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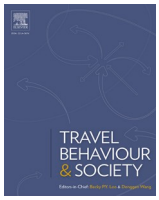

Gender differences in travel and everyday life: A data-driven approach to address the intersectional nature of gender as a social construct

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ABSTRACT

Gender differences in travel patterns have been extensively studied in the transportation realm. Recent studies have started to adopt an intersectional lens to acknowledge that the convergence of gender and other social identities can create unique travel needs and experiences. However, studies often focus on gender differences in trip characteristics instead of putting trips in the context of daily schedules. Further, existing studies often select one to two socio-demographic characteristics along with gender to define intersectional groups and compare trip characteristics of these groups. So, findings from these studies are largely influenced by the pre-selected socio-demographic characteristics and may neglect some key characteristics that significantly affect behaviors in a given region during specific periods. To address these gaps, this study first applies the sequence alignment method (SAM) to detect behavior patterns that can account for both trips and activities in daily schedules. Then, the study applies the Chi-square automatic interaction detection (CHAID) to identify key characteristics that have significant impacts on the behavior patterns. Last, the study defines intersectional groups using these identified key characteristics and gender and examines whether each group tends to have a unique set of behavior patterns. To demonstrate the methods, this study uses the travel survey data collected in Minnesota as a study case. The SAM results reveal that the behavior patterns on weekdays and weekends are different, and the CHAID analysis also identifies different key characteristics for weekdays and weekends. Moreover, we find several gender gaps that have rarely been addressed in the literature, such as women tending to lose their after-work personal time after having kids. These findings prove that our approach can derive intersectional groups directly from the data and provide novel insights into gender gaps in travel and activity participation in the context of everyday life.

1. Introduction

Understanding gender differences in travel patterns has been an important topic in transportation planning and practices (De Madariaga, 2013; Ng and Acker, 2018). Recognizing and addressing transportation needs and experiences for vulnerable gender groups, such as women, can promote gender equity and sustainable transportation (Hasson and Polewoy, 2011; De Madariaga, 2016). Studies have provided rich evidence on different travel behaviors of men and women, such as trip purposes, frequencies, distances, and mode choices. For instance, women are often found to have shorter travel distances, rely more on personal vehicles, and are more likely to have trips for household duties (Elias *et al.* 2009; Loukaitou-Sideris, 2020). However, most studies have focused on the characteristics of trips and ignored the interdependency of trips and activities in everyday task scheduling.

In contrast to trip-based approaches, gender gaps can be inherently explained by activity-based approaches, which view trips as a derived demand for activity participation (Miller, 2021). For instance, cultural and gender norms generally show that women take more responsibility for domestic chores and caregiving for children and elders. Activity-based approaches recognize the impacts of such norms and how women's mobility is largely restricted by these responsibilities (Kwan, 2000). For example, escorting children requires women to arrive at school during specific periods of the day. Consequently, women may reduce their discretionary activities such as recreation, have less available time to access services such as health care, and choose jobs closer to homes and schools with shorter commuting times (Kwan, 1999; Pollard and Wagnild, 2017). This suggests that the activity-based approach can provide a more comprehensive explanation of gender gaps by putting trips in the context of everyday task scheduling. Therefore, this article will adopt the activity-based approach and account for both trips and activities while studying travel patterns.

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Moreover, the intersectionality nature of gender has recently started to attract attention in transportation studies. Intersectionality refers to the interaction between gender, race, and other social categories in shaping people's lives, social practices, institutional arrangements, cultural ideologies, and structures of power (Davis, 2008). The intersection of gender and other identities creates unique travel needs and experiences that should not be simply explained by each identity independently. A few studies have adopted an intersectional lens to study gender and travel, and they argued that gender gaps cannot be understood in isolation from other social identities (Hu, 2021; Kim and Ulfarsson, 2021). These studies often selected two or three social identities (e.g., race and employment status) along with gender to define intersectional groups and compare the travel behaviors of people across these groups (Hjorthol, 2016; Craig and Van Tienoven, 2019; Sersli et al., 2021). However, using predefined intersectional groups may cause problems. First, studies often focus on social groups that are commonly viewed as disadvantaged such as women, people of color, and unemployed people, and select attributes accordingly. This may ignore some key attributes and lead to unexamined deprived populations. Second, studies often selected only two or three attributes to define the intersectional groups. This is partly because including more attributes will exponentially increase the number of groups, which will cause small sample issues and bring challenges for data visualization and analysis (Hibino et al., 2020). To address these limitations, this study applies data-driven methods to identify key attributes from all surveyed socio-demographic characteristics that have significant combined impacts on behavior patterns. By doing so, we may uncover potential new intersectional groups with unique behavior patterns that have been ignored by previous studies. After identifying the key attributes from the survey data and defining the intersectional groups, we compare the behavior patterns of these groups to reveal the typical behavior patterns of these intersectional groups and identify possible gender gaps in activity-travel behavior patterns.

The next section provides a brief review of studies on gendered travel behavior and the intersectionality nature of gender to identify the research gaps in the existing literature. The data section describes the study area and the survey data used in our study case. The method section illustrates the SAM modified to account for gender roles, the CHAID method to identify key attributes and define the intersectional groups, and the statistical method to compare behavior patterns across these groups. The result section presents the visual and statistical analysis results. The conclusion section summarizes key findings and discusses practical implications and future research.

2. Literature review

2.1. Empirical gendered travel behaviors

To study gender gaps in transportation, empirical studies have often used various survey data and compared trip characteristics between gender groups using descriptive statistics (McGinnity and Russell, 2008). For instance, studies have used time-use surveys to investigate time allocations among various tasks and found that women tend to spend more time than men on household chores and caring (Ettema and van der Lippe, 2009; Taylor et al., 2015). Other studies have used travel surveys to study travel time, trip purposes, and mode choices and found that, compared to men, women have shorter trips and more household-supporting trips, such as grocery shopping and escorting kids (Scheiner and Holz-Rau, 2017; Authority, L.A. 2019). Studies on travel mode choices have found that women in developed countries tend to rely more on driving, which can provide greater flexibility to juggle all their duties (Dobbs, 2005). However, with limited access to personal vehicles, women are likely to use public transit and carpool in the Global North and limit their activities within walking distance in the Global South (Elias et al., 2015; Colley, 2017; Loukaitou-Sideris 2019). Studies have also found that, for households that have limited access to personal vehicles, women have less access to household vehicles than men and are less likely to have driver's licenses, which largely restrict their mobility level (Matsuo, 2016; Olivieri and Fageda, 2021). A few studies have designed new surveys to collect gender-disaggregated data and study gender-specific travel behaviors. These studies have found that women tend to avoid traveling at night because they are more likely to suffer sexual harassment and other safety issues during travel (Zhou et al., 2005; Wilson and Little, 2008). All of these findings suggest gender gaps in transportation and the need to understand women's travel needs and experiences.

Some studies have adopted a broader gender term to study the time allocations and travel needs of non-binary people. These studies have found that non-binary people tend to share household tasks more equally with their partners/spouses (Kurdek, 2007). Studies have also found that non-binary people tend to travel shorter distances, which may be because they usually choose to live in metropolitan areas with better access to LGBT-oriented activity sites and services (Smart and Klein, 2013). Moreover, studies have also found non-binary are more sensitive to being exposed to public spaces and concerned more about safety than men and women (Linander et al., 2019).

Although these studies have addressed gender differences in various aspects, they often neglected the interdependency between trips and activities in everyday life. For instance, travel time as a key trip characteristic is constrained by the available time that can be allocated to travel in a day given all activities and tasks scheduled on that day. Meanwhile, the available transport resources such as access to personal vehicles determine what tasks can be accomplished within a day and limit people's choices of activity locations and times. To address such interdependency, some studies have adopted activity-based approaches to identify and explain gender differences in activity-travel behavior patterns (Portoghese et al., 2011; Islam and Habib, 2012). For example, McGuckin and Nakamoto (2005) studied trip-chaining behaviors and found that women tended to make short trips with multiple destinations to juggle their household duties, while men tended to make stops for meals or coffee themselves. A few other studies have also revealed that women make complex chained trips in terms of both job tours and non-job tours (Strathman and Dueker, 1995; Chu, 2003; Noland and Thomas, 2007; Cao et al., 2008; Paleti et al., 2011).

In addition to chained trips, studies have quantitively measured the complexity of activity and trip schedules and compared the complexities between men and women. These studies found that, in general, women tended to have more complex schedules. A common complexity measure is the fragmentation of activity-trip schedules to recognize the challenges of scheduling many activity and trip fragments in a day (Couclelis, 2000). Various spatial and temporal measures of fragmentation have been developed, such as the number of activities per day and the similarity of activity durations (Lenz and Nobis, 2007; Hubers et al., 2008; Alexander et al., 2011). Some other measures focused on complexity beyond fragmentation, such as Shannon's entropy and the mean number of trips per tour (Scheiner, 2014). However, these measurements did not consider activity types or only focus on work-related activities. Hence, they failed to capture that gender gaps may be more significant for certain activity types and/or travel modes than others.

Time geography has also been employed to study the complexity of everyday schedules and compare activity-travel patterns among genders (Miller, 2016). Gender differences are often described based on the theoretical hypothesis that women may face more space–time constraints caused by coordinating schedules among household members (Cullen and Godson, 1975). Some studies have mapped space–time paths to visually compare constraints between men and women (Kwan, 1999). Some studies have focused on the spatial and temporal fixities of activities and found that, compared to men, women regularly engaged in fixed household maintenance tasks and thus experienced more binding constraints (Kwan, 2000; Schwanen et al., 2008). However, these studies usually examined the fixity of only one specific type of activity and ignored the interrelationships between different types of activities and

trips on a given day. For instance, although women may appear to be less constrained by working activities than men due to the fewer working hours as part-time workers, women may rely more on personal vehicles due to their irregular working hours and other household supporting tasks. Hence, this study will study activity-travel patterns in the context of daily schedules, aiming to better understand the gender disparities in behavior patterns concerning trips, activities, and their interdependencies.

2.2. Intersectionality nature of gender in transportation

Intersectionality acknowledges that one's identity is defined by the convergence of gender, race, life stage, and other social identities (Shields, 2008). Crenshaw's work (1990) is one of the first studies that address the intersectional nature of gender. Crenshaw argued that studying gender independently from other identities such as race would marginalize groups such as women of color (Crenshaw, 1990). Ignoring the intersectional nature of gender in transportation studies may misinterpret the gender gaps caused by the combined effect of gender and other social identities. For example, studies have revealed that women made more mid-day trips than men. However, such patterns may be caused by the fact that women were more likely to work part-time while men were more likely to be full-time employees (The Corrosive Impact of Transgender Ideology, 2020). Another example is that low-income women, particularly those of color, often travel longer in distance and time than others, which contradicts a general conclusion in many existing studies that women have shorter trips than men (Crane and Takahashi, 2009). Hence, it is crucial to study gender and travel from an intersectional perspective. This can provide a comprehensive view of different travel needs and behaviors across genders as well as among people in the same gender group with various backgrounds.

To examine how intertwined social identities lead to different travel needs, constraints, and experiences, recent studies have mainly used cross-tabulation methods (Gao and Kerstetter, 2016; Lewis, 2013). These studies often selected one or two social identities besides gender to define intersectional groups and then compared the behavior patterns of these groups with the entire sample population. Besides gender, the four commonly selected attributes were race and ethnicity, family members (young kids in particular), employment status, and age (to recognize life stage). For instance, studies considering gender, family members, and employment status found that gender gaps were more pronounced in male breadwinner households and with the presence of small children (Fan, 2017; Chidambaram and Scheiner, 2020). Studies considering gender and employment found that women working part-time or unemployed had more chained trips for household supporting tasks (Olabarria et al., 2013; Boarnet and Hsu, 2015; Authority, L.A. 2019). Besides cross-tabulation descriptive analysis, some studies also conducted statistical regressions, which used selected socio-demographic attributes of each gender group as predictors and studied their associations with trip characteristics. However, selecting attributes based on the domain knowledge or project needs may limit the understanding of gender gaps beyond these selected identities. Moreover, studies have rarely discussed how the selected attributes interacted with each other in shaping people's activity-travel patterns, i.e., which social identities play more dominant roles than other identities.

This paper aims to address these gaps in gender and travel studies. Instead of examining specific trip characteristics, we consider daily schedules to capture the interrelationships between activities and trips during everyday task scheduling and extract activity-travel patterns that are distinctly different from each other. Then, instead of selecting socio-demographic attributes to define the intersectional groups and compare their behaviors, we account for all surveyed socio-demographic characteristics and apply data mining and statistical methods to identify attributes that are significantly associated with the extracted behavior patterns and their interactions. Last, we used these key attributes derived from the data along with gender to define the intersectional groups and compare the behavior patterns across these groups. The comparison results can reveal gender-typical behavior patterns and the corresponding set of socio-demographic characteristics.

3. Data

This article uses the Travel Behavior Inventory (TBI) data collected by the Metropolitan Council from 2018 to 2019 in the Twin Cities Metropolitan Area and some outlying regions. The Twin Cities metropolitan area encompasses seven counties around Minneapolis-St. Paul Twin Cities, including Hennepin, Ramsey, Anoka, Carver, Dakota, Scott, and Washington counties. Based on the U.S. Bureau of Labor Statistics, there were about 3 million jobs from 2018 to 2019, and the majority of the jobs were located in the seven-county metropolitan area. To meet people's daily transport needs, the metropolitan area has an extensive network of roads and highways and also various forms of transit services such as express bus services connecting residents in suburbs to the transit networks in downtown areas.

The TBI survey collected person- and household-level socio-demographic information and travel diaries of all household members (Gisdata.mn.gov. 2020). In total, 8,587 participants completed the survey via the smartphone application, rMove, which tracks users' movement and detects trips. For each detected trip, users are asked to confirm or edit the imputed travel modes and provide a few trip properties, such as travel companionship. The original TBI survey did not record activities, so we used the trip purpose to impute the activity type at each trip destination. We also post-process the original survey data to make sure there are no spatial or temporal gaps between two consecutive activities and/or trips (Zhang et al., 2022). If a larger temporal gap is detected, we create a 'Missing' episode to fill in the gap. Each survey day in the final dataset is formatted as a series of activities and trips with recorded or imputed details:

$$Ep_i : \left\{ \left(T_{ij}, A_{ij} \right) \right\}_{j=1,2,\cdots,J_i} \tag{1}$$

where a person i's daily log (Ep_i) is represented as a sequence of activity-travel episodes. For each person i's daily log, it contains J_i activity or trip episodes. T_{ij} stores the start and end time of a single episode Ep_{ij} with a temporal resolution of 1 min. A_{ij} stores the activity type or travel mode for the j th episode of person i. The eight activity types are labeled as Home, Work, School, Escort, Dine-out, Shop, Social/Recreation, and Errand. The five possible travel modes are labeled as Walk, Bike, Bus, Rail, and Car.

4. Method

This study applies the sequence alignment method (SAM) to extract travel behavior patterns of a person during one day and then applies the CHAID (Chi-square automatic interaction detection) method to investigate which intersectionality groups are attributed to the extracted patterns. The article then selects key social characteristics based on the CHAID results in addition to gender to define intersectional groups and compares behavior patterns across these groups. This section illustrates each method in detail.

4.1. Analyzing travel patterns on a daily schedule Base: Sequence alignment method

To analyze travel patterns in the context of daily schedules, we transform activities and trips into a sequence of states and apply SAM to compare activity-trip sequences (Song et al., 2021). The SAMs were originally developed to quantify the similarity of DNA or RNA strings in molecular biology (Corpet, 1988). Later, transportation studies modified the SAMs to compare and measure interpersonal activity-travel similarity (Wilson, 1998; Noh and Joh, 2012). The SAMs format activities and trips in a given period as consecutive states in a sequence. Then, the

similarity of two schedules is measured by comparing two sequences and calculating the minimum cost of operations needed to transform one sequence to the other. The two fundamental operations are: 1) inserting a state into or deleting a state from the sequence, and 2) substituting one state with another state. An insertion (or deletion) operation has often been modeled as substituting a NULL state with a state (or vice versa). Thus, the key task in applying the SAMs to a specific research problem is to assign weights (costs) to substitution operations between all possible states (Studer and Ritschard, 2016). In our case, the weights need to reflect the dissimilarity between particular activities and trip types based on domain knowledge or specific research aims (e.g. high costs for substituting biking with other travel modes while studying active travel).

4.1.1. Creating Activity-Travel sequences

We reclassify activity types and travel modes to better reflect traditional gender roles and define the SAM cost matrix correspondingly to capture behavior patterns that are commonly perceived as gender-typical. Firstly, we categorize each activity into household-supporting (HH) activity (e.g., escort, shopping, family errand) or non-household-supporting (nHH) activity (e.g., work, school, personal errand). This is because the perception of gender-typical patterns is rooted in the persistent social and cultural norms that women are primarily responsible for domestic chores and caregivers. We also categorize each activity considering whether it occurred at home (Home) or out of home (outHome) to distinguish activities that occurred in private space and those that occurred in public and shared space.

For trips, we categorize each trip based on the activity at its destination accordingly and label it as a going home (Home), household supporting (HH), or non-household-supporting (nHH) trip. We also label each trip based on the travel mode. Trips using the household vehicle are labeled as PvtTrip, and trips using other modes such as public transit and walking are labeled as PubTrip. The household vehicle, therefore, is viewed as a private space similar to home, while other vehicles are viewed as shared space. For activities or trips with missing activity types or travel modes, we label them as missing (MI).

Table 1 shows an example encoding result between 12:00 and 16:30. Each activity or trip episode includes an identifier, the user's identifier, its start and end times, its original type, and the reclassified type. We also create a short label for each reclassified type to be used in Fig. 1 to show the corresponding activity-trip sequence. We chose 5 min as the interval to create the activity-trip sequence for each day, which allows us to capture short trips and activities while managing the computational costs. For those activities or trips that start or end in the middle of the 5-minute interval, we label the interval as the first activity or trip that happens within the time interval. For a complete day of 24 h (1440 min), therefore, the sequence contains 288 states, each labeled with a reclassified type defined earlier.

4.1.2. Defining substitution cost matrix

We define the substitution cost metrics to specify the dissimilarity (cost, distance) between each pair of states considering the empirical findings from gendered travel patterns. The cost metrics can be defined either by researchers based on domain knowledge for specific research questions or by data-driven methods based on the transition probabilities between different activities/trips derived from the survey data (Gabadinho et al., 2011). To better capture gender-related behavior, we define the cost matrix to highlight gender roles following the social and culture norms (Eagly and Wood, 2012). We consider three levels to define the substitution cost between two states: (1) whether it was an activity or a trip, (2) whether it was at home or out-of-home, and (3) whether it was household-supporting (HH) or non-household-supporting (nHH) to reflect likely more HH tasks shared by women:

$$D^{\alpha\beta} = d^{\alpha\beta}_{AcTr} + d^{\alpha\beta}_{Pvt} + d^{\alpha\beta}_{HH} \quad (2)$$

Table 1
Example Activity-Travel Episodes and Encoding Strategy.

Episode ID	User ID	Start Time	End Time	Activity/ Trip Type	Reclassified Type	Abbr.
8001	1001	02/01/ 2019 09:00	02/01/ 2019 12:15	Work	OutHome nHH	a
8002	1001	02/01/ 2019 12:15	02/01/ 2019 12:28	Walk	PubTrip nHH	b
8003	1001	02/01/ 2019 12:28	02/01/ 2019 12:50	Dine-Out	OutHome nHH	a
8004	1001	02/01/ 2019 12:50	02/01/ 2019 13:03	Walk	PubTrip nHH	b
8005	1001	02/01/ 2019 13:03	02/01/ 2019 15:00	Work	OutHome nHH	a
8006	1001	02/01/ 2019 15:00	02/01/ 2019 15:15	Car	PvtTrip HH	c
8007	1001	02/01/ 2019 15:15	02/01/ 2019 15:24	Escort	OutHome HH	d
8008	1001	02/01/ 2019 15:24	02/01/ 2019 15:36	Car	PvtTrip HH	c
8009	1001	02/01/ 2019 15:36	02/01/ 2019 15:55	Shopping	OutHome HH	d
8010	1001	02/01/ 2019 15:55	02/01/ 2019 16:16	Car	PvtTrip Home	e
8011	1001	02/01/ 2019 16:16	02/02/ 2019 08:05	Home	Home	f

where $D^{\alpha\beta}$ is the assigned distance between states α and β. At the first level ($d^{\alpha\beta}_{AcTr}$), an activity and a trip have a unit distance of 1.0. At the second level ($d^{\alpha\beta}_{Pvt}$), an activity or trip that occurred in a private space (e.g., at home, in household vehicles), and an activity or trip that occurred in a public space (e.g., at a recreation center, on a bus) has a unit distance of 1.0. At the third level ($d^{\alpha\beta}_{HH}$), HH and nHH tasks also have a unit distance of 1.0. Further, the distance from 'missing' states MI to another state is 0.5 for each of the three levels. The overall distance ($D^{\alpha\beta}$) is the sum of distances at all three levels. For example, the distance between a car trip to a grocery store (PvtTrip.HH) and a work activity (OutHome.nHH) is 3.0.[1] In this study, we choose three levels to distinguish trips from activities, highlight the gender roles, and distinguish private and public spaces, and we assign equal weight to the three levels since we consider these three aspects as equally important. Future research on gender equity or other research may modify the selection of levels given specific research aims or assign different weights to each level.

Given the defined cost matrix, we calculate the distance between each pair of sequences, that is, the minimum cost of operations to transfer one to the other. Then, we apply hierarchical clustering (Murtagh, 1983) to group similar sequences with shorter distances into clusters, each corresponding to an implicit daily activity-travel pattern that is distinctly different from others. Hierarchical clustering is a bottom-up iterative approach that results in a tree-like structure to minimize the variations within clusters, which could capture different

[1] In this case, the car trip and the work activity have a distance of 1.0 at the activity-trip level; the car trip occurs in the private space (PvtTrip) and the work activity (OutHome) occurs in the public space, so their distance is 1.0 at the second level; the car trip is for household-supporting (HH) tasks and the work activity is for non-household-supporting (nHH) tasks. So their distance is 1.0 at the third level. Thus, $D^{\alpha\beta} = d^{\alpha\beta}_{AcTr} + d^{\alpha\beta}_{Pvt} + d^{\alpha\beta}_{HH} = 1 + 1 + 1 = 3$.

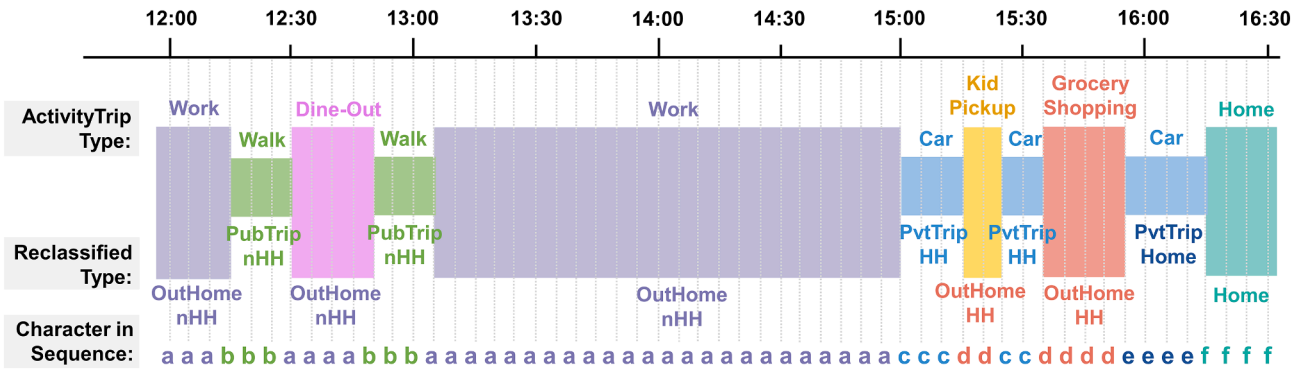

Fig. 1. An Example Activity-Travel Sequence at 5-Minute Intervals.

levels of discrepancy in activity-travel behaviors.

To determine the number of clusters, we apply several cluster quality indicators, which measure the distances between sequences in different clusters and within the same clusters. The five measures include Point Biserial Correlation (Milligan and Cooper, 1985), Hubert's Gamma (Hubert and Arabie, 1985), Weighted Average Silhouette Width (Kaufman and Rousseeuw, 2009), Calinski-Harabasz index (Caliński and Harabasz, 1974), and Reversed Hubert's C (Hubert and Levin, 1976). We choose the number of clusters that can achieve an overall good quality for all indicators and locally achieve the best quality for most indicators.

We use the programming language R to implement our methods. We use the package 'TraMineR' (Gabadinho et al. 2021) to implement the SAM and calculate the pairwise distances for all activity-trip sequences. Then, we use the package 'WeightedCluster' (Studer, 2013) and 'stats' for hierarchical clustering to get clusters of sequences with similar behavior patterns.

4.2. Gender and intersectionality analysis

We apply the CHAID to examine interactions among various socio-demographic characteristics and identify key attributes that can define intersectional groups with unique behavior patterns. CHAID is a tree-based segmentation technique that can discover groups of people that are most associated with the identified travel patterns (Beckman and Goulias, 2008). CHAID splits and merges the sample with different predictors, which are the socio-demographic characteristics of participants in our case. Each split will categorize the input group into several sub-groups based on one predictor (e.g., the employment status). The method finds the split that can maximize the difference in outcomes among the subgroups, and the outcomes in our case are behavior patterns. For instance, participants will be split into three groups based on employment statuses: (1) full-time employees, (2) part-time employees, and (3) unemployed or retired people. We may also use another way to split employment status, or we may split the participants based on another socio-demographic. However, CHAID will choose to split participants into the above three sub-groups, because these three groups have behavior patterns that are most significant from each other compared to other split results. The same split procedure is performed for each sub-group until no split can result in sub-groups that are statistically different from each other (Magidson and Vermunt, 2005). Thus, CHAID can take all socio-demographics as input predictors and study their intersections in forming outcomes of travel patterns. We use the R package 'CHAID' to implement CHAID analysis (Kass, 1980).

CHAID analysis can identify key socio-demographic characteristics and corresponding intersectional groups defined by them. Gender, however, may only have significant impacts on behavior outcomes on some of the branches towards the lower levels of the tree. For instance, we may use gender to further split the employed sub-group, but age to further split the unemployed sub-group from the previous split.

Therefore, to further examine how gender intersects with all other socio-demographic characteristics, we select characteristics on the upper levels of the tree that significantly shape the behavior patterns, and we use them in addition to gender to define intersectional groups and compare their behavior patterns statistically. Considering the various sizes of the intersectional groups, we compare the distribution of travel patterns for each intersectionality group with the distribution for the total population (Gart, 1971). For each intersectionality group i with size N_i, we use the number of people with the travel pattern j, y_{ij}, to calculate the proportion of travel pattern j in group i, $p_{ij} = y_{ij}/N_i$. We also calculate the proportion of the pattern j in the total population $p_{\bullet j} = Y_{\bullet j}/N$. Under the null hypothesis, the two proportions are expected to be the same, that is, $p_{ij} = p_{\bullet j}$. The statistic for testing the difference in two proportions can be formulated as:

$$Z_{ij} = \frac{(\hat{p}_{ij} - \hat{p}_{\bullet j}) - 0}{\sqrt{\hat{P}_j(1-\hat{P}_j)\left(\frac{1}{N_i} + \frac{1}{N}\right)}} \tag{3}$$

where:

$$\hat{P}_j = \frac{Y_{ij} + Y_{\bullet j}}{N_i + N} \tag{4}$$

$$(\hat{p}_{ij} - \hat{p}_{\bullet j}) \sim \mathcal{N}\left((p_{ij} - p_{\bullet j}), \left(\frac{p_{ij}(1-p_{ij})}{N_i} + \frac{p_{\bullet j}(1-p_{\bullet j})}{N}\right)\right) \tag{5}$$

For each intersectional group, the null hypothesis can be rejected based on Z-score value at various confidence levels (in Eq. (3). If the null hypothesis is rejected, travel patterns for that intersectionality groups can be considered distinctly different. This allows us to identify gender subgroups that have distinct behavior patterns and further examines whether these patterns are commonly perceived as gender-typical.

5. RESULTS

This study uses the TBI data described in the data section as a study case to demonstrate the methods and results. First, we create activity-trip sequences for each person, each day from 3 a.m. to 3 a.m. the next day (Joh et al., 2002). Then, we remove sequences with total missing data longer than 12 h. After data cleaning, we have 49,094 valid sequences for 8,535 participants.

5.1. Exploratory analysis for gender groups

Table 2 shows the descriptive summaries of basic trip characteristics and socio-demographic backgrounds for each gender group. The socio-demographic summaries show that women are more likely to live alone with kids than other genders, and women are more likely to have part-time jobs or be unemployed than men. Non-binary people are more likely to have low education attainment, be non-white, and live in low-

Table 2
Descriptive Analysis of Socio-Economic Backgrounds and Trip Characteristics.

	Women (54.04 %)	**Men** (44.64 %)	**N-B** (1.32 %)
(a) Socio-Economic Backgrounds	Pct.	Pct.	Pct.
Household Type			
Couple, No Kid	39.10 %	46.45 %	44.33 %
Couple, With Kid	26.53 %	32.56 %	20.62 %
Single, No Kid	29.47 %	18.51 %	34.02 %
Single, With Kid	4.90 %	2.49 %	1.03 %
Employment Status			
Full-Time	64.72 %	74.36 %	69.07 %
Part-Time	12.74 %	6.07 %	13.40 %
Self-Employed	4.25 %	4.87 %	6.19 %
Not Employed	18.29 %	14.70 %	11.34 %
Age			
Young (18–24)	4.60 %	4.22 %	7.22 %
Middle (25–54)	83.27 %	83.31 %	91.75 %
Old (55 +)	12.13 %	12.47 %	1.03 %
Education (Below Bachelor)	17.59 %	21.18 %	14.43 %
Student Status (Is a student)	7.09 %	5.81 %	17.53 %
Race (Non-White)	12.20 %	12.75 %	55.67 %
Income (Low-Income)	11.20 %	8.66 %	24.74 %

	Women (54.04%)		**Men** (44.64%)		**N-B** (1.32%)	
(b) Basic Trip Characteristics	Mean	S.D.	Mean	S.D.	Mean	S.D.
Weekdays						
Total Travel Time (min)	115.16	115.25	124.22	120.69	124.74	125.86
Car Trip Time (min)	101.69	106.58	103.63	106.42	109.32	120.68
Transit Trip Time (min)	65.75	63.83	77.42	89.49	51.90	35.05
Activity Count	5.47	2.90	5.68	3.12	5.27	2.91
HH Activity Count	2.04	1.43	1.97	1.47	1.85	1.20
HH Activity Time (min)	79.47	152.81	74.82	156.71	98.94	195.88
Weekends						
Total Travel Time (min)	117.78	118.22	122.00	125.91	129.15	182.39
Car Trip Time (min)	103.60	107.34	106.41	115.38	112.61	170.62
Transit Trip Time (min)	65.90	98.09	62.22	64.24	51.68	31.82
Activity Count	5.09	2.99	5.17	3.11	4.79	3.06
HH Activity Count	2.10	1.45	2.03	1.37	2.16	1.64
HH Activity Time (min)	93.46	154.08	90.76	165.52	133.77	227.66

income households than other genders.

The descriptive statistics of trip characteristics show that women tend to spend less time on trips than men on both weekdays and weekends. As for travel modes, women tend to have car trips with shorter duration than men. Women have shorter transit trips than men on weekdays but have longer transit trips on weekends. As for the household supporting trips and activities, there are no large differences between women and men, but non-binary people spend more time than women and men, especially during the weekends. These descriptive statistics among genders are consistent with findings from previous studies (McGinnity and Russell, 2008; Ettema and van der Lippe, 2009). Next, we will use the modified cost metrics to extract travel patterns using SAMs.

5.2. Extract travel behavior patterns in daily schedule context

Considering different travel behaviors between weekdays and weekends, we perform sequence alignment analysis for activity-travel sequences from Monday to Friday and from Saturday to Sunday separately. Fig. 2 shows the seven distinct patterns on weekdays from the 37,640 sequences on weekdays. The x-axis shows the time of the day, in our case the 288 of 5-minute intervals from 3 a.m. to 3 a.m. the following day. The y-axis shows the proportions of all types of activities or trips within one of these 5-minute intervals, and each color corresponds to one type of activity or trip. The higher proportion of a specific color means that more sequences have their corresponding activity or trip type. Take group 3 as an example, the proportion of the light purple (OutHome.nHH) gradually gets larger from 6 a.m., remains large between 9 a.m. and 3p.m., and gradually decreases after 3p.m. This suggests that people in group 3 tend to conduct out-of-home activities during regular working hours that are not for household supporting tasks and return home directly afterward. Regarding trips, the proportions of pink (PvtCar.nHH) and dark purple (PubTrip.nHH) are much larger than other trip types during morning peak hours around 7 a.m., and the proportions of light blue (PvtCar.Home) and dark blue (PubTrip.Home) become larger than other trip types during afternoon peak hours around 4p.m. The proportion of red (OutHome.HH) also increases during this time, which indicates that some people make trips for household supporting tasks before going home (e.g., getting groceries after work). We briefly describe the behavior patterns of these seven groups as follows:

- Group 1 spent most of the time at home and heavily relied on cars when they went out.
- Group 2 had some out-of-home activities, mostly during the mid-day, and shared a decent amount of HH tasks across the day.
- Group 3 had nHH activities during regular working hours and shared HH tasks in the late afternoon (after working hours). Some of them took public transit for commuting but few of them used public transit for HH tasks.
- Group 4 also had nHH activities during regular working hours similar to Group 3, but they went home later (after 6 p.m.) and had many nHH activities before going home.
- Group 5 shared HH tasks during the day and went out for nHH activities mostly at night.
- Group 6 was out of home overnight and shared lots of HH tasks.
- Group 7 was also out of home most of the day but mostly for nHH tasks.

Fig. 3 shows seven distinct activity-travel patterns on weekends extracted from 11,454 sequences. Compared to weekdays, the out-of-home activities have various clustered periods. Such differences were most likely attributed to full-time employees and students who did not work or have classes during the weekends and allocated their time for other tasks such as shopping (HH) and recreation (nHH). The behavior patterns of these seven groups are:

- Group 1 stayed at home most of the time. Compared to weekdays, they did more HH tasks when they went out.
- Group 2 had out-of-home trips starting in the late morning, mostly using household vehicles for non-household-supporting tasks. They did more HH tasks in the afternoon.
- Group 3 had out-of-home activities mostly around 3 p.m.
- Group 4 had out-of-home activities mostly around 7 a.m.
- Group 5 was out of the home before 3 a.m. and started to go back home in the morning.
- Group 6 had out-of-home activities spreading toward the late evening and many people did not even return home at 3 a.m. the following day.
- Group 7 was also out of home most of the day but mostly for nHH tasks.

After extracting travel patterns, we visually explore different socio-demographic profiles of these identified behavior patterns. Fig. 4 (a) shows the proportions of each behavior pattern in each gender group on

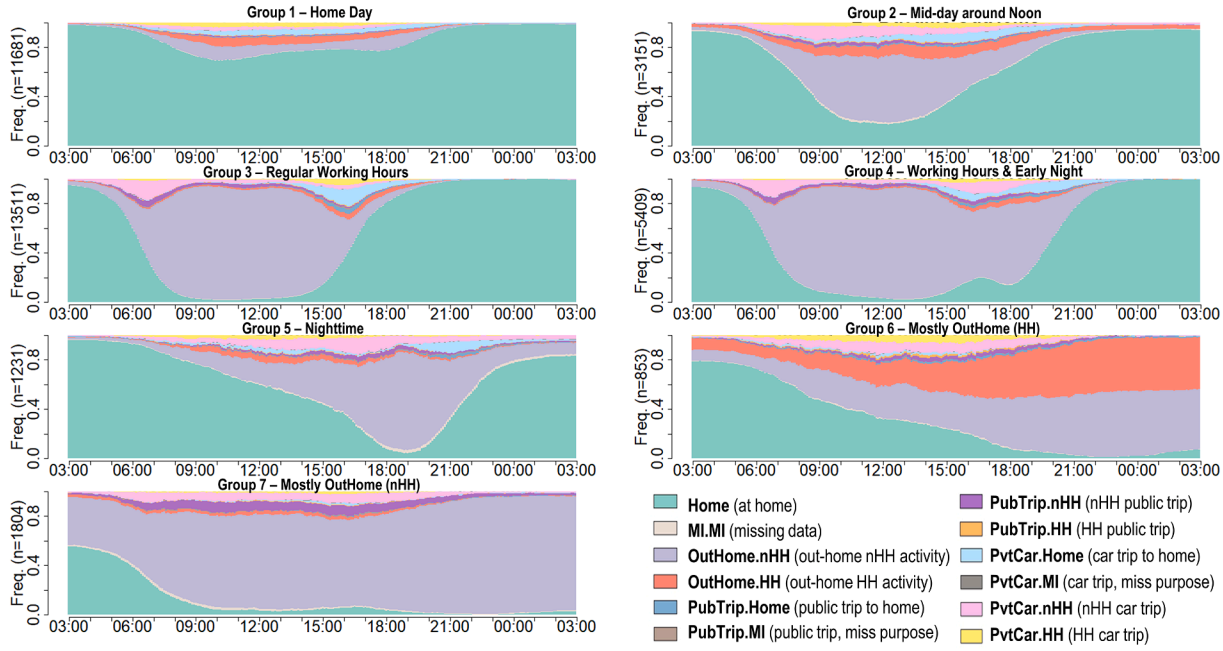

Fig. 2. Seven Activity-Travel Patterns on Weekdays.

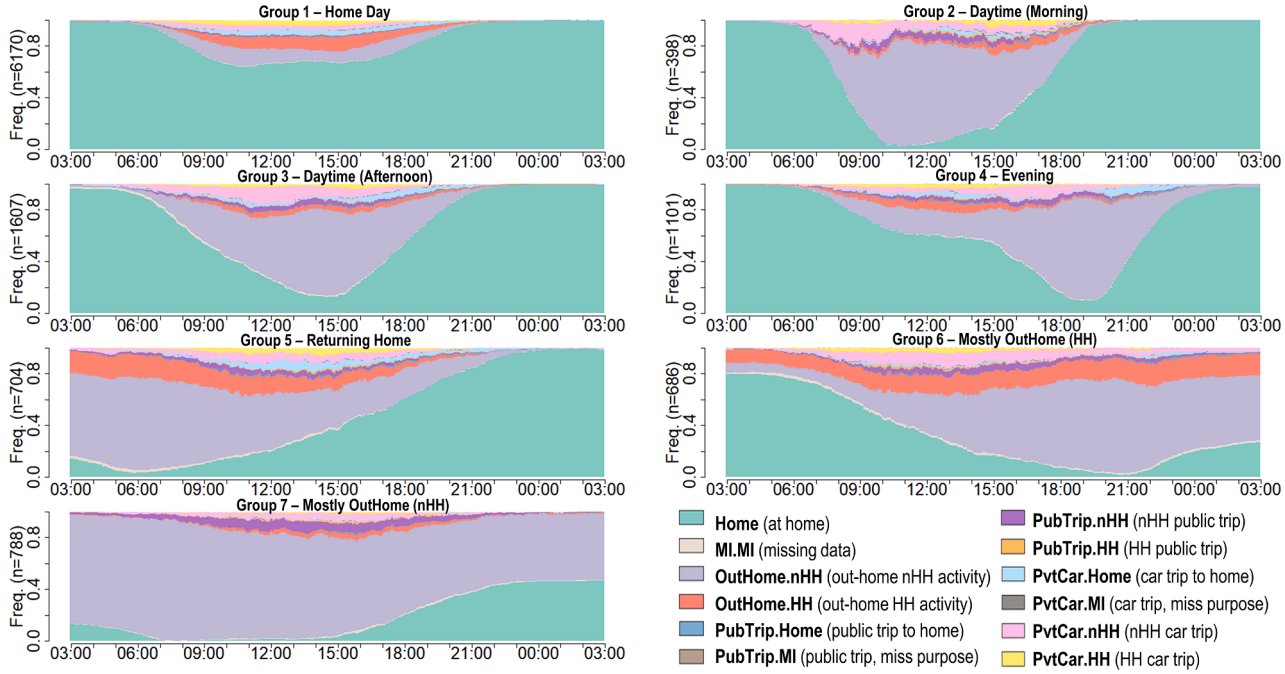

Fig. 3. Seven Activity-Travel Behavior Patterns on Weekends.

weekdays. The gray bars on the back depict the proportions of women, men, and non-binary people in the entire population. Each colored bar represents the proportion of people in each gender group having a specific travel behavior pattern. For instance, the three bars show the result for Group 1 who stay at home mostly, and these red bars from left to right show the percentage of people in Group 1 who are women, men, and non-binary. Note that the three bars should add up to 1.0 (100 %).

As shown in Fig. 4(a), on weekdays, we observe that the red and green bars surpass the background grey bars for women. Using Fig. 2 as the reference, this indicates that women tend to stay at home (Group 1 or make trips around mid-day (Group 2. Similarly, we observe that men tend to go out during regular working hours and spend a more extended period outside the home (Groups 3 to 7 in Fig. 2).

Fig. 4(c) shows gender differences on weekends. The disparity in the duration of time spent at home diminishes, while the primary difference becomes the timing of outdoor activities and trips. We use Fig. 3 as the reference for behavior patterns. Women tend to make trips either in the morning (Group 2 or in the afternoon (Group 3. In contrast, men are more likely to travel in the evening (Group 4 or stay out overnight (Groups 5 to 7).

We also show the behavior patterns across various household types with a focus on the presence of couples and kids. Fig. 4(b) for weekdays shows that couples with kids exhibited a higher propensity for engaging in out-of-home activities and trips during regular working hours and

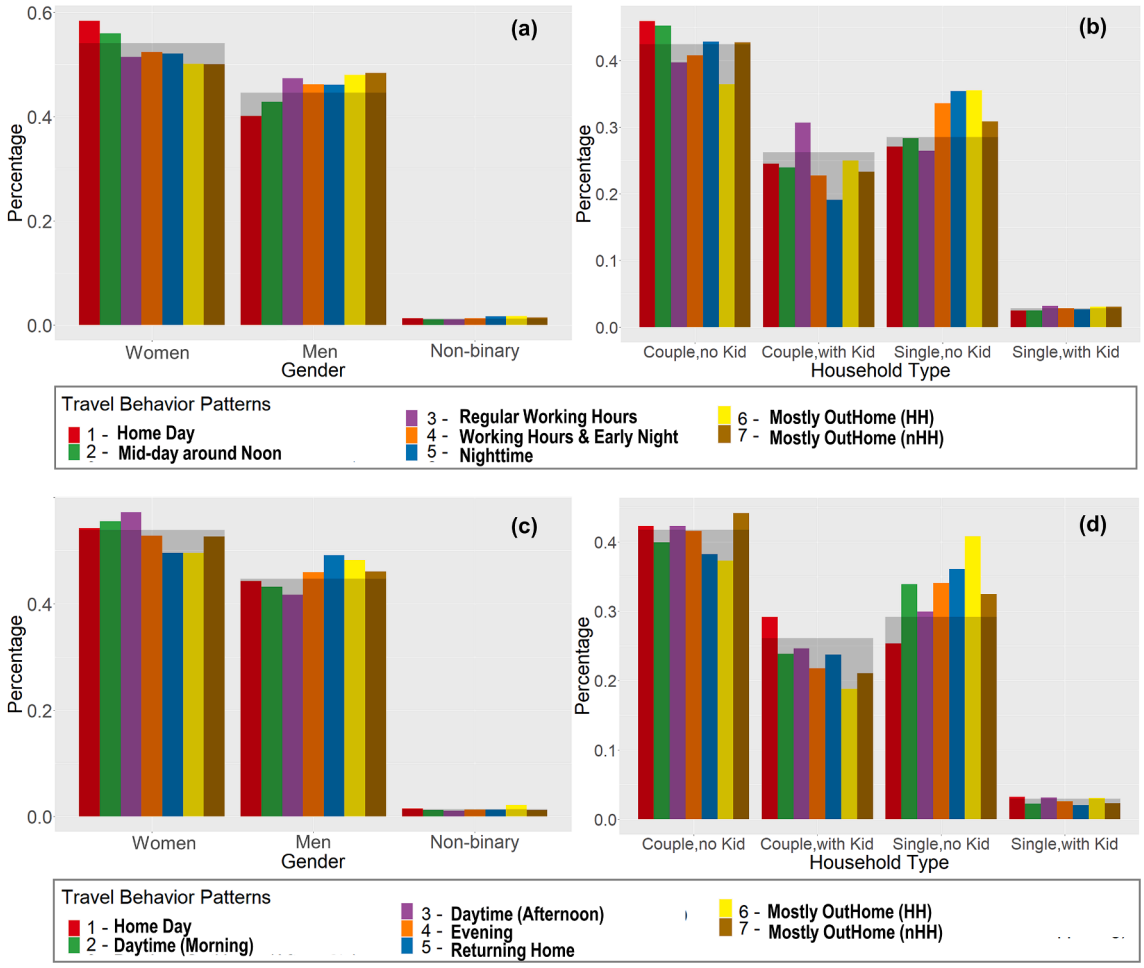

Fig. 4. Social-demographic Profiles of Travel Behavior Groups: a) Gender, on Weekdays, b) Household Type, on Weekdays; c) Gender, on Weekends; d) Household Type, on Weekends.

staying at home during the night (Group 3. Fig. 4(d) for weekends suggests that couples with kids tend to stay at home mostly (Group 1. Conversely, people without kids engage in out-of-home activities and trips throughout the day (Groups 2 to 7), particularly notable among those not living with partners.

These observations show that both gender and household types largely affected people's behavior patterns. However, it is important to note that this visual analysis only considers one person-level characteristic at a time, and thus, the intersectionality is not explicitly addressed. Hence, we continue with the CHAID analysis.

5.3. Address the intersectionality nature of gender in travel behaviors

The CHAID analysis uses travel patterns as the outcomes and the socio-demographic variables as the predictors. We consider key attributes identified in the literature. The attributes and the corresponding categories are *gender* (women; men; non-binary), *household type* (couple, no kid; couple, with kids; single, no kid; single, with kids), *employment status* (full-time; part-time; self-employed; not employed), *student* (yes, no), *race* (White, non-Hispanic, non-White), *age* (young, 18–24; middle, 25–54; old, 55 +), *the education level* (without bachelor degree; bachelor degree or higher), and *low-income* (yes; no).

Fig. 5 presents the visualization of Chi-squared Automatic Interaction Detector (CHAID) results for weekdays. The tree-like structure unravels how the intersectionality of various social identities contributes to travel behavior patterns. We include the distribution of all participants across the seven travel patterns as a reference at the top (above "employment status"). At the highest level of the tree, employment status emerges as the most influential factor in determining travel patterns. Each level of the tree is accompanied by a histogram, depicting the proportions of people in that sub-group across the seven behavior patterns. For instance, moving to the second level, the left histogram (above "household type") shows how full-time employed individuals are distributed among the seven travel patterns. Compared to the distribution for all participations on the top, this histogram reveals a higher likelihood for full-time employees to belong to Group 3 and Group 4 (i.e., those who go out during regular working hours). In contrast, the histogram on the right (above "student status") for unemployed individuals demonstrates a stronger propensity to belong to Group 1 (i.e., those who stay at home most of the time).

Continuing to the third level, for full-time employed individuals, the influence of household type becomes significant. People who are living with their partners/spouses show significantly different travel patterns compared to single people. For unemployed people, the household type does not appear to be the most significant factor, instead, student status has the most significant impact on behavior patterns. These results suggest the interaction of employment and household type has a combined impact on the travel behaviors of full-time employees, while employment and student status have a combined impact on the travel behaviors of unemployed people. Hence, by tracking the interaction of socio-demographic attributes within the branching structure of the plot, we can delve deeper into the combined impact of these attributes on behavior patterns.

We summarize some key findings of the CHAID analysis for the

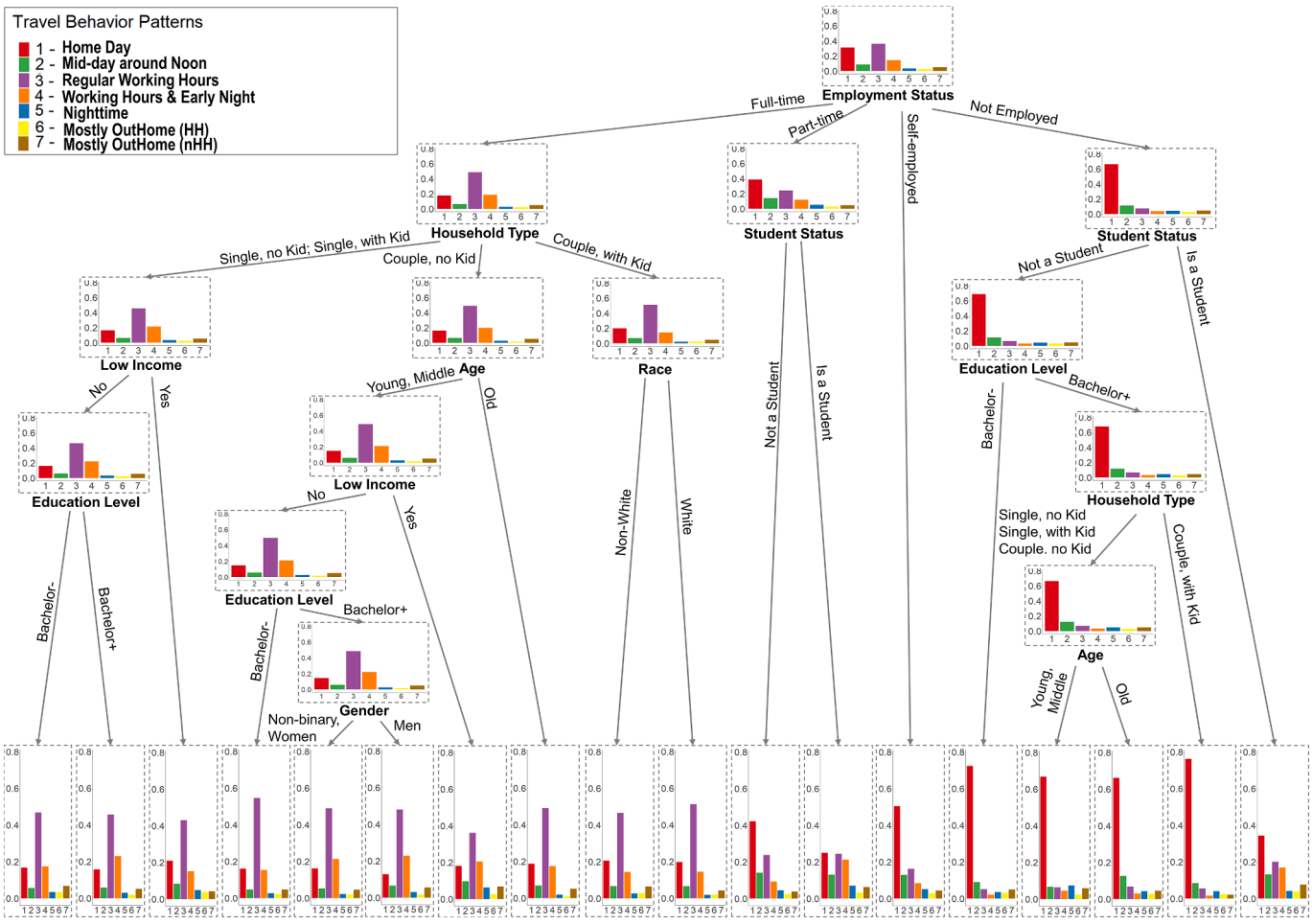

Fig. 5. CHAID Analysis Result: Weekday.

weekdays, using Fig. 2 as a reference for the behavior patterns for each group:

- Full-time employed people tend to go out during regular working hours in general (Groups 3 and 4. For, full-time employed people, the presence of kids is associated with fewer out-of-home activities that are not for household supporting tasks after regular working hours, e.g., happy hours after work less likely in Group 4.
- For full-time employees who live with partners and kids, non-white people are less likely to go out during regular working hours (Group 3) and they tend to stay out overnight (Group 7) compared to white, non-Hispanic people.
- Part-time and self-employed people are more likely to stay at home (Group 1) or travel during mid-day (Group 2).
- Most unemployed people stayed at home the entire day (Group 1).
- For part-time and unemployed people, being a student is related to having more out-of-home activities and trips (less likely to be in Group 1).
- People with low income, low education levels, senior age, non-white racial backgrounds, and those identifying as women or non-binary exhibit distinct travel patterns compared to other demographic groups within the same employment group. For example, within the subset of full-time employed individuals who live solely with partners, the low-income subgroup is less likely to engage in out-of-home activities during regular working hours. Instead, they are more likely to belong to Group 2 (i.e., going out during mid-day) and Group 5 (i.e., going out in the evening).

According to the CHAID analysis results presented in Fig. 5, gender only plays an important role in shaping travel patterns on the lower level of the tree. The subgroup that has significant gender gaps comprises people who are full-time employed, living with couples but without kids, not senior, not classified as low-income, and possess a bachelor's degree. However, we cannot conclude that gender effects are exclusively limited to this particular population subgroup. Instead, this finding suggests that gender exerts a relatively less dominant impact on travel behaviors when compared to other socio-demographic factors. Furthermore, this result also suggests that certain gender disparities in travel patterns may be the manifested outcome of intricate intersections between various social identities. Hence, solely comparing travel behaviors across gender groups may fail to comprehend the complex interactions of socio-demographic characteristics and how they can either magnify or mitigate gender differences.

To gain a deeper insight into how the interplay of gender with mixed identities shapes one's travel behaviors, we select *employment status* and *household type* that are identified as the most significant factors affecting travel behaviors (Fig. 5). These two factors, together with *gender*, are used to define intersectional groups and statistically compare the travel patterns of these intersectional groups. Although employment and household type have been widely used to define intersectional groups in gender studies, we derive these attributes from the data instead of selecting them based on domain knowledge.

Table 3 presents proportional differences in travel patterns (P1-P7) across intersectional groups compared to the entire population. The result is presented in 4 table blocks, organized by employment status (full-time, part-time, self-employed, not employed). Within each block,

Table 3
Intersectionality on weekdays: employment status, household type, gender.

Full-time Employed														
	Couple, no Kid							**Couple, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	−0.659	−0.284	0.559	0.414	−0.348	−0.272	–	−0.474	−0.215	0.632	–	−0.416	–	–
Men	−0.735	−0.282	0.563	0.460	−0.148	−0.339	–	−0.564	−0.239	0.659	–	−0.470	–	–
N-B	–	–	0.383	–	–	–	–	–	–	–	–	–	–	–
	Single, no Kid							**Single, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	−0.662	−0.297	0.392	0.641	–	–	–	−0.536	–	0.460	–	–	–	–
Men	−0.758	−0.346	0.440	0.531	–	–	0.303	−0.653	–	0.438	–	–	–	–
N-B	−0.581	–	0.512	–	–	–	–	–	–	–	–	–	–	–
Part-time Employed														
	Couple, no Kid							**Couple, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	0.349	0.881	−0.418	−0.324	–	–	–	0.663	0.773	−0.597	−0.487	–	–	–
Men	0.244	0.699	−0.394	−0.261	–	–	–	0.574	–	−0.453	–	1.584	–	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	Single, no Kid							**Single, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	0.298	0.674	−0.957	–	0.656	–	–	0.543	–	–	–	–	–	–
Men	–	0.764	−0.658	–	1.715	1.118	–	–	–	–	–	–	–	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Self-employed														
	Couple, no Kid							**Couple, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	0.987	0.493	−0.834	−0.510	0.887	–	–	1.786	–	−1.174	−0.716	–	–	–
Men	0.582	0.966	−0.800	−0.423	0.651	–	–	0.759	0.654	−0.869	0.522	–	–	0.600
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	Single, no Kid							**Single, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	0.792	–	−0.771	−0.381	–	–	–	–	–	–	–	–	–	–
Men	0.614	0.652	−0.904	−0.506	0.988	–	–	–	–	–	–	–	–	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Not Employed														
	Couple, no Kid							**Couple, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	1.648	0.491	−1.260	−0.873	0.289	–	–	2.061	–	−1.344	−1.006	–	–	−0.365
Men	1.714	0.423	−1.286	−0.968	0.413	–	–	1.856	–	–	–	–	–	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	Single, no Kid							**Single, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	1.499	0.367	−1.168	−0.753	–	–	–	1.990	–	–	–	–	–	–
Men	1.187	–	−1.123	−0.581	0.636	1.246	–	–	–	–	–	–	–	–
N-B	0.599	–	–	–	–	–	–	–	–	–	–	–	–	–

Notes: P1 – Home Day; P2 - Midday around noon; P3 - Regular working hours; P4 - Working hours & early night; P5 - Nighttime; P6 - Mostly OutHome (HH); P7 - Mostly OutHome (nHH).

there are 4 sub-blocks organized by household type (couple with kids, couple without kids, single with kids, single without kids). Within each sub-block, we show the difference in proportions in travel patterns (P1-P7) for women, men, and non-binary (N-B) gender groups.

Specifically, the value in each cell is calculated as the proportion (p_{ij}) of travel pattern j within the intersectional group i (defined by employment status, household type, and gender) subtracted from the proportion ($p_{\bullet j}$) of travel pattern j within the total population. Considering that the distribution of travel patterns is not equal, we standardize the value by $p_{\bullet j}(1-p_{\bullet j})$ so the values are comparable within and across table blocks. For example, in the full-time employment block, coupled women without kids have the number −0.659 on travel pattern P1. This indicates that this group has a proportion on P1 that is 0.659 standardized units lower than the proportion for all participations for P1. This suggests that full-time employed, coupled women without kids are less likely to stay at home all day (P1).

Moreover, we apply statistical tests as described in Equations (3)-(5) to examine whether the difference in proportion is statistically significant for a given confidence level. To simplify the table, we only include the result that the null hypothesis is rejected at the significance level of 0.05 based on the Z-score in Eq. (3). We can identify several gender differences from Table 3:

- Among full-time employees, all genders (women, men, and non-binary) exhibit similar travel patterns across various household types. For couples without kids, women (-0.348) are less likely to go out at night (P5) than men (-0.148). For single people without kids, non-binary people tend to go out during regular working hours (P3) and not stay at home all day (P1).
- Among part-time employees, coupled women with kids have a higher tendency to engage in trips during mid-day (P2) and are less likely to stay out late after regular working hours (P4). In contrast, men tend to go out at night (P5).
- Among self-employed people, women overall tend to stay at home (P1) compared to men. Especially for coupled women with kids, they are less inclined to stay out late after regular working hours (-0.716 in P4), while men behave conversely (0.522 in P4).

In summary, gender disparities are notable among part-time employees and self-employed individuals. Within these groups, women tend to be less likely to participate in after-work activities (P4) and nighttime trips (P5), particularly when they live with partners and kids.

We continue with the analysis for weekends and present the CHAID result in Fig. 6. We use Fig. 3 as the reference for behavior patterns on weekends. As shown in Fig. 6, age plays the most significant role in affecting travel patterns. Young people tend to spend less time at home (less likely in Group 1 and stay outside the entire day (Groups 5 to 7). Senior people mostly stayed at home (Group 1 and some of them went out in the afternoon (Group 3). For middle-aged people, the presence of kids is associated with more time staying at home (Group 1. In terms of gender, a notable difference emerges among single individuals without children, where women and non-binary individuals are more inclined to stay at home (Group 1 and less likely to engage in night (Group 4 or overnight activities (Groups 5 to 7) compared to men.

Similar to weekdays, we select age and household type based on Fig. 5 in addition to gender to define the intersectional groups. Table 4 shows the analysis results:

- Gender differences are not very significant among young people. Both women and men not living with kids are more likely to stay out overnight (P5-P7) compared to other age groups.
- Among middle-aged people, coupled women with kids are less likely to stay out overnight (P5-P7), while single men are more likely to do so.
- Among senior individuals, women who live only with their partners are less inclined to go out in the evening (P4) or stay out overnight (P5-P6).
- Furthermore, we do not observe significant differences for the non-binary gender group on both weekdays and weekends. This absence of statistical significance may be attributed to the relatively small sample sizes within intersectional subgroups for non-binary individuals. Given the inherently low percentage of non-binary individuals within the general population, our study data only includes a limited sample of 1.32 % non-binary participants. Therefore, future researchers interested in exploring research questions related to non-binary gender may find it necessary to design data collection processes that specifically aim to gather a more substantial number of non-binary participants.

6. Discussion and conclusion

6.1. Summary of key findings

This study investigates gender differences in travel behaviors from an intersectional perspective. Rather than treat trips separately from the everyday schedule, we account for the sequence and interrelationships of activities and trips and use the sequence alignment method (SAM) to extract distinct activity-travel patterns. To examine the gendered travel patterns, we apply the CHAID (Chi-square automatic interaction detection) method to reveal key socio-demographic attributes that interact with each other and create distinct travel patterns. We further select key attributes, informed by CHAID results, together with gender to perform statistical comparisons, which reveal how the interaction of gender with key attributes influences people's behavior patterns.

Using the Travel Behavior Inventory (TBI) data collected in Minnesota as a study case, we find some gendered travel patterns align with previous studies, such as women's higher likelihood to stay at home and travel during mid-day on weekdays compared to men (Fig. 4). Our SAM and CHAID analyses also provide some novel insights into the intersectional groups and their travel patterns.

First, since SAM accounts for sequences and timing of activities and trips, we identify some gender differences regarding temporal patterns. For instance, we find that men, especially men not living with couples or kids are more likely to stay out late at night after working hours (Group 4 in Fig. 2). In contrast, women are less likely to make trips during the evening or stay out overnight (Groups 5–7 in Fig. 2, Groups 4–7 in Fig. 3). Moreover, by distinguishing household-supporting (HH) tasks and non-household-supporting (nHH) tasks and assigning costs in SAM accordingly, we find some gender differences in household task sharing. For example, people of all genders working during regular hours tend to

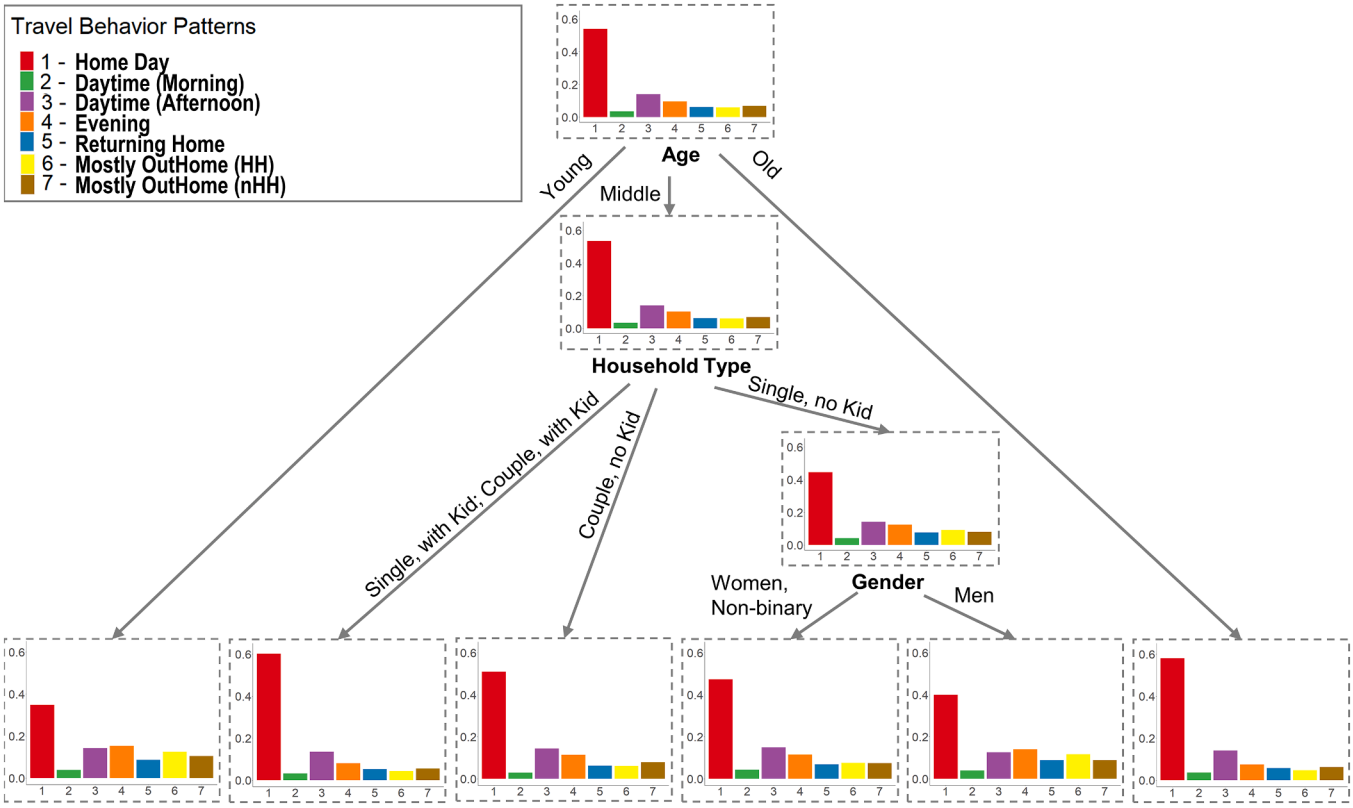

Fig. 6. CHAID Analysis Result: Weekends.

Table 4
Intersectionality on weekends: age, household type, gender.

Young: 18–24														
	Couple, no Kid							**Couple, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	−0.677	–	–	–	–	–	1.239	–	–	–	–	–	–	–
Men	−0.587	–	–	–	–	–	–	–	–	–	–	–	–	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	Single, no Kid							**Single, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	−0.826	–	–	0.664	0.649	1.148	–	–	–	–	–	–	–	–
Men	−0.805	–	–	1.172	–	1.064	0.715	–	–	–	–	–	–	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Middle: 25–54														
	Couple, no Kid							**Couple, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	–	–	–	0.225	–	–	–	0.301	–	–	–	−0.352	−0.430	−0.249
Men	−0.146	–	–	–	–	–	–	0.227	–	–	−0.194	–	−0.311	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	Single, no Kid							**Single, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	−0.279	–	–	0.238	–	0.320	–	–	–	–	–	–	–	–
Men	−0.562	–	–	0.506	0.475	1.023	0.313	–	–	–	–	–	–	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
Old: 55+														
	Couple, no Kid							**Couple, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	0.217	–	–	−0.227	−0.315	−0.415	–	–	–	–	–	–	–	–
Men	0.172	–	–	–	–	–	–	–	–	–	–	–	–	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–
	Single, no Kid							**Single, with Kid**						
	P1	P2	P3	P4	P5	P6	P7	P1	P2	P3	P4	P5	P6	P7
Women	–	–	–	−0.317	–	–	–	–	–	–	–	–	–	–
Men	–	–	–	−0.422	–	–	–	–	–	–	–	–	–	–
N-B	–	–	–	–	–	–	–	–	–	–	–	–	–	–

Notes: P1 – Home Day; P2 – Daytime (Morning); P3 – Daytime (Afternoon); P4 - Evening; P5 - Returning Home; P6 - Mostly OutHome (HH); P7 - Mostly OutHome (nHH).

conduct HH tasks on their way home using household cars (Group 3 in Fig. 2). Women are also more likely to go out during mid-day, and some of these trips are for HH tasks (Group 2 in Fig. 2).

Second, the CHAID results reveal new combinations of socioeconomic characteristics that are most associated with the identified behavior patterns. On weekdays, employment status, household type, and student status play the most significant role in shaping behavior patterns. On weekends, however, employment status no longer plays a key role. Instead, age, household type, and gender are most associated with distinct activity-travel patterns. Further, for both weekdays and weekends, gender difference is only observed as the most significant factor within a specific sub-group (Fig. 5). This suggests that gender disparities in activity-travel behavior patterns are the manifested outcome of intricate intersections between various social identities.

Third, the statistical comparisons of travel patterns among the intersectional groups lead to some new insights. For example, among part-time employed and self-employed individuals, coupled women with kids are less likely to engage in activities and trips after regular working hours on weekdays (P4). This suggests that women may lose their after-work personal time, likely due to childcare responsibilities. However, Tables 3 and 4 are already complex enough by considering three characteristics, so it is hard to compare more than three. So, we recommend that future researchers choose the most significant two factors based on CHAID results besides gender when conducting this statistical analysis to further examine gender differences.

6.2. Policy implications

The insights gained from our data analysis suggest the importance of capturing the complex, intersectional nature of gender and supporting continuous efforts and investments to advance gender equity in transportation. Specifically, this study brings several policy implications to researchers and policymakers in future research and practice:

- *Gender-Responsive Transportation Planning*: This study recognizes the travel needs considering sequences and timing of activities and trips in transportation planning, especially when addressing gender disparities. Policies should acknowledge that men and women may have distinct travel behaviors during different times of the day. Example practices based on the findings of this study include tailoring transportation solutions that accommodate late-night travel to address safety concerns for women and non-binary people. Implement flexible work policies to support women's work-life balance since women, especially those with kids, have less personal time after work due to household responsibilities. These action items can enhance overall transportation inclusivity.
- *Intersectional Approach for Inclusive Transportation*: To promote equitable transportation systems, policymakers should adopt an intersectional approach, recognizing that gender differences in travel patterns are intertwined with other socio-demographic characteristics. This study reveals the multifaceted nature of these disparities and highlights the interplay between factors such as employment status, household type, and age. Future transportation policies should consider these intersections to better serve diverse populations.
- *Customized Data Collection for In-Depth Analysis*: This study demonstrates the value of combining methods like sequence alignment, CHAID, and statistical comparison analysis. This approach provides a deeper understanding of how gender interacts with other identities to influence travel behaviors. Policymakers and researchers are encouraged to customize data collection to align with the specific

research interests of the study to yield in-depth insights about gender disparities to inform decision-making in transportation planning.

6.3. Future research directions

The current study can be extended in several directions. First, due to the small sample size of non-binary people, we do not get solid findings about activity-travel patterns for non-binary people. So, more and continuing efforts are needed to engage non-binary and other vulnerable population groups. Second, the cost matrix used in SAM considers three dimensions to distinguish (1) activities with trips, (2) public space with private space, and (3) household-supporting tasks with non-household-supporting tasks. Future studies can modify such a matrix given other specific research questions. For example, studies on gender differences in social interactions can include travel companionship as another dimension to define the cost matrix. In such cases, traveling alone, with families, and with others have different degrees of interactions during travel and therefore have a unit distance between each other. Third, in-depth qualitative surveys are needed to explain some of the discovered travel patterns of intersectional groups. For instance, we find that women with kids are less likely to have activities after working hours on weekdays, and we expect that this is largely due to their childcare responsibilities. Future studies can use such findings to design survey questions and directly ask whether and how the presence of kids may limit people's available time for activities outside of the home. Last, different travel patterns among genders may result in quite distinguished experiences and well-being outcomes. Future studies can collect data on user experiences and well-being status and investigate which travel patterns are most likely to lead to positive user experiences and well-being outcomes. The findings from these studies can further promote gender equity beyond travel needs by addressing people's subjective well-being and quality of life more comprehensively.

CRediT authorship contribution statement

Yaxuan Zhang: Methodology, Formal analysis, Visualization, Writing - original draft, review & editing. **Ying Song:** Conceptualization, Funding acquisiton, Data curation, Supervision, Writing - original draft, review & editing, Project administration.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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