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What motivates the use of shared mobility systems and their integration with public transit? Evidence from a choice experiment study

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ABSTRACT

Shared mobility, including bike-sharing, shared e-scooter, and ride-hailing, could improve transportation sustainability when substituting private car use and integrating with public transit. However, if shared mobility competes with other green modes, it cannot guarantee sustainability benefits. The competing and synergistic relationships between conventional modes and shared mobility are complex and not well-studied to date. Understanding users' preferences in mode choice decisions among shared mobility, conventional modes, and multimodal systems can help better evaluate the impact of shared mobility adoption and support related policies. This paper presents the design and results of a stated-preference choice experiment study conducted in Indianapolis, Indiana. An integrated choice and latent variable (ICLV) model was estimated to identify attributes that affect travelers' mode choices for both non-commuting and commuting purposes. Results show that (1) travel cost and travel time are significant variables and their impact on mode choice for system integration and competition is elastic; and (2) user heterogeneity can be observed through three latent variables (perceptions of shared mobility, travel attributes importance, and social values) to identify traveler's preferences and concerns for mode choice. The contributions from this study include: (1) developing quantitative models to estimate mode choice behavior with regard to shared mobility use, and (2) identifying a set of policy guidelines for system development to encourage multimodal usage and decrease car dependency.

1. Introduction

Shared mobility, viewed as part of a sustainable transportation system, has become widespread globally in the past decade (Deka, 2019; Shaheen et al., 2016). Shared mobility commonly includes shared micro-mobility (e.g., bike-sharing, shared e-scooter) and ride-hailing systems (Shaheen et al., 2019). Shared micro-mobility systems launch bikes or e-scooters as shared fleets to allow users to ride for a short time without having to own a bike or e-scooter. Ride-hailing systems allow users to use a smartphone-based app for hailing a car ride. In the United States (U.S.), over 200 cities are operating shared micro-mobility systems with 150 thousand shared fleets, and

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174 cities are providing ride-hailing services operated by multiple companies (Diao et al., 2021; NABSA, 2021). The motivation for many cities to offer shared mobility services is to benefit urban transportation sustainability, such as relieving traffic congestion, reducing fossil consumption and greenhouse gas (GHG) emissions, and offering equitable and affordable mobility options (Jiao and Wang, 2021; Qian et al., 2020).

How shared mobility affects transportation sustainability is still unclear, due to its complex competing and synergistic relationship with conventional transportation systems. The competing effect (i.e., mode substitution) occurs when a traveler shifts the mode choice from conventional modes (private cars, public transit, and walking) to shared mobility. On the other hand, by solving the first-mile/last-mile issue, shared mobility can also be integrated with public transit to provide a synergistic effect as a multimodal system. The different competing and synergistic roles may lead to diverse sustainability impacts. If shared mobility competes with other green transportation modes (e.g., public transit and walking), it may not bring any sustainability benefits. Survey studies on the bike-sharing systems in Washington, D.C., Lyon, France; Dublin, Ireland; and Minneapolis, Minnesota revealed that 14 % to 50 % of users shifted from public transit, and 31 % to 66 % replaced walking with bike-sharing trips (Fishman et al., 2013). Shared mobility system usage data analysis also showed that increased demand for shared e-scooter and ride-hailing services could lead to significant bus ridership reduction, indicating the potential competing relationship between the two services (Grahn et al., 2021; Luo et al., 2021). Replacing public transit or walking with shared mobility cannot reduce the vehicle-miles-traveled (VMT), instead may increase vehicle usage (e.g., from shared fleet rebalancing with trucks), energy consumption (e.g., battery charging), and GHG emissions (Fishman et al., 2014; Luo et al., 2019; Severengiz et al., 2020). Therefore, achieving sustainability advantages through shared mobility hinges on its ability to substitute car journeys or seamlessly integrate within the existing public transit framework. A survey study of the shared e-scooter system in Portland, Oregon showed that about 40 % of e-scooter trips were estimated to have shifted from cars, which resulted in a decrease of 415,286 car miles (Portland Bureau of Transportation, 2020). In addition, about 8 % of users reported that they rode shared e-scooters as a first-mile/last-mile connection with public transit. The multimodal system can extend the service of the existing public transit system to serve more people. The improved accessibility can further encourage mode shift from private car to public transit. Given both negative and positive impacts from potential competing and synergistic effects, simply having a shared mobility system cannot guarantee to yield sustainability benefits. Transportation planners need guidance on how to deploy and regulate these services to achieve those potential benefits from car replacement and mode integration, and to avoid the competition with green transportation modes. This would require a comprehensive understanding of the travel behavior changes, considering both the mode substitution and integration effects between shared mobility and conventional systems.

Discrete travel mode choice analysis has been widely used to support policies for shared mobility systems by estimating travel behavior and quantifying influence factors (Etzioni et al., 2021). However, existing mode choice studies on shared mobility have limitations and cannot fully shed light on the complex interactions between shared mobility and conventional transportation systems, and the corresponding impacts on sustainability (detailed discussion in Section 2). First, current literature mainly investigates only one side of the effect, either mode substitution or mode integration. However, the complex interactions between shared mobility and conventional modes could generate mixed impacts on the urban transportation system, which require a holistic estimation. Second, current studies mainly focused on only one type of shared mobility service, ignoring the co-existence of different types of shared mobility services in a city. The areas with overlapping services (e.g., downtown) could exist competition among different shared mobilities and affect travelers' mode choices.

In view of the above research gaps, this paper presents the design and results of a stated-preference (SP) survey on users' mode choice among three shared mobility systems (bike-sharing, shared e-scooter, and ride-hailing), conventional modes (walking, bus, and private car), and multimodal systems (different shared mobility services connected with bus) via a set of mode choice experiments. We distributed the SP survey in Indianapolis, Indiana to study the mode choice behavior subject to the availability of shared mobility. Accounting for different travel behaviors for different trip purposes, choice experiments for the commuting trip case and non-commuting trip case were separately conducted. We also built a discrete choice model to identify the key factors that could shift trips from cars to shared mobility services, and the drivers that encourage the integration between shared mobility and public transit as a multimodal system.

This study mainly has two contributions. First, we developed mode choice model that can estimate the determinants that affect travelers' choices. The utility derived for each travel mode can provide crucial methodological support for modelers to update the mode choice process in travel demand forecasting, accounting for the impacts of emerging shared mobilities. Second, analysis from this study can help understand the sustainability impacts of the existing shared mobility adoption. As more cities are incorporating shared mobility into their strategic planning, insights from this study can inform policymakers, urban planners, and transportation agencies to design policies that could encourage multimodal usage and reduce car dependence towards a more sustainable transportation system.

2. Literature review

This section reviews existing literature that investigates the competing and synergistic relationship between shared mobility and conventional transportation systems. Section 2.1 discusses studies examining historical usage of these systems and provides evidence of the complex mode substitution and integration effects of different shared mobility systems. Section 2.2 presents a summary of previous work employing discrete choice methods to understand travelers' decision rules on travel mode choice and estimate shared mobility's impact on conventional systems. Detailed research gaps and motivations of this work are discussed in Section 2.3.

2.1. Relationship between shared mobility and conventional transportation systems based on historical data

2.1.1. User survey studies

Many researchers, private companies, and city governments are interested in evaluating the type of relationship (i.e., competing or synergistic) between shared mobility and conventional transportation systems. To achieve this, user surveys have been designed to inquire about users' substitution and integration usage frequencies and assess this relationship based on descriptive statistics.

Evidence from bike-sharing and shared e-scooter user surveys have shown both competing and synergistic relationships with different conventional modes. Shaheen et al. (2013) distributed a survey to bike share users in four North American cities to analyze the mode shift patterns. They found that about 17 % to 47 % of respondents claimed that they used bus less often as a result of bike-sharing, while only 2 % to 14 % claimed more frequent use. Although many respondents strongly agreed that bike-sharing was an enhancement to the local public transportation system, the generally decreased frequency of transit usage showed that the competing relationship between bike-sharing and public transport overweighed the synergistic relationship. However, on the other hand, in all four cities, there was an evident decrease in car driving frequency, indicating the potential of bike-sharing to substitute vehicle trips and the sustainability benefits of urban transportation. Such mixed mobility impacts were also found in different shared mobility systems in other cities. North American Bikeshare & Scootershare Association (NABSA) conducted user surveys in 17 U.S. shared micro-mobility systems. They found that, on average, about 36 % of shared micro-mobility trips were to replace car trips, while 29 % and 22 % of trips replace walking and transit use, respectively (NABSA, 2021). They also found that 16 % of riders used shared micro-mobility to connect to transit on their last trip. Although the degree varies, shared micro-mobility was generally observed to have both mode substitution and integration effects in different cities (Arlington County Commuter Services, 2018; LDA Consulting, 2013; NACTO, 2019; Portland Bureau of Transportation, 2018; The City of Austin Transportation, 2019).

User survey studies on ride-hailing mainly revealed the mode substitution impacts with limited mode integration benefits. Ride-hailing user surveys in seven major U.S. cities concluded that the mode substitution rate is 40 % from car, 15 % from transit, and 24 % from walking/biking, while only 3 % of respondents claimed that they increased their usage of heavy rail after the adoption of ride-hailing service (Clewlow and Mishra, 2017). Although many studies have assessed the feasibility of connecting ride-hailing with public transit for multimodal usage (Liu et al., 2019; Ma, 2017), obstacles still exist for mode integrations, such as uncertain waiting time for both ride-hailing and transit vehicles, inconvenience from mode transfers, and service reliability (Wang et al., 2019).

The existing user survey studies and corresponding descriptive statistics illustrate that different shared mobility systems may have different patterns of competing and synergistic relationships, resulting in mixed impacts on transportation sustainability. To encourage car users to shift to shared mobility and to better connect shared mobility with transit in the future, it is critical to understand the rationales behind different usage patterns. Only knowing the current system use pattern without understanding the causes, user survey studies might not be adequate to guide policymaking to improve shared mobility's sustainability benefits.

2.1.2. Studies based on ridership data

With the support of GPS devices and other information and communications technologies used in shared mobility systems, the availability of ridership data (trip information such as Origin-Destination locations and time) enables researchers to conduct statistical modeling to understand the competing and synergistic relationships at trip-level and investigate the rationale behind these patterns. Analyzing the bus ridership changes before-and-after shared e-scooter systems were launched using a Difference-in-Differences (DID) model, Luo et al. (2021) found that bus ridership significantly dropped at stops with more competing e-scooter trips, indicating the mode substitution patterns and competing relationship. Similar results were documented by Ziedan et al. (2021). The authors estimated a fixed effects regression model between bus ridership and e-scooter trips in Nashville, Tennessee, and found that utilitarian e-scooter trips (e.g., longer trips in downtown during weekdays) were associated with a 0.94 % bus ridership reduction, while social e-scooter trips (e.g., trips in restaurant areas during weekend evenings) can increase bus ridership by 0.86 % (Ziedan et al., 2021). A similar analysis between bike-sharing trip count and bus ridership in Chengdu, China found that the bike-sharing system increased bus ridership on weekdays, indicating the potential mode integration benefits, while negatively affecting the ridership on the weekends (Ma et al., 2019). These statistical studies quantified the impacts of shared mobility and provided insights on the trip factors (e.g., trip location, time, purpose) and urban characteristics (e.g., built environment and weather) that lead to mode substitution and integration impacts. For ride-hailing, Diao et al. (2021) conducted a national-level analysis to evaluate the impacts of ride-hailing system by comparing public transit ridership in U.S. Metropolitan Statistical Areas (MSAs) with and without ride-hailing services. Results show that the entry of ride-hailing services may reduce public transit ridership by 8.9 %, and MSAs with a lower gross domestic product (GDP) and smaller populations encountered a higher transit substitution rate. Similar conclusion was reported in a study in Pittsburgh, which identified the impacts of ride-hailing trip count on bus ridership via a regression model (Grahn et al., 2021). The authors found that bus boarding significantly dropped when there was high ride-hailing usage during evening hours or on low-temperature days.

Shared mobility ridership analysis can investigate the correlation between competing or synergistic relationships and external characteristics (e.g., socioeconomic and built environment) that may cause the patterns. Based on real-world historical data, these studies provide valuable estimations of shared mobility's impacts on other modes. However, given that shared mobility is an emerging transportation system and in rapid development, it may not be appropriate to use the results based on historical systems to forecast the future and inform policies. System changes, such as the spatial expansion of service regions, price reduction, and infrastructure development, could change travelers' behaviors leading to different mode substitution and integration patterns. Therefore, scientific knowledge of user preferences across different modes is imperative to help planners and decision-makers to evaluate what policies are beneficial for urban transportation sustainability and what the potential impacts are in future shared mobility developments.

2.2. Mode choice studies of shared mobility

Discrete mode choice studies usually design choice experiments surveys and ask respondents to choose between different transportation modes under different hypothetical travel conditions, such as travel time, travel cost, built environment, and infrastructure. Discrete choice models have been widely applied to study traveler's mode preference, travel demand forecasting, and transportation planning. By analyzing the SP choice experiment survey responses, researchers can measure travelers' decision-making rules with utility theory to identify the important factors and trade-offs among multiple attributes that affect mode choice. Such models not only can estimate how people make choices under the existing transportation system development, but also can inform how they would change their choices in the future when the influencing attributes change. Hence, many researchers have conducted mode choice analyses to identify the factors that would change travelers' choice decisions between shared mobility and conventional transportation modes, which can inform the potential mobility impacts of shared mobility on conventional systems.

The existing mode choice studies in the context of shared mobility have mainly focused on the mode substitution between shared mobility and conventional modes, while less attention has been paid to multimodal usage. Shen et al. (2020) estimated a nested-logit model using mode choice survey data in Nanjing, China to examine mode choice decisions between ride-hailing and conventional models (bus, subway, and private car). They found that the probability of choosing ride-hailing increased during peak hours, compared with transit and private car, due to the over-crowded transit service and traffic congestion. Shi et al. (2021) also examined the substitution of ride-hailing for conventional travel modes (car, transit, walking, bike, and taxi) based on a travel survey in Chengdu, China. They found that about 50 % of respondents stated that they would replace sustainable modes (e.g., bike, walking, public transit) with ride-hailing. Reck et al. (2022) estimated the mobility impacts between bike-sharing (e-bike) and shared e-scooter on conventional transportation modes (personal bike/scooter, public transit, and car) in Zurich, Switzerland, by comparing the mode choice between the observed choice (tracked by GPS) and other available modes (non-chosen alternatives). Their results also suggested that docked shared micro-mobility was preferred for commuting purposes and the docking infrastructure could be an important factor that makes shared micro-mobility more attractive and replacing private car trips. Campbell et al. (2016) conducted an SP choice experiment and analyzed the factors that would trigger the mode choice shift from conventional modes (bus, subway, car, bike, and walking) to bike-sharing (pedal bike and e-bike) using a multinomial logit (MNL) model. They found that shifting from conventional modes to bike-sharing was more likely for short-distance trips, and the lower trip cost was found to be insignificant in attracting riders to shift to bike-sharing. Recent advancements in developing Mobility-as-a-service (MaaS) platforms can inform travelers with more emerging mobility options. Existing studies on mode choice decision with the assistance of MaaS also examined how travel cost, time, and attitudinal variables could affect traveler's decision among public transit, car, and shared mobility (Hensher et al., 2021; Ho et al., 2020; Kim et al., 2021; Vij et al., 2020). However, their empirical studies did not take the multimodal services with different transit feeders into their choice experiment. The above discussed mode choice studies estimated the factors of mode substitution effects of shared mobility on different conventional modes. Their results can provide insights into critical policies to encourage shared mobility to replace private car trips. However, as discussed in Section 2.1, shared mobility has both mode substitution and integration effects. Without including multimodal service (different shared mobilities serving as the first-/last-mile connection with public transit) as alternative mode options in the mode choice studies, the mobility impacts from mode integration cannot be well-estimated.

With the interest of understanding the mode integration benefits from shared mobility, many studies also conducted discrete choice analysis on the multimodal system. Liu et al. (2022) designed a choice experiment survey that estimated the mode choice between bus and bike-sharing as the feeder options for urban rail system. They found that bike lane infrastructure, especially with isolation belts from the motorway, was the key factor that could encourage bike-sharing to serve as a feeder for the urban rail system. Yan et al. (2019) combined SP and revealed preferences (RP) surveys to estimate the commuting mode choice between a multimodal system (ride-hailing with bus) and conventional modes (walking, bike, car, bus). Their results showed that the transfer requirement (park and ride) and the additional passenger pick-ups (i.e. ride-hailing vehicles to pick up additional passengers for a shared ride) were the main deterrents for multimodal use. Reducing the waiting time for ride-hailing vehicles was argued as the key factor in improving multimodal usage.

Existing mode choice studies of multimodal systems often investigate the impacts of one single shared mobility, without considering the co-existence of multiple shared mobility systems and the impacts of their competition in serving as transit feeders. However, studies have already pointed out the potential competition between different shared mobility modes due to their overlapping service areas (Guo and Zhang, 2021; Mckenzie, 2019; Reck et al., 2021). The competition among different shared mobility systems can affect not only the mode choice for mono-modal, but also the choice of feeder for transit. The competition cannot be neglected when analyzing the mode choice and potential impacts of multimodal systems on urban mobility.

2.3. Research gaps and motivation

Sections 2.1 and 2.2 discuss the existing literature that studies the competing and synergistic relationships between shared mobility and conventional transportation systems. The literature review points out several limitations of the existing studies. First, studies based on historical system use, either from user surveys or revealed ridership data, only estimated the impacts based on the current shared mobility system setting and cannot provide insights for future sustainable development and potential impacts when the system setting changes. Second, existing SP mode choice studies on shared mobility not only lack a holistic view of both competing and synergistic impacts in their mode choice analysis, but also, they ignore the potential competition among different shared mobility systems. A mode choice study of shared mobility which considers both substitution and integration effects on conventional systems, as well as the transit feeder competitions between different shared mobility systems, is needed to comprehensively estimate the competing and synergistic impacts. To address this research gap, this study designed and distributed such a choice experiment survey in Indianapolis. Based on the collected survey data, we built an integrated choice and latent variable (ICLV) model to estimate the factors that affect travelers' mode choice between shared mobility, conventional modes, and multimodal systems considering different trip purposes and trip distances.

3. Choice experiment survey

We designed an SP choice experiment survey to evaluate the factors influencing the choice of travel mode to complete a certain trip and distributed it in Indianapolis. The existing literature on shared mobility has primarily concentrated on major metropolises, such as Chicago, D.C., and New York City. However, most of the 200-plus American cities that have implemented shared mobility systems are not considered large cities (Diao et al., 2021; North American Bikeshare & Scootershare Association, 2020). Travel patterns in these smaller cities differ significantly from their larger counterparts due to a range of factors, including the built environment, automobile ownership rates, public transit availability, and road density. However, very few existing studies focused on understanding shared mobility and multimodal behaviors in cities of that size. Indianapolis is a typical mid-sized city with a heavy dependence on automobiles and limited public transportation options compared to large cities. It exemplifies the transportation infrastructure and urban planning of many cities in the U.S.

The alternative mode options include shared mobility (bike-sharing, shared e-scooter, and ride-hailing), conventional modes (walking, private car, and public transit), and multimodal options (different shared mobility systems as a feeder for public transit). The survey includes four sections: 1) Choice experiment, 2) General travel behavior, 3) User opinions on shared mobility, and 4) Sociodemographic information. In this section, we introduce the survey design (Section 3.1), present the collected survey data (Section 3.2), and discuss the descriptive statistics of the collected data (Section 3.3) and results of the factor analysis (Section 3.4).

3.1. Survey design

To evaluate travel behaviors under different trip purposes, our survey included two different choice experiments: a non-commuting trip and a typical commuting trip. We separated the trip purposes because some studies found a strong association between shared mobility and recreational use (Caspi et al., 2020), while others found shared mobility is mainly used for commuting (Chicco and Diana, 2022; Mckenzie, 2019). Trip purposes would also affect trip characteristics such as trip duration (Yang et al., 2021), speed (Almannaa et al., 2020), and temporal distribution (Liu and Lin, 2022). Therefore, having separate choice experiments for commuting and non-commuting trips can better capture the mode choice rules for different trip purposes given that they could have a multitude of unique characteristics that can significantly impact an individual's mode choice decision (Barry et al., 2002; Hasan et al., 2013).

Furthermore, we utilized a fractional factorial design to determine the choice sets received by participants given the mode alternatives that are presented in Tables 1 and 2. We used JMP 16 (SAS Institute Inc, 2021) to construct an orthogonal design that aimed to minimize correlations between attributes, maintain the independence of main effects, and allow all levels to occur with equal frequency in the choice set. To that end, we generated sixteen different choice sets, which were split into two blocks of eight choice sets each. Ultimately, each participant was asked to answer eight choice sets for each trip purpose, with the aim of avoiding a very lengthy survey. This eventually helped prevent distraction and ensured better performance of respondents while avoiding exhaustion. More details on the choice experiment setting are discussed in Section 3.1.1.

We also asked for the respondents' general travel behaviors, opinions on shared mobility, and their sociodemographic information (Section 3.1.2). Overall, we followed the process in (Hensher et al., 2005) to design the choice experiment while considering many other references (as discussed in the sub-sections). In this regard, several measures were incorporated to mitigate the effects of hypothetical bias. The survey utilized cheap talk (Section 3.1.1) and implemented multiple attention checks to ensure reliability and enhance data quality. The choice experiment also heavily relied on the usage of visual aids and graphics, coupled with statements

Table 1
Attribute values for scenarios in the choice experiment for the non-commuting trip case.

	Mode-specific attributes [a]					
Mode	Cost ($)		In-vehicle time (min)		Out-vehicle time (min)	
Base scenario						
Private car	2		5		7	
Bus	1.75		15		4	
Walking	0		0		23	
Additional scenarios [b]	**Low**	**High**	**Low**	**High**	**Low**	**High**
Base scenario choice	–	–	–	–	–	–
Bike-sharing	3.4	4	16	20	4	6
Shared e-scooter	3.8	5.2	7	15	2	4
Ride-hailing	8	14	4	7	8	10

Notes:
[a] Data sources for the mode-specific attributes are summarized in Supplementary Information (SI) Section S1.
[b] Values are shown to different survey attendees based on the rule of experimental design (Table S-2 in SI).

Table 2
Attribute values for scenarios in the choice experiment for the commuting trip case.

Mode	Mode-specific attributes [a]					
	Cost ($)		In-vehicle time (min)		Out-vehicle time (min)	
Base scenario						
Private car	4.3		14		3	
Bus	1.4		22		21	
Ride-hailing	12		14		7	
Additional scenarios [b]	**Low**	**High**	**Low**	**High**	**Low**	**High**
Bus + Bike-sharing	4	4.6	38	42	4	6
Bus + Shared e-scooter	5.2	6.6	29	37	2	4
Bus + Ride-hailing	6.9	8.9	26	29	8	10

Notes:
[a] Data sources for the mode-specific attributes are summarized in Supplementary Information (SI) Section S1.
[b] Values are shown to different survey attendees based on the rule of experimental design (Table S-2 in SI).

intended to emphasize the influence of the participants' responses on their commuting experience within the city.

3.1.1. Choice experiment setting

The choice experiment examines how changing specific attributes may impact respondents' preferred transportation modes. Acknowledging the potential limitations imposed by personal geographical location and shared mobility availability, respondents in Indianapolis may not have much experience in using shared mobility in their daily lives. Necessary attributes (e.g., trip details, travel time, and cost) may not be available for every respondent. As the goal of the survey was to understand their potential willingness to adopt these services if they were accessible, we asked respondents to imagine a new hypothetical trip involving the availability of shared mobility options. Additionally, each choice experiment began with a cheap talk aiming at minimizing hypothetical bias (Cummings et al., 1995; List et al., 2006). The cheap talk provided a detailed description of the hypothetical trip, including the trip origin/destination, trip distance, and trip purpose (Figures S-1 and S-2 in Supplementary Information (SI) Section S1). For each choice experiment, participants were asked to choose a travel mode that they would use to make the trip.

The choice experiment incorporated three conventional modes, private vehicles, walking, and public transit, that were selected based on their prevalence as the most used travel modes in Indianapolis, as reported by the National Household Travel Survey (Federal Highway Administration, 2017). Furthermore, the experiment considered three prominent shared mobility services that have enjoyed a dated introduction in Indianapolis namely, bike-sharing, shared e-scooter, and ride-hailing. The study did not consider car-sharing services because the primary car-sharing service provider in the city, BlueIndy, discontinued its services in 2020, and Zipcar, a prominent car sharing company, does not operate in the city, making it impractical to include car sharing as an alternative in the study.

To that end, alternative mode options for the non-commuting trip case included conventional modes (private car, walking, and bus) and shared mobility (bike-sharing, shared e-scooter, and ride-hailing), and options for the commuting trip case included single mode (private car, bus, and ride-hailing) and multimodal modes (bus with bike-sharing, shared e-scooter, and ride-hailing as the feeder).

3.1.1.1. Mode choice experiment for non-commuting trip. The choice experiment of the non-commuting trip is based on a one-mile lunch trip in downtown Indianapolis (Table 1). To identify the respondents' original mode choice when shared mobility is unavailable, we first asked respondents to select among conventional modes (marked as the "base scenario"). To understand whether they would shift from conventional modes to shared mobility and how mode-specific attributes (travel time and travel cost) would affect their choice, we then asked the respondents whether they would change their choices from the base scenario decision to different shared mobility options (marked as "additional scenarios"). Each survey respondent would be presented with eight additional scenarios to estimate the trade-offs between different travel cost, in-vehicle time, and out-vehicle time settings.

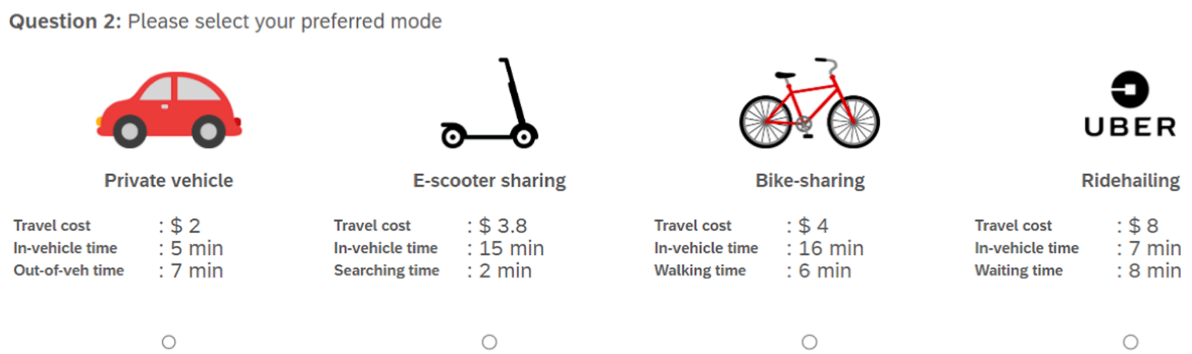

Fig. 1. Example of a non-commuting choice set for an additional scenario.

The settings for eight additional scenarios are based on the rule of factorial design of experiments, with different combinations of low- and high-level values for the mode-specific attributes (Hensher et al., 2005). The mode-specific attribute settings (travel cost and travel time) were estimated based on multiple data sources to reflect real-world travel conditions (Section S1 in SI). The in-vehicle time represents the travel time spent riding/driving a vehicle (e.g., car, bus, bike-sharing, etc.). The out-vehicle travel time mainly covers the connection time, such as the walking time to bike stations, e-scooter/private car pick-up locations, and bus stations, as well as the waiting time for the bus and ride-hailing vehicle. Specifically, we took into consideration the fact that bike-sharing services are typically docked in Indianapolis, while e-scooter sharing services are often dockless, which may affect the out-vehicle times for both services. By assuming shorter out-of-vehicle times for dockless services, we aimed to capture the perceived advantages associated with their flexibility and improved accessibility (Chen et al., 2020). Fig. 1 shows an example of a non-commuting choice set for one of the additional scenarios when the respondent chooses “private car” as the base scenario.

3.1.1.2. Mode choice experiment for commuting trip. Following a similar approach, the choice experiment of the commuting trip case (Table 2) is based on a typical six-mile home-based commuting trip (from a suburb area to downtown Indianapolis). In the base scenario, respondents were given three single-modal options to represent the available options when multimodal service is unavailable. In this regard, we assumed that the bus fare is lower than a one-way trip fare. Travelers who commute by bus are more probable to have a monthly membership, which would lead to a reduced fare per trip compared with those who pay for daily fare. The additional choice sets offered respondents four choice options: using a shared e-scooter along with the bus (bus + shared e-scooter), using bike-sharing along with the bus (bus + bike-sharing), and using ride-hailing along with the bus (bus + ride-hailing), and the mode that they had selected in the base scenario. We did not consider bike sharing and shared e-scooter as a single mode alternative in the commuting trip case due to the trip distance. The existing literature showed that the average trip distance for shared bikes and e-scooters is between 0.8 and 31.5 miles. A study by Mathew (2019) found that the mean trip length of shared e-scooters in Indianapolis is around 1.12 miles (95th percentile equals 3.69 miles). NACTO (2022) also showed a similar mean trip length for station-based bike sharing services (2.4–2.7 miles for casual users). Considering that the 6-mile trip in this scenario is significantly longer than this average distance, it is unlikely that shared bikes or e-scooters alone would be the preferred mode of transportation for such a trip. For more information about survey design please refer to Section S1 in SI. In this scenario, eight additional choice sets were provided to each respondent with various combinations of mode-specific attributes based on the factorial design of experiment to understand the trade-offs between travel cost and time (Table S2 (b)).

3.1.2. Travel behavior and sociodemographic information

Although travel cost and travel time are the most commonly used attributes to estimate the mode choice, existing studies also show that mode choice is also related to an individual’s socioeconomic status and travel preference (e.g., how people care about comfort, safety, and convenience when traveling) (Abe, 2021; Scorrano and Danielis, 2021; Ton et al., 2019). To understand how these attributes would affect mode choice, in the survey, we asked questions about respondents’ general travel preference (e.g., the importance of comfort, convenience, companion, safety, and environmental concern) as well as their sociodemographic information (e.g., gender, age, employment status, income, educational attainment, race, vehicle ownership, and household size). Given that the survey focuses on shared mobility, we designed several opinion questions related to shared mobility, soliciting user perceptions and preferences of different shared mobility benefits and barriers. The influence of perception of benefits and barriers on shared mobility adoption has been previously explored in the literature such as weather (Kimpton et al., 2022; Kutela and Teng, 2019), parking spots (Guo and Zhang, 2021; Loa and Nurul Habib, 2021; Min et al., 2016), and connection to public transit (Godavarthy et al., 2022; Luo et al., 2021; Shi et al., 2021). In addition, we provided questions that investigate reasons that would incentivize respondents to use shared mobility, such as congestion (Weschke et al., 2022), cost (Alimo et al., 2023; Loa and Nurul Habib, 2021), and designated infrastructure (Almannaa et al., 2021; Zhang et al., 2021). Lastly, the survey also asked for reasons that might discourage respondents from using the services, such as technological barriers (i.e., not having access to a smartphone or laptop (Ratan et al., 2021)).

Table 3
Descriptive statistics of social demographic variables (after weighting).

Variable	Value	Response percentage (%)	Response frequency
Gender	Male/Female	46/54	194/226
Age	18–24/25–34/35–44/45–54/55–64/65 and over	12/22/17/16/16/17	50/91/73/68/67/71
Household income	Under $25,000/$25,000-$49,999/$50,000-$74,999/$75,000-$99,999/$100,000-$149,999/$150,000 and over/ Prefer not to answer	14/26/15/15/8/5	60/111/65/65/62/34/23
Employment	Work full time/ Work part time/Homemaker/Student/Unemployed/Retired/Other	47/14/5/5/7/18/4	199/60/19/22/28/75/17
Education level	0: No schooling completed /1: Nursery or preschool through grade 12/2: High school graduate /3: College graduate	1/1/43/55	6/4/180/230
Car ownership	0: No/ 1: Yes	5/95	19/401
Driver’s license	0: No/ 1: Yes	6/94	23/397
Household children count	0: No child/1: One child/2: Two children/3: Three children/4: Four children and more	60/14/17/7/3	252/57/72/28/11

3.2. Survey data

We distributed the online survey in Indianapolis, IN as a case study. Indianapolis is an automobile-oriented city, where people highly rely on private cars for their travel (Federal Highway Administration, 2017). The American Community Survey (ACS) in Indianapolis metropolitan area indicates that the modal split in Indianapolis is highly skewed and that most people (over 90 %) use car for commuting whereas less than 1.5 % use public transportation (U.S. Census Bureau, 2018). To obtain enough observations from public transit and shared mobility users, we used a stratified sampling strategy based on the mode of transportation to work (SI Section S2). We hired a professional company to distribute the online survey to individuals residing in Indianapolis and collected 2430 observations. The data underwent several validity checks to ensure reliability, such as including attention checks in the questionnaire, and applying a strict selection criterion pertaining to completion time, and non-logical and repeated answers. This eventually reduced the final sample size to N = 420 responses. Additionally, because the collected survey data is based on the stratified sampling strategy and might have a bias on the population distribution, the data was weighted to ensure representativeness. The detailed weight values are summarized in SI Section S2. Table 3 shows the sociodemographic distributions of the survey observations after weighting.

3.3. Descriptive statistics of attitudinal statements

The descriptive statistics pertaining to attitudinal statements from the survey (Table 4) can provide insight into both the general travel behavior and opinions regarding shared mobility. Using the results of several statements as attitudinal variables (AV), we can estimate latent class of travelers (further information available in Table 5). In general, it was observed that more than 80 % of respondents indicated they typically do not make transfers in order to complete their journeys. This suggests that multimodal transportation is not a prevalent choice given the current situation of spatial coverage, availability, integration with bus services, and infrastructure of shared mobility. This finding is further substantiated by the fact that 69 % of respondents did not express agreement

Table 4
Descriptive statistics of attitudinal statements (after weighting).

Attitudinal statements	Response percentage (%)	Response frequency
General travel experience		
Have you ever used the bike-sharing service? 0: No/ 1: Yes	84/16	353/67
Have you ever used the shared e-scooter service? 0: No/ 1: Yes	82/18	344/76
Have you ever used the ride-hailing service? 0: No/ 1: Yes	38/62	160/260
Generally, do you make mode transfers (i.e., change mode) to complete your trips? 0: No/ 1: Yes	81/19	340/80
Shared mobility opinion		
AV 1: Respondents who think shared mobility grants them **more options** to travel. Level 1–5: strongly disagree - strongly agree.	12/7/32/34/16	50/29/134/143/67
AV 2: Respondents who think shared mobility can somehow solve the **traffic congestion** issue. Level 1–5: strongly disagree - strongly agree.	16/17/23/29/14	67/71/97/122/59
AV 3: Respondents who think shared mobility would solve the issue of finding a **parking spot**. Level 1–5: strongly disagree - strongly agree.	9/7/20/38/26	38/29/84/160/109
AV 4: Respondents who think shared mobility can make **bus connection** easier. Level 1–5: strongly disagree - strongly agree.	13/10/46/21/10	55/42/193/88/42
AV 5: Respondents who agree or strongly agree that designated **bike lanes** would encourage them to use shared mobility. Level 1–5: strongly disagree - strongly agree.	17/12/29/25/17	71/50/122/105/71
AV6: Respondents who agree or strongly agree that **technology** (Having to deal with a phone application) discourages them from using the shared mobility services	20/14/28/25/13	84/59/118/105/55
AV7: Respondents who agree or strongly agree that having to ride shared mobility on the **sidewalk** discourages them from using the service	14/12/23/36/15	59/50/97/151/63
AV8: Respondents who agree or strongly agree that the **absence of a basket** (or a saddlebag) on a shared micro-mobility discourages me from using the service	14/12/33/25/15	59/50/139/105/63
Travel concern		
AV 9: Importance level of **travel reliability** when choosing a transportation mode. Level 1–5: not at all important – very important.	22/15/22/24/17	92/63/92/101/71
AV 10: Importance level of **travel convenience** when choosing a transportation mode. Level 1–5: not at all important – very important.	2/43/21/8/26	8/181/88/34/109
AV 11: Importance level of **travel comfort** when choosing a transportation mode. Level 1–5: not at all important – very important.	2/10/33/36/19	8/42/139/151/80
AV 12: Importance level of **travel safety** when choosing a transportation mode. Level 1–5: not at all important – very important.	2/3/15/32/49	8/13/63/134/206
AV 13: Importance level of **social image** when choosing a transportation mode. Level 1–5: not at all important – very important.	13/18/37/21/10	55/76/155/88/42
AV 14: Importance level of **environmental concern** when choosing a transportation mode. Level 1–5: not at all important – very important.	5/11/28/30/25	21/46/118/126/105
AV 15: Importance level of **health** when choosing a transportation mode. Level 1–5: not at all important – very important.	37/7/3/18/36	155/29/13/76/151
AV 16: Importance level of **travel companion** when choosing a transportation mode. Level 1–5: not at all important – very important.	22/15/22/24/17	92/63/92/101/71

Table 5
Exploratory Factor analysis.

Attitudinal variables	Short interpretation	LV1: Perceptions of shared mobility	LV2: Travel attributes importance	LV3: Social values
AV1	More options	0.762	–	–
AV2	Avoid congestion	0.655	–	–
AV3	Avoid parking	0.679	–	–
AV4	Bus connection	0.548	–	–
AV5	Bike lanes	0.746	–	–
AV9	Travel reliability	–	0.678	–
AV10	Travel convenience	–	0.707	–
AV11	Travel comfort	–	0.759	–
AV12	Travel safety	–	0.812	–
AV13	Social image	–	–	0.692
AV14	Environment concern	–	–	0.75
Cronbach α		0.731	0.779	0.714

or hold a neutral stance towards shared mobility's ability to enhance their experience with bus services. This result implies that the current bike-sharing and shared e-scooter systems in Indianapolis are not effectively resolving the first-mile/last-mile problem associated with bus transportation. In terms of shared mobility usage experience, a relatively small proportion of individuals (between 16 % and 18 %) had prior experience with bike-sharing or shared e-scooter services, while the majority of respondents (62 %) reported having used ride-hailing services. This could be attributed, at least in part, to the limited spatial coverage of the current bike-sharing and shared e-scooter systems in Indianapolis, which primarily cover the downtown regions while providing limited service in other areas (B-cycle LLC, 2022; Mathew (2019)).

Shared mobility can also bring forth positive impacts on urban mobility. According to the survey, 64 % of respondents expressed agreement with the notion that shared mobility can potentially resolve the issue of parking space scarcity. Utilizing shared mobility options can significantly reduce the time spent searching for parking, thereby enhancing the overall travel experience. Moreover, as shared mobility usage increases and private car usage decreases, the need for parking spaces and garages could decrease in the future, particularly in downtown regions. Furthermore, 43 % of respondents agreed that shared mobility could aid in mitigating traffic congestion and decreasing vehicle mileage, particularly when replacing private car trips. Additionally, 50 % of respondents expressed agreement or strong agreement that shared mobility provides them with more mobility options, making it an essential mode of transportation for those without personal vehicles or residing in transit-desert areas.

3.4. Factor analysis of latent variables

To further understand the heterogeneity of travelers based on these attitudinal variables, we conducted an exploratory factor analysis to identify the potential latent variables. First, we used the principal component analysis (PCA) to extract the factors and we used the Kaiser-Varimax for the rotation approach to maximize the correlations between variables and factors. Second, we only kept

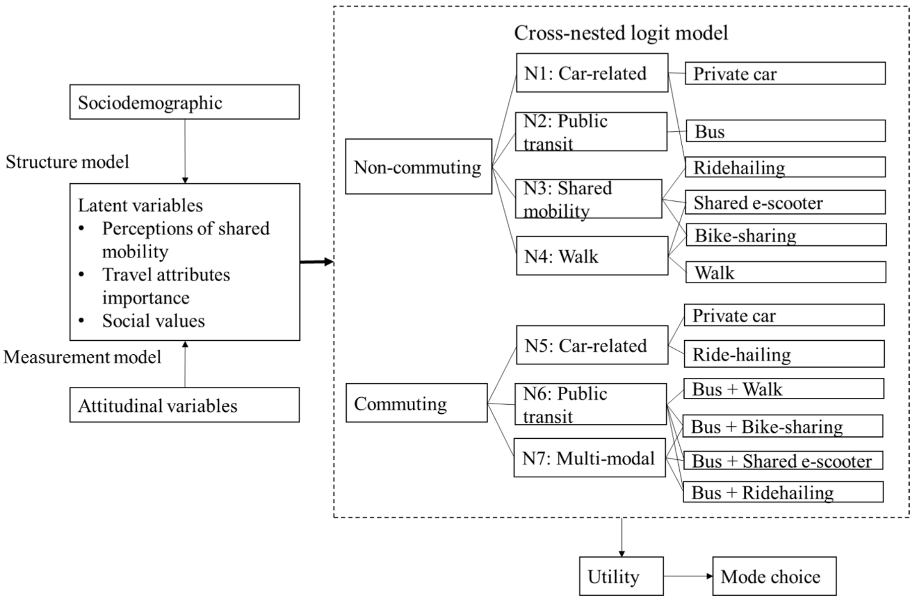

Fig. 2. ICLV-CNL model structure.

the factors with an eigenvalue greater than 1, which resulted in three factors. The cumulative variance explained is 88.5 %, indicating that the selected three factors are good for explaining the data variance. Last, we did a Kaiser-Meyer-Olkin (KMO) test to measure whether our collected indicators are suitable for factor analysis (Cerny and Kaiser, 1977). The KMO value for the indicator variables is 0.828, showing that the data is valid and adequate for exploratory factor analysis.

Table 5 summarizes the results. Based on the factor analysis, we were able to structure three latent variables. The "Perception on shared mobility" variable denotes the satisfaction level of respondents with shared mobility. The "Travel attributes importance" variable indicates the importance of personal travel-related values when choosing a mode of transportation, while "Social value" represents the importance of external factors that can impact mode choice decisions. The factor loading of each attitudinal statement on these three latent variables is presented in the table, indicating the degree of relevance. We removed attitudinal variables with a relevance degree lower than 0.4. Cronbach's alpha is the most commonly used parameter to measure the reliability of survey results and consistency within each latent variable (Cronbach, 1951). Results suggest that these ordered attitudinal variables from survey statements are internally consistent with latent variables at an acceptable level ($\alpha > 0.7$). We integrated the identified latent variables into our discrete choice model (Section 4).

4. Model specification

In this section, we first introduce the modeling technique that we used to estimate the travel mode choice and utility functions (Section 4.1). To support policy implications based on the model results, we then analyzed the critical variables' marginal effects (Section 4.2) and travelers' value of travel time savings (VTTS) (Section 4.3).

4.1. ICLV-CNL for discrete travel mode choice

To understand travelers' travel mode choice behavior, we developed an ICLV (Integrated Choice and Latent Variable) framework based on cross-nested logit (CNL). The ICLV-CNL model comprises a latent variable model with both structural and measurement equations and a discrete choice model (Bhat, 2014). The model framework follows a two-step process, depicted in Fig. 2. The measurement model defines the association between latent variables and attitudinal variables, and we structure the latent variables with sociodemographic attributes with an ordered-probit model (details in Section 4.1.1) to estimate the scale for each latent variable for each traveler. We, then, include the estimated latent variables into the discrete choice model. In this study, we selected the cross-nested logit (CNL) model to formulate the discrete choice with random utility. The logit model, which we have chosen over the traditional multinomial logit (MNL) model, is useful as it relaxes the assumption of independence of irrelevant alternatives (IIA) by grouping several alternatives into nests. This grouping of alternatives can effectively capture the unobservable shared features among alternatives. Moreover, CNL is a more flexible model than nested logit (NL), as it allows for alternatives to be grouped into multiple nests, which can capture the shared features of alternatives under different groups (Verbas et al., 2016). Section 5.1.1 further justifies the selection of this method.

4.1.1. Latent variable structure

Latent variable structure encapsulates the interconnection between unobservable and observable variables. "Perceptions of shared mobility", "Travel attributes importance", and "Social values" are potentially the three unobservable variables that categorize the heterogeneity of travelers. Each of these variables is linked to the observed sociodemographic variables through a structural equation. The latent variable c of traveler n is denoted by α_c^n, which is expressed as a linear formulation:

$$\alpha_c^n = \beta_c^0 + \boldsymbol{\beta}_c \boldsymbol{Z}^n + \varepsilon_c^n \quad (1)$$

where $\boldsymbol{\beta}_c$ is a vector of coefficients to be estimated, β_c^0 is the interception for each latent variable, $\boldsymbol{Z}^n$ is a vector of observed exogenous variables (e.g., sociodemographics), and ε_{kc}^n is the stochastic error term assumed to be normally distributed$\varepsilon_c^n \sim \mathrm{N}(0, \sigma_{\eta c})$.

4.1.2. Latent variable measurement equations

Based on the factor analysis outcomes presented in Table 5, we identified 11 attitudinal variables that will serve as the foundation for our measurement model. Each response to a statement is regarded as an indicator to capture its association with the corresponding latent variables. Instead of relying on linear models, we followed the approach employed in previous studies (Guo et al., 2023; Pan et al., 2019) using an ordered probit model to describe the observed indicator value based on the 5-level response scale for attitudinal statements. The indicator $I_{s,c}^{n*}$, which is linked with the s^{th} attitudinal statement of respondent n and uses the unobservable variable c as an explanatory factor, can be defined as follows:

$$I_{s,c}^{n*} = \beta_{s,c}^0 + \boldsymbol{\beta}_{s,c} \alpha_c^n + \varepsilon_{s,c}^n \quad (2)$$

$$I_{s,c}^{n} = \begin{cases} \eta_{s,c}^{1} if -\infty < I_{s,c}^{n*} < \delta_{s,c}^{1} \\ \eta_{s,c}^{2} if \delta_{s,c}^{1} < I_{s,c}^{n*} < \delta_{s,c}^{2} \\ \eta_{s,c}^{3} if \delta_{s,c}^{2} < I_{s,c}^{n*} < \delta_{s,c}^{3} \\ \eta_{s,c}^{4} if \delta_{s,c}^{3} < I_{s,c}^{n*} < \delta_{s,c}^{4} \\ \eta_{s,c}^{5} if \delta_{s,c}^{4} < I_{s,c}^{n*} < \infty \end{cases} \tag{3}$$

$$P_{s}^{n}\left(I_{s,c}^{n} = \eta_{s,c}^{x}\right) = P\left(\delta_{s,c}^{x-1} < I_{s,c}^{n*} < \delta_{s,c}^{x}\right) \tag{4}$$

where $\beta_{s,c}^{0}$ and $\boldsymbol{\beta}_{s,c}$ are the interception and coefficients to be estimated for attitudinal statement s. The random disturbance term $\varepsilon_{s,c}^{n}$ is assumed to be normally distributed. $I_{s,k}^{n}$ represents the final estimated value ($\eta_{s,c}^{1} \sim \eta_{s,c}^{5}$) for the attitudinal statement s. $\delta_{s,c}^{x-1}$ and $\delta_{s,c}^{x}$ are the two thresholds for the indicator $I_{s,c}^{n*}$ for the ordinal scale calculation, where $\delta_{s,c}^{1}$ is forced to be zero.

4.1.3. Discrete choice model

We formulated the decision rules for model choice model as utility functions:

$$U_{n}(j) = \beta_{j}X_{jn} + \varepsilon_{j}^{n} \tag{5}$$

where the utility $U_{n}(j)$ for each traveler n to choose alternative j can be expressed as exogenous terms X_{jn} (e.g., travel time, travel cost, latent variables, and sociodemographic) that can be observed, and the unobservable error term ε_{j}^{n}. We assume that ε_{j}^{n} is the extreme value following the independent and identical type I distribution based on the formulation of general nested-logit (GNL) for all logit-based models (Wen and Koppelman, 2001). Based on our modeling structure, a two-level CNL can be formulated as:

$$P(j) = \sum_{k \forall K} P(j|k) \times P(k) \tag{6}$$

$$P(j|k) = \frac{\lambda_{jk}^{-\theta_{k}} e^{\frac{\beta_{j}X_{jn}}{\theta_{k}}}}{\sum_{j} \lambda_{jk}^{-\theta_{k}} e^{\frac{\beta_{j}X_{jn}}{\theta_{k}}}} \tag{7}$$

$$P(k) = \frac{\left(\sum_{j} \lambda_{jk}^{-\theta_{k}} e^{\frac{\beta_{j}X_{jn}}{\theta_{k}}}\right)^{\theta_{k}}}{\sum_{K}\left(\sum_{j} \lambda_{jk}^{-\theta_{k}} e^{\frac{\beta_{j}X_{jn}}{\theta_{k}}}\right)^{\theta_{k}}} \tag{8}$$

The probability of choosing alternative j ($P(j)$) depends on the conditional probability of selecting j given the nest k ($P(j|k)$) and the probability of selecting nest k. $\tau_{k} \in [0,1]$ is the scale parameter of nest k. The CNL hypothesizes that each alternative j could be classified into any nested group $k \in K$, with allocation parameters $\lambda_{jk} \in [0,1]$ representing the degree of belongings to group k. We applied the normalization equation$\sum_{k}\lambda_{jk} = 1$ to estimate the allocation parameters. β_{j} is the vector of coefficients to be estimated for mode choice and X_{jn} is a vector of exogenous variables for traveler n to choose alternative j, including trip-specific variables (time and cost), latent variables $I_{s,c}^{n}$, and sociodemographic variables.

We applied Python Biogeme 3.11, an open-source package for discrete choice modeling, to solve the model coefficients with the maximum likelihood method (Bierlaire, 2023).

4.2. Elasticity analysis

To understand which variable influences mode choice decisions more, we also calculated elasticities. With the estimated direct and cross elasticities, we can propose policies to more effectively increase the probability of choosing green travel modes and guide users to shift their travel behavior to more sustainable options. The direct- and cross-elasticity estimation is computed using the following equations (Equations (9) and (10), adapted from (Wen and Koppelman, 2001).

$$e_{x_{j}}^{P(j)} = \frac{\left\{\sum_{k} P(j|k) \times P(k)\left[(1-P(j)) + \left(\frac{1}{\theta_{k}} - 1\right)(1-P(j|k))\right]\right\}}{P(j)}\beta_{j}X_{jn} \tag{9}$$

$$e_{x_j}^{P(j')} = -\left[P(j) + \frac{\sum_k \left(\frac{1}{\theta_k} - 1\right) P(j|k) \times P(k)P(j'|k)}{P(j')}\right]\beta_j X_{jn} \tag{10}$$

The calculated elasticity value roughly means the percentage change of choosing mode j (or j') given a 1 % change of variable x_j. The variable is seen as elastic when the absolute value of the estimated elasticity is greater than 1, which means a small change of the elastic variable on a certain mode could significantly increase or decrease the probability of choosing this mode. In this study, we estimated the elasticities for travel cost, in-vehicle travel time, and out-vehicle travel time because this elasticity estimation method is only applicable to continuous variables.

Table 6a
ICLV-CNL non-commuting trip model estimation.

	Variables	N1: Car-related	N2: Public transit	N3: Shared mobility			N4: Walk
		Private car	Bus	Bike-sharing	Shared e-scooter	Ride-hailing	Walk
		Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
Alternative specific variables	Constant	–	–	-1.745^{***}	–	-2.467^{***}	–
				(−4.71)		(−7.85)	
	Travel cost ($)	-0.051^{**}	-0.039^{**}	-0.048^{***}	-0.054^{**}	-0.056^{***}	–
		(−2.23)	(−2.19)	(−3.56)	(−2.34)	(−4.89)	
	In-vehicle time (min)	−0.012	−0.010	-0.016^{**}	-0.016^{**}	−0.014	–
		(−1.56)	(−1.23)	(−1.98)	(−1.90)	(−1.57)	
	Out-vehicle time (min)	-0.018^{**}	-0.013^{***}	-0.021^{***}	-0.026^{**}	-0.026^{***}	-0.012^{**}
		(−2.37)	(−3.11)	(−3.29)	(−2.02)	(−4.89)	(−2.13)
Latent variables	Perceptions of shared mobility	-0.300^{***}	0.012*	0.934^{***}			–
		(−5.10)	(1.67)	(4.57)			
	Travel attributes importance	1.555^{**}	-0.23^{**}	-0.238^{**}			–
		(1.99)	(−2.15)	(−2.33)			
	Social values	-0.922^{**}	0.864^{***}	0.108*			–
		(−2.52)	(3.27)	(11.65)			
Social-demographic variables	Bachelor's degree (1: yes/ 0:no)	0.248^{***}	-0.127^{**}	-0.152^{***}			–
		(3.07)	(−2.09)	(4.18)			
	Children (1: yes/ 0:no)	0.487^{**}	-0.068^{***}	-0.528^{**}			–
		(2.55)	(−3.09)	(−2.07)			
	Car ownership (1: yes/ 0:no)	0.162^{***}	-0.204^{***}	–			–
		(5.22)	(−3.45)				
	Age < 35 (1: yes/ 0:no)	0.158^{***}	0.149^{***}	0.581^{***}			–
		(3.10)	(2.67)	(2.80)			
	Age > 55 (1: yes/ 0:no)	0.811^{***}	-0.437^{***}	-0.854^{***}			–
		(6.58)	(−2.77)	(−2.75)			
	Male (1: yes/ 0:no)	–	–	0.056^{***}			–
				(4.68)			
	Student (1: yes/ 0:no)	−0.008*	0.367^{**}	0.585^{***}			–
		(−1.75)	(2.11)	(4.11)			
	Driver's license (1: yes/ 0:no)	0.277^{***}	-0.139^{***}	0.182^{***}			–
		(5.14)	(−4.24)	(−2.58)			
	Income < 25 k ($) (1: yes/ 0:no)	−0.396*	0.384^{**}	-0.277^{**}			–
		(−1.91)	(2.52)	(−1.96)			
	Income > 75 k ($) (1: yes/ 0:no)	0.893^{***}	-0.719^{***}	0.028^{***}			–
		(4.12)	(−3.89)	(3.03)			
Scale coefficients	Scale coefficient	0.575*	1	0.289^{**}			0.170
		(1.72)	(fixed)	(2.19)			(1.64)
Allocation parameters	Ride-hailing (N1)	–	–	–	–	0.115	–
	Ride-hailing (N3)	–	–	–	–	0.885	–
	Bike-sharing (N3)	–	–	0.628	–	–	–
	Bike-sharing (N4)	–	–	0.372	–	–	–
	Shared e-scooter (N3)	–	–	–	0.739	–	–
	Shared e-scooter (N4)	–	–	–	0.261	–	–
Model summary	No. of observations		3360				
	No. of coefficients		63				
	Log-likelihood (0)		−7278				
	Log-likelihood (converge)		−4678				
	McFadden Pseudo adj-ρ^2		0.427				

Note: ***, **, * represent the statistical significance at 0.01, 0.05, and 0.1 level.

Table 6b
ICLV-CNL commuting trip model estimation.

	Variables	N5: Car-related		N6: Public transit	N7: Multi-modal		
		Private car	Ride-hailing	Bus + Walking	Bus + Bike-sharing	Bus + Shared e-scooter	Bus + Ride-hailing
		Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)	Coeff. (t-value)
Alternative specific variables	Constant	–	−7.435*** (−11.50)	–	–	4.942*** (4.23)	−8.741*** (−7.64)
	Travel cost ($)	−0.017** (−2.13)	−0.047** (−2.06)	−0.021* (−1.67)	−0.024* (−1.94)	−0.035** (−2.37)	−0.033* (−2.16)
	In-vehicle time (min)	−0.009 (−1.24)	−0.029 (−1.64)	−0.010 (−1.59)	−0.011* (−1.79)	−0.017** (−1.97)	−0.021 (−1.03)
	Out-vehicle time (min)	−0.014** (−2.01)	−0.051*** (−2.70)	−0.016** (−2.48)	−0.023** (−2.37)	−0.030** (−2.50)	−0.041** (−2.54)
Latent variables	Perceptions of shared mobility	–		–	0.532** (2.45)		
	Travel attributes importance	0.721** (3.33)		–	−0.465** (−2.90)		
	Social values	−0.014* (−1.68)		–	0.108** (3.57)		
Social demographic variables	Bachelor's degree (1: yes/ 0:no)	–	0.15* (1.70)	–	–		
	Children (1: yes/ 0: no)	–	−0.324*** (−4.50)	–	−0.438*** (−5.23)		
	Car ownership (1: yes/ 0:no)	–	−0.242*** (−6.33)	–	−0.148*** (−3.56)		
	Age < 35 (1: yes/ 0: no)	–	0.246*** (2.06)	–	0.151*** (3.64)		
	Age > 55 (1: yes/ 0: no)	–	−0.157*** (−2.66)	–	−0.042*** (−2.71)		
	Male (1: yes/ 0:no)	–	0.016** (2.04)	–	0.064* (1.69)		
	Student (1: yes/ 0:no)	–	0.046* (1.88)	–	0.116* (1.65)		
	Driver's license (1: yes/ 0:no)	–	−0.782*** (−5.28)	–	−1.858*** (−4.57)		
	Income < 25 k($) (1: yes/ 0:no)	–	−0.153** (−2.41)	–	0.147** (2.44)		
	Income > 75 k($) (1: yes/ 0:no)	–	0.077*** (3.75)	–	−0.19** (−2.04)		
Scale coefficients	Scale coefficient	0.67* (1.92)		1 (fixed)	0.57** (2.25)		
Allocation parameters	Bus + Bike-sharing (N6)	–	–	–	0.349	–	
	Bus + Bike-sharing (N7)	–	–	–	0.650	–	–
	Bus + Shared e-scooter (N6)	–	–	–	–	0.302	–
	Bus + Shared e-scooter (N7)	–	–	–	–	0.698	–
	Bus + Ridehailing (N6)	–	–	–	–	–	0.279
	Bus + Ridehailing (N7)	–	–	–	–	–	0.721
Model summary	No. of observations		3360				
	No. of coefficients		54				
	Log-likelihood (0)		−8401				
	Log-likelihood (converge)		−4492				
	McFadden Pseudo adj-ρ^2		0.459				

Note: ***, **, * represent the statistical significance at 0.01, 0.05, and 0.1 level.

4.3. *Value of travel time savings (VTTS) estimation*

Travelers place a monetary value to represent their willingness to pay to save travel time. VTTS analysis can estimate people's decisions based on trade-offs between travel cost and travel time. In the existing literature, the most common way to calculate the VTTS is to use the marginal rate of substitution based on the ratio of estimated coefficients for travel time and travel cost (Gkartzonikas et al., 2022; Konstantinou et al., 2023; Washington et al., 2020). People who choose different travel modes may also have different VTTS for different trip purposes. To estimate how people value their in-vehicle and out-vehicle travel time by different modes, we calculated the VTTS (Equation (11) for different mode alternatives for both commuting and non-commuting trips based on travel time and travel cost coefficients from mode choice model results (Section 4.1).

$$VTTS_j = \frac{\beta_j^{time}}{\beta_j^{cost}} \tag{11}$$

5. Results and discussion

This section first introduces the results from the ICLV-CNL models for non-commuting and commuting purposes and discusses how people would choose among different shared mobility modes, conventional modes, and multimodal services (Section 5.1). Based on the results, we further provide policy suggestions for urban planners, transportation agencies, and shared mobility operators to guide the future development of shared mobility systems with better system design and mode integration. In addition, we also discuss the VTTS estimations for different travel modes (Section 5.2).

5.1. Model estimation results

5.1.1. Goodness of fit

The ICLV-CNL model estimation results are summarized in Table 6. Two models were evaluated: the non-commuting trip model and the commuting trip model. The adjusted ρ^2 values are used to assess the fitness of the models, whose value is 0.427 for the non-commuting trip model and 0.459 for the commuting trip model. The scale coefficients of nest structures (θ) are found to be statistically significant in the range between zero and one, rejecting the hypotheses of H_0: θ=0 and $\theta = 1$ at least at 0.1 level. Scale coefficients indicate that the IIA assumption of the traditional MNL model may be violated due to the similarity among alternatives and we need to nest several alternatives due to shared unobserved features. The allocation parameters showed that different travelers treated shared mobility as different groups of modes. For example, some people treated ride-hailing as the car nest (N1) instead of shared mobility due to its similarity to the riding experience, while others treated shared micro-mobility as the walk nest (N4) due to the inclusion of walking efforts. In the commuting trip model, some people thought that those three multimodal services were similar to taking public transit (N6) with probabilities ranging from 27 % to 35 %. These results also justify the necessity and advantages of using CNL.

5.1.2. Mode-specific attributes

The constant values (Table 6) represent the relative preference of each alternative under each nest when other variables are at the reference level. For a non-commuting trip (Table 6a), the shared e-scooter is preferred over bike-sharing under the shared mobility group, while ride-hailing has the lowest preference. A similar trend is found for the multimodal service, where respondents are more

Table 7
Elasticity analysis. (a) Direct elasticity of 1 % decrease of mode specification parameters on the increase of mode choice probability; (b) Cross elasticity of travel cost for non-commuting trip; (c) Cross elasticity of travel cost for commuting trip.

		Cost (%)	In-vehicle time (%)	Out-vehicle time (%)
Non-commuting trip	Bike-sharing	1.33	1.63	2.46
	Bus	0.39	0.50	0.98
	Shared e-scooter	1.47	1.98	1.84
	Walk	–	–	–
	Private car	0.51	0.03	0.53
	Ride-hailing	2.12	0.63	2.76
Commuting trip	Bus + Bike-sharing	1.19	1.70	1.92
	Bus + Shared e-scooter	1.43	2.15	2.34
	Bus + Ride-hailing	1.68	0.78	3.01
	Bus + Walk	0.79	1.09	0.75
	Private car	0.75	0.35	0.08
	Ride-hailing	3.39	0.54	1.30

1 % price reduction for mode	**Probability changes on mode selection (%)**					
	Bike-sharing	**Bus**	**Shared e-scooter**	**Walk**	**Private car**	**Ride-hailing**
Bike-sharing	–	−2.14	−1.73	−1.59	−0.16	−0.03
Bus	−0.86	–	−0.62	−1.16	−0.54	−0.24
Shared e-scooter	−1.96	−2.20	–	−2.57	−0.81	−0.20
Private car	−0.50	−0.25	−0.20	−0.65	–	−0.10
Ride-hailing	−0.49	−0.99	−1.38	–	−1.12	–

1 % price reduction for mode	**Probability changes on mode selection (%)**					
	Bus + Bike-sharing	**Bus + Shared e-scooter**	**Bus + Ride-hailing**	**Bus + Walk**	**Private car**	**Ride-hailing**
Bus + Bike-sharing	–	−1.21	−0.12	–	−1.50	−1.26
Bus + Shared e-scooter	−1.35	–	−0.24	−1.25	−1.57	−2.40
Bus + Ride-hailing	−0.83	−0.92	–	−0.18	−2.35	−1.84
Bus + Walk	−0.42	−0.44	−0.10	–	−0.24	−0.19
Private car	−0.87	−1.36	−2.14	−1.10	–	−2.78
Ride-hailing	−0.45	−0.7	−1.52	−1.02	−3.46	–

Table 8
Results for structural and measurement model components.

	Variables	LV1: Perceptions of shared mobility					LV2: Travel attributes importance					LV3: Social values
		AV1: More options	AV2: Avoid congestion	AV3: Avoid parking	AV4: Bus connection	AV5: Bike lane	AV9: Travel reliability	AV10: Travel convenience	AV11: Travel comfort	AV12: Travel safety	AV13: Social image	AV14: Environmental concern
Measurement model	Coefficients for attitudinal indicator	1	0.629 (8.34)	1.142 (7.62)	1.464 (2.65)	2.252 (16.25)	1	0.284 (3.17)	0.149 (6.25)	1.807 (5.09)	1	1.937 (34.55)
	Interception for attitudinal indicators	0	1.846 (47.83)	0.496 (35.42)	−0.808 (−40.06)	0.854 (25.39)	0	1.707 (21.63)	0.955 (12.79)	1.572 (13.85)	0	1.284 (46.10)
	1st threshold	0.364 (31.12)					0.784 (31.79)					0.723 (9.21)
	2nd threshold	0.541 (31.65)					1.263 (28.50)					1.343 (7.01)
	3rd threshold	1.315 (25.01)					1.56 (41.35)					1.658 (6.44)
Structural model	Bachelor's degree (1: yes/ 0:no)	–					–					0.139 (7.88)
	Has children (1: yes/ 0:no)	−0.928 (−6.67)					0.346 (4.45)					–
	Car ownership (1: yes/ 0:no)	–					0.268 (2.20)					–
	Age $<$ 35 (1: yes/ 0:no)	0.884 (2.45)					–					0.864 (2.89)
	Age $>$ 55 (1: yes/ 0:no)	−0.231 (−1.67)					0.308 (2.35)					0.29 (3.57)
	Male (1: yes/ 0:no)	0.191 (1.93)					0.924 (3.18)					–
	Income $<$ 25 k($) (1: yes/ 0:no)	0.164 (2.59)					–					0.095 (2.48)
	Income $>$ 75 k($) (1: yes/ 0:no)	−0.766 (−2.31)					0.631 (3.90)					0.83 ()
	Interception for latent variables	2.331 (34.68)					0.514 (41.03)					0.947 (22.36)

likely to use shared e-scooters as the bus feeder than bike-sharing and ride-hailing. This finding raises competition concerns within shared mobility service, especially given their overlapped spatial coverage in Indianapolis (Luo et al., 2022). For example, users' preference for shared e-scooters may cause a reduction in bike-sharing ridership and result in more bike-sharing system idleness. An integrated system planning of the shared fleet distribution that considers different users' preferences to avoid service overlaps could minimize competition among the systems.

The estimated coefficients also highlight that travel cost is an important factor in mode choice decisions, for both commuting and non-commuting trips. Pricing strategies of shared mobility modes could significantly change the probability of their usage. The elasticities presented in Table 7 support this finding, with direct elasticity showing that a 1 % price reduction on shared mobility-related services (including multimodal) can increase their mode choice probabilities by 1.19 % to 3.39 %. A cheaper service not only could attract more shared mobility usage and connect to the bus but also can replace more car trips. Cross-elasticity analysis on travel cost shows that the price reduction on shared mobility could effectively decrease the probability of driving private cars (Table 7 (c)) for commuting trips. However, blindly reducing the shared mobility price for all customers could also lead to more trips switching from green transportation modes, such as bus and walking (Table 7 (b)) to shared mobility, worsening the traffic condition and increasing energy consumption and emissions. It may also lead to severe competition among different shared mobility and bus feeder modes. Therefore, the pricing plan for shared mobility options needs to be carefully designed to better achieve the benefits, such as offering specific discounts for multimodal and car displacing users to improve the synergistic relationship with public transit.

Given the fixed origin–destination pairs in our designed hypothetical trip scenarios, the in-vehicle travel time can be viewed as a measurement of traffic conditions which may be affected by traffic congestion, designated lanes (sidewalks, biking lanes, and bus routes), and speed limits. Statistical significance (Table 6) and elasticity (Table 7) results show that the in-vehicle travel time is mainly critical for shared micro-mobility-related modes (including multimodal services), compared with car and ride-hailing. Riding bikes and e-scooters requires certain physical activities, so the user experience is highly influenced by the duration of travel. Negative traffic conditions such as the need to navigate around pedestrians or automobiles can prolong the in-vehicle travel time, making it more challenging to ride shared micro-mobilities. This can potentially increase the cost of using e-scooters due to their time-based pricing policy. To mitigate these challenges and improve the user experience, one potential solution is to design isolated bike lanes. By providing dedicated lanes for bicycles and e-scooters, the in-vehicle travel time can be reduced, enhancing the user experience and attracting more individuals to utilize shared mobility and multimodal services, resulting in a higher rate of vehicle substitution.

The estimated coefficients of out-vehicle time are significant for both commuting and non-commuting trips across all travel modes, with greater elasticities observed for shared mobility and multimodal systems (Table 7). Implementing dedicated pick-up and drop-off zones for shared mobility and multimodal services can effectively reduce waiting and walking time. Additionally, machine-learning-based algorithms have been shown in previous studies to better predict shared mobility demand, facilitating improved shared vehicle siting, rebalancing, and dispatching rules to enhance service accessibility and decrease out-vehicle connection time (Ai et al., 2018; Haliem et al., 2020; Zhang et al., 2016). Additionally, integrating shared mobility and public transit services through real-time information sharing and ticket integration could further reduce the out-vehicle time and improve the overall travel experience. Moreover, promoting the usage of digital platforms for booking and payment can also help reduce out-vehicle time by eliminating the need for physical transactions.

5.1.3. Latent variable analysis

In the discrete choice model, we included the latent variables based on the attitudinal variables from the survey to estimate the heterogeneity among travelers. The estimated coefficients clearly show that people with different opinions and values may have different preferences on mode choice (Table 6). Table 8 summarizes the structural and measurement model results for latent variables.

First, travelers' perceptions of shared mobility significantly affect their choices (Table 6). The estimated coefficients for both commuting and non-commuting trips indicate that the latent variable is positively correlated with the likelihood of selecting shared mobility and multimodal services. The measurement model reveals several potential advantages of shared mobility that may prompt individuals to use it, including expanding mobility options, circumventing traffic congestion and parking woes, and facilitating bus connections. To leverage these potential benefits, shared mobility companies could manage their operations accordingly. For example,

Table 9
Value of travel time savings estimation.

		Value of in-vehicle time savings ($/hour)	Value of out-vehicle time savings ($/hour)
Non-commuting trip	**Bike-sharing**	21.12	26.37
	Bus	15.84	20.61
	Shared e-scooter	18.55	29.44
	Walking	–	–
	Private car	14.52	21.29
	Ride-hailing	15.21	28.82
Commuting trip	**Bus + Bike-sharing**	26.72	55.87
	Bus + Shared e-scooter	28.55	51.16
	Bus + Ride-hailing	38.36	56.45
	Bus + Walking	30.14	46.56
	Private car	34.18	48.83
	Ride-hailing	36.95	65.01

deploying more shared bikes and e-scooters in areas with severe congestion issues could potentially persuade people to switch from private cars to shared micro-mobility or multimodal systems, ultimately reducing traffic. Nevertheless, ride-hailing systems are unable to guarantee a decrease in traffic congestion, as they may lead to additional vehicle miles traveled (VMT), such as deadheading, which can exacerbate traffic issues. The integration of ride-hailing and bus services is a viable option for mitigating car mileage and solving traffic congestion issues. Ride-pooling services, which allow for additional passengers to share routes, present another potential solution for reducing the negative impacts on VMT and aiding ride-hailing in benefiting urban transportation (Ke et al., 2021; Lokhandwala and Cai, 2018). The measurement model also demonstrates that shared mobility may be more appealing to those who have limited mobility options, such as non-car owners. Shared mobility can complement the bus system and expand the service area, making the bus service more accessible to people who are currently unable to use it. Providing shared mobility services in areas with limited travel options can encourage multimodal use, improve transportation equity by adding mobility options, reduce travel costs, and lessen car dependence. Additionally, our findings reveal that the availability of bike lanes is a crucial factor for shared micro-mobility users. Riding bikes and e-scooters on sidewalks or motorways create a sense of insecurity and frustration for individuals. This finding is consistent with related studies on shared micro-mobility that are based on historical data and existing system settings (Campbell and Brakewood, 2017; Tavassoli and Tamannaei, 2020; Zhang et al., 2017). Constructing more bike lanes, particularly in suburban areas, can enhance the safety of riders, drivers, and pedestrians, encourage shared micro-mobility use, and promote vehicle replacement.

Second, our results indicate that individuals who prioritize their personal travel attributes importance, including travel reliability, comfort, convenience, and safety, tend to prefer using private cars over shared mobility and multimodal systems. The positive correlation that we estimated illustrates the difficulties in promoting the adoption of shared mobility services, which currently have a low market share in Indianapolis (Table 4). More efforts should be made to improve the competitiveness of shared mobility to replace private car trips to improve urban sustainability. Travel convenience and reliability can also be increased by Mobility-as-a-service (MaaS) system, which integrates trip planning, service reservation, and payment across different transportation systems (Alonso-González et al., 2020; Jittrapirom et al., 2017; Shaheen et al., 2019). Moreover, implementing safety measures, such as providing helmets for micro-mobility riders and employing certified ride-hailing drivers, can also promote travel safety. By improving shared mobility services in these ways, providers can transform travelers' perceptions of shared mobility and encourage more private car users to shift to shared mobility and multimodal systems for developing a more sustainable transportation system.

Third, travelers who care more about their social values are less likely to drive cars and instead opt for public transit and shared mobility services. Of particular importance among these social values is their attitude toward the environmental impact of transportation methods. Shared mobility, which is regarded as a green transportation mode, could potentially reduce GHG emissions if it can replace carbon- or energy-intensive transportation modes (Luo et al., 2019; Kou et al., 2020). Better educating the public on the environmental impacts of all transportation modes and the consequences of their mode choice could enable people to make more conscious travel decisions and switch from private cars or ride-hailing to shared mobility and multimodal system. This shift in transportation patterns can further amplify the environmental benefits that shared mobility has to offer in the future.

5.2. *Value of travel time savings estimation*

Understanding the value of travel time is critical for estimating the benefits of future transportation planning and infrastructure investment in shared mobility and multimodal system. The values of in-vehicle and out-vehicle travel time savings for different travel modes are summarized in Table 9. In general, people value their travel time for commuting trip more than non-commuting trip, because people are more concerned about the travel time reliability for commuting. For the non-commuting trip, bus has a lower VTTS than shared mobility, indicating that replacing bus trips with shared mobility not only may cause environmental issues (discussed in Section 5.1) but also may lead to economic inefficiency. For commuting trip, VTTS values for multimodal systems are lower than private car and ride-hailing in Indianapolis. Therefore, integrating shared micro-mobility and public transit can provide affordable travel options for people with no car or lower income. Developing such a multimodal system can also benefit transportation equity. The VTTS estimations for different multimodal systems are quite different, showing their different potentials as bus feeders. "Bus + Bike-sharing" has the lowest VTTS and is the most affordable option. However, the fixed station locations limit the system's spatial coverage. "Bus + Shared e-scooter", although has a slightly higher VTTS, has more spatial flexibility to cover a wider range of potential users for multimodal usage. The spatial coverage of bike-sharing and the shared e-scooter system should be organized in a more complementary way, instead of only focusing on the downtown area and competing with each other as what happens in many cities. Moreover, people who choose "Bus + ride-hailing" are estimated to have the highest VTTS than other multimodal systems. This suggests that the future development of a multimodal system with ride-hailing should pay attention to the out-vehicle travel time reduction. Potential strategies, such as increased vehicle availability, an accurate passenger demand prediction, time-saving vehicle routing planning, and more convenient infrastructures for transfers can encourage commuting mode to shift from private car to a more sustainable mode (USDOT, 2018).

6. Conclusions

This research conducted a choice experiment survey and built ICLV-CNL models to identify the key attributes that affect people's mode choice among shared mobility, conventional modes, and multimodal system. Using Indianapolis, Indiana as a case study, the estimated mode choice model can quantify the importance of different variables on shared mobility choice, considering both mode substitution and integration with conventional transportation modes. The results also point out the potential policies for promoting shared mobility usage, vehicle trip reduction, and mode integration. The key research findings from this study are summarized as follows. First, travel cost, in-vehicle time, and out-of-vehicle time are crucial attributes with statistical significance and elasticities that affect an individual's choice of shared mobility and multimodal system. Second, perceptions of shared mobility, travel attributes importance, and social values are identified as three latent variables that correlate with travelers' attitudes and mode choices. People who hold a positive perception of shared mobility and care more about their social values are more likely to select shared mobility and multimodal services, while people who prioritize their travel-related benefits may stick to cars.

The contribution of this study includes two aspects. First, to the best of our knowledge, this is the first study to conduct a mode choice analysis that considers all different shared mobility systems and their multimodal services. The utility functions derived from our ICLV-CNL model for different transportation modes present methodological contributions to support travel demand modeling and forecasting. Moreover, this study shows the necessity of including shared mobility options in travel demand modeling because travelers may change their mode choices and cause different travel patterns from the competing and synergistic effects. Existing four-step or activity-based travel demand models may not include different shared mobility systems and multimodal options when modeling the mode choice (Becker et al., 2020). The utility functions derived from this study provide crucial insights for travel demand researchers and modelers to evaluate the travel demand impacts from shared mobility and reconsider their mode choice models. Furthermore, results from this study can support multiple policies for urban planners, policymakers, and shared mobility system operators to improve the future development of shared mobility to obtain mobility benefits to the city. For operators, price reductions for multimodal users, such as discounts or membership plans, can attract more private car users to switch to multimodal system and reduce VMT. The out-vehicle connection is also one major barrier to shared mobility and multimodal adoption. Appropriately increasing the availability of shared mobility fleets, especially in the regions that are not well covered by public transit service, can reduce out-vehicle travel time such as walking and waiting, and can also encourage people's multimodal mode choices for their daily commuting trips. In addition to the increased fleet size, elaborative operation, such as an improved dispatch plan with more accurate ridership demand prediction, can also reduce the efforts required to reach shared mobility fleet and save travel time. For planners, a Mobility-as-a-service system, which integrates multimodal trip planning, reservation, and payment can improve the system's convenience and reliability, can help reduce the technical barriers, and enhance the cooperation between public and private transportation agencies. Educating the public about the environmental impacts of different mode choices can raise the environmental concern of local travelers and attract them to turn to a more sustainable travel mode choice.

Although this study contributes to the mode choice analysis of shared mobility and multimodal systems, it also has several limitations. First, to avoid having a very lengthy survey, we only designed two hypothetical trip cases, one for a short non-commuting trip and the other for a typical commuting trip. Despite the inclusion of a cheap talk section to enhance realism, it is important to recognize that hypothetical bias may still exist in the study. This bias arises from the inherent nature of hypothetical scenarios, which may not fully capture the real-world decision-making contexts for all respondents. For instance, individuals who do not work or lack realistic access to shared mobility services in their daily lives may find it challenging to fully relate to the presented scenarios. Additionally, the designed trip case has the same trip distance, same candidate mode options, trip start time, and trip Origin-Destination for all respondents, which cannot reflect the various travel demands and the heterogeneous availability of all alternative modes. The model may have limited capacity to estimate the mode choice for various trip distances, such as a long non-commuting trip or a short commuting trip. Additional surveys that target the heterogeneous travel demands and people's mode choices can complement this research and estimate travel behavior in a more comprehensive way. Turning to the multimodal system, we did not differentiate whether it serves as the first-mile or last-mile, or both connections due to the limited number of choice experiment questions. People's travel behavior and mode choice may be different when using shared mobility for a first-mile or a last-mile connection because of the service reliability (e.g., no guarantee to find a bike/scooter for the last-mile connection after the bus trip). Additional choice experiments that differentiate the first-mile and last-mile trip can comprehensively estimate people's preferences under different multimodal service conditions.

CRediT authorship contribution statement

Hao Luo: Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Ricardo Chahine:** Conceptualization, Data curation, Formal analysis, Writing – original draft, Writing – review & editing. **Konstantina Gkritza:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing. **Hua Cai:** Conceptualization, Investigation, Writing – original draft, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

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