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An Exploratory Analysis of Alternative Travel Behaviors of Ride-Hailing Users

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ABSTRACT

The emergence of ride-hailing, technology-enabled on-demand services such as Uber and Lyft, has arguably impacted the daily travel behavior of users. This study analyzes the travel behavior of ride-hailing users from an activity-based approach that uses *tours* and activity *patterns* as basic units of analysis. Tours are analyzed based on the dominant sequence of activities and trips, and daily patterns are classified via Latent Class Analysis to identify ride-hailing users based on key travel behavior indicators. The empirical results using data from the 2017 National Household Travel Survey show that 76 percent of ride-hailing tours can be represented by five dominant tour types. The Latent Class model suggests that the ride-hailing user population can be divided into four distinct classes where each class has a representative activity-travel pattern defining ride-hailing usage. Class 1 is composed of younger, employed users who use ride-hailing for work. Single-living older individuals comprise Class 2 and use ride-hailing for maintenance activities during midday. Ride-hailing Class 3 are younger, employed individuals who use it during evenings for discretionary purposes. Last, Class 4 members use it for mode change purposes. Since each identified class has different activity-travel patterns, they will show different responses to policy directives. This can help ride-hailing operators to address user travel needs as users respond to various policy constraints.

Keywords: Ride-hailing; activity-travel pattern; tours; latent class analysis; NHTS

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Introduction

In recent years, the emergence of *ride-hailing*, technology-enabled on-demand ride services (e.g., Uber and Lyft), has created new opportunities for transportation and arguably has impacted daily activity-travel behavior. Since the effective birth of ride-hailing (circa 2009), these services have experienced significant growth in demand. Recent studies in American cities show that about 21 percent of adults now personally use ride-hailing services and an additional 9 percent use it with friends (Clewlow and Mishra, 2017). Ride-hailing services expand the set of travel alternatives and substantially increase flexibility in activity scheduling and travel choices, thus affecting travel behavior in several ways, including increasing travel options, reducing travel uncertainty, and potentially replacing the use of other travel modes (Alemi *et al*., 2018a). These services can offer superior user experiences through a set of benefits that other transport choices have difficulty providing, such as real-time information about wait time, the identification of both drivers and passengers before making a trip, and a simple payment method.

Despite the rising demand for ride-hailing services, the lack of available data from major companies limits the comprehensive examination of the travel behavior of ride-hailing users. Prior studies considered ride-hailing in terms of its emergence (Taylor *et al*., 2015), user demographics (Young and Farber, 2019; Grahn *et al*., 2019; Sikder, 2019), use among older adults (Leistner and Steiner, 2017; Shirgaokar, 2018; Vivoda *et al*., 2018), factors affecting the choice (Dias *et al*., 2019; Alemi *et al*., 2018a), regulations and legal issues (Beer *et al*., 2017; Flores and Rayle, 2017), deadheading and pick-up trips (Nair *et al*., 2020), differences and similarities with taxi service (Rayle *et al*., 2016), as well as impacts on transit and taxi (Hall *et al*., 2018; Contreras and Paz, 2018), VMT (Henao and Marshall, 2019a), and parking (Henao and Marshall, 2019b; Wadud, 2020).

Previous studies, however, have focused on independent ride-hailing trips and thus, have not considered the complete sequence of activities and trips (*an activity pattern*) made by a ride-hailing user over a full day and consequently are unable to address key interrelationships regarding the choice of time, destination, and mode usage for other trips in connection with the ride-hailing trip(s). In this paper, we analyze these interrelations in a holistic manner via an activity-based approach that uses full activity-travel *patterns* and *tours* as basic units of analysis, with a tour being defined as a sequence of trips that begins and ends at the same location and contains one or more activities within it. We apply this approach to explore the complex travel behavior of ride-hailing users. Our particular research questions in this context are: How do people use ride-hailing in their daily life? Do heterogeneous groups of ride-hailing users with representative activity-travel patterns exist among the user population?

Following a literature review describing relevant studies regarding ride-hailing, an overview of the data and the sample used in this study is provided. The trip characteristics of ride-hailing are then presented followed by a description of methods applied to analyze ride-hailing tours and patterns. A discussion of results and conclusions are then presented.

Literature Review

An overview of prior research on ride-hailing is provided, with a particular focus on user characteristics, trip characteristics, and the overall impact of such services on travel behavior.

Ride-hailing User Demographics

Prior studies on app-based ride-hailing indicated that this service is more widely adopted by younger, well-educated, and affluent adults (Rayle *et al*., 2016; Clewlow and Mishra, 2017; Dias *et al*., 2017; Young and Farber, 2019; Grahn *et al*., 2019; Conway *et al*., 2018; Alemi *et al*., 2018a; Lavieri and Bhat, 2019). Smith (2016) reported that about 28 percent of younger adults 18-29 years of age use app-based ride-hailing compared to about 4 percent among adults aged 65 years and over. While younger people tend to ride more frequently, older people tend to make longer and more expensive rides (Kooti *et al*., 2017). In contrast to the common observation on a positive association between income and ride-hailing usage, Brown (2019) found that ride-hailing is more frequently used in low-income neighborhoods in Los Angeles that previously have been excluded by the taxi industry.

Although Smith (2016) and Kooti *et al*. (2017) did not find any impact of user race on the adoption of ride-hailing, Sikder (2019) observed that African-Americans are less likely to adopt ride-hailing services compared to other races. On the other hand, individuals with non-Hispanic origins are more likely to use ride-hailing (Alemi *et al*., 2018a). While Smith (2019) did not find any gender differences in the adoption and frequency of ride-hailing usage, other studies suggested that females have a lower tendency than males to use ride-hailing frequently (Sikder, 2019; Grahn *et al*., 2019). A user's employment status also contributes to the adoption and frequency of ride-hailing usage; for example, travelers having a full-time job, flexibility in work schedule and a job in the sales or service sector are more likely to adopt ride-hailing services (Sikder, 2019). A user's household characteristics tend to influence the use of ride-hailing. Sikder (2019) observed that the presence of children or elderly persons reduces the tendency to adopt ride-hailing. Moreover, having a vehicle in a household negatively affects ride-hailing use (Conway *et al*., 2018). More specifically, having a household vehicle reduces the frequency of ride-hailing use in low-density neighborhoods but increases the propensity of ride-hailing use in high-density neighborhoods (Dias *et al*., 2017). It is observed that the tendency of ride-hailing use increases among residents living in higher density areas (Conway *et al*., 2018) and metropolitan statistical areas having rail connections (Sikder, 2019).

Reasons for Choosing Ride-hailing

Previous studies found that social/leisure/recreation (e.g., bars, restaurant, visiting) is the most common trip purpose for using ride-hailing services (Rayle *et al*., 2016; Young and Farber, 2019; Dias *et al*., 2019; Clewlow and Mishra, 2017). About half of ride-hailing trips occur over weekends (Rayle *et al*., 2016; Dias *et al*., 2019) and a majority of trips are made at night (10 pm-7 am) (Young and Farber, 2019; Dias *et al*., 2019). Two primary reasons for using ride-hailing instead of driving a private vehicle are to avoid the need for parking and to avoid driving while intoxicated (Rayle *et al*., 2016; Clewlow and Mishra, 2017). Moreover, Rayle *et al*. (2016) suggested that shorter wait times and lower travel times contribute to considering ride-hailing as a substitution for public transit. Users who replaced taxi with ride-hailing reported that the convenience of payment, shorter wait time, and an easy hailing system were primary reasons.

Impacts of Ride-hailing on the Transportation System

Given prior studies, it remains a debatable issue whether the impact of ride-hailing on other modes should be considered a modal substitution or complementary. Henao and Marshall (2019a) and Alemi *et al*. (2018a) reported private vehicles and Rayle *et al*. (2016) observed taxi and public transit as the modes most substituted with ride-hailing. Gehrke *et al*. (2019) found that walking and biking trips are more likely to be replaced by ride-hailing for shorter distance trips and under poor weather conditions. There are ambiguous findings regarding relationships between public transit and ride-hailing. Several studies argued that ride-hailing serves as a complementary service rather than a substitution for public transit (Contreras and Paz, 2018; Conway *et al*., 2018; Grahn *et al*., 2019; Sikder, 2019; Young and Farber, 2019). Hall *et al*. (2018) suggested that as a complementary mode, ride-hailing had increased public transit ridership by five percent in larger cities. In contrast, Graehler *et al*. (2019) showed that the use of ride-hailing was expected to decrease bus ridership by 1.7 percent and heavy rail by 1.3 percent per year. Similarly, Clewlow and Mishra (2017) concluded that ride-hailing decreased bus and tram ridership in urban areas but increased ridership on suburban trains. In addition to travel modes, ride-hailing poses impacts on traffic externalities. For example, Henao and Marshall (2019a) report that ride-hailing lead to a total VMT increase of about 83 percent. In contrast, Dills and Mulholland (2018) report that the introduction of ride-hailing reduced traffic fatalities by 17 to 40 percent. Ride-hailing also can decrease parking demand near airports, bars, and restaurants (Henao and Marshall, 2019b; Wadud, 2020).

This Study in the Context of Prior Studies

Since publicly available data is not readily available from major ride-hailing companies, limited research has been conducted to date on the travel behavior of ride-hailing users. Most prior studies have been conducted using data collected either at the regional or local-level via intercept surveys, paper-based or online surveys, or GPS traffic data (e.g., Clewlow and Mishra, 2017; Hall *et al*., 2018; Henao and Marshall, 2019a, 2019b; Rayle *et al*., 2016; Alemi *et al*., 2018a, 2018b; Brown, 2109; Lavieri and Bhat, 2019). A limited number of studies have utilized household-level travel survey data. For instance, Young and Farber (2019) used household travel survey data from Ontario, Canada and Dias *et al*. (2017) used travel survey data from the Puget Sound Regional Council. Recently, the 2017 National Household Travel Survey (NHTS) conducted in the US provided a unique opportunity to explore the travel behavior of ride-hailing users. A few studies have already examined ride-hailing behavior using this data (e.g., Sikder, 2019; Grahn *et al*., 2019; Conway *et al*., 2018). Most prior studies of travel behavior of ride-hailing users have focused on user characteristics, identifying factors that affect adoption and frequency of use and exploring its impact on other travel modes (e.g., taxi, transit, walk) as well as on traffic externalities (e.g., VMT, parking, congestion).

This current research, on the other hand, analyzes the travel behavior of ride-hailing users from an activity-based approach that considers daily *patterns*, the complete sequence of activities and trips, or component *tours* made by ride-hailing users over a full day as the basic unit of analysis. The intent is to capture the interrelationships of ride-hailing trips with other trips within a day's overall activity. To the best of our knowledge, this study is the first to analyze tours and patterns of ride-hailing users in an integrated manner in consideration of both ride-hailing user demographics and trip characteristics by using national-level household travel survey data. This study's findings will provide first-hand information in the understanding of the complex travel behavior of ride-hailing users.

Data and Sample

This study analyzes data from the 2017 National Household Travel Survey (NHTS), a source of information about travel by US residents in all 50 states and the District of Columbia. This serial cross-sectional survey was sponsored by Federal Highway Administration and includes data on trips made by all modes of travel (private vehicle, public transportation, pedestrian, biking, etc.) and for all purposes (travel to work, school, recreation, personal/family trips, etc.). The dataset contains the following four data tables:

- Households (socio-economic and location characteristics of surveyed households)
- Persons (demographic characteristics of all individuals living in those households)
- Trips (attributes over 24-hours by all household members aged 5 and up)
- Vehicles (used by the responding households)

The dataset contains 264,234 persons from 129,696 households who took a total of 923,572 trips. For our analysis, we identified *ride-hailing users* as those individuals who make at least one trip on the survey day by using ride-hailing. Since ride-hailing was identified in NHTS as using a taxi, limo, or Uber/Lyft, services provided by Transportation Network Companies cannot be separated from conventional taxi services. Therefore, in this study, *ride-hailing* denotes a service of hiring a vehicle and driver by customers for transportation to a desired activity location, accessed either by hailing a traditional taxi from the street or via telephone, or by virtually hailing a service via smart phone apps (for example, Uber or Lyft). The total sample was 1,677 individuals making 2,813 ride-hailing trips. After our initial analyses, an approximation is applied using a 30-day recall variable included in NHTS that may allow taxi trips to be separated from ride-hailing trips.

Demographics of Ride-hailing Users

Figure 1 depicts the socio-demographic characteristics of ride-hailing users. The majority of users belong to households of high income (47 percent), two members (44 percent), and more than one vehicle (50 percent). Also, a greater portion of users are Caucasians (75 percent), millennials (39 percent), employed, and well-educated (62 percent have at least a bachelor's degree). These observations are consistent with prior studies (Rayle *et al*., 2016; Young and Farber, 2019; Grahn *et al*., 2019; Conway *et al*., 2018; Lavieri and Bhat, 2019; Sikder, 2019).

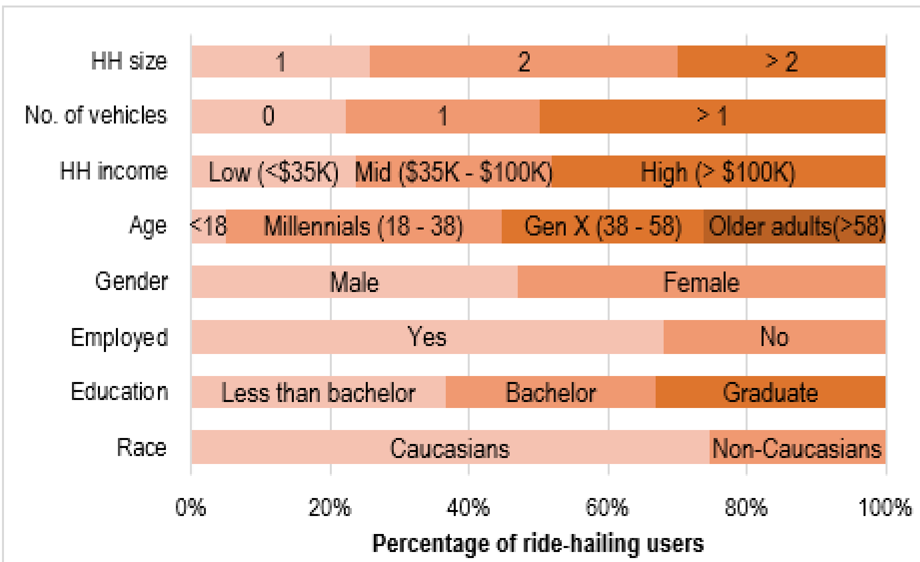


Figure 1: Socio-demographic characteristics of ride-hailing users (N = 1,677)

Analysis of Ride-hailing Trips

We categorize activity purpose for which ride-hailing trips are made into five groups: (1) work (work- and work-related trips); (2) maintenance (school/daycare/religious activity, medical/dental services, buying goods (groceries, clothes, appliances, gas), buying services (dry cleaners, banking, service a car, pet care), other general errands (post office, library), and drop off/pick up someone); (3) discretionary (buying meals (go out for a meal, snack, carry-out), recreational activities (visit parks, movies, bars, museums), and visiting friends or relatives) (4) change of mode (a transfer between modes, such as using Uber/Lyft to catch a flight); and (5) return home. A considerable fraction of ride-hailing trips were reported to access discretionary activity locations (24 percent), whereas 9 percent of trips were used for change of mode. The use of ride-hailing for returning home was reported as quite high (about 37 percent). Returning home is indeed a very common use of ride-hailing (Young and Farber, 2019).

Table 1: Ride-hailing trips per day by ride-hailing users

No. of ride-hailing trips	Total % of travelers	Three dominant trip purposes	% of travelers
1	51.8	Return home	**39.9**
		Change of mode	18.1
		Discretionary	16.3
2	36.7	Return home and Discretionary	**35.3**
		Return home and maintenance	23.4
		Return home and work	6.2
> 2	11.5	Return home and two discretionary activities	**11.9**
		Return home and two maintenance activities	10.9
		Three discretionary activities	4.7
	100		

Table 1 shows the daily frequency of ride-hailing trips. Over half of ride-hailing users (51.8 percent) made only one ride-hailing trip, 36.7 percent made two ride-hailing trips, and the remaining 11.5 percent made more than two trips per day. In all cases, returning home is the dominant activity purpose, followed by discretionary activities. Change of mode is also a common trip purpose for ride-hailing, especially when travelers make only one ride-hailing trip.

Figure 2 and Figure 3 show the distribution of travel times (in minutes) and travel party size for various activities for ride-hailing trips respectively. Since an estimated travel time from

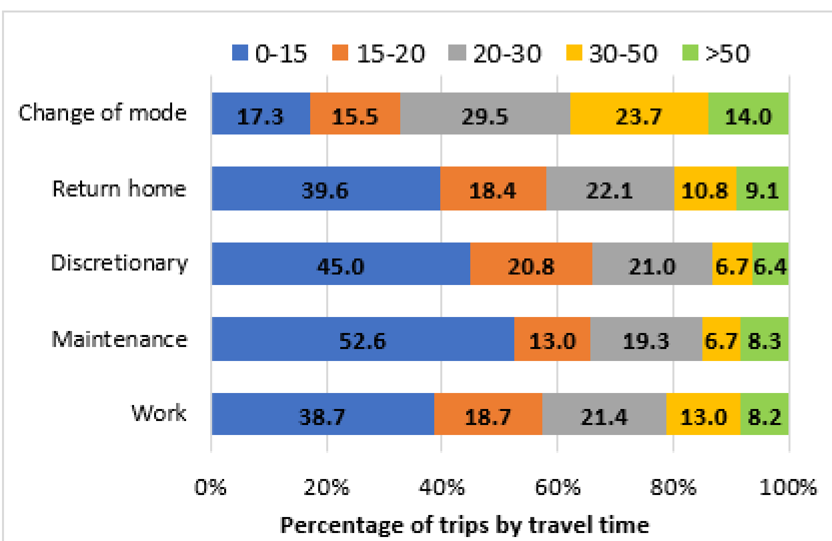


Figure 2: Distribution of travel time by activity type

mapping services or ride-hailing apps infers a better understanding of the spatial distance between two locations than the actual distance, we here examine the distribution of travel time for various activities rather than travel distance. Maintenance trips are typically shorter than other trip purposes, while change of mode trips are in general longer. More specifically, a higher fraction of maintenance trips (53 percent) is less than 15 minutes, whereas the same fraction of change of mode trips (53 percent) reflect travel times between 20 to 50 minutes (Figure 2).

Regarding travel party size, ride-hailing users mostly travel alone (cf. Figure 3) for out-of-home activities (over 50 percent for all activities). In particular, about 91 percent of ride-hailing trips for *work* are unaccompanied trips whereas trips for other purposes tend to be shared with other persons (the fraction of trips with two travelers is 34 percent for *discretionary* and 36 percent for *change of mode*). Lavieri and Bhat (2019) reported similar findings for work trips.

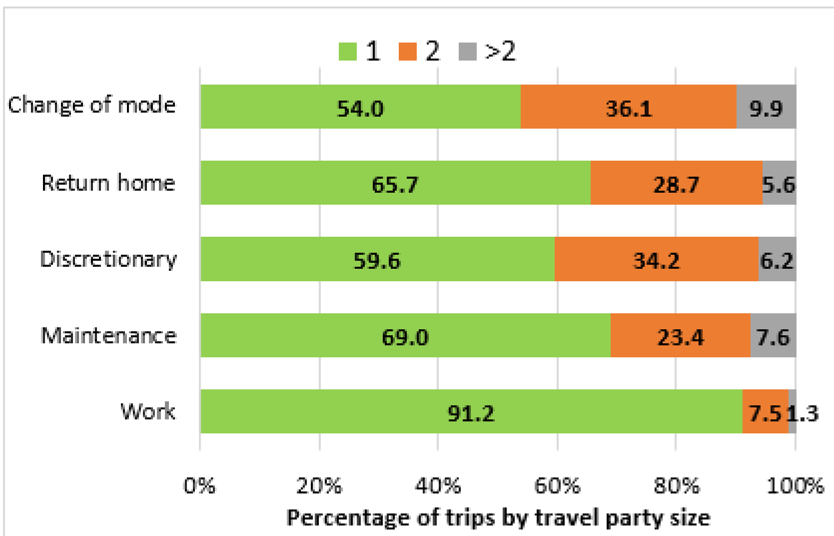


Figure 3: Distribution of travel party size by activity type

Next, we consider how the demand for ride-hailing trips varies over time-of-day. Figure 4 shows that for all conventionally defined time-periods, the majority of ride-hailing trips (about one-third) occur during evening period (7 pm-6 am) (Young and Farber, 2019; Komanduri *et al.*, 2018), with only 10 percent of ride-hailing trips being made during the AM peak period (6 am-9 am). The demand for ride-hailing also varies between weekdays and weekends. The share of trips during weekdays is higher than weekends in most time-periods (except evening when the trend is reversed). Figure 2 also shows that the majority of weekend ride-hailing trips are made during the evening period.

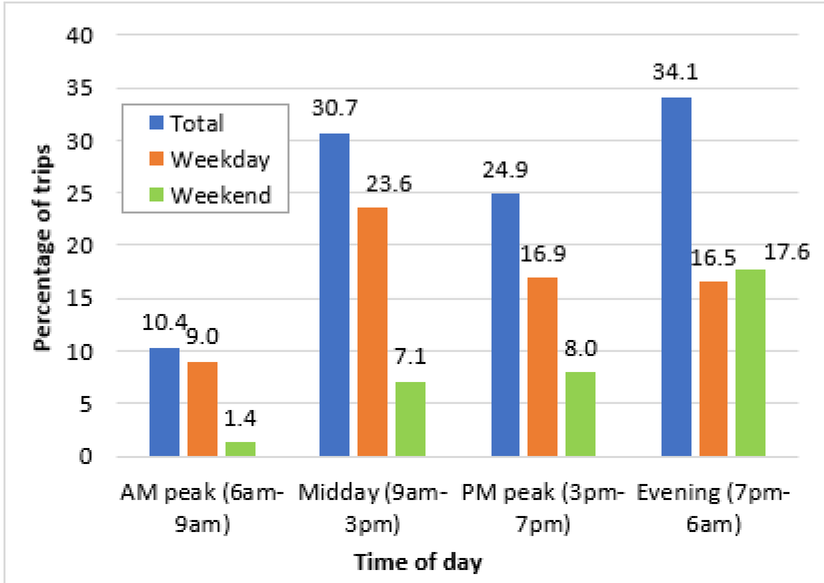
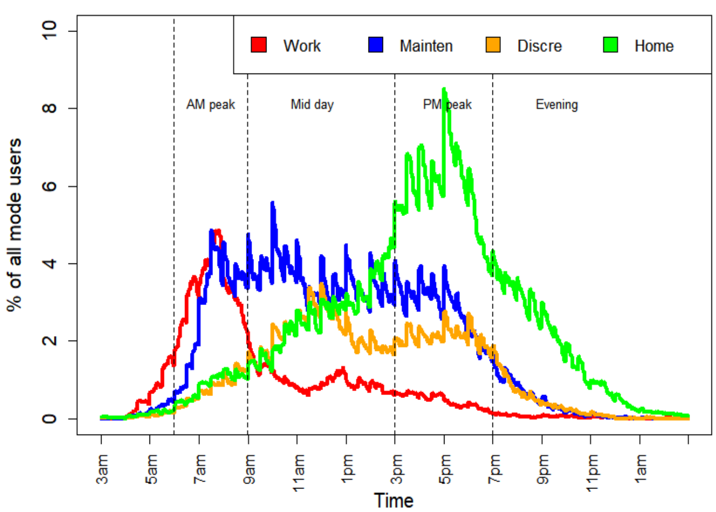
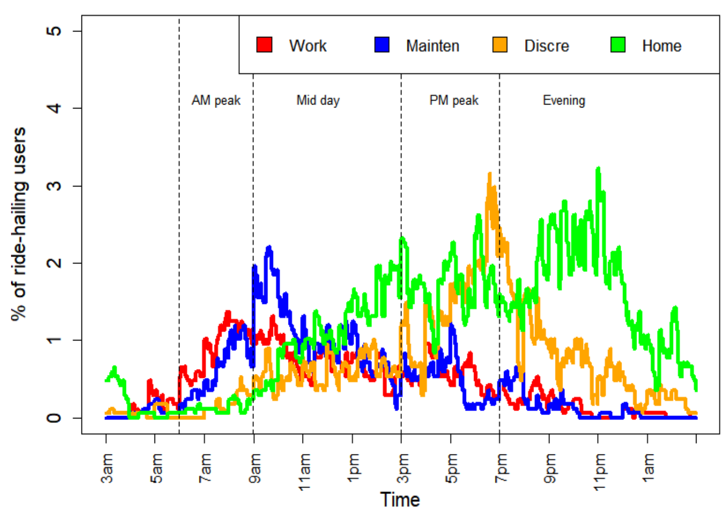


Figure 4: Temporal distribution of ride-hailing trips

The fraction of people traveling for different activity purposes (work, maintenance, discretionary, and return home) can be displayed in a *time in motion plot* as shown in Figure 5.



(a) All travelers by all modes



(b) Ride-hailing users by ride-hail (N = 1,677)

Figure 5: Time in motion of travelers by activity purposes

The figure compares travelers making trips by (a) *all modes* versus (b) *ride-hailing only*. Note that the *range* of the vertical axis of these two figures is different. It is observed that while travelers generally return home during the PM peak period (see Figure 5(a)), they tend to return home later in the evening when using ride-hailing. Regarding discretionary trips, we observe that two peaks are occurring during the midday and PM peak periods. When travelers use ride-hailing for discretionary purposes they make a higher portion of those trips during the PM peak period.

Analysis of Ride-hailing Tours

We turn our attention to analyzing the travel behavior of ride-hailing users that extends the single trip-based analysis presented earlier. This part of the analysis is explicitly *complex* in that it involves analyzing trips as portions of *tours* and *patterns*. A *tour* is defined as a sequence of travel and activities that starts and ends at the same location, whereas *pattern* suggests a 24-hour depiction of activities and trips, comprising one or more tours. All tours considered in this study are home-based tours: starting and ending at home. A simple tour starts and ends at home and includes a single non-home activity. If the activity performed is work, then it is a *simple work* tour; for any other activity type, it is a *simple non-work* tour. A tour containing more than one non-home activity location is defined as a *complex* tour. If all non-home activities are work, then the tour is a *complex work* tour; if all the non-home activities are non-work, then the tour is a *complex non-work* tour. Complex tours that combine work and non-work activities on the same tour are deemed *work-non-work mixed* tours (Rafiq and McNally, 2020).

We generate home-based ride-hailing tours by linking person trip sequences that start and end at home and contain at least one trip by ride-hailing. The result was a total of 1,198 home-based tours. Among all ride-hailing tours, 45 percent of tours have exactly one ride-hailing trip and another 45 percent of tours have two ride-hailing trips. To analyze *tours* we identified a small number of dominant tour types and then examined their activity-travel characteristics as well as the associated socio-demographics. In contrast, in our analysis of full *patterns,* we identified groups of ride-hailing users based on their socio-demographic and activity-travel characteristics and then examined each group's activity patterns.

In *tour* analysis, we defined tour types by three activities: work, non-work, and home. However, 'change of mode' was not considered an activity purpose itself since its inclusion as a separate non-work activity could artificially increase tour complexity (Ho and Mulley, 2013). In the case of *pattern* analysis, however, 'change of mode' is included as a trip purpose since the focus of this analysis was to classify travelers by their activity over a travel day. From this perspective, change of mode is defined as the connection of access or egress modes to a major trip which for ride-hailing users can be an important option for access/egress at both ends of trips that are often associated with incomplete tours (such as to an airport). Both of these approaches are legitimate and complementary, but serve different research purposes. We analyze tours in this section and patterns in the next section.

Extracting Tours from Survey Data

We constructed tours in the form of a *sequence of activities*. To do so, we extract trips for each person from the trip data table and code them as W (work), N (non-work), or H (home) based on the trip's "to" purpose (for the first trip of the tour we also record the trip's "from" purpose. The trips are ordered by start times. Consecutive trips are separated by a time gap assumed equal to the duration of the activity performed. This represents each tour as a sequence of trips denoted by a string of three symbols (H, W, N), deemed a *tour string*. An example of a tour string is HNNWNNH, which indicates that the individual left home and performed two non-work activities before work and then two more non-work activities before returning home. In addition to the sequence of activities captured in the tour strings, the activity type of each non-work activity (maintenance, discretionary, etc.), the time spent at each activity, the mode of transportation, and the duration of each trip are also recorded by tour.

Dominant Categories of Tours

After constructing all tours, we identify the five most dominant strings, which are: HNH, HNNH, HNNNH, HWH, and HWNH (their distribution is shown in Figure 6). These strings represent about 76 percent of the total tours while the remaining 24 percent of tours demonstrate a total of 67 diverse and more complicated tour strings. Based on our definition of tours, these five tour strings can be placed under four broad tour categories: simple non-work, complex non-work, simple work, and work-non-work mixed (cf. Figure 6). Note that HNNH and HNNNH belong to the same category 2 (simple non-work tours) so they are marked as 2a and 2b respectively. We next identify the characteristics of the individuals who made these tours and provide summary statistics of their socio-demographic and travel characteristics.

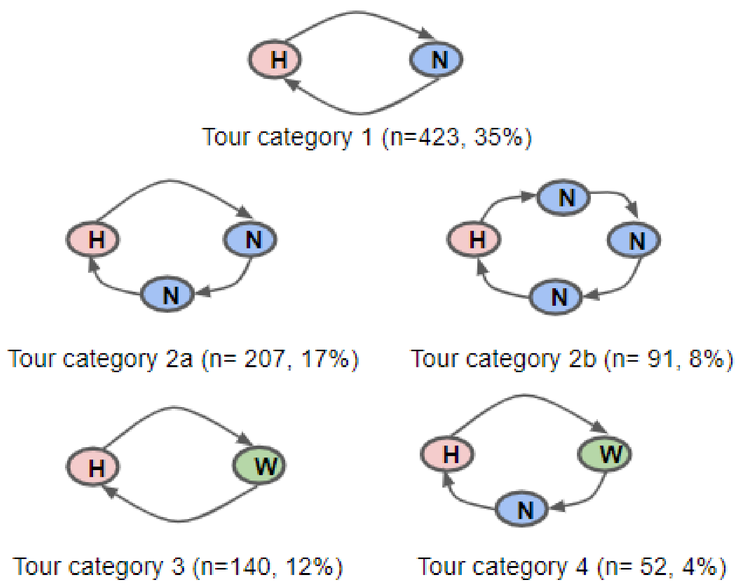


Figure 6: Dominant categories of ride-hailing tours: (1) simple non-work tour, (2a, 2b) complex non-work tour, (3) simple work tour, and (4) work-non-work mixed tour

Socio-demographic Characteristics of Users making Tours

The distribution of socio-demographic characteristics of ride-hailing users by tour category is shown in Figure 7.

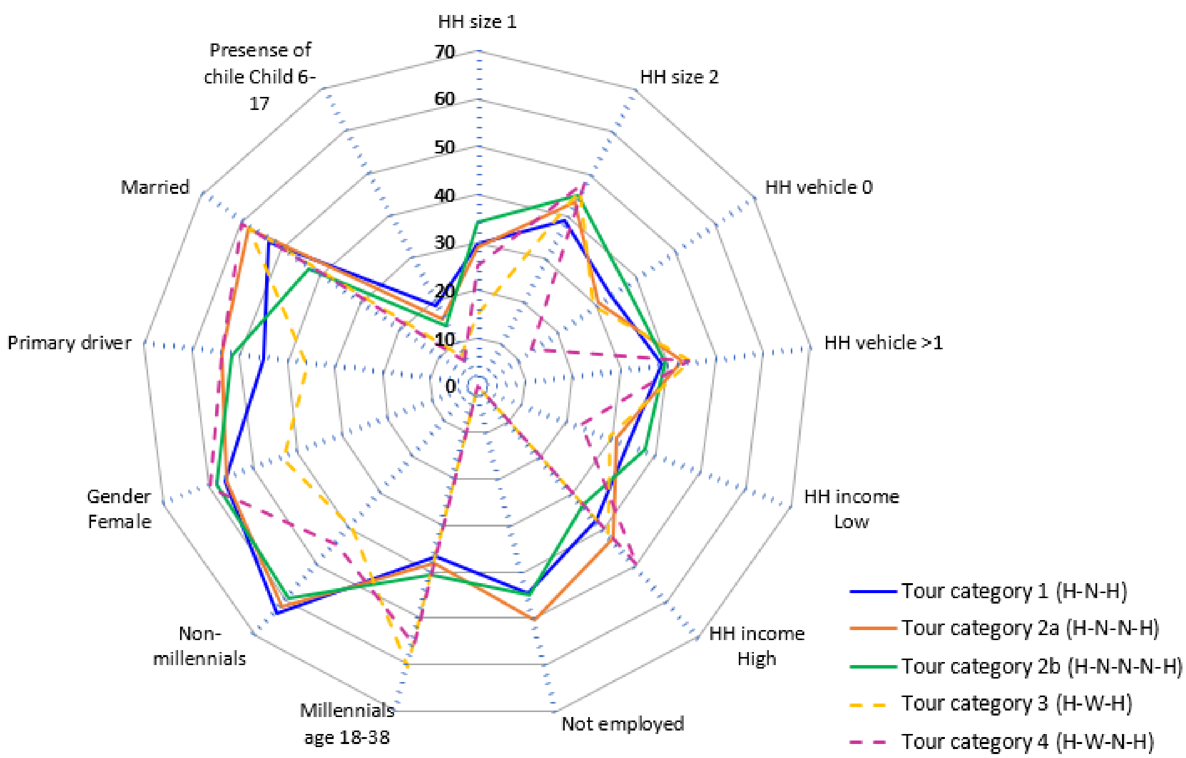


Figure 7: Socio-demographic characteristics of travelers for identified tour categories

A difference between the characteristics of people who use ride-hailing for work tours and those who use it for non-work tours is observed. The dominant socio-demographic characteristics of non-work tour makers (categories 1 and 2, shown as solid lines in Figure 7) are non-millennials (age > 38 years) and married females. They typically belong to households that have at least two members, have more than one vehicle, and have higher incomes. In contrast, travelers who make work tours by ride-hailing are typically millennials (age 18-38) and married with high income (categories 3 and 4, shown as dashed lines in Figure 7). Simple work tour makers tend to be male whereas work-non-work mixed tour makers tend to be females. Most of the simple work tour makers (65 percent) are not the primary driver in their households.

Activity-travel Characteristics within Tours

Table 2 displays the mode for each trip of a tour as well as the purposes for non-work activities within the tour for each identified tour category. For non-work activities, it shows how non-work purposes vary across the different tour categories. The table reveals ride-hailing is predominantly used in both legs of most of the *simple* tours (about 80 percent of non-work and 75 percent of work tours). In *complex* tours, ride-hailing is mostly used for the first and last trips within a tour. However, for intermediate trips, the walk mode is common for traveling from one non-work activity location to another and private vehicles are used to connect the workplace with non-work activity locations.

Table 2: Percentage of tours for trip modes and non-work activities

Trip Mode	Simple non-work (%)		Complex non-work (%)							Simple work (%)		Complex work (%)		
	Tour category 1		Tour category 2a			Tour category 2b				Tour category 3		Tour category 4		
	H-N-H		H-N-N-H			H-N-N-N-H				H-W-H		H-W-N-H		
	n = 423		n = 207			n = 91				n = 140		n = 52		
	H-N	N-H	H-N	N-N	N-H	H-N	N-N	N-N	N-H	H-W	W-H	H-W	W-N	N-H
Public Transit	7.1	2.4	13.5	6.3	3.9	20.9	5.5	6.6	5.5	12.9	5.7	25	17.3	1.9
Walk	5	5.4	14	**31.4**	13.5	20.9	**45.1**	**42.9**	14.3	2.9	3.6	3.8	15.4	7.7
Private vehicles	10.2	9.2	19.3	14	11.6	17.6	15.4	14.3	19.8	16.4	16.4	21.2	**28.8**	**42.3**
Ride-hailing	**79.4**	**83.7**	**57.5**	**51.7**	**75.8**	**41.8**	**31.9**	**37.4**	**62.6**	**71.4**	**77.9**	**53.8**	**46.2**	**51.9**
Other	4	4.7	4.8	4.8	3.4	8.8	3.3	1.1	2.2	12.1	11.4	3.8	0	3.8
Nonwork activity purpose														
School/Daycare/Religious	10.6		9.2	1.4		6.6	5.5	4.4					1.9	
Medical/Dental	16.1		11.6	4.3		6.6	1.1	2.2					3.8	
Shopping/Errands	18.9		16.4	25.6		28.6	29.7	27.5					**32.7**	
Social/Recreational	**33.3**		**33.3**	**39.1**		**30.8**	20.9	**44**					**30.8**	
Pick up/Drop off	2.1		3.9	1		8.8	2.2	2.2					1.9	
Buying meals	17		22.2	26.6		15.4	**35.2**	16.5					25	
Others	1.9		3.4	1.9		3.3	5.5	3.3					3.8	

Table 2 shows that discretionary activities (e.g., socializing with friends or relatives, recreational activities, buying meals) are the most frequent activities performed in non-work tours. However, when non-work activity is performed within a work tour, both maintenance (e.g., buying goods, services, or other general errands) and discretionary activities are reported in a larger fraction of tours.

Analysis of Activity Patterns of Ride-hailing Users

We now extend our activity analysis to an entire day's agenda, represented as a full sequence of activities (in-home and out home) and trips (i.e., activity patterns), to better analyze the complex travel behavior of ride-hailing users. We postulate that, despite the complexity of individual activity-travel patterns, the overall user population of ride-hailing users falls into a small number of heterogeneous sub-groups and that each sub-group will have a representative activity-travel pattern defined in terms of ride-hailing usage. The identification of these distinct groups is accomplished by using Latent Class Analysis (LCA).

LCA offers several advantages over the traditional K-means clustering techniques. For example, the LCA method provides goodness-of-fit statistics, such as the Akaike Information Criterion and Bayesian Information Criterion (discussed later in detail) that are useful in determining the number of classes. The standardization utilized in K-means clustering is not necessary for LCA and while K-means clustering is usually limited to interval scale quantitative variables, the extended LCA model can be estimated with variables of different scale types (e.g., continuous, count, and/or any combination). While K-means clustering can be paired with discriminant analysis to describe differences between clusters based on exogenous variables, LCA allows for simultaneous estimation of the class measurement model and prediction model by using a single Maximum Likelihood (ML) estimation algorithm (Magidson and Vermunt, 2002).

LCA has been used in a range of travel behavior research including the classification of immigrants based on their travel behavior (Beckman and Goulias, 2008), of individuals based on their residential location preferences (Liao *et al*., 2015), of millennials based on their mode usage (Molin *et al*., 2016; Ralph, 2017; Lee *et al*., 2019), individuals based on mobility patterns (Schneider et al., 2020), and attitudes towards mobility as a service (MaaS) (Alonso-González *et al*., 2020). Alemi *et al*. (2018b) classified ride-hailing users of particular age groups (millennials:

aged 18-34 and the preceding Generation X: aged 35-50) using the LCA technique to capture the heterogeneity in *individual lifestyles* across classes based on socio-economic and demographic attributes. They found three distinct groups of users: (1) highly educated and independent millennials who frequently use ride-hailing; (2) affluent individuals and dependent millennials or older members of Generation X, and (3) less affluent and lower educated individuals who rarely use ride-hailing. In contrast, we apply LCA to probabilistically assign an individual ride-hailing user to a set of classes where each class represents homogeneity of activity-travel patterns based on *ride-hailing usages* (in the timing of trips and their purposes) within classes and heterogeneity of patterns across classes.

Latent Class Analysis for Clustering Ride-hailing Users

LCA is a mixture model that hypothesizes that there is an underlying *unobserved* categorical variable that divides a population into mutually exclusive and exhaustive latent classes (Lanza and Rhoades, 2013). The following formal construct for the model is based on Linzer and Lewis (2011). Suppose each member of the population (indexed by i) contains J indicator variables (indexed by j), each of which can take a value from a set of K_j possible outcomes (all indicators variables are categorical). Let $Y_{ijk} = 1$ if respondent i takes the k-th outcome for its j-th categorical variable, and $Y_{ijk} = 0$ otherwise (Y_i denotes the corresponding vector). For a given number of classes R, LCA attempts to simultaneously compute: (a) the probability that a respondent falls into a certain class, denoted by p_r, for $r = 1, 2,\ldots R$, and (b) the class-conditional probability, denoted by π_{jrk}, that an observation in class r produces the k-th outcome on the j-th variable. The likelihood of observing a certain respondent is therefore given by:

$$f(Y_i|\pi,p) = \sum_{r=1}^{R} p_r \prod_{j=1}^{J} \prod_{k=1}^{K_j} (\pi_{jrk})^{Y_{ijk}}$$

The parameters that the LCA model estimates are p_r and π_{jrk}, which are found via maximum log-likelihood estimation (MLE). In a more generalized LCA model, the class probabilities, p_r's, are regressed (by using a logit link function) from a set of observed variables, called covariates. Hence, the estimation technique finds a set of per class coefficient vectors, β_r (instead of p_r), along with π_{jrk} (refer to Linzer and Lewis (2011) for details).

LCA Model Indicator Variables and Covariates

As stated, LCA requires a set of indicator variables that estimate the class *measurement* model and a set of covariates that estimate the prediction or *structural* model (predict the probability of an individual belonging to a latent class). The indicator variables we chose include the timing and purposes of ride-hailing trips, vehicle ownership and employment status of the traveler, frequency of ride-hailing app usage (in last month), and the day of travel (weekend or weekday). The covariates serve to understand the class membership profiles and consist of various socio-demographic characteristics, such as gender, age, household income and household size, and population density (persons per sq. mile) in the census block group at the home location. Figure 8 shows the conceptual latent class model used in this study.

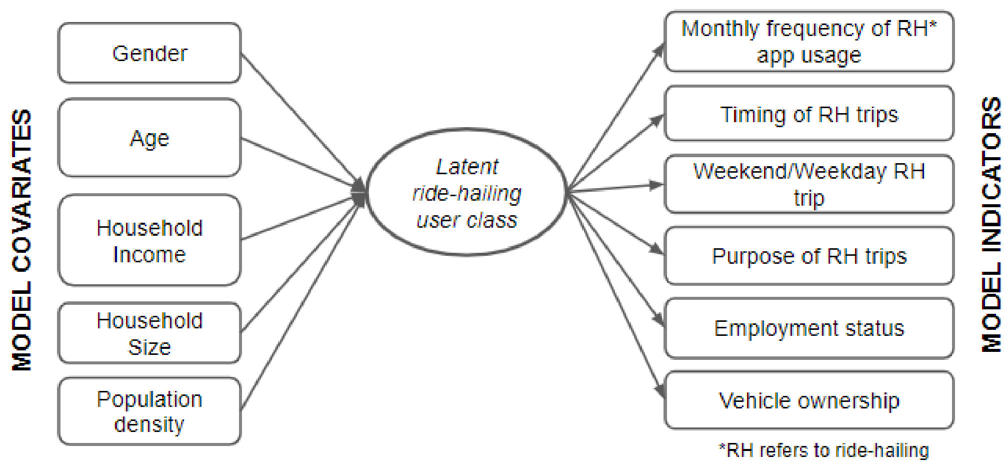


Figure 8: Latent class cluster model

LCA Model Estimation and Fit Statistics

We used poLCA (Polytomous variable Latent Class Analysis) in the statistical software package R to run LCA. R provides model parameters and goodness of fit measures. The most common and widely used model fit measures are AIC (Akaike Information Criterion) (Akaike, 1973) and BIC (Bayesian Information Criterion) (Schwartz, 1978) (Linzer and Lewis, 2011; Oberski, 2016). These two measures are parsimony measures where the criteria is to establish a balance between over- and under-fitting a model to the data by penalizing log-likelihood by a function of the estimated parameters. The functional forms of these two measures are: $AIC = -2\Lambda + 2\Phi$ and $BIC = -2\Lambda + \Phi \ln N$, where Λ, Φ, N denotes the maximum likelihood of the model, the total number of estimated parameters, and the total sample size respectively (Linzer and Lewis, 2011). AIC and/or BIC are used to compare the relative fit of models with differing numbers of latent classes, where a lower value suggests a more optimal balance between model fit and parsimony (Lanza and Rhoades, 2013). Pearson's χ^2 fit and G^2 likelihood ratio chi-square statistics for the observed versus predicted cell counts are other methods of determining model fit with data for a particular model (Goodman, 1970). Preferred models are those that minimize the χ^2 and G^2 statistics without estimating an excessive number of parameters. A detailed definition and functional forms of these two measures are available in Linzer and Lewis (2011).

We varied class sizes from 2 to 6 and observed the associated fit measures. We also empirically assessed the extent that the resulting classes could be described and interpreted. Table 3 shows the fit statistics and the class probability values for models with two through six latent classes. Although the five-class model has slightly lower AIC and BIC values than the four-class model, we accepted the four-class model for our study because it can be easily identified, has greater parsimony, has a minimum class share of 15% users (at least 250 users in a class for better analysis and illustrations), and can be logically interpreted in terms of ride-hailing usage.

Table 3: Model fit statistics and class probability values for 2 to 6 class models

No. of classes	No. of parameters	G^2	χ^2	AIC	BIC	Class probability					
2	38	5865.5	20071.2	25302.3	25508.4	0.21	0.79				
3	62	4881.1	16229.8	24235.7	24572.0	0.21	0.39	0.40			
4	86	4431.9	16997.3	23812.1	24278.7	0.27	0.36	0.17	0.20		
5	110	4042.6	18673.8	23427.4	24024.1	0.17	0.20	0.21	0.11	0.31	
6	134	4011.3	17548.3	23317.9	24044.8	0.20	0.13	0.21	0.11	0.25	0.10

Note: G^2, χ^2, AIC, BIC denote likelihood ratio chi-square statistics, chi-square value, Akaike Information Criterion, and Bayesian Information Criterion respectively.

Four latent classes, each corresponding to an underlying group of individuals who are characterized by a particular pattern of social-demographics features and ride-hailing usage, are summarized in Table 4. The class-conditional membership probabilities for the indicator variables and covariates are shown in Table 5 and the effects of covariates on class membership are presented in Table 6. This is followed by a description of (a) who belongs to which class and their ride-hailing characteristics, (b) class membership profiles (which factors influenced an individual belonging to a certain class), and (c) detailed activity-travel patterns of the four classes of ride-hailing users.

Table 4: Summary of ride-hailing users by four latent classes

Class	Ride-hailing user class	Class size	Class share	Class properties
1	*Work trip users*	292	17.0%	Young, mostly employed who use ride-hailing for work purpose and they are frequent ride-hailing users.
2	*Midday maintenance trip users*	332	19.8%	Older adults, living alone, a low-income group who use ride-hailing midday for maintenance and return home purpose, and infrequent ride-hailing users.
3	*Evening discretionary trip users*	611	36.1%	Young, employed, live with spouse/partner, use ride-hailing solely at night for discretionary and return home purposes.
4	*Mode change trip users*	442	27.1%	Young, affluent who use ride-hailing during midday and PM-peak periods as access and egress modes

The Four Identified Ride-hailing User Classes

The first class (and the smallest with 17 percent) is the *work trip users* who, as the name suggests, use ride-hailing trips for the work commute (100 percent) and make ride-hailing trips on weekdays (85.7 percent). This group comprises frequent ride-hailing users with 43.5 percent using ride-hailing apps more than 5 times in the last 30 days. The group constitutes millennial (aged between 18 to 38) males who are mostly employed (98.3 percent), have a high income (58 percent with annual income higher than $100K), and have at least one car in their household (85.1 percent). In addition to going to work, a considerable fraction of them (30.8 percent) uses ride-hailing to return home but only infrequently to perform other activity types. Their ride-hailing trips uniformly span the day, which can be attributed to their using ride-hailing to go to work, perhaps during AM peak (6 am – 9 am) or Midday (9 am – 3 pm), and then again to return home in the late afternoon and the evening. Several studies (Tirachini, 2019; Rayle *et al*. 2016; Henao, 2017; Tirachini and del Río, 2019; de Souza Silva *et al*., 2018) reported work or commuting as the second most reported trip purpose of ride-hailing in different countries.

The second ride-hailing user group is deemed *midday maintenance trip users* (19.8 percent of total users) who make ride-hailing trips during mid-day and mostly make ride-hailing trips for maintenance activities and for returning home (69.2 and 80.4 percent, respectively). In terms of sociodemographic characteristics, these individuals are typically single-living (43.5 percent), older women who are not employed, and have low income (75.9 percent earn below $35K per year). Importantly, this group of people does not have a personal vehicle available

(66.2 percent), in contrast to other classes with over 80 percent of members having at least one vehicle. This class uses ride-hailing occasionally. The majority of this class might be the traditional taxi users since 78 percent of them did not use a ride-hailing app during the last 30 days (this is considered in the discussion section). Leistner and Steiner (2017) found a similar class of potential ride-hailing users among seniors in their study.

The third class is the largest ride-hailing user group identified (36.1 percent of 1677 users) and is deemed *evening discretionary trip users*. Members of this class use ride-hailing mostly for discretionary purposes such as socialization and recreation (59 percent have at least one discretionary trip) and in the evening (83.5 percent between 7 pm and 6 am)). This finding is in line with prior studies (Rayle *et al*., 2016; Young and Farber, 2019; Henao, 2017; Tirachini and del Río, 2019; de Souza Silva *et al*., 2018) stating that social/leisure activities, specifically going to bars, parties, and restaurants are the most common activity purpose for ride-hailing usage. Members of this class are mostly millennials, equal split between men and women, mostly employed (80 percent), higher-income group (51.5 percent earn more than $100K per year), and from car-owning households (82.9 percent have at least one car) with two or more members. Unlike other classes, this class makes more ride-hailing trips on weekends than weekdays (59.4 percent versus 40.6 percent). Class members use ride-hailing for evening discretionary trips despite owning household vehicles, perhaps to avoid parking or legal constraints as reported in some studies (Clewlow and Mishra, 2017; Rayle *et al*., 2016).

Finally, members of the last class (class 4) use ride-hailing for a very specific purpose, that is, to change of mode of transport. This change of mode corresponds to users going to a train/bus station or airport where they access another transport mode. This class is, therefore, called *mode change trip users* and constitutes a fairly large fraction of ride-hailing users (27.1 percent). While only a few individuals (5 percent or less) report using ride-hailing to change modes in other classes, 50 percent in this class made ride-hailing trips to do so, mostly during midday on weekdays. This group is fairly uniform over gender and age groups. They belong to higher-income households having at least one vehicle with nearly 85 percent having two or more household members, and they live in medium density areas.

Table 5: Class-conditional membership probabilities by each class

	Work trip users (%)	Midday maintenance trip users (%)	Evening discretionary trip users (%)	Mode change trip users (%)
Class size[a]	292	332	611	442
Class share	**17.0**	**19.8**	**36.1**	**27.1**
Indicator variables				
Purpose of ride-hailing trip				
Work	**100.0**	6.4	2.4	0.7
Maintenance	3.5	**69.2**	8.1	15.0
Discretionary	10.6	12.0	**59.0**	28.4
Return home	30.8	**80.4**	**81.5**	29.5
Change of mode	5.8	0.0	0.9	**49.7**
Timing of the ride-hailing trip				
AM peak (6am - 9am)	33.2	24.0	0.2	20.4
Midday (9am - 3pm)	**48.1**	**71.5**	13.5	**46.1**
PM peak (3pm - 7pm)	40.5	26.9	41.0	35.8
Evening (7pm - 6am)	35.0	15.9	**83.5**	20.8
Day of travel				
Weekend	14.3	17.5	**59.4**	25.8
Weekday	**85.7**	**82.5**	40.6	**74.2**
Frequency of rideshare app usage (in last 30 days)				
None	30.5	**78.3**	18.7	35.2
1-5 times	25.7	9.6	38.3	**38.6**
more than 5 times	**43.8**	12.1	**43.0**	26.2
Household vehicle ownership				
Own at least one vehicle	**85.1**	33.8	**82.9**	**98.1**
Does not own vehicle	14.9	**66.2**	17.1	1.9
Employment status				
Employed	**98.3**	20.9	**80.2**	**66.4**
Not employed	1.7	**79.1**	19.8	33.6
Covariates				
Gender of the traveler				
Male	**54.6**	34.8	48.9	48.8
Female	45.4	**65.2**	**51.1**	**51.2**
Age of the traveler				
Millennials (18-38 years)	**44.5**	19.6	**55.7**	**29.2**
Generation X (38-58 years)	37.5	28.1	24.6	**29.5**
Older adults (more than 58 years)	15.4	**45.6**	14.6	**32.8**
Yearly household income				
Low income (less than $35K)	16.1	**75.9**	11.0	6.0
Middle income ($35K - $100K)	24.5	16.7	36.4	25.4
High income (more than $100K)	**58.0**	2.6	**51.5**	**67.1**
Household size				
One person	20.8	**43.5**	27.4	13.9
Two persons	**40.1**	30.1	**48.3**	**51.9**
more than two persons	**39.1**	26.4	24.2	34.2
Population density (persons per sq. mile) in census block group				
Low density (0 - 2,000)	25.8	31.0	17.4	32.5
Medium density (2,000 - 10,000)	**49.1**	**48.3**	37.5	**43.9**
High density (more than 10,000)	25.1	20.7	**45.0**	23.6

[a] Class of each sample is determined by modal assignment (so the percentage may not match).

Prediction of Latent Class Membership

Table 6 shows covariate coefficients for three classes relative to the first class (i.e., work trip users). Females are more likely to belong to class 2 (midday maintenance) and class 4 (mode change) than to class 1 (due to negative sign of the associated coefficients). Generation X and older ride-hailing users have higher tendency to belong to midday users (class 2) and lower tendency to be evening users (class 3). Moreover, this group of people is more likely to use ride-hailing for change of mode of transport (class 4). Household income does affect the class membership: people with middle and higher-income belong to class 3 and class 4 whereas lower-income people belong to class 2. The effect of household size is rather limited: persons from single-person households, especially elderly women, tend to belong to class 2, whereas persons from larger households are less likely to belong to class 3. Interestingly, we find an association of location variable with class membership, particularly people living in high-density areas are more likely to belong to class 3.

Table 6: Prediction of latent class membership (N = 1,677)

Covariates	Midday maintenance trip users vs work trip users	Evening discretionary trip users vs work trip users	Mode change trip users vs work trip users
Gender of traveler: Male	-0.460**	-0.163	-0.333*
Age of traveler (baseline: Millennials, 18-38 yrs.)			
Generation X (38-58 years)	0.915***	-0.645***	-0.088
Older adults (more than 58 years)	2.163***	-0.450*	0.875***
Household income (baseline: low income, < $35K)			
Middle income ($35K - $100K)	-2.089***	0.778***	0.790**
High income (>$100K)	-4.751***	0.412*	0.963***
Household size (baseline: single person)			
Two persons	-0.179	-0.008	0.457*
more than two persons	0.331	-0.639***	0.299
Population density (persons per sq. mile) in census block group (baseline: low density, 0-2,000)			
Medium density (2,000 - 10,000)	0.004	0.053	-0.286
High density (more than 10,000)	0.102	0.738***	-0.222

*, **, and *** indicate statistical significance respectively at 10%, 5%, and 1%.

Activity-travel Patterns of Identified User Classes

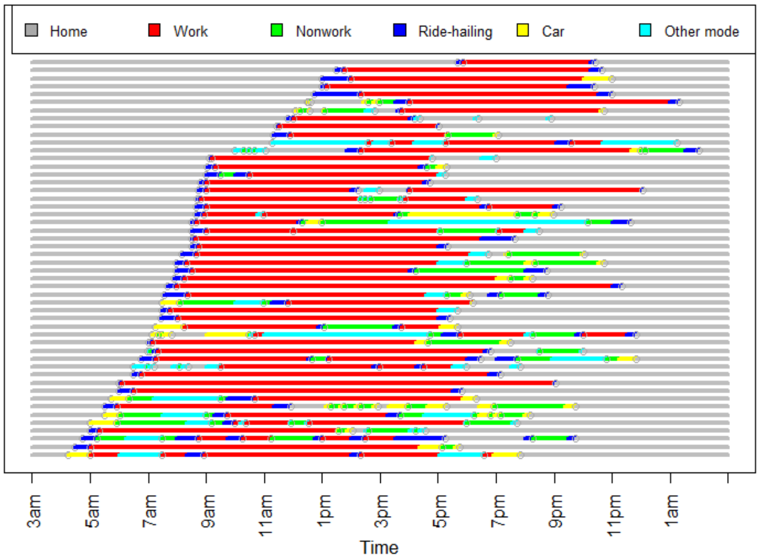
We now analyze activity-travel patterns of the identified four ride-hailing users. A graphical representation is utilized for each class that shows the sequence of *all* activities and travel reported in a travel diary day for a *randomly* selected 50 individuals from a given class. Ideally, we would depict the plots for all individuals in the class but for reasons of space and clarity of display we generated ten random samples of 50 patterns each, each yielding similar results. We report one of those ten results in Figure 9 that shows the plots for each class (the horizontal axis denotes the time of day and the vertical axis denotes a sampled individual with their activities and trips). The sequence of activities and travel is shown as segments based on the activity and travel duration, color-coded based on activity purposes and mode use.

Class 1. Work trip users

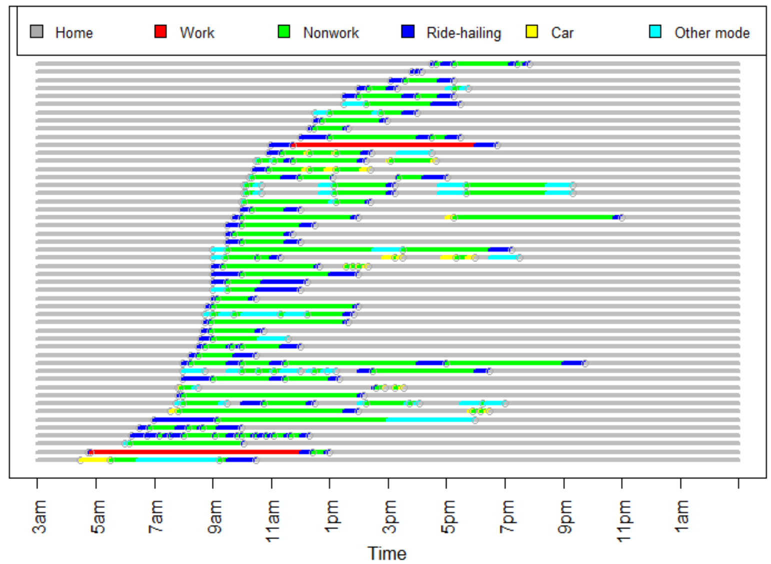
The number of work segments (shown in red in the figure) best illustrates the work focus in this class. The blue segments show ride-hailing use, predominantly preceding the red work segments indicating ride-hailing as a commute mode from home. The presence of a good number of ride-hailing trips made in the late afternoon or evening suggests the use of ride-hailing after hours to return home. The majority of this class uses either private vehicles (42 percent) or ride-hailing (32 percent) as their regular work mode choice. The absence of or lower access to transit services might be one of the reasons for using ride-hailing service as work mode since data shows that only 39 percent of travelers of this class live in a metropolitan statistical area (MSA) with a rail connection. A similar observation is found in Dias *et al*. (2019). It is observed that on the diary day 50 percent of travelers use ride-hailing to work whereas 25 percent use this service to return home and 20 percent use it both ways.

Green segments visible in the figure during the late PM peak or evening period show non-work activity either within the work tour or on separate non-work tours. While a majority of the class (37 percent) make work only tours, a large fraction mix non-work activities within work tours (26 percent) and a smaller fraction make separate non-work tours (15 percent). About 59 percent use ride-hailing as their travel mode while traveling between two non-home locations (e.g., work to work, work to non-work, or non-work to non-work). Interestingly, about 36 percent of this class did not make a complete tour during the day. Analysis reveals that most of these people did not start from their home on the travel day, starting instead from a non-home location with a ride-hailing trip to work.

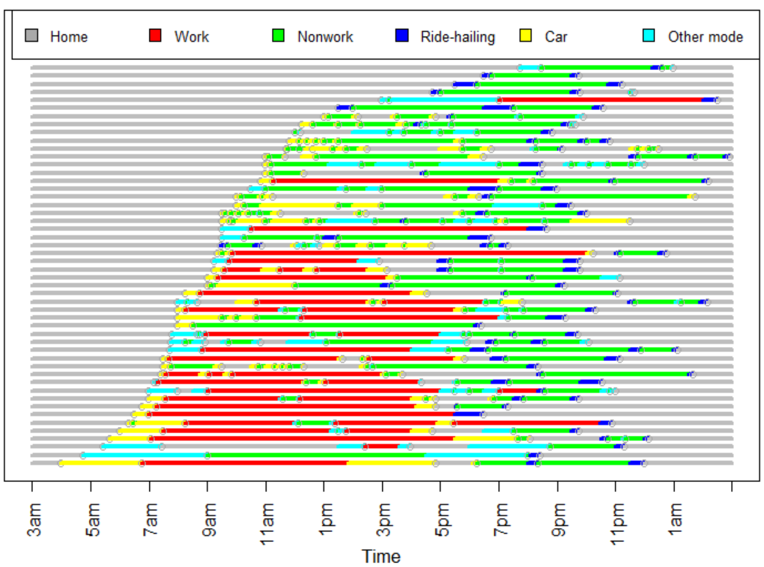
Members of latent class 1 average 4.4 trips per day, with ride-hailing accounting for 50 percent of the trips (with private vehicle use at 21 percent and walk at 14 percent). This class has longer commute times to work than other classes (26 minutes versus 18 minutes for evening users and 13 minutes for mode change trip users).



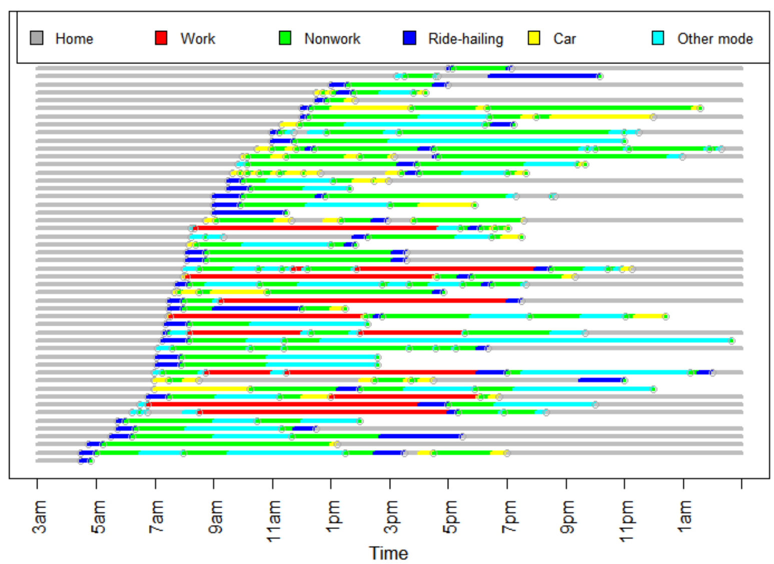
(a) Class 1. Work trip users
(50 random samples out of 292)



(b) Class 2. Midday maintenance trip users
(50 random samples out of 332)



(c) Class 3. Evening discretionary trip users
(50 random samples out of 611)



(d) Class 4. Mode change trip users
(50 random samples out of 442)

Figure 9: Sampled activity-travel patterns by ride-hailing class

Class 2. Midday maintenance trip users

Figure 9(b) shows that class 2 demonstratively performs more non-work activities (green segments) and make most of their ride-hailing trips during midday (blue segments spanning 8 am to 3 pm). Ride-hailing is used to perform non-work activities (blue segments juxtaposed with green segments) and also to return home. Interestingly, these return to home ride-hailing trips occur during midday, unlike evening occurrences in other classes. About 60 percent use ride-hailing to access a non-work location from home, 77 percent use ride-hailing to return home, and 50 percent use ride-hailing for both.

Most members of this class complete non-work tours (53 percent simple and 41 percent complex) for activities such as grocery shopping and medical visits. This class is dominated by low income, older, single living individuals who tend to not own a car. A large fraction of users (63 percent) in this group gave up driving due to medical conditions.

Members of class 2 average 3.9 trips per day, with ride-hailing accounting for the majority the trips (60 percent, a higher share than in other classes). Other shares of travel modes correspond to walk (16 percent) and private vehicles (11 percent). The blue segments representing ride-hailing trips of midday users are longer than for evening users (Figure 9(c)), with class 2 having longer average travel times by ride-hailing (32 minutes compared to 24 minutes for evening users).

Class 3. Evening discretionary trip users

Members of class 3 make their ride-hailing trips in the evening (after 5 pm) illustrated by a high concentration of blue segments on the right side of Figure 9(c). These ride-hailing trips are preceded and followed by non-work activities (green segments), which are predominantly discretionary activities (e.g. visiting recreational centers, restaurants, friends). About two-thirds of this class make at least one non-work tour (42 percent simple and 41 percent complex). Regarding mode usage, 35 percent use ride-hailing to go from home to non-work locations and 32 percent use it to travel between non-work locations. A high percentage of travelers use ride-hailing to return home from a non-work place (74 percent).

Some members work (red segments) during midday but then access discretionary activities from work or via separate non-work tours after hours. While ride-hailing (blue) is associated with non-work (green) evening activities, other modes are associated with work (red) activities. This suggests that this class uses ride-hailing for non-work trips, but use either private vehicles or other modes on their AM-peak work commute (55 and 26 percent report private vehicle and public transit, respectively, as regular the commute mode). Members of class 3 average the greatest average trip rates compared to other user classes (5.6 compared to 4.4, 3.9, 4.8 for class 1, class 2, and class 3, respectively).

Class 4. Mode change trip users

The activity-travel pattern of class 4 is displayed in Figure 9(d) and show distinctly different travel patterns with members making trips using *other* travel modes (cyan segments). This class features long-distance travelers (cyan colors with longer travel times) who do not return home within the same day. It is found that about 40 percent of members do not make any complete home-based tours.

Travel by other modes is preceded by or followed by ride-hailing (blue) which indicates that this class use ride-hailing to access airports, train stations, and other mode change locations or to reach the final destination (typically home) from these transportation hubs.

Discussion

In the 2017 NHTS data, the trip information of conventional taxi users and the app-based Uber/Lyft users are coded under the same category of mode usage. Therefore, in this study, our identified four groups of ride-hailing users represent both the usage of traditional taxi-based ride-hailing and recent app-based ride-hailing (Uber/Lyft) services. To identify potential differences and similarities between these types of services, we tried to separate *taxi-only* users from the app-based users in our sample dataset by using a person-level variable reflecting the count of rideshare app usage in the last 30 days. We assume that individuals who reported zero for this count variable are most likely using taxis on the travel diary day. Hence, we flag them as *taxi-only* users (assuming their behavior continued to be the same as the past 30 days), and the rest (who used at least one rideshare app) are being flagged as *ride-hailing/taxi* users.

The socio-demographic and trip characteristics of our two identified groups of travelers are shown in Table 7. To draw a contrast between these two groups, we conducted *chi-square tests* (at a 5% level of significance) for all sets of variables representing a fraction of users with a

Table 7: Socio-demographic and trip characteristics of two traveler groups

	Taxi-only users (Rideshare app usage = 0 in last 30 days) (%)	Uber/Lyft or taxi users (Rideshare app usage >= 1 in last 30 days) (%)	% Difference
	N = 595	N = 1023	
Household characteristics			
Yearly household income			
Low income (less than $35K)	38.8	14.2	+ 24.6*
Middle income ($35K - $100K)	27.6	27.8	- 0.2
High income (more than $100K)	31.3	56.7	- 25.4*
Household (HH) size			
HH size 1	29.2	25.3	+ 3.9
HH size 2	41.3	48.2	- 6.8*
HH size >2	29.4	26.5	+ 2.9
Zero vehicle households	32.6	15.9	+ 16.7*
Presence of a child in the household			
Presence of child 0 – 5	1.2	1.7	- 0.5
Presence of child 6 – 17	16.1	11.7	+ 4.4*
Personal characteristics			
Age of the traveler			
Millennials (18-38 years)	18.8	53.8	- 34.9*
Generation X (38-58 years)	32.6	28.2	+ 4.5
Older adults (more than 58 years)	45.4	15.9	+ 29.4*
Male	43.7	48.4	- 4.7
Educational qualification			
Less than bachelor degree	54.3	25.4	+ 28.9*
Bachelor degree	18.7	37.3	- 18.7*
Graduate or professional degree	26.6	37.2	- 10.7*
Traveler has driving license	67.6	84.0	- 16.4*
Employed	48.1	79.9	- 31.8*
Residential location information			
Household in an urban area	88.2	97.1	- 8.8*
MSA has rail	28.7	48.8	- 20.0*
Trip characteristics			
Timing of trip			
AM peak (6am – 9am)	18.5	14.9	+ 3.6
Midday (9am – 3pm)	47.7	34.9	+ 12.8*
PM peak (3pm – 7pm)	34.6	37.5	- 2.9
Evening (7pm – 6am)	36.1	50.6	- 14.5*
Weekend	25.7	39.5	- 13.8*
Purpose of trip			
Work	17.8	21.1	- 3.3
Maintenance	31.6	14.8	+ 16.8*
Discretionary	22.5	39.4	- 16.9*
Return home	60.3	56.8	+ 3.5
Mode change	15.6	14.6	+ 1.1

* indicates that the fraction of travelers with a particular characteristic differs significantly (at 5% level of significance) across two groups in the chi-square test.

particular characteristic. We observe that compared to the other group of travelers, a significantly higher fraction of taxi-only users belongs to low income and carless households. Also, the majority of the taxi-only users are older adults (more than 58 years old), unemployed, and belong to low- income households whereas the other group represents mostly the younger and well-educated adults. Our findings are consistent with Wang and Ross (2019) and Rayle *et al*. (2016). In contrast to the taxi-only users, a larger fraction of users who use either ride-hailing or taxi lives in urban areas and in MSAs having rail connections.

Using data from San Francisco, Rayle *et al*. (2016) observed that ride-hailing services and taxis serve a similar market demand since the majority of ride-hailing users responded that they would have otherwise used a taxi for the same trip and that these two types of services covered similar areas and trip lengths. From the perspective of trip purpose, we observe that similar market demand exists for work, return home, and mode change purposes between our two identified groups, as the fraction of taxi-only users vs ride-hailing/taxi users do not differ significantly across those activities. The same, however, does not hold for maintenance and discretionary activities. It is observed that the fraction of taxi-only users who made trips for maintenance purposes is higher than the fraction of the other group making trips for the same purpose (31.6 percent versus 14.8 percent with a 5% level of significance). Conversely, for discretionary activity, the fraction in the taxi-only group is lower than the other group (22.5 percent vs 39.4 percent) (c.f. Table 7).

Next, we examine the cross-classification of our four identified LCA classes with zero versus one or more rideshare app usage. Figure 10 depicts that in all the classes *except* class 2, the majority of the travelers used the rideshare app at least once in the last 30 days. In class 2, about 78 percent of people did not use the rideshare app in the prior month. It might be due to several reasons. For instance, class 2 consists of a larger portion of older adults who make fewer trips per day (Lynott and Figueiredo, 2011) and perhaps make trips quite occasionally by ride-hailing for hospital visits. Another reason may be that this age group was raised on taxi services, and they are less familiar with app technologies (Vivoda *et al*., 2018) so perhaps use app-based services less.

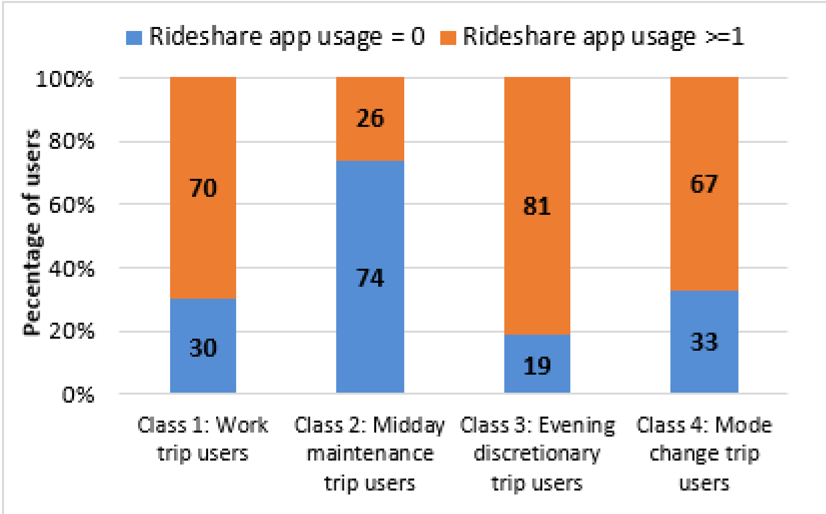


Figure 10: Distribution of travelers by rideshare app usage (in the last 30 days) across four LCA classes

Despite the low usage of app-based services by older adults, recent literature such as Shirgaokar (2018) suggested that, compared to taxi, app-based ride-hailing services pose higher prospects of usage among older adults in the future for several reasons. First, ride-hailing involves a lower cost per ride than taxi (Kolanko and Gallinger, 2015). Second, the share of smartphone possession among older adults is rising (Smith, 2016), which increases the chance of being familiar with app technologies and thereby, adopting ride-hailing services. Third, some third-party services are now available (e.g., GoGoGrandparent, GreatCall), which provide access to ride-hailing for seniors by offering convenient features to attract this group. For example, a ride service called GoGoGrandparent allows riders to reserve a ride from their home phone, provide a call-back feature to inform the riders when the vehicle is available, offer telephone customer support, and a ride tracking facility (GoGoGrandparent, 2020). Moreover, ride-hailing services are now providing mobility to people with physical disabilities and cognitive limitations utilizing specially equipped vehicles and other facilities to support the riders (Uber, 2020).

Although our sample data represents both traditional taxi-based ride-hailing and the recent app-based ride-hailing services, it is anticipated that a considerable portion of users corresponds to app-based users. Prior studies found that app-based ride-hailing is proving tough competition for taxis by replacing a considerable number of taxi trips (Rayle *et al.*, 2016; Young and Farber, 2019; Contreras and Paz, 2018). This is because app-based services are reported to be more convenient and efficient services than for taxi (Cramer and Krueger, 2016). For instance, ride-hailing provides a vehicle's real-time location and estimated arrival time, shorter waiting times, lower travel costs, identification of both drivers before making a trip, and an easy and simple payment method to its riders. SFMTA (2014) reported that in San Francisco the number of taxi trips per month decreased by more than half between March 2012 and July 2014. According to Schneider (2018), ride-hailing services in New York City exceeded taxi pickups by 65 percent from February 2017 to December 2017. Moreover, Cramer and Krueger (2016) observed that the capacity utilization rate[3] is higher (on average 30 percent) for Uber drivers than taxi drivers. App-based ride-hailing services appear to be a "modern transformed version" of traditional taxi-based ride-hailing service, which is experiencing drastic growth in the past decade and the trend of growth is expected to continue (Nair et al., 2020; Komanduri et al., 2018).

Summary and Conclusions

Ride-hailing has become the pre-dominant shared-mobility service. The emergence of this technology-enabled (app-based) on-demand ride services expands the set of travel alternatives and substantially increase flexibility in activity scheduling and travel choices, thus affecting travel behavior in several ways. This study analyzed the travel behavior of ride-hailing users from an activity-based approach that uses full activity-travel *patterns* or *tours* as a basic unit of analysis. Tours are analyzed based on the dominant sequence of activities and trips. Whereas patterns are analyzed by clustering ride-hailing users based on travel behavior indicators and by using a Latent Class Analysis (LCA) technique. The empirical results using data from the 2017 NHTS show that 76 percent of ride-hailing tours can be represented by the five most dominant sequence of tours with non-work tours being the most frequent. We also observe a wide variation in socio-demographic characteristics of ride-hailing users between work and non-work tours. The Latent Class model suggests that the ride-hailing user population can be divided into four distinct classes where each class has a representative activity-travel pattern defining their respective ride-hailing usage. This implies that people utilize ride-hailing in distinctly different ways (although any user could have behaviors exhibited in any of the four identified classes). Class 1 is composed of young and employed users who use ride-hailing for work. Single-living older

[3] Capacity utilization rate is measured as the fraction of time when drivers have a fare-paying passenger in the car (Cramer and Krueger, 2016).

individuals comprise Class 2 and use ride-hailing for maintenance activities during midday. Ride-hailing Class 3 are younger, employed individuals who use it during evenings for discretionary purposes. Last, Class 4 members use it for mode change purposes.

The results of this study can help ride-hailing operators to identify potential market groups of ride-hailing users with particular socio-demographic characteristics. The results also can identify users' demand for ride-hailing by time-of-day, which can help to evaluate current ride-hailing services and to implement market strategies addressing different groups of users to meet their travel needs and to improve the quality of service provided. For example, ride-hailing work trips towards employment centers in peak hours might involve increased vehicle-miles traveled (VMT) due to greater distances or deadheading trips[4]. Since work trips are typically made alone (Lavieri and Bhat, 2019), a higher number of single-occupancy vehicles during peak hours might increase VMT (Henao and Marshall, 2019a) and may lead to increased traffic congestion in those periods. In this context, to reduce the deadheading distance and to reduce congestion, the effectiveness of shared ride-hailing services (also known as ride-splitting), such as UberPool and Lyft Line, can be evaluated. Li *et al*. (2019) suggested that ride-splitting trips can significantly reduce 22 percent of vehicle-hours traveled (VHT). This can be done in consideration of delays due to the pickup of other passengers and the social barriers (e.g., security concerns to ride with strangers) associated with shared services.

Single-living older-adults who can no longer drive due to medical and other conditions still need transportation services to occasionally access non-home activity locations form a potential group of ride-hailing users. Marketing strategies, for example, making senior-friendly apps, providing subsidized rides, disability-supportive services, and easy payment systems, need to be provided to make ride-hailing accessible and user-friendly to this group. Two other potential groups of ride-hailing users are young employed people who would use this service during the evening or late night for discretionary purposes and affluent people who use ride-hailing for access to and from airports or transit stations. Pickup/drop-off facilities, such as curbside or nearby designated areas for waiting, as well as pickup/drop-off at airports and terminals, needs to be provided to offer convenient access to the long-distance travelers. Special

[4] Deadheading trips refers to the trips made by ride-hailing services when there are no passengers in the vehicle (Nair *et al*., 2020).

attention needs to be given so that passengers with luggage and children can be conveniently accommodated.

To the best of our knowledge, this study is the first to analyze tours and full activity-travel patterns of ride-hailing users in an integrated way. The study considered both ride-hailing user demographics and trip characteristics by using national-level household travel survey data. The findings of this study provide first-hand information on heterogeneity among ride-hailing user groups based on their ride-hailing usage and their representative activity-travel patterns. The study thus provides a broader perspective of user activity scheduling and integration of ride-hailing with other travel modes that can lead toward the development of better tour-based or activity-based travel demand forecasting models reflecting the demand of ride-hailing services.

Author Contribution Statement

The authors confirm contribution to the paper as follows: study conception and design: R. Rafiq, M. G. McNally; data processing: R. Rafiq; analysis and interpretation of results: R. Rafiq, M. G. McNally; draft manuscript preparation: R. Rafiq, M. G. McNally. All authors reviewed the results and approved the final version of the manuscript.

Conflict of Interest

On behalf of all authors, the corresponding author states that there is no conflict of interest.

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