UNDERSTANDING DETERMINANTS AND BEHAVIORAL INFLUENCES OF CARPOOLING ADOPTION FOR EDUCATIONAL TRIPS IN THAILAND

BY

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ABSTRACT

Carpooling is emerging as a more appealing "sharing economy" form with promising benefits in reducing carbon emissions, traveling costs, and traffic congestion. However, a thorough understanding of carpooling adoption for commuting trips is lacking for policymakers and transport planners in developing countries due to limited scientific research, specifically in Southeast Asia. Therefore, the present study aimed to understand the determinants and behavioral influence of carpool adoption for tertiary educational trips in Thailand by conducting a multivariate analysis on a dataset of 307 observations gathered at Thammasat University, Pathum Thani, Thailand. A conceptual model was developed primarily based on the Consumer Acceptance and Use of Information Technology (UTAUT2) model with modifications of replacing habit construct with perceived safety and adding two additional constructs related to COVID-19 and time credits. The sample data were analyzed using Structural Equation Modelling (SEM). It was found that hedonic motivation, social influence, and time credit factors play statistically significant roles in the intention to use carpool for tertiary educational trips, while effort expectancy, perceived safety, and perception towards COVID-19 and carpool do not. Further, hedonic motivation mediates the effect of social influence and effort expectancy. Through multigroup analysis, it was identified that hedonic motivation and time credits factors are highly significant for motorized mode users compared to active mode users. Furthermore, SEM with interaction terms revealed that social influence and time credits factors could be used to attract people who drive cars towards carpooling even though they are less inclined to carpool. Also, hedonic motivation and social influence factors can be used to attract people who live closer to their school. Upon analysis of the findings, policy implications are presented that can be used to improve carpooling adoption for educational trips in Thailand.

Keywords: Carpooling, Behavioral influences, Structural Equation Modelling, Tertiary educational trips

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LIST OF SYMBOLS/ABBREVIATIONS

Symbols/Abbreviations	Terms
GHG	Green House Gas
WWI	World War 1
TDM	Transportation Demand Management
NEPO	National Energy Policy Office
UTAUT2	Consumer Acceptance and Use of Information Technology
SEM	Structural Equation Modelling
RRM	Random Regret Minimization
LUT	Lazy User Theory
PLE	Principle of Least Effort
RUT	Random Utility Theory
OR	Odd Ratios
MNL	Multinomial Logit
HOV	High Occupancy Vehicles
MPM	Multinomial Probit Modelling
IIA	Independence of Irrelevant Alternatives
NLM	Nested Logit Models
ML	Maximum Likelihood
LVM	Latent Variable Modelling
TPB	Theory of Planned Behaviour
TRA	Theory of Reasoned Action
ICT	Information Communication Technology
VAM	Value-based Adoption Model
TAM	Technology Adoption Model
C-TAMTPB	Combined TAM & TPB

PCB	Perceived Control Behaviour
SCT	Social Cognitive Theory
SOR	Stimulus-response Organism theory
UTAUT	Unified Theory of Acceptance and Use of Technology.
HOT	High Occupancy Toll
VoTT	Value of Travel Time
CR	Composite Reliability
AVE	Average Variance Extracted
HTMT	Heterotrait-Monotrait ratio of correlations
RMSEA	Root Mean Square Error of Approximation
SRMR	Standardized Root Mean Residual
CFI	Comparative Fit Index
PNFI	Parsimonious Normed Fit Index

CHAPTER 1
INTRODUCTION

This chapter aims to guide the concept of carpooling, followed by a description of the carpool situation in developed countries. The problem statement will be discussed after introducing the carpool situation in Thailand. The latter part of the chapter will explain the objectives and scope of the study.

1.1 Introduction to carpooling

Internet-based technological development is the backbone of the rapid rise of the "sharing economy" concept, and individuals get to share goods and services among the community (Asgari, Zaman, & Jin 2017; Genç 2020). It is a sustainable economic practice formed due to globalization and many other reasons. Carpooling is a more appealing form of the concept thanks to its various benefits for service users and society. Carpooling users can receive many advantages, such as monetary gain, travel timesaving, travel comfort, and social exposure. For the community, it contributes to reducing traffic congestion, fuel consumption, and greenhouse gas (GHG) emissions and generating solid social bonds (Librino et al., 2020). Correspondingly, the carpooling platform benefits the economy, society, and the environment. Presently, an interest in carpooling adoption and diffusion research is increasing.

Regarding the literature, the definition of carpooling has different versions. Bachmann, Hanimann, Artho, and Jonas (2018) defined carpooling as sharing a ride among two or more persons traveling together in a vehicle. However, this definition ignored the economic feature. Overcoming this weakness and introducing specifications to the car, Olsson, Maier, and Friman (2019) defined it as an arrangement between at least two individuals traveling together in a private vehicle and splitting the travel costs. Monchambert (2020) made a narrower definition by adding an element to categorize individuals who do not belong to the same household. The description will aid in distinguishing carpooling from other ride-sharing economy paradigms, such as car sharing, ride hailing, slugging, etc. For example, a car-sharing driver might drive alone. If a passenger does not initiate the arrangement, the trip may not take place for ride-hailing. Unlike ride-hailing, carpooling drivers make their trips regardless of whether the carpooling agreement is made. Slugging is similar to carpooling; however, there is no expense sharing.

1.2 Carpooling in developed countries

Currently, most carpoolers use the digital platform through which matching services are made among strangers for carpooling participation (Adelé & Dionisio, 2020). These developments have made dynamic carpooling more prevalent in urban areas. “BlaBlacar” is one such application developed in France in 2006 (Carrese et al., 2017). It was reported that there are more than 25 million users in 22 countries (Shaheen, Stocker, & Mundler 2017). “Moovit carpool” and” Karos” are similar applications developed later dedicated to real-time carpooling (Adelé & Dionisio, 2020; Carrese et al., 2017). Due to the attractiveness of carpooling, now ride-hailing applications also offer carpooling features where their customers can share their rides with others. "Lyft shared," "UberPool," and "Didi hitch" are widespread applications in developed countries (Brown, 2020; Wu & Neill, 2020). The conceptual initiation of dynamic carpooling dates back to the early 1990s (Ciasullo et al., 2018). This technology overcomes the barriers of traditional carpooling through the reduction of matching time (Carrese et al., 2017). However, some studies reported that carpooling became popular in the 1970s due to the oil crisis (Bulteau, Feuillet, & Dantan, 2019; Park, Chen, & Akar, 2018; Shaheen, Stocker, & Mundler, 2017). According to Olsson, Maier, and Friman (2019), the success was short beyond WWI. It was driven to save rubber and gasoline for the war effort (Neoh et al., 2018). Due to the rise of environmental awareness in the late 1990s, carpooling became popular. At present, the popularity of carpooling may be at risk during the COVID-19 pandemic (Chen et al., 2020). However, carpooling is shifting as an alternative way to avoid crowded transport modes during the global pandemic(Molina, Ignacio Giménez-Nadal, & Velilla, 2020). Among Transportation Demand Management (TDM) strategies, carpooling promotion is more attractive than other transport modes, such as public transit, walking, and biking (Bulteau, Feuillet, & Dantan, 2019). The financial burden is minimum for the authorities as it uses the existing transportation facilities and resources (Bulteau, Feuillet, & Dantan, 2019). Moreover, it is a tempting travel mode for commuters because it provides a sustainable alternative mode without asking people to entirely give up car use (Bachmann et al., 2018; Bulteau, Feuillet, & Dantan, 2019). However, the empirical evidence revealed that many commuters did not practice carpooling as a commuting travel mode (Molina, Ignacio Giménez-Nadal, & Velilla 2020). A sound understanding of carpooling adoption and diffusion determinants is vital for policymakers and transport planners to introduce carpooling programs in the market. Bulteau, Feuillet, and Dantan (2019) studied the determinants of carpooling and car-sharing communities using the information of 2002 workers in Paris. The transport budget, household income, travel mode, travel time, and carpooling service availability were the significant determinants of carpooling choice for work trips. Similar findings were found for the tertiary educational trips (Park, Chen, & Akar, 2018). Moreover, job status and marital status were statistically significant. Also, the results highlighted that low cost, low travel time, and environmental concern were the main motives for carpooling for the work trip. Further, Bulteau, Feuillet, and Dantan (2019) reported that the carpooling behavior of family members and colleagues also drives the other family members and co-workers to join carpooling, which is called subjective norm. Similar findings were elaborated that perceived peer and family pressure is the best predictor of carpooling for work or casual trips (Gheorghiu & Delhomme, 2018). Asgari, Zaman, and Jin (2017) emphasized that age, gender, household income, and household life cycle were also the statistically significant determinants of carpooling choice for work or casual trips. However, carpooling advantages were the best predictors for shopping trips (Gheorghiu & Delhomme, 2018). Carpooling for shopping trips was also affected by gender, driver status, race, household type, and household life cycle (Asgari, Zaman, & Jin, 2017). For the carpooling choice behavior of long-haul trips, other than individual factors (i.e., age, gender, and income), the number of extra passengers and access time to the closest railway station were significant determinants, irrespective of the passenger or driver role (Monchambert, 2020). For short-haul trips, attitude, trust, and reciprocity had strong, medium, and weak significant impacts on the intention toward carpooling adoption (Amirkiaee & Evangelopoulos, 2018). These studies have been conducted in developed countries where carpooling is successfully adopted and diffused in the community.

1.3 Statement of the problem

A thorough understanding of carpooling adoption is lacking for policymakers and transport planners in developing countries due to limited scientific research, specifically in Southeast Asia. In Thailand, the popularity of carpooling began in 1997 due to the Asian financial crisis (Rudjanakanoknad, 2010). National Energy Policy Office (NEPO) of the Ministry of Energy, Thailand, issued that carpooling campaigns had limited success (Rudjanakanoknad, 2010). As the economy rebounded, no efforts were retaken. The movements started again during 2008-2009 due to the peaked gas prices (Rudjanakanoknad, 2010). The fluctuations in carpooling have taken place throughout the years since then. Rudjanakanoknad (2010) conducted a carpool experiment with 213 government officials in Thailand. Most of the participants positively viewed the benefits of carpooling, but the program's success was limited due to the inefficiency of the carpool arrangement.

Furthermore, it was reported that many carpooling activities occur in Bangkok due to personal relationships rather than organized campaigns. Tayakee (2017) examined the determinants of participation in carpooling services in Thailand. The experimental test was conducted on 100 participants who had already experienced carpooling at least once. The results showed that perceived quality, emotional value, product image, consumer aspiration, and attitude towards the service significantly influenced the intention to participate in carpooling. The study further highlighted that with proper promotional efforts and enough information, it is possible to attract Thai people to a new ride-sharing economy paradigm. Vayouphack (2020) reported that due to dissatisfaction with local taxi services, ride-sharing services in Thailand are highly appreciated even though they are not entirely regulated. Therefore, it is evident that people in Thailand are willing to adopt carpooling services. However, scientific research has not been conducted to understand the impacts of various determinants to offering carpooling services during the global pandemic for educational trips to support policy development in the developing countries of Southeast Asia, specifically Thailand.

Sovacool and Griffiths (2020) pointed out that the promotion of carpooling or any smart ridesharing will require tailoring to the local context. For instance, studies conducted in developed countries considered vehicle ownership as the effect of car ownership due to their homogenous traffic context. However, as many Asian countries have mixed travel mode conditions, it is crucial to give attention to vehicle ownership by type. For example, in Thailand, motorcycle registration under the motor vehicle act is higher than private cars (Department of land Transport, 2020). This situation highlights the significance of investigating the effect of vehicle ownership by vehicle type. However, many studies have overlooked the indirect influences of the variables considered, leading to unclear findings regarding some variables. For example, some studies reported that the presence of children is significant in carpooling (Gheorghiu & Delhomme, 2018), while some report otherwise (Guensler et al., 2020). Identifying these effects will aid in not only developing policies that will indirectly persuade people towards carpooling and clarify these conflicting findings.

Furthermore, travel mode choice would be influenced by both objective and subjective factors (Yum, 2020). Therefore, investigating these subjective and psychological factors will aid in identifying key marketing points in promoting carpooling. However, the lack of attention given to some critical determinants regarding carpooling makes it challenging to recognize sound marketing strategies. Therefore, this study will provide close attention to these identified issues.

Financial motivation is highly significant in carpooling adoption, according to many studies. However, it risks highlighting the business values of carpooling rather than its social importance. Studies have pointed out that ridesharing should not be a business but rather proclaim ecological values, social values, helping out others, and a sense of community (Eskelinen & Venäläinen, 2020). Time banking is emerging as a popular form in the sharing economy, introducing time credit as an alternative currency. In this concept, people provide services and earn time credits instead of money to use those earned time credits to receive benefits. Currently, it is gaining more popularity in the neighbors-helping-neighbors-based currency system that has also received public attention as an example of sharing economy. By adopting the time banking concept into carpooling, the social values of carpooling can be highlighted rather than the business values. However, as no studies have been conducted to assess how people's perception of the time-credit concept affects carpooling adoption intention, it is challenging to integrate it into carpooling.

Further, ridesharing services worldwide are facing a significant drop due to the global pandemic. The lack of studies to assess this impact makes it difficult for authorities to bounce back with effective policy responses. The current study will address the recognized issues by presenting policy implications based on the findings.

1.4 Objectives and scope of the study

The present study is driven to increase understanding of commuters' influential factors and psychological behavior towards carpooling adoption. Accordingly, the following key objectives were identified,

- To identify critical determinants associated with carpooling in the context of educational trips in Thailand.
- To understand both direct and indirect associations of the determinants on intention to participate in carpooling.
- To propose policy implications based on the findings.

The current study focused on the psychological determinants (performance expectancy, effort expectancy, social influence, hedonic motivation, price value, facilitating conditions, perceived safety, perception toward COVID-19 and carpool, time credits, and behavior intention). A web-based online questionnaire survey was conducted as the primary data source. A conceptual model was developed primarily based on Consumer Acceptance and Use of Information Technology (UTAUT2). Observed variables for each behavioral construct were mainly set based on past studies. In addition, new observed variables were formed as well. As present study focuses on dynamic carpooling, observed variables were modified to reflect aspects of carpooling using a mobile application. The survey instrument consisted of five sections that were developed to collect information. The first part aimed to gather information on psychological factors related to carpool behavior with 5 points Likert scale, while the second part focused on perception towards COVID-19. The third section gathered people's perception of time-credit with carpooling, while the fourth section focused on sociodemographic information about the individuals. The final section of the survey is dedicated to collecting information regarding the individuals' travel patterns. The questionnaire survey was conducted at Thammasat University, Pathum Thani. The location is illustrated in Figure 1. Thammasat University is the second oldest university in Thailand, consisting of 4 campuses, and the survey was conducted on the Thammasat University-Rangsit Campus. Pathum Thani province is located in the north of Bangkok, the national metropolitan area with an area of 1,526 km^2 and consists of seven districts while being responsible for the fifth largest population density in Thailand. All the analyses were done using a multivariate statistical analysis called Structural Equation Modeling (SEM).

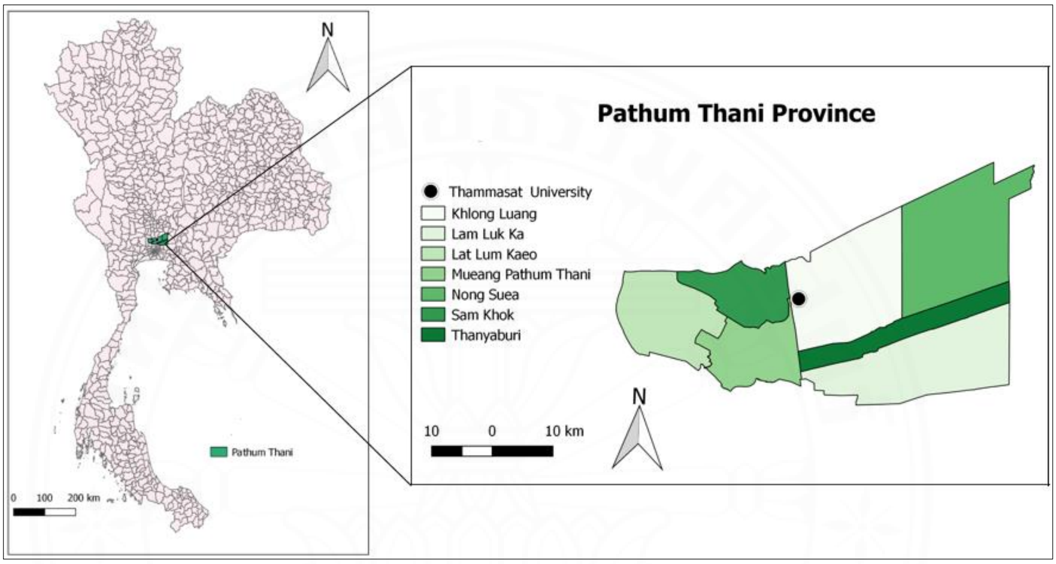

Figure 1.1 The study area

The findings of this study are informative to design policies to promote carpooling adoption towards sustainable mobility and identify key marketing points to promote dynamic carpooling among different groups for educational trips.

CHAPTER 2
REVIEW OF LITERATURE

2.1 Mathematical models for data analysis

Discrete choice models are successfully used in the Transportation planning sector due to their ability to analyze individuals' random behavior when choosing discrete alternatives. These models are driven by theories explaining the underlying individual decision-making process. For example, Random Regret Minimization (RRM) states that individuals seek to minimize negative emotions rather than maximize positive ones, which is a vital alternative theory (Hancock, Hess, & Choudhury 2018). In addition, Lazy User Theory (LUT), which argues that the individual decision-making process can be explained by the principle of least effort (PLE), is also capable of fulfilling the purposes of discrete choice models (Pinto et al. 2019). Even though both these theories can explore the underlying cognitive process, Random Utility Theory (RUT) which assumes that individuals make choices that maximize their utility, has been the basis for these mathematical models for more than 40 years (Hancock, Hess, & Choudhury 2018). Specifically, RUT has been extensively used by many authors in the past when it comes to travel mode choice.

Many versions of discrete choice models have been developed and applied: logit, probit, binary logit, multinomial logit, mixed logit, etc. Based on the expected outcome and the available information, the choice of the model varies. For instance, past studies have widely utilized binary logit and probit models when choosing between two alternatives. In both models, the dependent variable is dichotomous. For example, Bulteau, Feuillet, and Dantan (2019) viewed carpooling as a binary decision and developed a binary logit model to identify the significant variables that differentiate carpoolers from non-carpoolers.

Further, they used Odd Ratios (OR) to recognize the most significant variables. For example, it was reported that having family members/friends or colleagues who carpool, which had higher ORs, strongly influenced carpool decisions. Odds are defined as the ratio of the probability of a choice divided by the probability of not choosing that particular alternative. ORs (odds between two groups) allow us to interpret odds between groups related to dependent variables(King, 2014). Therefore, a high OR indicates the high significance of the particular variable. Huang, Liu, Zhang, Zhu, and Kim (2019) developed a binary logit model to explore the interaction between travel time and cost. They found that odds of joining the carpool will decrease to 25.9% if travel time increase by one unit while other influencing factors remain unchanged.

Similarly, the influence of other factors (travel cost and safety) was explored using odd values. The main difference between logit and probit models lies in the assumption of the distribution of the errors. It is assumed that the errors follow standard logistic distribution in the logit models, while for probit models, it is the normal distribution (Alsoruji, Binhimd, & Abd Elaal 2018). Park, Chen, and Akar (2018) developed two probit modes for carpool drivers and passengers. They used bivariate probit regression and found that carpool interest and actual carpooling choice are highly interrelated. These authors have viewed carpooling as a binary choice, leading them to use binary logit and probit models. Both models can model carpool behavior when viewed as a dichotomous decision. However, some authors investigated carpooling behavior considering multiple travel modes.

In such situations, data analysis uses a model that can handle multiple dependent variables. Multinomial logit regression (MNL) is used in several studies (Asgari, Zaman, & Jin, 2017; Schubert, Henning, & Lopes, 2020). It is a widely used generalized linear model to estimate the probabilities for several dependent variables using a set of explanatory variables. Asgari, Zaman, and Jin (2017) developed four multinomial logit models for different trip purposes as they expected to study the influences of the determinants on individuals' travel mode choices. Dependent variables contained three travel options: high occupancy vehicles (HOV), public transport, and non-motorized vehicles. Schubert, Henning, and Lopes (2020) developed two distinct multinomial logit models in their study. One to understand the current transport mode choice behavior and the other to study the possibility of an eventual commute mode shift. Car, Bus, Walking, and a bicycle were the four-mode choices available for individuals. Findings revealed which factors are significant for choosing the travel mode and which influence the possible mode switch.

Further, specific discoveries were made using odds ratios, such as male students are approximately twice as likely to switch from car to bicycle. Like MNL, Multinomial

Probit Modelling (MPM) can handle multiple outcomes for probit regression. However, due to computation complexity and difficulty in data interpretation, authors do not commonly use the method. Therefore, it is evident that MNL models perform better in a single-choice situation where a choice must be made among a given set of alternatives.

While MNL models seem to be a better option for this study, it has a few limitations. The first is the assumption of Independence of Irrelevant Alternatives (IIA). It implies that the choice between two options depends only on the characteristics of these options and not on the attributes of other possible options. Nested Logit Models (NLM) relax this assumption, allowing for a combination of similar alternatives and avoiding potential bias due to correlations (Zhou, Wang, & Wu, 2018). Zhou, Wang, and Wu (2018) considered three nests (driving, transit, and non-motorized). They found that peer effects and self-selection could have introduced biases if they were not controlled, which indicates that NLM provides more probable estimations in the presence of similar alternatives. The second assumption of MNL is that repeated choices made by an individual are independent. Monchambert (2020) investigated long-distance carpooling behavior in France. For this purpose, the author conducted a choice experiment where individuals were presented with different scenarios and asked to choose their preferred travel mode. Mix logit modeling approach was used to analyze data as the repeated choices made by an individual are correlated. Mix logit is an extension of MNL where the two assumptions of MNL are relaxed, which is the main advantage of mix logit (Pfaff, 2019). Hence the author was able to study how people trade-off between travel time and travel cost when carpooling. Therefore, it becomes apparent that the model used for analysis varies based on the study purpose. However, data type also affects the choice of the mathematical model used for data analysis.

Poisson regression is typically used to model count data (as the dependent variable). It assumes that data follows the Poisson distribution, which is one of the drawbacks of this approach. It estimates the probability of occurrence of an event (Ex: frequency of carpooling). The regression coefficients are calculated using the Maximum Likelihood (ML) method. Therefore, this method is appropriate when the investigation is focused on the frequency usage of one travel mode. Bulteau, Feuillet, and Dantan (2019) developed both logit and Poisson models to assess carpooling frequencies and found that findings are pretty similar from both approaches. Similar to odd ratios in logit models, incidence ratios from Poisson regression can be used to understand the effects of different determinants on carpooling when other things are equal. All the mathematical models discussed so far can model easily measurable hard variables[1] related to carpooling behavior. However, soft variables[2] also play a highly significant role in carpooling behavior. Psychological variables are one such category that belongs to soft variables. The most convenient and common approach to analyzing them is the Structural Equation Modelling (SEM) approach. The main advantage is capturing latent constructs (psychological variables) with measurement errors. This approach has two stages. First, Latent Variable Modelling (LVM) is used to develop constructs using measurable variables. Then set constructs are related to one or more dependent variables. The method has some restrictions, such as data should follow the assumptions of LVM (Bachmann et al., 2018). Bachmann, Hanimann, Artho, and Jonas (2018) used this approach to generate a modified model to compare it with the original model. They investigated the theory of planned behavior (TPB) model and found that the modified model performed better. Furthermore, they used the multi-group comparison approach to differentiate the findings between drivers and passengers.

All these mathematical models are appropriate for predictive analysis. Conversely, there are different methods used for exploratory purposes. For example, Malodia and Singla (2016) utilized the Part-worth model to identify the relative importance of the utility of the carpooling attributes. They found the most critical feature is cost savings, followed by extra travel, walking, and waiting time. The method can capture different utility values for different levels of the given attributes; hence it can identify the order of importance. Therefore, the approach is more suitable for in-depth studies related to carpooling as it can recognize the importance of different levels of the given attributes. Guensler, Ko, Kim, Khoeini, Sheikh, and Xu (2020) used the classification tree technique to identify interactions between factors. This approach is substantially functional when complex interaction effects may exist. However, the method may overlook the vital data structure due to the lack of strict guidelines. These findings raise the argument that the modeling approach should be selected carefully as

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[1] Hard variables can be measured directly such as age, gender etc. They reflect unchangeable reality.
[2] Soft variables cannot be measured directly such as attitude, intention etc. They reflect respondents' opinions.

it is affected by many factors. Table 2.1 summarize different mathematical models used in past studies and their aims.

Table 2.1 Different mathematical models with references and study aims.

Model	Aim of the study	Reference
Binomial logit model	To explore the potential determinants of the use of carpooling and car-sharing for commuting	(Bulteau, Feuillet, and Dantan, 2019)
	To identify the most important influencing factors for carpooling and their impact on each other	(Huang et al., 2019)
Binomial probit model	To enhance the understanding of carpooling interests and choices, taking into account driver versus passenger choice	(Park, Chen, and Akar, 2018)
Multinomial logit model	To study the mode choice behavior of immigrants	(Asgari, Zaman, and Jin, 2017)
	To identify and understand the factors influencing the switching of transportation modes	(Schubert, Henning, and Lopes, 2020)
Nested logit model	To specifically explore influence factors of the mode choice of college town students	(Zhou, Wang, and Wu, 2018)
Mix logit model	To investigate choice model behavior for drivers and passengers separately	(Monchambert, 2020)
	To assess the prospective users' willingness to pay for different service characteristics for the ride pooling system	(König and Grippenkoven, 2020)
Poisson regression	To explore the potential determinants of the use of carpooling and car-sharing for commuting	(Bulteau, Feuillet, and Dantan, 2019)
	To study what factors are associated with where ridesharing occurs? And what factors are associated with who rideshares?	(Brown, 2020)
Structural Equation Modelling	To study the determinants systematically concerning both parties involved in carpooling	(Bachmann et al., 2018)
	To investigate psychological factors & contextual factors that may influence individuals' decision to participate in ridesharing	(Amirkiaee and Evangelopoulos, 2018)

2.2 Psychological theories

Understanding the cognitive process behind individuals' behavioral adoption is essential to recognize the critical marketing points to build sound promotional efforts.

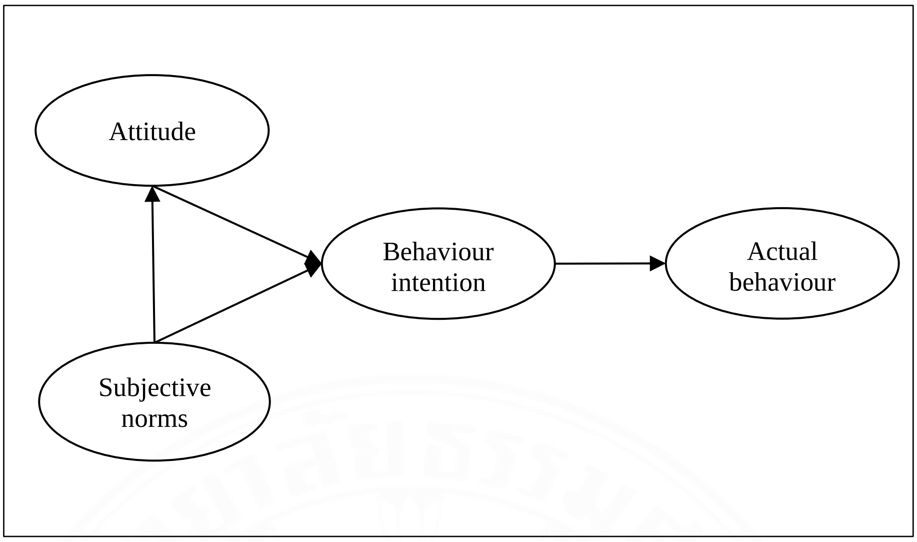


Figure 2.1 Theory of Reasoned Action (TRA) adopted from Fishbein and Aizen (1975)

Theory of Reasoned Action (TRA) is one of the major theories developed in this context. Fishbein and Aizen proposed it in 1975. According to it, the intention to perform a particular behavior is affected by attitude and subjective norms, and subjective norms affect attitude towards that behavior. Figure 2.1 graphically illustrates the theory. Subjective norms refer to the social influence that affects participating decisions in the behavior. Attitudes generally refer to the beliefs of individuals about a particular behavior. The intention is the resultant behavior of the combined effects. It is one of the most fundamental theories of human behavior and is designed to explain virtually any human behavior (Momani, Jamous, & Hilles, 2017). Alam, Jani, Omar, Hossain, and Ahsan (2012) successfully utilized the theory to examine the determinants of Information Communication Technology (ICT) adoption of employees. They found that model relationships are highly significant in ICT adoption. One of the flaws of TRA is that it is general and does not refer to other variables like fear, threat, mood, or previous experience (Momani, Jamous, & Hilles 2017). Especially when it comes to carpooling behavior adoption, determinants such as trust, safety, and prior experience play essential roles which cannot be explained using TRA.

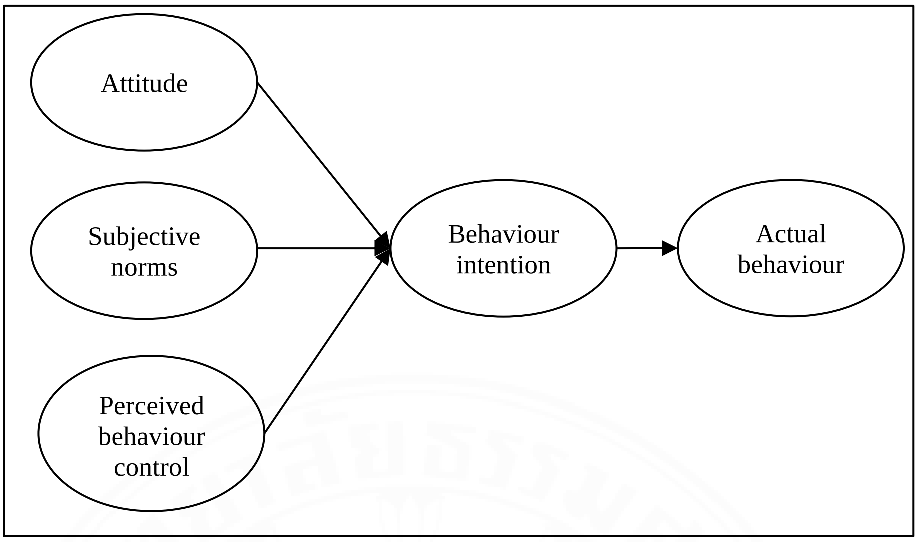


Figure 2.2 Theory of Planned Behaviour (TPB) adopted from Aizen (1985)

To improve the predictive power of TRA, the Theory of Planned Behaviour (TPB) was initially proposed by Aizen in 1985. The theory regards intension as the primary driver of performing a specific behavior, and intension is predicted by three determinants: Attitude, subjective norms, and perceived behavior control. Figure 2.2 graphically illustrates the relations in theory. Here perceived behavior control refers to the internal and external factors obstructing users from performing (Abutaleb, El-Bassiouny, & Hamed, 2021). It is successfully applied to understanding individual acceptance and usage of many different technologies (Momani et al., 2017). TPB is successfully used in the carpooling context. Bachmann, Hanimann, Artho, and Jonas (2018) modified TPB to assess determinants of carpooling from a psychological perspective by adding personal norms (internalized self-expectations) and descriptive norms (what many others do) and found that the modified model performs better than the original model. Abutaleb, El-Bassiouny, and Hamed (2020) used TPB with personal norms, economic benefits, and sustainability to examine consumer intentions toward carpooling as a collaborative consumption practice. They found the two components that had the most significant impact on intention were subjective norms and attitudes, which slightly disagree with Bachmann, Hanimann, Artho, and Jonas (2018). Despite the conflicts in the findings, it is pretty clear that TPB can explain carpooling adoption behavior successfully with the aid of modifications. However, the theory suggests that the behaviors are already planned and do not refer to other variables that affect behavioral intention. For instance, Park, Chen, and Akar (2018) reported that even though both potential carpoolers and current carpoolers value specific characteristics of carpooling, potential carpoolers are more concerned about privacy, system flexibility, and most in need of technical assistance that aids them in carpooling. As the present study aims at investigating potential carpoolers, utilizing TPB might not be the best option.

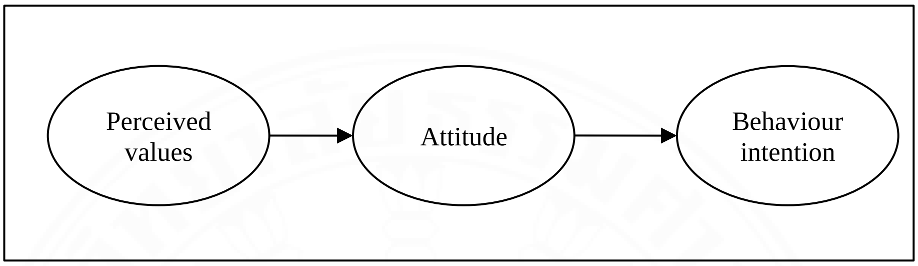


Figure 2.3 Value-based Adoption Model (VAM) adopted from Zeithmal (1988)

Zeithmal originally proposed the Value-based Adoption Model (VAM) in 1988. It states that perceived values are the antecedent of attitude towards a particular adoption behavior, and attitudes directly affect adoption intention on behavior. Figure 2.3 visualizes the VAM. It is powerful in explaining consumer values and choices as it states that consumers mentally trade off what is given and what is received (Momani, Jamous, & Hilles 2017). Sharma (2019) developed a conceptual model based on VAM to assess consumers' motives for buying ridesharing services. They investigated perceived values under three subgroups; functional, social, and personal. Findings revealed that functional values are not significant in consumers' intention to buy ride-sharing services, while social and personal values are highly significant. While the theory is capable of explaining consumer buying behavior, it does not include some considerable behavior driving factors such as curiosity, habits, etc. For instance, curiosity is one of the main reasons to use carpooling (Ciasullo et al., 2018). Therefore, VAM alone is not capable of explaining carpool adoption behavior.

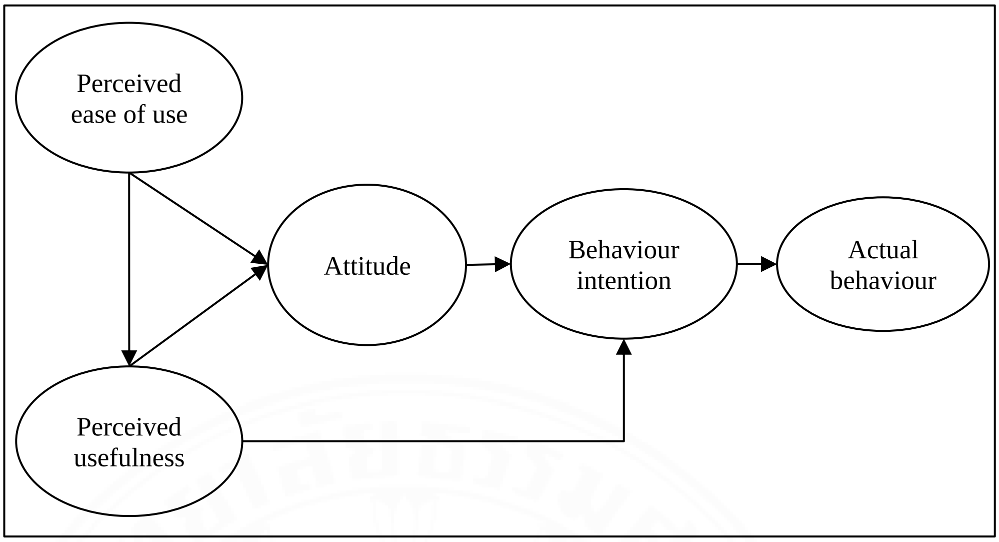


Figure 2.4 Technology Adoption Model (TAM) adopted from Davis (1989)

Davis built the Technology Adoption Model (TAM) in 1989 based on the TRA. It states that perceived usefulness (expected improvements by using the service) and perceived ease of use (expected easiness of using the service) influence the attitude, and attitude drives intention, resulting in the actual behavior. The relationships between these factors are illustrated in figure 2.4. Ardra and Rejikumar (2017) proposed a modified model based on TAM by adding perceived safety and price advantages as additional drivers to assess the intention of the women to adopt Uber services. Findings revealed that perceived safety and ease of use play significant roles in forming intention while price advantage and usefulness are insignificant. Wang, Wang, Wang, Wei, and Wang (2020) also conducted a similar study regarding consumer intention to use ride-sharing services in China. Their proposed model included personal innovativeness (the degree to which an individual tends to try new things), perceived risk, and environmental awareness. They found that personal innovativeness, environmental awareness, and perceived usefulness are positively associated with the intention and perceived usefulness. TAM is a powerful model for technology applications. However, it is less general than TRA and TPB. It provides feedback on two factors: usefulness and ease of use (Momani, Jamous, & Hilles, 2017). However, it does not explain how social influence affects individual behavior. Regarding carpooling, social influence is a valuable determinant that explains personal behavior adoption. Therefore, TAM does not fit the purpose of the present study.

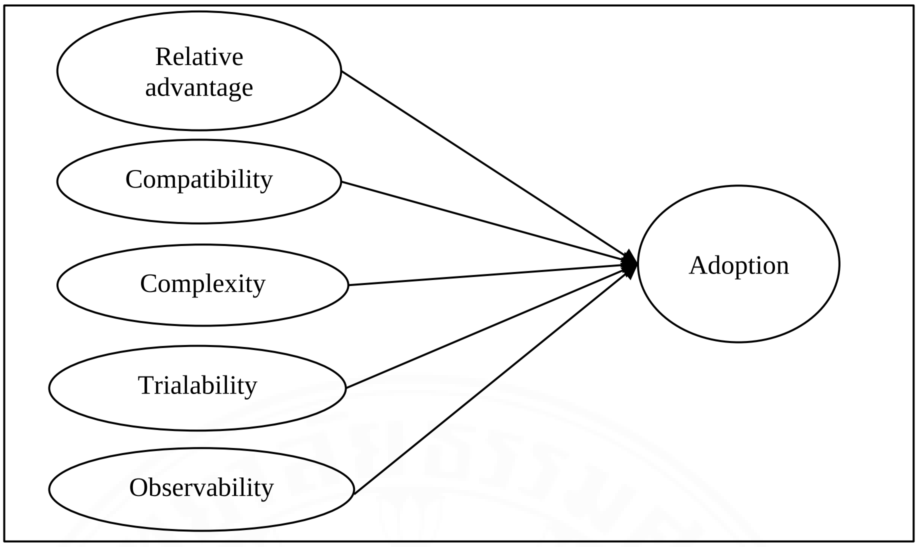


Figure 2.5 Innovation Diffusion Theory (IDT) adopted from Roger (1983)

Rogers first proposed Innovation Diffusion Theory (IDT)n 1983 to study a wide range of innovations (Chen, Salmanian, & Akram, 2017). According to the theory, the adoption of an invention is affected by five factors: relative advantage, compatibility, complexity, trialability, and observability. Figure 2.5 provide a graphical explanation of the theory. Yuen, Wong, Ma, and Wang (2020) combined IDT with perceived value theory and trust theory to assess the determinants of public acceptance of autonomous vehicles. They reported that the influence of the innovation diffusion attributes on public acceptance is fully mediated by the public's perceived value of autonomous vehicles. In addition, the public's trust partially mediates the effect of perceived value on public acceptance. The theory is capable of investigating any innovation. It explains the decision of invention and predicts the rates of the adoption factors of innovation (Momani, Jamous, & Hilles 2017). However, the theory does not hold in the context of carpooling adoption as it does not provide any concern for social influence or individual resources. Modifications may require utilizing IDT in explaining carpooling adoption behavior.

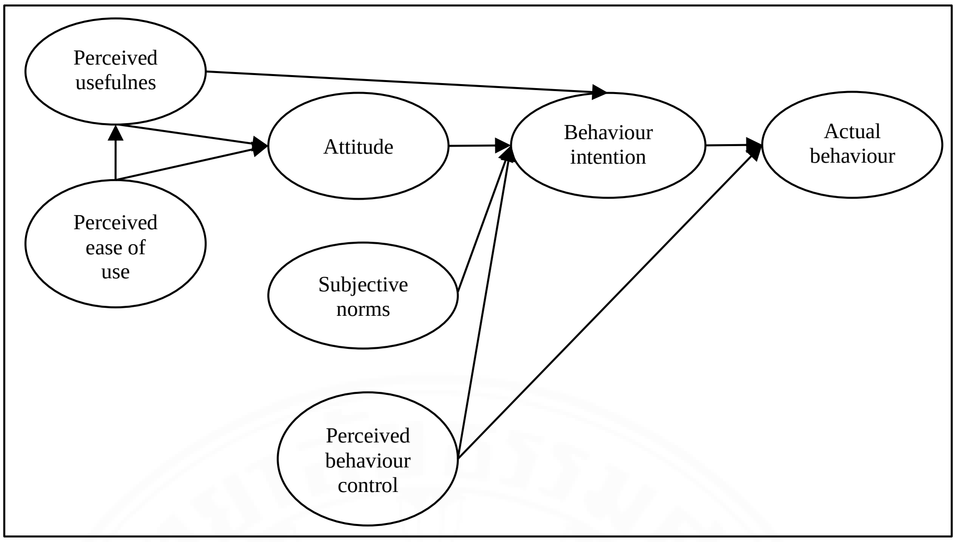


Figure 2.6 Combined TAM & TPB (C-TAMTPB) adopted from Taylor and Todd (1995)

Taylor and Todd (1995) combined TAM and TPB to propose a new model that performs better in information technology usage prediction (Chen, Salmanian, & Akram 2017). Accordingly, to the model, behavior intention is predicted by three determinants: attitude, subjective norms, and perceived behavior control (PCB). Attitude is formed by perceived ease of use and perceived usefulness. The relationships are illustrated in figure 2.6. Tavallaee, Shokouhyar, and Samadi (2017) used the model to examine the acceptance of mobile learning by students at Tehran universities. They found that perceived usefulness, ease of use, attitude towards behavior, and the subjective norm influence the students' behavior intentions. Even though the model performs better than other models, TAM constructs do not fully reflect the specific impacts of the usage-context factor that may change users' acceptance (Momani, Jamous, & Hilles 2017). For example, it does not pay attention to trust and safety regarding usage. Therefore, many modifications may require changes in the carpooling context as many other determinants influence it that the model cannot explain.

Social Cognitive Theory (SCT) is considered one of the most influential theories of human behavior, especially in studying the human learning process. Bandura proposed the model in 1989. It states that human behavior occurs due to the interaction between personal factors, behavior, and environment. Compeau and Higgins (1995) extend this to research on computer utilization (Chen, Salmanian, & Akram, 2017), leading to increasing theory usage. Figure 2.7 illustrates the model graphically. Zhu, So and Hudson (2017) proposed a modified model to assess what motivates consumers to adopt one of the emerging mobile applications of the sharing economy, the ridesharing application. They combined VAM with SCT to fulfill their study purposes. However, the theory is not substantially organized, especially when studying the relations among individuals, behavior, and the environment (Momani, Jamous, and Hilles, 2017). Therefore, theory alone cannot be utilized to understand carpooling behavior adoption.

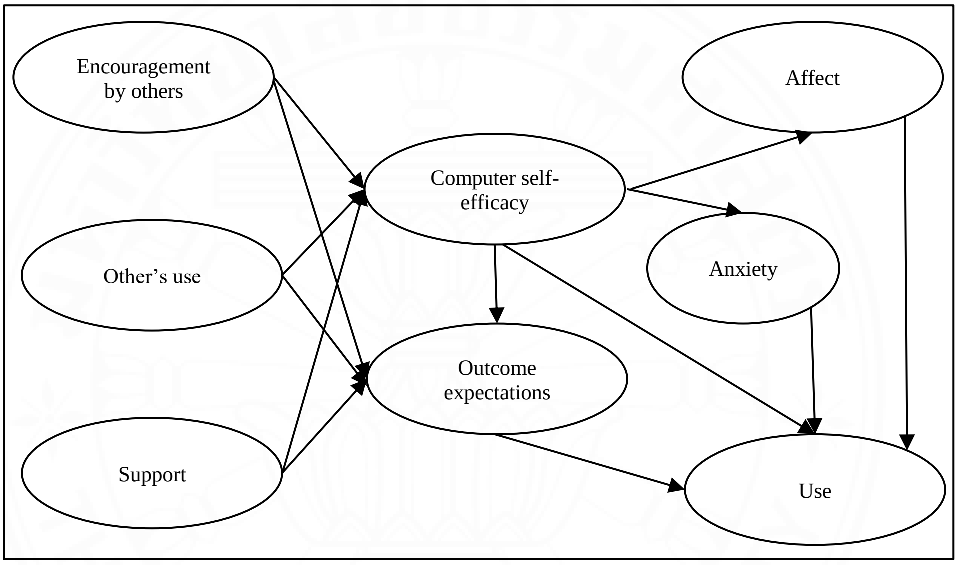


Figure 2.7 Social Cognitive Theory (SCT) adopted from Compeau and Higgins (1995)

Boateng, Kosiba, and Okoe (2018) examined the factors that drive customers in Ghana to use Uber based on the Social Exchange theory. The theory highlights that people choose relationships based on their rewards and costs. It can be successfully used to understand sharing economy participation intentions (Yuen et al., 2020). However, it does not explain the roles of some important factors such as sustainability concerns, altruism, etc. For instance, in carpooling, environmental concern is regarded as a significant motivational factor that cannot be explained using the theory. Social Comparison theory is another similar theory that states that people self-evaluate their opinions by comparing themselves to others. Li, Liu, Ma, and Zhang (2019) combined this theory with the expectation confirmation theory[3] to investigate the users' intention to continue using social fitness-tracking apps. The Social Comparison theory can be successfully used to explain continuous intention to adopt technology, though it fails to capture significant drivers of first-time adopters. Stimulus-response Organism theory (SOR) is also a similar type of theory. Mehrabian and Russell proposed it in 1974. It states that environmental stimuli affect people's emotions, which cause changes in their behavior. Aggarwal and Rahul (2017) combined this theory with TAM to assess the impact of perceived usability and perceived information quality on consumer purchase intentions. The theory can explain how cognitive factors are formed; however, it cannot be used alone to describe how psychological determinants are related.

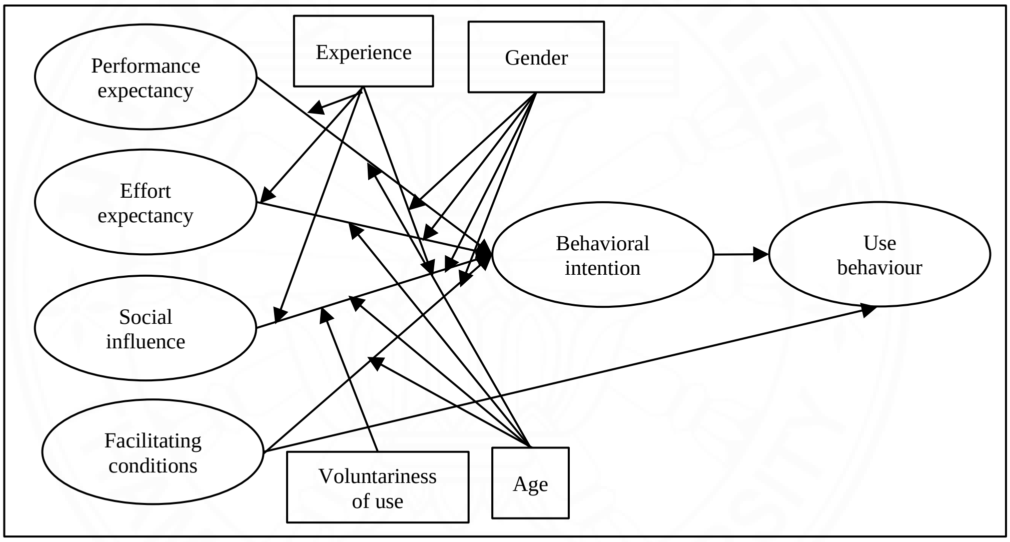


Figure 2.8 Unified theory of acceptance and use of technology (UTAUT) adopted from Venkatesh, Morris, Davis, and Davis (2003)

The unified theory of acceptance and use of technology (UTAUT) was developed based on eight theories by Venkatesh, Morris, Davis, and Davis (2003).; Theory of Reasoned Action (TRA), Theory of Planned Behavior (TPB), Technology Acceptance Model (TAM), The model of PC utilization (MPCU), Innovation Diffusion Theory (IDT), Motivational Model (MM), Social Cognitive Theory (SCT) and Combined TAM and TPB (C-TAM-TPB) (Chen, Salmanian, and Akram, 2017).

[3] Theory states that that satisfaction is determined by the interplay between prior expectations and perception of delivery (Li, Liu, ma and Zhang, 2019)

According to figure 2.8, which illustrates the model relationships, behavioral intention is formed from four constructs; performance expectancy (the degree to which expected benefits from using technology or service), effort expectancy (the degree to which anticipated easiness of using technology or service), social influence (the degree to which individual value the behavior of important others) and facilitating conditions (the degree to which expected resources available to use technology or service). These constructs are moderated by voluntariness of use, age, gender, and experience. Moderating variables affect the direction or strength of the relationship(King, 2014). The model is a robust framework in the organizational context for accepting technology. With relevant extensions, it can be used to understand important phenomena (Venkatesh et al., 2003). However, it does not concern individuals' hedonic motivations, habits, attitudes, etc., which are significant in some behavioral contexts. For example, Hossain (2020) reported that hedonic motivation positively affects consumers' propensity to participate in sharing economy phenomena. Therefore, utilizing UTAUT in the context of carpooling may not be effective.

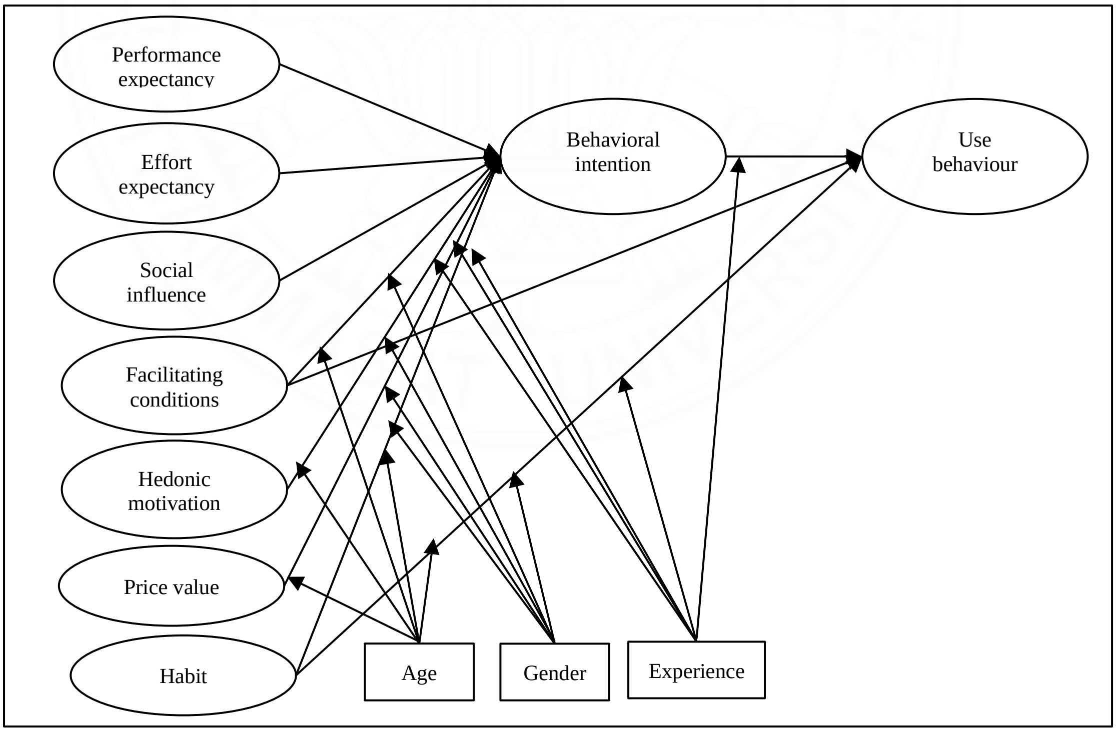


Figure 2.9 Consumer Acceptance and Use of Information Technology (UTAUT2) adopted from Venkatesh, Thong, and Xu (2012)

Consumer Acceptance and Use of Information Technology (UTAUT2) is an extension of UTAUT developed in the consumer use context. It provides substantial improvement to the UTAUT. Figure 2.9 provides a graphical illustration of the model. The previous authors have successfully used it to assess determinants of acceptance of mobile applications. Chen, Slamanian, and Akram (2017) evaluated the determinants of acceptance of Transport Network Company (TNC) vehicles in China using UTAUT2. They found that all seven factors of UTAUT2, such as performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit, influence user acceptance. Soares, Christino, Gosling, Vera, and Cardozo (2020) utilized the model to investigate the acceptance and use of e-hailing technology (Uber) in Brazil. Findings revealed that price value, performance expectancy, and habit are the most significant factors in e-hailing. Even though the model has been introduced recently, it has already been cited in over 5000 articles from various research streams on Google scholar alone (Tamilmani, Rana, & Dwivedi 2020). Compared to previous models, UTAUT2 contains many constructs capable of capturing carpooling behavior. One of the drawbacks of the theory is that it does not explain how perceived safety aspects influence behavior intention. Especially when it comes to potential carpoolers, safety aspects of carpooling play a significant role in carpool adoption behavior (Park, Chen, & Akar, 2018). Further, a study that investigated the UTAUT2 model's practical usage found that most studies did not use the habit construct in their research (Tamilmani, Rana, & Dwivedi 2020). One of the underlying reasons was “technology at early adoption stages.”. Despite the drawbacks, UTAUT2 is a possible candidate model for investigating carpooling behavior.

Moreover, no studies have used the UTAUT2 model to investigate psychological behavior in carpooling adoption. Therefore, it is evident that the UTAUT2 model is the most appropriate candidate model for the present study. However, modifications must address the drawbacks and comply with study objectives. Table 2.2 provide a summary of the psychological theories considered.

Table 2.2 Different psychological theories and their features with references

Model/Theory	General and fundamental model	The intention is the primary driver of actual behavior	Explain the effect of social influence	Consider cognitive tradeoffs	Explain how cognitive factors are formed	Highlights the impact of attitude on intention	Pay attention to factors such as habits, experience, etc.	Include moderating factors	Reference
Theory of Reason Action (TRA)	√	√	√			√			(Alam et al., 2012; Chen, Salmanian, and Akram, 2017; Momani, Jamous, and Hilles, 2017)
Theory of Planned Behaviour (TPB)		√	√			√			(Altinay and Taheri, 2019; Bachmann et al., 2018);Momani, Jamous, and Hilles, 2017)
Value-based Adoption model (VAM)		√		√		√			(Zhu, So, and Hudson, 2017; Sharma, 2019; Momani, Jamous, and Hilles, 2017)
Technology Adoption Model (TAM)		√				√			(Zhu, So, and Hudson, 2017; Wang et al., 2020);Arda and Rejikumar, 2017); Momani, Jamous, and Hilles, 2017)
Innovation Diffusion Theory (IDT)	√			√					(Turan, Tunç, and Zehir, 2015;Yuen et al., 2020); Momani, Jamous, and Hilles, 2017)
Combined TAM & TPB		√	√			√			(Tavallaee, Shokouhyar, and Samadi 2017; Momani, Jamous, and Hilles 2017)
Social Cognitive Theory	√								(Altinay and Taheri, 2019; Momani, Jamous, and Hilles,2017)
Social Comparison Theory	√			√					(Altinay and Taheri 2019; Li et al. 2019))
Social Exchange Theory	√			√					(Altinay and Taheri

Model/Theory	General and fundamental model	The intention is the primary driver of actual behavior	Explain the effect of social influence	Consider cognitive tradeoffs	Explain how cognitive factors are formed	Highlights the impact of attitude on intention	Pay attention to factors such as habits, experience, etc.	Include moderating factors	Reference
									2019;Koohikamali , Sarkar, and Pick 2017;Boateng, Kosiba, and Okoe 2019)
Stimulus-response-organism Theory (SOR)	√				√				(Altinay and Taheri, 2019;Wu and Neill, 2020)
Unified Theory of Acceptance and Use of Technology (UTAUT)		√	√	√			√	√	(Chen, Salmanian, and Akram, 2017;Dico, 2021))
Consumer Acceptance and Use of Information Technology (UTAUT2)		√	√	√			√	√	(Turan, Tunç, and Zehir, 2015; Yuen et al., 2020)

2.3 Psychological factors of carpooling adoption

Many psychological theories highlight the importance of several significant drivers of behavioral intention or actual behavior in relevance to carpooling. These determinants vary significantly according to whether the focus is on intentions or actual behaviors (Lanzini & Khan, 2017). However, the underlying assumption of many theories is that the actual behavior is driven by behavioral intention. Depending on the theory, antecedents of intention vary.

TRA suggests that the intention to perform a particular behavior is formed by attitude and subjective norms. Attitudes are the feelings or beliefs of individuals toward the behavior. Lanzini and Khan (2017) studied determinants of travel mode choice and found that attitude has a good predictive capability on intention. Amirkiaee and Evangelopoulos (2018) examined the motivations behind adopting ride-sharing services in the USA and found that attitude is vital in participating in ridesharing. Malodia and Singla (2016) reported that carpoolers have a positive attitude towards carpooling while solo drivers have a neutral attitude towards carpooling. This study was conducted in India. The attitude seems more critical in developing countries than in developed countries. Sofi Dinesh, Rajkumar, Gynendra, and Sisodia (2021) conducted an empirical investigation into carpooling behavior and found that a positive attitude towards carpooling will lead to positive adoption intentions carpooling, which supports this argument.

Further, many studies conducted in developed countries reported otherwise. Bachmann, Hanimann, Artho, and Jonas (2018) studied Switzerland carpoolers and found that attitude does not predict intention for either driver or passenger. Adelé and Dionisio (2020) studied "Karos" carpooling app users in France and found that there is not always a link between a positive attitude toward carpooling and an increased intention to practice. Therefore, it appears the argument holds. The importance of subjective norms in forming intention is highlighted in many psychological theories; TRA, TPB, and C-TAMTPB. "Social influence' construct in UTAUT and UTAUT2 theories also represents a similar influence despite their differences in the definitions. Both factors represent the influence of other people (people who are essential to the individual)—specifically, family, friends, and co-workers. Therefore, subjective norms have sound predictive capabilities on intention (Lanzini & Khan, 2017). Bulteau, Feuillet, and Dantan (2019) investigated carpooling and carsharing behavior of 2002 french workers. They found that the influence of family members and colleagues is more vital for carpooling than carsharing. Gheorghiu and Delhomme (2018) reported that this influence is significant irrespective of the trip purpose. Bachmann, Hanimann, Artho, and Jonas (2018) said that the effect is marginal for passengers while it is highly influential for drivers in Switzerland. Due to the lack of studies conducted in developing countries, it is difficult to conclude that social influence may remain the same in developing countries. However, Rudjanakanoknad (2010) reported that carpooling activities occur in Bangkok due to personal relationships rather than organized campaigns. These shreds of evidence indicate that social influence may be significant in developing countries and relevant to carpooling behavior.

According to the UTAUT and UTAUT2, performance expectancy is one of the significant drivers of intention. It is defined as "the degree to which using a technology will benefit consumers in performing certain activities" (Venkatesh et al., 2012a). In the context of carpooling behavior, it can be defined as the expected benefits from participating in carpooling—the term "Perceived usefulness" is also similar to this determinant. TAM and C-TAMTPB highlight the significance of this factor in forming an intention. Gheorghiu and Delhomme (2018) found that carpooling advantages are one of the main predictors of carpooling behavior. Among many advantages, socializing and comfort seem to be highly appreciated benefits. Ciasullo, Troisi, Loia, and Maione (2018) analyzed the Twitter feedback regarding carpooling and found that socialization and comfort are some of the motives behind adopting carpooling, and effectiveness is the main disadvantage stated by the carpool users. Molina, Nadal, and Velilla (2020) studied carpooling behavior across ten countries and reported that socializing is the primary reason for carpooling.

Further, Amirkiaee and Evangelopoulos (2018) found that time benefit significantly influences ride-sharing attitudes. Therefore it could be inferred that carpoolers appreciate the benefits they are receiving from carpooling, which primarily affects their use of carpooling. Carrese, Troisi, Loia, and Maione (2017) stated that carpool service users find it more comfortable and valuable than potential users, supporting the idea that performance expectancy is a significant factor in carpooling. Not only current carpoolers but potential carpoolers also seem to expect carpooling benefits. Park, Chen, and Akar (2018) reported that potential carpool users emphasize system flexibility more than current carpool users. Therefore, both groups expect the benefits of carpooling, which significantly affects the diffusion of carpooling. These studies are conducted in developed countries such as the USA, France, etc. There is little evidence that supports this argument will hold across developing countries as well. Rudjanakanoknad (2010) conducted a carpool experiment among 213 government officials in Thailand, and they found that most participants viewed the benefits of carpooling positively. Therefore it is reasonable to assume that performance expectancy is significant in carpooling behavior despite whether the country is developed.

Perceived ease of use is another significant variable contributing to forming attitudes according to the TAM. It is the expected ease of using a particular system or service (Arda and Rejikumar, 2017). TPB introduces the "perceived behavior control" term, similar to the ease of use. It is defined as perceived ease or difficulty in performing the behavior. Effort expectancy in UTAUT and UTAUT2 also indicates a similar definition. Adelé and Dionisio (2020) stated that carpooling could be socially and emotionally demanding, meaning that users have to put some effort into carpooling. Their study found that difficulties associated with the application's smart functions keep users from carpooling again. Further, these difficulties lead to misunderstandings between users. It creates fuzzy negative feelings in carpoolers, indicating that their challenges in carpooling use act as barriers that prevent them from carpooling again. Not only carpoolers but potential carpoolers also perceive these difficulties as barriers. Park, Chen, and Akar (2018) reported that arrangement barriers influence current and potential carpoolers. The influence of these difficulties seems to be significant despite the role of interest. Bachmann, Hanimann, Artho, and Jonas (2018) found that perceived behavior control is highly effective for passengers' and drivers' intention to carpool. The pattern appears to be similar in developing countries as well. Ardra and Rejikumar (2017) found that perceived ease of use strongly contributes to the intention to participate in ridesharing in India. Further, in his experimental study, Rudjanakanoknad (2010) found that the carpool program's success was limited due to the inefficiency of the carpooling arrangement. This evidence implies that perceived ease of use is a significant psychological determinant influencing the intention to carpool in developing countries.

Compatibility is the degree to which adoption of a particular behavior is perceived as consistent with the existing values, lifestyles, experiences, and needs of the public (Yuen et al., 2020). It is one of the driving factors of adoption, according to DOI. For example, carpooling is an emerging form of the "sharing economy" concept (Asgari, Zaman, & Jin, 2017; Genç, 2020), which is compatible with the existing values of society. Further, among TDM strategies, carpooling promotion is more attractive than other transport modes, such as public transit, walking, and biking (Lanzini & Khan, 2017). Moreover, carpooling reduces traffic congestion, fuel consumption, and GHG emissions and generates solid social bonds (Librino et al., 2020). Currently, carpooling is shifting as an alternative way of avoiding crowded transport modes (Molina, Ignacio Giménez-Nadal, & Velilla, 2020). These shreds of evidence imply that carpooling is compatible even during this global pandemic; therefore, it is significant for the diffusion of carpooling in society.

Both UTAUT and UTAUT2 suggest that facilitating conditions directly influence the intention to adopt technology or service. Venkatesh, Thong, and Xu

(2012) defined it as perceived resources and support available to perform a behavior. Many studies highlight the significance of this variable. For example, the availability of carpooling services at work was significant in carpooling (Bulteau, Feuillet, and Dantan, 2019). Park, Chen, and Akar (2018) found that the availability of alternative options for getting back home may positively impact an individual's carpooling propensity. This indicates that support available at the workplace will positively influence carpooling behavior. Wu and Neill (2020), who studied "Didi" application users in China, reported that carpooling applications' reputation and security assurance positively influence passengers' cognitive trust in drivers. These imply that support and resource availability increase users' trust in the service, influencing their propensity to carpool.

Moreover, proper facilitating conditions will lead to high usage frequency (Shaheen, Stocker, & Mundler, 2017). The situation seems to be similar in developing countries as well. Sofi Dinesh, Rajkumar, Gynendra, and Sisodia (2021) found the importance of perception related to the technology platform's quality and carpooling safety aspects. Vayouphack (2020) reported that due to dissatisfaction with local taxi services, ride-sharing services in Thailand are highly appreciated even though they are not entirely regulated. Therefore, it is evident that the availability of resources and support to perform carpooling influences the propensity to carpool.

Hossain (2020) conducted a comprehensive literature review regarding sharing economy using 219 articles. It was found that hedonic motivation tends to positively affect consumers' propensity to participate in sharing economy. Hedonic motivation is the fun or pleasure of performing a specific behavior (Venkatesh, Thong, & Xu, 2012). Hamari, Sjöklint, and Ukkonen (2016) studied the consumer behavior of collaborative consumption in Finland. Findings indicated that perceived enjoyment significantly positively affected attitude and intention to participate in collaborative consumption services. Therefore it seems that people enjoy participating in sharing economy or collaborative consumption. It is a driving factor influencing their tendency to participate in these programs. Since carpooling falls into collaborative consumption and sharing economy, hedonic motivation may be a significant psychological factor related to carpooling behavior. Park, Chen, and Akar (2018) found that people who prefer to be a driver only focus on the convenience and entertaining aspects. These imply that carpoolers may enjoy carpooling as drivers rather than passengers. However, many authors hardly consider the impact of this effect.

On the other hand, the economic benefits of carpooling received much attention in the carpooling literature. Hossain (2020) found that financial motivation is pivotal in sharing economy. Supporting this argument, Ciasullo, Troisi, Loia, and Maione (2018) found that economic efficiency is the main motive behind carpool choice, followed by environmental efficiency, based on Twitter feedback. Park, Chen, and Akar (2018) studied carpoolers based on their role of interest and found that people who value monetary benefits are interested in carpooling as passengers. Therefore, the cost is crucial for carpool interest and actual behavior. The argument seems to be valid for developing countries as well. Malodia and Singla (2016) investigated the carpooling behavior of Indian drivers and found that carpoolers believed carpooling is economically beneficial. Therefore, financial motivation is a highly significant psychological parameter influencing an individual's propensity to carpool. However, it also risks shifting the view of carpooling towards a business opportunity point of view. Eskelinen and Venäläinen (2020) investigated the economic moralities of ridesharing and time-banking. They point out that ridesharing should not be a business but rather proclaim ecological values, social values, helping out others, and a sense of community. As time banking focuses on social rather than economic improvements, combining the two concepts will make carpooling more sustainable and increase the social value of carpooling practice. Time banking is a time-based currency system that has also received public attention as an example of sharing economy (Eskelinen & Venäläinen 2020). They were initiated in the US. Time banks are typically community-based organizations that provide the framework for giving and receiving services in exchange for time credits. For example, one hour helping another network member equals one-time credit, which can be used to buy another hour of someone else’s time. In carpooling, time credit can be viewed as one ride equals one-time credit, which can be used to obtain rides from someone else. Therefore, the perception of time credits integrated with carpooling will also be a significant factor.

The associated risk of sharing economy is high (Wu & Neill, 2020). Regarding ridesharing, it seems that it significantly impacts the carpool participation intention. Even though psychological theories do not highlight the importance of safety aspects, authors have modified the existing models by including safety aspects. Sofi Dinesh, Rajkumar, Gynendra, and Sisodia (2021) found a significant influence of perceived safety on carpooling adoption as it influences attitude towards carpooling. It implies that the more people perceive carpool applications to be safe, the more likely they adopt carpooling. A quantitative study conducted in Belgium showed that insurance, privacy, safety, and security features of carpooling are among the main themes discussed among the participants (Cools et al., 2013).

Furthermore, Park, Chen, and Akar (2018) reported that potential carpoolers are more concerned about privacy and system flexibility than current carpoolers. Therefore it is evident that the perceived safety of carpooling significantly affects carpooling adoption irrespective of whether it is a developed country or a developing country. Table 2.3 summarizes the findings regardings psychological factors.

Table 2.3 Different psychological factors and their influence on carpooling

Factor	Definition	Relevance to carpooling behavior	Reference
Attitude	Feelings or beliefs of individuals towards the behavior	Main antecedence of intention A positive attitude leads to positive adoption intention	(Sofi Dinesh, Rejikumar, and Sisodia 2021;Malodia and Singla 2016);Lanzini and Khan 2017;Bachmann et al. 2018; Adelé and Dionisio 2020)
Subjective norm/ social influence	Influence of people who are important to an individual (family, friends, and co-workers)	Antecedence of intention and attitude Positive influence encourages positive carpool behavior	((Lanzini and Khan 2017;Bachmann et al. 2018;Rudjanakanoknad 2010;Bulteau, Feuillet, and Dantan 2019)
Performance expectancy/ perceived usefulness	Expected benefits (that are helpful in day-to-day life) from participating in carpooling	One of the main motives behind carpool adoption for both current and potential users	(Venkatesh, Thong, and Xu 2012;Molina, Ignacio Giménez-Nadal, and Velilla 2020;Amirkiaee and Evangelopoulos 2018;Carrese et al. 2017;Park, Chen, and Akar 2018;Rudjanakanoknad 2010)
Perceived behavior control/ effort expectancy/ perceived ease of use	Perceived easiness or difficulty of performing the behavior	Antecedence of attitude and intention Act as a barrier to carpool diffusion	(Park, Chen, and Akar 2018;Rudjanakanoknad 2010;Bachmann et al. 2018;Adelé and Dionisio 2020; Arda and Rejikumar 2017)
Compatibilit y	Adoption of a particular behavior is	A significant factor for the diffusion of carpooling in society.	(Yuen et al. 2020;Asgari, Zaman, and Jin 2017;Genç 2020;Lanzini and Khan 2017;Molina, Ignacio

Factor	Definition	Relevance to carpooling behavior	Reference
	perceived as consistent with the existing values of individuals and society		Giménez-Nadal, and Velilla 2020; Librino et al. 2020)
Facilitating conditions	Perceived resources and support available to perform a behavior	Influences adoption intention Favorable facilitating conditions encourage carpool behavior	(Bulteau, Feuillet, and Dantan 2019;Park, Chen, and Akar 2018;Wu and Neill 2020; Shaheen, Stocker, and Mundler 2017;Sofi Dinesh, Rejikumar, and Sisodia 2021; Vayouphack 2020)
Hedonic motivation/ perceived enjoyment	fun or pleasure receive from performing a specific behavior	Antecedence of attitude and intention Encourage positive carpool behavior	(Hossain 2020; Park, Chen, and Akar 2018;Venkatesh, Thong, and Xu 2012; Hamari, Sjöklint, and Ukkonen 2016)
financial motivation	Economic benefits receive from performing a specific behavior	Antecedence of attitude and intention Monetary benefits significant for both carpool interest and actual behavior	(Hossain, 2020); Park, Chen, and Akar 2018;Ciasullo et al. 2018; Malodia and Singla 2016)
Perceived safety	The feeling of safety to privacy and security threats in a carpooling application	Antecedence of attitude Higher perceived safety tends to have a positive influence on carpooling	(Sofi Dinesh, Rejikumar, and Sisodia, 2021; Cools et al., 2013; Park, Chen, and Akar, 2018)

2.3.1 Factors of carpooling adoption

The psychological factor category is not the only significant factor group when it comes to carpooling. There are hard variables that have a high impact on carpooling behavior. Neoh, Chipulu, and Marshall (2017) categorized factors based on whether they are internal or external to the individuals. Hard variables include internal factors such as socio-demographic factors and external factors such as Interventional, situational, and contextual factors. Unlike psychological factors, these factors can be directly measured, representing the unchangeable reality.

Age, gender, and income are typically considered socio-demographic variables, and studies found them statistically significant (Asgari, Zaman, & Jin, 2017; Park, Chen, & Akar, 2018; Gheorghiu & Delhomme, 2018). Male and younger people are more likely to adopt carpooling (Park, Chen, & Akar, 2018), while other literature reported that women are more likely to join carpooling than men (Bulteau, Feuillet, & Dantan, 2019; Rudjanakanoknad, 2010). Income is one of the most significant sociodemographic factors in carpool adoption (Asgari, Zaman, & Jin, 2017; Monchambert, 2020;Bulteau, Feuillet, and Dantan, 2019; Brown, 2020; Guensler et al., 2020; Malodia and Singla, 2016). On the other hand, some studies showed that income was not statistically significant (Olsson, Maier, & Friman, 2019; Shaheen, Stocker, & Mundler, 2017; Neoh, Chipulu, & Marshall, 2017). Despite its significance, the income factor was used to differentiate carpoolers (Shaheen, Stocker, & Mundler 2017). In other words, low-income people are more susceptible to carpooling adoption than high-income people. Other sociodemographic factors, such as education level, marital status, occupation, etc., are hypothesized to affect carpooling choice. The effects of sociodemographic characteristics are noticeably varied throughout the literature, probably due to different sample sizes, data collection methods, culture, behavior, data analytical methods, etc. More household income earners increase the likelihood of carpooling participation (Guensler et al., 2020). The presence of children encouraged their parents and family members to join carpooling (Guensler et al., 2020), while another study indicated no significant impact (Asgari, Zaman, & Jin, 2017). These findings lead to identifying the population segment that is more likely to carpool.

Intervention factors represent the effects of third-party interventions relevant to carpooling. Mainly these factors are investigated with the purpose of performance evaluation. For example, Guensler et al. (2020) studied people's perception of the High Occupancy Toll (HOT) lane after converting the HOV lane to a HOT lane. Findings pointed out that HOV conversion did not necessarily improve carpoolers. Brown (2020) investigated ride-hailing behavior after introducing a carpooling feature. Results illustrated that even though most ride hailers do not use the carpool feature (only one-third of the trips are shared), more frequent ride hailers highly appreciate the carpool feature. Some authors examined the effects of other factors such as availability of carpooling at the workplace and mobile application use and revealed that they positively influence carpool mode choice behavior (Shaheen, Stocker, & Mundler, 2017; Neoh, Chipulu, & Marshall, 2017. Therefore, studying carpool behavior after introducing an intervention seems vital to evaluate its performance.

The situational factor category is the most important as it is associated with economic and transportation characteristics related to the individuals. Findings showed that Carpooling is mainly used for leisure and shopping trips (Shaheen, Stocker, & Mundler, 2017; Gheorghiu and Delhomme, 2018; Malodia & Singla, 2016). However, Gheorghiu & Delhomme (2018) reported that people who carpool to work/school trips only used carpool for that purpose. Further, Shaheen, Stocker, and Mundler (2017) pointed out that low-income people use carpooling for mandatory trips more than others. Travel mode also plays a vital role in carpooling. Park, Chen, and Akar (2018) found that active mode users are less likely to carpool. Having a fixed work schedule also increases carpooling likelihood ((Neoh, Chipulu, & Marshall, 2017; Guensler et al., 2020). It primarily represents carpooling among co-workers who share a similar work schedule; carpooling is more appealing. Travel time and travel cost, which are traditional attributes, seem to be more significant than other factors related to psychological factors. Even though it was not among the best predictors, Gheorghiu and Delhomme (2018) found a significant correlation between travel time and carpooling trips (work/school). Bulteau, Feuillet, and Dantan (2019) also reported the association and further illustrated that people with higher travel times are more likely to carpool.

Moreover, Monchambert (2020) reported that utility is negatively associated with travel time, decreasing faster if the individual is younger and wealthier. It indicates that these factors vary among people with different socio-economic backgrounds. Strong preferences for cost savings were obtained by some authors (Genç, 2020; Bulteau, Feuillet, & Dantan, 2019). Specifically, Monchambert (2020) found that 1 euro of monetary gain increases carpooling odds over driving alone by about 2% when other things are equal. Further, the study investigated the Value of Travel Time (VoTT) and the Value of having an extra passenger. Results pointed out that VoTT is generally higher for carpooling than other modes. All these findings indicate the significance of evaluating situational factors. Some authors have considered contextual factors under situational factors that represent an individual's living/working environment.

Brown (2020) investigated the effects of employment and population density, road network density, activity diversity, transit rideness, and parking supply on carpooling behavior to quantify the built environment features. Findings showed that associations between ridesharing and built environment factors are weak relative to neighborhood socioeconomic characteristics. Park, Chen, and Akar (2018) found that employment, population, and housing densities were not statically significant. Bulteau, Feuillet, and Dantan (2019) attempted to use these factors to differentiate carpoolers and non-carpoolers and ended up with similar results. It was reported that people from relatively deprived neighborhoods are more likely to carpool. Asgari, Zaman, and Jin (2017) also found contextual factors significant. They derived two factors, namely "social status" and "family bonding," using secondary data to represent the neighborhood conditions. These factors have received less attention in the literature. Despite the mixed indications, these are vital to understanding the geographical distribution of carpoolers. It will aid policy planners and relevant other authorities drive their promotional efforts efficiently.

2.4 Policy implications of carpooling adoption

Various strategies and policies have been applied to promote sustainable mobility. However, proper techniques driven by a rich understanding of people's travel behavior can attract more commuters towards sustainable travel mode adoption without much effort. In this regard, many studies presented policy recommendations relevant to the ride-sharing economy to aid the government with its future projects. These data-driven policy implications are studied under two categories: policy implications in developed counties and developing countries.

2.4.1 Policy implications in developed countries

Investigating socio-demographic factors ultimately leads to identifying the population segment more inclined to carpool. Neoh, Chipulu, and Marshall (2017) recommended that authorities target the right group of people for promotional efforts based on their findings. Monchambert (2020) studied the long-distance carpool behavior in France and suggested similar policy implications. The study recommended that promotion campaigns and matching platforms should consider socio-economic characteristics to target the right people. It implies that the effectiveness of promotional activities depends on addressing the correct target group. However, Olsson, Maier, and Friman (2019) advised that policymakers and carpooling companies must be aware of promotional efforts targeting the wrong group, which could lead to adverse effects. Bachmann, Hanimann, Artho, and Jonas (2018) studied the psychological aspects of carpooling in Switzerland. Their findings suggested that consideration should be given to participants' simplicity, trust, and visibility and that programs should emphasize environmental benefits when carpooling programs are implemented. Gheorghiu and Delhomme (2018) highlighted similar policy implications. They investigated the behavior of French drivers to promote carpooling and suggested that the authorities should create financial motivation for the first time (but not only) carpoolers. Further, Huang, Liu, Zhang, Zhu, and Kim (2019) studied carpooling adoption in China and highlighted that carpooling companies should offer more options for travel time and travel cost services as these two factors noticeably influence carpooling choice. However, Neoh, Chipulu, and Marshall (2017) emphasized that more significant selling points should be used to market carpooling benefits other than traditional motivational factors (e.g., cost benefits). These policy implications stress the importance of using the key selling point to promote carpool services.

Neoh, Chipulu, and Marshall (2017) suggested implementing partner matching programs as it will be a solution for arrangement barriers. It will aid users in finding riding partners without much effort, which will increase their propensity to carpool. Gheorghiu and Delhomme (2018) recommended that relevant authorities and carpool companies consider finding alternative means for a ride back for carpoolers who face unavailability situations. It will increase the reliability of the carpool service and is essential in gaining the users' trust. Therefore, this type of policy implication is vital in the long run. Neoh, Chipulu, and Marshall (2017) further presented about creating large pools of potential workplace carpoolers. These pools have higher trust levels as members know each other well. Therefore, people are more likely to carpool if such collections are available at workplaces. Authors have also suggested some policy implications that affect the general public. Monchambert (2020) recommended establishing HOV lanes if it can reduce travel time, as it was found that carpool drivers value time more than solo drivers. Guensler et al. (2020) suggested that when implementing lane conversion (HOV to HOT) projects, policymakers may need to develop innovative strategies to increase carpool formation as their findings point out that lane conversion did not necessarily improve carpooling. Therefore, these policy implications should be taken into account with careful consideration. Monchambert (2020) highlighted that carpool prices and awards should be accurately calculated using information such as the number of passengers and length of the trip. Park, Chen, and Akar (2018) studied the role of interest in carpooling in the USA and recommended that policies for promoting carpooling culture should be a bundle of targeted policies according to people's preferences for different carpool roles. Huang, Liu, Zhang, Zhu, and Kim (2019) suggested that travel time evaluation should be based on a significant number of historical traffic flow measurements using big-data technology in carpooling. All these policy implications will aid in developing and maintaining more reliable and accurate carpooling services capable of attracting more potential carpoolers.

The transport sector is one of the leading sectors primarily affected by the COVID-19 pandemic. Abdullah, Dias, Muley, and Shahin (2020) found that movement restrictions have effectively reduced the mobility of people in many countries. In the USA, 95% of transit stations were affected due to COVID-19 leading to an average drop of 72.4% in transit ridership (Hu and Chen, 2021). Further, it was observed that people rely more on private cars and active modes than public transport due to the fear of getting infected (Przybylowski, Stelmak, and Suchanek, 2021). It was reported that internet searches for second-hand (used) cars for sale in the United Kindom increased (Serafimova, 2020). A similar mode share increment was observed in Chinese cities (Riggs and Appleyard, 2020). This trend will have a negative impact in the long run. Riggs and Appleyard (2020) stated that despite the reduction in mobility, travel for secondary trips has increased due to work-from-home policies imposed by the governments. Many of these trips are conducted via private cars and via carpooling. Przybylowski, Stelmak, and Suchanek (2021) found that almost 75% of respondents are willing to return to public transport after the pandemic. It implies that people will return to their usual travel habits once the pandemic is over, even though this social stigma toward transport mode choice will likely last (Falchetta and Noussan, 2020). Therefore, promoting other sustainable travel modes such as carpooling would seem appropriate.

2.4.2 Policy implications in developing countries

Due to the lack of studies conducted in developing countries, the policy implications identified are limited compared to developed countries. Many studies considered in this section are limited to India and Thailand. As both countries are developing and attempting to promote sustainable travel modes as their long-term development strategies, policy implications recognized here are exceedingly valuable for future studies as well.

Malodia and Singla (2016) studied carpooling behavior by targeting Indian drivers, and they suggested that carpooling promotion campaigns should positively reinforce cost saving as an advantage of carpooling. Similar policies have been presented in developed countries as well. Further, they recommended that carpooling promotion should address the negative perceptions of comfort, pleasure, reliability, time-saving, and convenience regarding carpooling. Similarly, Rudjanakanoknad (2011), who studied carpooling in Thailand, highlighted that the leaders of large organizations would support carpool programs officially and financially, which will likely be effective in establishing more reliable carpooling service. Further, it was suggested that they could reward the participants with reserved or free parking spaces.

Moreover, the government might draw more participants by designating an HOV lane on freeways during peak hours or reducing expressway toll charges for an HOV. Similar policy implications were observed in developed countries. It implies that despite the locations, promoting rewarding features of carpooling will attract more commuters to carpooling. The carpool history in Thailand suggests that carpool campaigns are temporary and usually follow a financial crisis. Therefore it was pointed out that the carpool campaigns should be permanent regardless of the state of the economy or energy prices (Rudjanakanoknad, 2010). However, inefficient campaigns will be pointless. Therefore campaigns should be driven with proper background knowledge about how and what to address. Sofi Dinesh, Rajkumar, Gynendra, and Sisodia (2021) emphasized that marketers could create communications to reinforce sustainable transportation behavior that will significantly influence positive attitudes towards carpooling. The proposition seems to be valid for Thailand as well. Tayakee (2017) recommended that marketers could promote and give more information to customers or provide a good quality application. Suyarnsettakorn (2018) also made similar recommendations. It was suggested to arrange agreements with internet-based matching agencies, rental companies, and employers to provide carpooling programs for employees. As the study pointed out that Thai people are unlikely to share rides with strangers, these strategies are significant as they can increase trust levels. One of the substantial policy implications suggested by Suyarnsettakorn (2018) is to increase carpooling standards by setting social norms. Tayakee (2017) made a similar suggestion as well. It was pointed out that creating customer involvement and engagement through social media or marketing campaigns can make the customers interested in the service. Sofi Dinesh, Rajkumar, Gynendra, and Sisodia (2021) emphasized that perceptions of cognitively complex and psychologically empowered commuters should appear in the public domain more prominently. Further, their reviews should be used to circumvent any negative information that can adversely affect carpooling penetration. Therefore promotional campaigns should be driven by considering discussed points.

The impact of COVID-19 is worse for developing countries compared to developed countries for many reasons. First, the outbreak caused a worldwide economic crisis; in Thailand, more than 10 million people will face unemployment (Tantrakarnapa, Bhopdhornangkul, & Nakhaapakorn, 2020). Nationwide lockdown restrictions forced people to work from home, which was considered a social distancing measure (Katewongsa et al., 2020). Barbieri et al. (2021) studied the impact of COVID-19 on ten different countries from six continents and found that disruptions for commuting and non-commuting travel of all types of trips and use of all modes. However, with a certain level of virus control, most countries started to partially re-open the workplaces. It pushed people to commute at their own risk. Carpooling seems to be a proper choice for this situation mainly for two reasons. First, it is one way to avoid crowded travel modes such as public transport, which is perceived to be one of the riskiest transport modes (Barbieri et al., 2021). Secondly, it will reduce the demand for public transport, increasing the safety of captive public transport passengers. Therefore, policies that support carpooling are highly significant for developing countries.

2.5 Summary

Many mathematical models can be used to explain carpool choice behavior. Depending on the study purpose, and the type of data available, the choice of the model or theory varies. SEM is the most popular and commonly used method for analysis in the presence of psychological factors. SEM can handle measurement models that explain the relationship between indicators and constructs and the structural model that simultaneously describes the relations between constructs. Psychological theories illustrate how these constructs are related. The theory of planned behavior is the most common psychological theory that has received scholarly attention regarding carpooling behavior. Consumer Acceptance and Use of Information Technology (UTAUT2) was developed based on TPB and seven other dominating theories which have not been used to explain carpooling behavior.

Past studies suggest that the theory contains many highly significant constructs in carpooling (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, and price value). These constructs drive individuals' intention to adopt carpooling. Therefore, UTAUT2 is capable of explaining psychological behavior in the context of carpooling adoption. Understanding determinants related to carpooling and psychological behavior is crucial to building sound policies to promote carpooling. Mainly for educational trips, as empirical findings suggest, many commuters do not practice carpooling for work/school trips. Limited studies in developing countries make it difficult for policymakers to develop effective policies. During this pandemic, as many developing countries face economic crises, sound policy responses are essential to countries' well-being. No studies have been conducted during this pandemic period to study carpooling adoption specifically from a psychological perspective in the context of educational trips. Further, the present study investigated the influence of factors such as hedonic motivation, which has received less attention in past studies. Moreover, the impact of COVID-19 on carpool adoption was examined. Additionally, it was investigated how people perceive the time-credit concept regarding carpool adoption and its influence on its intention. Therefore, the present study is timely, essential, and exceedingly crucial for both the academic and practical worlds.

CHAPTER 3
METHODOLOGY

3.1 Research framework

The research framework of the present study is graphically illustrated in figure 3.1. The research goal of the study is to increase the understanding of carpool adoption's determinants and behavioral influences. Three main vital objectives have been identified to reach that goal. The literature review was conducted as the first step to achieving these objectives successfully. The literature review aid in identifying significant determinants relevant to carpooling in both developed and developing countries and their impact on carpooling adoption and diffusion. As the present study aims to study psychological aspects of carpooling, psychological theories and determinants were also identified. The determinants can be viewed according to the variable type.

The preliminary study was driven to identify the critical determinants of carpooling and how they affect commuters' propensity to carpool. Further, it aids the authors in being familiarized with the data analysis method. The influence of incentive attributes (hypothetical attributes of carpooling), socio-demographic variables, and travel-related variables was mainly investigated. In addition, the effect of primary reasons for private car use on carpool behavior is also concentrated. A stated choice experiment conducted for drivers as a case study of educational trips in Thailand from 07 of April to 01 of May 2020 was used as the primary data source for the preliminary research. The current study focuses on psychological determinants, and a different survey instrument was developed to collect data. Observed variables are used to measure psychological determinants. The primary data source is an online questionnaire survey with a Likert scale. The conceptual model was developed primarily based on Consumer Acceptance and Use of Information Technology (UTAUT2). The model assessed the influence of effort expectancy, social influence, hedonic motivation, time-credit, perception towards COVID-19, and perceived safety on intention to participate in carpooling in the context of educational trips. The data analysis was done using Structural Equation Modelling (SEM). The package 'lavaan' of the R programming language was used in data analysis work. The results obtained from the data analysis were used to interpret and make exciting discoveries. Policy implications based on these findings are presented as the research contribution. Further, since the conceptual model was developed based on the theoretical background, the results also enhanced the theoretical knowledge of the socio-psychological mechanism behind carpool adoption.

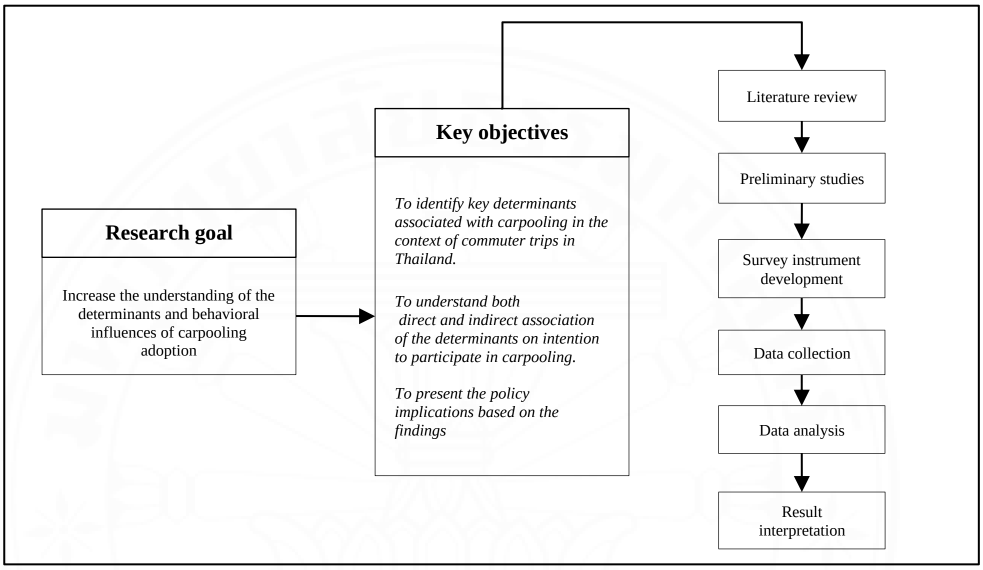


Figure 3.1 The research framework

3.2 Preliminary study

A stated choice experiment conducted for drivers as a case study of educational trips in Thailand from 07 of April to 01 of May 2020 was used for the analysis. The survey has conducted online using a google forum. It seems to be the best approach to seek reasonable respondents during this global pandemic. The questionnaire combined stated preferences and revealed preference formats with three sections dedicated to different purposes. The first section took the stated preference format. Then, the participants were asked to make decisions on different scenarios. The decision was whether participants preferred to engage in carpooling as a driver in a particular scenario and how many days they were willing to participate. A total of 8 scenarios were created utilizing four characteristics (travel cost, travel time, reserved parking, and annual car registration tax renewal). There are two levels in each attribute. It led to 1440 data points from 180 individuals. Table 1 illustrates the descriptions of the scenarios.

The second and third parts took a revealed preference format. The second section obtained information about individual commuting travel patterns, while the third section was dedicated to sociodemographic characteristics.

Table 3.1 Scenario descriptions

Scenario number	Travel cost	Travel time	Reserved parking	Car registration renewal
1	25%	70%	1	1
2	75%	130%	1	0
3	25%	70%	1	0
4	75%	70%	0	0
5	75%	130%	1	1
6	25%	130%	0	0
7	75%	70%	0	1
8	25%	130%	0	1
25% - 25%of current travel mode 70% - 70% of current travel mode 1- Reserved parking is available 1-annual car registration tax renewal is free		75%-75% of current travel mode 130%-130% of current travel mode 0- Reserved parking is not available 0-annual car registration tax renewal is not free		

The responders were given eight choice situations to assess their behavior towards carpooling. The results showed that most participants (53.5%) are inclined to carpool, which indicates the possibility of attracting daily commuters to sustainable travel modes in Thailand. Especially from the university community. The model estimation was done after 114 iterations. The Comparative Fit Index (CFI) and Tucker-Lewis Index (TLI) were higher than 0.90. Further, the Root Mean Squared Error of Approximation (RMSEA) value was lower than 0.06, suggests that the model fits the sample data well, and the results are reliable for interpretation (Bentler, 1990; Tucker and Lewis, 1973; Steiger and Lind, 1980).

Four of the stated primary reasons for car use did not show a statistically significant effect on carpooling at 0.1 level. However, the “non-availability of public transport” factor and privacy and luggage factor (“I need privacy and luggage space”) did show a significant influence on carpooling at 0.05 level. It suggests that drivers who use private cars on account of the non-availability of public transport are more inclined to offer carpool rides. Past studies have shown that the non-availability of public transport is one of the critical motives for using private cars (Neoh et al. 2018). As the present findings show, it also positively influences the likelihood of carpooling. These drivers with lower access to public transport may view carpooling as an economical travel mode compared to driving alone. “Privacy and luggage” factor also showed a significant favorable influence on carpool choice, implying that drivers who use private cars on account of privacy and luggage are likely to offer carpool rides.

The factors of occupation status, population density, and travel days per week did not show a statistically significant direct impact on carpool participation at a 0.1 significance level. However, indirect effects of occupation status and travel days per week were substantial. The indirect impact of occupation status indicates that students who use cars on account of privacy are more prone to provide carpool rides. The indirect effect of travel days per week suggests that drivers who use cars on account of privacy and luggage travel many days per week are less motivated to carpool. Many studies have shown that population density is not a significant factor in carpool behavior (Bulteau, Feuillet, & Dantan, 2019; Park, Chen, & Akar, 2018), which is consistent with the present findings.

For incentive attributes, travel cost and time factors showed significant negative coefficients implying that an increment in travel cost or travel time will reduce the likelihood of drivers offering carpool rides. This outcome is consistent with many studies (Olsson, Maier, & Friman, 2019; Park, Chen, & Akar, 2018; Monchambert, 2020; Malodia & Singla, 2016). Reserved parking has the most significant positive effect size among the four factors considered. Due to limited parking spaces, drivers would have difficulty finding a parking spot at the university. Therefore, these individuals are willing to offer rides for reserved parking spaces. In addition, it was found that the university community considers reserved parking as an essential characteristic of carpooling (Liakopoulou et al., 2017). The findings also suggest that free annual car registration renewal encourages drivers also to offer carpool rides.

For the sociodemographic characteristics, the coefficients of females, age 18-39 years old and married, were positive and significant for carpool participation. As shown in Table 3, their influences are mainly direct. Findings are consistent with the past studies (Molina, Ignacio Giménez-Nadal, & Velilla 2020;Carrese et al. 2017). The coefficient household car ownership showed a positive significance implying that car ownership positively affects carpool choice. As drivers get to share the travel expenses, carpooling may seem economical for those who own multiple cars. As many studies conducted in developed countries, the influence of motorcycle ownership on carpooling has not been studied. The findings showed that household motorcycle ownership negatively influences the carpool decision. Having many income earners in the household also negatively affects carpooling. Except for vehicle ownership and the number of income earners, other household factors did not directly impact carpool participation at 0.1. However, there were significant indirect effects. Having children in the household indirectly increases the likelihood of carpooling. As carpooling with friends and family provides a safe and secure trip, it may seem more attractive to them. Nevertheless, the presence of senior citizens may negatively affect them. Drivers who use cars on account of the non-availability of public transport are more inclined to offer carpool rides in the presence of many children, senior citizens, and adults in the household. As they have less access to public transport, carpool advantages may influence this behavior.

For the travel-related variables, it was found that people who leave home late are less inclined to offer carpool rides compared to early leavers. Travel distance showed a significant negative impact on carpool choice, which tells that people who live far from school are less likely to carpool. These findings have been considered when developing the survey instrument for the present study.

3.3 Structural Equation Modelling (SEM)

SEM is a multivariate statistical analysis method, and the usual intent is to assess cause and effect between variables. The technique can analyze the relationship between indicators and latent variables and the relations between latent variables in a single model (Rick, 2012), which is the main reason for utilizing it for the present study. It can consist of at least two dependent variables, and each dependent variable can affect other dependent variables in a complex system. Further, it can be used to explore the direct and indirect effects of the explanatory variables on the dependent variables and allow variables to be correlated, unlike other statistical modeling approaches. SEM is widely used by many researchers who studied psychological determinants (Neoh et al., 2018; Wang et al., 2020; Wu & Neill, 2020; Shaheen, Stocker, & Mundler, 2017). There are four main steps involved in implementing SEM analysis. The first step is specifying a conceptual model based on a hypothesis discussed in the previous sections. The second step in implementing SEM is the estimation. There are mainly two approaches to analysis; Covariance based SEM (CB-SEM) and Variance based SEM (PLS-SEM) (Fuller et al., 2016). In CB-SEM, parameter estimation minimizes the difference between the observed and estimated covariance. PLS-SEM estimation is done by reducing the error terms and maximizing the R^2 values of the endogenous constructs. Despite the pros and cons of both approaches, CB-SEM is used, which suits the present study.

The third step is the evaluation of fit. It decides whether the specified model can offer a reasonable account for the sample data. SEM has two models: the measurement model and the structural model. For the measurement model, validity and reliability should be ensured. The validity of the measurement model is mainly considered under two types of validities. The first one is convergent validity. It is defined as the 'degree to which a scale measuring the same construct provides the same results' (Li et al., 2019). There are a few ways to assess convergent validity. The most common way is to conduct a Confirmatory Factor Analysis (CFA). The acceptable fit of the model indicates the hypothesis that items reflect the latent variables. It ensures the construct validity, the extent to which the assumed relationships between observed and latent variables are consistent with the theoretical hypothesis—also, having statistically significant (p-value <0.05) observed variables belonging to the latent variable indicate the convergent validity. Cheung and Wang (2017) recommended if the Average Variance Extracted (AVE) is not significantly less than 0.5, and the factor loadings of all items are not considerably less than 0.5, it can also conclude the convergent validity (Cheung and Wang, 2017). The second one is the discriminant validity. It is defined as the 'Extent to which a construct is truly distinct from other constructs by empirical standards' (Hair et al., 2017). Several methods can ensure discriminant validity: Cross-loadings criteria, Fornell and Larcker (1981) criterion, Kline criterion, and Heterotrait-Monotrait ratio of correlations (HTMT). HTMT criterion is a stringent measure compared to other criteria (Ab Hamid, Sami, and Mohmad Sidek, 2017). The reliability of the measurement model can be ensured by using Composite Reliability (CR) or Cronbach's Alpha values. CR is an indicator of the shared variance among the observed variables (Fornell and Larcker, 1981). It takes the measurement error into account. Therefore, it is considered to be a proper measure of reliability. Table 3.2 summarizes these measures and their required values extracted from past studies.

Table 3.2 Measures used to ensure validity and reliability of the measurement model.

Criterion		Description
Reliability	Composite Reliability (CR)	Sometimes it is called construct reliability. It is an indicator of the shared variance among the observed variables (Fornell and Larcker, 1981). Values above 0.7 indicate acceptable reliability (Alsheikh et al., 2021).
	Cronbach's alpha	Indicate how closely items are related. For example, assume unidimensionality and items are equally related to the construct and therefore interchangeable. Values of 0.6 or above are acceptable (Taber, 2018).
Construct validity	Model fit of CFA	Having an acceptable fit of the model's CFA indicates the hypothesis that items reflect the latent variables.
Unidimentionality	Factor loadings	High outer loadings on a construct indicate the associated indicators have much in common (Hair, Hult, Ringle, and Sarstedt, 2017) Factor loadings higher than 0.5 are acceptable (Alsheikh et al., 2021).
Convergent validity	AVE and factor loadings	AVE is the sum of the squared loadings divided by the number of indicators. It indicates how much variance of the indicators is explained by the construct. AVEs and factor loadings are not significantly less than 0.5 (Cheung and Wang, 2017).
Discriminant validity	Cross-loadings criteria	Confirming that all items corresponding to a specific construct had a higher loading with the appropriate construct than any other (Hamari, Sjöklint, and Ukkonen, 2016).
	Kline criterion	Not having severe correlations (higher than 0.85) between exogenous constructs (Alsheikh et al. 2021; Cheung and Wang 2017)
	Fornell and Larcker (1981) criterion	The square root of the AVE of each construct should be higher than related correlations (Jeon, Ali, and Lee, 2019).
	Heterotrait-monotrait ratio of correlations (HTMT)	HTMT should be below the threshold of 0.9 (Alsheikh et al., 2021). It is an estimate of what the actual correlation between two constructs would be if they were perfectly measured (Hair et al., 2017).

Once the validity and reliability of the measurement model are ensured, the model fit of the structural model should be assessed. As there are no specific rules for evaluating the model fit in SEM, it is sensible to use fit indices which are more insensitive to sample size, model misspecification, and parameter estimates: Chi-Square statistic, Degrees of freedom and p-value, Root Mean Square Error of Approximation (RMSEA), Standardized Root Mean Residual (SRMR), Comparative Fit Index (CFI) and parsimony fit index such as the Parsimonious Normed Fit Index (PNFI) (Hooper, Coughlan and Mullen, 2008). Table 3.3 summarizes the measures of assessing the structural model fit. CFI, TLI, and RMSEA are the most used fit indices. The final step of the implementation process of SEM is interpreting the model results.

Table 3.3 Measures used to test the model fit of the structural model.

Criterion		Description
Overall model fit indices	goodness-of-fit index (GoF)	Higher values indicate a good model fit (Hair et al., 2017).
	standardized root means square residual (SRMR)	RV < 0.09. It is an absolute measure of fit (Hu and Bentler, 1999).
	Chi-Square statistic	for a better global fit chi-square, the p-value should be >0.05 (Rick, 2012).
	Root Mean Squared Error of Approximation (RMSEA)	RV < 0.06 (Steiger and Lind 1980).
	Comparative Fit Index (CFI)	RV >0.90 (Hu and Bentler 1999)
	Tucker-Lewis Index (TLI)	RV >0.90 (Hu and Bentler 1999)
RV: Required Value		

3.4 Proposed conceptual model

The first step of SEM is the model specification. As discussed, some constructs of Consumer Acceptance and Use of Information Technology (UTAUT2) theory are highly related to carpool behavior. Therefore, UTAUT2 was primarily used as the basis for the conceptual model. The original model UTAUT2 assesses the impact of performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, habits, and price value on intention. The proposed conceptual model includes modifications to the original model, including replacing the “habit” construct with the “perceived safety” construct. It is because habit may not be significant at the early stages of adoption. The second modification is the addition of two new constructs, "perception towards covid-19 and carpool” and “time credits,” to assess the influence of covid-19 and time credits on carpool behavior intention.

Figure 3.2 provides a graphical illustration of the conceptual model. As all the factors are psychological constructs, they are represented by ovals. Ovals with arrow tails represent exogenous variables, while Ovals with arrowheads act as endogenous variables. Accordingly, behavioral intention is the endogenous variable in the model. Rectangles represent observed variables which used to measure the latent variables.

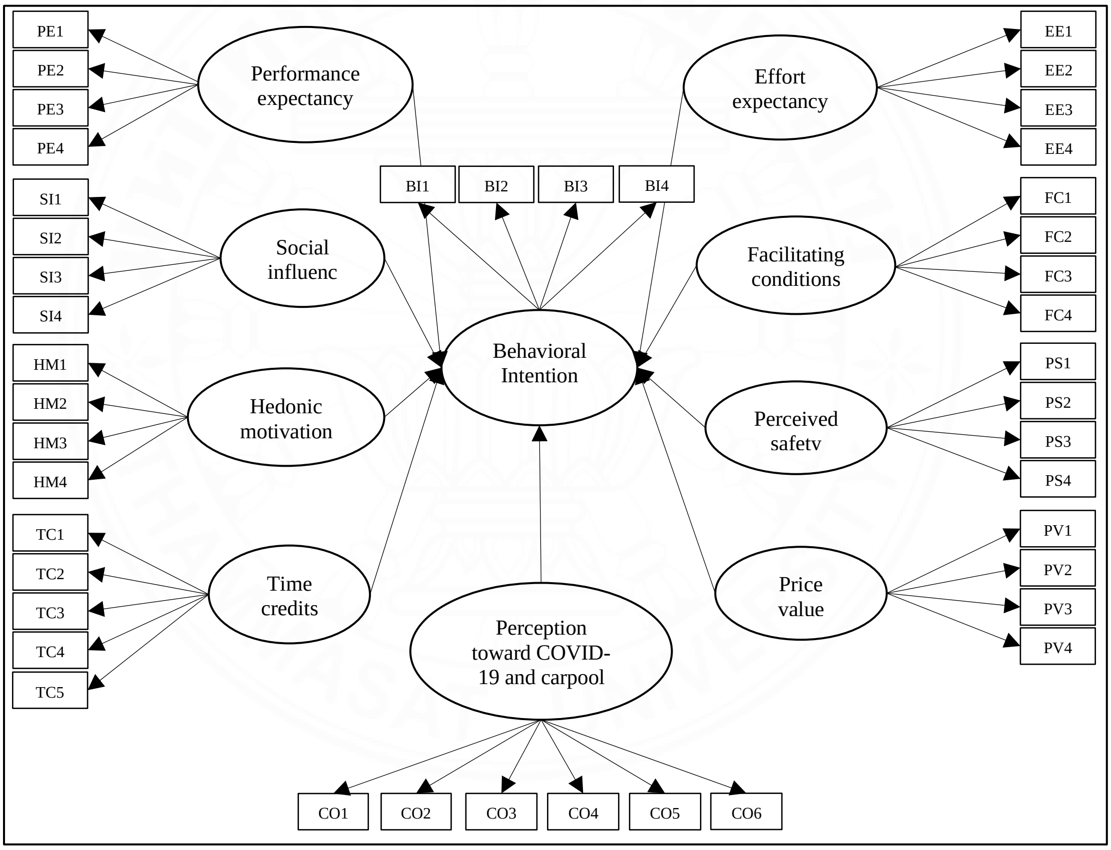


Figure 3.2 Conceptual framework of the proposed model

3.5 Hypothesis development

3.5.1 Performance Expectancy (PE)

In the context of carpooling behavior, performance expectancy can be viewed as the degree to which individuals believe that carpooling will be beneficial and valuable in their daily lives. Carpooling conveys many benefits to individuals as well as society. It can reduce travel expenses and time and allow individuals to meet new people. Further, it is a sustainable travel mode that reduces traffic congestion. Therefore, people who intend to carpool expect these benefits. Specifically, the daily commuters can travel comfortably for a lower cost and lower travel time to their workplace/school. Therefore, it can be assumed that,

Performance expectancy (PE) is positively related to the intention to participate in carpooling.

3.5.2 Effort Expectancy (EE)

Effort expectancy can be defined as the degree to which an individual believes participating in carpooling will be easy or difficult. Carpooling is an effort-demanding travel mode due to many reasons. Therefore, individuals are required to have a certain level of resources and knowledge to participate in carpooling. It leads individuals to perceive these requirements as an effort when they intend to participate in carpooling. Therefore, the easier the individuals view carpooling, the less reluctant they are to participate in carpooling. It indicates that lower effort expectations (less complicated) lead to a higher likelihood of carpool participation. As the term describes the easiness of carpooling, it can be assumed that,

Effort expectancy (EE) is positively related to the intention to participate in carpooling.

The present study focused on dynamic carpooling. Therefore, associated easiness is related to making carpool arrangements using a mobile application. Past studies suggest that associated easiness positively influences hedonic motivation when technology is involved. Salimon, Yusoff, and Mohd Mokhtar, (2017) found that EE positively influences hedonic motivation in e-banking adoption. Further, Siyal et al. (2020) found that associated EE positively influences hedonic motivation for using mobile taxi booking apps. Dynamic carpooling could be socially and emotionally demanding, meaning that users have to put some effort into carpooling (Adelé and Dionisio, 2020). Their study found that difficulties associated with the application's intelligent functions create fuzzy negative feelings in carpoolers. Therefore when dynamic carpooling becomes more manageable, it could lead to satisfaction. Therefore, since the present study investigates dynamic carpooling, it is assumed that, *Effort expectancy (EE) is positively related to hedonic motivation regarding carpooling.*

3.5.3 Social Influence (SI)

Social influence is the degree to which individuals value other people's opinions and behavior. Empirical evidence suggests that in the context of carpooling, this influence is highly significant. It could be due to two reasons. One is the unfamiliarity with the concept of carpooling. When people are unfamiliar with behavior, they tend to rely on others (Bachmann et al., 2018). The second one is extrinsic motivation. Opinions and suggestions of people who are essential to individuals directly influence their intention. Specifically, people rely on family members, friends, and colleagues. Therefore, the positive influence drives individuals to participate in carpooling. Consequently, it can be assumed that,

Social influence (SI) is positively related to the intention to participate in carpooling.

Studies have found that SI motivates technology adoption (Siyal et al., 2019). It indicates that encouragement from social surroundings motivates people to adopt new technology. The encouragement coming from the social environment could be due to their satisfaction. It was found that satisfied consumers are more inclined to recommend a service (Fan et al., 2005). Regarding the usage of mobile applications for transport services, it was found that SI positively impacts HM. Siyal et al. (2020) found that associated SI positively influences HM for using mobile taxi booking apps. Since dynamic carpooling is a relatively new experience, especially for Thailand, most potential participants are more likely to follow the perceptions and encouragement of their social environment. Therefore, the present study assumes assumed that,

Social influence (SI) is positively related to hedonic motivation regarding carpooling.

3.5.4 Facilitating Conditions (FC)

In carpooling, facilitating conditions can be defined as the degree to which an individual believes enough resources and support are available to perform a behavior. As carpooling require a certain level of help and knowledge, individuals may expect the government or workplace/school to provide facilitating conditions. For instance, studies have found that carpooling service availability at the workplace positively influences carpooling behavior (Bulteau, Feuillet, and Dantan, 2019). Hence one's belief that facilities will be provided will increase the inclination to participate in carpooling. Therefore, it can be assumed that,

Facilitating conditions (FC) is positively related to the intention to participate in carpooling.

3.5.5 Hedonic Motivation (HM)

The hedonic motivation construct describes the fun or pleasure obtained from carpooling. Both collaborative consumption and sharing economy concepts are viewed as entertaining concepts. Carpooling falls under both ideas, and studies have found that carpoolers value the fun aspects of carpooling (Park, Chen, and Akar, 2018). Carpooling allows people to meet new people and interact comfortably, making carpooling more enjoyable than other travel modes. Therefore, it can be assumed that,

Hedonic motivation (HM) is positively related to the intention to participate in carpooling.

3.5.6 Price Value (PV)

Price values can be defined as users' cognitive tradeoff between the perceived benefits and carpooling costs. Cost-saving is one of the most significant motivations for participating in carpooling (Ciasullo et al., 2018). As carpooling has many benefits, people tend to compare these benefits with the carpool price. Thus, individuals' belief in reasonable carpool prices increases their propensity to participate in carpooling. Therefore, it can be assumed that,

Price value (PV) is positively related to the intention to participate in carpooling.

3.5.7 Perceived Safety (PS)

There are some risks associated with carpooling. Therefore, it is essential to understand how people's perception of the safety aspects of carpooling affects their participation behavior. The empirical results reveal that perceived value is positively associated with consumer willingness to participate in ridesharing, but the perceived risk is negatively related to consumers 'ride-sharing intention(Wang et al., 2019). However, in the present study, "perceived safety" is defined as an individual's perception of safety and security associated with performing a behavior. The more people view carpooling as a safe travel mode in terms of privacy, security, conflict, and finances, the more people are prone to participate in carpooling. Therefore, it is assumed,

Perceived safety (PS) is positively related to the intention to participate in carpooling.

3.5.8 Perception toward COVID-19 and carpool (CO)

COVID-19 has severely influenced people's decisions on transportation modes choice. Studies have shown people move to private transport modes to avoid crowded public transport. Further carpooling is also at risk due to its potential for being a venue of COVID-19 spreading. Therefore, people believing that carpooling is not a risky travel mode that could potentially spread COVID-19 if safety guidelines are correctly followed may significantly impact their decision to carpool. The present study attempted to test this relationship by including the "perception towards COVID-19 and carpool" factor in the conceptual model. If guidelines are correctly followed, it is defined as the extent to which individuals believe carpooling is not a venue for COVID-19 spreading. Therefore, it is assumed,

Perception toward COVID-19 and carpool (CO) is positively related to the intention to participate in carpooling.

3.5.9 Time credits (TC)

The time credit concept is getting attention worldwide as an alternative payment option, especially in the sharing economy. It is introduced under the time banking concept where people exchange services among them in exchange for time. Time banking communities are introduced into universities in many countries, and they are getting positive feedback from students. During 7-week time banking project initiated in University of Georgia, USA, it was found that transportation (e.g., providing rides) is one of the most common types of exchange (Matthew, 2020). Therefore, in the context of carpooling, it can be arranged that offering someone a ride will earn the offeror time credits. The offeror can use the earned time credits to receive free carpool rides. On-campus time banking program initiated in Dharma Drum university in Taipei, Taiwan allowed students to earn time credits by performing on-campus jobs such as being a research or teaching assistant, operating the university website, or working at the campus library (Hirwa et al., 2021) . Therefore, in the university context, other volunteer services could be offered to earn time credits. Informal tutoring, help with assignments, and helping organize campus events could such voluntary services.

Further, there could be other ways to spend the earned time credits. The feasibility study conducted in University of Canterbury, New Zealand found that educational needs, such as informal tutoring, proof reading, grammar and spelling help, help with assignments as the needs that could be catered for through a time bank at UC(Geary, 2010). Therefore, students may spend earned time credits on activities such as participating in conferences and special workshops. Getting a free parking pass is also such activity that is more appropriate for universities. As participants get exchange different services, combining the time credit concept with carpooling will shift the cost-saving perception of carpooling to helping others. It highlights the social value. The time credit variable is defined in the present study as the extent to which individuals perceive time credit as an alternative payment option for carpooling to investigate its impact on behavior intention. The more people believe time credits to be a better payment option for carpooling, the more they recognize the social value of carpooling. Therefore, it is assumed,

Time credits (TC) is positively related to the intention to participate in carpooling.

The conceptual model was designed according to the hypothesis developed in this section. The survey instrument was developed to measure above discussed constructs using measurement items. It is described in the next section.

3.6 Survey instrument development

The questionnaire for the present study consists of five subsections. At the beginning of the questionnaire, an introduction is given to carpooling for respondents who are unaware of carpooling. The first subsection of the questionnaire collects information related to psychological factors. For each psychological factor, four questionnaire items were used. Questionnaire items were developed based on the previous studies. The observed variables are presented in Table 3.5. Respondents are asked to read the item sentences and state the extent of their agreement with the sentence.

A 5-point Likert scale is used as the measurement scale for the questionnaire items. The scale is ranked from strongly disagree to strongly agree, with a neutral point in the middle. The Likert scale can vary from 2-11 points. However, the most used scales are 5, 6, and 7 (Weijters et al., 2010). Preston and Colman (2000) pointed out that 2-,3- and 4-point scales performed poorly while indices which measured stability, validity, and discriminating power were highly significant for other scales up to 7-points. Weijters, Cabooter, and Schillewaert (2010) revealed that scale 5-point scale with labels at the extremes results in better data quality.

Moreover, some studies revealed that the respondents perceive the 5-point scale as relatively quick and easy to use, preventing the respondents from becoming frustrated and demotivated and increasing the response rate and quality (Sachdev and Verma 2004; Babakus and Mangold 1992; Devlin, Dong, and Brown 1993). Similarly, Revilla, Saris, and Krosnick (2014) also recommend a 5-point scale over a 7 or 11 scale when agree-disagree (AD) rating scales, as the latter scales tend to yield poor quality data. Further, it can compare findings of cognitively different populations (Weijters, Cabooter, and Schillewaert, 2010). Therefore, a 5-point Likert scale is used for the present study. The second section is dedicated to viewing respondents' perception of COVID-19. For this latent variable, six questionnaire items are used. The health guidelines provided by the Center for Disease Control and Prevention (CDC)-in the USA for carpoolers during COVID-19 fall under four aspects.

The first piece of advice is to limit the number of participants. Further, it is advised to wear face masks for all participants. The following advice is regarding the sharing vehicle. To provide proper ventilation, CDC recommends carpoolers use open windows whenever they carpool. Further, keeping the sharing vehicle disinfected and cleaned all the time is highlighted. Considering these aspects, four measurement items were developed to address them. In addition, another measurement item was developed regarding protection against COVID-19. Finally, another item regarding the influence of pandemics on the decision was created. It is assumed that these six items theoretically cover the main aspects of the impact of COVID-19 on carpooling. The third section was devoted to gathering information about the people's perception of the time-credit concept. For this latent variable, five questionnaire items are used. Since the idea is new, a small introduction is given at the beginning of the third section to familiarize respondents with term time credits. The respondents' socio-economic backgrounds, such as age, gender, income, etc., were gathered in the fourth section. Altogether, eleven questions are included for this purpose. The final section is used for travel patterns. It contains six questions regarding respondents commuting travel patterns such as travel mode, departure times from home and school, travel distances, etc. For more information on the questionnaire, refer to Appendix A and B.

Table 3.4 Questionnaire items

Latent variable	Questionnaire items	
Performance expectancy	PE1	I think carpooling would take me to the workplace/school quickly.
	PE2	I think carpooling would be a comfortable travel mode.
	PE3	I believe carpooling would be flexible (can arrange rides quickly).
	PE4	I believe carpooling is a reliable travel mode.
Effort expectancy	EE1	Carpooling using a mobile application would seem clear and understandable.
	EE2	Carpooling seems easy in terms of making payments.
	EE3	Carpooling seems easy in terms of planning rides according to my schedule.
	EE4	Carpooling seems easy as it will provide me a convenient travel route according to my needs.
Hedonic motivation	HM1	I think carpooling would be exciting.
	HM2	I think carpooling would be exciting.
	HM3	I think carpooling would be interesting.
	HM4	I think that I would be satisfied with the carpooling experience.
Facilitating condition	FC1	I think I can get help from others (the operator of the carpool) when I have difficulties in participating in carpooling.
	FC2	I think the workplace/school will provide the necessary infrastructure/ incentives to support carpooling.
	FC3	I think the government will provide the necessary guidelines and regulations to support carpooling.
	FC4	I think other carpoolers will support riding without causing any problems.
Social influence	SI1	I think I will use carpool if my friends use it
	SI2	I think I will use carpool if my family uses it.
	SI3	I think I will use carpooling if my colleagues/coworkers use it.

Latent variable	Questionnaire items	
	SI4	I think I will use carpool if the general public uses it.
Price value	PV1	I think travel costs would be cheaper compared to traveling alone.
	PV2	I think carpooling would be economically beneficial (Travel costs can be shared).
	PV3	I expect carpooling to provide appropriate service to the price I pay/receive.
	PV4	I think Irrespective of the price, carpooling service will be a good deal.
Perceived safety	PS1	I think I will feel safe disclosing personal information to the carpool application.
	PS2	I think carpooling rides will be safe (crime-free, no physical harm).
	PS3	I think carpooling accidents will be properly compensated for.
	PS4	I think that I will feel safe in my transactions through the carpool application
Behavioral intention	BI1	I consider carpooling as a good transport option.
	BI2	I am curious (want to know more about) to using carpooling.
	BI3	I will carpool to work/school if it is available.
	BI4	I think I will carpool and recommend carpooling as a transportation mode to others.
Perception towards COVID-19 and time credits	CO1	COVID-19 does not affect my decision to use Carpooling.
	CO2	Carpooling is not a venue of COVID-19 spreading if the sharing car is well disinfected.
	CO3	Carpooling is not a venue of COVID-19 spreading if all participants (including the driver) wear facemasks properly.
	CO4	Carpooling is not a venue of COVID-19 spreading if the sharing car uses open windows.
	CO5	Carpooling is not a venue of COVID-19 spreading if participants are limited to a driver and a passenger.
	CO6	I will use Carpooling if all participants (including the driver) are vaccinated against the COVID-19
time-credits	TC1	I think time credits would be an interesting form of payment method for carpooling.
	TC2	I think it is convenient to use time credits as a payment method for carpooling rather than money.
	TC3	I think time credits is an acceptable payment method for carpooling.
	TC4	I think, through carpooling with time credits, I will be able to help others.
	TC5	I think carpooling with time credits helps create a better-connected campus society.

3.5.1 Sample size requirement

There are several guidelines given to find the minimum sample size requirement. Anderson, Schermelleh-Engel, and Moosbrugger (1984) stated that any type of SEM requires approximately 150 responses for models where constructs comprise three or four indicators. However, Bentler and Chou (1987) recommended having a ratio of five responses per observed variable. There are 43 observed variables considered in the present study. Therefore, the minimum sample size required is 43 x 5 (215 responses).

Even though a minimum of 215 responses would be enough for SEM analysis, the sample size should be enough to represent the students of Thammasat University, Rangsit campus. Therefore, the sample size formula, which considers four criteria for estimation, was used (Cochran, 1977). The criterion considered are population size (27,386), the margin of error (acceptable range 4%-8%), confidence level, and standard deviation (SD).

$$Sample\ size = \frac{SS}{1+\frac{SS-1}{Population}} \tag{3.1}$$

Formula (3.1), where SS is Cochran's sample size, is recommended to calculate the sample size for a known population. The confidence level was considered as 90% while assuming the margin of error was 5%. SD was thought to be 0.5. According to the formula (1) minimum sample size required to represent the students of Thammasat University, Rangsit campus, is 271. Therefore, considering both criteria, 300 responses were expected from the survey.

CHAPTER 4
RESULTS AND DISCUSSIONS

4.1 Sample characteristics

The online questionnaire survey was conducted at Thammasat University, Rangsit Campus, Pathum Thani, Thailand. Data was collected from 20/02/2022 to 29/03/2022. Responses from students were collected from 24 faculties at Thammasat University, Rangsit campus. Out of all the answers, 253 responses were collected by distributing the google forum link online. However, due to a lack of responses, the author had to collect the rest of the responses by meeting people. The author met people at familiar places within Thammasat University and asked them to help with the questionnaire survey. A QR code was developed, which led to the link to the google forum, and the researcher displayed it to the potential respondents. Towards the end of the survey, 341 responses were collected. After cleaning, 307 remain valid responses for the analysis, satisfying the minimum number of responses required. Figure 4.1 shows the student representation from each faculty from the actual database and survey. The actual data of the students was obtained from the Thammasat University registration office (Office of the Registrar, 2021).

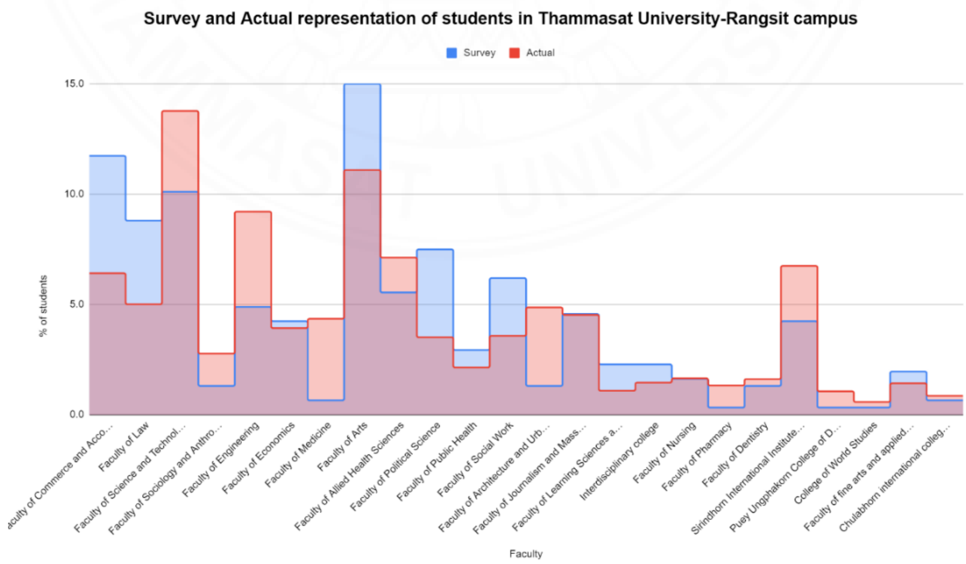


Figure 4.1 Survey and actual representation of students in Thammasat University-Rangsit campus

The sample data collected here is representative of Thammasat University students of the Rangsit campus in terms of faculties. However, some faculties such as Commerce and Accountancy, Economics, Arts, Political Science, Public Health, Social Work, Learning Sciences and Education, Interdisciplinary college, and fine arts and applied arts show a slightly higher representation of students. In contrast, faculties such as Science and Technology, Sociology and Anthropology, Engineering, Medicine, Allied Health Sciences, Architecture, and Urban Planning, Pharmacy, Dentistry, Sirindhorn International Institute of Technology, Puey Ungphakorn College of development, World Studies, and Chulabhorn international college of medicine show under-representation slightly. The sample was checked according to the gender distribution as well. Figure 4.2 compare the sample and actual distribution of students in terms of gender.

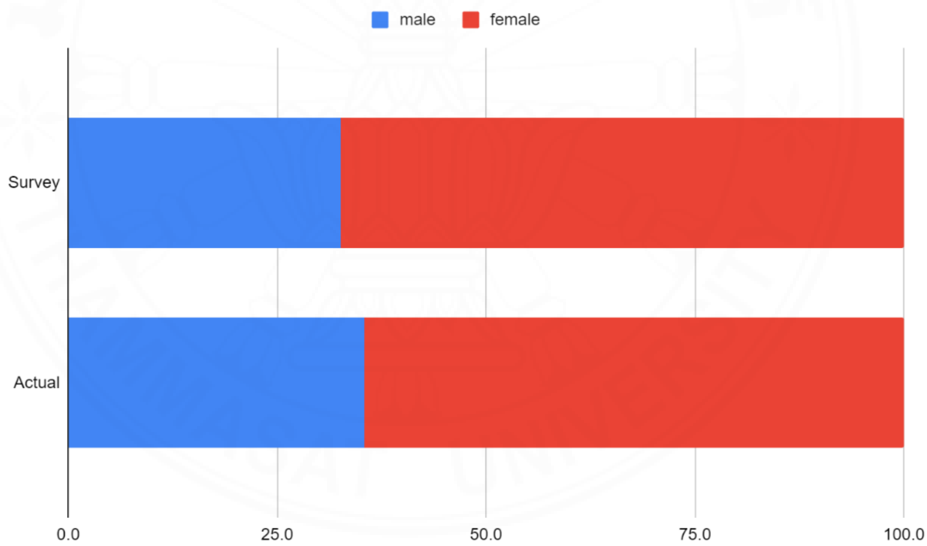


Figure 4.2 Male and Female representation of Thammasat University- Rangsit campus students

In terms of gender actual ratio of males to females is 32.6%/67.4%, whereas, in the survey data, it is 35.4%/64.6%. Therefore, it can be said that sample data represent Thammasat University- Rangsit campus students in terms of faculties and male/female ratio.

Regarding age, as they are all students, all the respondents were 18-29 years old. Regarding household vehicle ownership of the respondents, it was considered by vehicle type. Figure 4.3 illustrates the household vehicle ownership percentages of the sample. 26.71% of the respondents have one car in their household, while only 5.86% do not have any cars in their homes. The remaining sample (67.43%) have two or more cars in their families. Therefore, in terms of car ownership, the majority have cars in their household. About 24.43% of the respondents do not have motorcycles, while 31.92% have one motorcycle. However, 18.25% do have three or more motorcycles in their households. Regarding motorcycles, 75.58% of the sample have at least one motorcycle in their household.

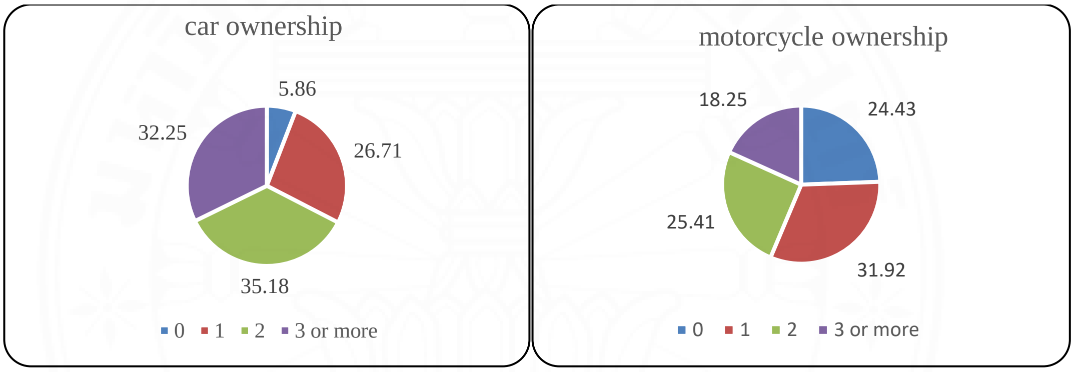


Figure 4.3 Household car ownership and motorcycle ownerships of the sample

Household monthly income data reveal that 45.27% of respondents' household incomes are 30,000 bhat or above, whereas the average monthly income per household in Thailand in 2021 amounted to approximately 27,000 bhat (Statista Research Department, 2022). As shown in figure 4.4, 12.05% stated that their household income is less than 10,000 bhat while 7.17% said it is between 10,000-19,000 bhat. About a quarter (25.73%) of the respondents did not want to tell their household income.

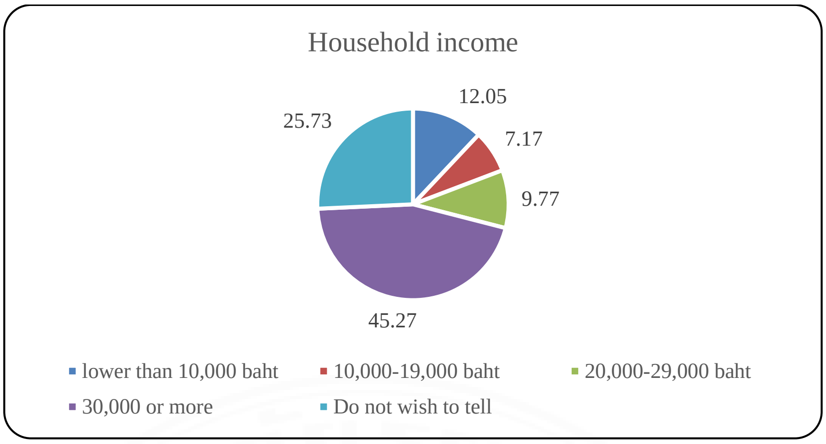
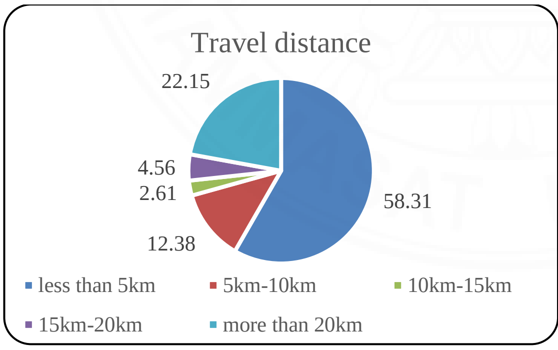


Figure 4.4 Household monthly income of the respondents

When traveling distance is considered, 58.31% of the respondents travel less than 5km to school, while the rest travel more than 5km. As carpooling considered in the present study is from home to school, this is the travel distance they will imagine carpooling. As shown in figure 4.5, 22.15% travel more than 20 km, while 12.38% travel only 5-10 km. Respondents who travel about 10-15km are about 2.61%, whereas 4.56% have to travel 15-20km. Most (60.91%) of the respondents travel at least four days per week. The respondents who travel 1 and 2 days are 6.51% and 8.47%, respectively, while 17.59% travel three days per week.



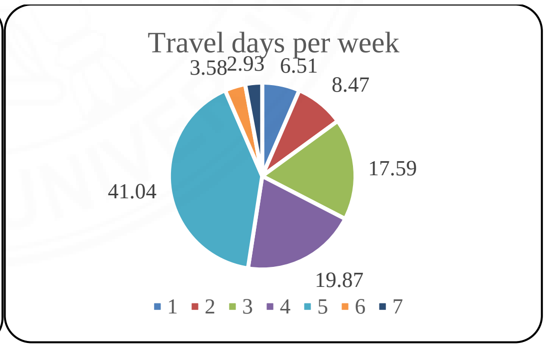


Figure 4.5 Travel distance and traveling days per week of the respondents

Characteristics related to carpooling reveal exciting information. The questionnaire asks respondents to state which carpool role they are interested in and whether they have carpooled before. Figure 4.6 illustrates the information on these questions. The majority (89.9%) do not have experienced carpooling before. Only 10.1% have stated that they have carpooled before. Therefore, information coming from inexperienced carpoolers are extensively valuable to developing and presenting sound policy implication that can increase carpool adoption in Thailand.

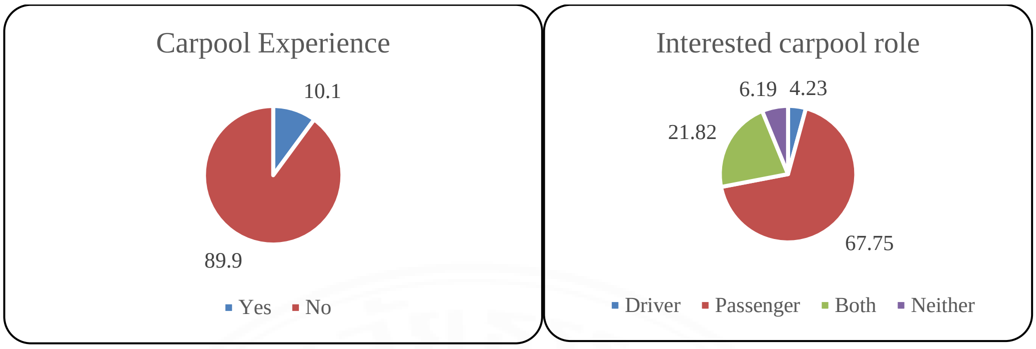


Figure 4.6 Carpool experience and interested carpool roles of the respondents

According to figure 4.6, it can be observed that most of the respondents (93.8%) showed an interest in carpooling. Coming from a young generation, this indicates that Universities and other educational institutes will be perfect candidates to initiate carpool programs in Thailand to spread carpool adoption. However, 67.75% stated they are interested in carpooling as passengers, while only 4.23% showed interest in the driver role. This could be problematic due to the possibility of supply-demand unbalance in carpooling. Therefore, recognizing the driving points that attract car drivers to carpooling is also essential.

4.2 Descriptive statistics

Descriptive analysis was conducted to get an oversight of the responses for different latent aspects related to carpooling. The response for “behavior intention” was first assessed to understand people's overall perceptions of carpooling. The questionnaire asks respondents to rate their agreement on four different statements regarding behavior intention to carpool from home to school. Figure 4.7 illustrate the distribution of the responses on them.

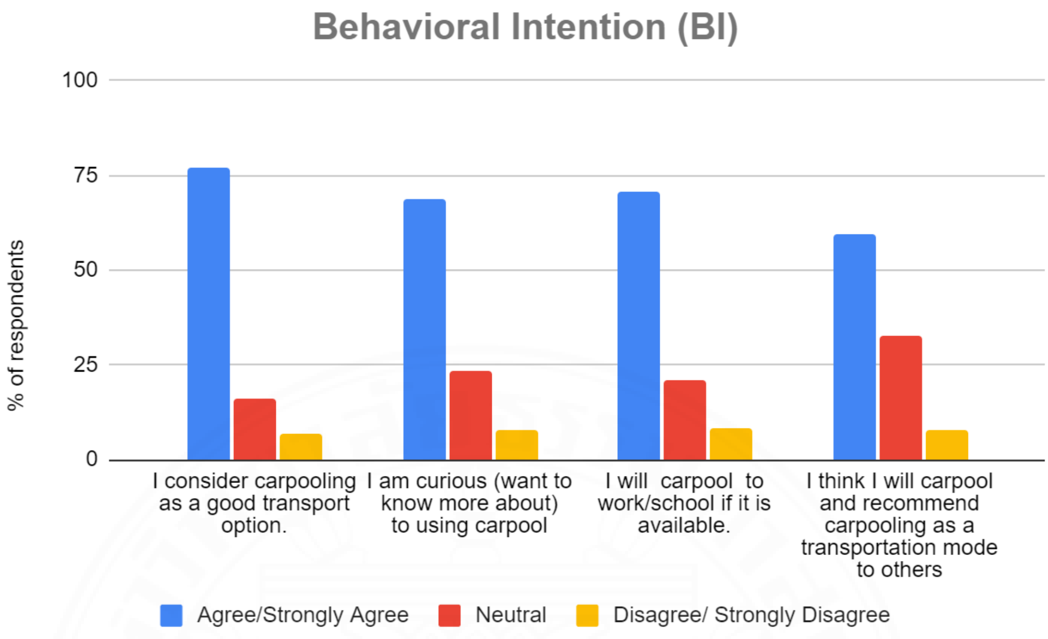


Figure 4.7 Response to behavior intention

The majority (77.20%) consider carpooling as a good transport mode, while 68.73% stated that they are curious about carpooling and want to know more about it. Many (70.68%) said they would carpool to school if available. Furthermore, 59.28% think they will also recommend carpooling to others. Therefore, overall, respondents have viewed carpooling positively. Positive student responses can be expected if carpooling is promoted among university students.

One of the most critical latent aspects that are considered in the present study is the "perception towards COVID-19 and carpool". The questionnaire asked respondents to state their agreement on six different statements regarding COVID-19 and to carpool. Figure 4.8 illustrate the distribution of the responses on them.

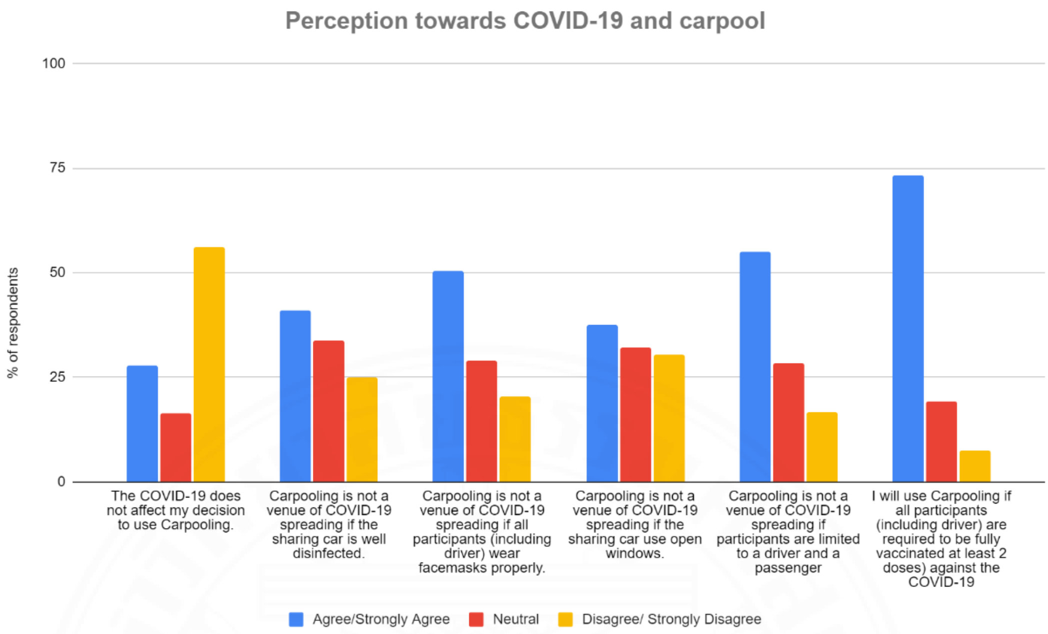


Figure 4.8 Response to perception towards COVID-19 and carpool

According to figure 4.8, the majority (56.03%) stated that they believe their decision to carpool is affected by COVID-19. However, 73.29% think they will use carpooling if all participants (including the driver) are requested to be fully vaccinated (at least two doses) against COVID-19. Further majority of the respondents believe that carpooling is not a venue for COVID-19 spreading if proper guidelines are followed. Of 307 respondents, 43.01% believe carpooling is not a venue for COVID-19 spreading if the sharing car is well disinfected. The proportion of respondents (37.46%) who say that carpooling is not a venue of COVID-19 spreading if the sharing car use open windows is slightly higher than the proportion of respondents (30.29%) who do not believe that.

Furthermore, more than 50% of the respondents believe carpooling is not a venue of COVID-19 spreading if all participants (including drivers) wear facemasks properly and if participants are limited to drivers and passengers. Therefore, looking overall, it is quite clear that the younger generation considers carpooling as a safe travel mode during this COVID-19 pandemic if safety guidelines are correctly followed. Further, they are willing to carpool if all participants are vaccinated, including the driver.

Another newly introduced important aspect considered in the present study is the "time credits." It is a sharing economy concept gaining popularity as an alternative to monetary payment. Time credits can be used to develop well-connected and sustainable communities in developed countries. The present study asked respondents to state their level of agreement with five statements regarding carpooling and time credits. Figure 4.9 illustrates their responses to them.

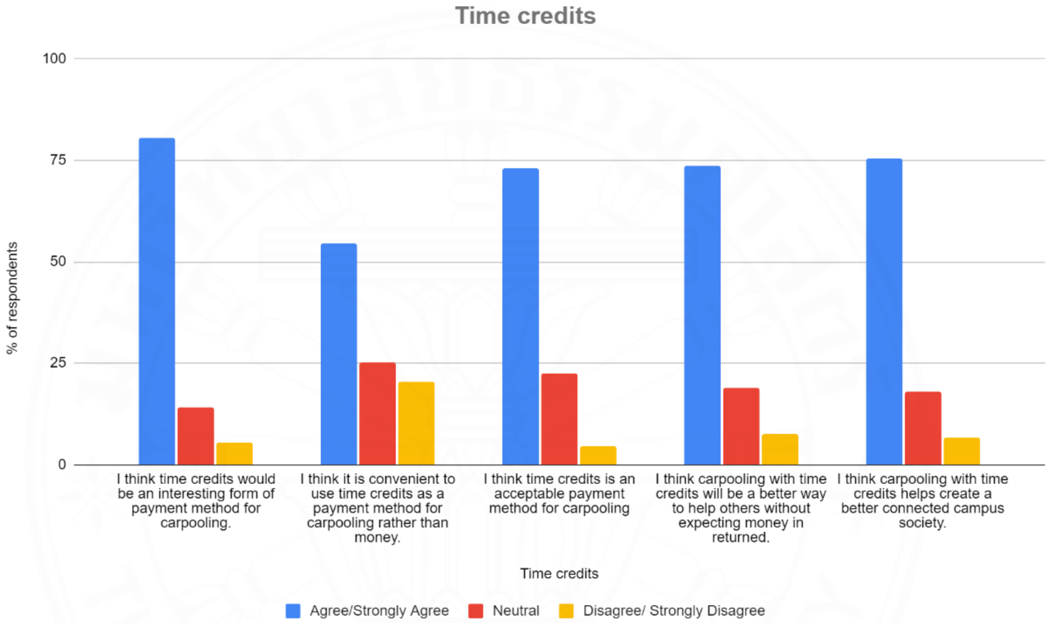


Figure 4.9 Response to time credits

Many (80.46%) believe that time credits would be an interesting form of payment method for carpooling. Furthermore, 72.96% think it would be an acceptable payment method. However, when it comes to convenience, the portion of respondents who agree that time credits would be a convenient payment method reduced to 54.4%. Still, it is more than 50% of the respondents. Furthermore, most students see the social value of using time credits instead of money, as 73.62% recognize that carpooling with time credits will be a better way to help others without expecting cash in return.

Moreover, 75.57% believe carpooling with time credits helps create a better-connected campus society. Therefore, looking at the overall outcome, it is quite clear that students positively have view time credits. As this comes from a university community, it opens the possibility of introducing the time credit concept among the university community and developing a well-connected society.

4.3 Structural Equation Modelling

A few assessments must be conducted on the data set to continue to the SEM. The first step would be testing for multicollinearity and normality of the data set. Severe multicollinearity between measurement items could lead to trouble in SEM analysis. As highly correlated measurement items are so close as to be almost repetitive, they should be eliminated before moving on to SEM. The correlation matrix between the measurement items was developed to identify items with severe correlation. The maximum correlation observed was 0.701, and the minimum correlation was 0.028, which can be considered less severe as they are less than 0.85 (Weston & Gore, 2006). Therefore, none of the measurement items were removed at this stage.

Investigating the normality of the data set is essential because it will give researchers an overview of the data set. Further, it will aid in deciding which estimator to be used in the analysis. As there are several estimators, some estimators work well with non-normal data. Therefore, for the present study, univariate and multivariate normality were investigated using R. Univariate normality distribution of each observed variable was examined for skewness and kurtosis. Values of skewness range between -1.68 to 0.19, while kurtosis values range from -0.70 to 3.69 for all observed variables. For more information, refer to table C1 in appendix C. Absolute skewness values less than or equal to 1.25 and kurtosis values less than 3.75 indicate moderate non-normality (Flora & Curran, 2004). Conversely, skewness values higher than 3 indicate severe non-normality. Therefore, the sample can be considered moderately non-normal in univariate normality.

Multivariate normality is assessed using Mardia's test for multivariate normality. Two statistics are calculated for skewness and kurtosis in this test. The skewness statistic is compared against the chi-squared distribution, and the kurtosis statistic is compared against the standard normal distribution. The null hypothesis is that samples come from a normal distribution (Cain, Zhang, & Yuan, 2017). Therefore p-value <0.05 indicate non-normality. For both statistics, p-values were less than zero, indicating the presence of multivariate non-normality in the data set. Therefore, the model parameters can be estimated using the Weighted Least Square Mean and Variance adjusted (WLSMV) estimator. It is a variant of the Diagonally Weighted Least Square (DWLS) estimator and can handle categorical endogenous and non-normality of the data (Hair et al., 2017). All the analyses have been conducted using R studio. For related R codes, refer to Appendix D. For SEM, the *lavaan* package has been utilized in the present study.

4.3.1 Assessment of measurement model

Once the multicollinearity and normality of the data set are checked, the measurement model should be developed. Then it should be assessed for validity, reliability, and unidimensionality. To evaluate the construct validity CFA (Confirmatory Factor Analysis) was conducted. Construct validity is the extent to which the measure is consistent with the theoretical hypothesis. The acceptable fit of the model's CFA indicates the assumption that measurement items reflect the latent variables. The three most commonly used fit indexes were used to examine the model fit. First, Comparative Fit Index (CFI) is an incremental fit index that compares a model with a baseline model. Values close to 1 indicate a ‘good’ fit. Values above 0.9 indicate acceptable model fit (Hu & Bentler, 1999). Second, the Tucker-Lewis index (TLI) is an incremental fit index that compares a model with a baseline model. Values close to 1 indicate a ‘good’ fit (Tucker & Lewis, 1973). Values above 0.9 indicate acceptable model fit (Hu & Bentler, 1999). Finally, the Root Mean Squared Error of Approximation (RMSEA) is an absolute fit index that determines how well the a priori model fits. Values closer to 0 indicate a ‘good’ fit. Values less than 0.06 show an acceptable model fit (Steiger & Lind, 1980). For the measurement model of the present study, index values were CFI (0.994), TLI (0.993), and RMSEA (0.036). Therefore, having an acceptable fit of CFA of the model ensured the construct validity.

Factor loadings and their statistical significance were examined to assess the unidimensionality and convergent validity of the model. Unidimensionality is the extent to which all measurement items measure only one dimension. Acceptable factor loadings indicate unidimensionality. Higher factor loading indicates higher variance of the latent variable reflected by the observed variable. Cutoff value for unidimentionality may vary by different field of studies. Ding and Zhang (2021) who studied dynamic associations between temporal behavior changes caused by the COVID-19 pandemic have considered factor loadings lower as 0.2. Wu and Neill (2020) who studied trust transfer and the intention to use app-enabled carpooling service, considered 0.5 as an allowable factor loading. Hence measurement items with factor loadings less than 0.5 were eliminated from the model to ensure unidimensionality. Convergent validity is the degree to which a scale measuring the same construct provides the same results. All items belonging to constructs were statistically significant. Therefore, it ensured convergent validity.

Discriminant validity is the extent to which a construct is genuinely distinct from other constructs. Many criteria can be used to measure discriminant validity. The Kline criterion for discriminant validity is to examine the correlation between latent variables. Not having a severe correlation between exogenous variables (higher than 0.85 (Alsheikh et al., 2021; Cheung & Wang, 2017)) ensures the latent variables are genuinely distinct from others. Another way is to examine the Heterotrait-Monotrait ratio of correlations (HTMT) between constructs. HTMT criterion is a stringent measure compared to other criteria (Ab Hamid, Sami, & Mohmad Sidek, 2017). HTMT value between constructs should be less than 0.9 for discriminant validity. The correlation matrix revealed there are severe correlations between latent variables. Performance Expectancy (PE) was highly correlated (higher than 0.85) with Effort Expectancy (EE), Facilitating Conditions (FC), Price value (PV), and Perceived safety (PS). FC was highly correlated (higher than 0.85) with PV and PS. PV was highly correlated with PE, EE, and FC as well. HTML values between these constructs were also high (higher than 0.9). All these findings indicate the lack of discriminant validity. Composite Reliability (CR) values were estimated for each of the constructs to assess the reliability of the measurement model. Reliability is the extent of the measurement model's reliability in measuring the intended latent construct. CR values (0.7 >) indicate acceptable reliability. Higher values indicate higher shared variances. CR is an indicator of the shared variance among the observed variables (Fornell & Larcker, 1981). It takes the measurement error into account. Therefore, it is considered to be a proper measure of reliability.

The measurement model was rearranged and then evaluated again due to the lack of discriminant validity and reliability. The new measurement model was established by exploring different combinations of the latent variables. Figure 4.10 illustrates these explorations properly. PE was highly correlated with EE and PS. The correlation was higher than 0.85. Therefore, PE was removed, a new measurement model (M2) was developed, and all criteria were reevaluated. High correlations were detected from PV with EE and FC. Also, PS with FC. Three different options were discovered. The first option was to remove FC from the model. It led to the model "M2.1". The second option was to drop PV. It led to the model "M2.2". The third option was to drop PS, which led to the "M2.3". Model "M2.1" showed a high correlation between PV and EE, leading to two new models that do not have a high correlation. Model "M2.1.1" was developed by dropping PV, while model "M2.1.2" was created by dropping EE. Model "M2.2" showed a higher correlation between PS and FC. It led to the development of another two measurement models without higher correlation between latent variables. Model "M2.2.1" was developed by dropping FC, while "M2.2.2" was created by dropping PS. Model "M2.3" showed high correlations between PV, EE, and FC. Dropping PV led to model "M2.3.1". Dropping EE led to model "M2.3.2," and dropping FC led to model "M2.3.3".

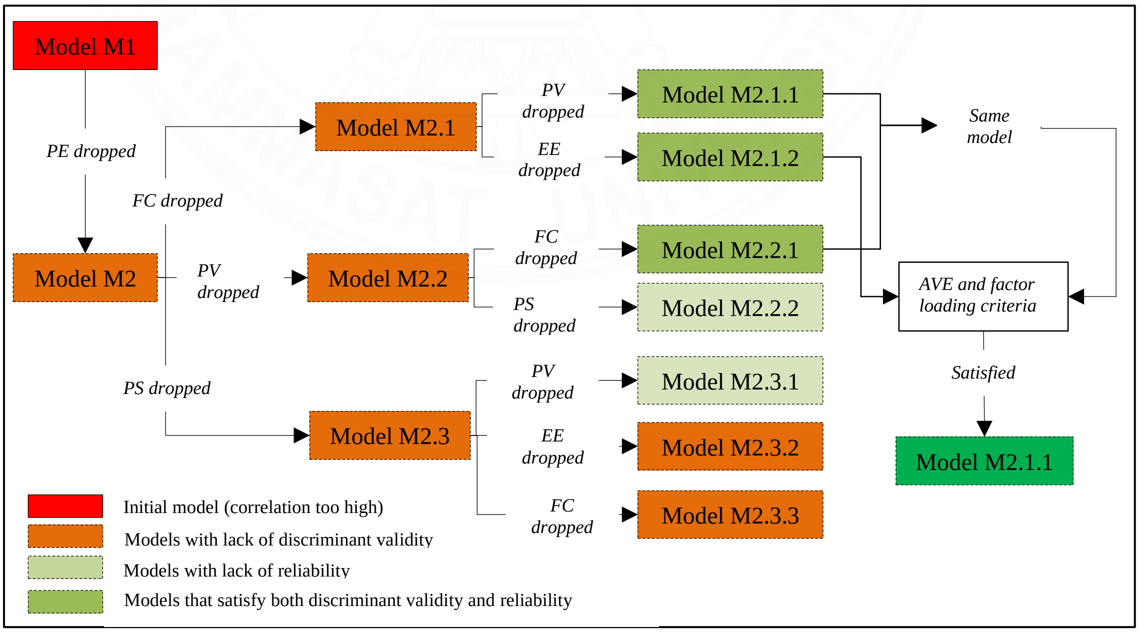


Figure 4.10 Exploration of different combinations of latent variables

In the end, the models that satisfied both discriminant validity and reliability were "M2.1.1"," M2.1.2," and "M2.2.1". Among these, "M2.1.1" and "M2.2.1" turned out to be the same model. Since both "M2.1.1" and M2.1.2" models satisfy all criteria (unidimentionality, construct validity, convergent validity, discriminant validity, and reliability), an additional measure was required to compare the two models. Chang and Wang (2017) recommended if the Average Variance Extracted (AVE) is not significantly less than 0.5, and the factor loadings of all items are not substantially less than 0.5, it can conclude the convergent validity (Cheung & Wang, 2017). Even though convergent validity is achieved when all observed variables related to latent variables show statistical significance (p-value <0.05), the above criterion was used to select the better measurement model. The factor loadings of both models are already higher than 0.5. However, M2.1.2 contains two variables (PS and PV) which have lower AVE values (0.460 and 0.459, respectively), while M2.1.1 contain only one such variable (PS). Therefore M2.1.1 was chosen as the best measurement model that satisfies all the criteria.

CFA was conducted on the new measurement model (M2.1.1). The values of CFI (0.996), TLI (0.995), and RMSEA (0.029) values indicated that the new measurement model fit the data well. It ensured the construct validity of the model. All the factor loadings were kept above 0.5 for the unidimensionality of the model. Convergent validity was also achieved as all measurement items were statistically significant and had AVE values that were not significantly lower than 0.5. CR values were reevaluated, and all values were higher than 0.7 indicating the reliability of the model constructs.

Table 4.1 Measurement model estimation- Factor loadings, variances, and CR values

Latent variable	Items	Loadings	Variance	CR
Effort expectancy (EE)	EE2	0.599	0.641	0.759
	EE3	0.821	0.325	
	EE4	0.718	0.484	
Hedonic motivation (HM)	HM1	0.702	0.507	0.839
	HM3	0.879	0.227	
	HM4	0.805	0.352	
Social influence (SI)	SI1	0.705	0.503	0.830

Latent variable	Items	Loadings	Variance	CR
	SI2	0.721	0.481	
	SI3	0.856	0.267	
	SI4	0.677	0.542	
Perceived safety (PS)	PS1	0.638	0.592	0.718
	PS2	0.727	0.472	
	PS4	0.667	0.556	
Behavioral intention (BI)	BI1	0.615	0.662	0.752
	BI3	0.739	0.454	
	BI4	0.789	0.378	
Perception towards COVID-19 and carpool (CO)	CO2	0.794	0.370	0.860
	CO3	0.870	0.244	
	CO4	0.740	0.454	
	CO5	0.639	0.592	
Time credits (TC)	TC1	0.748	0.440	0.847
	TC2	0.762	0.420	
	TC3	0.727	0.471	

Table 4.2 Correlations and HTML of the constructs

	EE	HM	SI	PS	BI	CO	TC
EE	1	-	-	-	-	-	-
HM	0.730/0.680	1	-	-	-	-	-
SI	0.648/0.616	0.743/0.720	1	-	-	-	-
PS	0.817/0.833	0.708/0.672	0.714/0.698	1	-	-	-
BI	0.812/0.796	0.881/0.873	0.841/0.821	0.814/0.779	1	-	-
CO	0.551/0.552	0.448/0.455	0.458/0.446	0.543/0.583	0.560/0.566	1	-
TC	0.677/0.661	0.489/0.441	0.489/0.448	0.612/0.608	0.637/0.605	0.498/0.503	1
EE: Effort Expectancy, HM: Hedonic Motivation, SI: Social Influence, PS: Perceived Safety, BI: Behavior Intention, CO: perception towards COVID-19 and carpool, TC: Time credits Lower triangle cells contain Correlation / Heterotrait-Monotrait ratio of correlations HTML values.							

Table 4.1 contain all CR values of each construct in the new measurement model. It also includes Factor loading and variances as well. Table 4.2 contain correlations and HTML values between the constructs. Correlations between the exogenous constructs are not severe (less than 0.85). High correlations exist between exogenous constructs and endogenous constructs (behavior intention). It is possible to exist this sort of high correlation as the model itself expect exogenous variables to be

highly correlated with endogenous variables. Further, HTML values are less than 0.9, indicating that new measurement modes achieve discriminant validity. Figure 4.11 graphically illustrates the resultant model. Dropped measurement items and latent variables are light colored.

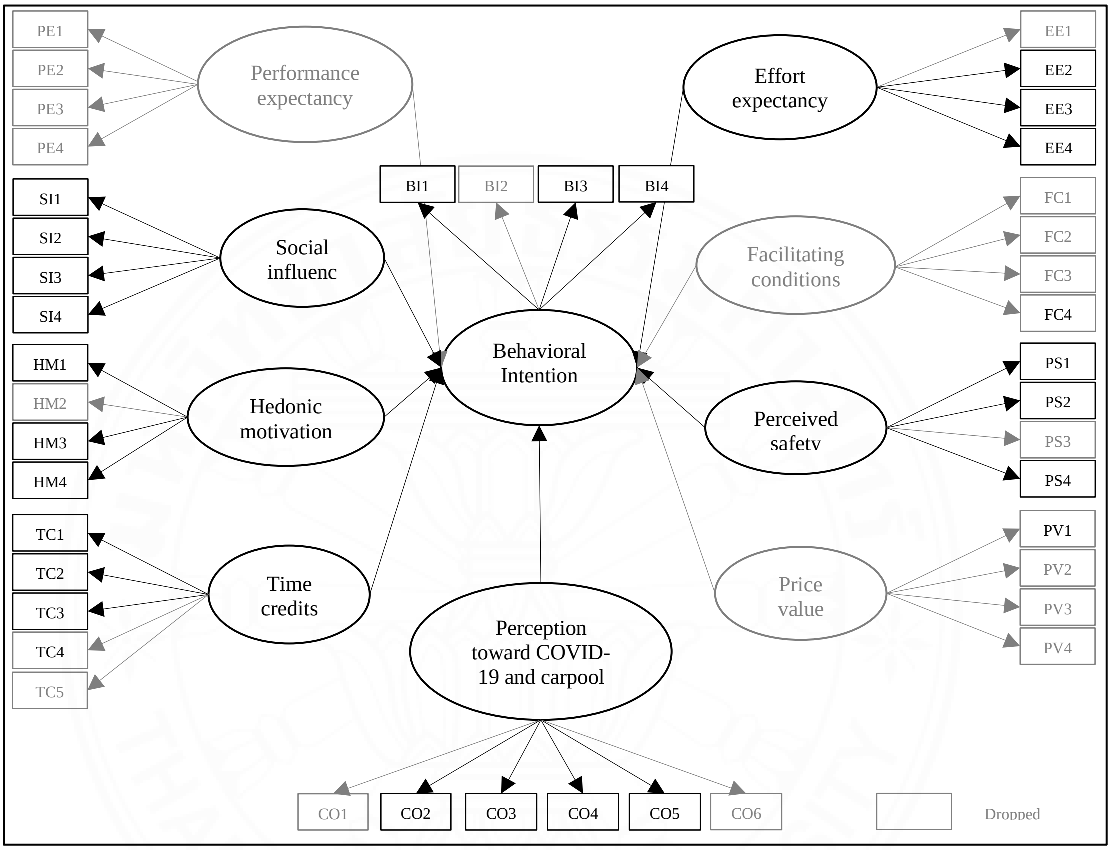


Figure 4.11 The resultant model

4.3.2 Assessment of structural model

The structural model was established based on the new measurement model. The structural model assessment also considered CFI, TLI, and RMSEA values. CFI (0.996), TLI (0.995), and RMSEA (0.029) values indicated that the structural model fit the data well. For related R codes, refer to Appendix D. Figure 4.12 graphically explains the model relationship between the latent variables.

Table 4.3 contains the summary of the model outcomes. According to the table, it can be observed that all the relationships showed a positive impact on behavior intention to carpool despite its statistical significance. All exogenous variables influenced endogenous variable positively. Effort expectancy and perceived safety factors did not significantly influence behavior intention. It indicates that the young generation does not concern about the easiness or safety associated with carpooling when they form an intention to carpool. It is interesting to notice that the young generation pays less attention to the safety aspects of carpooling when forming an intention to carpool. This mimics a finding of a recent study conducted in Bangkok. Tsai, Yu, and Boonprakob (2021) also reported that risks do not affect carpool intention for the younger generation. Although studies have shown that the easiness or difficulty associated with carpooling has a significant impact on carpooling (Park, Chen, and Akar, 2018), the present study examined the easiness associated with carpooling using a mobile application. As the study sample is from a university (a young generation is considered tech-savvy), it is possible that they do not find using a mobile application to participate in carpooling as tricky. Therefore, it is possible that effort expectancy is not highly significant from their point of view. The perception of COVID-19 and the carpool factor did not significantly impact behavior intention. Therefore, its effect on behavioral intention is very low. It indicates that whether people believe carpooling is not a venue of COVID-19 spreading if guidelines are correctly followed has no impact on behavioral intention to carpool. Therefore COVID-19 situation is not a significant factor when forming an intention to carpool, especially among the young generation. Studies have shown that commuters are more conscious of COVID-19 preventive measures (Xu, Chen, and Liu, 2021). During the survey period, Thailand was partially re-opened, and people traveled cautiously. Therefore, it is possible that believing or not that carpooling is a venue of COVID-19 spreading has no significant effect on behavior intention.

Table 4.3 Model estimation results- structural model

Exogenous variables	Unstandardized parameter	Standardized parameter	Standard error	Z- value	Significance
Effort expectancy	0.112	0.109	0.146	0.766	
Hedonic motivation	0.373	0.425	0.085	4.382	**
Social influence	0.253	0.290	0.077	3.274	**
Perceived safety	0.129	0.134	0.135	0.954	
Time credits	0.123	0.150	0.048	2.565	**
Perception towards COVID-19 and carpool	0.006	0.008	0.044	0.147	

Exogenous variables	Unstandardized parameter	Standardized parameter	Standard error	Z- value	Significance
Iterations: 51 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.998 Tucker-Lewis index (TLI) = 0.997 Root mean square error of approximation (RMSEA) = 0.024 ** significant at 5% level and * significant at 10% level.					

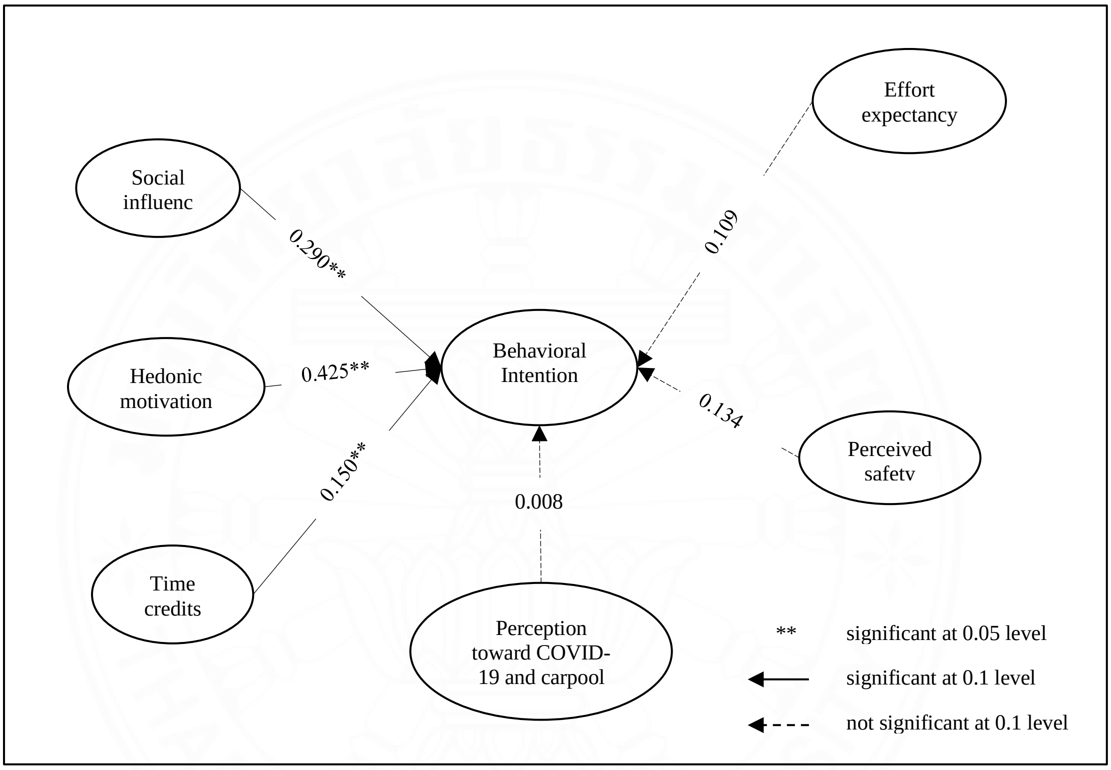


Figure 4.12 The structural model

Social influence, hedonic motivation, and time-credit factors significantly positively influenced behavior intention. The positive impact of social influence indicates that the effect of family members, friends, and colleges is vital for carpooling. Further, the more carpooling becomes general to the people, the more people will carpool. This finding is consistence with many studies (Lanzini & Khan, 2017; Bachmann et al., 2018; Gheorghiu & Delhomme, 2018). Among the three influential factors, the standardized parameter estimate is high for hedonic motivation indicating its impact is high compared to the other two factors. The positive effect of hedonic motivation suggests that when forming an intention to carpool, people give more attention to the enjoyment, socialization, and pleasure associated with carpooling.

Especially this young generation is more concerned about the joyfulness of carpooling than other aspects when they intend to carpool. Even though it is not specific to carpooling, past studies have shown that hedonic motivation tends to have a significant positive effect on consumers' propensity to participate in sharing economy and collaborative consumption services (Hossain, 2020), which is consistence with the present study findings.

On the other hand, the impact of the time-credit factor is relatively low compared to the other two factors. Still, time credit's positive impact shows the possibility of adopting time credits for carpooling. It shows that the young generation is willing to consider time credits as an alternative payment option, and the more they think about it, the more they are likely to adopt carpooling. Therefore, adopting time credits for carpooling will effectively highlight the social values of carpooling. Even though studies have investigated and initiated time banking communities within universities (Hirwa et al., 2021; Geary, 2010), no studies have investigated time credits in carpooling. As the present study findings showed, if time credit is introduced as a payment option for carpooling, a positive response from university students can be expected.

Table 4.4 Proposed hypotheses and their results

Hypothesis proposed	Results
Performance expectancy (PE) is positively related to the intention to participate in carpooling.	-
Effort expectancy (EE) is positively related to the intention to participate in carpooling.	Rejected at 0.1 significance level
Social influence (SI) is positively related to the intention to participate in carpooling.	Accepted at 0.05 significance level
Facilitating conditions (FC) is positively related to the intention to participate in carpooling.	-
Hedonic motivation (HM) is positively related to the intention to participate in carpooling.	Accepted at 0.05 significance level
Price value (PV) is positively related to the intention to participate in carpooling	-
Perceived safety (PS) is positively related to the intention to participate in carpooling.	Rejected at 0.1 significance level

Hypothesis proposed	Results
Perception toward COVID-19 and carpool (CO) is positively related to the intention to participate in carpooling.	Rejected at 0.1 significance level
Time credits (TC) is positively related to the intention to participate in carpooling.	Accepted at 0.05 significance level
'-'hypothesis was not tested by the model due to lack of discriminant validity and reliability of the latent variable	

Table 4.4 summarized hypotheses results. Even though proposed model expected examine nine hypotheses, resulted model only tested six of them. Resulted model left PE, FC and PV factors out due to lack of discriminant validity and reliability. Among the six hypotheses tested, three of them were accepted at 0.05 significance level, while other three were rejected at 0.1 significance level.

4.3.3 Assessment of structural model with mediating effects

Investigation of mediated influences allows us to find both direct and indirect effects of exogenous variables. In mediation analysis, some variables act as both exogenous and endogenous variables. For example, as discussed in the methodology section, hedonic motivation could mediate the influence of effort expectancy and social influence. In that case, hedonic motivation plays both exogenous and endogenous roles in the model. It is an exogenous variable for behavior intention while an endogenous variable for social influence and effort expectancy. Table 4.5 provides the parameter estimates of the model with these mediating effects. Figure 4.13 provides a graphical visual of the model.

The streamlined model was developed after 61 iterations. CFI (0.998), TLI (0.997), and RMSEA (0.024) values indicated that the structural model fit the data well. According to the model results, effort expectancy indirectly affects behavior intention through hedonic motivation. It suggests that the easier it becomes for people to make carpool arrangements through mobile applications, they are more likely to view carpooling as a joyful travel mode and, therefore, more inclined to adopt carpooling. Even though it may not be tricky for the young generation to use mobile applications for carpooling, increasing the easiness associated with it will indirectly attract more people to carpool. Its indirect impact is 0.173, while the total effect is 0.258. The significant full effect of effort expectancy is higher than the effect of time credits. Therefore, even though effort expectancy did not directly affect behavior intention, due to its significant indirect impact, its influence is relatively more substantial than the influence of time credits. It highlights the importance of the effort expectancy factor compared to the time credit factor.

Table 4.5 Model estimation results- structural model with mediating effects

Exogenous variables	Hedonic motivation (mediating variable)	Behavior intention (Endogenous variable)		
	Direct effect (Standardized)	Direct effect (Standardized)	Indirect effect (Standardized)	Total effect (Standardized)
Effort expectancy	0.414**	0.113	0.173**	0.285**
Perceived safety	-	0.151	-	0.151
Perception toward COVID-19 and carpool	-	0.008	-	0.008
Social influence	0.479**	0.288**	0.200**	0.487**
Time credits	-	0.136**	-	0.136**
Hedonic motivation	-	0.417**	-	0.417**
Iterations: 61 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.998 Tucker-Lewis index (TLI) = 0.997 Root mean square error of approximation (RMSEA) = 0.024 ** significant at 5% level and * significant at 10% level.				

Model results show social influence has a significant positive effect of 0.288 on behavior intention. However, results also point out that it has a positive indirect impact of 0.200 hedonic motivation. It implies that higher the encouragement they would receive from social surroundings to carpool, individuals are more likely to view carpooling as a joyful travel mode and, therefore, more inclined to adopt carpooling. Due to the significant indirect impact, the total effect of social influence on behavior intention is higher than the direct impact of hedonic motivation. This tells us that compared to hedonic motivation, social influence is vital for potential carpoolers to consider carpooling for educational trips.

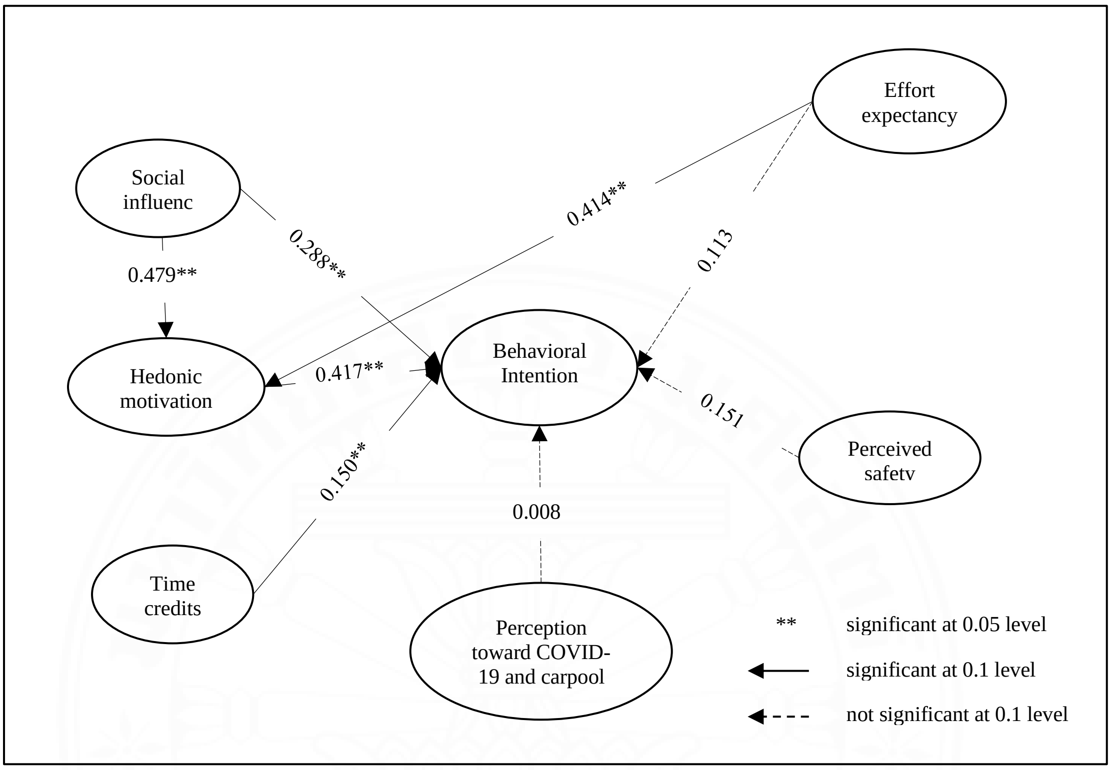


Figure 4.13 The structural model with mediating effects

4.3.4 Moderation with multigroup analysis (MGA)

While it is crucial how different psychological factors influence carpool behavior intention, it is exceedingly essential to identify how these relationships vary across different population groups. For this purpose, moderation analysis is conducted. A moderator variable is a qualitative (e.g., gender) or quantitative (e.g., amount of social support) variable that affects the direction or strength of the relationship between an independent or predictor variable and a dependent or criterion variable (King, 2014). Multigroup analysis (MGA) is one of the ways of assessing the moderation effects. MGA is used primarily when the moderator variable is categorical. The measurement invariance test is mandatory for MGA. The primary purpose is to ensure that the measurement model assessment conducted under different conditions yields equivalent representations of the same constructs. There are four levels of measurement invariance. Each of these levels builds upon the previous by introducing additional equality constraints on the measurement model parameters to achieve more substantial forms of invariance. To proceed to MGA, researchers must achieve at least an invariance result from the metric invariance test.

For the present study, the authors considered different forms of groups. Such as gender (male -98)/female-203), travel distance (less than 5km-179/higher than 5km-128), main travel mode (active-79/ motorized-228), and drive car (drive car to school-86/ do not drive-221). In addition, there were several other groups identified based on carpool experience, carpool interest, and carpool role interest. The latter groups drew back due to insufficient responses for one group to continue with MGA. Only the main travel mode group (active/motorized) among the former groups made it through the measurement invariance tests. Other groups failed to achieve at least metric invariance, disqualifying them from continuing through the MGA. For these groups configural model showed higher correlation between latent variables for one group. For example, in the gender group configural model, higher correlations existed for men group. Therefore, measurement models for these were unable to achieve at least metric invariance. For information on invariance test results refer to Appendix F. Table 4.6 summarizes the measurement invariance test results on the active/motorized travel mode group.

Table 4.6 Test of measurement invariance across active and motorized mode users

Model	Chi-Square	DF	CFI	TLI	RMSEA	Chi-square test (P value)
Configural model	508.897	418	0.967	0.960	0.038	-
Metric model	509.426	434	0.973	0.968	0.034	0.653
Scalar model	528.630	450	0.972	0.968	0.034	1.000
Strict model	528.630	450	0.972	0.968	0.034	1.000
DF: Degrees of freedom, CFI: Comparative Fit Index, Tucker-Lewis index (TLI), Root Mean Squared Error of Approximation (RMSEA)						

The configural model is the model fitted for each group separately, without any equality constraints. This model allows us to test whether the same factorial structure holds across all groups. Once the configural model fits the data well, the metric model is developed. It is a constrained version of the configural model where the factor loadings are assumed to be equal across groups. After that, two models are compared using the chi-square test to see the difference between the two models. It involves calculating the difference between the chi-square statistic for the two models, and the resulting statistic is distributed chi-square with degrees of freedom equal to the difference in the degrees of freedom (DF) between the two models. The test indicates whether the second model fits the data well than the first model. A P-value less than 0.05 suggest that the second model fits the data well than the first one (Pavlov, Shi, and Maydeu-Olivares, 2020). Here p-value becomes higher than 0.05, indicating that the metric model fits the data well as the configural model. However, looking at the other fit indexes, it can be observed that the metric model fits better. For related R codes, refer to appendix D.

The values of CFI, TLI, and RMSEA have been improved in the metric model. Since metric invariance is achieved, the scalar model is compared with the metric model. The scalar model is a constrained version of the metric model where both the factor loadings and intercepts are assumed to be equal across groups. The Chi-square test indicated that the scalar model also fits nicely as the metric model. However, RMSEA, CFI, and TLI values have not been improved. Then the strict model was also developed and compared with the scalar model. Therefore, it was concluded that the main travel mode group (active/motorized) achieved metric invariance. Consequently, it is possible to continue with MGA.

The structural model for the multigroup indicated the data fit the model well. CFI (0.973), TLI (0.968), and RMSEA (0.034) values are the evidence for the model fit. For related R codes, refer to Appendix D. Table 4.7 contains the MGA summary on active/motorized travel mode users. Figure 4.14 provides the graphical illustration of the model. Effort expectancy, perceived safety, perception towards covid-19 and carpool, and social influence did not show a statistically significant impact on behavior intention for active mode users or motorized users. Therefore, there’s no significant difference between active and motorized mode users in terms of easiness or safety associated with carpooling. Also, there’s no significant difference between active and motorized mode users regarding social influence and covid-19 situation. However, time credit and hedonic motivation factors statistically significantly impact behavior intention only for motorized mode users.

Interestingly none of the factors show a statistically significant impact on behavior intention for active mode users. Therefore, promotional efforts using these factors will not affect the active mode user. Past studies have reported similar findings (Park, Chen, and Akar, 2018).

Table 4.7 Model estimation results- the structural model for MGA (active and motorized travel mode users)

Exogenous variables	Unstandardized parameter	Standardized parameter	Standard error	Z- value	Significance
Effort expectancy	1.767/-0.036	1.464/-0.033	4.083/0.212	0.433/-0.171	
Hedonic motivation	-0.197/0.617	-0.181 /0.735	0.582/0.157	-0.339/3.927	-/**
Social influence	0.597/0.170	0.669/0.220	0.486/0.136	1.229/1.249	
Perceived safety	-1.331/0.014	-1.171/0.013	3.973/0.205	-0.335/0.066	
Time credits	0.137/0.169	0.173/0.209	0.231/0.100	0.592/1.700	/**
Perception towards COVID-19 and carpool	0.302/-0.015	0.337/-0.018	0.242/0.077	1.246/-0.194	
Iterations: 104 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.973 Tucker-Lewis index (TLI) = 0.968 Root mean square error of approximation (RMSEA) = 0.034 ** significant at 5% level and * significant at 10% level. active mode users/motorized mode users					

The positive impact of hedonic motivation indicates that when forming an intention to carpool, motorized mode users give more attention to the enjoyment, socialization, and pleasure associated with carpooling. Therefore, promotional strategies highlighting the socialization, entertainment, and fun aspects will be beneficial to attracting motorized mode users to carpooling. Furthermore, the positive impact of time credits indicates that motorized mode users consider time credits an alternative payment option for carpooling. Therefore, if time credits can be incorporated into carpooling, it will attract motorized mode users to carpooling. Consequently, it is evident that both these aspects can be used to promote carpooling among motorized mode users.

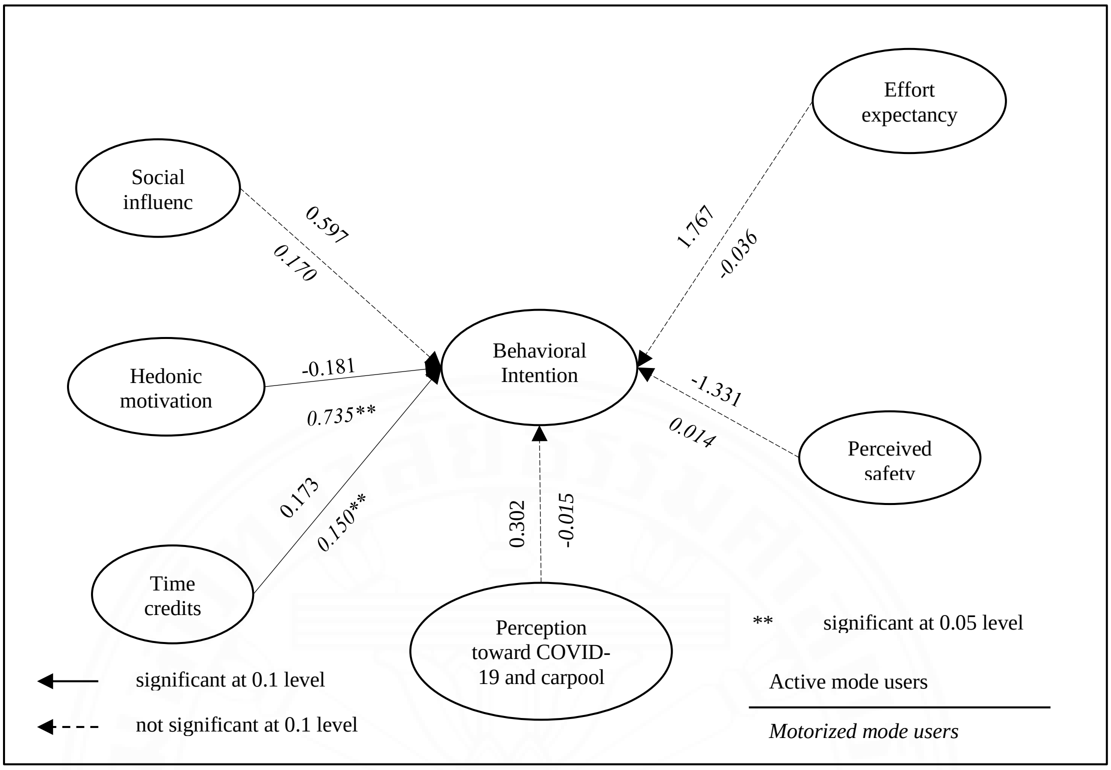


Figure 4.14 The structural model with multigroup

Motorized mode user does not necessarily mean car users. Out of 228, 27.19% of the motorized mode users are public transport users, while 10.53% use taxis and 19.74% use private motorcycles. However, a majority (42.54%) of them are car users. Of the 97 private car users, 52.6 % use it as drivers. There is also a possibility that people who drive cars do not use their cars as the primary travel mode. Therefore, it is crucial to investigate the difference in the model relationship between people who drive cars and people who do not. As discussed above, interaction terms were used for analysis since multigroup analysis failed for this group.

4.3.5 Moderation with interaction terms

As discussed in the previous section, MGA is one way of conducting moderation analysis, especially when the moderating variable is categorical. When the moderating variable is continuous, simple moderation is used. However, still, it is possible to conduct moderation with interaction terms when the moderating variable is categorical. Therefore, SEM with interaction terms was used to analyze the moderating effects when multigroup analysis failed. Four groups failed MGA. They are Gender (male/female), Travel distance (less than 5km/ higher than 5km), Main travel mode (public/private), and Drive car (yes/no). Moderation with interaction terms was attempted for each group separately at first. The travel distance (less than 5km/ higher than 5km) group and the Drive car (yes/no) group reveal exciting results. Therefore, a model was developed combining all the interaction terms related to “travel distance” and “drive car” groups. Altogether, there were 12 latent interaction variables at the beginning. After that, only statistically insignificant (p-value >0.05) interaction latent factors were removed; only significant factors were kept in the final model.

Simple moderation is conducted by developing interaction terms between the independent and moderating variables. Here one of the moderating variables considered is the “Drive car,” a binary variable. Firstly, the product variables were developed (product between “Drive car” and observed variables related to each latent variable). This process was done using the *semtool* package in R. Then, product terms were used to define the interaction latent variable used in the final model. The streamlined model was developed after 271 iterations. For related R codes, refer to Appendix D. CFI (0.984), TLI (0.983), and RMSEA (0.039) values indicated that the structural model developed with interaction terms fit the data well. Table 4.8 summarizes the model outcome. Figure 4.15 provides a graphical illustration of the model developed.

Table 4.8 Model estimation results- the structural model developed with interaction terms

Exogenous variables	Unstandardized parameter	Standardized parameter	Standard error	Z- value	Significance
Effort expectancy	0.018	0.017	0.171	0.107	
Hedonic motivation	0.405	0.460	0.094	4.310	**
Social influence	0.220	0.250	0.084	2.623	**
Perceived safety	0.165	0.171	0.146	1.135	
Time credits	0.190	0.222	0.064	2.989	**
Perception towards COVID-19 and carpool	-0.021	-0.027	0.048	-0.435	
Effort expectancy & Drive car	-1.090	-0.302	0.338	-3.226	**

Exogenous variables	Unstandardized parameter	Standardized parameter	Standard error	Z- value	Significance
Social influence & Drive car	0.559	0.263	0.177	3.159	**
Time credits & Drive car	0.306	0.140	0.145	2.105	**
Social influence & Travel distance less than 5km	0.584	0.280	0.209	2.799	**
Hedonic motivation & Travel distance less than 5km	-0.377	-0.194	0.157	-2.402	**
Drive car (ref. Do not drive car)	-0.180	-0.130	0.097	-1.858	*
Travel distance less than 5km (ref. Travel distance higher than 5km)	-0.112	-0.089	0.089	-1.251	
Iterations: 271 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.984 Tucker-Lewis index (TLI) = 0.983 Root mean square error of approximation (RMSEA) = 0.034 ** significant at 5% level and * significant at 10% level.					

The resultant model contains latent variables, interaction latent variables, and observed variables. The factors that showed statistically significant impact are Social influence, hedonic motivation, and time-credit factors. Interaction terms related to hedonic motivation, social influence, effort expectancy, and time credits showed statistical significance. Interestingly, the “Drive car” factor negatively impacted behavior intention to carpool at a 10% significant level. It indicates that people who drive cars are less likely to engage in carpool behavior compared to people who do not drive cars. However, interaction factors of social influence (Drive car) and time credits (Drive car) showed a positive impact on behavior intention. It indicates that even though people who drive cars are less likely to adopt carpooling, if their friends, family, or colleagues carpool, it will increase their likelihood of carpooling. Further, introducing time credits as an alternative payment method for carpooling will increase the possibility of carpooling for people who drive cars. Therefore, promotional efforts highlighting the above two aspects will be beneficial to attract car drivers towards carpooling compared to people who do not drive. When focusing on car drivers, there were 86 presents in the sample, and most (44.2%) stated they are interested in both roles if carpool is available, and only 9.3% showed interest in only driver roles. It indicates that 53.5% of the people who drive cars (about 46) are potential drivers that could offer carpool rides. Therefore, attracting people who drive cars to carpool is essential.

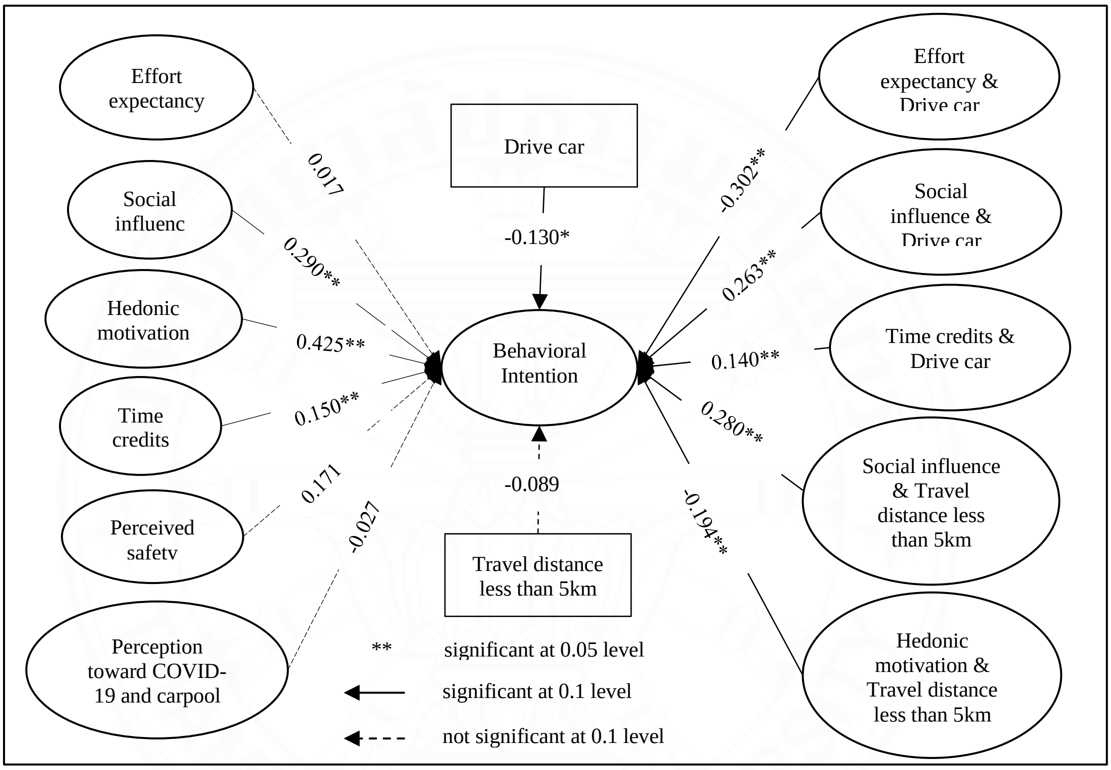


Figure 4.15 The structural model with interaction terms

Travel distance less than 5km factor also negatively impacted carpool behavior intention despite its statistical insignificance. It indicates that people who live closer to their school are less likely to adopt carpooling. However, the interaction term of social influence related travel distance variable positively impacts behavior intention. It indicates that the effect of family, friends, and colleges is significant for the people who travel less than 5km compared to people who travel higher than 5km. Therefore, even though these people (who travel less than 5km) are less likely to adopt carpooling, the above aspect can be used to attract them to carpooling.

4.4 Discussion

4.4.1 Significant findings for practical implications

The descriptive statistics showed that most respondents perceive carpooling positively. Therefore, with proper promotional efforts, it will be possible to increase the carpooling adoption for tertiary educational trips in Thailand. However, the pandemic situation may influence this behavior. The present study found that the young generation finds carpooling to be a safe travel mode in terms of COVID-19 spreading if the safety guidelines are correctly followed. Further, many respondents believe they will use carpooling if all participants (including the driver) are requested to be fully vaccinated (at least two doses) against COVID-19. These findings highlight the necessity of providing proper safety guidelines for carpooling during the pandemic.

According to empirical findings, social influence has a positive impact on carpooling. Previous studies also have reported similar results. A survey of the working community in France found that the effect of family members and colleges is essential for carpooling (Bulteau, Feuillet, & Dantan, 2019). Previous studies found that descriptive norms (Following most others do) are significant for carpooling (Lanzini & Khan, 2017), miming the present study's findings. Adding to these findings present study found an indirect impact of social influence through hedonic motivation. Therefore, the encouragement from the family, friends, and colleagues as well as from the general public to carpool is vital for not only adopting carpooling but also to view carpooling as a joyful travel model mode and to have a satisfying experience in carpooling to school. This information can be used to promote carpooling among university students.

Past studies have shown that hedonic motivation tends to positively affect peoples' propensity to participate in sharing economy (Hossain, 2020). Furthermore, a recent study conducted in Bangkok found that enjoyment predicts perceived value, which influences the intention to use carpooling (Tsai, Yu, & Boonprakob, 2021). Although their study did not reveal a direct link between behavioral intention and enjoyment, the present study found that hedonic motivation significantly positively affects carpool adoption. Furthermore, hedonic motivation mediates the impact of social influence and effort expectancy. Effort expectancy did not show a direct effect on behavior intention. However, past studies have shown a direct influence of effort expectancy on behavior intention, as present findings imply its indirect impact is highly significant. Therefore, associated easiness in dynamic carpooling is vital in promoting carpooling for education trips in Thailand.

Multigroup analysis showed that no factors are significant for active mode users, indicating that promotional efforts highlighting these factors will not affect active mode users. Active modes are sustainable travel modes that are popular among university communities. Therefore, attracting active users to carpool will be pointless, which is consistent with the present study findings. The Multigroup model revealed the influence of hedonic motivation is highly significant for motorized mode users compared to active mode users. Therefore, it is evident that motorized mode users give more attention to the enjoyment, socialization, and pleasure associated with carpooling. Time credits also showed a positive influence on motorized mode users as well as people who drive cars. Further, the present study found that people who drive cars are less likely to engage in carpooling compared to people who do not drive cars. However, promotional efforts highlighting carpooling as a travel mode widely shared by others and encouraging carpooling with friends, family, and colleagues will effectively increase their likelihood of carpooling. These significant findings aid policymakers in developing good promotional campaigns that will attract motorized mode users toward carpooling, which is sustainable for the university and society. Results also showed that people who travel less than 5km are less likely to carpool than others. However, interaction term related to social influence show positive signs for people who travel less than 5km, indicating that they can be attracted toward carpooling with promotional efforts that highlight carpooling as a travel mode widely shared by others and encourage carpooling with friends, family, and colleagues.

4.4.2 Significant findings for theoretical implications

All the findings were based on the proposed model analyzed using SEM. This model was primarily based on the UTAUT2 model, which has seven exogenous latent variables. The present study proposed replacing habit construct with perceived safety and adding two new constructs regarding COVID-19 and time credits. Due to a lack of discriminant validity, reliability, and higher correlation, three variables (Performance expectancy, price value, and facilitating conditions) were dropped from the final modeling process. Therefore, future studies that use the UTAUT2 model to investigate carpool adoption behavior could refer to the measurement variables used for the above, latent variable to make effective measurement items. In addition, the influences of other factors were investigated, and the effects of hedonic motivation, social influence, effort expectancy, and perceived safety on carpool behavior intention were found. Therefore, out of nine developed hypotheses, six were tested from the model estimation. Despite the statistical significance, all the relationships positively impacted the behavior intention in the proposed model, indicating that all six hypotheses are true. The influence of effort expectancy, perceived safety, and COVID-19 was statistically insignificant, while social influence, hedonic motivation, and time credits factors showed statistical significance. Therefore, out of the six hypotheses only three of them are backed up statistically. The direct effect of effort expectancy was seen to be statistically insignificant. However, past studies have found perceived behavior control (perceived ease or difficulty of performing the behavior) to be significant for the intention to carpool (Park, Chen, and Akar, 2018). Although the present study defines effort expectancy as the degree to which an individual believes participating in carpooling will be easy or difficult, it is more related to carpooling using a mobile application. Perceived safety also showed a statistically insignificant impact on behavior intention to carpool. A recent study in Bangkok pointed out that perceived risks do not affect the younger generation regarding carpool intention (Tsai, Yu, & Boonprakob, 2021), which the present study's findings agree with.

The hedonic motivation was also found to have a significant positive impact on carpool intention. Even though it is not specific to carpooling, studies have found that hedonic motivation tends to have a significant positive effect on consumers' propensity to participate in sharing economy and collaborative consumption services (Hossain, 2020).The present study found that there's a positive link between social influence and behavior intention when it comes to carpooling. Many past studies have established this fact in different ways. Perceived peer and family pressure are among the main predictors of carpooling frequency irrespective of the trip purpose (Gheorghiu and Delhomme, 2018). Descriptive norms (Following what most others do) are marginally significant for passengers while highly effective for drivers (Bachmann et al., 2018). The present study also checked the hypothesis that hedonic motivation mediates the influence of social influence and effort expectancy. Accordingly, it was found that in fact the mediating effects are significant hence the hypotheses are true. Therefore, it is evident that UTAUT2 model variables can be used to describe carpool behavior intention. Further hedonic motivation mediates the influence of social influence and effort expectancy. However, further studies need to be conducted to assess the influences of performance expectancy, price value, and facilitating conditions on carpool behavior intention.

4.5 Policy Implications

It is observed from the descriptive statistics that most people believe that they will use carpooling if all participants (including the driver) are requested to be fully vaccinated (at least two doses) against COVID-19. It is interesting as carpooling faced a risk of decreasing during the lockdown period. Since the vaccinations started, people have been traveling with less fear. Therefore, regulations or policies that request all carpool participants to be vaccinated will be beneficial in increasing carpool adoption in Thailand. Since the majority believe that their decision to carpool is affected by the COVID-19 situation, providing proper safety guidelines to follow is an essential step in promoting carpooling. As private car usage increases during the pandemic due to fear of getting infected, providing good guidelines will make people view carpooling as a safe travel mode. The policies should be consistent with the public health protocols. Due to the positive feedback from the university students on time credits as an alternative payment method for carpooling, it is possible to initiate time banking programs through universities. Therefore, Carpooling can be highlighted as the main action of the program. With time banking programs offering and receiving carpool rides occur without monetary involvement. It will help create a well-connected campus society and a sense of helping others among students. With more background studies, it can be expanded from universities to the community. It will aid people to see the social values of carpooling instead of monetary values.

According to empirical findings, social influence has a positive impact on carpooling. Previous studies also have reported similar results. For example, a survey of the working community in France found that the effect of family members and colleges is essential for carpooling (Bulteau, Feuillet, & Dantan, 2019). Therefore, promotional efforts should highlight that carpooling is possible with friends, family, and co-workers and encourage them to carpool. Further, its indirect effect will lead participants to view carpooling as a pleasurable experience, effectively increasing carpool adoption in Thailand. In addition, previous studies found that descriptive norms (Following most others do) are significant for carpooling (Lanzini & Khan, 2017), miming the present study's findings. Therefore, the promotional effort should highlight carpooling as people's travel mode, and its widely used by others. As a result, it will increase the likelihood of people using carpooling for educational trips.

Past studies have shown that hedonic motivation tends to positively affect peoples' propensity to participate in sharing economy (Hossain, 2020). Furthermore, a recent study conducted in Bangkok found that enjoyment predicts perceived value, which influences the intention to use carpooling (Tsai, Yu, & Boonprakob, 2021). Although their study did not reveal a direct link between behavioral intention and enjoyment, the present study found that hedonic motivation significantly positively affects carpool adoption. Therefore, the campaigns could promote carpooling as an existing experience. Also, carpooling is interesting, and the participants would enjoy it. Thus, promotional efforts highlighting these enjoyment aspects of carpooling will effectively increase carpool adoption in Thailand. Further, as Tsai, Yu, and Boonprakob (2021) proposed, carpooling companies should focus on making the carpool service engaging and pleasurable as enjoyment is one of the key factors driving the intention to use carpooling.

The present study found that effort expectancy indirectly influences the behavioral intention to carpool for educational trips through hedonic motivation. Therefore carpooling campaigns should promote dynamic carpooling is easy in terms of paying and arranging a convenient carpooling. Consequently, it will increase the joyfulness in the carpool experience and lead to higher adoption of carpooling for educational trips. Also, carpooling service providers should make dynamic carpooling as simple as possible. For example, they could provide more accessible payment methods. Furthermore, they could give a program that could ease planning the rides according to the user's schedule. Also, a good and straightforward mapping program could offer convenient travel routes according to user requirements. These actions will increase the carpool adoption for educational trips in Thailand.

The Multigroup model revealed the influence of hedonic motivation is highly significant for motorized mode users compared to active mode users. Therefore, the promotional efforts highlighting the enjoyment aspects of carpooling should be directed to motorized mode users. For example, the carpool promotional campaigns that highlight carpooling experience as an interesting and exciting one could be directed to the people who travel in motorized modes. It should be emphasized for the motorized mode users that they would enjoy carpooling. The majority of the motorized users are private mode users. Therefore, policies like the above will effectively attract private mode users to carpool. The empirical findings of the present study reveal that people who drive cars are less likely to engage in carpooling compared to people who do not drive cars. However, promotional efforts highlighting carpooling as a travel mode widely shared by others and encouraging carpooling with friends, family, and colleagues will effectively increase their likelihood of carpooling. For those who drive cars, it should be stressed that carpooling is a widely used travel mode by others. Also, they should be encouraged to carpool with their friends, family, and colleagues. Such promotional efforts directed at those driving cars will effectively attract commuters towards carpooling.

Time credits also showed a positive influence on motorized mode users as well as people who drive cars. Therefore, promotional efforts that introduce time credits to carpooling should also be directed to motorize mode users and car drivers as it will likely increase their participation in carpooling. Specifically, the campaigns introducing time credit as an attractive, convenient, and acceptable payment method for carpooling should be directed their way. Furthermore, the campaign above should target students who drive cars to initiate time banking programs, especially in universities. Results also showed that people who travel less than 5km are less likely to carpool than others. However, interaction term related to social influence showed a positive sign for people who travel less than 5km. Therefore, promotional efforts that highlight carpooling as a travel mode widely shared by others and encourage carpooling with friends, family, and colleagues should be directed to those who live closer to their school.

CHAPTER 5
CONCLUSION AND RECOMMENDATIONS

Sharing economy concepts like carpooling are more prevalent in developed countries and have been widely adopted by daily commuters. However, due to a lack of understanding and background studies, it has received less attention in developing countries. Therefore, the present study aims to understand the determinants and behavioral influences of carpooling adoption in Thailand. Utilizing the UTAUT2 model, modified SEMs were analyzed. Modifications were made by replacing habit construct with perceived safety and adding two additional constructs named "perception towards COVID-19 and carpool" and "Time-credits." A sample of 307 respondents from Thammasat university was gathered through an online survey for SEM analysis. Mediation, multigroup analysis, and SEM with interaction terms were used to examine model relationships in depth. It was observed that despite the statistical significance, all the model relationships are positive. Furthermore, it was found that statistically, hedonic motivation, social influence, and time credits positively influence carpool behavior intention.

In contrast, effort expectancy, perceived safety, and "perception towards COVID-19 and carpool" do not significantly influence behavior intention. Although mediation analysis revealed effort expectancy indirectly impacts behavior intention through hedonic motivation. It was recognized that hedonic motivation also mediates the impact of social influence. Through multigroup analysis, it was identified that hedonic motivation and time credits factors are highly significant for motorized mode users compared to active mode users. Furthermore, SEM with interaction terms revealed that social influence and time credits factors could be used to attract people who drive cars towards carpooling even though they are less inclined to carpool. Also, hedonic motivation and social influence factors can be used to attract people who live closer to their school. Based on the findings, both practical and academic implications are presented.

Regarding practical implications, it was proposed to provide regulations or policies requesting that all carpool participants be vaccinated. Further, providing proper safety guidelines was highlighted as well. For promotional efforts, it was proposed to highlight carpooling as people's travel mode that can offer a pleasurable experience. Further, encouraging carpooling with friends, family, and co-workers was emphasized. Moreover, introducing time credits with carpooling was stressed as a promotional point. Active mode users, car drivers, and students who live closer to university were identified as the groups that can be persuaded to carpool for educational trips using the above-discussed promotional efforts. Finally, regarding academic perspectives, it was recognized that UTAUT2 model variables could be used to describe carpool behavior intention. However, it was recommended to conduct further studies on the influences of performance expectancy, price value, and facilitating conditions on carpool behavior intention.

The sample represents the young generation as the responses were collected from Thammasat University, Rangsit center. While it is important to understand young generations', especially the students' perception of carpooling as they are daily travelers, it is also vital to understand the perception of working commuters who are also daily travelers. Therefore, future studies could consider different samples and compare student and non-student commuters. Furthermore, as a lack of interest in driver role was discovered, future studies could focus on studying what makes car drivers offer carpool rides. As students have recognized the importance of time credits, in-depth studies could be conducted to introduce the time-credits concept with carpooling for the university community. After that, it could expand to general society with more background studies.

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APPENDICES

APPENDIX A

QUESTIONNAIRE SURVEY- ENGLISH VERSION

Table A.1 Section 1 of the questionnaire

Carpooling in Thailand					
This survey is being conducted by a master’s student at the School of Civil Engineering and Technology, SIIT-TU, to fulfill a part of the research requirement for graduation. Your answers will be treated with the utmost confidence.					
Please watch the video below before answering the questionnaire in this part.					
Please read the sentences below carefully and then choose an answer that best describes your opinion.					
	Strongly Disagree [1]	[2]	[3]	[4]	Strongly Agree [5]
1. I think carpooling would take me to the workplace /school quickly.					
2. Carpooling using a mobile application would seem clear and understandable.					
3. I think carpooling would be exciting.					
4. I consider carpooling as a good transport option.					
5. I think I can get help from others (operator of the carpool) when I have difficulties in participating in carpooling.					
6. I think the travel cost would be cheaper compared to traveling alone.					
7. I think I will feel safe to disclose personal information to the carpool application.					
8. I think I will use carpool if my friends use it					
9. I think carpooling would be a comfortable travel mode.					
10. Carpooling seems easy in terms of making payments					
11. I think carpooling is a reliable travel mode.					
12. I believe the workplace/school will provide the necessary infrastructure/incentives to support carpooling.					
13. I think I will use carpool if my family uses it.					
14. I think carpooling would be economically beneficial (Travel cost can be					
15. I think carpooling rides will be safe (crime free, no physical harm)					
16. I am curious (want to know more about) to using carpool					
17. I think carpooling would allow me to meet new people and travel together.					
18. Carpooling seems easy in terms of planning rides according to my schedule					
19. I think carpooling would be interesting.					
20. I think the government will provide the necessary guidelines and regulations to support carpooling.					
21. I will carpool to work/school if it is available.					
22. I think I will use carpooling if my colleagues/coworkers use it.					
23. I think other carpoolers will support riding without causing any problems.					
24. I think carpooling would be enjoyable.					
25. I think carpooling accidents will be properly compensated.					
26. I think carpooling would be flexible (can arrange rides quickly)					
27. I think carpooling will provide appropriate service to the price I pay / receive.					

Carpooling in Thailand								
28. I think that I will feel safe in my transactions through the carpool application								
29. I think I will use carpool if the general public uses it.								
30. Carpooling seems easy as it will provide me with convenient travel route according to my needs.								
31. I think Irrespective of price, carpooling service will be a good deal.								
32. I think I will carpool and recommend carpooling as a transportation mode to others								
33. If COVID-19 situation is over, how many days/weeks on average do you drive a car to work/school?	No car	1	2	3	4	5	6	7
34. Have you ever carpool before?	Yes				No			
35. If carpooling is available, would you like to be a carpooling driver or passenger?	Carpool driver	Carpool passenger			Both		Neither	

Table A.2 Section 2 of the questionnaire

Perception towards COVID-19 and carpooling					
Please read the sentences below carefully and then choose an answer that best describes your opinion.					
	Strongly Disagree	[2]	[3]	[4]	Strongly Agree
2.1 The COVID-19 does not affect my decision to use Carpooling.					
2.2 Carpooling is not a venue of COVID-19 spreading if the sharing car is well disinfected.					
2.3 Carpooling is not a venue of COVID-19 spreading if all participants (including driver) wear facemasks properly.					
2.4 Carpooling is not a venue of COVID-19 spreading if the sharing car use open windows.					
2.5 Carpooling is not a venue of COVID-19 spreading if participants are limited to a driver and a passenger.					
2.6 I will use Carpooling if all participants (including driver) are required to be fully vaccinated at least 2 doses) against the COVID-19.					

Table A.3 Section 3 of the questionnaire

Perception towards Time-credits and carpooling					
Please watch the video below before answering the questionnaire in this part.					
Please read the sentences below carefully and then choose an answer that best describes your opinion.					
	Strongly Disagree [1]	[2]	[3]	[4]	Strongly Agree [5]
3.1 I think time credits would be an interesting form of payment method for carpooling.					
3.2 I think it is convenient to use time credits as a payment method for carpooling rather than money.					
3.3 I think time credits is an acceptable payment method for carpooling.					
3.4 I think carpooling with time credits will be a better way to help others without expecting money in returned.					

Perception towards Time-credits and carpooling					
3.5 Please select "Strongly Disagree" here.					
3.6 I think carpooling with time credits helps create a better-connected campus society.					

Table A.4 Section 4 of the questionnaire

socio-demographic characteristics											
4.1 Gender	Female	Male	Other……								
4.2 How old are you?	18-29 years old	30-39 years old	40-49 years old	50-59 years old	60 or more						
4.3 What is your marital status?	Single	Married									
4.4 What is your occupation?	Student	Professor	University staff								
4.5 What is your educational attainment?	Highschool and lower	College degree	Masters/ doctoral								
4.6 How many cars are there in the family?											
4.7 How many motorcycles in the family?											
4.8 How many family members are there (including you)											
4.9 Are you a parent?	No	Yes, with preschoolers (3-5)	Yes, with early school children (6-8)	Yes, with preteens (9-12)	Yes, with early teenagers (13-17)	Yes, with adult children (18-26)					
4.10 What is your family income per month (Baht)?	<10,000 baht	10,000 - 19,999 baht	200,000 - 29,999 baht	30,000 - 39,999 baht	40,000 - 49,999 baht	50,000 - 59,999 baht	60,000 - 69,999 baht	70,000 - 79,999 baht	> 80,000 baht	Prefer not to say	
4.11 Where do you live? (We respect your privacy; you may indicate the detail only down to the street or sub district level)											

Table A.5 Section 1 of the questionnaire

Travel Related Information							
Because of COVID-19 at the time of collecting the questionnaire the travel information may be distorted from the normal behavior. Please answer these questions based on your travel behavior before COVID-19 pandemic.							
5.1 What is the main mode do you use to travel to work/study?	1. Private car (as a driver) 2. Private car (as a passenger) 3. Private motorcycle 4. Motorcycle taxi 5. Train 6. Public bus 7. Shuttle (staff) bus/van 8. Songthaew 9. Tuk-tuk 10. Motor-taxi 11. Cycling 12. Walking 13. Carpool 14. Other….						
5.2 What is an approximate distance from home to school/workplace?	< 5 km	5-10 km	10-15 km	15-20 km	>20 km		
5.3. How many days do you go to study/work per week?	1	2	3	4	5	6	7
5.4. What time do you leave home/dormitory usually for school/workplace?	Before 7:30	7:30-8:00	8:00-8:30	8:30-9:00	After 9:00		
5.5. What time do you leave usually from school/workplace for home/dormitory?	Before 4:00	4:00-4:30	4:30-5:00	5:00-5:30	After 5:30		

Travel Related Information					
Because of COVID-19 at the time of collecting the questionnaire the travel information may be distorted from the normal behavior. Please answer these questions based on your travel behavior before COVID-19 pandemic.					
5.6. How many family members traveling with you to work/school?	No one	1	2	3	4 or more

APPENDIX B
QUESTIONNAIRE SURVEY- THAI VERSION

Table B.1 Section 1 of the questionnaire

คาร์พูล ในประเทศไทย

แบบสอบถามนี้จัดขึ้นเพื่อรวบรวมข้อมูลในการศึกษาวิจัยของนักศึกษาระดับปริญญาโทของคณะวิศวกรรมโยธาและเทคโนโลยี สถาบันเทคโนโลยีนานาชาติสิรินธร มหาวิทยาลัยธรรมศาสตร์ โดยมีวัตถุประสงค์เพื่อการพัฒนาระบบคาร์พูล (Carpool) ซึ่งเป็นรูปแบบการขนส่งแบบใช้รถยนต์ส่วนตัวร่วมกัน ข้อมูลในแบบสอบถามนี้ จะถูกเก็บเป็นความลับและนำไปใช้ประโยชน์ทางการศึกษาเท่านั้น ทั้งนี้ทางคณะผู้วิจัย ขอขอบพระคุณทุกท่านเป็นอย่างยิ่งที่ให้ความร่วมมือในการให้ข้อมูลและแบบสอบถามมา ณ โอกาสนี้

ก่อนตอบแบบสอบถามใส่ส่วนนี้ กรุณารับชมวิดิโอแนะนำเกี่ยวกับคาร์พูลและวิธีตอบแบบสอบถามก่อนค่ะ

กรุณาอ่านข้อความต่อไปนี้ และพิจารณาเลือกคำตอบที่ตรงกับความคิดเห็นของท่านมากที่สุด

	ไม่เห็นด้วยอย่างมาก [1]	[2]	[3]	[4]	เห็นด้วยอย่างมาก [5]
1. ท่านคิดว่าว่าคาร์พูลจะช่วยให้การเดินทางไปยังที่ทำงาน/สถานศึกษา รวดเร็วมากขึ้น.					
2. แอปพลิเคชั่นมือถือสำหรับการใช้บริการคาร์พูลนั้นน่าจะช่วยให้มีความชัดเจนและเข้าใจง่าย					
3. ฉันคิดว่าคาร์พูลนั้นน่าตื่นเต้น					
4. ท่านคิดว่าคาร์พูลเป็นทางเลือกที่ดีในการเดินทาง.					
5. ท่านคิดว่าจะได้รับความช่วยเหลือจากผู้ให้บริการหากติดปัญหาในการใช้บริการคาร์พูล					
6. ฉันคิดว่าค่าใช้จ่ายในการเดินทางของของคาร์พูลนั้นถูกกว่าการเดินทางคนเดียว					
7. ท่านคิดว่าท่านจะรู้สึกปลอดภัยในการเปิดเผยข้อมูลส่วนบุคคลของท่านบนแอปพลิเคชั่นคาร์พูล					
8. ฉันคิดว่าฉันจะใช้คาร์พูลหากเพื่อนของฉันใช้คาร์พูลด้วย					
9. ท่านคิดว่าคาร์พูลเป็นรูปแบบของการขนส่งที่สะดวกสบาย.					
10. คาร์พูลนั้นใช้งานง่ายในด้านการชำระค่าบริการ					
11. ท่านคิดว่าการเดินทางแบบคาร์พูลมีความน่าเชื่อถือ					
12. ท่านเชื่อว่าสถานที่ทำงานและสถานศึกษา จะมีการเตรียมพร้อมระบบและโครงสร้างและสิ่งจูงใจที่สนับสนุนการให้บริการคาร์พูล.					
13. ฉันคิดว่าฉันจะใช้คาร์พูลหากครอบครัวของฉันใช้ด้วย					
14. ท่านคิดว่าการใช้บริการคาร์พูลจะช่วยให้ท่านประหยัดค่าใช้จ่ายได้ (ค่าเดินทางสามารถจ่ายร่วมกันได้)					
15. ท่านคิดว่าการใช้คาร์พูลนั้นมีความปลอดภัย (ปราศจากการโจรกรรม และการทำร้ายร่างกาย)					
16. ท่านสงสัยหรืออยากรู้ข้อมูลเพิ่มเติมเกี่ยวกับการใช้คาร์พูล					
17. ท่านคิดว่าคาร์พูลจะทำให้ท่านได้พบเจอผู้คนหน้าใหม่และได้เดินทางร่วมกัน.					
18. การใช้คาร์พูลนั้นง่ายในการวางแผนการเดินทางสำหรับกำหนดการเดินทางของท่าน					
19. ท่านคิดว่าคาร์พูลนั่นดูน่าสนใจ					
20. ท่านเชื่อว่าหน่วยงานของรัฐควรมีการกำหนดแนวทางและข้อบังคับในการสนับสนุนคาร์พูล					
21. ท่านคิดว่าจะใช้คาร์พูลในการเดินทางไปยังสถานศึกษาหรือที่ทำงานถ้ามีการเปิดให้บริการ					
22. ท่านคิดว่าท่านจะใช้คาร์พูลหากเพื่อนนักศึกษาหรือเพื่อนร่วมงานของท่านใช้มัน					
23. ท่านคิดว่าผู้ใช้คาร์พูลท่านอื่นๆ จะช่วยทำให้บริการคาร์พูลไม่มีปัญหาใดๆ					
24. ท่านคิดว่าคาร์พูลนั้นน่าสนุก					
25. ท่านคิดว่าหากเกิดอุบัติเหตุจากคาร์พูล ท่านจะได้รับการชดเชยอย่างสมเหตุผล					
26. ท่านคิดว่าคาร์พูลนั้นจะมีความยืดหยุ่น สามารถจัดหาผู้ขับขี่หรือผู้โดยสารได้อย่างรวดเร็ว					
27. ท่านคิดว่าคาร์พูลจะเป็นการให้บริการที่เหมาะสมกับค่าบริการที่จ่ายไปหรือค่าตอบแทนที่ได้รับ					
28. ท่านคิดว่าท่านจะรู้สึกปลอดภัยในการชำระเงินผ่านแอปพลิเคชั่นคาร์พูล					
29. ท่านคิดว่าท่านจะใช้คาร์พูลหากประชาชนทั่วไปใช้					
30. ท่านคิดว่าระบบคาร์พูลนั้นจะสามารถจัดเส้นทางที่สะดวกกับความต้องการของท่านได้					
31. ท่านคิดว่าไม่ว่าจะมีค่าใช้จ่ายเท่าไรก็ตาม คาร์พูลจะเป็นบริการที่คุ้มค่า					
32. ท่านคิดว่าท่านจะใช้และแนะนำบริการคาร์พูลให้แก่คนอื่นๆ					

33. (เมื่อสถานการณ์โควิด-19 กลับสู่ภาวะปกติ) ท่านเดินทางมาเรียน/ทำงาน โดยการขับรถยนต์กี่วันต่อสัปดาห์	ไม่ ฉันไม่มี	1	2	3	4	5	6	7
34. ท่านเคยเดินทางโดยคาร์พูลมาก่อนหรือไม่?	ใช่				ไม่			
35. ถ้ามีโอกาสท่านคิดว่าจะใช้คาร์พูล โดยเป็นผู้ขับหรือผู้โดยสารหรือไม่?	ต้องการเป็นผู้ขับขี่		ต้องการผู้โดยสาร		ต้องการทั้ง 2 อย่าง		ไม่ทั้ง 2 อย่าง	

Table B.2 Section 1 of the questionnaire

ความคิดเห็นที่เกี่ยวกับ **COVID-19** และคาร์พูล					
กรุณาอ่านข้อความซึ่งเกี่ยวข้องกับโรคระบาดโควิด 19 ด้านล่างนี้ และเลือกคำตอบที่ตรงกับความคิดเห็นของท่านมากที่สุด					
	ไม่เห็นด้วยอย่างมาก [1]	[2]	[3]	[4]	เห็นด้วยอย่างมาก [5]
2.1 โรคระบาดโควิด 19 ไม่ส่งผลต่อการตัดสินใจของท่านที่มีต่อการใช้คาร์พูล					
2.2 คาร์พูลจะไม่ใช่แหล่งแพร่กระจายของเชื้อโควิด 19 หากรถที่ใช้ร่วมกันนั้นมีการฆ่าเชื้อทำความสะอาดอย่างดี					
2.3 คาร์พูลจะไม่ใช่แหล่งแพร่กระจายของเชื้อโควิด 19 หากผู้ร่วมโดยสาร (รวมทั้งคนขับ) สวมใส่หน้ากากอนามัยอย่างถูกต้อง					
2.4 คาร์พูลจะไม่ใช่แหล่งแพร่กระจายของเชื้อโควิด 19 หากรถที่ใช้ร่วมกันนั้นเปิดหน้าต่าง.					
2.5 คาร์พูลจะไม่ใช่แหล่งแพร่กระจายของเชื้อโควิด 19 หากมีการจำกัดจำนวนผู้ใช้งาน โดยมีเพียงผู้ขับขี่และผู้โดยสาร 1 คน					
2.6 ท่านจะใช้คาร์พูล ถ้าผู้โดยสารทุกคน (รวมทั้งผู้ขับขี่) ต้องเป็นผู้ได้รับวัคซีนป้องกันโรคระบาดโควิด 19 ครบถ้วน (อย่างน้อย 2 เข็ม)					

Table B.3 Section 3 of the questionnaire

ความคิดเห็นที่เกี่ยวกับเครดิตเวลาและคาร์พูล					
ก่อนตอบแบบสอบถามใส่ส่วนนี้ กรุณารับชมวิดีโอแนะนำเกี่ยวกับแนวคิดเรื่องเครดิตเวลาก่อนค่ะ					
กรุณาอ่านข้อความด้านล่าง และเลือกคำตอบที่ตรงกับความเห็นของท่านมากที่สุด					
	ไม่เห็นด้วยอย่างมาก [1]	[2]	[3]	[4]	เห็นด้วยอย่างมาก [5]
3.1 ท่านคิดว่าเครดิตเวลานั้นเป็นรูปแบบการชำระค่าบริการที่น่าสนใจสำหรับคาร์พูล					
3.2 ท่านคิดว่าการชำระการให้บริการแบบเครดิตเวลานั้นสะดวกกว่าการใช้เงิน					
3.3 ฉันคิดว่าเครดิตเวลานั้นเป็นการชำระค่าบริการที่ยอมรับได้					
3.4 ท่านคิดว่าการให้บริการคาร์พูลแบบคิดเครดิตเวลา เป็นวิธีการที่ดีในการช่วยเหลือผู้อื่นโดยไม่หวังค่าตอบแทนเป็นเงิน.					
3.5 กรุณาเลือกตัวเลือก “เห็นด้วยอย่างมาก” ในข้อนี้					
3.6 ท่านคิดว่าการให้บริการคาร์พูลแบบคิดเครดิตเวลานั้นจะทำให้สังคมในมหาวิทยาลัยมีการเชื่อมโยงกันได้ดีขึ้น					

Table B.4 Section 4 of the questionnaire

<table>
<tr><td colspan="8">คุณลักษณะทางสังคม-ประชากร</td></tr>
<tr><td>4.1 เพศของท่าน</td><td colspan="2">หญิง</td><td colspan="2">ชาย</td><td colspan="3">Other……</td></tr>
<tr><td>4.2 อายุของท่าน</td><td>18-29 ปี</td><td>30-39 ปี</td><td>40-49 ปี</td><td colspan="2">50-59 ปี</td><td colspan="2">60 ปี</td></tr>
<tr><td>4.3 สถานภาพการสมรสของท่าน</td><td colspan="3">โสด</td><td colspan="4">แต่งงานแล้ว</td></tr>
<tr><td>4.4 อาชีพของท่าน</td><td colspan="2">นักศึกษา</td><td colspan="2">อาจารย์</td><td colspan="3">พนักงานของมหาวิทยาลัย</td></tr>
<tr><td>4.5 ระดับการศึกษาสูงสุดของท่าน</td><td colspan="2">มัธยมหรือต่ำกว่า</td><td colspan="2">ปริญญาตรี</td><td colspan="3">ปริญญาโท/ปริญญาเอก</td></tr>
<tr><td colspan="8">4.6 จำนวนรถยนต์ส่วนบุคคลในครอบครัวของท่าน</td></tr>
<tr><td colspan="8">4.7 จำนวนรถจักรยานยนต์ในครอบครัวของท่าน</td></tr>
<tr><td colspan="8">4.8 จำนวนสมาชิกในครอบครัวของท่าน (รวมตัวท่านด้วย)</td></tr>
<tr><td>4.9 ท่านมีบุตรหรือไม่</td><td>ไม่มีบุตร</td><td>ใช่ เป็นผู้ปกครองของเด็กวัยอนุบาล (อายุ 3-5 ปี)</td><td>ใช่ เป็นผู้ปกครองของเด็กวัยประถม (อายุ 6-8 ปี)</td><td>ใช่ เป็นผู้ปกครองของเด็กก่อนวัยรุ่น (อายุ 9-12 ปี)</td><td>ใช่ เป็นผู้ปกครองของเด็กวัยรุ่น (อายุ 13-17 ปี)</td><td colspan="2">ใช่ เป็นผู้ปกครองของเด็กโต (อายุ 18-26 ปี)</td></tr>
</table>

<table>
<tr><td colspan="11">คุณลักษณะทางสังคม-ประชากร</td></tr>
<tr><td>4.10 รายได้ต่อเดือนของครอบครัวท่าน (บาท/เดือน/ครอบครัว)</td><td>ต่ำกว่า 10,000 บาท</td><td>10,000 – 19,999 บาท</td><td>20,000 – 29,999 บาท</td><td>30,000 – 39,999 บาท</td><td>40,000 – 49,999 บาท</td><td>50,000 – 59,999 บาท</td><td>60,000 – 69,999 บาท</td><td>70,000 – 79,999 บาท</td><td>80,000 บาทหรือมากกว่า</td><td>ไม่ประสงค์ระบุจำนวน</td></tr>
<tr><td colspan="11">4.11 ท่านพักอาศัยอยู่ที่ใด (เราเคารพความเป็นส่วนตัวของท่าน ท่านอาจระบุรายละเอียดถึงแค่ระดับถนนหรือตำบลเท่านั้น)</td></tr>
</table>

Table B.5 Section 5 of the questionnaire

<table>
<tr><td colspan="8">ข้อมูลที่เกี่ยวข้องกับการเดินทาง</td></tr>
<tr><td colspan="8">เนื่องจากสถานการณ์ COVID-19 ณ ขณะเวลาที่เก็บข้อมูลแบบสอบถามนี้ ทำให้ข้อมูลการเดินทางอาจถูกบิดเบือนไปจากสถานการณ์ปกติ กรุณาตอบคำถามในส่วนนี้โดยอ้างอิงถึงการเดินทางของท่านในช่วงก่อนสถานการณ์ COVID-19.</td></tr>
<tr><td>5.1 ท่านใช้วิธีการเดินทางใดเป็นหลักในการเดินทางไปที่ทำงาน/สถานศึกษา</td><td colspan="7">1. รถยนต์ส่วนบุคคล (ผู้ขับขี่) 2. รถยนต์ส่วนบุคคล (ผู้โดยสาร) 3. รถจักรยานยนต์ของตนเอง 4. รถจักรยานยนต์รับจ้าง (วินมอเตอร์ไซค์) 5 รถไฟ 6. รถตู้ 7. รถโดยสารประจำทาง 8. รถรับส่งที่มหาวิทยาลัย/คณะจัดให้ 9. รถสองแถว 10. รถตุ๊ก ๆ11. รถแท็กซี่ 12. จักรยาน 13. เดิน 14. ขับ/นั่งรถมากับเพื่อน/คนรู้จัก</td></tr>
<tr><td>5.2 ระยะทางโดยประมาณจากบ้านถึงมหาวิทยาลัย/ที่ทำงาน</td><td>< 5 km</td><td colspan="2">5-10 km</td><td>10-15 km</td><td colspan="2">15-20 km</td><td>>20 km</td></tr>
<tr><td>5.3. คุณไปเรียน/ทำงาน กี่วันต่อสัปดาห์</td><td>1</td><td>2</td><td>3</td><td>4</td><td>5</td><td>6</td><td>7</td></tr>
<tr><td>5.4. วงเวลาที่ท่านออกจากบ้าน/ที่พัก เพื่อเดินทางไปมหาวิทยาลัย/ที่ทำงาน โดยปกติ</td><td>ก่อน 7:30 น.</td><td colspan="2">7:30- 8:00 น.</td><td>8:00- 8:30 น.</td><td colspan="2">8:30- 9:00 น.</td><td>หลัง 9:00 น.</td></tr>
<tr><td>5.5. ช่วงเวลาที่ท่านออกจากมหาวิทยาลัย/ที่ทำงาน เพื่อเดินทางกลับบ้าน/ที่พัก โดยปกติ</td><td>ก่อน 4:00 น.</td><td colspan="2">4:00- 4:30 น.</td><td>4:30- 5:00 น.</td><td colspan="2">5:00- 5:30 น.</td><td>หลัง 5:30 น.</td></tr>
<tr><td>5.6. จำนวนสมาชิกในครอบครัวที่เดินทางมาพร้อมกับท่านในการเดินทางมาทำงาน/เรียน</td><td>ไม่มี</td><td colspan="2">1</td><td>2</td><td colspan="2">3</td><td>4 คนหรือมากกว่า</td></tr>
</table>

APPENDIX C

NORMALITY TEST RESULTS

Table C.1 Normality test results

Observed variable	skewness	standard error	kurtosis	standard error
PE1	-0.4367	0.1391	-0.3427	0.2774
PE2	-0.5117	0.1391	0.0681	0.2774
PE3	-0.1259	0.1391	-0.1769	0.2774
PE4	-0.5501	0.1391	-0.5428	0.2774
EE1	-0.7939	0.1391	-0.1480	0.2774
EE2	-0.4288	0.1391	-0.0910	0.2774
EE3	-0.3350	0.1391	-0.5524	0.2774
EE4	-0.7741	0.1391	0.1922	0.2774
HM1	-0.9133	0.1391	0.0879	0.2774
HM2	-1.2563	0.1391	1.4569	0.2774
HM3	-1.0160	0.1391	0.7077	0.2774
HM4	-0.7492	0.1391	0.2107	0.2774
FC1	-0.4545	0.1391	-0.5126	0.2774
FC2	-0.4498	0.1391	-0.5433	0.2774
FC3	-0.9502	0.1391	0.1640	0.2774
FC4	-0.1640	0.1391	-0.3001	0.2774
BI1	-1.0437	0.1391	0.9564	0.2774
BI2	-0.7663	0.1391	0.0043	0.2774
BI3	-0.9456	0.1391	0.4802	0.2774
BI4	-0.3197	0.1391	-0.3884	0.2774
PV1	-1.6144	0.1391	2.5886	0.2774
PV2	-1.6840	0.1391	3.6901	0.2774
PV3	-0.3660	0.1391	-0.7038	0.2774
PV4	-0.0124	0.1391	-0.6778	0.2774
PS1	0.2265	0.1391	-0.3321	0.2774
PS2	0.0300	0.1391	-0.4376	0.2774
PS3	-0.9293	0.1391	0.0819	0.2774
PS4	-0.4438	0.1391	-0.0737	0.2774
SI1	-1.2120	0.1391	1.0043	0.2774
SI2	-0.7801	0.1391	-0.1663	0.2774
SI3	-1.4360	0.1391	2.0176	0.2774
SI4	-1.1836	0.1391	1.0131	0.2774
CO1	-0.4936	0.1391	-1.1321	0.2774
CO2	-0.1052	0.1391	-0.7294	0.2774
CO3	-0.2799	0.1391	-0.7804	0.2774
CO4	-0.0938	0.1391	-0.8576	0.2774
CO5	-0.5550	0.1391	-0.4195	0.2774
CO6	-1.0573	0.1391	0.4854	0.2774
TC1	-1.1361	0.1391	1.1560	0.2774
TC2	-0.4280	0.1391	-0.7862	0.2774
TC3	-0.6659	0.1391	0.1024	0.2774
TC4	-0.8232	0.1391	0.1073	0.2774
TC5	-0.7071	0.1391	-0.1403	0.2774

APPENDIX D
R CODES

Normality test R Code

```
Tham_data<-read.xlsx(file.choose(), sheet = "English version") # loading data

Model_variables<-data.frame(Tham_data$PE1,Tham_data$PE2,Tham_data$PE3,Tham_data$PE4,
Tham_data$EE1,Tham_data$EE2,Tham_data$EE3,Tham_data$EE4,Tham_data$HM1,Tham_data$HM2,Tham_data$HM3,Tham_data$HM4,Tham_data$FC1,Tham_data$FC2,Tham_data$FC3,Tham_data$FC4,
Tham_data$BI1,Tham_data$BI2,Tham_data$BI3,Tham_data$BI4,Tham_data$PV1,Tham_data$PV2,Tham_data$PV3,Tham_data$PV4,Tham_data$PS1,Tham_data$PS2,Tham_data$PS3,Tham_data$PS4,Tham_data$SI1,Tham_data$SI2,Tham_data$SI3,Tham_data$SI4,Tham_data$CO1,Tham_data$CO2,Tham_data$CO3,Tham_data$CO4,Tham_data$CO5,Tham_data$CO6,
Tham_data$TC1,Tham_data$TC2,Tham_data$TC3,Tham_data$TC4,Tham_data$TC5) # creating data frame with the variables

##checking normality using skewness and kurtosis values
### code extracted from past studies######

###test hypothesis for Univarite normality###
#Univariate normality considers the distribution of one variable while multivariate normality considers joint distribution of multiple variables

#univarite normaility : for each variable skewness and kurtosis values and thier standard errors are calculated
#multivaraite normality : 2 statstics are calculated for skewness and kurtosis
#skewness statistic is compared against the chi-squared distribution and kurtosis statistic is compared against standard normal distribution
#null hypothesis: samples come from a normal distribution. p-value <0.05 indicate non normal

skewkurt<-function(x, na.rm=TRUE){
 if (na.rm) x <- x[!is.na(x)]
 n <- length(x)
 skew1 <- (sum((x - mean(x))^3)/n)/(sum((x - mean(x))^2)/n)^(3/2)
 skew2 <- n/((n-1)*(n-2))*sum((x - mean(x))^3)/(sd(x))^3
 skew.se <- sqrt(6*n*(n-1) / ((n-2)*(n+1)*(n+3)))

 temp<- sum((x - mean(x))^4)/(sum((x - mean(x))^2)^2)
 kurt1 <- n * temp -3
 kurt2 <- n*(n+1)*(n-1)/((n-2)*(n-3))*temp - 3*(n-1)^2/((n-2)*(n-3))
 kurt.se <- sqrt(4*(n^2-1)*skew.se^2 / ((n-3)*(n+5)))
 list(skew1=skew1, skew2=skew2, skew.se=skew.se, kurt1=kurt1, kurt2=kurt2, kurt.se=kurt.se)
}
multi.skewkurt<-function (x, na.rm = TRUE){
 x <- as.matrix(x)
 if (na.rm)
   x <- na.omit(x)
   n <- dim(x)[1]
   p <- dim(x)[2]
```

```
  x <- scale(x, scale = FALSE)
  S <- cov(x)*(n-1)/n
 #S.inv <- solve(S)
  S.inv <- ginv(S)
 D <- x %*% S.inv %*% t(x)
 b1p <- sum(D^3)/n^2
 b2p <- tr(D^2)/n
 chi.df <- p * (p + 1) * (p + 2)/6
 k <- (p + 1) * (n + 1) * (n + 3)/(n * ((n + 1) * (p + 1) - 6))
 small.skew <- n * k * b1p/6
 M.skew <- n * b1p/6
 M.kurt <- (b2p - p * (p + 2)) * sqrt(n/(8 * p * (p + 2)))
 p.skew <- 1 - pchisq(M.skew, chi.df)
 p.small <- 1 - pchisq(small.skew, chi.df)
 p.kurt <- 2 * (1 - pnorm(abs(M.kurt)))

 results <- list(n.obs = n, n.var = p, b1p = b1p, b2p = b2p,
               skew = M.skew, small.skew = small.skew, p.skew = p.skew,
                p.small = p.small, kurtosis = M.kurt, p.kurt = p.kurt)
 return(results)
}

mardia<-function(x, na.rm=TRUE){
 if (na.rm)
  x <- na.omit(x)
  n <- dim(x)[1]
  p <- dim(x)[2]

  uni <- function(x){
   n <- length(x)
   xbar <- mean(x)
   m2 <- sum((x-xbar)^2)/n
   m3 <- sum((x-xbar)^3)/n
   m4 <- sum((x-xbar)^4)/n

   skewness <- sqrt(n*(n-1))/(n-2)*m3/m2^1.5
   kurtosis <- (n-1)/((n-2)*(n-3))*((n+1)*(m4/m2^2-3)+6)

   skew.se <- sqrt(6*n*(n-1) / ((n-2)*(n+1)*(n+3)))
   kurt.se <- sqrt(4*(n^2-1)*skew.se^2 / ((n-3)*(n+5)))
   c(skewness, skew.se=skew.se, kurtosis, kurt.se)
 }

 univariate <- apply(x, 2, uni)
 rownames(univariate) <- c('Skewness', 'SE_skew', 'Kurtosis', 'SE_kurt')

 x <- scale(x, scale = FALSE)
```

```
  S <- cov(x)*(n-1)/n
  S.inv <- ginv(S)
  D <- x %*% S.inv %*% t(x)
  b1p <- sum(D^3)/n^2
  b2p <- sum(diag(D^2))/n
  chi.df <- p * (p + 1) * (p + 2)/6
  k <- (p + 1) * (n + 1) * (n + 3)/(n * ((n + 1) * (p + 1) - 6))
  small.skew <- n * k * b1p/6
  M.skew <- n * b1p/6
  M.kurt <- (b2p - p * (p + 2)) * sqrt(n/(8 * p * (p + 2)))
  p.skew <- 1 - pchisq(M.skew, chi.df)
  p.small <- 1 - pchisq(small.skew, chi.df)
  p.kurt <- 2 * (1 - pnorm(abs(M.kurt)))

  multivariate <- rbind(c(b1p, M.skew, p.skew), c(b2p, M.kurt, p.kurt))
  rownames(multivariate) <- c('Skewness', 'Kurtosis')
  colnames(multivariate) <- c('b', 'z', 'p-value')

  results <- list(n.obs = n, n.var = p, univariate = univariate, multivariate=multivariate)

  cat('Sample size: ', n, "\n")
  cat('Number of variables: ', p, "\n\n")

  cat("Univariate skewness and kurtosis\n")
  print(t(univariate))

  cat("\nMardia's multivariate skewness and kurtosis\n")
  print(multivariate)
  cat("\n")

  invisible(results)
}
mardia(Model_variables)
```

Measurement model assessment R Code

```
library(lavaan)
cfa.model2.2 <-
  '
Effo.Expectancy =~  EE2 + EE3 + EE4
Hedo.motivation =~ HM1 + HM3 + HM4
Social.influnce =~ SI1 + SI2 + SI3 + SI4
Perc.Safety     =~ PS1 + PS2 + PS4
Behav.intention =~ BI1 + BI3 + BI4
COVID_19_imp    =~ CO2 + CO3 + CO4 +CO5
Time_credit_int =~ TC1 + TC2 + TC3
'
```

```
fit2.2 <- cfa(cfa.model2.2, data=Tham_data , estimator = "WLSMV",ordered = TRUE)
summary(fit2.2, fit.measure = TRUE , standardized=TRUE)

cov2cor(lavInspect(fit2.2  , what = "Std.all")$psi)
```

Structural model assessment R Code

```
library(lavaan)
sem.model9 <-
  '
Effo.Expectancy =~ EE2 + EE3 + EE4
Hedo.motivation =~ HM1 + HM3 + HM4
Social.influnce =~ SI1 + SI2 + SI3 + SI4
Perc.Safety     =~ PS1 + PS2 +PS4
Behav.intention =~ BI1 + BI3 + BI4
COVID_19_imp    =~ CO2 + CO3 + CO4 +CO5
Time_credit_int =~ TC1 + TC2 + TC3

Behav.intention ~ Hedo.motivation + Social.influnce +  Perc.Safety + Time_credit_int + COVID_19_imp
'
fitsem9 <- sem(sem.model9, data=Tham_data , estimator = "WLSMV",ordered = TRUE)
summary(fitsem9, fit.measure = TRUE , standardized=TRUE)
```

Measurement invariance assessment R Code

```
library(lavaan)
#### Measurement Invariance for model  by travel mode (active or motorized)

##configural invariance: model fitted for each group separately, without any equality constraints,
##This model allows us to test whether the same factorial structure holds across all groups

cfa.TMmodel2.1 <-
  '
Effo.Expectancy =~  EE2.collapsed  + EE3.collapsed  + EE4.collapsed
Hedo.motivation =~ HM1.collapsed + HM3.collapsed + HM4.collapsed
Social.influnce =~ SI1.collapsed + SI2.collapsed + SI3.collapsed + SI4.collapsed
Perc.Safety     =~ PS1.collapsed + PS2.collapsed  + PS4.collapsed
Behav.intention =~ BI1.collapsed + BI3.collapsed + BI4.collapsed
COVID_19_imp    =~ CO2.collapsed + CO3.collapsed + CO4.collapsed +CO5.collapsed
Time_credit_int =~ TC1.collapsed + TC2.collapsed + TC3.collapsed
'
fitTM2.1 <- cfa(cfa.TMmodel2.1, data=Tham_data , estimator = "WLSMV",ordered = TRUE, group = "Active_modes")
summary(fitTM2.1, fit.measure = TRUE , standardized=TRUE)

##metric invariance: A constrained version of the configural model.
##where the factor loadings are assumed to be equal across groups
```

```
cfa.TMmodel2.3 <-
  '
Effo.Expectancy =~  EE2.collapsed  + EE3.collapsed  + EE4.collapsed
Hedo.motivation =~ HM1.collapsed + HM3.collapsed + HM4.collapsed
Social.influnce =~ SI1.collapsed + SI2.collapsed + SI3.collapsed + SI4.collapsed
Perc.Safety     =~ PS1.collapsed + PS2.collapsed  + PS4.collapsed
Behav.intention =~ BI1.collapsed + BI3.collapsed + BI4.collapsed
COVID_19_imp    =~ CO2.collapsed + CO3.collapsed + CO4.collapsed +CO5.collapsed
Time_credit_int =~ TC1.collapsed + TC2.collapsed + TC3.collapsed
'
fitTM2.3 <- cfa(cfa.TMmodel2.3, data=Tham_data , estimator = "WLSMV",ordered = TRUE, group =
"Active_modes",group.equal = "loadings")
summary(fitTM2.3, fit.measure = TRUE , standardized=TRUE)

summary(compareFit(fitTM2.1, fitTM2.3 ))

##scalar variance: A constrained version of the metric model
##where both the factor loading and intercepts are assumed to be equal across groups

cfa.TMmodel2.4 <-
  '
Effo.Expectancy =~  EE2.collapsed  + EE3.collapsed  + EE4.collapsed
Hedo.motivation =~ HM1.collapsed + HM3.collapsed + HM4.collapsed
Social.influnce =~ SI1.collapsed + SI2.collapsed + SI3.collapsed + SI4.collapsed
Perc.Safety     =~ PS1.collapsed + PS2.collapsed  + PS4.collapsed
Behav.intention =~ BI1.collapsed + BI3.collapsed + BI4.collapsed
COVID_19_imp    =~ CO2.collapsed + CO3.collapsed + CO4.collapsed +CO5.collapsed
Time_credit_int =~ TC1.collapsed + TC2.collapsed + TC3.collapsed
'
fitTM2.4 <- cfa(cfa.TMmodel2.4, data=Tham_data , estimator = "WLSMV",ordered = TRUE, group =
"Active_modes",group.equal = c("loadings","intercepts"))
summary(fitTM2.4, fit.measure = TRUE , standardized=TRUE)

summary (compareFit(fitTM2.3 , fitTM2.4 ))


##strick invariance: A constrained version of the scalar model
##where the factor loadings, intercepts, and residual variances are fixed across groups

cfa.TMmodel2.5 <-
  '
Effo.Expectancy =~  EE2.collapsed  + EE3.collapsed  + EE4.collapsed
Hedo.motivation =~ HM1.collapsed + HM3.collapsed + HM4.collapsed
Social.influnce =~ SI1.collapsed + SI2.collapsed + SI3.collapsed + SI4.collapsed
Perc.Safety     =~ PS1.collapsed + PS2.collapsed  + PS4.collapsed
Behav.intention =~ BI1.collapsed + BI3.collapsed + BI4.collapsed
COVID_19_imp    =~  CO2.collapsed + CO3.collapsed + CO4.collapsed +CO5.collapsed
```

```
Time_credit_int =~ TC1.collapsed + TC2.collapsed + TC3.collapsed
'
fitTM2.5 <- cfa(cfa.TMmodel2.5, data=Tham_data , estimator = "WLSMV",ordered = TRUE, group =
"Active_modes",group.equal = c("loadings","intercepts", "residuals"))
summary(fitTM2.5, fit.measure = TRUE , standardized=TRUE)

summary (compareFit(fitTM2.4 , fitTM2.5 ))
```

Structural model assessment for multigroup analysis R Code

```
library(lavaan)
sem.TMmodel2.4 <-
  '
Effo.Expectancy =~  EE2.collapsed  + EE3.collapsed  + EE4.collapsed
Hedo.motivation =~ HM1.collapsed + HM3.collapsed + HM4.collapsed
Social.influnce =~ SI1.collapsed + SI2.collapsed + SI3.collapsed + SI4.collapsed
Perc.Safety     =~ PS1.collapsed + PS2.collapsed  + PS4.collapsed
Behav.intention =~ BI1.collapsed + BI3.collapsed + BI4.collapsed
COVID_19_imp    =~ CO2.collapsed + CO3.collapsed + CO4.collapsed +CO5.collapsed
Time_credit_int =~ TC1.collapsed + TC2.collapsed + TC3.collapsed

Behav.intention ~ Effo.Expectancy + Hedo.motivation + Social.influnce  + Perc.Safety + Time_credit_int + COVID_19_imp

'
fitTM2.4 <- sem(sem.TMmodel2.4, data=Tham_data , estimator = "WLSMV",ordered = TRUE, group =
"Active_modes",group.equal = c("loadings"))
summary(fitTM2.4, fit.measure = TRUE , standardized=TRUE)
```

Developing interaction terms R Code

```
library(semTools)
DF6<-indProd(Tham_data, var1=c("HM1","HM3","HM4"), var2="Drive.car.to.work", var3 = NULL, match = FALSE, meanC
= FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
DF7<-indProd(Tham_data, var1=c("SI1","SI2","SI3","SI4"), var2="Drive.car.to.work", var3 = NULL, match = FALSE, meanC
= FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
DF8<-indProd(Tham_data, var1=c("EE2","EE3","EE4"), var2="Drive.car.to.work", var3 = NULL, match = FALSE, meanC =
FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
DF9<-indProd(Tham_data, var1=c("PS1","PS2","PS4"), var2="Drive.car.to.work", var3 = NULL, match = FALSE, meanC =
FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
DF10<-indProd(Tham_data, var1=c("CO1","CO2","CO3","CO4","CO5","CO6"), var2="Drive.car.to.work", var3 = NULL,
match = FALSE, meanC = FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
DF11<-indProd(Tham_data, var1=c("TC1","TC2","TC3","TC4","TC5"), var2="Drive.car.to.work", var3 = NULL, match =
FALSE, meanC = FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)

DF12<-indProd(Tham_data, var1=c("HM1","HM3","HM4"), var2="Traveldislessthan5km", var3 = NULL, match = FALSE,
meanC = FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
```

```
DF13<-indProd(Tham_data, var1=c("SI1","SI2","SI3","SI4"), var2="Traveldislessthan5km", var3 = NULL, match = FALSE, meanC = FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
DF14<-indProd(Tham_data, var1=c("EE2","EE3","EE4"), var2="Traveldislessthan5km", var3 = NULL, match = FALSE, meanC = FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
DF15<-indProd(Tham_data, var1=c("PS1","PS2","PS4"), var2="Traveldislessthan5km", var3 = NULL, match = FALSE, meanC = FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
DF16<-indProd(Tham_data, var1=c("CO1","CO2","CO3","CO4","CO5","CO6"), var2="Traveldislessthan5km", var3 = NULL, match = FALSE, meanC = FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
DF17<-indProd(Tham_data, var1=c("TC1","TC2","TC3","TC4","TC5"), var2="Traveldislessthan5km", var3 = NULL, match = FALSE, meanC = FALSE,residualC = FALSE, doubleMC = TRUE, namesProd = NULL)
```

Structural model assessment for model with interaction terms R Code

```
library(lavaan)
sem.TDmodel9.1 <-
  '
#independent variables

Effo.Expectancy =~ EE2 + EE3 + EE4
Hedo.motivation =~ HM1  + HM3 + HM4
Social.influnce =~ SI1 + SI2 + SI3 + SI4
Perc.Safety     =~ PS1 + PS2  + PS4
COVID_19_imp    =~   CO2 + CO3 + CO4 +CO5
Time_credit_int =~ TC1 + TC2 + TC3



#dependent variables
Behav.intention =~ BI1 + BI3 + BI4

#interaction term
int1 =~ HM1.Traveldislessthan5km +  HM3.Traveldislessthan5km + HM4.Traveldislessthan5km
#int2 =~ EE2.Traveldislessthan5km + EE3.Traveldislessthan5km + EE4.Traveldislessthan5km
int3 =~ SI1.Traveldislessthan5km + SI2.Traveldislessthan5km + SI3.Traveldislessthan5km + SI4.Traveldislessthan5km
#int4 =~ PS1.Traveldislessthan5km + PS2.Traveldislessthan5km + PS4.Traveldislessthan5km
#int5 =~ CO2.Traveldislessthan5km + CO3.Traveldislessthan5km + CO4.Traveldislessthan5km +  CO5.Traveldislessthan5km
#int6 =~ TC1.Traveldislessthan5km + TC2.Traveldislessthan5km + TC3.Traveldislessthan5km

#int7 =~ HM1.Drive.car.to.work +  HM3.Drive.car.to.work + HM4.Drive.car.to.work
int8 =~ EE2.Drive.car.to.work + EE3.Drive.car.to.work + EE4.Drive.car.to.work
int9 =~ SI1.Drive.car.to.work + SI2.Drive.car.to.work + SI3.Drive.car.to.work + SI4.Drive.car.to.work
#int10 =~ PS1.Drive.car.to.work + PS2.Drive.car.to.work + PS4.Drive.car.to.work
#int11 =~ CO2.Drive.car.to.work + CO3.Drive.car.to.work + CO4.Drive.car.to.work +  CO5.Drive.car.to.work
int12 =~ TC1.Drive.car.to.work + TC2.Drive.car.to.work + TC3.Drive.car.to.work

#structural model

Behav.intention ~ Effo.Expectancy + Hedo.motivation + Social.influnce + Perc.Safety+ COVID_19_imp + Time_credit_int + int1  + int3  +int8 + int9 + int12  + Traveldislessthan5km + Drive.car.to.work
```

'

```
fitsemTD9.1 <- sem(sem.TDmodel9.1, data=Tham_data , estimator = "WLSMV",ordered =
c("BI1","BI3","BI4","EE2","EE3","EE4","HM1","HM3","HM4","SI1","SI2","SI3","SI4","PS1","PS2","PS4","CO2","CO3","CO
4","CO5","TC1","TC2","TC3"))
summary(fitsemTD9.1, fit.measure = TRUE , standardized=TRUE)
```

APPENDIX E

CORRELATION MATRICES OF MEASURMENT MODELS

Table E.1 Model M2 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	EE	HM	FC	SI	PV	PS	BI	CO	TC
EE	EE2	0.612	1								
	EE3	0.803									
	EE4	0.727									
HM	HM1	0.698	0.734	1							
	HM3	0.874									
	HM4	0.813									
FC	FC1	0.535	0.800	0.705	1						
	FC2	0.666									
	FC4	0.674									
SI	SI1	0.714	0.649	0.745	0.797	1					
	SI2	0.721									
	SI3	0.860									
	SI4	0.661									
PV	PV2	0.534	0.909	0.711	0.910	0.673	1				
	PV3	0.756									
	PV4	0.722									
PS	PS1	0.640	0.818	0.708	0.900	0.715	0.848	1			
	PS2	0.731									
	PS4	0.661									
BI	BI1	0.627	0.815	0.882	0.821	0.843	0.850	0.813	1		
	BI3	0.724									
	BI4	0.793									
CO	CO2	0.784	0.541	0.417	0.520	0.416	0.539	0.503	0.501	1	
	CO3	0.868									
	CO4	0.751									
	CO5	0.647									
TC	TC1	0.746	0.611	0.421	0.638	0.440	0.587	0.526	0.597	0.460	1
	TC2	0.744									
	TC3	0.749									

Iterations: 67 times; Estimator: DWLS; Optimization method: NLMINB

Comparative fit index (CFI) = 0.997

Tucker-Lewis index (TLI) = 0.996

Root mean square error of approximation (RMSEA) = 0.0028

Table E.2 Model M2.1 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	EE	HM	PS	PV	SI	BI	CO	TC
EE	EE2	0.610	1							
	EE3	0.806								
	EE4	0.726								
HM	HM1	0.695	0.732	1						
	HM3	0.883								
	HM4	0.805								
PS	PS1	0.641	0.819	0.708	1					
	PS2	0.725								
	PS4	0.798								
PV	PV2	0.530	0.908	0.711	0.848	1				
	PV3	0.755								
	PV4	0.725								
SI	SI1	0.710	0.649	0.744	0.715	0.673	1			
	SI2	0.724								
	SI3	0.858								
	SI4	0.665								
BI	BI1	0.621	0.814	0.880	0.814	0.848	0.842	1		
	BI3	0.725								
	BI4	0.798								
CO	CO2	0.787	0.541	0.417	0.503	0.539	0.416	0.501	1	
	CO3	0.868								
	CO4	0.747								
	CO5	0.648								
TC	TC1	0.751	0.611	0.422	0.527	0.586	0.41	0.597	0.460	1
	TC2	0.754								
	TC3	0.732								
Iterations: 59 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.996 Tucker-Lewis index (TLI) = 0.996 Root mean square error of approximation (RMSEA) = 0.0029										

Table E.3 Model M2.2 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	EE	HM	FC	SI	PS	BI	CO	TC
EE	EE2	0.603	1							
	EE3	0.817								
	EE4	0.721								

Latent variable	Items	Loadings	EE	HM	FC	SI	PS	BI	CO	TC
HM	HM1	0.705	0.732	1						
	HM3	0.869								
	HM4	0.813								
FC	FC1	0.530	0.797	0.704	1					
	FC2	0.670								
	FC4	0.674								
SI	SI1	0.710	0.648	0.745	0.796	1				
	SI2	0.718								
	SI3	0.859								
	SI4	0.671								
PS	PS1	0.638	0.816	0.707	0.899	0.714	1			
	PS2	0.733								
	PS4	0.661								
BI	BI1	0.623	0.814	0.884	0.821	0.843	0.814	1		
	BI3	0.737								
	BI4	0.784								
CO	CO2	0.791	0.541	0.418	0.521	0.417	0.503	0.502	1	
	CO3	0.870								
	CO4	0.744								
	CO5	0.639								
TC	TC1	0.743	0.610	0.421	0.638	0.440	0.526	0.598	0.452	1
	TC2	0.749								
	TC3	0.746								

Iterations: 52 times; Estimator: DWLS; Optimization method: NLMINB
Comparative fit index (CFI) = 0.997
Tucker-Lewis index (TLI) = 0.997
Root mean square error of approximation (RMSEA) = 0.0024

Table E.4 Model M2.3 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	EE	HM	FC	PV	SI	BI	CO	TC
EE	EE2	0.597	1							
	EE3	0.809								
	EE4	0.733								
HM	HM1	0.701	0.732	1						
	HM3	0.878								
	HM4	0.806								
FC	FC1	0.536	0.799	0.704	1					
	FC2	0.663								

Latent variable	Items	Loadings	EE	HM	FC	PV	SI	BI	CO	TC
	FC4	0.675								
PV	PV2	0.549	0.911	0.712	0.912	1				
	PV3	0.755								
	PV4	0.711								
SI	SI1	0.709	0.648	0.744	0.797	0.674	1			
	SI2	0.723								
	SI3	0.864								
	SI4	0.658								
BI	BI1	0.641	0.815	0.884	0.823	0.855	0.821	1		
	BI3	0.724								
	BI4	0.781								
CO	CO2	0.787	0.541	0.418	0.521	0.540	0.407	0.502	1	
	CO3	0.875								
	CO4	0.747								
	CO5	0.634								
TC	TC1	0.750	0.611	0.421	0.638	0.588	0.407	0.569	0.452	1
	TC2	0.741								
	TC3	0.748								
Iterations: 61 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.997 Tucker-Lewis index (TLI) = 0.996 Root mean square error of approximation (RMSEA) = 0.0028										

Table E.5 Model M2.1.1/M2.2.1 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	EE	HM	PS	SI	BI	CO	TC
EE	EE2	0.599	1						
	EE3	0.821							
	EE4	0.718							
HM	HM1	0.702	0.730	1					
	HM3	0.879							
	HM4	0.805							
PS	PS1	0.638	0.816	0.708	1				
	PS2	0.727							
	PS4	0.667							
SI	SI1	0.705	0.648	0.744	0.715	1			
	SI2	0.721							
	SI3	0.856							
	SI4	0.677							

Latent variable	Items	Loadings	EE	HM	PS	SI	BI	CO	TC
BI	BI1	0.615	0.812	0.873	0.814	0.842	1		
	BI3	0.739							
	BI4	0.789							
CO	CO2	0.794	0.541	0.418	0.503	0.418	0.502	1	
	CO3	0.870							
	CO4	0.740							
	CO5	0.639							
TC	TC1	0.748	0.610	0.422	0.527	0.441	0.598	0.452	1
	TC2	0.762							
	TC3	0.727							
Iterations: 51 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.998 Tucker-Lewis index (TLI) = 0.997 Root mean square error of approximation (RMSEA) = 0.0024									

Table E.6 Model M2.1.2 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	HM	PS	PV	SI	BI	CO	TC
HM	HM1	0.700	1						
	HM3	0.871							
	HM4	0.814							
PS	PS1	0.635	0.707	1					
	PS2	0.738							
	PS4	0.658							
PV	PV2	0.528	0.711	0.847	1				
	PV3	0.748							
	PV4	0.734							
SI	SI1	0.721	0.745	0.714	0.673	1			
	SI2	0.716							
	SI3	0.856							
	SI4	0.664							
BI	BI1	0.618	0.882	0.813	0.846	0.843	1		
	BI3	0.728							
	BI4	0.797							
CO	CO2	0.796	0.419	0.503	0.540	0.418	0.502	1	
	CO3	0.879							
	CO4	0.728							
	CO5	0.629							
TC	TC1	0.763	0.422	0.526	0.587	0.441	0.597	0.461	1

Latent variable	Items	Loadings	HM	PS	PV	SI	BI	CO	TC
	TC2	0.738							
	TC3	0.738							
Iterations: 58 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.997 Tucker-Lewis index (TLI) = 0.996 Root mean square error of approximation (RMSEA) = 0.0027									

Table E.7 Model M2.2.2 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	EE	HM	FC	SI	BI	CO	TC
EE	EE2	0.583	1						
	EE3	0.826							
	EE4	0.727							
HM	HM1	0.709	0.730	1					
	HM3	0.873							
	HM4	0.806							
FC	FC1	0.530	0.795	0.704	1				
	FC2	0.668							
	FC4	0.676							
SI	SI1	0.704	0.648	0.744	0.796	1			
	SI2	0.719							
	SI3	0.864							
	SI4	0.669							
BI	BI1	0.639	0.814	0.887	0.823	0.844	1		
	BI3	0.739							
	BI4	0.769							
CO	CO2	0.793	0.540	0.419	0.522	0.418	0.503	1	
	CO3	0.877							
	CO4	0.740							
	CO5	0.624							
TC	TC1	0.747	0.609	0.421	0.638	0.440	0.598	0.461	1
	TC2	0.747							
	TC3	0.744							
Iterations: 59 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.997 Tucker-Lewis index (TLI) = 0.997 Root mean square error of approximation (RMSEA) = 0.0025									

Table E.8 Model M2.3.1 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	EE	HM	FC	SI	BI	CO	TC
EE	EE2	0.583	1						
	EE3	0.826							
	EE4	0.727							
HM	HM1	0.709	0.730	1					
	HM3	0.873							
	HM4	0.806							
FC	FC1	0.530	0.795	0.704	1				
	FC2	0.668							
	FC4	0.676							
SI	SI1	0.704	0.648	0.744	0.796	1			
	SI2	0.719							
	SI3	0.864							
	SI4	0.669							
BI	BI1	0.639	0.814	0.887	0.823	0.844	1		
	BI3	0.739							
	BI4	0.769							
CO	CO2	0.793	0.540	0.419	0.522	0.418	0.503	1	
	CO3	0.877							
	CO4	0.740							
	CO5	0.624							
TC	TC1	0.747	0.609	0.421	0.638	0.440	0.598	0.461	1
	TC2	0.747							
	TC3	0.744							
Iterations: 59 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.997 Tucker-Lewis index (TLI) = 0.997 Root mean square error of approximation (RMSEA) = 0.0025									

Table E.9 Model M2.3.2 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	HM	FC	PV	SI	BI	CO	TC
HM	HM1	0.708	1						
	HM3	0.864							
	HM4	0.816							
FC	FC1	0.525	0.704	1					

Latent variable	Items	Loadings	HM	FC	PV	SI	BI	CO	TC
	FC2	0.672							
	FC4	0.677							
PV	PV2	0.551	0.713	0.910	1				
	PV3	0.749							
	PV4	0.716							
SI	SI1	0.719	0.745	0.795	0.674	1			
	SI2	0.715							
	SI3	0.864							
	SI4	0.656							
BI	BI1	0.642	0.887	0.822	0.855	0.845	1		
	BI3	0.727							
	BI4	0.777							
CO	CO2	0.795	0.420	0.522	0.540	0.419	0.504	1	
	CO3	0.887							
	CO4	0.727							
	CO5	0.614							
TC	TC1	0.764	0.421	0.639	0.588	0.439	0.598	0.461	1
	TC2	0.723							
	TC3	0.755							
Iterations: 53 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.997 Tucker-Lewis index (TLI) = 0.996 Root mean square error of approximation (RMSEA) = 0.0027									

Table E.10 Model M2.3.3 output (factor ladings and correlations between latent variables)

Latent variable	Items	Loadings	EE	HM	PV	SI	BI	CO	TC
EE	EE2	0.594	1						
	EE3	0.813							
	EE4	0.732							
HM	HM1	0.699	0.730	1					
	HM3	0.889							
	HM4	0.797							
PV	PV2	0.547	0.910	0.712	1				
	PV3	0.755							
	PV4	0.714							
SI	SI1	0.704	0.648	0.743	0.673	1			
	SI2	0.726							
	SI3	0.863							

Latent variable	Items	Loadings	EE	HM	PV	SI	BI	CO	TC
	SI4	0.662							
BI	BI1	0.636	0.814	0.882	0.854	0.844	1		
	BI3	0.725							
	BI4	0.785							
CO	CO2	0.790	0.541	0.417	0.540	0.417	0.502	1	
	CO3	0.874							
	CO4	0.743							
	CO5	0.634							
TC	TC1	0.757	0.610	0.422	0.587	0.441	0.598	0.460	1
	TC2	0.753							
	TC3	0.729							
Iterations: 61 times; Estimator: DWLS; Optimization method: NLMINB Comparative fit index (CFI) = 0.997 Tucker-Lewis index (TLI) = 0.996 Root mean square error of approximation (RMSEA) = 0.0028									

APPENDIX F
MEASUREMENT INVARIANCE RESULTS ACROSS DIFFERENT GROUPS

Table F.1 Test of measurement invariance for gender (Female/ male) group

Model	Chi-Square	DF	CFI	TLI	RMSEA	Chi-square test (P value)
Configural model*	497.976	418	0.974	0.969	0.036	-
Metric model*	517.365	434	0.973	0.969	0.034	0.1415
Scalar model*	532.988	450	0.973	0.970	0.035	1.000
Strict model*	532.988	450	0.973	0.970	0.035	1.000
DF: Degrees of freedom, CFI: Comparative Fit Index, Tucker-Lewis index (TLI), Root Mean Squared Error of Approximation (RMSEA) *High correlation between latent variables exist for group 2 (male)						

Table F.2 Test of measurement invariance for travel distance (Less than 5km/ higher than 5km) group

Model	Chi-Square	DF	CFI	TLI	RMSEA	Chi-square test (P value)
Configural model*	503.116	418	0.971	0.965	0.036	-
Metric model*	498.679	434	0.978	0.975	0.031	0.710
Scalar model*	526.782	450	0.974	0.971	0.035	1.000
Strict model*	526.782	450	0.974	0.971	0.035	1.000
DF: Degrees of freedom, CFI: Comparative Fit Index, Tucker-Lewis index (TLI), Root Mean Squared Error of Approximation (RMSEA) *High correlation between latent variables exist for group 2 (travel distance higher than 5km)						

Table F.3 Test of measurement invariance for drive car (yes/no) group

Model	Chi-Square	DF	CFI	TLI	RMSEA	Chi-square test (P value)
Configural model*	492.398	418	0.973	0.968	0.034	-
Metric model*	504.180	434	0.975	0.971	0.033	0.342
Scalar model*	530.400	450	0.971	0.968	0.034	1.000
Strict model*	530.400	450	0.971	0.968	0.034	1.000
DF: Degrees of freedom, CFI: Comparative Fit Index, Tucker-Lewis index (TLI), Root Mean Squared Error of Approximation (RMSEA) *High correlation between latent variables exist for group 2 (travel distance higher than 5km)						