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The potential of microtransit for regional commuting

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Abstract

Shared on-demand mobility services, also known as microtransit, have become a major mobility provider around the world, yet this has predominantly taken place within urban areas. In areas with lower population density and poor quality public transport, such services could substantially improve accessibility. In early 2023, a regional microtransit pilot was carried out in the Ljubljana Urban Region in Slovenia. To assess the preferences towards such a service, a stated preference experiment is carried out among pilot participants, comparing car, public transport and microtransit for their daily commute. The obtained data is modelled using a Panel mixed logit model, with random parameters modelled as normally or log-normally distributed. Additionally, we also model for potential nesting effects among the alternatives. The results show participants perceive microtransit as a viable alternative, with public transport commuters finding it particularly attractive, whereas car commuters see it on par with the car. Parking price and a guaranteed parking spot tended to be key factors for decision-making. Simulating different policies, we conclude that combining subsidising microtransit and higher parking prices is the most effective strategy for achieving a modal shift primarily from car to microtransit while not affecting public transport as much.

Keywords On-demand mobility, Microtransit, Regional commute, Stated preference, Choice modelling, Mixed logit

1 Introduction

In recent years, various ridesourcing companies have gained a foothold in the transportation market. Companies like Uber, Lyft and DiDi are present in urban areas around the world, connecting drivers with passengers through a smartphone-based application. With the advancement of smartphones, many cities also saw the introduction of microtransit, a similar style of on-demand service, although often, but not always, operated in coordination with fixed public transport and utilising larger vehicles such as minivans, as opposed to cars in ridesourcing. Some notable examples include Bridj, Chariot, Via etc. [32]. Another type of on-demand mobility, arguably a predecessor to microtransit, is Demand Responsive Transit (DRT) [29], also known as dial-a-ride [7]. Such services have predominantly been implemented in lower density, lower demand, rural areas, where a fixed line public transport service cannot be justified. The main difference between DRT and microtransit seems to be that DRT is primarily a publicly funded service, whereas microtransit is primarily a private venture [31]. From the passenger's perspective however, there is little difference between the two: both use vans or minibuses and operate an on-demand door-to-door service. In this paper, we will use the term microtransit in referring to a regional on-demand service, however we make no assumptions on the model of ownership of such a service.

Past studies suggest that leisure is the primary purpose of ridesourcing and microtransit trips, while commuting has a lower, yet often still a significant share. [11, 15, 23, 36]. Yet despite the growing prominence of such services, they are almost exclusively limited to urban areas,

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depriving those travelling from rural to urban areas or between urban areas of a car-free door-to-door alternative. Private ridesourcing may not be a viable option for most for such longer distances due to the likely high cost associated with it. Microtransit on the other hand, with higher vehicle utilisation, could be under certain circumstances. DRT services already operate in lower density rural areas [5], yet the majority tend to operate as a feeder service or within the rural area, i.e. without providing a door-to-door service into a nearby urban area.

Introducing a regional microtransit service could provide substantial benefits to regional travellers. For existing public transport users, microtransit could improve the level-of-service of their commute by (1) reducing their access and egress walking time by offering a door-to-door service, (2) providing a transfer-free connection, (3) reducing waiting time and (4) guaranteeing a seat. Walking and waiting times are generally perceived more negatively than in-vehicle time [39], meaning that they contribute more negatively to the overall travel experience and passengers are willing to pay more to minimize those. At the same time, crowding [17, 41] and especially standing [17] on public transport are both known to substantially impact the negative perception of in-vehicle time, further decreasing the attractiveness of public transport. Additionally, as transfers are part of many public transport trips, the transfer penalty—which is a perceived disutility on top of the already incurred extra waiting time—further adds to the disutility of public transport, with an equivalent in-vehicle time of five to ten minutes or even more [41].

On the other hand, regional microtransit could offer car users a way to make better use of their commute time: giving them the option to work or relax during travel [21]. Undertaking other activities during travel, such as reading, listening to music etc. has been found to reduce the negative perception of in-vehicle time, making travel time less dominant in the decision-making process [10, 24]. Another highly impactful part of car commuting is parking. Feeney [9] summarises that parking-related factors may be more important in the decision-making process than travel time or travel cost. Similar to public transport, the walking associated with parking, i.e. walking to/from a parking lot, is also perceived as significantly more negative [9]. Hess & Polak [13] also considered the parking search time and concluded that it is perceived as the most negative aspect, likely due to the uncertain nature of finding a parking spot.

The topic of regional commuting has been addressed by Ryley et al. [29], who investigated the role and potential of rural DRT services in North England, through an in-person stated preference survey, comparing people's current mode with DRT. The service was characterised by the travel time, cost, walking time and departure time (on-time or late). They found that niche services can be viable, although making the system profitable and attractive is challenging, particularly due to the direct competition with the car. Bronsvoort et al. [5] also studied DRT in the rural context, but compared it with bus and a bus-bike combination. Similar to Ryley et al. [29], they also used travel time, walking time, cost and (potential) delay, while also adding a pre-booking time. Their main conclusion is that travel time and cost parameters are the most influential in the decision-making process, while flexibility and reliability seem to be less relevant.

Our study contributes to the literature by investigating the role of microtransit for regional commuting and what factors drive the decision-making process. Additionally, since previous research has indicated the importance of car parking provision and pricing [9, 13], we highlight this by including multiple parking-related attributes, allowing us to add valuable insight into the impact of parking on mode-choice decision-making. We expand the work of Ryley et al. [29] by not limiting respondents to their current mode, but rather showing all commuters both car and train alternatives, irrespective of their actual commute behaviour, while still accounting for it, i.e. we did not limit a-priori our market analysis to current public transport or car users. The rest of this paper is structured as follows. The methodology, including the survey design, data collection and modelling approach, are presented in Sect. 2. Section 3 then discusses the model results and their implications, with the conclusion provided in Sect. 4.

2 Methodology

2.1 Survey design

To obtain a better understanding and be able to quantify the preferences of regional commuters, a stated preference (SP) discrete choice experiment (DCE) is designed. Three alternatives are presented to respondents, namely the car, train and microtransit. The microtransit alternative is named GoOpti, since respondents' recognize the service by this brand name. Train is used rather than "public transport" to make the alternative more specific and more tangible for respondents. Train is chosen rather than bus as it is a more distinct form of transport, due to its independence from road congestion and thus higher reliability. The area where the survey is conducted has a reasonable railway connection, meaning that such an alternative can be considered relevant by respondents.

The characteristics describing both the train and microtransit alternative are in-vehicle time, access time, egress walking time and the cost of a monthly subscription. Walking on either side is included to evaluate the benefits of a door-to-door service. A monthly subscription is used instead of a single ticket as this is what most commuters are familiar with and can easily relate to. Other attributes such as waiting time, frequency and on-board crowding are excluded to retain the simplicity of the experiment and avoid overwhelming the respondents with information. The attributes for car are somewhat different. It too is described by the in-vehicle time and egress walking, but access walking is excluded, as most people have their car next to their home. Travel cost is split into fuel and parking cost to evaluate a potential difference in the perception of the different cost components. Finally, a binary"guaranteed parking spot" attribute is added, to analyse the value commuters attach to the peace of mind of not having to roam the street in search of a parking space. Guaranteed employer provided parking is also a fairly common occurrence in the study area.

Attribute levels for train and car are determined based on the current travel times and travel costs. The in-vehicle times are obtained from Google Maps [12] based on the range of travel times during the morning peak. Monthly travel expenses for car are based on a past range of fuel prices (1–2 €/l), fuel consumptions rates of different vehicles (5–10 l/100 km) and monthly commute distance (15–40 km per direction per day) for the study area. Parking prices and public transport tickets are based on the current prices, with monthly parking ranging between €0 and €200 per month (LPT, [20]; Parkiraj, [27]; Parkirna hiša Trg republike, [28]) and public transport ranging between €53 and €94 per month (Arriva Slovenija, [2]; Ljubljanski potniški promet, [18];

Table 1 Alternatives, attributes and attribute levels of the stated choice experiment

		Car	Train	GoOpti (microtransit)
Access walking time	[min]		3, 8, 13	0, 3, 6
In-vehicle time	[min]	25, 35, 45	25, 35, 45	25, 35, 45
Egress walking time	[min]	0, 5, 10	3, 8, 13	0, 5, 10
Monthly ticket	[€]		30, 60, 90	30, 130, 230
Monthly fuel	[€]	30, 100, 170		
Monthly parking	[€]	0, 80, 160		
Guaranteed parking		Yes, No		

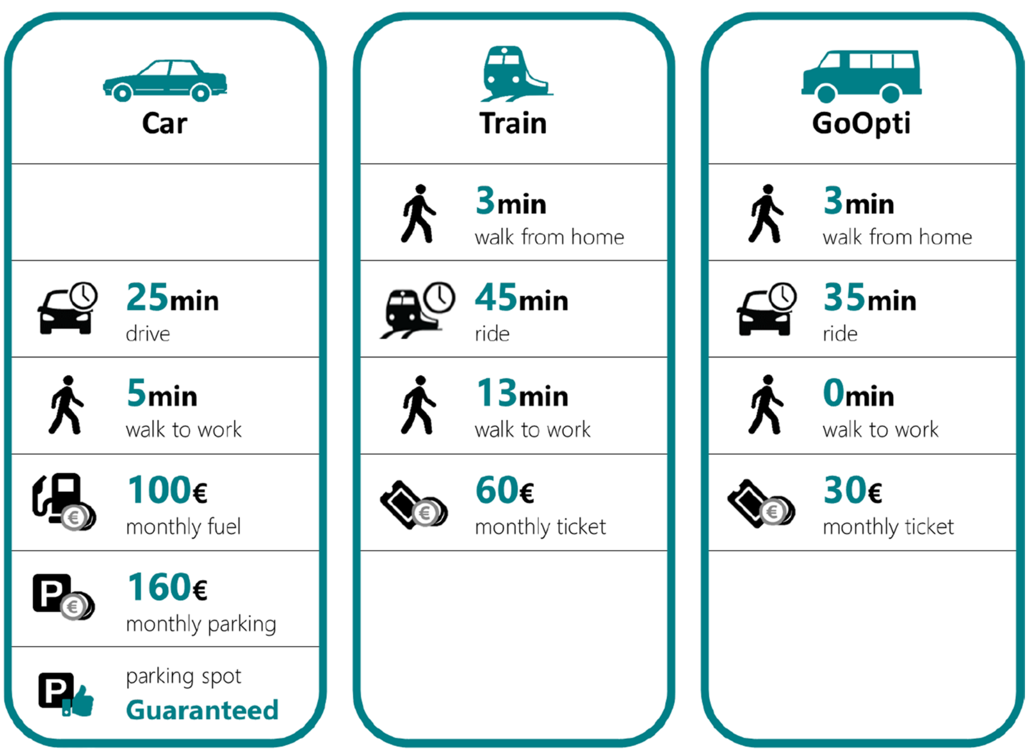

Fig. 1 Example choice task from the survey

Nomago, [25]; Slovenske železnice, [33]). Walking times are determined based on expected and acceptable levels for people to access/egress a stop/station/parking lot. Additionally, 0 min of walking time is included for egress time of car and both access and egress time of microtransit to mimic a door-to-door service. All attribute ranges are expanded and rounded to make it easier for respondents and to comply with equidistance. The full set of alternatives, attributes and attribute levels is presented in Table 1, with an example choice task shown in Fig. 1.

A Bayesian D-efficient design with prior values is used to generate the survey [38]. A Bayesian efficient design uses a mean and standard deviation of the prior, running a simulation with the parameter values drawn randomly, based on the mean and standard deviation. This is a less deterministic approach than the typical D-efficient design, allowing for a broader range of prior values when the researcher is less certain about the exact value [38]. Based on the results of Wardman et al. [40], we set an average value of 12€/h for in-vehicle time is selected. Although their study suggests a slightly lower value of time for Slovenia (6–10€/h), these values are imputed and not directly based on studies carried out in Slovenia. These values were also calculated for 2010 incomes and prices, which have increased since. Additionally, the Bayesian efficient design applied in this study is especially well suited for such tasks, when the exact value is not certain. Using the value of 12€/h, we use the priors for in-vehicle time and cost of -0.03 and -0.15 respectively. As the survey includes costs in the form of monthly tickets/expenses, the prior parameter for cost is divided by 40, representing approximately 20 return trips per month. This results in -0.00375, or an equivalent of 8€/min: individuals would be willing spend 8€ more on a monthly ticket to save 1 min on each trip. For the standard deviation of the time and cost priors, we assume a standard deviation at half the scale of the mean. This allows for sufficient variation, while at the same time maintaining a 97.5% certainty that the prior has the correct sign. The prior value for parking guarantee is set to -1, while the alternative specific preferences for train and microtransit are assumed to be 0. All three are given a standard deviation of 1, again to allow for ample variation. To retain attribute level balance, a design with 9 choice tasks is selected as optimal. The final design is the one with the lowest D-error following the first 5000 iterations. The tool Ngene [6] is used to generate the design.

Together with the DCE, participants were also given a questionnaire to collect socio-demographic and travel behaviour information. Not all the questions from that questionnaire are relevant for this study. Among the questions asked on travel behaviour information were (1) the mode(s) used for work commuting, (2) average commute travel time, (3) how frequently they use the car, (4) whether they have to pay for car parking at work and if they use the travel time with microtransit to do (5) work-related or (6) leisure-related activities. With respect to socio-demographic data, respondents were asked for their (1) gender, (2) age (3) completed level of education and (4) in which of the two pilot work areas they were employed.

2.2 Modelling approach

The obtained DCE data is analysed by means of discrete choice modelling (DCM) techniques, We assume that respondents make decisions based on the utility maximisation framework [22]. We first estimate a series of multinomial logit (MNL) models to test a variety of different model specification, including attribute non-linearity, interaction effects and the influence of socio-demographic characteristics on decision-making.

We then expand on the obtained MNL model into a Panel Mixed logit model (as shown in Eq. 1), allowing is to capture the panel effect, respondent heterogeneity and nesting effects [37]. As the the name suggests, the Panel Mixed logit accounts for the panel effect, meaning that choices made by the same respondent are not considered independent but as correlated.

The respondent heterogeneity is captured through random parameters (b) which, unlike fixed parameters (d), are distributed according to a prespecified distribution with an estimated mean (m) and variance (s^2). Mode specific constants are randomised, testing a normal and lognormal distribution. For in-vehicle time, walking time and guaranteed parking parameters, we specify a log-normal distribution with additional restricting conditions, in order to guarantee a negative/positive sign of the parameter while still allowing for an asymptotic trend towards lower/higher perceived values. This is done by restricting the range within which both the mean and sigma of the distribution can vary. For in-vehicle time and walking time, both are restricted to a range of $(-\infty, 0)$, whereas for guaranteed parking, the restricted range is $(0, \infty)$. This ensures a fully negative log-normal distribution for the former two parameters and a fully positive distribution for the latter. The cost parameter is kept fixed to allow for an easier calculation of trade-offs like value-of-time, value of guaranteed parking etc.

Equation 1 Utility function specification of the mixed logit model

$$V_{ni} = \sum_{k \in K} \beta_{kn} X_{kni} + \sum_{l \in L} \delta_l X_{lni} \quad (1)$$

where

V_{ni} Systematic utility of respondent n for alternative i.

β_{kn} Distributed parameter for attribute k and respondent n.

δ_l Fixed parameter for attribute l.

X_{kni} Attribute level for attribute k, observed by respondent n in alternative i.

K Set of attributes that are modelled with a random parameter.

L Set of attributes that are modelled with a fixed parameter.

Adopting a mixed logit approach also allows us to test different (cross-)nesting specifications. If alternatives are nested, they share certain unobserved similarities which are not captured by the existing attributes. If this is not accounted for, the assumed IIA property (independence from irrelevant alternatives) is violated. Mixed logit models allow for cross-nesting, which is where an alternative can be part of multiple nests at the same time. We test all three possible combinations among the three alternatives [37].

2.3 Case study and data collection

The research is caried out in Slovenia, among regional commuter into Ljubljana, the largest city and capital of the country. Ljubljana hosts over a quarter of all jobs in the country, despite being home to only 14% of the population. This puts significant pressure on the transportation network in and around the city, with every second employee being an out-of-town or regional commuter, resulting in over 100.000 daily commuters entering the city [35].

To assess the potential of microtransit the SmartMOVE project was initiated, part of which was a pilot involving a free door-to-door microtransit service, offered to a group of travellers commuting between towns in the Ljubljana Urban Region and the city of Ljubljana. The pilot took place between 1.2 and 30.4.2023 and targeted those currently working in either the University Medical Centre or the "BTC city" industrial and commercial district. These two locations were chosen as the former has limited parking availability in its vicinity while the latter has poor regional public transport accessibility. Participants were recruited through various forms of direct advertising in the target employment areas as well as online advertising. From over 500 interested individuals, 131 were selected to participate, based on the ease of integrating them into the commute route for the microtransit service and based on their current commute mode. The latter prioritised car commuters, as one of the project goals was to assess the potential of shifting existing car users to microtransit. They were then assigned to minivans based on their origin, destination and preferred arrival/departure time, based on the starting/finishing time of work. Microtransit service was provided by GoOpti, an established company in the country, providing primarily (private and pooled) on-demand shuttle services to/from nearby airports.

Table 2 Sample characteristics

		Count	Share (%)
Gender	Female	59	73
	Male	21	26
	Prefer not to say	1	1
Age	< 30	7	9
	31–44	36	46
	45–64	36	46
	> 65	0	0
Highest level of education	Elementary	0	0
	High school	21	27
	Higher vocational education	26	33
	University	31	40
Current commute mode[a]	Car (driver or passenger)	76	94
	Public transport (bus, train)	53	65
	Active mode (walking, cycling)	8	10

[a] In this category, the shares add up to > 100%, as respondents could choose more than one mode

The data collection for this study took place during the course of the pilot period. Participants were handed two printed questionnaires, one containing the DCE and the other collecting travel behaviour and socio-demographic information. The survey was handed out to respondents during the morning commute between 22.03. and 06.04.2023. In total, 90 participants filled in the survey. Given the limited number of participants, partially complete responses are also included in the final dataset, resulting in a total of 704 unique choice observations. The sample characteristics are presented in Table 2. While the sample is not representative of the overall population, we cannot say much about its representativeness of the commuting population. Given that commuters tend to be of working age, the sample may be well aligned with the commuting population. The same cannot be said with respect to gender. Information regarding modal splits for regional commuters is also not known, however a share of > 90% for car is plausible.

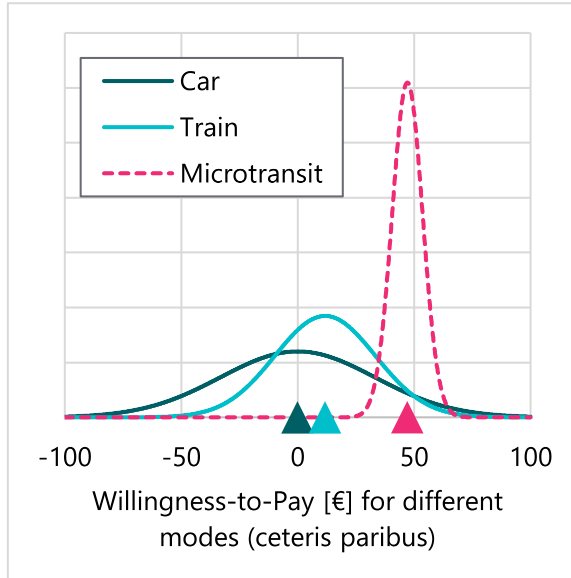

Fig. 2 Willingness-to-pay for different travel modes given all else being equal

Table 3 Mixed logit model outcomes

Model fit				
Null LL	−773.42			
Final LL	−315.30			
Rho-square	0.5923			
Adj. Rho-square	0.5691			
BIC	709.47			
	Parameter estimate	Robust t-stat [param]	σ	Robust t-stat [σ]
Taste parameters				
Constant [car]	0 [ref]		1.37	2.69***
Constant [train]	0.4852	0.46	0.89	2.86***
Constant [microtransit]	1.9386	1.97**	−0.27	−0.88
Cost	−0.0411	−8.11***		
In-vehicle time	0		−0.03	−2.44 **
Useful in-vehicle time	0.0014	0.09		
Walking time	0		−0.05	−4.36***
Guaranteed parking	0		0.84	3.21***
Nesting parameters				
Car-Train nest			0.3797	1.43*
Car-Microtransit nest			1.9133	6.01***
Train-Microtransit nest			−0.6822	−1.30*
Interaction parameters				
Public transport → Train	1.0451	1.41*		
Car → Microtransit	−1.7843	−2.17**		
Medium car use → Train	−2.2886	−2.17**		
High car use → Train	−3.3390	−3.26***		

*** $p \leq 0.01$, ** $p \leq 0.05$, * $p \leq 0.2$

3 Results & Discussion

3.1 Model outcomes

The final model outcomes, including the model fit, as well as taste, nesting and interaction parameters, are presented in Table 3. All models are estimated using the pandas Biogeme python package [3], with the mixed logit model estimated using 10,000 Halton draws.

All three mode-specific constants (MSC) are set as random, with their distribution following a normal distribution, with the car constant fixed as the baseline. We find that when all other attribute levels are equal, the mean of the microtransit mode is preferred over car and train, whereas there is no significant difference in perception among the means of the latter two. Looking at the variation of the modal preferences, the variability of microtransit is insignificant even at a value of $p = 0.2$. Considering only the mean, it is the most preferred mode for most participants. Car and train both have highly significant standard deviation parameters ($p < 0.01$), with a substantial overlap, meaning that on average, there is no clear preference for one or the other. The distribution of modal preferences is plotted in Fig. 2.

Testing different interaction effect, the MSCs were interacted with various travel behaviour and socio-demographic characteristics and two resulted in significant results, namely which modes of transport are currently used at least on a weekly basis and how frequently the car is used for commuting. Since the MSCs are interacted, it is important to highlight the baseline showcased in Table 1 and Fig. 2, which are low car use (almost never) and active modes. Baseline values are also indicated with shading in Tables 4 and 5. Considering the interaction effects, commuters using public transport have a more positive perception of the train compared to car commuters and active mode commuters. Notably, car commuters have a significantly less positive perception of microtransit compared to commuters travelling by other means. Additionally, both medium- and especially high-frequency car users have a substantially more negative perception of the train. This suggests that it will be quite difficult to get car users to switch to either microtransit or line- and scheduled-based public transport. The monetary trade-off for microtransit and train over the car (ceteris paribus) can also be seen in Tables 4 and 5, respectively.

This is not unexpected, as many employers currently provide parking on or near the premise, with workers having limited incentive not to travel by car. Additionally, many current public transport users can be considered so-called "PT-captives", meaning that they use it because they have no other option and would happily switch to another mode if it performed similarly in terms of its travel attributes. A similar preference order is reported by Ryley et al. [29], where car was seen as superior, while DRT and bus were not significantly different. Their research however did not include any parking-related characteristics, which can, as show later on in our research, substantially affects the attractiveness of the

Table 4 Willingness-to-pay more for microtransit over a car (ceteris paribus)

Microtransit over car		Car use		
		Low	**Medium**	**High**
Current commute mode	Car	€ 3.75	€3.75	€3.75
	PT	€47.11	€47.11	€47.11
	Active	€47.11	€47.11	€47.11

Table 5 Willingness-to-pay more for train over a car (ceteris paribus)

Train over car		Car use		
		Low	**Medium**	**High**
Current commute mode	Car	€11.79	€− 43.83	€− 69.35
	PT	€37.19	€− 18.43	€− 43.96
	Active	€11.79	€− 43.83	€− 69.35

*The shaded field indicates the baseline

**Text in red indicates negative values, meaning that the mode in question is perceived more negatively than the baseline (car)

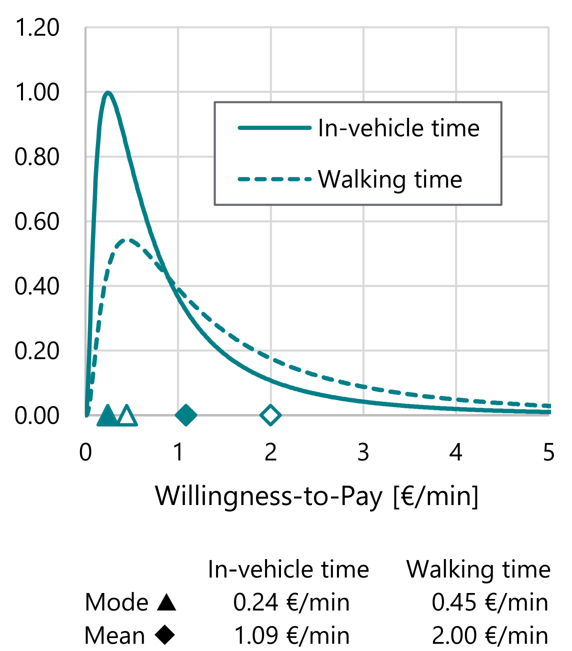

Fig. 3 Willingness-to-pay for saving in-vehicle and walking time, i.e. how much travellers are willing to pay per month to save a minute in each trip

Fig. 4 Willingness-to-pay for guaranteed parking, i.e. how much (more) per month are travellers willing to pay for a guaranteed parking spot

car. Bronsvoort et al. [5] also finds that DRT is perceived more positively than public transport, whereas no comparison can be made to the car.

In-vehicle time, walking time and guaranteed parking are all estimated as random parameters with a log-normal distribution. The log-normal distribution yields a better model fit than a normal distribution and it also allows us to restrict the parameters to take only positive (guaranteed parking) or negative (in-vehicle and walking time) values. The parameters are restricted to only positive or negative values as outline in Sect. 2.2. Walking time and guaranteed parking result in an indistinguishable model fit if modelled as a random log-normally distributed parameter or a fixed parameter. A random parameter was chosen as it captures the effect of heterogeneity and thus provides more information on the preferences of the sample, while maintaining the same number of parameters. The distribution of willingness-to-pay (WtP), including the mean and mode of the distributions, for in-vehicle time and walking time saving is presented in Fig. 3. It shows that walking time is more widely distributed within the sample, with both the mode and mean of the walking time distribution being roughly double that of the in-vehicle time values. This is broadly in line with past research [39]. With respect to parking guarantee, the distribution of willingness-to-pay is displayed in Fig. 4. It shows that people are willing to spend on average €33.83 per month to secure a parking place. Somewhat surprisingly, the distribution starts at zero and not a higher positive value, but it seems that a substantial number of people have a very low willingness-to-pay for a parking guarantee or rather, they do not mind spending some time searching for parking place rather than paying. Looking at percentile values, the 25th percentile (Q1) is €10.44, the median WtP sits at €20.49, 75th percentile (Q3) at €40.23, with the 90th percentile WtP at €73.81.

Considering other interaction effects, respondents were asked if they made use of their time in microtransit for other work or leisure activities, such as reading, communication, listening to music… For those that indicated yes, in-vehicle time in microtransit is modelled with a separate random in-vehicle time parameter. However, all model outcomes resulted in estimates which are insignificantly different from zero. When applying a normal distribution, the sigma parameter is significant, yet did not result in a significant improvement in model fit. In combination with having a 50% chance of the parameter taking a positive value, it was decided to estimate the parameter as fixed. While showing a slight positive value, it is highly insignificant. This indicates that passengers who use their travel time productively do not really consider in-vehicle in their decision-making, which is not in line with the findings reported by past studies [24]. This may be due to a microtransit vehicle not providing for the same level of comfort as a train. Another explanation could be that car commuters, who have limited experience with public transport and microtransit, do not yet see the benefits of using travel time for other activities [24]. This was also not a key aspect of this study and thus was not particularly emphasized, which may have contributed to the parameter estimate being insignificant.

Finally, estimating a mixed logit model allows us to analyse potential nesting effects among the evaluated alternatives [37]. Three error components with a mean of zero are specified, capturing the three potential nests: (1) car-train nest: the alternatives travellers are familiar with and have used in the past, (2) car-microtransit nest: road-based modes, (3) train-microtransit nest: both allow travellers to undertake other activities during the trip as they do not have to drive. Table 3 shows that the error component of the car-microtransit nest shows a weak (0.54), albeit highly significant correlation ($p < 0.01$), indicating that there do seem to be underlying similarities and substitution patterns between the car and microtransit alternatives. One reason for this could be that both are prone to getting stuck in congestion. Another reason could be a fairly negative view of the population towards what is perceived as an outdated and uncomfortable (rail) public transport service. Two other error components indicate a very weak correlation (0.19 and 0.29) with a low level of significance ($p = 0.15$ and $p = 0.19$).

3.2 Model implications

Having analysed the results and the monetary trade-offs of different modes and trip characteristics, we now evaluate the potential modal split if such a service would have been introduced. In the following, we test four different implementation schemes and policy measures with respect to their impact on travel behaviour and decision-making:

1. **PUDO** (Pick-up Drop-off locations)

In the pilot, passengers were offered a door-to-door service. In the survey, we tested a potential access and egress walking time to see if implementing specific pick-up and drop-off locations would have a substantial impact on decision-making. Walking tends to be perceived more negatively, but the question is if a shorter in-vehicle time can compensate for it.

2. **Car parking**

Expenses are often a deciding factor in decision-making and with parking often being used as a pricing measure, we test what the impact of varying the parking price on modal split is.

3. **GoOpti subsidy**

Another way of influencing choices is by lowering the cost of a desirable alternative. By varying the price of a microtransit service, we can better understand how providing subsidy may encourage people to opt for microtransit.

4. **Parking + Subsidy**

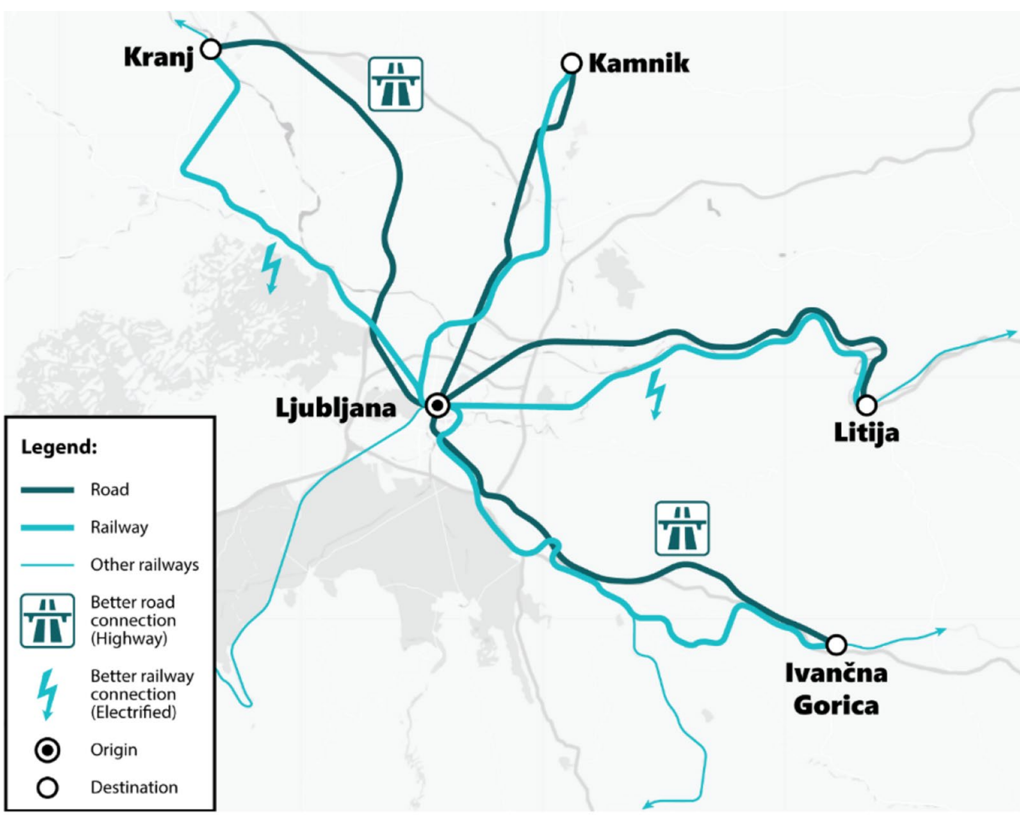

Fig. 5 Map of the case study area

A combined measure of parking cost and microtransit subsidy is also tested. The idea is that parking-related revenue can be used directly to subsidise microtransit, so the two are varied simultaneously (as parking costs go up, the level of subsidy does too and thus the cost of microtransit goes down).

We simulate the implementation of regional microtransit on four different corridors within the study area of the Ljubljana Urban Region by applying the obtained behavioural results presented in Sect. 3.1. All four corridors have a railway connection to the capital, with two of the four having a higher quality connection, meaning faster and/or more frequent services on electrified rails and two corridors having a higher quality road connection, i.e. a highway. The four corridors exhibit all four possible combinations: good/bad road + good/bad rail connection. A map of the four corridors and their characteristics is provided in Fig. 5. The detailed attribute levels used in the analysis are based on current travel times and costs and are listed in Tables 6 and 7 in Appendix A.

The full results are presented in Fig. 6, with the measures shown in columns and the different corridors in the different rows. For PUDO, we assume that for every minute of walking time, one minute of in-vehicle time can be spared. This is assuming a neighbourhood street where the van would need to drive slowly and turn around after picking up the passenger. Assuming a full vehicle of eight passengers, the first passenger would benefit the most, while the last would see hardly any benefit. On average, for each additional minute of walking time, each passenger would be spared 3.5 min of in-vehicle time. Considering the results in Fig. 6, we can see a slight increase in the share of microtransit with the walking distances to PUDO getting longer, although the impact is marginal. The impact is even more negligible if we consider that it primarily affects the rail modal split whereas the share of trips by car stays fairly unaffected across all four corridors.

Unlike PUDO, the two pricing policies have much more considerable impacts on modal split. In the baseline scenario, an average monthly price of €40 was considered. Offering free parking tends to increase the share of car trips by some 20–25 p.p. across the corridors, affecting both the train and microtransit modal split. Considering the option of increasing parking price, Fig. 6 shows that on three of the four corridors, the car share drops below 10% at an average monthly price of €90, with the exception of Kamnik where it stands at 25%. At high parking prices, it is interesting to observe that microtransit shares are somewhat higher on the Kranj and Ivančna Gorica corridors, both of which have a highway connection, whereas Kamnik and especially Litija have slightly lower microtransit shares, with Litija having the largest train share. The latter is also logical, as the railway connection is very good, whereas the road connection is not.

Subsidising the microtransit service has a similar impact as parking pricing, albeit when tested for a wider range of values. A somewhat free market price of > €200 per month would result in very few microtransit users, with car and train having distributions in accordance with the quality of service at the moment. Conversely, increasing the subsidy and having the users pay only a fraction of the cost would result in very high shares of microtransit use, exceeding a 50% market share when price drops below ~ €100. Depending on the market shares of car and train on the corridor in question, microtransit seems to affect both roughly to the same extent.

Finally, it is interesting to consider both pricing policies together. The main noticeable trend is that with increasing parking price and decreasing microtransit cost, those two modes adjust accordingly, with the share of train trips staying fairly stable or increasing slightly when microtransit becomes less affordable and parking cheaper. This approach is thus not only good in terms of financial transparency, as the money obtained through increased pricing is used to directly subsidise microtransit, and thus stays within the mobility domain, but it also has the advantage that it does not have a substantial impact on existing public transport, but rather targeting car users. Some train trips do seem to be substituted when microtransit prices get very low, but with slightly higher parking prices and a medium microtransit subsidy, the model shows an ambitious yet realistic target modal split.

4 Conclusion

This study provides, to the best of our knowledge, the first insight into the potential and preferences of passengers for using pooled microtransit-style services for regional and intercity commuting. In areas with poor public transport accessibility and a sparse and dispersed population, a door-to-door microtransit solution could provide an attractive and more sustainable alternative to the private car. Additionally, microtransit allows travellers to use their travel time more effectively and also to forgo the difficulties of finding and paying for a parking space, particularly in downtown areas, where space is often scarce.

Our results show that microtransit can provide a serious alternative for daily regional commuters. Considering the overall preference for modes and not accounting for differences in time and cost, car commuters see the car and microtransit as equally attractive if car parking is not guaranteed. If car parking is provided by the employer however, car is by far the most preferred mode, even before accounting for the shorter travel time and the lack of access/egress walking. Public transport commuters see microtransit as substantially better than both car and public transport, meaning they may be the more likely users to adopt microtransit.

Time and guaranteed parking perception are all modelled as varying within the population. In line with past results [39], the ratio between walking and in-vehicle time is found to be approximately two. Guaranteed parking is highly valued by commuters, with a mean WtP of ~€34 which is the equivalent of a monthly subscription of €37 for the urban public transport network in the city (Ljubljanski potniški promet, [18]).

Performing an application simulation and testing potential policies, we find that there is real potential for users to adopt microtransit for everyday commuting. Price seem to be the driving factor of decision-making, with microtransit share being driven by lowering its price, as well as increasing parking price. The combination of the two measures seems to be the most advantageous as it shifts commuters away from the car while maintaining the share of train trips. In contrast, implementing specific PUDO locations to streamline microtransit operations and potentially combine the pick-ups of multiple travellers has a limited impact of a few percentage points. If policymakers wish to encourage microtransit, combining a parking pricing policy and subsidising microtransit, potentially with the revenue from parking, seems to be the most beneficial policy to achieving this goal, while implementing PUDO points is, based on our findings, expected to yield a limited impact on modal split.

While the results of this study seem promising, it is also important to highlight certain limitations of the work, which can also provide an outlook for future research. Sample characteristics—size and a self-selection bias—are likely to result in an overestimated potential for microtransit services for regional commuting. Future studies may want to analyse larger, more representative samples. Having a good overview of all types of travellers would result in a clearer understanding of the preferences for and the potential of microtransit services for regional commuting. Additionally, a larger sample may allow for the estimation of a latent class choice model, resulting in distinct user profiles and a clearer understanding of the types of users more predisposed to taking up microtransit services. Simulation studies on the potential of (shared) on-demand mobility [1, 4, 8, 14, 16, 19, 26, 30, 34] can also be extended to assess the viability of a microtransit services on a regional/rural scale, testing the required demand characteristics. It is also interesting to compare the perception and potential of microtransit services in rural areas as a door-to-door service vs. a feeder service for public transport.

Table 6 Attribute levels used in the case study (part 1)

	Kranj			Kamnik		
	Car	Train	Micro	Car	Train	Micro
Walking time [min] (access and egress)	5	30	0	5	20	0
In-vehicle time [min]	45	35	60	45	40	60
Total monthly cost [€]	125	65	130	85	65	130
Fuel cost [€]	40			40		

Table 7 Attribute levels used in the case study (part 2)

	Litija			Ivančna Gorica		
	Car	Train	Micro	Car	Train	Micro
Walking time [min] (access and egress)	5	20	0	5	20	0
In-vehicle time [min]	50	30	65	55	50	70
Total monthly cost [€]	160	65	130	165	65	130
Fuel cost [€]	40			40		

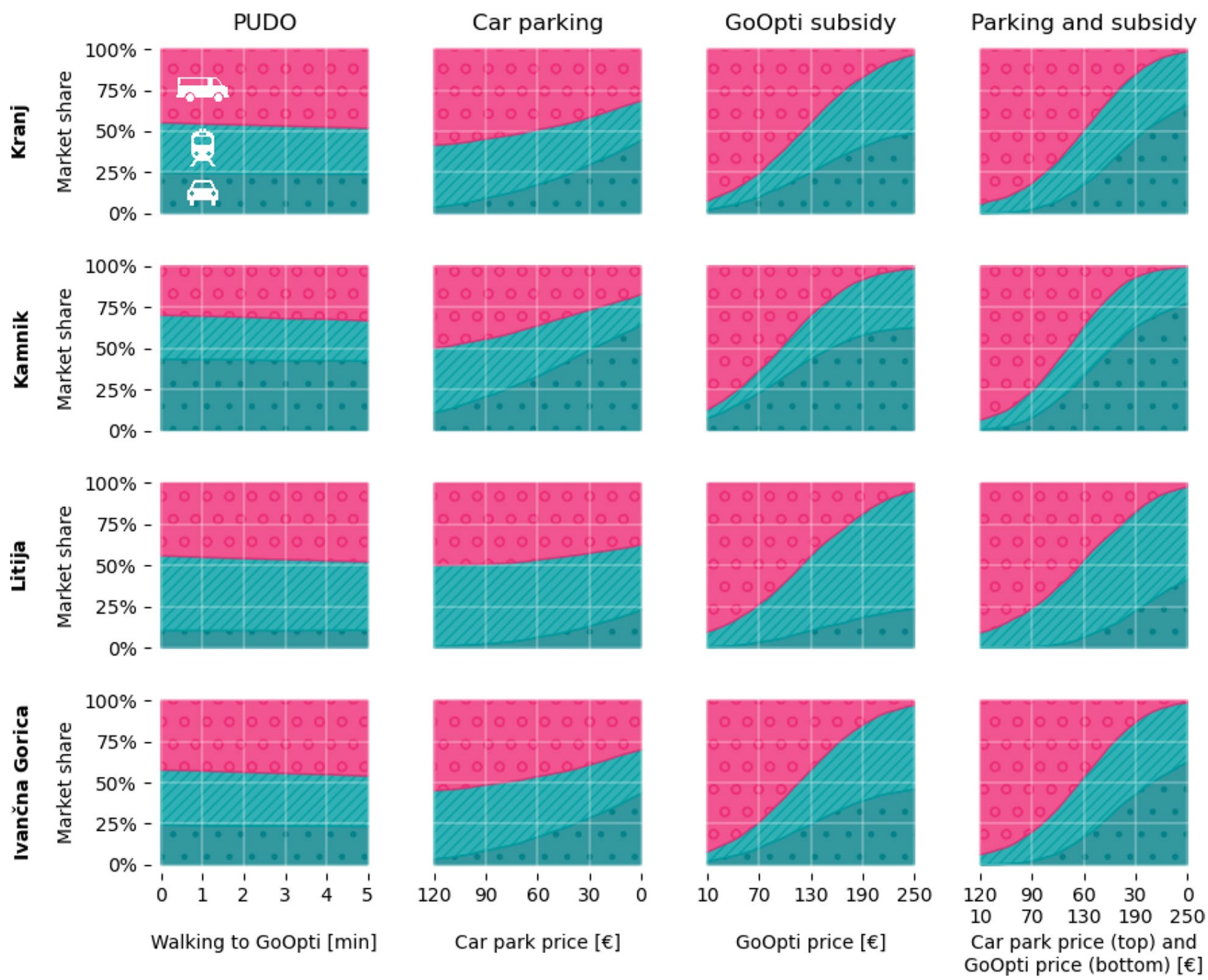

Fig. 6 Results of the policy analysis (car park price shown in reverse order to highlight the potential of using parking revenue to subsidise microtransit service)

Appendix A Attribute levels in the case study

To analyse the choice behaviour of regional commuters, existing travel times and expenses are considered. The values are based on current travel times (*Google Maps*, [12]) and expenses (Arriva Slovenija, [2]; Ljubljanski potniški promet, [18]; LPT, [20]; Nomago, [25]; Parkiraj, [27]; Parkirna hiša Trg republike, [28]; Slovenske železnice, [33]). The values are listed in Tables 6 and 7.

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Nejc Geržinič: conceptualization, methodology, software, formal analysis, data curation, writing—original draft, visualization. Marko Guček: investigation, writing—review and editing, supervision, project administration. Oded Cats: conceptualization, methodology, writing—review and editing, supervision.

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