Autonomous Mobility On-Demand (AMoD) Systems and their Potential Impacts on Weekly Activity Patterns: A Case Study in Singapore

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Abstract

The use of on-demand ride services continues to grow rapidly in recent years. At some point, given current technologies of automation, it is plausible that these rides will be driverless. This research examines the following questions: are people eager to adopt autonomous mobility on-demand (AMoD) ride services and will they shift their travel behaviors and activity patterns as a response to these services? In this paper, we leverage a rich and one-of-a kind week-long data set from a context-aware stated preference survey collected through the mobile phone application called Future Mobility Sensing (FMS) and estimate an ordered logit model to answer these questions. Our key findings suggest that people would like to try AMoD, but they are not willing to completely or significantly shift to the new alternative mode. Moreover, those who are likely to try AMoD tend to be car-less, young, and frequent users of ride-hailing services. They would use AMoD to perform additional leisure, personal, and meal activities, most preferably in the morning.

Keywords

Autonomous mobility-on-demand, ride-hailing, Transportation Network Companies, smart mobility, activity patterns, activity rescheduling.

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Introduction

Since their founding in 2009, ride-hailing services such as Uber, Lyft, Didi Chuxing, and Grab have been growing rapidly and become a popular mode of transportation. They are also known as Transportation Network Companies (TNCs), ride-sourcing, or app-based, on-demand rides. According to a survey conducted by Pew Research, in 2018, more than a third of Americans have used a TNC service and only 3% have never heard of it. This is a great jump from 15% who have used it and 33% who have never heard of it in 2015. Of those who have used a TNC service, 32% ride at least once a month, while 10% ride at least once a week. The boom in the demand for TNCs is not just in the U.S. For example, Grab, which operates in several countries in Southeast Asia (including Malaysia, Singapore, Indonesia and Thailand), served about 1 billion rides in 2012-2017, and another billion rides in 2018 alone. Expanding to all types of rides, they also offer pool (shared among multiple parties), premium (higher end), XL (higher capacity), and Express Pool services (either flexible schedule or stops). Together, they make up "Mobility on-Demand" (MoD) services. We anticipate driverless TNCs in the future. Uber, Didi Chuxing, Lyft, as well as other companies that were not in the ride-sharing business (Waymo, Nissan, Volkswagen, and Daimler) are racing to provide driverless mobility on-demand ride services (CB Insights, 2018). We refer to those services as "Autonomous Mobility on-Demand" (AMoD).

This paper strives to further understand AMoD's potential impacts on people's weekly activity patterns. Specifically, we aim to answer the following questions: are people eager to incorporate AMoD as one of their modes of transportation? What factors affect their preferences? Will AMoD trigger the performance of more activities and will it affect the scheduling of activities? To the best of our knowledge, this paper is the first to model whole-week activity schedules that include travel by various modes including AMoD. The technology used to collect the week-long, high-quality travel diaries and stated preference (SP) data, called Future Mobility Sensing (FMS), made this possible.

FMS is a user-friendly trip and activity diary mobile application that was deployed in Singapore, in conjunction with Singapore's Land Transport Authority's (LTA) Household Interview Travel Survey (HITS). FMS addresses the shortcomings of purely paper-based or online-based activity diary surveys (Zhao et al., 2015). Since it functions in real-time and utilizes smartphone sensors including GPS, accelerometer, etc., and a machine learning backend which makes responding to surveys easier, less intrusive, and more accurate, it is able to collect high quality revealed preference (RP) data over multiple days. At the end of each day, the user verifies their daily travel diary inferred by the machine learning backend, and they do this for an entire week. FMS can be used and customized for a variety of purposes; we also used FMS to conduct a pre-survey as well as a SP survey in addition to the RP. Before they begin the RP, respondents fill out a pre-survey about themselves and their households (age, gender, employment status, income, car ownership, bike ownership, frequency of using different modes of transportation, membership to TNC service, household size). Following the RP survey, they answer the SP survey, where they are asked to rate their preferences for an alternative weekly pattern relative to their actual weekly pattern on a 5-point scale. Alternative weekly patterns were created based on the pre-survey and the RP. In this paper, we analyze the SP data collected using FMS.

We followed He et al. (2018) who first proposed generating multi-day activity pattern profiles that form choice sets for SP surveys. Based on the user demographic characteristics that we collected in the pre-survey (such as vehicle-ownership, membership of shared bike or car service) and the characteristics of the actual activities and trips performed, which we collected in the RP (these include activity types, locations, frequencies, durations, start and end times, and travel modes, times, and distances), we slightly modified the actual pattern to include AMoD options and have specific additional activities (one or two more discretionary activities in the morning and or evening, outside of work hours). Meanwhile, AMoD fares are assumed to be to a fraction to no more than MoD fares, and are even lower when they are shared. Non-pooled AMoD tends to have the same travel time as MoD. The algorithm in FMS (based on He et al., 2018) optimizes and personalizes the alternative activity pattern by excluding selections that are dominant, inferior, or with unrealistic attribute combinations. In this way, generated patterns are context-aware or closely resemble the user and his or her actual choice sets and make the SP more realistic.

There are limited data on MoD and AMoD services. Fortunately, a growing number of studies have carried out online SP surveys and inquire about one's willingness to use shared, autonomous vehicles. Krueger et al. (2016) conducted an online SP survey at major cities in Australia in which they referred to actual trips respondent recently took. They analyzed variability in travel cost, travel time, waiting time, and demographic factors and found that young individuals or individuals with multimodal travel patterns are more likely to adopt SAV. The online SP in Moreno et al. (2018) was conducted in Munich for commuting and other home-based trips. An online SP in Lisbon (Choudhury et al., 2018) is on a MoD system consisting of shared taxi, one-way car rental, and a combination of park-ride and school bus facilities. None of these surveys are app-based and real-time, over the course of multiple days, or inclusive of a context-aware SP.

Data

The FMS survey was conducted between June and July of 2018. Respondents who validated or verified their RP for seven consecutive days were then asked a follow-up SP. Each person is solicited 3 SP questions (the proposed pattern in each question has about a third, two-thirds, or all of the travel substituted by AMoD). There is a total of 259 respondents and the sample statistics are shown below (**Fig. 1**). Respondents are at least 17 years old, with a significant portion between the ages of 21-25. Nearly all have subscribed to TNC while over 60% took a TNC at least once the previous week they were surveyed. Over 60% are in households without a car. Most have a household size of four. The sample is also nearly evenly split by gender. Lastly, nearly half of respondents are full time workers, while the rest are students, national service members, part time workers, retirees and home makers, and self- employed workers.

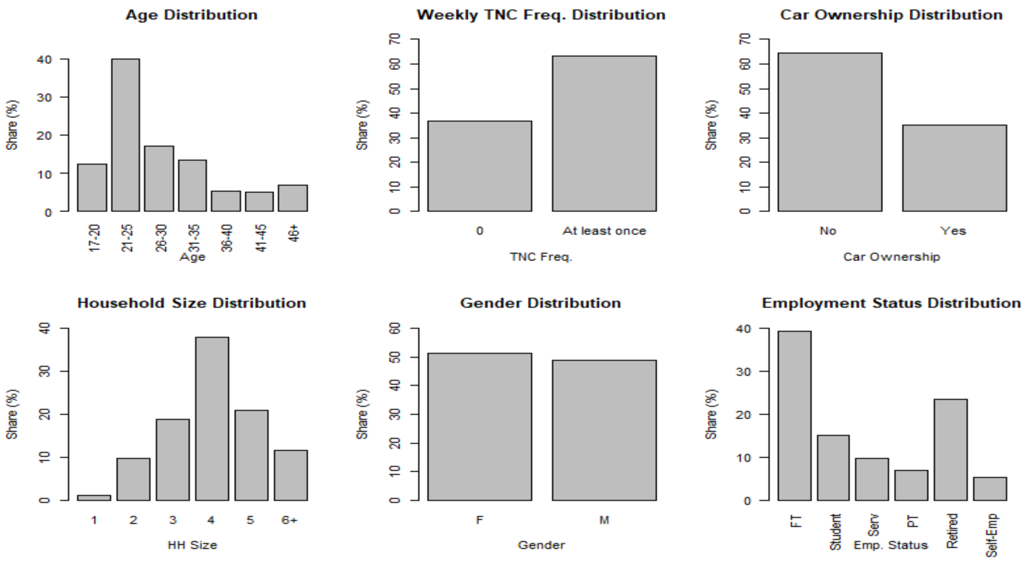


Fig.1 Sample Statistics

Methods

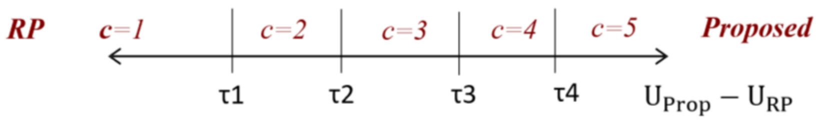
Defining an Activity and Its Duration

FMS sensed various stops throughout the day. We processed the data so that work activities in the same home-based tour would be collapsed into a single work activity, and its duration is net of the activities in between work. For all other activities, if they are consecutive and of the same activity type, they would also be collapsed into a single activity.

Model

Our model is an ordered logit model (I). Since we asked how much people are willing to switch their actual pattern with the proposed pattern, essentially, they are choosing between two patterns. We assume their choices depend on the differences in utilities of the two activity patterns, and that the errors of the utility differences are i.i.d. logistic. The strength of likeliness to change the RP (i.e. the actual activity pattern) to the proposed pattern (we call *c* here) are ordered from 1 to 5, respectively as “very unlikely”, “unlikely”, “indifferent”, “likely”, and “highly likely”. If the difference in utilities is ∞, they are expected to choose *c*=5. If the difference in utilities is between τ_3 and τ_4 (where $\tau_3 \le \tau_4$), then they are expected to choose *c*=4, and so on. The τs are cutoffs values of the difference in utilities.

$$P(m) = P(\tau_{c-1} \le U_{Prop} - U_{RP} \le \tau_c) \qquad \text{(I)}$$



$$\text{Answer} = \begin{cases} 1 \text{ highly unlikely} & -\infty \le U_{Prop} - U_{RP} \le \tau_1 \\ 2 \text{ unlikely} & \tau_1 \le U_{Prop} - U_{RP} \le \tau_2 \\ 3 \text{ neutral} & \tau_2 \le U_{Prop} - U_{RP} \le \tau_3 \\ 4 \text{ likely} & \tau_3 \le U_{Prop} - U_{RP} \le \tau_4 \\ 5 \text{ highly likely} & \tau_4 \le U_{Prop} - U_{RP} \le \infty \end{cases}$$

Utility Specifications

We characterize the utility of the weekly patterns as having two main components— the utility from performing activities and the travel disutility that must be incurred to travel to perform the activities. These components are for the entire week. The utility of weekly pattern *i* for individual *n* is (II).

$$U_{in} = U_{in}^{\text{activity ut.}} + U_{in}^{\text{travel disut.}} \tag{II}$$

The first component is based on activity durations and scheduling preferences (III).

$$U_{in}^{\text{activity ut.}} = \text{Activity Durs.}_{in} + \text{Scheduling Pref.}_{in} \tag{III}$$

The first term of (III) is the sum of logarithmic function of per-activity durations (IV). The function is nonlinear and decreasing at the margin; the longer the activity, the higher the utility, but the utility increases diminish with longer durations (because of boredom, exhaustion, or inefficiencies). The utility from each activity duration is aggregated for the entire week and for all activity types. Because the function is nonlinear, an activity that is 2 hours vs. two activities that are an hour each have different total utilities. The specification also accounts for the number of activities.

$$\text{Activity Durs.}_i = \sum_{a=1}^{A} \sum_{c=1}^{n_a} [\alpha_a^{dur} \cdot \ln(\, dur_{i,a,c} + 1)] \tag{IV}$$

a={leisure, personal, home} activity types.
c={1, 2,…, n_a} all the activities of type a for the entire week

Alternatively, we can calculate the utility of activities on a per week basis (V). For some activities, such as work, too much of it (instead of how long each time is) reduces the marginal utility. Typically, these are activities with “roll-over” characteristics or duration interdependencies (i.e. a person who works a lot one-time can work less the next time, but extending the duration in that sitting is easier or more efficient. Still if they work too much in general, then the marginal utility decreases). In that case duration is aggregated for the entire week first before they enter the function.

$$\text{Activity Durs.}_i = \sum_{a=1}^{A} [\alpha_a^{dur} \cdot \ln\,([\sum_{c=1}^{n_a} dur_{i,a,c}] + 1)] \tag{V}$$

a={work, meal} activity types.
c={1, 2,…, n_a} all the activities of type a for the entire week

For specific groups of people, when activities are performed at convenient or preferred times, there is additional utility which we refer to as scheduling preferences. For example, normal hours for full time workers are probably from 8 to 5, and they will achieve more utility if they stick to those hours. We follow Zeid et al. (2006) to specify the utility from scheduling preferences, using Fourier series that resemble the cyclicality of time or hours-of-the-day

(VI). For any trigonometric functions F, F(0) = F(2π· m) where $m \epsilon Z^+$. In our application, we require the value of the function to be constant for every multiples of 24-hours (so that the value is the same at say 10:05 am on Monday, Tuesday, or any other day). Therefore, we define a mapping function, $G(t)=\frac{2\pi \cdot m \cdot t}{24}$ where $0 \leq t \leq 24$ and $m \epsilon Z^+$ to guarantee that for any trigonometric function, F, we have F(G(0))=F(G(24)). The scheduling preferences have both sines and cosines of the start and end times of each activity (in (VI), they are respectively $t^{p=arr}$ and $t^{p=dep}$). Each trigonometric function in the series has *m* from 1 to 4. The series is then aggregated for the entire week and for all activity types (s_i^p). Finally, the Fourier series is further interacted with a constant or some sociodemographic variables, *r*. We used employment status to differentiate part-time workers with non-part-time workers ($X_{Part\ Time}$ is a binary variable for whether the respondent is a part-time worker). Only work activities are interacted.

$$\text{Scheduling Pref.}_i = \sum_{r=1}^{R} \sum_{p=1}^{P} X_r \cdot s_{i,r}^p \tag{VI}$$

$$s_{i,r}^{p=arr} = \sum_{a=1}^{A} \sum_{c=1}^{n_a} \sum_{m=1}^{4} [\alpha_{a,r,m}^{p=arr} \cdot \sin\left(\frac{2m\pi}{24} \cdot t_{i,a,c}^{p=arr}\right)] + \sum_{a=1}^{A} \sum_{c=1}^{n_a} \sum_{m=1}^{4} [\alpha_{a,r,m+4}^{p=arr} \cdot \cos\left(\frac{2m\pi}{24} \cdot t_{i,a,c}^{p=arr}\right)]$$

$$s_{i,r}^{p=dep} = \sum_{a=1}^{A} \sum_{c=1}^{n_a} \sum_{m=1}^{4} [\alpha_{a,r,m}^{p=dep} \cdot \sin\left(\frac{2m\pi}{24} \cdot t_{i,a,c}^{p=dep}\right)] + \sum_{a=1}^{A} \sum_{c=1}^{n_a} \sum_{m=1}^{4} [\alpha_{a,r,m+4}^{p=dep} \cdot \cos\left(\frac{2m\pi}{24} \cdot t_{i,a,c}^{p=dep}\right)]$$

a={work, leisure, personal, meal} activity types
c={1, 2,…, n_a} all the activities of type a for the entire week
p={arr, dep}
m={1,2,3,4} multipliers in the trigonometric functions
r= {1, part time (PT) workers} socio-demographic variables

The second component, which is of travel disutility, usually comprises of travel time and travel costs (fares, surge pricing, parking, gasoline, electronic road pricing). We did not include travel time in our model because it is implicitly already accounted for in the utilities of activities. More specifically, because there are only 24*7 hours in a week, the longer the weekly travel time, the shorter the weekly activity duration, which means we could not add as much activities in the proposed pattern. Thus, the disutility from travel time is equivalent to disutility from the opportunity cost. Therefore, we only considered travel costs as part of the disutility component in the model (VII). The utility is linear in the parameters and variables. Each part is aggregated for the entire week and for all mode types.

$$U_i^{\text{travel disut.}} = \sum_{o=1}^{O} \sum_{j=1}^{n_o} [\alpha^{cost} \cdot cost_{i,o,j}] \tag{VII}$$

o={driverless taxi, driverless shared taxi, driverless minibus, driverless premium, public transit, taxi, walk, car, bike, and motorcycle} mode types
j={1,2,…, n_o} all the travel by mode o for the entire week

In addition to the two major components, we also controlled for other pattern and individual characteristics. These variables include share of AMoD (the number of trips by AMoD divided by the total number of trips), age, use of TNC, and car ownership.

We estimated the model using BIOGEME (Bierlaire, 2018).

Results

Estimation Results

The estimation results of the model described in the previous section (with activity durations, disutility, other variables, and scheduling preferences) are listed in the following table (**Table 1**). The coefficient of AMoD share is negative, which means the higher the share of travel by AMoD in the proposed pattern, the less likely it is for one to switch activity pattern. For example, if the only difference between the patterns is about a third of one's travels shifted to AMoD, then he or she is expected to *likely* switch to the proposed pattern. However, if the only difference is about a two-thirds to a 100% shift to AMoD, then he or she would be indifferent to switch patterns. This suggests that although people are eager to adopt this new mobility option, they also might not want a major shift to AMoD. Perhaps they want to take other modes in conjunction with AMoD. The coefficient of cost is also negative. Shifts to AMoD are associated with higher costs, and higher travel cost reduces one's likeliness to switch activity pattern.

Table.1 Estimated Results

Variable	**Coefficient**	**Std. Error**
Home duration (hours)	0.0139	0.133
Work duration (hours)	4.05	2.17
Leisure duration (hours)	0.0697	0.103
Personal duration (hours)	0.303*	0.124
Meal duration (hours)	-0.194	0.524
AMoD share (%)	-0.00934*	0.00301
Travel cost ($)	-0.604*	0.137
Did not use TNC dummy	-0.247	0.162
Does not own a car dummy	0.125	0.159
Age 47 and up dummy	-0.584*	0.3
τ_2-τ_1	1.72*	0.123
τ_3-τ_2	1.13*	0.0785
τ_4-τ_3	2.48*	0.143
τ_1	-3.42*	0.329
Sample size: 777 Null log-likelihood: -5296.852 Full log likelihood: -1042.421 ρ^2: 0.803 Adjusted ρ^2: 0.785		

Note: * p value for t-test<0.05. The scheduling preferences coefficients are in Table 2 in the appendix.

Other variables in the model include binary variables pertaining to the respondent. Almost all of the respondents we interviewed have subscriptions to a TNC, but only some use it regularly. Their usage of TNC the previous week is more distributed— nearly 40% did not use a TNC at all the previous week. These individuals are less likely to switch activity patterns. Our results suggest that early adopters (of AMoD) are not just those who subscribed to a TNC but also those who use it regularly. Most likely these are individuals without a private vehicle. The coefficient of car-less is positive although it is not significant; this may be because non car-owners' shifts from one ride service to another (e.g. public transit to driverless taxi) is less drastic than car owners' shifts from their cars to a ride service. However, income was not controlled, so car owners might also have higher incomes to be able to afford more expensive modes. Finally, early adopters tend to be younger. Those over the age of 47 are less likely to switch patterns.

All of the activity durations except for meal activities have the anticipated sign and shape (**Fig. 2**). Our model suggests that increased activity durations in the proposed pattern is favorable and increases one's likeliness to switch their original weekly pattern. For home, leisure, and personal activities, the longer the per activity duration, the greater the utility. At certain high duration lengths however, marginal utility starts to level off. For work activities, its total weekly duration is directly related to utility. The weekly work duration also experiences diminishing marginal utility at high levels of weekly duration. The coefficient of meal activity durations is negative which is counterintuitive, but it is also insignificant.

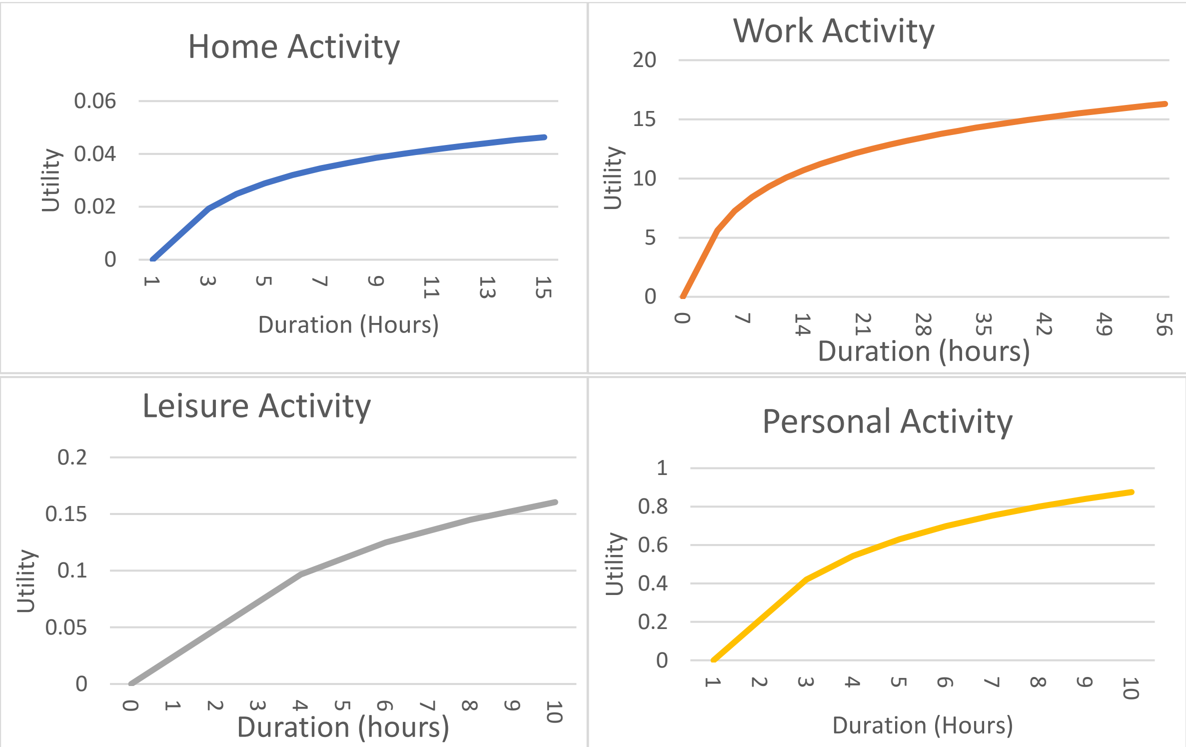


Figure 2. Utility Functions from Activities by Activity Types

Finally, we show the plotted estimated coefficients from scheduling preferences of leisure, personal, and meal activities in the following figure (**Fig.3**). The actual estimates are in the appendix. We performed a likelihood ratio test that compares a model with and without scheduling preferences. The test suggests that scheduling preferences do affect utility, which is why we included them. In Fig.3, each plot is normalized to its value at 8 am. The start times of the activities are in blue while the end times are in yellow; end times occur to the right of start times. Leisure activities inserted between 9 and 10 am achieve the highest utility, while those inserted at night achieve much less utility. Personal activities that occur around 4 am, between 9 and 10 am, or 9 pm achieve the highest utility. On the other hand, personal activities that start in the middle of the day between noon and 7 pm, achieve the least utility. For meal activities, breakfast at 8 am attains the highest utility, followed by lunch around noon, and dinner around 7 pm. Unfortunately, those of work activities could not capture the true impacts; it may be because there were no significant changes in the scheduling of work activities since we did not add additional work activities.

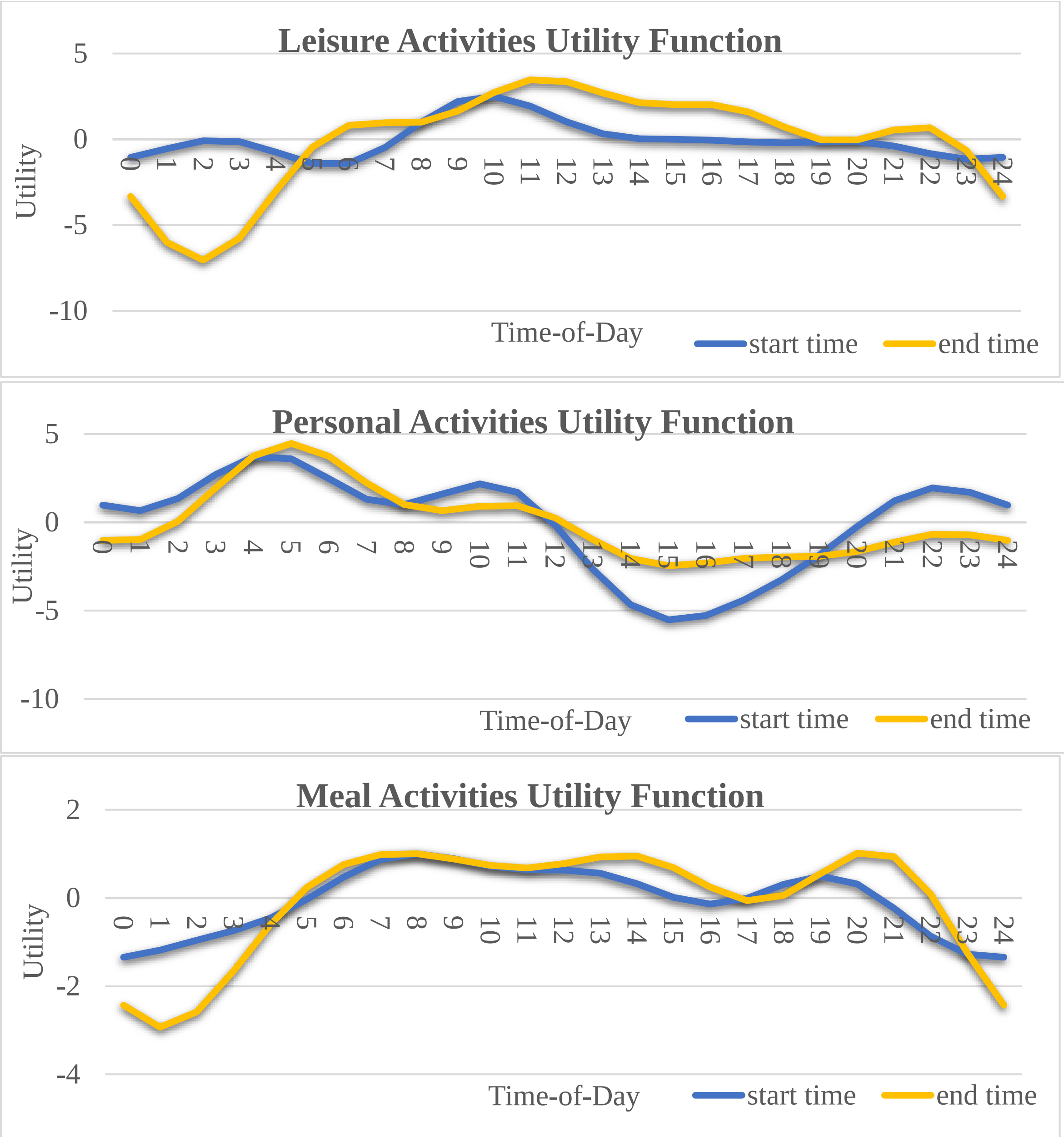


Fig. 3 Utility Functions from Scheduling Preferences

Conclusion

We found that people are eager to adopt AMoD, and will not only use it but also use it to perform additional activities. They are however not keen on shifting to AMoD completely or in a major way. Those who are likely to adopt AMoD tend to be frequent users of TNCs, car-less, and young. Early adopters will perform additional leisure, personal, and meal activities;

if they did not perform these activities in the morning, the new alternative may encourage them to leave the house early to do so.

Our study has limitations. Weekly patterns are complicated. They involve interrelated activities and travel. People decide not only activity and mode types, but also activity duration, scheduling, and sequence. Viewing these options on a smartphone is even more challenging. People might not fully understand or want to spend much time trying to understand every small detail and differences. Thus, our limitation lies in the assumption that respondents were able to identify all if not most of the differences between the patterns.

At the same time, this is also the first time that a smartphone application was used to enable us to collect high-quality SP survey data spanning an entire week. We tried to simplify the pattern and summarize key differences. We made the SP survey context-aware and applied the approach in He et al. (2018) to generate optimized choice sets or alternative weekly activity patterns. In this paper, we model the week-long data by specifying week-long activity durations, disutility, and scheduling preferences. In this way, we started the foundation for collecting and understanding data on the potential demand for driverless ride services, beyond the trip-level. We strive to capture the inter-dependencies between activities and travel. We can then build on this and further develop this approach.

To extend this work, we plan to incorporate other data sources related to the built-in environment. In addition to the activity pattern characteristics we considered (duration, schedules, and disutility in terms of travel costs), the built-in environment presumably also plays a role in the decision whether or not to adopt. Our results hinted that people who are less car-dependent and who are already using ride services, may be likelier to adopt this new technology. Perhaps additionally, those living in downtown, near public transit stations or stops, or with more extensive public transit coverage, would use AMoD, because they can supplement the other modes with AMoD. Perhaps reliable public transit and a diverse menu of mobility options are necessary to ensure the success of AMoD.

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Appendix

Table.2 Estimated Results—Scheduling Preferences Coefficients

Coefficient Name	**Estimated Coefficient**	**Std. Error**
$\alpha^{p=arr}_{a=work,r=1,m=1}$	-0.569	0.511
$\alpha^{p=arr}_{a=work,r=1,m=2}$	-0.0384	0.328
$\alpha^{p=arr}_{a=work,r=1,m=3}$	0.314	0.22
$\alpha^{p=arr}_{a=work,r=1,m=4}$	0.112	0.133
$\alpha^{p=arr}_{a=work,r=1,m=5}$	1.93*	0.526
$\alpha^{p=arr}_{a=work,r=1,m=6}$	0.997*	0.346
$\alpha^{p=arr}_{a=work,r=1,m=7}$	0.471*	0.229
$\alpha^{p=arr}_{a=work,r=1,m=8}$	-0.105	0.145
$\alpha^{p=dep}_{a=work,r=PT,m=1}$	-1.82	7.79
$\alpha^{p=dep}_{a=work,r=PT,m=2}$	-8.59	7.16
$\alpha^{p=dep}_{a=work,r=PT,m=3}$	-5.14	3.85
$\alpha^{p=dep}_{a=work,r=PT,m=4}$	0.884	1.57
$\alpha^{p=dep}_{a=work,r=PT,m=5}$	6.54	7.58
$\alpha^{p=dep}_{a=work,r=PT,m=6}$	5.1	3.47
$\alpha^{p=dep}_{a=work,r=PT,m=7}$	-0.685	3.29
$\alpha^{p=dep}_{a=work,r=PT,m=8}$	-0.224	1.52
$\alpha^{p=dep}_{a=work,r=1,m=1}$	0.197	0.586
$\alpha^{p=dep}_{a=work,r=1,m=2}$	-0.26	0.314
$\alpha^{p=dep}_{a=work,r=1,m=3}$	-0.375	0.222
$\alpha^{p=dep}_{a=work,r=1,m=4}$	-0.382*	0.136
$\alpha^{p=dep}_{a=work,r=1,m=5}$	-0.614	0.374
$\alpha^{p=dep}_{a=work,r=1,m=6}$	-0.252	0.295
$\alpha^{p=dep}_{a=work,r=1,m=7}$	-0.258	0.232
$\alpha^{p=dep}_{a=work,r=1,m=8}$	0.18	0.137
$\alpha^{p=dep}_{a=work,r=PT,m=1}$	-3.51	4.51
$\alpha^{p=dep}_{a=work,r=PT,m=2}$	-6.36*	2.37
$\alpha^{p=dep}_{a=work,r=PT,m=3}$	-2.6	2.17
$\alpha^{p=dep}_{a=work,r=PT,m=4}$	-0.596	1.09
$\alpha^{p=dep}_{a=work,r=PT,m=5}$	-4.77	2.59
$\alpha^{p=dep}_{a=work,r=PT,m=6}$	-0.744	2.11
$\alpha^{p=dep}_{a=work,r=PT,m=7}$	0.654	1.04
$\alpha^{p=dep}_{a=work,r=PT,m=8}$	0.495	0.999
$\alpha^{p=arr}_{a=leis.,r=1,m=1}$	-0.0346	0.313

$\alpha^{p=arr}_{a=leis.,r=1,m=2}$	0.128	0.161
$\alpha^{p=arr}_{a=leis.,r=1,m=3}$	-0.193	0.124
$\alpha^{p=arr}_{a=leis.,r=1,m=4}$	0.00233	0.0885
$\alpha^{p=arr}_{a=leis.,r=1,m=5}$	0.261	0.262
$\alpha^{p=arr}_{a=leis.,r=1,m=6}$	-0.103	0.141
$\alpha^{p=arr}_{a=leis.,r=1,m=7}$	0.0103	0.106
$\alpha^{p=arr}_{a=leis.,r=1,m=8}$	0.109	0.0865
$\alpha^{p=dep}_{a=leis.,r=1,m=1}$	-0.148	0.328
$\alpha^{p=dep}_{a=leis.,r=1,m=2}$	-0.191	0.167
$\alpha^{p=dep}_{a=leis.,r=1,m=3}$	-0.155	0.127
$\alpha^{p=dep}_{a=leis.,r=1,m=4}$	-0.118	0.089
$\alpha^{p=dep}_{a=leis.,r=1,m=5}$	-0.417	0.258
$\alpha^{p=dep}_{a=leis.,r=1,m=6}$	-0.0475	0.144
$\alpha^{p=dep}_{a=leis.,r=1,m=7}$	-0.0137	0.115
$\alpha^{p=dep}_{a=leis.,r=1,m=8}$	0.0499	0.0883
$\alpha^{p=arr}_{a=pers.,r=1,m=1}$	0.526	0.369
$\alpha^{p=arr}_{a=pers.,r=1,m=2}$	-0.251	0.209
$\alpha^{p=arr}_{a=pers.,r=1,m=3}$	0.0156	0.155
$\alpha^{p=arr}_{a=pers.,r=1,m=4}$	-0.132	0.12
$\alpha^{p=arr}_{a=pers.,r=1,m=5}$	0.297	0.301
$\alpha^{p=arr}_{a=pers.,r=1,m=6}$	0.0714	0.187
$\alpha^{p=arr}_{a=pers.,r=1,m=7}$	-0.196	0.151
$\alpha^{p=arr}_{a=pers.,r=1,m=8}$	0.000748	0.111
$\alpha^{p=dep}_{a=pers.,r=1,m=1}$	-0.462	0.371
$\alpha^{p=dep}_{a=pers.,r=1,m=2}$	0.00298	0.22
$\alpha^{p=dep}_{a=pers.,r=1,m=3}$	0.0615	0.164
$\alpha^{p=dep}_{a=pers.,r=1,m=4}$	0.114	0.117
$\alpha^{p=dep}_{a=pers.,r=1,m=5}$	-0.0271	0.3
$\alpha^{p=dep}_{a=pers.,r=1,m=6}$	0.117	0.194
$\alpha^{p=dep}_{a=pers.,r=1,m=7}$	0.143	0.149
$\alpha^{p=dep}_{a=pers.,r=1,m=8}$	-0.0449	0.128
$\alpha^{p=arr}_{a=meal,r=1,m=1}$	0.0496	0.373
$\alpha^{p=arr}_{a=meal,r=1,m=2}$	-0.161	0.219
$\alpha^{p=arr}_{a=meal,r=1,m=3}$	0.0105	0.157
$\alpha^{p=arr}_{a=meal,r=1,m=4}$	0.0948	0.102
$\alpha^{p=arr}_{a=meal,r=1,m=5}$	-0.383	0.361
$\alpha^{p=arr}_{a=leis.,r=1,m=6}$	-0.173	0.183

$\alpha^{p=arr}_{a=leis.,r=1,m=7}$	-0.0752	0.138
$\alpha^{p=arr}_{a=leis.,r=1,m=8}$	0.00812	0.0976
$\alpha^{p=dep}_{a=meal,r=1,m=1}$	0.0978	0.342
$\alpha^{p=dep}_{a=meal,r=1,m=2}$	0.276	0.218
$\alpha^{p=dep}_{a=meal,r=1,m=3}$	0.236	0.149
$\alpha^{p=dep}_{a=meal,r=1,m=4}$	0.00483	0.101
$\alpha^{p=dep}_{a=meal,r=1,m=5}$	0.477	0.393
$\alpha^{p=dep}_{a=meal,r=1,m=6}$	0.244	0.211
$\alpha^{p=dep}_{a=meal,r=1,m=7}$	0.157	0.166
$\alpha^{p=dep}_{a=meal,r=1,m=8}$	0.0835	0.11

Note: * p value for t-test<0.05

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