mode behavior is the complex decision-making process of travelers throughout a trip in regard to their mode of transportation selection.

Unobserved variables are variables that cannot be measured directly in a dataset.

Urban area is an area where many people live and work practically together in cities and towns with a high population density.

Satisfaction is the act of fulfilling a need, desire, or appetite, as well as the resulting feeling.

Segmentation is the process of dividing the market into separate segments, or segments, that can be defined.

Service provider is an individual or entity that provides specialized services (here it means passenger transportation or related services to an agency) to another party.

SEM is structural equation model that is a methodology for analyzing travel behavior and psychological attitudes.

Short-term is a period of time that takes place over a short period of time, or something temporary or not meant to last.

Socio-demographics are characteristics of a population involving a combination of social and demographic factors, including age, sex, education, ethnicity, income, etc.

SPSS is short for Statistical Package for the Social Sciences. It is a statistical software suite developed by IBM for data management, advanced analytics, and complex statistical data.

Structural model is a diagram which consists of a set of nodes and connections between the nodes to describe the structural, or conceptual, objects.

Suburb/Suburban is an area outside the main city of a metropolitan area that may include commercial and mixed-use but is mostly residential and exists as part of a larger city or urban area.

Subjective norms are the perceived social pressures from others that influence one to perform, engage, or not to engage in a particular behavior.

Subway is a type of high-capacity extensive rapid transit system also known as heavy rail, metro, subway, tube, or underground.

Walkability is a measure of an area's friendliness to walking. The degree to which the built environment facilitates the movement of pedestrians and its quality.
