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Integrating ridesourcing services with public transit: An evaluation of traveler responses combining revealed and stated preference data☆

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ABSTRACT

Inspired by the success of private ridesourcing companies such as Uber and Lyft, transit agencies have started to consider integrating ridesourcing services (i.e. on-demand, app-driven ride-sharing services) with public transit. Ridesourcing services may enhance the transit system in two major ways: replacing underutilized routes to improve operational efficiency, and providing last-mile connectivity to extend transit's catchment area. While an integrated system of ridesourcing services and public transit is conceptually appealing, little is known regarding whether and how consumers might use a system like this and what key service attributes matter the most to them. This article investigates traveler responses to a proposed integrated transit system, named MTransit, at the University of Michigan Ann Arbor campus. We conducted a large-sample survey to collect both revealed preference (RP) and stated preference (SP) data and fit a RP-SP mixed logit model to examine the main determinants of commuting mode choice. The model results show that transfers and additional pickups are major deterrents for MTransit use. We further applied the model outputs to forecast the demand for MTransit under different deployment scenarios. We find that replacing low-ridership bus lines with ridesourcing services could slightly increase transit ridership while reducing operations costs. The service improvements offered by ridesourcing mainly come from reductions in wait time. Though relatively small in our study, another source of improvement is the decrease of in-vehicle travel time. Moreover, we find that when used to provide convenient last-mile connections, ridesourcing could provide a significant boost to transit. This finding verifies a popular notion among transit professionals that ride-sourcing services can serve as a complement to public transit by enhancing last-mile transit access.

1. Introduction

The coupling of information technology with transportation has generated new travel options such as ride-hailing services (e.g. Uber, and Lyft) and microtransit (e.g. Bridj, Chariot, and Via), which are disrupting the personal travel market. Amid competition, transit operators have started to introduce on-demand, app-driven ridesharing services (here termed ridesourcing services), either run by themselves or by partnering with private companies, into their suites of transportation options. Common initiatives include

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offering subsidized on-demand rides to and from transit stations, providing ridesourcing services to persons with disabilities as an extension to traditional demand-responsive services such as taxi subsidies and dial-a-ride services, and piloting dynamic on-demand shuttle services in low-density areas (Feigon and Murphy, 2016).

Some transit operators have taken a step further to consider revamping their transit systems with a "hub-and-spoke" idea—fixed-route lines running along transit hubs with ridesourcing services acting as a feeder (Chen and Nie, 2017; Errico et al., 2013; Mahéo et al., 2017; Stiglic et al., 2018). Unlike existing ridesourcing services which primarily operate in an independent manner, this flavor of transit-system integration features synchronization between on-demand rides and fixed-route services. Integrated ridesourcing services can improve transit systems in two principal ways. First, ridesourcing could be used to substitute for fixed-route transit lines in low-demand areas in order to improve operational efficiency. To meet the political and service needs of geographic coverage, transit operators often need to run transit lines in low-density areas that generate very low ridership, particularly during the evenings and weekends. If an on-demand, flexible-routing transit system were operated to replace these lines or certain segments of them, it might be able to serve existing transit demand while reducing costs by replacing large buses with cars or other small vehicles with reduced capital and operating costs. Second, ridesourcing can act as a complement to transit. Constrained by fixed routes and vehicle scheduling, public transit faces the "last-mile" problem, which refers to its inability to serve travelers all the way from their point of origin to their destination. The last-mile problem is commonly viewed as a major deterrent to transit use among people who do not live within walking distance of a transit stop. If designed in a way to provide convenient last-mile connections between the point of origin/destination and the transit network, ridesourcing services could extend the catchment area of public transit.

While an integrated system of ridesourcing services and public transit is conceptually appealing, transit agencies need to anticipate how travelers will respond to it. Transit operators need information on customer response in order to design a transit system that is both attractive and financially sustainable. This study seeks to advance research in this area by examining commuting mode choice in a hypothetical scenario of switching from a conventional bus system to an integrated system of ridesourcing services and bus lines. The study approach involves conducting a survey to collect revealed preference (RP) and stated preference (SP) data on mode choice behavior and calibrating a joint data model to investigate the main determinants of the choice process. Our focus is on quantitatively evaluating how changes in different service attributes of the new system impact transit use. We apply the model results to predict future demand for the new transit system under different deployment scenarios, which can help transit operators evaluate the feasibility of the new system and decide which service attributes to prioritize while designing and implementing it.

The study context situates in the University of Michigan Ann Arbor campus, where the University of Michigan Logistics, Transportation, and Parking (UM-LTP) currently operates free bus services in an area measuring approximately eight square miles. Currently testing a pilot of on-demand transit services in the North Campus (an area of about two square miles), UM-LTP is evaluating a proposal to reinvent the current bus system. The concept is to replace the existing twelve fixed bus routes with four fixed higher-frequency bus routes in the central, high-volume corridors, together with on-demand shared shuttle services in the outer area, in an integrated system termed MTransit. The shuttles will pick up passengers who share similar destinations at designated marked locations (i.e. virtual stops) and follow ever-changing routes based on real-time demand. For short trips that are within a shuttle's predefined service zone, it will send the passengers directly to a virtual stop close to their destination; for longer trips, the shuttle will send the passengers to a nearby bus stop. Thus passengers may need to take a maximum of two transfers: a shuttle-to-bus transfer at the origin end and a bus-to-shuttle transfer at the destination. Optimization algorithms will be applied to synchronize each leg of the trip in order to minimize the wait time involved in a transfer.

The contemplated replacement, like the current system, would be directly operated by UM-LTP, featuring university-owned vehicles and university-employed drivers. While the question of on-demand/conventional-transit integration frequently plays out within the context of interaction between public-transit operators and private-sector actors such as Uber or Lyft, the entire proposed system, across its conventional and on-demand components, would be under the University's direct control. This institutional design provides latitude to test options that can then serve as models for more complex public-private systems. And switching to MTransit would lead to dramatic changes in system functioning. While MTransit improves last-mile transit access and provides convenient short trips, it also carries undesirable features such as the need to share car rides and potentially more transfers for longer trips. Therefore, a quantitative evaluation of how changes in different service attributes of MTransit affect its anticipated adoption among campus travelers is instrumental to assess the desirability of MTransit and to guide its system design. Findings presented here, while not directly transferable to large metropolitan systems, can suggest policy options for further investigation in a range of specific contexts.

The remainder of this paper is organized as follows. Section 2 presents a brief review of the existing literature on ridesourcing services, with an emphasis on its impacts on public transit and users' travel behavior. Section 3 describes the method of combining RP and SP data. Section 4 describes the data, and Section 5 discusses the results of model estimation. Section 6 presents simulated demand results under several deployment scenarios, and Section 7 concludes.

2. Literature review

2.1. The rise of ridesourcing services

Ridesourcing services such as Uber and Lyft experienced explosive growth in the past few years. The largest ridesourcing company, Uber, for instance, has drawn more than 50 million riders worldwide since its founding in 2009 and claimed more than 3 billion trips in 2016 alone (Uber Newsroom, 2017). The increase in on-demand rides situates in the larger context of shared mobility options (which also includes carsharing, bikesharing, scooter sharing, microtransit, etc.) becoming increasingly popular all around the world.

These emerging shared modes provide consumers with convenience, flexibility, and cost savings on an as-needed basis. While the idea of shared mobility is not new, what distinguishes ridesourcing services from traditional modes such as taxi and paratransit is their capability to capture, match, and serve individuals' travel demand in real time. Made possible by the widespread adoption of smartphones and GPS-enabled mobile technology, ridesourcing services have quickly disrupted the existing transport market. Early growth of ridesourcing companies was powered by personal rides which had traditionally been provided by private vehicles, taxi, and rental cars, but their recent growth strategy appears to be moving into the direction of public transit. In the past several years, there has been a rapid emergence of on-demand transit (minibus) service providers such as Chariot, Bridj, and Via, creating a so-called "microtransit" movement in urban mobility (Jaffe, 2015). As for now, ridesourcing companies are mainly challenging the taxi industry, and their impacts on public transit and private automobile trips are less obvious. A future integration of ridesourcing services and the autonomous vehicle technology, however, has led to great optimism regarding the potential of shared autonomous vehicles to reform both public transit and the private auto industry (Fagnant and Kockelman, 2014).

2.2. The relationship between ridesourcing services and public transit

Researchers have started to assess the impact of ridesourcing services on transit use empirically. A 2016 study by the Shared Use Mobility Center shows that regular users of shared modes are more likely to use transit frequently and that shared modes mostly complement public transit (Feigon and Murphy, 2016). Similarly, a Pew Research Center report shows that frequent ridesourcing users are more likely to use a range of other transit options (Pew Research Center, 2016). However, based on survey responses from 4074 individuals, Clewlow and Mishra (2017) reported a 6% net reduction in transit use among ridesourcing users in major cities. The findings in this study are two-fold: while ridesourcing attracts travelers away from bus services (a 6% reduction) and light rail services (a 3% reduction), it serves as a complementary mode for commuter rail services (a 3% increase). All of these surveys were distributed in 2015 when on-demand transit services (i.e. microtransit) were just starting to emerge, and so these survey results do not capture how microtransit might affect transit use. Considering that microtransit provides services that are more similar to public transit, and they often start in high demand corridors along which transit lines operate, microtransit is more likely to siphon off transit riders.

The continuing growth of ridesourcing services thus brings both opportunities and challenges to public transit agencies. There seems to be a common notion that on-demand shared rides can serve as a potential solution to the first- and last-mile problem of public transit (Shaheen and Chan, 2016). Recognizing this potential, transit agencies around the world have begun to actively engage with innovative shared mobility services. Their approaches vary from establishing strategic partnerships with private mobility operators to operating shared mobility services directly (Feigon and Murphy, 2016). Some researchers have recognized these trends and started to test the feasibility and impacts of introducing ridesourcing services to reform traditional public transit (e.g. Fagnant et al., 2015; Levine et al., 2018; Mahéo et al., 2017). Often based on agent-based modeling and simulation analysis, these studies generally reported improvements in transit services, cost savings, and even environmental benefits.

2.3. Traveler responses to ridesourcing services

The literature on traveler response to emerging shared modes is growing. Early studies on carsharing have found that carsharing members tend to be young, well-educated, of moderate-income, and living in dense, mixed-use neighborhoods that offer high walkability and convenient public transit (Clewlow, 2016; Millard-Ball, 2005). More recent studies have suggested that the socio-economic, demographic, and neighborhood characteristics that support ridesourcing are generally similar to those of carsharing programs (Clewlow and Mishra, 2017; Dias et al., 2017; Pew Research Center, 2016).

Another strand of research that is relevant to our study uses stated-preference methods to examine user responses to service attributes of new mobility options. De Luca and Di Pace (2015) gathered SP data from a sample of commuters in the Salerno metropolitan area to analyze the feasibility of an inter-urban carsharing program and to investigate the main determinants of their choice behavior. Krueger et al. (2016) used a mixed logit model fitted to SP data on shared autonomous vehicles to examine the influence of level-of-service (LOS) attributes on the use of shared autonomous vehicles and dynamic ride-sharing. Frei et al. (2017) applied SP data collected from the Chicago region to examine the influence of wait time, access time, travel time, service frequency, cost, and number of transfers on the demand for a demand-adaptive transit service. Our study extends research in this area by investigating traveler responses to an integrated system of ridesourcing services and public transit, and in particular how changes in its service attributes affect aggregate demand for transit use.

3. Methodology

3.1. Stated preference methods

In recent years, stated-preference methods have become increasingly popular in choice model applications. Unlike revealed-preference models, which describe actual travel behavior, SP data are usually elicited from hypothetical choice experiments which are carefully constructed by researchers. Choices are constructed from combinations of attributes, but since this process would often lead to an inordinately large number of choice experiments, researchers often apply experimental design techniques to reduce the number of choice experiments in a research project. Each choice experiment corresponds to a choice question in which individuals are required to choose one alternative from a choice set based on their respective combination of characteristics (attributes and attribute levels). This process is based on the premise that any good or service can be described by its attributes, and individuals' valuations of the good or service depend on the levels of these attributes. Accordingly, similar to choice data obtained in RP settings, results obtained from choice experiments can be readily analyzed using random utility choice models.

SP methods were originally developed in marketing research in the 1970s and have received increasing attention in the transportation field since 1980s. For example, researchers have applied SP methods to examine the effect of advanced traffic information on drivers' route choice (Abdel-Aty et al., 1997), the impact of road pricing and parking charges on commuter mode choice (Washbrook et al., 2006), and airport and airline choice behavior (Hess et al., 2007).

3.2. Why combining revealed and stated preference data

While RP data are generally favored over SP data for their validity, both data types offer distinct strengths and weaknesses. SP data are commonly criticized due to the observed differences between stated choices and actual market behavior. Moreover, the context and format of the SP elicitation process are expected to affect the response, casting more doubt on the credibility of estimation results. However, only SP data can be collected for analysis in many research contexts. For example, when new products with new features or attribute values that are beyond the range of existing products are to be introduced into the market, researchers have to rely on SP data to forecast their impacts. Another common application of SP methods is the evaluation of public goods such as environmental amenities and freeways, since RP data for these goods do not carry obvious price signals like private goods. Other well-known limitations with RP data are the potential statistical issues involved, such as multicollinearity and lack of variability in key explanatory variables (Louviere et al., 2000). By contrast, SP data obtained from carefully designed elicitation methods are particularly rich in attribute-tradeoff information that can easily eliminate these concerns.

Some researchers have developed techniques to combine RP and SP data in order to address their respective weaknesses. By assuming that individuals face similar trade-offs among important attributes such as price and quality, researchers can pool RP and SP data together to fit a joint model (Morikawa, 1989). The essence of this idea is to set RP data as the standard of comparison that captures market equilibrium information while applying SP data to enrich the attribute trade-offs that are undesirable in RP data (a detailed description of the process can be found in Louviere et al., 2000, p. 231–233).[1] This data-enrichment scheme thus makes the RP and SP data complementary, effectively compensating the weaknesses of one by the strengths of the other. Ben-Akiva et al. (1994) noted that the key advantages of combining RP and SP data include efficiency (using all available data to increase number of observations), bias correction (using actual market information from RP data to reduce response bias in SP data), identification (estimating trade-offs among attributes and the effects of new products that are not identifiable from RP data).

3.3. The RP-SP joint modeling framework

Applications of joint RP-SP models have become increasingly popular in transportation research. Early models mostly focused on two issues in RP-SP joint estimation: scale differences in unobserved error variances between RP data and SP data, and state-dependence effects (i.e. the influence of individuals' actual choices on their stated choices) (Hensher, 1994; Louviere et al., 2000). More recent applications have often accounted for the issue of serial correlation, which results from multiple responses from the same individuals. This is usually achieved by the use of mixed logit models, which allows the specification of unobserved heterogeneity effects (including preference heterogeneity for alternatives and response heterogeneity for attributes) (Hensher and Greene, 2003; Train, 2003). Moreover, some studies relaxed the usual assumption of a multinomial logit structure for the RP and SP choice processes and instead specified a correlated inter-alternative error structure (Bhat and Castelar, 2002; Brownstone et al., 2000). Recent advances on this topic apply generalized mixed logit models to also account for scale heterogeneity among individuals (e.g. Hensher, 2012).

Another strand of studies has specifically focused on potential issues associated with the SP data collection process and the SP choice responses. For example, Train and Wilson (2008) discussed the issue of endogeneity between SP attributes and unobserved factors (when SP alternatives were constructed from respondents' actual choice in the RP setting) and developed econometric models to account for it. Some studies raised concerns about the overall reliability of SP choices. Given the hypothetical nature of the SP data collection process, respondents may make an SP choice even though they did not consider the alternatives seriously. Some researchers have thus asked respondents to elicit certainty or confidence in their SP choices and incorporated this information into the choice model (e.g. Rashedi et al., 2017).

In this paper, we apply the mixed logit framework laid out in Bhat and Castelar (2002) and Hensher (2008), which can account for inter-alternative error correlation, RP-SP scale difference, unobserved heterogeneity, and heterogeneous state dependence effects. In this model, the utility U_{kit} that an individual k gains from an alternative i on choice occasion t is specified as:

$$U_{kit} = \alpha_{kit} + \boldsymbol{\beta}_k^{'}\boldsymbol{X}_{kit} + \varphi_k(1-I_{kt,RP})R_{ki} + \theta_{km}E_{km} + \epsilon_{kit}, \tag{1}$$

where α_{kit} is the alternative-specific constant (the subscript t implies that the ASCs are data-specific), $\boldsymbol{X}_{kit}$ is a vector of observed variables (which may differ between RP data and SP data) and $\boldsymbol{\beta}_k$ is its corresponding coefficient vector, φ_k is the individual-specific

[1] The majority view on pooling RP and SP data conforms with Fig. 8.3 in Louviere et al. (2000, pp. 232), where the tradeoff information contained in RP data is combined with that in SP data for a joint estimation. Some researchers proposed that the tradeoff information in RP data should be ignored because of its deficiencies, but it is rarely the case in later applications.

state-dependence effect, $I_{kt,RP}$ is a dummy variable that takes a value of 1 if the tth choice occasion for individual k is in the RP setting and 0 otherwise,R_{ki} is another dummy variable that takes a value of 1 if individual k chooses mode i in his/her RP choice, E_{km} is an individual-specific error term that enters the utility function only if alternative i belongs to error component group m ($m = 1, 2, \ldots, M$, and M is the number of inter-alternative error component groups which is similar to the nests in a nested logit model), E_{km} is assumed to follow a standard normal distribution and θ_{km} is the dispersion factor (standard deviation) for error component m, ϵ_{kij} is independent and identically distributed random error term which is assumed to follow Gumbel distribution across alternatives and individuals for each choice occasion.

The scale parameter of ϵ_{kit} is specified as $\lambda_{qt} = [(1-I_{qt,RP})\lambda] + I_{qt,RP}$. This specification normalizes the RP scale to 1 while allows the SP scale λ to be estimated. Following the tradition of joint RP-SP models (Morikawa, 1989), we assume the variance of ϵ_{kit} to satisfy $Var(\epsilon_{ki}^{RP}) = \mu^2 Var(\epsilon_{ki}^{SP})$, and it can be deduced that $\mu = \lambda_{SP}/\lambda_{RP} = \lambda$. This assumption allows the unobserved error variances in the RP and SP data to be scaled to become equal, a necessary condition for joint RP-SP estimation.[2] Theoretically, the SP-to-RP scale parameter μ can take any positive values: a value smaller than one indicates that the SP error variance is larger, which may result from the SP experimental design effects and the hypothetical nature of SP responses; on the other hand, a value larger than one suggests that the RP error variance is larger, which is likely due to the influence of more unobserved factors in a real-life setting.

In this model, α_{kit} and $\boldsymbol{\beta}_k^{'}$ account for preference and response heterogeneity, φ_k accounts for heterogeneous state-dependence effects, θ_m measures the degree of inter-alternative error correlation, and λ_{qt} accommodate scale differences between RP data and SP data. We specify $\beta_{kn} = \beta_n + \sigma_n v_{kn}$, where β_n is the population mean for the nth attribute ($n = 1, \ldots, N$),v_{kn} is the individual specific response heterogeneity with mean zero and standard deviation one, and σ_n is the standard deviation of the distribution of β_{kn} around β_n. The state-dependence effects term φ_k is specified as the same. The ASCs α_{kit} are specified similarly except that each set of ASCs is RP-specific or SP-specific.

Assuming these random parameters to be uncorrelated, they can be written as:

$$(\alpha_{kit}, \boldsymbol{\beta}'_k, \varphi_k)' = (\alpha_{it}, \boldsymbol{\beta}', \varphi)' + \boldsymbol{\Gamma}\boldsymbol{\Omega}_k v_k,$$

where $\boldsymbol{\Gamma}$ is equal to an identity matrix $\mathbf{I}$, $\boldsymbol{\Omega}_\mathbf{k}$ is a diagonal matrix with diagonal elements equal to the standard deviation of the distribution of each random parameter, and $\boldsymbol{v}_k$ is a random, multivariate, and normally distributed parameter vector. We further simplify the notation by defining $\boldsymbol{\psi} = (\alpha_{it}, \boldsymbol{\beta}^{'}, \varphi)'$ and $\boldsymbol{W}_{kit} = (1, \boldsymbol{X}_{kit}^{'}, R_{ki})'$.

Conditional on $\boldsymbol{v}_k$ and E_k, the probability that individual k will choose alternative i at the tth choice situation can be written in a familiar MNL form:

$$P(y_{kt}=i|\boldsymbol{v}_k, E_k) = \frac{e^{\lambda_{qt}[(\boldsymbol{\psi}+\boldsymbol{\Gamma}\boldsymbol{\Omega}_k\boldsymbol{v}_k)\boldsymbol{W}_{kit}+\theta_{km}E_{km}]}}{\sum_{j=1}^{I} e^{\lambda_{qt}[(\boldsymbol{\psi}+\boldsymbol{\Gamma}\boldsymbol{\Omega}_k\boldsymbol{v}_k)\boldsymbol{W}_{kit}+\theta_{km}E_{km}]}}, \tag{2}$$

The unconditional probability can be obtained by integrating out the random terms:

$$P(y_{kt} = i) = E_{\boldsymbol{v},E}[P(y_{kt}=i|\boldsymbol{v}_k, E_k)] = \int_{\boldsymbol{v}_k}\int_{E_k} P(y_{kt}=i|\boldsymbol{v}_k, E_k) f(\boldsymbol{v}_k, E_k) dE_k d\boldsymbol{v}_k$$

This multiple integral does not have an analytical solution, which could only be estimated using simulations (Bhat and Castelar, 2002; Train, 2003). Therefore, all unknown parameters must be estimated by maximizing the simulated log-likelihood function as shown below:

$$\log L = \sum_{k=1}^{K} \log\frac{1}{R}\sum_{r=1}^{R}\prod_{t=1}^{T_k}\frac{e^{\lambda_{qt}[(\boldsymbol{\psi}+\boldsymbol{\Gamma}\boldsymbol{\Omega}_k\boldsymbol{v}_{kr})\boldsymbol{W}_{kit}+\theta_{km}E_{km,r}]}}{\sum_{i=1}^{I} e^{\lambda_{qt}[(\boldsymbol{\psi}+\boldsymbol{\Gamma}\boldsymbol{\Omega}_k\boldsymbol{v}_{kr})\boldsymbol{W}_{kit}+\theta_{km}E_{km,r}]}}, \tag{3}$$

where R is the number of replications, $\boldsymbol{v}_{kr}$ is the rth multivariate normal draw for individual k, and $E_{km,r}$ is the rth normal draw for individual k.

4. The data

A web-based survey made in Qualtrics was sent to 5353 University of Michigan faculty members, 6443 staff members, and 8093 students via email. We pretested an early version of the survey among a small group of individuals, whose feedback was incorporated into the final questionnaire. The survey contains three major components: RP questions on current mode choice and trip attributes, SP experiments on hypothetical travel mode choice situations, and questions on demographic, socioeconomic and attitudinal information related to travel. The survey was divided into two branches—one about commute trips and the other on-campus trips. Respondents living within a mile from existing campus bus stops were directed to the commute trip branch and others to the other branch. A total of 814 faculty members, 1920 staff members, and 1739 students responded to the survey, resulting in a response rate of 9.9%, 22.6%, and 16.2% for faculty, staff, and students, respectively. This paper only analyzes data generated from the commute-trip branch, which drew a total of 1900 responses. After a careful data-cleaning process, we kept a final sample of 166 faculty members, 209 staff members, and 978 students for subsequent analysis. About 500 cases were excluded due to incomplete or inconsistent responses, or unrealistic travel-attribute estimates.

[2] The SP-to-RP scale λ can either be estimated in a joint estimation procedure or in a sequential estimation procedure (Morikawa, 1989). A sequential estimation process, used in this paper, is less efficient but is able to generate consistent estimators.

Table 1
Comparing our sample with the SCIP dataset.

	Total counts (estimated)	Number of respondents		Commute mode choice: taking a bus		Car ownership: owning a car	
	Living in a mile to nearest bus stop	Our sample	SCIP	Our sample	SCIP	Our sample	SCIP
Faculty	2350	166	1223	28.0%	7.8%	94.3%	95.1%
Staff	6746	209	466	31.3%	20.2%	91.6%	91.9%
Students	34,803	978	4074	35.8%	30.3%	48.0%	48.4%

To test for potential systematic bias in our samples, we assessed the representativeness of the final sample against other university data sources. The ideal source for comparison would have a wide coverage of the university population and record their home location, since the population in question is faculty, staff, and students living within a radius of campus bus stops. A qualifying source we found is the University of Michigan Sustainability Cultural Indicators Program (SCIP) survey results. We compared it to our sample, by identity status (faculty vs student vs staff), across attributes of commute mode choice and car ownership (Table 1). As expected, people who are more likely to “care for” the campus transit system have a higher chance of responding to our survey. While car ownership rates are about the same in the two datasets, respondents in our sample are more likely to take a bus. To better represent the population, we thus constructed sample weights based on two variables: identity status and travel mode choice.[3] These sample weights, as shown in Table 2, are used in the subsequent statistical analysis.

To increase the validity and reliability of SP data, it is of crucial importance to ensure that the stated choice experiments (SCEs) presented to respondents are realistic and accessible. A common approach to achieve these goals is to first ask the respondent to describe a recent trip, and then to construct individually tailored SCEs by pivoting around the attribute levels of this trip (Rose et al., 2008). This procedure, applied in our survey, assures that the hypothetical choices are similar to those which the respondent has experienced in an RP setting.

4.1. RP data

To collect RP data, we first asked respondents to select their most frequently used travel mode among six alternatives (including drive a car, rideshare, park and ride, take a bus, walk, and bike) and an “other, please specify” option. For the analysis in this paper, these alternatives were regrouped into four alternatives—driving, taking transit, walking, and biking. We then asked respondents to estimate travel attributes associated with the four travel modes. The travel attributes solicited are common level-of-service variables in travel mode-choice models, including: time in walking, driving, and finding parking for the driving mode; time in walking, waiting, and riding the bus, and the number of transfers for taking transit; and total travel time for walking and biking. Trip costs were not examined in this study because the variable cost of driving is negligible for the short commute trips concerned here, and transit is free for the university-related population. To facilitate the travel-time estimates for driving and taking transit, we developed graphs to illustrate the different segments of a trip associated with each mode. We also encouraged respondents to use Google Maps to assist their estimation but alerted them that Google Maps provides no estimates for certain travel components (e.g. time in finding parking). As expected, the estimation tasks were demanding for many participants. About 4% of them quit the survey right at this point, another 12% provided no or incomplete estimates, and a final 8% provided unrealistic estimates. These individuals were excluded from the model estimation. The self-reported mode-specific trip attributes are the essential independent variables for the RP model and also serve as the basis for constructing individually tailored SCEs.

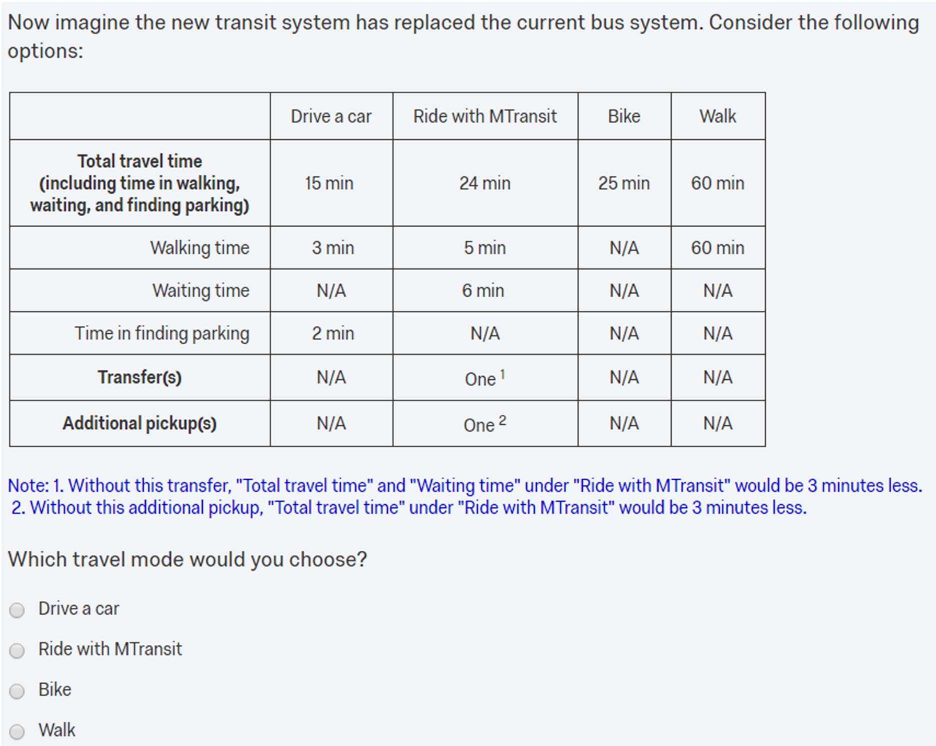
4.2. SP data

To better orient respondents to the stated-choice experiments, we first presented respondents with an SCE whose values were based in their previously reported data. Specifically, respondents considered four travel modes with trip attributes they themselves provided in the RP section of the survey, and were asked to select a preferred commute travel mode. The SCE-version of the mode-choice question might be expected to yield answers similar to that of its RP counterpart. Surprisingly, however, about 31% of all respondents selected a travel mode different from what they had reported before. One reason for this discrepancy might be that these respondents did not carefully answer the questions, but many of these inconsistencies would have been caught in the data-cleaning process. Other possible reasons for the inconsistency include: negative state-dependence effects (i.e. the tendency to abandon a disliked RP choice), strategic voting behavior (e.g. “voting for” transit or biking due to political orientation even if not using it personally), and absence of important factors affecting mode choice in the SCE (e.g. cold weather and safety concerns prevented many from biking but these factors were not present in the SCE). By contrast, consistent responses either reflect positive state-dependence effects or suggest that unobserved factors are not interfering with choice decisions. These results justify the use of a mixed logit modeling framework to capture unobserved heterogeneity and indicate that heterogeneous, instead of homogenous, state-dependence effects should be specified in the model.

[3] The SCIP dataset does not represent population shares due to response rate differences among faculty, staff, and students. An intermediate step involves to estimate the total number of faculty, staff, and students living within a radius of campus bus stops.

Table 2
Sample weights.

	Car	Bus	Walking	Biking
Faculty	1.48	0.29	1.13	0.87
Staff	1.21	0.62	1.17	1.12
Student	0.85	1.51	0.59	1.52


Now imagine the new transit system has replaced the current bus system. Consider the following options:

	Drive a car	Ride with MTransit	Bike	Walk
Total travel time (including time in walking, waiting, and finding parking)	15 min	24 min	25 min	60 min
Walking time	3 min	5 min	N/A	60 min
Waiting time	N/A	6 min	N/A	N/A
Time in finding parking	2 min	N/A	N/A	N/A
Transfer(s)	N/A	One [1]	N/A	N/A
Additional pickup(s)	N/A	One [2]	N/A	N/A

Note: 1. Without this transfer, "Total travel time" and "Waiting time" under "Ride with MTransit" would be 3 minutes less.
2. Without this additional pickup, "Total travel time" under "Ride with MTransit" would be 3 minutes less.

Which travel mode would you choose?

- Drive a car
- Ride with MTransit
- Bike
- Walk

Fig. 1. Example of a stated choice experiment.

The survey followed with descriptions of MTransit, together with a before-after comparison of system-wide transit-service maps and graphical illustrations of the likely changes to participants' travel experiences. Respondents were then presented with seven SCEs (see Fig. 1 for an example), which required them to select one out of four alternatives—driving, walking, biking, and MTransit—for their home-to-campus commute trips based on the trip attributes associated with each mode. These SCEs were designed to infer how travelers' decisions to choose MTransit varies in response to changes in the levels of its service attributes. Therefore, the SCEs were constructed by pivoting around the trip attributes of MTransit, while the attribute levels for driving, walking, and biking were kept constant across choice scenarios and were equal to respondents' self-reported values in the RP part of the survey. The trip attributes of MTransit examined include out-of-vehicle time (OVTT, i.e. walk time to/from transit stops), wait time, number of transfers, and number of additional pickups (i.e. immediate stops to pick up other passengers).

Three attribute levels were examined for each attribute: 3, 5, and 8 min for OVTT and wait time; and 0, 1, and 2 for transfers and additional pickups. We made the following assumptions regarding these trip attributes: (1) For a direct point-to-point trip, the in-vehicle travel time (IVTT) of MTransit is the same as that of driving; (2) Each additional pickup adds 3 min of IVTT; (3) Each transfer (shuttle-to-bus or bus-to-shuttle) adds 3 min of wait time. Four attributes at three levels yields a 3^4 factorial design of 81 choice sets, but we simplified it into an orthogonal main-effects experimental design of nine choice sets. Respondents were first presented with the two choice sets that contained the best and worst MTransit profiles. Then, five of the remaining seven choice sets were randomly selected to reduce respondents' cognitive burden. More than 95% of all respondents answered all seven SCEs. While about a quarter of them always chose one alternative and thus provided no information on trade-offs between attributes, the majority varied their choices in accordance with the varying MTransit profiles.[4]

[4] While the percentage of non-traders is somewhat large, it is reasonable because a large proportion of the respondents are students who are either transit-dependent or living so close to campus that makes walking the unchallengeable mode choice.

Table 3
Model results.

Variable	Alternatives	RP MNL model		SP mixed logit model		RP-SP mixed logit model	
		Coeff.	t-Stat	Coeff.	t-Stat	Coeff.	t-Stat
Constants							
RP walking	Walking (RP)	2.705**	4.20			R:3.855**	5.35
RP biking	Biking (RP)	0.715	1.12			R: −1.578**	−2.21
RP bus	Bus (RP)	−1.267*	−1.98			R:2.699**	4.13
SP walking	Walking (SP)			R[1]: 2.665**	3.35	R:1.484**	2.09
SP biking	Biking (SP)			R: −1.734**	−2.16	R: −2.748**	−3.83
SP MTransit	MTransit (SP)			R:1.902**	2.42	R: −0.220	−0.33
Random parameter standard deviations							
RP walking	Walking (RP)					4.126**	15.48
RP biking	Biking (RP)					1.134**	5.90
RP bus	Bus (RP)					3.085**	14.97
SP walking	Walking (SP)			3.198**	22.71	3.482**	22.50
SP biking	Biking (SP)			4.118**	25.93	6.250**	31.47
SP MTransit	MTransit (SP)			3.107**	27.71	4.190**	33.26
Level of service variables							
In-vehicle travel time (min)	All modes (RP/SP)	0.015	1.00	R: −0.210**	−15.32	R: −0.161**	−10.02
Out-of-vehicle travel time (min)	All modes (RP/SP)	−0.084**	−12.42	R: −0.465**	−30.76	R: −0.307**	−35.06
Time in finding parking (min)	Car (RP/SP)	−0.115**	−3.92	R: −0.442**	−14.49	R: −0.191**	−9.04
Daily parking cost ($)	Car (SP)			R: −0.489**	−4.18	R: −0.994**	−9.54
Wait time (min)	Bus (RP), MTransit (SP)	0.038	1.57	R: −0.339**	−12.14	R: −0.253**	−12.87
Transfer	Bus (RP), MTransit (SP)	−0.372	−1.561	R: −1.930**	−21.90	R: −1.760**	−20.02
Additional pickup	MTransit (SP)			R: −1.211**	−14.87	R: −1.034**	−15.87
Random parameter standard deviations							
In-vehicle travel time (min)	All modes (RP/SP)	0.026	1.552	0.210**	15.32	0.161**	10.02
Out-of-vehicle travel time (min)	All modes (RP/SP)	−0.078**	−10.669	0.465**	30.76	0.307**	35.06
Time in finding parking (min)	Car (RP/SP)	−0.116**	−3.555	0.442**	14.49	0.191**	9.04
Daily parking cost ($)	Car (RP/SP)			0.489**	4.18	0.994**	9.54
Wait time (min)	Bus (RP), MTransit (SP)	0.038	1.57	0.339**	12.14	0.253**	12.87
Transfer	Bus (RP), MTransit (SP)	−0.337	−1.51	1.930**	21.90	1.760**	20.02
Additional pickup	MTransit (SP)			1.211**	14.87	1.034**	15.87
Socio demographic variables							
Household income (Faculty/staff)	Car (RP/SP)	0.271*	2.51	1.067**	4.53	0.727**	5.75
Living expenditure (Student)	Car (RP/SP)	0.116	0.89	0.036	0.36	−0.034	−0.45
Vehicle per capita (Faculty/staff)	Car (RP/SP)	1.068*	2.12	−0.569	−0.78	0.487	1.14
Car ownership (Student)	Car (RP/SP)	1.479**	4.64	2.317**	7.43	1.621**	9.06
Student	Walking (SP/RP), Biking (RP/SP)	0.664	1.04	0.687	0.49	1.102*	1.73
	Bus (RP), MTransit (SP)	2.098**	3.30	0.988	1.02	2.332**	3.81
Female	Walking (RP/SP), Biking (RP/SP)	−0.124	−0.81	−1.837**	−6.89	−0.239	−1.62
Residential preference variables							
Importance of bike- and walk-ability	Walking (RP/SP), Biking (RP/SP)	0.067	0.81	0.696**	5.01	0.415**	4.77
Importance of transit availability	Bus (RP), MTransit (SP)	0.663**	7.86	1.217**	6.72	0.952**	10.90
SP to RP scale parameter[2]						4.70	14.86
State dependence effects						R: 1.791**	20.64
State dependence effects standard deviation						0.804**	8.73
Inter-alternative error components	Walking (RP, SP), Biking (RP, SP)			1.114**	8.17	1.349**	13.88
Sample size		1163		1163		1163	
Log-likelihood at constant		−1315.95		−10056.38		−11372.33	
Log-likelihood at convergence		−963.88		−3708.33		−4744.21	
Adjusted pseudo R2		0.26		0.63		0.58	

Note: 1. R = random parameter mean estimate. The alternative-specific constants and state-dependence effects were assessed as normal distributions, and the LOS variables were specified as following a constrained triangular distribution (i.e. equal mean and standard deviation). We used 1000 Halton draws to perform the integrations.
2. T-test with respect to 1.
* Significant at the 5% level.
** Significant at the 1% level.

5. Results

Table 3 presents the results of three models (sample weights were applied to all of them): an RP MNL model, an SP mixed logit model, and an RP-SP mixed logit model. We tested a variety of specifications before deciding on the final models. We also tested a number of alternative groupings of alternatives in the inter-alternative error components and decided to specify a common error component for the non-motorized modes (walking and biking) and another for the motorized modes (driving and taking transit). The meaning of most variables should be self-explanatory and thus no detailed definitions are presented. We computed the variance inflation factor (VIF) value for all independent variables and found that all the variables have a VIF value of smaller than 5, which indicates little multicollinearity in the data.

IVTT and OVTT were specified as generic variables, while other variables were specified as alternative specific. The second column of Table 3 lists the modes associated with each independent variable. One LOS variable, daily parking cost, enters into the utility function of the driving mode only in the SP data, since there is no variation in this variable within the RP data. Economic status and vehicle access were modeled differently between students and faculty/staff. We believe that living expenditure instead of household income is a better measure of students' economic status and that vehicles per capita instead of vehicle ownership better captures faculty and staff access to vehicles. The residential preference variables were obtained by asking the following questions: "When you moved to your current residence, how important was being able to walk or bike (take the bus) to places?" These variables capture the attitudinal preferences of individuals for these travel modes, and thus controlling for them could reduce the degree of correlation among repeated responses from the same individuals.

5.1. RP and SP separate models

The goodness-of-fit values of these models, as measured by adjusted McFadden's pseudo R-square, indicate satisfactory model fit. The SP mixed logit model, which accommodates unobserved heterogeneity, has a much better performance than the RP MNL model.

The coefficient estimates from the SP model are significantly different from those from the RP model. In both models, the driving mode was set as the reference alternative. The ASC for MTransit is more positive in the SP sample relative to its counterpart in the RP sample, suggesting that individuals might overstate their tendency to use transit in the SP setting. The opposite is true for the biking mode. The SP mixed logit model shows that these ASCs have sizeable standard deviations, which reveals significant preference heterogeneity among the respondents. Regarding the LOS variables, the SP model appears to produce much more plausible results than the RP model. Consistent with theoretical prediction, all LOS variables in the SP model have negative signs and are significant at the 1% level. By contrast, in the RP model, IVTT and wait time have unexpected positive signs, but both coefficients are close to zero and are statistically insignificant. After carefully examining the data, we found that a major source of bias is the tendency of non-bus users to underestimate the time required for waiting for and riding the bus. This is probably an artifact of asking respondents to estimate travel times using Google Maps, which does not incorporate delays and return wait time estimates for the transit mode. Taken together, these results comport with findings in the literature, which suggest that SP data do not necessarily reveal actual market behavior but often contain richer attribute-tradeoff information than RP data.

Among the socio-demographic variables, both models show that faculty and staff with a higher household income are more likely to drive, while the living expense of students is unrelated to the chance of driving. While the RP model suggests that better vehicle access (as measured by vehicles per capita) tends to increase driving, the SP model finds no significant impact of this variable. Also, these models show that females are less likely to walk or bike than males and that students have a higher chance than faculty and staff to choose non-driving modes, particularly the transit mode. In addition, the two residential-preference variables are found to be significant predictors of mode choice. The more significant signs on importance of transit availability indicate that households' transit preference seems to be more likely to translate into actual mode choice behavior than their cycling preferences. Finally, in the SP model, the error component for the non-motorized modes is smaller than that for the motorized modes, which implies that there are more unobserved factors influencing the use of motorized modes than that of non-motorized alternatives.

5.2. RP-SP mixed logit model

The last column of Table 3 presents the results of the RP-SP mixed logit model. Again, the car mode was set as the reference alternative for both the RP and SP sample. Fusing RP data and SP data involves a decision to specify, for common attributes, generic or data-specific coefficients. Consistent with the current literature, our decision is to estimate data-specific coefficients for all ASCs and generic coefficients for all common variables (Train, 2003). The adjusted McFadden's pseudo R-square value for this model is 0.58, which indicates excellent model fit but is smaller than the value for the SP model. The SP-to-RP scale parameter is estimated to be 4.70, which suggests that the unobserved error variance in the RP data are larger than that in the SP data. While this parameter is usually smaller than one in early RP-SP studies, more recent studies that apply mixed logit models often estimate a larger-than-one value (see, for example, Brownstone et al., 2000; Bhat and Castelar, 2002; Train and Wilson, 2008). Bhat and Castelar (2002) argued that the larger-than-one value may have been an artifact of ignoring error correlations among repeated SP choices from the same individual. The mean state-dependence-effect parameter is positive and highly significant, implying a high tendency for individuals to stick with their RP mode choices. Both error components are highly significant, which means that individuals are more likely to switch within non-motorized modes and motorized modes than across the two groups.

All coefficients on LOS variables carry intuitive (negative) signs and are statistically significant. As a result of joint RP-SP estimation, the magnitudes of these coefficients have become smaller compared to their counterparts in the SP model. Consistent with previous findings in travel behavior studies, the model shows that individuals tend to value OVTT and wait time more than IVTT. The coefficients (mean estimates of random parameters) on OVTT and wait time are 1.91 and 1.57 times, respectively, that on IVTT, close to the mean values of 1.70 and 1.43 reported in a meta-analysis of values of travel time (Abrantes and Wardman, 2011). This implies that reducing OVTT and wait time could be more effective than reducing IVTT to enhance the desirability of a transit trip. Another important finding is that travelers appear to have a strong resistance to transfers and additional pickups. Even after ruling out the

Table 4
Elasticities and marginal effects.

	IVTT		Wait time		OVTT		Transfer	Additional pickup
	Marginal effect	Elasticity	Marginal effect	Elasticity	Marginal effect	Elasticity	Marginal effect	Marginal effect
Car	0.36	0.08	0.58	0.36	0.78	0.41	4.07	2.40
Walk	0.34	0.07	0.52	0.23	0.58	0.26	3.61	2.11
Bike	0.25	0.05	0.39	0.15	0.48	0.15	2.65	1.58
MTransit	**−0.95**	**−0.21**	**−1.49**	**−0.36**	**−1.84**	**−0.37**	**−10.37**	**−6.09**

Note: Values in bond font are direct elasticities and marginal effects and other values are cross-elasticities and marginal effects.

influence of additional travel time, transfers and additional pickups would still significantly reduce transit use due to the negative perceptions of them.

Within the category of socioeconomic and demographic attributes, as expected, income and vehicle access in general are found to contribute to driving. Given that economic status tends to be positively associated with personal vehicle use, the negative sign on living expenditure is somewhat unexpected. A plausible explanation is that students with higher spending tend to live closer to the campus where the rents are higher, which offsets the need to drive. Moreover, the model suggests that students are more likely to choose non-driving modes than faculty and staff. No significant differences are found between males and females regarding the use of non-motorized modes versus motorized modes, a finding that contradicts the SP model. Finally, this joint model shows that both residential-preference variables are major determinants of commuting mode choice.

5.3. Elasticities and marginal effects

Since coefficients from discrete choice models cannot be directly interpreted, it is common to convert the coefficients into elasticities and marginal effects in order to analyze the relative impacts of each independent variable. An elasticity measure shows the percentage changes in the choice probability of an alternative in response to a one percent change in a variable. The measure is termed *direct elasticity* when evaluating how an alternative's probability responds to a one percent change in its own attribute and is termed *cross elasticity* when evaluating responses to a one percent change in other alternatives' attribute. A marginal effect measure is similar to an elasticity measure except that marginal effects are expressed as *unit changes* instead of *percentage changes*. Given that the primary focus of this study is to evaluate how changes in the LOS attributes of MTransit affect its adoption among travelers, we calculate elasticities and marginal effects for these variables using the SP sample and applying the conditional parameters (i.e. individual-specific parameters) from the RP-SP joint model. Results are presented in Table 4. Note that the elasticities are obtained using the probability-weighted sample enumeration technique proposed by Louviere et al. (2000) rather than by averaging individual elasticities directly.

The direct elasticity of MTransit with respect to IVTT is −0.21, which is within the range of transit IVTT elasticity estimates in the 32 studies examined by Hensher (2008). However, the magnitude of this value is smaller than the average value in those studies, probably resulting from the fact that a large proportion of our sample is students who are very transit dependent. The direct elasticity of MTransit with respect to OVTT is −0.37, indicating a greater influence on the choice probability of MTransit than IVTT. Comparing the OVTT elasticity estimates among studies is nonetheless challenging, since researchers often define OVTT differently. While the OVTT for MTransit equates to walk time in the current study, in other studies it might also include wait time (Abrantes and Wardman, 2011). The wait time elasticity estimate is −0.36, smaller than the value of −0.64 summarized by Paulley et al. (2006). We offer two explanations for this discrepancy. First, a large proportion of our study population is comprised of highly transit-dependent students who have "dragged down" the estimate. Second, when taking MTransit, passengers will be able to wait for the on-demand shuttle indoors instead of at traditional bus stops, thus reducing the amount of disutility involved. As for marginal effects, the model estimates that a one-minute increase in IVTT, OVTT, and wait time would reduce the choice probability of MTransit by 0.95, 1.84, and 1.49 percentage points, respectively.

Finally, we evaluate two signature features associated with an integrated system of public transit and shared mobility—transfers and additional pickups. Existing literature that examines the impacts of these two attributes on the choice probability of shared mobility modes is relatively thin. Our results show that adding a transfer or additional pickup to a previous direct door-to-door personalized trip is likely to reduce the choice probability of MTransit by 10.4 and 6.1 percentage points respectively, which is equivalent to 10.9 and 6.4 min of IVTT respectively. To our knowledge, this is the first paper to quantify the impacts of additional pickups on the choice probability of ridesourcing services. These results have controlled for the impact of additional travel time introduced by a transfer or additional pickup, and so the effects completely come from individuals' negative perceptions of the transfer or additional pickup per se. That is to say, when presented two trips—one with a transfer or additional pickup and the other without, travelers would strongly prefer the second trip even when their travel time is the same. These negative perceptions are nonetheless subject to a status quo bias, i.e. the results are shaped by travelers' current experiences on transfers and additional pickups, and these penalties would be smaller if these experiences are improved under MTransit.

6. Demand forecasting under different deployment scenarios

Transit operators' decision to implement ridesourcing services are mostly driven by three goals—cutting operating costs, promoting ridership, and improving the level of transit service. While these goals may be achieved simultaneously, in most cases there are unavoidable trade-offs to be made. For example, an important consideration in the decision of replacing low-demand bus routes with ridesourcing is the number of virtual stops (i.e. pickup/drop-off points) to be placed. While adding virtual stops (thus enhancing last-mile transit access) may attract travelers who would otherwise lack nearby transit stops, this move, if not coupled with an increase in vehicle fleet size, will lead to increases in average wait time, number of additional pickups, and in-vehicle travel time. To increase the fleet size in order to maintain the level of service, however, would result in higher operating costs. Quantifying these trade-offs under alternative deployment scenarios of ridesourcing can help transit agencies evaluate the desirability of each option.

In this section, we forecast future demand for MTransit under different deployment strategies. These forecasts are based on outputs of transit trip profiles obtained from simulation models built by the operations group on this research project.[5] Applying the mean changes in trip attributes under MTransit versus the status quo, we modified values of these attributes for the transit alternative in our sample, calculated revised choice probabilities, and then aggregated them into market shares of commuting mode choice. Following the suggestions made by Cherchi and de Dios Ortúzar (2006), we used RP constants for walking and biking and the SP constant for MTransit in the prediction model. We examined three deployment scenarios of MTransit, each of which corresponding to a major policy consideration:

(1) *Use ridesourcing to reduce operating costs*, i.e. replace fixed-route bus lines (or segments of them) in low demand areas with ridesourcing services and use the existing bus stops as virtual stops. Thus, the out-of-vehicle time for a transit trip is assumed to remain the same. The levels of other service attributes such as wait time and IVTT are determined by the number of on-demand vehicles, which is set to equal as the tipping point from which further fleet size increase does not substantially improve service levels.
(2) *Use ridesourcing to enhance last-mile transit connectivity*, i.e. building on scenario 1, add enough virtual stops to the transit network to approximate a door-to-door service and increase the fleet size of on-demand shuttles in order to maintain the service level of MTransit as that in scenario 1. Compared to option 1, this option reduces the OVTT of an MTransit but would incur higher operating expenses.
(3) *Use ridesourcing to reduce operating costs and to enhance last-mile transit connectivity*, i.e. similar to scenario 2 except that the fleet size is kept the same as that in scenario 1. This deployment option would have a similar operating cost as scenario 1. Compared to scenario 1, this move would result in a reduction in OVTT but increases in average wait time, number of additional pickups, and in-vehicle travel time. Since we cannot precisely quantify these tradeoffs, we artificially came up with two plausible results to represent a reasonable range.

Table 5 shows the current modal split for commute trips among university populations who live within a mile of a campus bus stop and the forecasted results under these deployment scenarios. We made the following assumptions in the process. First, for a direct point-to-point trip, the IVTT of MTransit is the same as that of driving. Second, in all deployment scenarios, every MTransit trip would have an additional pickup, which adds 3 min of IVTT to the trip. Third, in deployment scenario 1, we assume the average wait time for an MTransit trip without transfers to be 3 min and with transfers to be 6 min.[6] Whether or not an MTransit trip involves transfers depends on if the trip travels across the predefined service zones of on-demand shuttles. Fourth, in scenario 2 and 3, we assume that enough virtual stops would be added to make the OVTT of all MTransit trips be 3 min or less (if their current OVTT is less than 3 min).[7] In addition, we assume that there will be a 3-min increase in IVTT because more virtual stops would lead to more circuitous routes. Finally, in scenario 3, we assume two plausible changes in wait time and the number of additional pickups: first, a 3-minute increase in average wait time and adding an additional pickup; second, a 2-minute increase in average wait time and 50% chance of adding an additional pickup. The former case produces a lower bound regarding the future demand for MTransit and the latter produces a higher bound.

The simulation results generate several important insights. First, comparing the results of deployment scenario 1 with the current modal split reveals that replacing low-demand bus routes with ridesourcing services could slightly boost transit use. This is largely because ridesourcing can significantly reduce the wait time for a transit trip. The average wait time for a bus among the study population is 8 min, and by matching supply and demand in real time, ridesourcing reduces it to approximately 3 min. The benefit of an on-demand system would be greater in places where the bus headway is larger (in the impacted areas of our study, headway is 10 min during rush hours and 20 min during non-rush hours). Another source of improvement is the reduction in in-vehicle travel time, but this benefit is relatively small (less than 2 min) here because the bus routes being replaced are short and not very circuitous. Moreover, the results for deployment scenario 2 verify the popular notion that ridesourcing could significantly enhance transit

[5] Based on the existing bus boarding/alighting data, these simulation models generated trip profiles for the existing bus system and MTransit. These trip profiles were then averaged to calculate mean changes in trip attributes. Further details of this work are to be published in a separate paper by Pascal Van Hentenryck.

[6] These numbers were informed by the outputs from simulation models of MTransit, which are kindly provided to us by Pascal Van Hentenryck.

[7] Reducing the OVTT of MTransit trips comes at the expense of increased IVTT. Setting the walking and driving speed at 3.1 and 25 miles per hour respectively, we assume the increase of IVTT to be one-eighth of the decrease in OVTT.

Table 5
Current modal split and simulation results of three deployment scenarios.

	Car	Walk	Bike	Transit (bus or MTransit)
Current modal split of commute trips among people living within 1 mile of a campus bus stop	17.7%	26.9%	8.6%	46.7%
Scenario 1: Replace fixed routes in low-demand areas with ridesourcing services	20.0%	23.8%	7.7%	48.5%
Scenario 2: Building on scenario 1, add more virtual stops to enhance last-mile transit access and increase the fleet size of on-demand shuttles	15.0%	19.5%	6.0%	59.5%
Scenario 3: Building on scenario 1, add more virtual stops to enhance last-mile transit access without increasing the fleet size of on-demand shuttles (lower bound)	20.5%	29.3%	8.7%	41.5%
Scenario 3: Building on scenario 1, add more virtual stops to enhance last-mile transit access without increasing the fleet size of on-demand shuttles (higher bound)	19.1%	26.1%	7.9%	46.9%

services by providing last-mile transit connections. By promoting transit access in areas that were not within comfortable walking distance of bus stops (the current average OVTT is about 13 min), ridesourcing services could increase the market share of transit by almost 13 percentage points, which equates to a 28 percent increase. Nonetheless, this option would require additional vehicles to ensure that other service attributes such as wait time and number of additional pickups do not grow. Without increasing the fleet size, a deployment option that promotes last-mile transit connections might end up reducing transit use, as demonstrated by the forecasted demand estimates for MTransit in scenario 3.

To evaluate the feasibility of each deployment scenario, UM-LTP would need to evaluate the costs associated with them. A detailed analysis is beyond the scope of this paper and so we only touch on this issue briefly. Based on bus boarding/alighting data, simulation results indicate that under deployment scenario 1, MTransit can serve current transit demand with a 36% reduction in operation costs (Van Hentenryck, personal communication).[8] This result is consistent with a recent study that applied agent-based modeling to simulate two hypothetical shared autonomous vehicle scenarios for the city of Ann Arbor, which reports large cost-savings from these scenarios compared to the existing bus system (Merlin, 2017). Taken together with the demand forecasting results, we find that switching to MTransit under deployment option 1 can slightly promote transit ridership while reducing operating costs. If these savings were used to purchase more on-demand shuttles in order to enhance last-mile transit connectivity, an MTransit trip would become even more attractive and thus further boost transit use. These findings, though preliminary, provide empirical support for the idea of integrating ridesourcing services with public transit currently under consideration among many transit operators.

7. Conclusion

This paper uses a joint Revealed-Preference/Stated-Preference model to evaluate traveler response to an integrated system of ridesourcing services and public transit. We investigated the main determinants of travel mode choice for commuting trips, with a focus on quantifying how changes in different service attributes of the integrated system impact transit use. We applied the model results to predict future demand for transit use in commuting trips under different deployment scenarios of the integrated transit system. Making some reasonable assumptions, we predicted that using existing bus stops as pickup/drop-off points, substituting ridesourcing services for low-demand bus routes would slightly boost transit use while reducing operational costs. The increase in transit use is largely due to reductions in wait time and slightly because of decreases in in-vehicle travel time. A further move to enhance last-mile transit access—by adding virtual stops to the transit network to reduce out-of-vehicle travel time—would significantly promote transit if the fleet size of on-demand shuttles is increased to ensure wait time and other pickups do not grow as a consequence of additional virtual stops. If the fleet size is kept the same, however, this move might end up reducing the mode share of transit.

Consistent with the results in existing travel behavior studies, we find that wait time and OVTT are valued more than in-vehicle travel time in the choice process. Also, travelers dislike transfers and are much more likely to use transit if the trip does not involve transfers. This finding suggests that microtransit provided by private companies could siphon off transit riders who are willing to pay a price premium to avoid transfers. In addition, our model results suggest that additional pickups have a significant negative impact on the choice probability of MTransit. Like transfers, such influence comes from not only the additional travel time generated by additional pickups but also consumers' negative perceptions of the pickups themselves. We estimated that the average penalties of a transfer and an additional pickup are equivalent to 10.9 min and 6.4 min of in-vehicle travel time respectively. Nonetheless, these negative perceptions are shaped by travelers' current experiences, and they could be alleviated if customer experiences in transfers and additional pickups are improved.

Therefore, the results of this study may be subject to a status quo bias. Another limitation of our study is that travel cost (i.e. transit fare) is not examined due to the special context of this project, but it certainly plays a significant role in commuting mode choice. Future studies should fill this gap, since appropriate pricing of transit services is a major concern for most transit agencies. Another potential issue is that we have treated the non-traders (those who always choose one alternative) as acting in accordance with the utility maximization decision rule. If other reasons—e.g. heuristic decision making and strategic voting—are behind these decisions, however, these non-traders could lead to biased model results (Hess et al., 2010).

[8] This cost analysis has accounted for costs for vehicle purchase and maintenance, insurance, gas, and driver payment.

This study has empirically supported the notion that ridesourcing can provide a measurable boost to transit use when used to provide convenient last-mile connections between travelers' point of origin/destination and transit stops. According to our estimates, reducing the OVTT of a transit trip to 3 min or less, which almost amounts to a door-to-door service, could increase transit's mode share by 13 percentage points (a 28 percent increase). This finding suggests that while the rise of ridesourcing services offered by private firms threatens to attract away transit riders, ridesourcing can also be utilized by transit agencies to complement conventional public transit.

The current study was implemented within the context of a campus transit system. Empirical findings presented here are not directly transferable to general-service metropolitan transit, yet it is likely that the major themes—rider sensitivity to transfers and additional pickups, transit-use-increasing potential of OVTT reductions, importance of fleet-size increases—would find echoes in other contexts. Most broadly, this research illustrates the tradeoffs among conflicting goals under different deployment options of ridesourcing services, a theme also stressed by Atasoy et al. (2015). The single operator spanning conventional and on-demand transit may be replicated in some other contexts and not in others. Where on-demand transit is a private affair, public-transit operators may seek to approximate the single integrated system analyzed here through arrangements such as contracting, subsidy, and preferential access. Results presented here suggest that payoffs can be great. By filling the service gaps of large-volume transit lines and extending the catchment area of transit, ridesourcing services provide an effective solution to the last-mile problem.

Conflict of interest

None declared.

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References

Abdel-Aty, M.A., Kitamura, R., Jovanis, P.P., 1997. Using stated preference data for studying the effect of advanced traffic information on drivers' route choice. Transp. Res. Part C Emerg. Technol. 5, 39–50.

Abrantes, P.A.L., Wardman, M.R., 2011. Meta-analysis of UK values of travel time: an update. Transp. Res. Part A Policy Pract. 45, 1–17.

Atasoy, B., Ikeda, T., Song, X., Ben-Akiva, M.E., 2015. The concept and impact analysis of a flexible mobility on demand system. Transp. Res. Part C Emerg. Technol. 56, 373–392. https://doi.org/10.1016/j.trc.2015.04.009.

Ben-Akiva, M., Bradley, M., Morikawa, T., Benjamin, J., Novak, T., Oppewal, H., Rao, V., Key, 1994. Combining revealed and stated preferences data. Mark. Lett. 5, 335–350.

Bhat, C.R., Castelar, S., 2002. A unified mixed logit framework for modeling revealed and stated preferences: formulation and application to congestion pricing analysis in the San Francisco Bay area. Transp. Res. Part B Methodol. 36, 593–616.

Brownstone, D., Bunch, D.S., Train, K., 2000. Joint mixed logit models of stated and revealed preferences for alternative-fuel vehicles. Transp. Res. Part B Methodol. 34, 315–338.

Chen, P., Nie, Y., 2017. Connecting e-hailing to mass transit platform: analysis of relative spatial position. Transp. Res. Part C Emerg. Technol. 77, 444–461. https://doi.org/10.1016/j.trc.2017.02.013.

Cherchi, E., de Dios Ortúzar, J., 2006. On fitting mode specific constants in the presence of new options in RP/SP models. Transp. Res. Part A Policy Pract. 40, 1–18.

Clewlow, R.R., 2016. Carsharing and sustainable travel behavior: results from the San Francisco Bay Area. Transp. Policy 51, 158–164.

Clewlow, R.R., Mishra, G.S., 2017. Disruptive transportation: The adoption, utilization, and impacts of ridesourcing in the United States (No. UCD-ITS-RR-17-07). Research Report–UCD-ITS-RR-17-07. University of California, Davis.

De Luca, S., Di Pace, R., 2015. Modelling users' behaviour in inter-urban carsharing program: a stated preference approach. Transp. Res. Part A Policy Pract. 71, 59–76.

Dias, F.F., Lavieri, P.S., Garikapati, V.M., Astroza, S., Pendyala, R.M., Bhat, C.R., 2017. A behavioral choice model of the use of car-sharing and ride-sourcing services. Transportation (Amst) 44, 1307–1323. https://doi.org/10.1007/s11116-017-9797-8.

Errico, F., Crainic, T.G., Malucelli, F., Nonato, M., 2013. A survey on planning semi-flexible transit systems: methodological issues and a unifying framework. Transp. Res. Part C Emerg. Technol. 36, 324–338. https://doi.org/10.1016/j.trc.2013.08.010.

Fagnant, D.J., Kockelman, K.M., 2014. The travel and environmental implications of shared autonomous vehicles, using agent-based model scenarios. Transp. Res. Part C Emerg. Technol. 40, 1–13.

Fagnant, D.J., Kockelman, K.M., Bansal, P., 2015. Operations of shared autonomous vehicle fleet for Austin, Texas, market. Transp. Res. Rec. J. Transp. Res. Board 98–106.

Feigon, S., Murphy, C., 2016. Shared mobility and the transformation of public transit. TCRP Research Report 188.

Frei, C., Hyland, M., Mahmassani, H.S., 2017. Flexing service schedules: assessing the potential for demand-adaptive hybrid transit via a stated preference approach. Transp. Res. Part C Emerg. Technol. 76, 71–89. https://doi.org/10.1016/j.trc.2016.12.017.

Hensher, D.A., 1994. Stated preference analysis of travel choices: the state of practice. Transportation (Amst) 21, 107–133.

Hensher, D.A., 2008. Empirical approaches to combining revealed and stated preference data: some recent developments with reference to urban mode choice. Res. Transp. Econ. 23, 23–29.

Hensher, D.A., 2012. Accounting for scale heterogeneity within and between pooled data sources. Transp. Res. Part A Policy Pract. 46, 480–486.

Hensher, D.A., Greene, W.H., 2003. The mixed logit model: the state of practice. Transportation (Amst) 30, 133–176.

Hess, S., Adler, T., Polak, J.W., 2007. Modelling airport and airline choice behaviour with the use of stated preference survey data. Transp. Res. Part E Logist. Transp. Rev. 43, 221–233.

Hess, S., Rose, J.M., Polak, J., 2010. Non-trading, lexicographic and inconsistent behaviour in stated choice data. Transp. Res. Part D Transp. Environ. 15, 405–417.

Jaffe, E., 2015. How the microtransit movement is changing urban mobility. Citylab. Available at: <https://www.citylab.com/transportation/2015/04/how-the-microtransit-movement-is-changing-urban-mobility/391565/> (accessed: 28 October 2017).

Krueger, R., Rashidi, T.H., Rose, J.M., 2016. Preferences for shared autonomous vehicles. Transp. Res. Part C Emerg. Technol. 69, 343–355.

Levine, J., Zellner, M., Arquero de Alarcón, M., Shiftan, Y., Massey, D., 2018. The impact of automated transit, pedestrian, and bicycling facilities on urban travel patterns. Transp. Plan. Technol. 41, 463–480.

Louviere, J.J., Hensher, D.A., Swait, J.D., 2000. Stated Choice Methods: Analysis and Applications. Cambridge University Press.

Mahéo, A., Kilby, P., Van Hentenryck, P., 2017. Benders decomposition for the design of a hub and shuttle public transit system. Transp. Sci.

Merlin, L.A., 2017. Comparing automated shared taxis and conventional bus transit for a small city. J. Public Transp. 20, 2.

Millard-Ball, A., 2005. Car-Sharing: Where and How It Succeeds. Transportation Research Board.

Morikawa, T., 1989. Incorporating Stated Preference Data in Travel Demand Analysis. Massachusetts Institute of Technology.

Paulley, N., Balcombe, R., Mackett, R., Titheridge, H., Preston, J., Wardman, M., Shires, J., White, P., 2006. The demand for public transport: the effects of fares, quality of service, income and car ownership. Transp. Policy 13, 295–306.

Pew Research Center, 2016. Shared, collaborative and on demand: The new digital economy. Available at: <http://www.pewinternet.org/files/2016/05/PI_2016.05.19_SharingEconomy_FINAL.pdf> (accessed: 28 October 2017).

Rashedi, Z., Mahmoud, M., Hasnine, S., Habib, K.N., 2017. On the factors affecting the choice of regional transit for commuting in Greater Toronto and Hamilton Area: application of an advanced RP-SP choice model. Transp. Res. Part A Policy Pract. 105, 1–13.

Rose, J.M., Bliemer, M.C.J., Hensher, D.A., Collins, A.T., 2008. Designing efficient stated choice experiments in the presence of reference alternatives. Transp. Res. Part B Methodol. 42, 395–406.

Shaheen, S., Chan, N., 2016. Mobility and the sharing economy: potential to facilitate the first-and last-mile public transit connections. Built Environ. 42, 573–588.

Stiglic, M., Agatz, N., Savelsbergh, M., Gradisar, M., 2018. Enhancing urban mobility: integrating ride-sharing and public transit. Comput. Oper. Res. 90, 12–21. https://doi.org/10.1016/j.cor.2017.08.016.

Train, K.E., 2003. Discrete Choice Methods with Simulation. Cambridge University Press.

Train, K.E., Wilson, W.W., 2008. Estimation on stated-preference experiments constructed from revealed-preference choices. Transp. Res. Part B Methodol. 42, 191–203.

UBER Newsroom, 2017. 5 billion trips. Available at: <https://www.uber.com/newsroom/5billion-2> (accessed: 28 October 2017).

Washbrook, K., Haider, W., Jaccard, M., 2006. Estimating commuter mode choice: a discrete choice analysis of the impact of road pricing and parking charges. Transportation (Amst) 33 (6), 621–639.