



Microtransit adoption in the wake of the COVID-19 pandemic: Evidence from a choice experiment with transit and car commuters[☆]

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ABSTRACT

On-demand mobility platforms play an increasingly important role in urban mobility systems. Impacts are still debated, as these platforms supply personalized and optimized services while also potentially exacerbating sustainability challenges. To alleviate these concerns, microtransit projects have emerged, promising to combine the advantages of pooled on-demand rides with more sustainable fixed-route public transit services. Specifically, microtransit provides, dynamic rider-driver matching to serve demand with fewer vehicles and design optimal routes if riders accept to wait to board vehicles at curbside boarding locations. The shift to microtransit calls for new research on user behavior, motivations, and acceptability to understand demand and its role in existing mobility systems. The COVID-19 pandemic context adds an additional layer of complexity. This study investigates the potential demand for microtransit options against the background of the pandemic. We use a pivoted efficient choice experiment to study the decision-making of Israeli public transit and car commuters when offered to use novel microtransit options (sedan vs. passenger van). By estimating commuter group-specific Integrated Choice and Latent Variable models with error component terms for the microtransit alternatives, we investigate the tradeoffs related to traditional fare and travel time attributes, along with microtransit features: walking time to the pickup location, vehicle sharing, waiting time, minimum advanced reservation time, and shelter at designated boarding locations. We analyzed two latent constructs: the attitudes toward sharing and the experiences and risk perceptions related to the COVID-19 pandemic. The results reveal three key takeaways. (1) New modal attributes significantly affect the utility of the microtransit alternatives, with a notable aversion to walking and waiting among drivers; (2) car and transit commuters have structural differences in attribute elasticities; (3) significant differences are noted for the magnitude of the latent variable effects. Sharing experience and COVID Comfort play a key role for drivers evaluating the choice of microtransit.

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1. Introduction

Public transit plays a vital role in shaping the future of cities by providing an affordable, and sustainable transportation option, reducing congestion, and improving accessibility for all residents. Transit forms the backbone of a sound urban transportation system, by providing fixed-route services, wide coverage, high passenger capacity, and scheduled operations. On-demand transportation plays a complementary role to transit by providing flexible, personalized, and convenient transportation options that can bridge the gaps in transit coverage, cater to specific needs, and offer last-mile connectivity, thereby enhancing overall urban mobility (Shaheen and Cohen, 2018). In an ideal world, the integration of these services would create a comprehensive and efficient transportation network, meeting the diverse needs of urban residents and contributing to sustainable and accessible cities. However, there is mounting evidence from North American cities e.g., New York, San Francisco, Chicago, Los Angeles, and Seattle, that ridehailing is a major contributor to traffic congestion and also competes with mass transit (Yan et al., 2020, Graehler et al., 2019, Erhardt et al., 2021, Wu and MacKenzie, 2021). Measures like ridepooling, which is ridehailing with multiple parties, can help curb vehicle miles traveled (VMT), a negative impact of ridehailing. Yet, the effectiveness of ridepooling in reducing congestion has come under scrutiny and depends on deadheading and local pooling rates (Schaller., 2021).

In response to these concerns, transit agencies and mobility startups have launched microtransit services—small-scale, on-demand transit fleets that can offer both fixed routes and scheduled operations, as well as more flexible routes and on-demand scheduling (APTA, 2021). This new service model may produce environmental and rider benefits relying on information and communication technology (ICT) platforms to enable on-demand service requests or coordination between riders and drivers for trip pooling. This coordination supports the transition from door-to-door to curb-to-curb (e.g., at transit stops) services.

The shift to microtransit calls for research on user behavior, motivations, and acceptability to understand demand and mobility system impacts. Beyond traditional transit attributes like travel time and fare, microtransit entails new attributes related to curb-to-curb routing, scheduling, and sharing configurations. Pinpointing how customers evaluate these new service dimensions is critical for researchers, operators, and policy-makers to design new mobility platforms that complement existing transportation systems. Different modal experiences are also likely to lead to different service feature perceptions. For instance, an attribute such as expected walking time to the boarding location can be viewed as a disadvantage against the baseline of private cars or ridehailing but is a familiar feature for transit users. Understanding how riders weigh microtransit attributes is key to designing and maintaining an efficient and user-friendly mobility service. Platform managers from the public or private sectors can analyze this demand to optimize their fleet, attract patronage, and minimize passenger delays. Moreover, knowledge of acceptability and attribute tradeoffs informs the relationships of microtransit with traditional commute options like personal vehicles and public transit, the outlook of public-private partnerships, and the need for additional infrastructure to support microtransit options (Shaheen et al., 2020).

During 2020 and 2021, the COVID-19 pandemic and associated restrictive measures have drastically disrupted mobility systems worldwide—adding another layer of uncertainty to mobility demand analysis (Barbieri et al., 2021). Stay-at-home orders, remote working, and other social distancing measures to prevent the coronavirus spread have led to steeply falling demand for mobility, especially public transit and shared mobility (Liu et al., 2020; Duarte. (2020); Higgins and Olson, 2020). Due to these changes and the lingering safety concerns, the pandemic has likely heightened travelers' sensitivity to close physical interactions and consequently changed riders' priorities when trading off cost and comfort against health and safety. As workers return to working in person and people start commuting anew with the dissipation of the pandemic, the need for shared mobility services is growing. Therefore, understanding the links between pandemic risk perceptions and mode preferences remains an ongoing research priority (Hensher. (2020)). Yet, we have limited insight into how people navigate the decisions to use different shared modes during the evolving pandemic (Shokouhyar et al., 2021; Rahimi et al., 2021).

This research analyzes commuting travelers' acceptability of novel microtransit commute options in Tel Aviv, Israel. We address three specific research questions: *First*, we analyze user acceptance of microtransit options, emphasizing several new microtransit-specific attributes. Specifically, we examine the factors that explain the shift from the status quo commute to microtransit travel and analyze attribute sensitivities and elasticities. *Second*, we explore the differences between current transit users and solo drivers. Commuters are likely to perceive attributes like scheduling and waiting time differently based on their past experiences. *Third*, we assess the joint impact of two latent factors, namely COVID experiences and concerns along with attitudes towards the sharing economy to build a new understanding of how vehicle sharing and other novel attributes are perceived in the COVID-19 context. Thereby, the evolving perception and potential recovery of shared mobility and the tradeoffs between traditional and novel mode attributes are further elucidated. Additionally, by examining pandemic perceptions and sharing experiences, we can disentangle how different commuter groups view these novel services and attributes.

We use data from a web-based survey conducted in Israel following the first COVID lockdown in May 2020. The study includes a Choice Experiment (CE) with a pivoted Bayesian efficient design. We employ an Integrated Choice and Latent Variable (ICLV) framework to examine the acceptance of these new commute options and the impact of user profiles, latent attributes of sharing motivations, and COVID perceptions. From the ICLV modeling results, we estimate elasticities of explanatory variables in the discrete choice portion and compare them across car and transit commuter models.

2. Literature review

2.1. On-demand shared mobility and traditional mobility options

The increased presence of ridehailing platforms in urban mobility systems presents both opportunities and challenges for policymakers and planners. Ridehailing provides several benefits for users. These benefits include serving as a transit gap-filler, the first-mile-last-mile connection to transit (BROWN. (2018); Shaheen and Cohen, 2018), improving mobility accessibility for underserved communities (Brown. (2019)), providing more personalized door-to-door services at lower fares than the traditional on-demand travel offered by taxis (Rayle et al., 2016), and circumventing limited parking (Clark and Brown, 2021). These benefits, however, may come at a cost.

Negative externalities related to novel mobility platforms have been highlighted. Owing to deadheading and induced trip-making, ridehailing has been observed to increase VMT, congestion, and pollution (Graehler et al., 2019, Erhardt et al., 2019, Nair et al., 2020), as well as indications of possible negative impacts on transit ridership and its financial sustainability (Schaller., (2021)). Several studies suggest that many users may substitute transit for hailing (Clewlow and Mishra, 2017; Dong. 2020). Aggregate trip data analysis shows that hailing demand is often higher where transit demand is also high (Brown. (2019); Correa et al., 2017). The demand relationship, and degree of substitution, vary according to several factors, such as transit service quality/coverage and type (Gehrke et al., 2019), and city geography and socio-economic factors (Hall et al., 2018; Jain et al., 2017; Soria and Stathopoulos, 2021).

Potential strategies to address ride-hailing's negative mobility externalities are to promote increased ridepooling and adopt more transit-inspired features (discussed further in sec. 2.2.). Pooled ride services have been offered by leading Transportation Network Companies (TNCs) (e.g., UberPool and Lyft Line), where multiple trips can be pooled together in the same vehicle to increase vehicle occupancy rates and reduce excess VMT (Hou et al., 2020; Soria and Stathopoulos, 2021). Ridehailing demand can also be shifted towards more sustainable usage. For example, Chicago introduced an extra fee for single-party rides beginning or ending within the downtown area to encourage pooling (Pratt et al., 2019). In terms of behavior, research shows that cost considerations are still crucial in pooled rides (Morales Sarriera et al., 2017, Soria et al., 2020, Lavieri and Bhat, 2019). Another way to increase pooled rides is by incorporating locally aligned values and culture into the sharing platform (Rong et al., 2021).

2.2. Emergence of microtransit options

Microtransit can be defined as a digitally-enabled transit service that is privately or publicly operated, using pooled shuttles or vans, to provide on-demand or fixed-schedule services with either dynamic or fixed routing (SAE, 2018). Calderón and Miller (2020) highlight the range of service types within microtransit. This service model is positioned between current (typically single occupancy) ridehailing, and traditional fixed-route transit, owing to the promotion of pooling rides, walking to the curb to connect with optimal routes, and scheduling rides in advance of the boarding time. In practical terms, we can characterize microtransit as a new form of ridehailing with transit-like attributes that aim to optimize trips collectively by minimizing vehicle miles traveled. Fig. 1 compares door-to-door ride-pooling with curb-to-curb microtransit. Fewer vehicles are needed to serve demand by pooling trips, thus reducing VMT (Fu and Chow, 2021). Providing curb-to-curb services where passengers walk to a designated boarding location and alight nearby their final destination reduces the amount of vehicle travel. In Fig. 1, Party 1 (P1) and Party 2 (P2) can be served directly at their origins and destinations or meet the driver at a designated boarding location and alight near their destination. In the latter scheme, the vehicle travels less. Additionally, reserving a seat in a shared vehicle well before boarding allows the operator time to pool trips optimally rather than relying on real-time driver-rider matching.

We can gain initial insight into the acceptance and behavior of shared rides by drawing on ridepooling and related literature. In simulations, large fleets of shared taxis have been shown to serve existing taxi demand without excessively long delays, without significantly reducing revenue, and, importantly, reducing VMT (Alonso-Mora et al., 2017, Martinez et al., 2015). However, achieving these outcomes requires a high market share of pooled trips, as VMT benefits can only be achieved with sufficiently large shared vehicle fleet sizes and passengers' demand (Rodier et al., 2016; Fagnant and Kockelman, 2018).

However, reported rates of ridepooling are typically low and vary considerably. Empirical estimates range from 6 to 35 % (California Air Resource Board, 2019, Chen et al., 2018, Chicago Metropolitan Agency for Planning, 2019, Li et al., 2019, Lyft, 2018, Soria

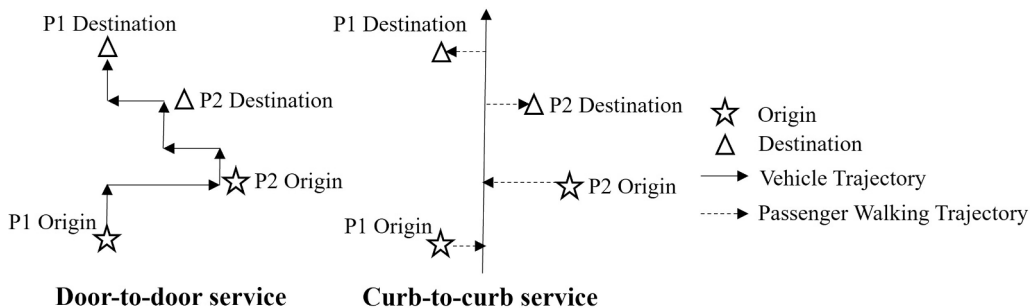


Fig. 1. Door-to-door and Curb-to-curb Service Types.

Table 1

Stated Choice Experiment Studies of Microtransit Options and Attributes.

Author(s)	Country	Alternatives (dependent var.)	Cost	IVTT	OVTT	Time Uncertainty	Headway	Additional Pax	Transfers	Additional Pickups	Integrated Advanced Technology	Minimum Reservation Time	Sheltered Boarding Location
Yan et al., (2018) (N = 1,163)	USA	Drive, Mtransit, Bike, Walk (choice)		✓	✓				✓	✓			
Frei et al., (2017) (N = 183)	USA	Car, Transit, Flexible transit (choice)	✓	✓	✓		✓		✓				
Chavis and Gayah (2017) (N = 173)	USA	Fixed route transit, flexible transit, solo driving (choice)	✓	✓	✓						✓		
Al-Ayyash et al., (2016) (N = 1,393)	Lebanon	shared-ride taxi (weekly frequency)	✓	✓	✓			✓			✓		
Alonso- Gonzalez (2020a) (N = 1,006)	Netherlands	Individual and Pooled (choice)	✓	✓				✓					
Alonso- Gonzalez (2020b) (N = 1,006)	Netherlands	Combined modes: flexi, flexi + bus, bus + bus (choice)	✓	✓	✓	✓			✓				
Current Study (N = 1,326)	Israel	Current mode (car vs. Transit), MT-S, MT-V (choice)	✓	✓	✓			✓				✓	✓

et al., 2020, Young et al., 2020). Lastly, there is much room to grow by wider adoption of pooling in many cities, e.g., 94 % of ridepooling trips in LA are made by just 10 % of riders (Brown, 2020)).

Few empirical studies are available to evaluate microtransit in practice. The “Brengh flex” pilot in the Netherlands stresses the risk of an excess shift of users away from transit towards microtransit in response to pricing differences (Alonso-González et al., 2018). A study of three U.S. microtransit pilots concluded that implementation was fraught, and low ridership was a recurring problem (Westervelt et al., 2018). Additionally, an Uber-based microtransit service case study found that it did not attract single-occupant vehicle users and instead mainly drew users away from public transit (Lewis and MacKenzie, 2017). Similarly, pooling users are typically found to be multimodal travelers (Kostorz et al., 2021). Lastly, microtransit users may highly enjoy the service but be unwilling to pay higher fees. The Finnish pilot Kutsuplus found that substantial subsidies were needed for the program to be financially viable (Rissanen, 2016). In summary, for shared microtransit services to succeed in mitigating externalities, further research is needed to understand the tradeoffs travelers are willing to make.

2.3. Choice experiment analysis of microtransit features

Stated choice experiments (CE) offer valuable insight into demand related to curb-to-curb microtransit, specifically its novel service features. Therefore, CE surveys are essential tools for measuring how travelers view these new attributes, such as advanced time to place a reservation, walking, pooling people, and additional passenger pickups. Table 1 summarizes relevant choice experiment-based studies involving microtransit and related modes and their attributes. We note that studies emphasizing automated vehicles (where the ride may be driverless) are not included in this analysis as the perceptions of sharing attributes can be highly affected by the automation feature (Krueger et al., 2016, Etzioni et al., 2021). Additionally, we exclude portfolio-based Mobility-as-a-Service studies where microtransit (and related attributes) is a minor focus, e.g., Caiati et al., (2020).

Table 1 shows that each study covers different definitions of microtransit-like services, with different sets of attributes and information presented to customers: Yan et al., (2018) provide survey-takers information about additional pickups; Frei et al., (2017) include headway for their flexible route, demand-responsive transit; Chavis and Gayah (2017) feature the availability of GPS tracking of vehicle for more traveler information; Al-Ayyash et al., (2016) consider in-vehicle WiFi capabilities. The two remaining studies, Alonso-González et al., (2020b) and Alonso-González et al., (2020a), were derived from the same survey. In Alonso-González et al., (2020b), the choice experiment included uncertainty for the waiting and in-vehicle times to determine Values of Time for individual and shared rides. Alonso-González et al., (2020a) then considered the mode choice of flexible transit alternatives. On the whole, the most common attributes included in choice experiments regarding microtransit are the out-of-vehicle travel time and additional passengers sharing the ride.

The current study is unique in including attributes for a minimum reservation time and availability of a sheltered boarding location akin to a bus stop shelter. Service providers can thus better optimize vehicle routing and possibly pool more trips together by knowing the demand for trips with earlier notice. Since curb-to-curb services rely on travelers walking to a boarding location, we hypothesize that shelter availability from adverse weather may significantly impact the utility of our pooled ride alternatives.

2.4. COVID-19 effects on shared transportation

The Coronavirus pandemic has tremendously impacted travel via both supply and demand effects (Ashkrof et al., 2022). Because the risk of exposure is a function of physical proximity, many countries enacted large-scale lockdowns, limited access to public spaces, and imposed social distancing directives. These lockdowns have dramatically decreased the demand for travel (Glanz et al., 2020) especially for transit (Barbieri et al., 2021). While demand for mobility has largely resumed over time, public transit ridership has yet to fully recover (Rothengatter et al., 2021). At the peak of the pandemic, public transit was significantly impacted, with some agencies reporting a 90 % decrease in ridership (Verma., (2020); Vos and J. (2020); Abdullah et al., 2020). Additionally, attitudes toward public transit relating to COVID-19 are revealed to be negative (Thomas et al., 2021). Ridehailing demand was similarly impacted, with an 80 % decrease in ridership (Higgins and Olson, 2020). While ridehailing remained operational during the pandemic for essential travel, one of the first actions of TNCs was to halt ridepooling operations (e.g., UberPool and Lyft Line) (Bond, 2020). As the pandemic evolved and lockdowns gradually eased, travel behavior has remained impacted by the virus-related risk perceptions and contraction risk. Travelers were faced with evaluating the tradeoffs between the need to travel (e.g., in hybrid work scenarios) and being exposed to COVID-19 in shared rides (Borowski et al., 2021, Rahimi et al., 2021). Ongoing work examines travelers' evolving perceptions and priorities in the (post) COVID-19 era. Said et al., (2021) indicate a change in intention to use pooled modes due to the pandemic. Another study found that only approximately 41 % of respondents would consider using ridehailing even if operators take extra precautions by providing masks, gloves, and sanitizing gel, whereas only 28 % would be willing to pay more for the added protective measures (Awad-Núñez et al., 2021).

The percentage of those willing to use public transit under the same conditions was similar. A Toronto survey found that 15 % of respondents declared they would never use ridehailing again, and 21 % would never use ridepooling (Loa et al., 2020). From the same report, approximately 30 % of riders prefer to wait until the virus is no longer a threat as the earliest they would consider using ridehailing or pooling. As a counter, work by Curtale et al., (2022) suggested that COVID-19 concerns did not affect the intention to use autonomous electric car-sharing services. Finally, behavior studies reveal counterintuitive results. According to Kaplan et al., (2022), riders taking more protective measures have an increased fear of infection while using transit, and more transit avoidance.

2.5. Summary and literature take-aways

In general, travelers have shifted from public and shared to private modes as a consequence of the pandemic (Das et al., 2021). Indeed, among the negative long-term consequences of the pandemic, we include the persistent reluctance to use shared modes, rebounding of car travel, and an increase in car purchases (Hensher, (2020)). The mode-specific demand patterns in the wake of COVID-19 are still an open research question. What is more, the role of risk-perceptions and user intentions over time and across cultures is not well understood (an exception is Barbieri et al., 2021). Specifically, it is still unclear how users view travel in shared vehicles, and where microtransit fits in as an intermediate model between on-demand and fixed transit. The proposed research will help map out preferences and values surrounding sharing and pandemic risks. This paper analyzes the willingness to engage in microtransit and how different serviced features, such as vehicle sizes and seating configurations related to the ability to distance socially, affect the demand for different service models.

3. Data

3.1. Study context

The data were collected using a choice experiment survey in Tel Aviv, Israel. The survey was distributed during the summer of 2020 to car and transit commuters throughout the metropolitan region which comprises nearly half of Israel's 9 M population and includes

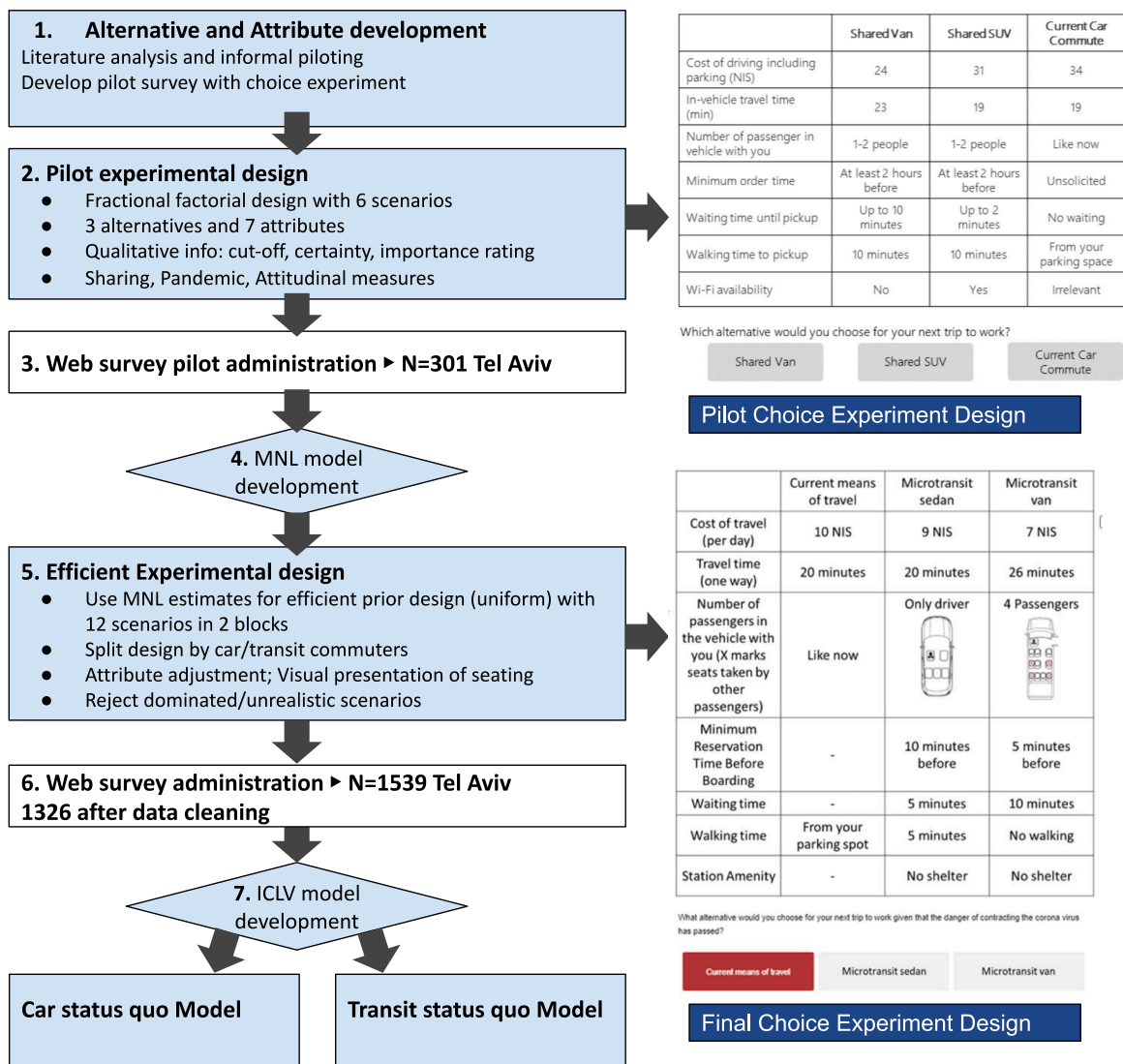


Fig. 2. Steps in the Development of a Discrete Choice Experiment.

the core city of Tel Aviv, the main business, culture, and high-tech hub.

The average motorization rate in Israel is moderate (406 per 1000 inhabitants in 2021; [CBS 2022](#)) compared to above 500 in the EU in 2020 ([ACEA 2022](#)). However, in Tel Aviv, this figure is almost double. Israel also had the worst traffic density per network length compared to any other OECD country (in 2014), while vehicle use intensity per year was the second highest after the US across OECD countries (in 2015) ([OECD 2022](#)). With no specific measure taken to tackle congestion, this issue will likely worsen as both car ownership and population continue to grow. Public investment in public transport infrastructure in Israel remains low in international terms ([Sharav et al., 2018](#), Fig. 2). [IMF \(2018\)](#) points out that the relative investment gap of Israel was 20 % lower compared to the OECD average, and amounts to 1.3 % of GDP in 2018 ([OECD 2022](#)). The Tel Aviv mass transit plan aims to reach a goal of 40 % of motorized trips by transit, carrying 4 million passengers per day in 2040 (in 2016, transit made up 20 % of trips). As most of the current transit journeys are made by bus or suburban railways, the plan schedules the construction of metro lines, light rail, and bus rapid transit, the first light rail line being due in mid-2023 (after extensive delays). Buses accounted for 85 % of Israeli transit trips in 2019, with more than 2 M passengers served daily by 17 bus operators, using 9,700 buses, conducting ~ 900 K trips. However, bus pre-emption remains insufficient, as manifested by few priority lanes (14 m per capita, compared to 300 m in the EU). The result is a rather poor level-of-service provided by Israel's transit (with mean running speeds of only 15 km/h or less, compared to double in the EU). Thus even where transit is an option, it is not the first choice for most people for their daily journeys: while 92 % of the population is connected to transit, only 20 % use it. Unsurprisingly, most bus users do so as they cannot afford to own a vehicle ([Suhoy and Sofer 2019](#), [CBS 2019](#)). This fact makes many transit passengers (pupils, students, senior citizens, and disabled people) captive users, and the rest of the population highly dependent on cars.

With the pandemic's first wave, like many countries, Israel set strict social distancing regulations at the start of the COVID pandemic, with the entire country in lockdown from early March to late April 2020. Only essential workers were allowed to travel (e. g., healthcare, grocery store, and medical logistic companies). Except for accessing a grocery store or healthcare, people were forbidden to travel beyond a 100-meter radius from their homes. Public transit operated with limited capacity and reduced frequencies. For example, train tickets had to be reserved well in advance of the trip. Eventually, these lockdowns were eased by May 2020 (during the time of data collection), but facemasks remained obligatory in indoor spaces, including transit vehicles. By late May, with the rise in cases, some restrictions were reintroduced, and some activities in closed spaces were prohibited. Lockdowns were reinstated once more in September 2020 as the second wave erupted.

To address the innovative nature of microtransit in Israel, the choice experiment scenarios were designed using the respondents' status quo mode and their stated travel time and cost as reference. Scenarios were designed to present two microtransit options. The smaller is a sedan-sized vehicle with a passenger capacity of 4 (not including the driver) which we will refer to as a Microtransit Sedan (MT-S). This service has not been introduced in Israel so far due to regulatory limitations that restrict the compensation of ridesharing activities to voluntary cost-sharing based on a fixed cost-per-km value. The second option is ridepooling in a van-sized vehicle with a capacity of 10 passengers, which we will refer to as Microtransit Van (MT-V). This service is operated only on a limited scale in Israel — on a pilot basis in the main cities of Tel Aviv, Jerusalem, and Haifa and one rural area. In Tel Aviv, this service is known as Bubble-Dan, which operated before and during the pandemic ([Bubble-Dan, 2021](#)) but closed down due to financial constraints at the end of 2022.

Given the limited exposure to microtransit and ride-hailing models, care was taken in the study design to explain scenarios, alternatives, and attributes clearly. Data about the respondents' political views, COVID-19 attitudes, and sharing experiences is also collected to better represent culturally and contextually relevant attitudes that shape the acceptance of microtransit.

3.2. Study design

A screening was applied to include only participants who commute at least three times a week with a commute duration of at least 10 min using only a personal vehicle or public transit. Data about current commute attributes, socio-demographics, past and expected future life events, latent attitudes, and choice experiments with microtransit alternatives were collected. Using the respondents' current commute attributes, we determine their commute mode, cost, and travel time for the reference alternative in the CE—referred to as the “Status Quo” (SQ).

Latent attitudes on respondents' sharing experience and comfort with situations related to risks of COVID-19 transmission were measured using survey item statements. Sharing attitudes and COVID Comfort statements used in this modeling are summarized in

Table 2
Sharing and COVID-19 Comfort Items with Coding and source.

Item	Coding	Source
I enjoy using sharing economy services	SI1_enjoy	Van der Heijden (2004)
I can see myself increasing my use of shared mobility in the future	SI2_increase	Bhattacharjee (2001)
I have never had a bad experience using sharing economy services	SI3_exp	Current study
Inclusion of Other in Self (IOS)	IOS	Adapted from Aron et al., (1992)
Given the current situation caused by the COVID-19 outbreak, I would feel comfortable engaging in the following activities:	–	Current study
Ridesharing with strangers	CC1_ride	
Eating out at a restaurant.	CC2_rest	
Going to the grocery store	CC3_grocery	

Table 2. The sharing-related items are drawn from previous research and modified to orient them around the sharing economy. The COVID-19 related items were created specifically for this survey. Each item uses a 5-point Likert scale that ranges from “Strongly Disagree” to “Strongly Agree” (Lehmann and Hulbert, 1972). In addition, we asked respondents to report the degree to which the COVID-19 pandemic had affected their lives. Respondents were asked to respond to this question by indicating “No Change, Little Change, Not Sure, “Big Change,” or “Very Big Change.” These questions were then used to identify latent variable effects on microtransit decision-making.

The experiment design and implementation was developed in seven sequential steps (Fig. 2) following best practice guidance (Johnson et al., 2013; Kløjgaard et al., 2012). Step 1 covered qualitative attribute development, focusing on identification, selection, and presentation. Guided by literature and industry report analysis, seven attributes were selected, representing two microtransit vehicle sizes. Further informal testing in step 2 led to a fractional factorial experimental design with six microtransit scenarios (see more details in Soria et al., 2019). Given Israel’s limited familiarity with microtransit services, several auxiliary questions were included to measure attribute acceptance cutoffs, importance, and choice certainty. In step 3, a full web survey implemented in Qualtrics was administered to 301 pilot respondents. Results were analyzed in step 4 using discrete choice modeling, leading to the development of priors for an efficient experimental design in step 5 using the Ngene software (ChoiceMetrics 2012, Yu et al., 2011). The resulting design included three alternatives: Status Quo (SQ, either car or public transit), Microtransit Sedan (MT-S), and Microtransit Van (MT-V). A total of 7 attributes are included in the choice experiment, which is in line with other choice experiment studies (Arentze & Molin, 2013; Mahmoud et al., 2015; Etzioni et al., 2021). The final choice experiment broadened attribute ranges and presented the seating variable visually. The travel time and travel cost attributes for current travel alternatives were pivoted off each respondent’s reported (RP) levels to improve the realism of the experiment (Hensher and Rose, 2007; Train and Wilson, 2008; Etzioni et al., 2020). Therefore the status quo travel times and costs did not differ within individual choice experiments. Fig. 2 includes a sample choice scenario from the choice experiment as seen by the respondents.

Table 3 lists the mode attributes included in the final experiment, along with the attribute levels. Importantly, in the models presented later, we entered the walking and waiting times as the maximum value of the range as seen by the respondent in the experiment. The a priori coefficient values (Rose et al., 2008) were obtained using model results from the pilot survey, with Bayesian uniform distributions (Soria et al., 2019). However, as this pilot survey considered only car commuters, we assumed that all attributes’ coefficient values were equal across groups. Dominated and unrealistic alternatives were excluded using the Federov algorithm (ChoiceMetrics, 2012). Because Bayesian design priors were utilized for all attributes, it was important to test the stability of the final designs. This was done by varying the number of draws and observing the D-error performance (we compared both Halton and Sobol draws from 10 draws to 500,000). The D-error showed stability from 200 draws and up, with minimal fluctuation for both car and transit commuter designs.

Several actions were put in place to ensure designs were plausible and realistic. For example, given that the transit fare was relatively low, the fare for the microtransit alternatives was constrained to always be greater than transit for transit commuters. In contrast, with car commuters, costs for MT-S and MT-V were consistently lower than the car cost. The design extracted 12 choice scenarios for each SQ mode randomly assigned to two fixed sets of 6 scenarios to prevent respondent fatigue (Caussade et al., 2005).

Graphics were presented in the choice experiment to reflect the number of additional passengers and which seats were available. The graphical presentation of the seating designation and vehicle seating configuration allows a more direct understanding of the specific links to mode-pooling decisions (Etzioni et al., 2021).

The respondents’ current travel cost and time were defined using the following logic. If the typical commute mode is driving, the respondent provides further information about parking such as search time, if there is a reserved parking area, and if they pay for that parking. The travel costs are approximated for drivers by summing the daily parking fee and their travel distance in kilometers multiplied by two, using this information.

In Israel, the value of 2 ILS (0.3 USD in 2020) per km is a standard gross estimate used by the public sector for reimbursing direct car use expenditures and is also the maximal value allowed by the Ministry of Transport regulations for determining direct cost-sharing in voluntary carpooling arrangements between driver and passengers. Travel time for car commuters is the sum of their stated commute time and parking search time. Travel cost corresponds to the single trip fare for transit commuters, and travel time is their current stated commute time. Because both car and transit commuters responded to this survey, the design was optimized for each commuter group separately. In step 6, a web-based respondent panel was used to collect 1539 survey responses in May 2020.

The data were cleaned by first removing responses that did not complete the choice experiment portion. Responses presenting

Table 3
Choice Experiment Alternative Attribute Levels.

	Status Quo (fixed)	Microtransit Sedan	Microtransit Van
Cost (per day)	Current Cost	−10 % −20 % −30 % (CAR) +75 % +125 % +175 % (PT)	−15 % −30 % −45 % (CAR) +50 % +100 % +150 % (PT)
Travel time	Current Door-to-door Time	−30 % 0 +30 % (CAR) −30 % 0 +30 % (PT)	0 +15 % 30 % (CAR) 0 −15 % −30 % (PT)
Number of occupants in a vehicle		1 person (driver) 2 people 4 people	1 person (driver) 5 people 8 people
Minimum Reservation Time Before Boarding		2hrs 10 min 5 min before	2hrs 10 min 5 min before
Waiting Time		2 min 5 min 10 min	2 min 5 min 10 min
Walking Time		No walking (0 min) 5 min 10 min	No walking (0 min) 5 min 10 min
Station amenity		Designated shelter (yes no)	Designated shelter (yes no)

inattentiveness patterns were removed to preserve data quality. We define inattentiveness based on survey completion duration, unreasonable responses (e.g., average parking search time greater than 1 h), and choosing the same response to all attitudinal items (i.e., straightlining) (Lavrakas, 2008). For the current analysis, responses with commute times greater than 90 min (which only accounted for only 9 responses) were excluded to maintain a reasonable commuter service area for microtransit. After cleaning and subsetting the database, 1326 responses (86 %) were retained, resulting in 7956 choice experiment observations. Of these 1326 responses, there were 879 (66 %) car and 447 (34 %) transit commuters.

Table 4 provides the descriptive statistics for the modeling variables, COVID-19 impacts, and attitudes. The travel cost has the largest between-group difference for the respondents' current commutes. Car commuters are also more likely to be male, married, and have more children. The voter variable is a dummy variable denoting if the respondent voted in the 2020 legislative elections in Israel, for which there is little difference between groups. The Inclusion of Other in the Self (IOS), measures, on a 7-point scale, how close the respondent feels to strangers (Aron et al., 1992). In this study, we specifically asked respondents how close they felt to a stranger sharing their ride. Overlapping circles depict IOS, where more overlap denotes a closer connection with other riders (Fig. 3). Surprisingly, car and transit commuters show no statistical difference in IOS scores. Lastly, both groups share nearly the same attitudes towards the sharing economy and COVID Comfort, with the most distinct difference being the CC1_ride. That is, transit commuters are comparatively more comfortable sharing a ride with a stranger during the pandemic.

4. Methodology

This research aimed to identify the acceptability and tradeoffs among novel microtransit attributes and quantify the effect of latent variables on the decision-making process. Models were estimated separately for drivers vs. transit users to examine distinct commute patterns. Modeling was done using the Integrated Choice and Latent Variable (ICLV) framework which extends the basic logit model to allow flexible error parameters that relax the IIA property, and allow us to explicitly model latent constructs (Temme et al., 2008, Bolduc and Alvarez-Daziano, 2010, Abou-Zeid and Ben-Akiva, 2014). The ICLV model is well suited to capture error correlation between the two microtransit options owing to their overlapping attributes. Preliminary testing of alternative Nested Logit models for car and transit users found no evidence for a significant grouping of alternatives. Therefore the ICLV is selected as the final structure, given the strength in explaining deeper reasons for mode preferences (Habib & Zaman 2012, Abou-Zeid and Ben-Akiva 2014).

Fig. 4 depicts the theorized relationship between the latent variables, mode attributes, utility of each mode, and, finally, mode

Table 4
Descriptive Statistics of Modeling Variables.

Variable	All Commuters	Car Commuters	Transit Commuters
Current Commute – Mean (S.D)			
Travel Cost (ILS)	35.31 (38.98)	50.34 (40.23)	5.78 (2.94)
Travel Time (minutes)	33.20 (15.75)	31.59 (14.71)	36.37 (17.18)
MT-S attributes – Mean (S.D)			
Additional occupants	1.71 (1.71)	1.84 (1.72)	1.47 (1.66)
Reservation time (minutes)	32.46 (47.15)	35.37 (48.85)	26.77 (43.06)
Walk time (minutes)	3.74 (4.14)	3.73 (4.14)	3.73 (4.13)
Wait time (minutes)	5.06 (3.12)	5.25 (3.03)	4.70 (3.26)
Designated pickup location	0.44 (0.50)	0.50 (0.50)	0.33 (0.47)
MT-V attributes – Mean (S.D)			
Additional occupants	3.55 (3.35)	3.67 (3.30)	3.31 (3.42)
Reservation time (minutes)	35.60 (49.00)	35.47 (48.92)	35.87 (49.19)
Walk time (minutes)	3.89 (4.11)	3.74 (4.14)	4.17 (4.02)
Wait time (minutes)	4.75 (3.26)	4.75 (3.27)	4.75 (3.24)
Designated pickup location	0.36 (0.48)	0.33 (0.47)	0.41 (0.49)
Individual Descriptors			
Married	55.81 %	61.43 %	44.74 %
Gender (Man)	50.45 %	53.12 %	45.19 %
Voter	89.97 %	89.30 %	91.28 %
Number of Children – Mean (S.D)	1.27 (1.63)	1.45 (1.60)	0.90 (1.64)
COVID Impact			
No Impact	1.96 %	1.37 %	3.14 %
Little Impact	32.81 %	31.63 %	35.12 %
Big Impact	41.86 %	42.54 %	40.49 %
Very Big Impact	12.67 %	12.97 %	12.08 %
Not Sure	10.70 %	11.49 %	9.17 %
Attitudes – Mean (S.D)			
IOS (min = 1, max = 7)	2.75 (1.60)	2.80 (1.64)	2.67 (1.52)
SI1_enjoy	3.05 (1.08)	2.97 (1.08)	3.20 (1.06)
SI2_increase	3.17 (1.04)	3.12 (1.06)	3.27 (1.01)
SI3_exp	3.25 (1.04)	3.25 (1.04)	3.26 (1.05)
CC1_ride	2.27 (1.11)	2.10 (1.04)	2.59 (1.16)
CC2_rest	2.46 (0.83)	2.45 (0.81)	2.49 (0.85)
CC3_grocery	3.66 (0.96)	3.63 (0.96)	3.75 (0.95)
N	1326	879	447



Fig. 3. Inclusion of Other in the Self (IOS) Scale.

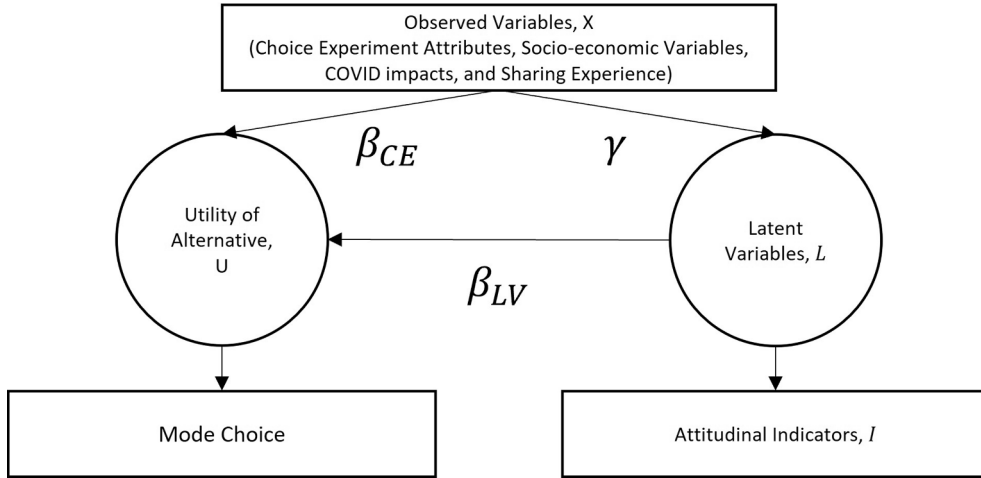


Fig. 4. Integrated Choice and Latent Variable Framework.

choice. To estimate the ICLVs, we follow the guidelines from Walker (2001). From the guidelines, the first steps are to identify the choice model and structural equation model separately. Once this is completed, the models are jointly estimated.

4.1. Discrete choice model

The first step of Walker's (2001) guideline is correctly identifying the utility specification of the choice model. We completed this step by estimating a Multinomial Logistic Regression (MNL) for each commuter group with PandasBiogeme (Bierlaire, 2018). Equations (1a) and (1b) describe the general utility specification. U_{in} is the latent utility of alternative i of observation n , X_{CE} is the matrix of explanatory variables from the choice experiment, L is the latent variables, β_{CE} and β_{LV} are the corresponding coefficients, μ_{MT} is the error component included in the microtransit alternatives, and ϵ is the independently and identically distributed (IID) error term. After testing several specifications, we did not include statistically insignificant variables such as walking and waiting time for the status quo alternative in the transit user model; however, these may be helpful in other analyses.

$$U_{in} = V_{in}(X, L; \beta) + \epsilon_{in} \quad (1a)$$

$$V_{in} = \beta_{CE}X_{CE} + \beta_{LV}L + \mu_{MT} \quad (1b)$$

4.2. Structural Equation model for attitudinal indicators

After identifying the mode choice model, the second step is identifying the latent variables. We estimated a Structural Equation Model (SEM) using the attitudinal items in the measurement component and explanatory variables, including socio-demographics, experience with sharing economy services, and the structural component's life impact and comfort related to COVID-19. Equations (2a) and (2b) describe the measurement and structural components, respectively. The SEM's were first estimated using the R package *psych*, and then confirmed again using PandasBiogeme (Revelle, 2018, Bierlaire, 2018). With both choice and latent variable models identified, the last step is to estimate the integrated models simultaneously.

Equations (2a) (structural) and 2b (measurement) below describe the SEM. L is the latent variable, the intercept θ , observed variables X_{LV} , the corresponding estimated coefficients γ , and the error term, η , which is IID multivariate normally distributed. σ is a random variable to capture the random taste heterogeneity of the sample and is added to numerically estimate the likelihood described in the following subsection. I is the response for the attitudinal items listed in Table 2. It is a function of α an intercept, λ the estimated coefficients, L a matrix of latent variables estimated from Equation 2, and ζ the IID multivariate normal error term.

Several latent variables were estimated representing the respondents' attitudes towards Environmental Sustainability, Schedule Making, Pro-Sharing Economy, and COVID Comfort. Only the last two were consistently significant in at least one commuter group,

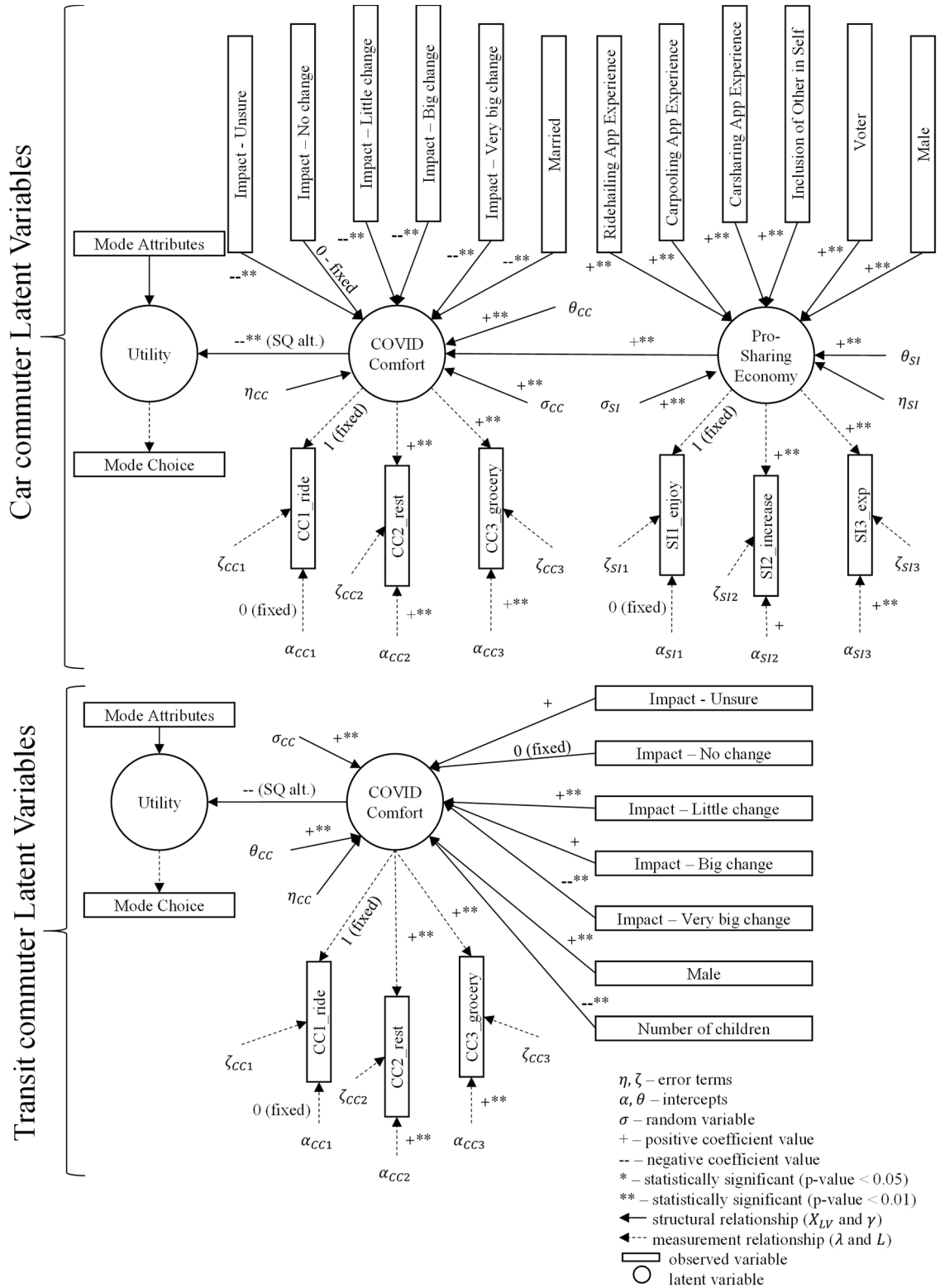


Fig. 5. Final structure of ICLV Models for Each Commuter Group.

with a hierarchical relationship shown in Fig. 5. We do not include attitudes towards Environmental Sustainability and Schedule-making in the final models as they worsened the internal validity. The latent variables were validated with the following metrics and threshold values: Comparative Fit Index (CFI) > 0.90, Root Mean Square Error of Approximation (RMSEA) < 0.06, and Standardized Root Mean Square Residual (SRMR) < 0.08 following recommendations in the literature (Hu and Bentler, 1999, Hooper et al., 2007).

$$L = \theta + X_{LV}\gamma + \sigma + \eta \quad (2a)$$

$$I = \alpha + \lambda L + \zeta \quad (2b)$$

4.3. Integrated choice and latent variable model

The models are estimated simultaneously by maximizing the joint log-likelihood of each component. Equation (3) shows the joint likelihood. This integrand cannot be solved analytically, so it was estimated numerically with random variables, ϕ , in the latent variable model. $p(X, L; \beta)$ is the likelihood from the standard MNL. $f(L, X_{LV}; \gamma)$ is the likelihood from the structural component of the SEM and $g(I, L, \sigma; \lambda)$ is the likelihood of the measurement component. The results section includes Fig. 5 which summarizes the final structure of the ICLV models and includes the SEM coefficient values for the different commuter groups. The results are further discussed in the next section.

$$Likelihood = \prod_{n=1}^N \int_L p(X, L; \beta) f(L, X_{LV}; \gamma) g(I, L, \sigma; \lambda) dL \quad (3)$$

5. Results

Two ICLV models were estimated, one for car commuters and one for transit commuters, and the results are illustrated in Fig. 5 with choice model results shown in Table 5. Fig. 5 shows the relationships among variables, coefficient signs (positive or negative values), and statistical significance of the coefficients. We accompany the latent variable diagram with Table A1 in the appendix showing the ICLV latent variable measurement model coefficient values and fit measures. Following extensive specification testing done individually, the models were similarly specified so that the results were as directly comparable as possible. Mode attributes were limited to the discrete choice portion of the ICLVs while attitudinal items and sociodemographic variables were limited to the latent variable models. Included in the choice model for both commuter groups is a shared error component μ_{MT} capturing the correlation between the two microtransit alternatives. In both models the error components are statistically significant, showing evidence that some of the unexplainable heterogeneity is due to the microtransit alternatives being closely related. Additionally, the latent variables were

Table 5
Microtransit ICLV Choice Model Results.

Coefficient	Alternative					
	Car (Std. Error)	Car MT-S (Std. Error)	MT-V (Std. Error)	Public Transit Transit (Std. Error)	MT-S (Std. Error)	MT-V (Std. Error)
Constant	0 - fixed	-4.676** (0.122)	-4.073** (0.135)	0 - fixed	-1.853** (0.126)	-1.962** (0.129)
Travel cost (ILS)	-0.00838* (0.00371)	-0.00737 (0.00457)	0.00938 (0.00504)	-0.116** (0.0341)	-0.0422** (0.0157)	-0.0682** (0.0174)
In-vehicle travel time (minutes)	-0.0526** (0.0061)	-0.0367** (0.0058)	-0.0387** (0.0056)	-0.0386** (0.00592)	-0.02896** (0.00614)	-0.0248** (0.00675)
Walk time (minutes)	-	-0.0508** (0.0116)	-0.102* (0.0148)	-	NS	NS
Wait time (minutes)	-	-0.0345* (0.0144)	-0.0645** (0.0178)	-	NS	NS
Minimum reservation time before boarding (minutes)	-	-0.00137 (0.00784)	-0.00295** (0.00111)	-	-0.00348** (0.00131)	0.00640** (0.00116)
Number of people in the vehicle	-	NS	-0.101** (0.0282)	-	-0.0976** (0.0380)	-0.0916** (0.0315)
Sheltered Boarding Location	-	NS	NS	-	NS	0.0378**
COVID Comfort	-1.395** (0.102)			-0.124 (0.0831)		
Error component μ_{MT}		0.372* (0.169)			0.334* (0.165)	
n observations	5274			2682		
ρ^2	0.170			0.296		
Final Loglikelihood	-47309.05			-13594.62		

(NS) Not statistically significant at $\alpha = 0.1$, not estimated in the final model.

* significant at $\alpha = 0.05$.

** significant at $\alpha = 0.01$.

hypothesized to exist for both commuter groups and, subsequently, share the same scales. The final utility specifications are described in Equations 4a to 4d where Equations 4c and 4d are similarly specified for both commuter groups. Therefore, for brevity, we do not repeat equations 4c and 4d with “car” and “transit” subscripts, hence the lack of “car” or “transit” commuter model designations. Additionally, recall that the car and transit ICLVs are independently estimated and the estimated coefficients are not restricted to be equal to each other between ICLVs. Equations 4c and 4d also include the shared error component μ_{MT} which is a generic coefficient meant to capture correlations among the unobserved microtransit attributes. Equation (4a) shows COVID Comfort in the utility specification for the car alternative. Two latent variables were identified and included in the final model for car commuters because the Pro-Sharing Economy construct was found to indirectly affect the utility of car commuters via a structural relationship with COVID Comfort as shown in Fig. 5. Equation 5 shows the formulation of the COVID Comfort structural equation specifically for the car commuter ICLV, including Pro-Sharing Economy as an explanatory variable. Equation (6) shows the structural equation for the Pro-Sharing Economy. Equation (7) then shows the structural equation for COVID Comfort in the transit commuter ICLV.

$$V_{car} = \beta_{Car} + \beta_{Car,Cost}CarCost + \beta_{Car,Time}CarTime + \beta_{Car,CovidComfort}COVIDComfort \quad (4a)$$

$$V_{PT} = \beta_{PT} + \beta_{PT,Cost}PTCost + \beta_{PT,Time}PTTime + \beta_{Transit,CovidComfort}COVIDComfort \quad (4b)$$

$$V_{MTS} = \beta_{MTS} + \beta_{MTS,Cost}MTSCost + \beta_{MTS,Time}MTSTime + \beta_{MTS,Walk}MTSWalkTime + \beta_{MTS,Wait}MTSWaitTime \\ + \beta_{MTS,MinRes}MTSMinResTime + \beta_{MTS,Passengers}MTSPassengers + \beta_{MTS,Shelter}MTSShelter + \mu_{MT} \quad (4c)$$

$$V_{MTV} = \beta_{MTV} + \beta_{MTV,Cost}MTVCost + \beta_{TV,Time}MTVTime + \beta_{MTV,Walk}MTVWalkTime + \beta_{MTV,Wait}MTVWaitTime \\ + \beta_{TV,MinRes}MTVMinResTime + \beta_{MTV,Passengers}MTVPassengers + \beta_{MTV,Shelter}MTVShelter + \mu_{MT} \quad (5a)$$

$$\begin{aligned} COVID\ Comfort_{Car} = & \theta_{Car,CC} + \\ & \gamma_{Car,Pro-sharing\ Economy}Pro-sharing\ Economy + \\ & \gamma_{Car,Impact\ Unsure}Unsure + \\ & \gamma_{Car,Impact\ Little\ Change}Little\ Change + \\ & \gamma_{Car,Impact\ Big\ Change}Big\ Change + \\ & \gamma_{Car,Impact\ Very\ Big\ Change}Very\ Big\ Change + \\ & \gamma_{Car,Married}Married + \\ & \sigma_{Car,CC} + \eta_{Car,CC} \end{aligned} \quad (5b)$$

$$\begin{aligned} Pro-sharing\ Economy_{Car} = & \theta_{Car,SI} + \\ & \gamma_{Car,Ridehailing\ Exp}Ridehailing\ Exp + \\ & \gamma_{Car,Carpooling\ Exp}Carpooling\ Exp + \\ & \gamma_{Car,Ridesharing\ Exp}Ridesharing\ Exp + \\ & \gamma_{Car,IOS}IOS + \\ & \gamma_{Car,Voter}Voter + \\ & \gamma_{Car,Male}Male + \\ & \sigma_{Car,SI} + \eta_{Car,SI} \end{aligned} \quad (6)$$

$$\begin{aligned} COVID\ Comfort_{Transit} = & \theta_{Transit,CC} + \\ & \gamma_{Transit,Impact\ Unsure}Unsure + \\ & \gamma_{Transit,Impact\ Little\ Change}Little\ Change + \\ & \gamma_{Transit,Impact\ Big\ Change}Big\ Change + \\ & \gamma_{Transit,Impact\ Very\ Big\ Change}Very\ Big\ Change + \\ & \gamma_{Transit,Male}Male + \\ & \gamma_{Transit,Num\ Children}Num\ Children + \\ & \sigma_{Transit,CC} + \eta_{Transit,CC} \end{aligned} \quad (7)$$

5.1. Microtransit acceptance and mode attributes

During model development, all mode attributes for all alternatives were tested in the choice portion of the ICLV. In the final estimations, statistically insignificant variables were not included. Though we focus on mode attributes in this model portion, socio-demographic variables are indirectly included through the latent variable causes. We discuss these results in later sections. Table 5 alternative intercepts show an inherent attraction to the status quo modes. We posited that transit commuters would find the on-demand sharing alternatives inherently more attractive than the status quo because they provide more flexible ride scheduling, smaller vehicles, and a more technology-forward service; however, the results show the opposite. When examining the attribute effects, all features have the expected sign, while we note several differences between the two commuter groups. The more traditional travel cost and travel time attributes are statistically significant for the status quo choice. It is important to note that given the pivoted design this relates to between-respondent differences rather than within-person differences. Yet, we note that transit commuters have a higher sensitivity to cost and lower sensitivity to time than solo drivers, which is true also for microtransit options, suggesting that transit commuters transfer their preferences onto the new options. Interestingly, the cost for the microtransit alternatives in the car

commuter model was not statistically significant, giving evidence that price is not a significant factor when deciding to use microtransit and that other variables outweigh it in the decision-making process. Dong et al., (2022) found similar outcomes where their model also showed statistically insignificant cost sensitivities. Given that the car commuter choice experiment was designed with the microtransit alternatives having a lower cost than private vehicle travel, it may seem concerning that MT-S and MT-V cost does not sway commuters away from their car. However, this finding aligns with earlier research in the Tel Aviv context showing that even relatively aggressive policy incentives to encourage more transit and decreased car use, had only a marginal impact on total vehicle miles traveled (Shiftan et al., 2015). We speculate that the limited cost sensitivity is due to drivers' difficulty in perceiving the largely hidden cost of driving and parking (Andor et al., 2020, Shoup, 2021), making drivers inelastic to discounted prices.

The novel attributes were only included for the microtransit alternatives. Overall, we note that car commuters are sensitive to a greater range of microtransit attributes than transit commuters. This likely reflects the fundamental dissimilarity between driving and microtransit, which comports several unfamiliar attributes (Alemi et al., 2018). Specifically, we note a major difference in time-related attributes of walking time to the curbside pickup location and waiting time until pickup. Car commuters appear to have a strong aversion to walking and waiting, with a strong penalty for the van option. Instead, transit users are only sensitive to the in-vehicle travel time, with insignificant walking and waiting parameters, similar to Frei et al., (2017) results. The last time-related attribute, minimum reservation time, is statistically significant for both alternatives, albeit with a lower magnitude than other time measures. The number of additional passengers sharing the vehicle matters for both vehicle sizes in the transit model while only impacting the larger MT-V among drivers. Finally, the 'designated shelter' attribute is only significant for MT-V in the transit model. The fact that car commuters are not sensitive to the number of additional passengers for MT-S, possibly stems from this mode being a familiarly sized vehicle with relatively low capacity. Alonso-González et al., (2020a) also posit that sharing perceptions reach a tipping point at four additional passengers since a vehicle larger than a regular car is needed.

In summary, transit users have likely interiorized the *transit-like* attributes of walking and waiting that are intrinsic to fixed-route scheduled services. This is reflected in the lack of significant coefficient effects for transit commuters. Instead, we note that transit users appear more sensitive than drivers to reservation time, shelter, and the number of other passengers. These attributes are more affected by the Information and Communication-supported mobility platform and the smaller vehicle sizes than what is typically experienced in current transit travel.

5.2. Latent variable effect

Overall, model fit for both latent variable models indicates good fit with CFI > 0.90, RMSEA < 0.06, and SRMR < 0.08 in both models (Hu and Bentler, 1999, Hooper et al., 2007). The most evident difference between car and transit commuters is in the latent variable portion of the ICLVs. The structure of the latent variables in the ICLV models is illustrated in Fig. 5. As shown by estimates in Fig. 5 decision-making by car commuters was affected by both latent variables, namely: *Pro-Sharing Economy* and *COVID Comfort*. Transit users, surprisingly, did not display any impact of a pro-sharing economy attitude, and the *COVID Comfort* latent variable had only a weak significance ($p = 0.7$) suggesting tentatively that commuters with more COVID Comfort will tend to swap transit for microtransit.

COVID Comfort is designed to represent a respondent's comfort with different COVID-19 risk situations. Respondents' comfort in grocery stores, eating in restaurants, and sharing a vehicle with a stranger are used to identify this latent variable. The COVID Comfort parameter in Table 5 shows a negative effect overall. That is, the more at ease respondents are with these situations, the more likely they are to accept trying the microtransit services. However, for transit users the effect is not significant at conventional levels, suggesting there is only weak evidence that microtransit adoption is driven by pandemic concerns ($\alpha = 0.10$). This echoes findings of Străuli et al., (2022) where transit riders who continued to use transit during the pandemic voiced fewer concerns and rated pandemic risk as lower than those who ceased ridership.

The structural component of this latent variable consists mostly of variables reflecting the impact the pandemic has had on respondents' lives, measured by the *Impact* variable. The impacts are ordinal in nature; however, we chose to model the impact as a discrete categorical variable to facilitate separate modeling of the opt-out where respondents indicate their uncertainty. This decision proved helpful as those uncertain of COVID impacts were found to be less comfortable with COVID exposure than those who experienced "Little Change." Additionally, it was advantageous because the effect jump from "No Change" to "Little Change" in the car commuter group resulted in a greater impact than the jump from other levels. We also considered the risk of COVID transmission to loved ones and found that families with more children were less likely to be comfortable with COVID-19 exposure situations. This effect is commonsensical as parents had to quarantine together with their infected children. Lastly, we found that men tended to be more comfortable with COVID-19 risk situations, which resonates with observations that men are less concerned about virus contraction and less likely to get vaccinated (Galasso et al., 2020, Lazarus et al., 2021). These sociodemographic variables indirectly affect the choice probabilities. Commuters who are married and have children are less likely to be comfortable in COVID risk situations, which decreases the probability of choosing the microtransit alternatives.

Modeling also reveals that COVID Comfort is directly affected by the Pro-Sharing Economy construct (albeit only for drivers, as depicted in Fig. 5). Because sharing in this context is of physical assets (including public areas), we hypothesized a structural relationship between these two latent variables. The positive sign implies that experience with sharing economy services — used to measure higher Pro-Sharing Economy attitudes — is underpinning higher comfort with shared resources during the pandemic. There are two issues to note here. First, the hypothesized hierarchical causation suggests that sharing is an established trait that affects how respondents behave in the novel and temporary context of pandemic social distancing. In practice, it is likely that the evolving objective and subjective risks, as well as experience and fatigue from social distancing, will continue to shape willingness to pool rides.

Kiriazes and Watkins (2022) obtained similar results, finding that pre-pandemic usage frequency of shared modes was negatively correlated with rider comfort during the pandemic. If a person is a non-user of ridehailing or transit prior to the pandemic, he or she is more likely to be uncomfortable. Second, we expected the Pro-Sharing Economy to be a driving factor for transit users. Instead, we could find no evidence of this construct affecting either COVID Comfort or the likelihood of using microtransit directly. We speculate that the transit users we observe, especially during COVID-19, are not choice-riders driven by sharing ideals but rather motivated by practical necessity.

In addition to the sharing economy constructs, the IOS scale measures sharing propensity. Our study confirms that the more closely a respondent identifies with other riders, the higher they score on Pro-Sharing Economy. Several personal characteristics are found to be related to sharing ideals. Being a voter in the latest election is positively correlated with sharing. We speculate that voters may have higher civic duty orientation associated with higher sharing identities (Fowler, 2006, Bolsen et al., 2014). Lastly, men tend to have higher sharing identities, and we attribute this to women's perceptions of (lack of) safety, especially in situations where personal space cannot be guaranteed (Morales Sarriera et al., 2017, Polydoropoulou et al., 2021). Therefore, the model suggests that drivers who are male, who have a sharing orientation, or are more comfortable in COVID-exposure situations have a higher probability of opting for the microtransit alternatives.

Finally, for the transit sample, initial transit ICLV specifications included the Pro-Sharing Economy latent variable; however, it was not identified even when the Structural Equation Model was estimated independently of the discrete choice model. Consequently, the only latent variable included for transit commuters is COVID Comfort.

6. Discussion, Implications, and limitations

6.1. Microtransit demand and curb-to-curb attribute elasticities

The curb-to-curb attributes involving out-of-vehicle travel time were only statistically significant in the car commuter ICLV. In contrast, transit commuters were unaffected by the walking and waiting time attributes. We consider this insensitivity to be due to the fact that transit commuters already experience these attributes for their daily commutes. Therefore, when promoting sustainability by attracting car commuters to microtransit, attention must be paid to the effort needed to access the service in terms of expected walking and waiting times that are unfamiliar for car drivers. One strategy to achieve this goal is by designing services that minimize waiting and walking times and, in exchange, may increase the minimum reservation time to facilitate better routing.

We derive attribute elasticities to explore such scenarios better, the relative importance of microtransit attributes and further understand differences between car and transit commuters. In meta-analyses, elasticities have been used to analyze the results of independently estimated models (Holmgren, 2007, de Jong and Gunn, 2001). Table 6 shows the elasticities at the mean of variables calculated using Equation 5 (Train, 2009).

$$E = (1 - P_i)\beta_{x,i}X_i \quad (5)$$

P_i is the probability of alternative i , $\beta_{x,i}$ is the coefficient of attribute x and alternative i , and x_i is the mean of the explanatory variable. These elasticities reflect the percent change in demand for the alternative as a function of a unit percent change in the attribute. We note that most elasticities are inelastic, with the exception of the microtransit travel time attributes. As expected from the model analysis, reservation time is less influential than in-vehicle, waiting, and walking time. In comparing the two commuter groups, the travel time elasticities are elastic for car commuters while for transit commuters it is not far behind. Clearly, drivers are sensitive to a greater range of attributes and display a significant aversion to access/walking time, while in-vehicle travel duration elasticity even clearly exceeds unity for the van option.

Operators can use these insights in several ways. Microtransit operators may unlock efficiency gains and reductions of passenger

Table 6
Elasticities and Difference between Commuter Groups.

Alternative	Variable	Elasticities		Difference (Car-Transit)
		Car Commuters	Transit Commuters	
Status Quo	Cost	−0.030	−0.10	0.070
Status Quo	TT	−0.12	−0.22	0.10
Status Quo	COVID	−0.27	NS	
Status Quo	Sharing (Indirect effect)	−0.23	NA	
MT-S	Cost	NS	−0.47	
MT-S	TT	−1.07	−0.85	−0.22
MT-S	Reservation Time	−0.046	−0.083	0.037
MT-S	Wait	−0.17	NS	
MT-S	Walk	−0.18	NS	
MT-V	Cost	NS	−0.72	
MT-V	TT	−1.41	−0.75	−0.66
MT-V	Reservation Time	−0.10	−0.24	0.13
MT-V	Wait	−0.30	NS	
MT-V	Walk	−0.38	NS	

NS – Not significant in the choice model; NA – Was not modeled.

Table A1
Latent variable measurement model table.

Coefficient	Model Car (Std. Error)	Transit (Std. Error)
COVID Comfort	–	–
CC1_ride	1 – fixed	1 – fixed
α_{CC1}	–	–
CC2_rest	0.496** (0.0323)	0.626** (0.0401)
α_{CC2}	1.41** (0.0696)	0.865** (0.106)
CC3_grocery	0.643** (0.0355)	0.649** (0.0425)
α_{CC3}	2.27** (0.0763)	2.07** (0.112)
θ_{CC}	1.02** (0.122)	2.46** (0.111)
Impact - Unsure	–0.572** (0.0976)	0.0887 (0.123)
Impact - No Change	0 – fixed	0 – fixed
Impact - Little Change	–0.539** (0.0939)	0.333** (0.111)
Impact - Big Change	–0.916** (0.0957)	0.0223 (0.112)
Impact - Very Big Change	–1.32** (0.102)	–0.383** (0.122)
Married	–0.138** (0.0220)	–
Male	–	0.186** (0.0389)
Number of Children	–	–0.0472** (0.0116)
σ_{CC}	0.113 (0.0641)	0.628** (0.0259)
Pro-Sharing Economy	^a 0.661** (0.0302)	–
SI1_enjoy	1 – fixed	–
α_{SI1}	–	–
SI2_increase	0.932** (0.0310)	–
α_{SI2}	–0.355** (0.0939)	–
SI3_exp	0.592** (0.0283)	–
α_{SI3}	1.49** (0.0856)	–
θ_{SI}	2.21** (0.0469)	–
Ridehailing App Experience	0.312** (0.0252)	–
Carpooling App Experience	0.292** (0.0249)	–
Carsharing App Experience	0.0301** (0.00621)	–
IOS	0.110** (0.00731)	–
Voter	0.201** (0.0371)	–
Male	0.112** (0.0230)	–
σ_{SI}	0.609** (0.0159)	–
χ^2/df	2.67	2.47
CFI	0.923	0.939
RMSEA	0.044	0.055
SRMR	0.032	0.028

(-) Not applicable.

* significant at $\alpha = 0.05$.

^a coefficient value and std. error of the Pro-Sharing Economy explanatory variable.

** significant at $\alpha = 0.01$.

wait times by knowing the demand for rides well in advance. Indeed, the smaller elasticity suggests that increasing the minimum reservation time would not be as consequential in promoting demand for the microtransit alternatives as increasing walk and wait times. Thereby, the elasticity findings suggest an opportunity to extend reservation times to obtain more favorable walking and waiting performance as a means to attract drivers to the curb-to-curb mobility options. Similarly to [Alonso-González et al., \(2020a\)](#), this reduction in travel time plays a prominent role in determining the likelihood of choosing microtransit. To further contextualize, [Alonso-Mora et al., \(2017\)](#) simulated scenarios with maximum waiting times of less than 7 min; however, this was in the highly-dense area of Manhattan, New York where high demand levels and the road network topology allow this. Therefore, for success in less dense areas, a large vehicle fleet size is another strategy to reduce wait and walking times but at the cost of higher operating costs or public subsidies.

For transit commuters, results suggest that the focus for microtransit operators will be on cost and travel time as these commuters did not exhibit significant sensitivity to waiting and walking times. One attribute that was only significant in a single instance was the sheltered boarding location. While this may be a prominent feature for public transit, it may not be a worthwhile investment in this context, where other curb-to-curb attributes play a greater role in shaping initial demand for microtransit.

6.2. Different perceptions for drivers and transit Commuters: Status quo effects

When considering the latent variables identified in the ICLVs, the lack of any significant Pro-Sharing Economy effect for transit commuters is intriguing. The Pro-Sharing trait appears to be a natural finding for the transit group since this mode embodies shared mobility, yet our modeling did not support this. COVID Comfort is also weakly significant ($0.10 < p\text{-value} < 0.05$). Taken together, these findings suggest that the transit users in this sample are likely captive users ([Etzioni et al., 2020](#)). Indeed, the analysis of

smartcard usage conducted before the pandemic shows that heavy users of transit in Israel are more likely to be regarded as captive with fewer mobility options—pupils, students, seniors, low income—while the modal split for the Tel Aviv metropolitan region is around 80/20 for car and transit respectively (Benenson et al., 2019, Etzioni et al., 2021). These findings are consistent with recent work by Sun et al., (2022) finding that COVID-19 risk concerns and perceptions have only a minor impact on satisfaction with transit among low-income riders before and after the pandemic. It appears that for riders reliant on transit, other concerns are more important than COVID-19 risks. Specifically, there are likely to be dynamic effects at play, connecting ridership to changing employment circumstances and COVID-19 risk levels. These issues warrant further research.

In contrast, both latent variables are strongly significant in the car ICLV. Because the Pro-Sharing Economy is mainly determined by experience with sharing economy services like Uber and Airbnb, we hypothesized that knowledge and familiarity with these types of services would lower the risk perceptions related to COVID-19. Additionally, operators have taken significant and public measures to increase patrons' safety (enforcing facemasks, fresh air, and limiting occupancy), which may have contributed to indirectly shaping virus exposure concerns in the context of hypothetical microtransit alternatives. Therefore, unlike transit commuters, car commuters do not appear to be captive to their status quo choice. Similarly, the elasticity of the COVID-19 comfort variable is much larger among car commuters. We interpret this strong effect to reflect the greater adaptiveness of drivers in response to COVID-19. It is reasonable to assume that those who rely on private vehicles have greater ease in adjusting ridership to reduce the risk of viral exposure.

6.3. Study limitations

Several limitations to this study should be noted. The sampling for this web-based survey may not represent the entire commuter population, especially digitally challenged citizens. Moreover, Israeli users may not have experienced microtransit or ridehailing in general before taking the survey. To address this lack of familiarity, we included descriptions of MT-S and MT-V, along with clear attribute definitions, and visual representations of vehicle pooling configurations in the experiment.

Another caveat is that the survey design and modeling were done separately for the two commuter groups. Given the group-specific tailoring of the experiment, the modeling needed to be separated. While a joint analysis could better confirm differences, we found the tailored approach to be more realistic. For example, transit commuters pay a relatively low price for their ride and do not need to consider parking costs. These commuters may also experience long travel times as fixed-route transit may need to stop frequently for passenger boarding and egress. To reflect this reality, the designed cost levels were higher for the MT-S and MT-V than for public transit. Moreover, travel times were just as fast or faster with one attribute level in MT-S being slower than public transit reflecting cases where transit has dedicated lanes. The choice experiment also sought to reflect the reality of Car commuters who must consider parking costs. These commuters saw scenarios where MT-S and MT-V were more affordable than driving, with the majority of travel time levels being slower for microtransit except in the cases when MT-S has access to high-occupancy lanes. Adding this realism to the choice experiments may have inadvertently affected the choice experiment results, leading to statistically insignificant cost parameters in the car commuter ICLV.

Finally, the timing of the study in the context of the pandemic makes it challenging to generalize findings for rapidly evolving circumstances. A later administration time would likely reflect different priorities and adoption decisions, given the proliferation of new viral variants, and the rapid immunization campaign that took place in Israel. Additional factors that warrant investigation are how travelers habituate to the pandemic over time, increasing their self-control perception regarding risks, and shifting background variables such as the rapid uptake of remote work as the default mode of employment for high-income employees who are mainly car commuters.

7. Conclusions

Microtransit with rider pooling may generate mobility system benefits, chief among them being the VMT reductions unlocked if enough riders share trips. Yet, the demand for microtransit, especially with a curb-to-curb service offering, is poorly understood. Specifically, it is challenging to promote the adoption of microtransit given that the service attributes lie at the intersection between door-to-door (private driving), on-demand (ride-hailing) mobility, and scheduled transit. This complexity implies that people's current mode experiences will likely shape the perception of microtransit attributes. Such insight becomes critical to consider, specifically given the need for microtransit to attract car drivers to ensure effective VMT and congestion reduction. In this study, we developed a choice experiment survey to identify how commuters perceive microtransit, including curb-to-curb attributes. Specifically, the experiment included tailored designs for car and transit commuters. Utilizing a pivoted design with the status quo alternative, we studied commuters' willingness to commute in an (MT-S) and a van option (MT-V) and quantified the impact of curb-to-curb attributes such as walking and waiting times at a designated boarding location. Additionally, we included attributes that represent the scheduling component of microtransit, where advanced planning and amenities are key attributes. Specifically, we tested the impact of a 'reserve-in-advance' attribute and a sheltered boarding location. The results reveal important differences among commuter groups. While drivers are highly sensitive to out-of-vehicle (walking and waiting) time, transit commuters are not. Drivers appear to be even more averse to the 'transit-like' attributes of microtransit when looking at the van option, while transit users had a more equal evaluation. Minimum reservation time significantly affected the utility of the microtransit alternatives overall; however, the elasticities show that in- and out-of-vehicle travel time have larger effects. Finally, among the novel attributes, the sheltered boarding location had no significant effect on the utility of the shared modes except for MT-V for transit commuters.

This analysis took place after the pandemic lockdown periods, and several questions were designed to measure COVID-19 risk and comfort to quantify the potential impacts. The latent variable portion of the ICLV reveals that COVID Comfort affects utility for car

commuters far more than for transit commuters. Furthermore, the Pro-Sharing Economy latent variable was not supported for transit commuters, despite the fact that public transit is defined by sharing. These results suggest that transit commuters are likely captive, reflecting a limited sensitivity to the latent constructs and focusing on the primary attribute effects. Instead, car commuters appear more responsive to the latent effects, suggesting more adaptiveness to changing circumstances for both shared vehicle space and COVID-exposure. Overall, this study gives an added understanding of nuances in COVID-19 impacts on mobility choices, showing that the risk perceptions across commuter groups are far from uniform.

Based on these results, operators of microtransit services should consider several strategies to attract riders. Firstly, ridership promotion strategies ought to be differentiated by commuter groups as they show major divergence in attribute and latent variable effects. Looking more carefully at the tradeoffs gives valuable insights. For instance, car commuters were not averse to adding more passengers in the sedan setting. Instead in the van context, additional passengers come at the cost of highly coveted travel time, suggesting that car commuters must be compensated by carefully calibrating cost-fare tradeoffs.

Future research should consider probing the lack of significant cost variables for car commuters. The choice experiment design used here aimed at realism by only providing tasks where microtransit costs were lower than the status quo, possibly at the cost of capturing the full cost sensitivity. One possibility to study both the evolving dynamics of the pandemic, and the effect of pricing variations, would be to incorporate gamification into the mode choice experiment (Klein and Ben-Elia, 2016). A dynamic choice experiment that updates mode attributes based on user responses may improve understanding of how pricing affects mode choice (Cherchi and Hensher, 2015, Danaf et al., 2020). For example, continually decreasing the cost of the microtransit alternatives until the respondent switches from the status quo may result in an improved understanding of the cost tradeoffs. However, researchers need to prevent endogeneity by carefully considering the experimental design, model initialization, how ‘random’ the choice environment is, and the respondent’s learning process (Guevara and Hess, 2019). Additionally, the context surrounding the COVID-19 pandemic has continuously evolved as information, vaccination rates, and people’s concerns and priorities are changing. Future research should incorporate broader pandemic effects, such as social distancing measures, and real-time information about pandemic indicators, to parse the effects on microtransit adoption, and more broadly what drives the competition among transportation modes with different levels of sharing and pandemic exposure.

CRediT authorship contribution statement

Jason Soria: Methodology, Data curation, Software, Formal analysis, Writing – original draft, Visualization, Investigation. **Shelly Etzioni:** Investigation, Software. **Yoram Shiftan:** Investigation, Resources. **Eran Ben-Elia:** Conceptualization, Investigation, Methodology, Writing – review & editing, Supervision, Project administration, Funding acquisition. **Amanda Stathopoulos:** Conceptualization, Investigation, Methodology, Writing – review & editing, Supervision, Project administration.

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.

Data availability

The data that has been used is confidential.

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