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STATISTICAL MODELING AND SEQUENCE ANALYSIS OF DAILY ACTIVITY AND TRAVEL BEHAVIOR IN QATAR.

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STATISTICAL MODELING AND SEQUENCE ANALYSIS OF DAILY ACTIVITY AND TRAVEL BEHAVIOR IN QATAR.

A thesis submitted in partial satisfaction of the

requirements for the degree Masters of Geography

in Geography

by

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"*The views expressed in this article are those of the author and do not necessarily reflect the official policy or position of the Air Force, the Department of Defense or the U.S. Government.*"

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ABSTRACT

STATISTICAL MODELING AND SEQUENCE ANALYSIS OF DAILY ACTIVITY AND TRAVEL BEHAVIOR IN QATAR.

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Understanding daily rhythms of activity and travel behavior is fundamental for developing new generations of travel demand forecasting models. These models enable the design of transportation systems better customized to the needs of people living in a region or city. This thesis aims to understand daily activity and travel behavior of a previously unexplored country, Qatar. More specifically, the daily time allocation and travel behavior patterns within Qatar are explored. In addition, we investigate if there are differences in various nationalities and household types. Finally, findings from this thesis on Qatar are compared with published data from a Western country, the United States.

Qatar offers a unique opportunity to identify any behavioral differences in daily activity and travel among ethnic groups while accounting for differences among household types (households with children and households without children). Based on existing literature, households from any ethnicity with children travel more than households without, and we do not expect any deviation in Qatar. Daily patterns are studied using survey data of 30,708 household residents and 1,047 laborers collected in Qatar during 2018. Laborers are defined as single, working-age, male foreigners who reside temporarily in Qatar on labor

contracts. Household residents are immigrants or Qatari citizens living together with all members of their household, including family and non-family members. We applied sequence analysis jointly with cluster analysis for the laborers and the household residents to identify distinct travel behavior patterns. In addition, we used Multinomial Logit Regression (MNL) Models to study membership in different clusters of daily activity and travel patterns.

Results for the laborer data reflect four daily patterns, but a simple pattern of going to work, working, and returning home is the most prominent. On the other hand, the results for household residents consisted of seven distinct daily patterns. These seven patterns include a group of people who stay at home all day; two workdays (with discernible differences in a lunch break and participation in after-work activities); two discretionary days (occurring at different times throughout the day); a pattern of mixed activities; and a school day.

Cluster analysis reveals diverse schedules within Qatar and some apparent similarities with previously published patterns in the United States that used similar analytical techniques and data collection methods. Examples include commuting to and from work, which characterizes the morning movement from home to work locations and returning home in the afternoon. A key difference in the composition of the work week between the two countries is that Qatar’s work week begins on Sunday and ends on Thursday.

A more in-depth look at the household types provided insights into differences among nationalities and household structure in travel behavior. The household residents in Qatar originate from 137 different countries. The multivariate analysis of the household residents using MNL models shows similarities in daily patterns for people from Qatar, Sudan, and Egypt compared to people from the Philippines and India. In Qatar, households with children travel slightly more than households without children, except for School Days. In addition, a large portion of the overall Qatar survey respondents are stay-at-home persons who are more likely to be women, domestic employees, and older adults. Overall, similar travel behavior patterns were detected within Qatar and the United States, indicating that current Western transportation policies could be transferred to Qatar. Furthermore, findings from this thesis can inform future research that seeks to explore whether the travel behavior patterns are region-specific or unique to a specific cultural and social context.

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A. Research Questions

Understanding daily rhythms of activity and travel behavior is fundamental for developing new generations of travel demand forecasting models and studying heterogeneity across generations, social segments, space, and calendar time (Bhat & Koppelman, 1999; Axhausen et al., 2002; Kitamura et al., 2006; Bayarma et al., 2007; Habib & Miller, 2008; Auld & Mohammadian, 2009; Pinjari & Bhat, 2011). Identifying daily patterns of specific activities, such as eating and exercise, is important for health and disease prevention (Zarrinpar et al., 2016). In addition, it is important to discern how physical and mental health is impacted by activity fragmentation, which refers to breaking a day into smaller segments of activity and travel (Garaulet et al., 2017; Shi et al., 2023). Activity fragmentation is further supported by studies exploring the relationship between culturally and spiritually motivated activity rhythms and health risks related to circadian rhythms (BaHammam & Almeneessier, 2020; López et al., 2005).

A unique opportunity is presented in this thesis to use data from a multi-ethnic country in the Arabian Peninsula where its daily rhythm is influenced by its constitution (based on Shari'a law and Islam religion – https://www.gco.gov.qa/wp-content/uploads/2016/09/GCO-Constitution-English.pdf); and a population with the majority of residents being non-Qatari (approximately 2.4 million over the total of 2.7 million at the time of the data collection used here). The data used here are based on a place-based diary with similar methods used in the United States and the added advantage of in-person interviews using computer-aided (tablets) design for data verification.

The importance of looking at travel behavior in Qatar grows from the need to develop travel simulations among different nationalities and household types. Travel behavior serves to develop new generations of forecasting model systems. A research gap surrounds not just current patterns in the country but also in other countries of the Middle East. A large proportion of the population in Qatar are either migrant workers or longer-term immigrants supporting goods production and services. Studies determined that longer durations of stay by immigrants in the United States lead toward an assimilation of travel behavior; that is, the travel behavior of immigrants begins to resemble that of native-born Americans (Beckman & Goulias, 2008). Travel assimilation can include changing transportation modes from public to private, including but not limited to using a public bus to driving a personal car. Modeling human behavior can illustrate interactions between humans and the built environment (Goulias, 2018). The outcome of these analyses can then illustrate the observed behavior of individuals (Goulias, 2018), and a comprehensive assessment of interactions people have with their environments can be created for policy analysis (Goulias, 2000). As Goulias (2000) states, these are "but are not limited to, the use of time and its allocation to travel and activities, the use of time in a variety of time contexts and stages in the life of people, and the organization and use of space at any level of social organization, such as the individual, the household, the community, and other formal or informal groups." This thesis focuses more specifically on time allocation (how time is used towards travel and activities), which influences travel behavior.

Qatar is investigated because it is a predominantly Islamic country with a social structure much different than Western societies (instead of a secular constitution, they follow Sharia Law; See https://www.gco.gov.qa/wp-content/uploads/2016/09/GCO-Constitution-

English.pdf). It has been determined that life cycle stages and events can influence travel behavior (Zimmerman, 1982; Sharmeen et al., 2013). Although we observe similar life cycle stages in Qatar to the United States, such as children attending school, working part-time, having a full-time job, or being retired, we do not know if the daily activity and travel patterns are the same. In addition, in Qatar, family arrangements such as polygamy are practiced, and this may add more motivation to have different daily activity and travel patterns (Al-Ammari and Romanowski, 2016). Moreover, religious engagement has different regularities within a day, such as multiple prayer times throughout the day, and this may necessitate additional travel (Diop et al., 2018). From a geographic perspective, the cultural differences and differing demographics between Western countries and those of the Middle East are reflected in our everyday lives (Nagy, 2006). One of the cultural differences includes the Qatar work week, which begins on a Sunday and lasts until Thursday.

In this thesis, we use existing methods, which have been developed to recognize daily activity patterns and travel among distinct groups using respondent daily schedules. (McBride et al., 2019). These methods have been applied in diverse settings, including activity fragmentation, telecommuting, spatial clustering of patterns, gender role analysis, and subjective well-being (McBride et al., 2020a; McBride et al., 2020b; Goulias et al., 2020; Su et al., 2021a; Shi et al., 2022). Four key research questions to answer in this study are:

I. What are the daily time allocation and travel behavior patterns in Qatar?

II. Are there major differences among the variety of nationalities residing in Qatar?

III. What are some differences in daily behavior among different household types in Qatar?

IV. Do we find similarities and differences with published daily patterns in the United States?

B. Background

Qatar is located on the peninsula adjacent to the Persian Gulf. Islam is the official religion of Qatar. The country is known to be more culturally tolerant than surrounding Middle Eastern countries, with increasing access to education and continuing impacts of globalization (Al-Ammari and Romanowski, 2016). With a population of roughly 2.7 million, Qatar is only about 100 miles by 50 miles in total area. This relatively small country is divided into eight municipalities, and most of its population lives in urban areas, mainly Doha, the capital city. The population is dominated by immigrants who come to Qatar for work. The immigrant population is closer to 2.4 million, while the Qataris comprise the other 300,000. (Sharda et al., 2019). The sizeable foreign population creates a large majority of working-age males within the country, while women are only a third of the population.

The discovery of petroleum and natural gas in the region during the Second World War has catalyzed the wealth and prosperity the country has seen in recent years. Prior to this, fishing and trade were significant drivers of the economy. Natural gas reserves have been a large portion of the country's economic prowess as they generate competitive revenue compared to their oil fields. Globalization has presented modern values to this more traditionally Islamic country, resulting in a spread of culture and information (Al-Ammari and Romanowski, 2016). The evolution of Qatar as a country shows its unique situation within the Middle East, making an exciting setting of comparison with the United States.

Travel behavior assimilation (i.e., motorization and use of owned private cars for travel) after extended stays in the United States is far more common than in Qatar (Beckman

& Goulias, 2008; Nagy, 2006). Understanding the travel behavior of immigrants in the United States is limited in published literature, even with their large populations (Blumenberg, 2013). Data analysis shows that six factors, including "individual and household characteristics, the process of spatial assimilation, access to ethnic-specific resources, ethnic employment patterns, cultural differences, and government regulations" influence immigrant travel behavior (Blumenberg, 2013). Qatar's desire to keep its residents only of historic Qatar birth has created friction for any possible assimilation of other immigrants (Nagy, 2006). This desire, in contrast to the United States, limits the vertical movement in the status of a foreign individual in Qatar over time. Immigrants in the United States are more likely than native-born to use transportation alternatives to private cars, including carpooling and public transportation (Blumenberg, 2013). A key finding from Blumenberg's study found an assimilation of transportation patterns to native-born Americans among immigrants after longer durations spent in the United States (Blumenberg, 2013), and these assimilation patterns are different among different ethnic groups (Beckman & Goulias, 2008). In this thesis, we explore ethnicity and similar daily patterns among certain immigrants and Qatari citizens (see Chapter V). Based on the barriers to assimilating, we would expect to see more public transportation usage among immigrants.

When examining published literature, immigration to Qatar is heavily influenced by labor contracts (Nagy, 2006). This reason, along with Qatari's loyalty to their nationality, makes obtaining citizenship highly unlikely (Nagy, 2006; Soudy, 2013). It also shows the likely work-related travel patterns among laborers in Qatar. In Western societies, the percentage of the foreign labor force is much lower. Only 8-10 percent of the labor force is foreign in these countries, whereas Qatar uses most of its foreign population for labor (Nagy, 2006). With a lack of procedural naturalization, foreign workers who stay in Qatar for long periods gain the status of perpetual workers (Nagy, 2006). Foreign workers who apply for residence visas can be filed by their Qatari sponsor or employer. In many cases, these supervisors control the worker's status in the country and can dictate their daily lives (Nagy, 2006). The immigration system of Qatar reinforces the existing hierarchy between foreign residents and Qatari nationals. The pay scale for most jobs can be dictated by the nationality of the foreign worker (Nagy, 2006). Labor recruiters offer jobs to foreigners that pay similar to their homes with added tax exemption benefits and employee-provided housing (Nagy, 2006). Immigration to Qatar is primarily driven by better economic opportunities (Nagy, 2006). These differences in immigration outcomes and assimilation processes between Qatar and Western countries will impact travel behavior patterns. This focus on immigrant labor in Qatar suggests that the travel behavior will reflect work-related patterns the most due to the nature of their social status. Although all immigrants are subject to the barriers of assimilation, laborers have less personal autonomy and will have more constrained schedules (i.e., going to work and returning home). This thesis fills a gap in a holistic representation of daily time allocation and travel patterns for a non-traditional Western country. The methods used here provide a basis for current travel behavior and a groundwork for temporal comparisons in the future. This approach also distinguishes among different types of immigrants, foreign residents versus laborers, and household types in travel behavior.

Many factors (Table 5) observed in the survey may impact travel behavior in Qatar. Studies conducted on Islamic communities found that religion and gender motivate travel behavior, concluding that women tend to travel less than men (Elias et al., 2008; Shakona et al., 2015). In these communities, women are more likely to stay at home and, when traveling, walk instead of driving a personal vehicle (Elias et al., 2008). Women are more likely to travel by car as passengers, whereas men tend to drive in Islamic communities (Elias et al., 2015). A study conducted in the United States concluded that women travel shorter commute distances and are likelier to drive automobiles, regardless of ethnicity (Hu, 2021). Older Americans tend to travel less, taking fewer trips over shorter distances (Collia et al., 2003). With children going to school and parents going to work, we should see more travel among younger and middle-aged people in Qatar. Higher levels of education (bachelor's degree or higher) are associated with more vehicle miles traveled throughout the United States (Polzin et al., 2014). Lower to middle-income groups favor non-motorized transportation due to associated cost and trip distance throughout the MENA (Middle East and North Africa) region (Andraos et al., 2021).

The presence of children in a household and their ages influence the travel behavior of the parents (Zwerts et al., 2007). Households with children often spend more time traveling, and households with younger children (under 14) make more trips per day than other household types (McBride et al., 2020a; Zwerts et al., 2007). Furthermore, women are more likely to make more child-serving trips than men in the United States (Elias et al., 2015). Attendance in educational systems requires the movement of children from home to school locations. This movement creates more complex daily travel patterns for parents in the United States (McBride et al., 2020b). A complex daily schedule contains more trips and often participation in more activities (McBride et al., 2020b). In contrast, an example of a simple pattern would resemble commuting to work, working, and then returning home. The Qatar data shows an average of 3.28 people per household, while the United States average is 2.60 people per household (United States Census Bureau 2017-2021 data). With these larger household sizes, we expect similar results in Qatar, as the inclusion of more people per household should increase overall travel and participation in activities.

II. Qatar Data Used

A. Data Collection Methods

The 2018 survey data collection for Qatar was based on collection methods used in the California Household Travel Survey (CHTS) that gathered data to support travel demand forecasting, such as the "simulator of activities, Greenhouse emissions, Networks, and Travel (SimAGENT)" (Goulias et al., 2019). This data collection method was modified to become contextually relevant for Qatar and provide data for the behavioral models in the Qatar Activity Based Model (QABM) and named the Activity Based Household Interview Survey (ABHHI) and the Activity Based Laborer Interview Survey (ABLI). The survey was conducted on laborers (working age, male, foreigners who reside in Qatar) and household members (all members within a household not considered laborers). The survey sample was designed as a stratified sample (Xiang et al., 2019) and was not nationally representative. However, the lack of accurate census data at the fine geographic level created an increase in interviews undertaken to represent Qatar properly (Xiang et al., 2019). Each of the eight municipalities of Qatar was accounted for in the survey by collecting added samples from the lower population municipalities. Still, most recruited survey respondents were from the capital city, Doha. Out of the 33,000 households contacted, the survey team had a success rate of 61.7%, excluding households where no contact was made (Xiang et al., 2019). A stratified random sampling method was required to sample difficult-to-reach population areas (Xiang et al., 2019). This sampling method resulted in over-sampling and an error reduction (Xiang et al., 2019). The report concludes that their findings "achieved considerable success with an acceptable degree of confidence, which provides a solid data foundation for the development of Qatar Activity Based Model" (Xiang et al., 2019). For the QABM, a synthetic population and sample and expansion weights were derived from multiple levels of population data to represent the Qatar population. The synthetic population is a recreation of the person-by-person and household-by-household population data that are used in forecasting models for future Qatari populations (Goulias et al., 2019). It was also required due in part to the absence of accurate and available census data at an acceptable spatial resolution needed for transportation models. Compared to the synthetic population, the final survey sample overrepresents some ethnic groups while underrepresenting others. However, other key characteristics, such as age, are accurately represented (Xiang et al., 2019), and no sample weights are used in the analysis here, as explained later.

A significant component of these surveys is in-person interviews conducted in 2018 using tablets with software that can verify the respondent's answers and, more precisely, identify locations visited supplemented by internal consistency checks for the timing of reported activities at places. The Qatar surveys (ABHHI and ABLI, referred to as Qatar survey herein) are place-based one-day diary that records the activity at each location and the arrival and departure modes from each place together with times visited that day. Collecting data from each recruited household (i.e., a group of people living together) was the survey's aim. Recruited households are random households selected for the Qatar survey. The diary reporting day starts at 3:00 a.m. on the assigned day for the interview day and extends to 3:00 a.m. the next day. The in-person survey conducted by trained interviewers with a tablet and a specifically designed interface to collect the data, plus the presence of officials at the interview location (usually the residence of respondents), is a significant difference from other similar surveys in the United States such as the California Household Travel Survey (CHTS) and the National Household Travel Survey (NHTS). Figure 1 shows one of the software interfaces.

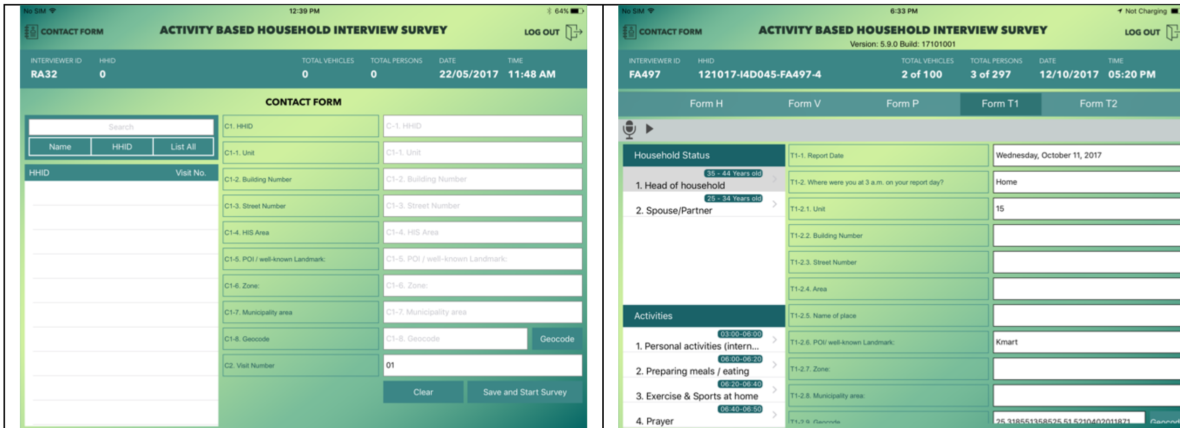


Figure 1 Tablet Software for the Qatar Survey

Table 1: Data Naming Example

Location	Data Type	Group Surveyed	Date
qt = Qatar	**p** = Person	**h** =Household Residents	**Oct18** = October 2018
	h = Household		
	t1/2 = Travel	**l** =Laborers	
	t1a/2a = Activity		

Table 2: Dataset Description

<table>
<tr><th>Type of Data</th><th>Data Files</th><th>Explanation of Data</th></tr>
<tr><td>Household</td><td>qt_p_h_Oct18.rds</td><td rowspan="2">Descriptive Characteristics of individual persons Including:
• HHID (Unique Household Identification)
• Person ID
• Relation status (head of household)
• Nationality
• Age
• Gender
• Main Occupation
• Monthly Income
• As driver (Primarily a driver)
• As passenger (Primarily a passenger)
• Household car (Type and year of vehicle)
• Highest education level attained.
• Report day of week</td></tr>
<tr><td>Laborer</td><td>qt_p_l_Oct18.rds</td></tr>
<tr><td>Household</td><td>qt_h_h_Oct18.rds</td><td rowspan="2">Descriptive Characteristics of households including:
• HHID
• Property Type
• Monthly Income</td></tr>
<tr><td>Laborer</td><td>qt_h_l_Oct18.rds</td></tr>
<tr><td>Household</td><td>qt_t1_h_Oct18.rds
qt_t2_h_Oct18.rds</td><td rowspan="2">Travel Descriptions Including:
• HHID
• PersonID
• Travel ID (Number of trips on report day)
• Start and End times for trips
• Report DOW</td></tr>
<tr><td>Laborer</td><td>qt_t1_l_Oct18.rds
qt_t2_l_Oct18.rds</td></tr>
<tr><td>Household</td><td>qt_t1a_h_Oct18.rds
qt_t2a_h_Oct18.rds</td><td rowspan="2">Activity Descriptions Including:
• HHID
• PersonID
• TravelID
• Activity ID (Number of activities on report day)
• Activity Type
• Start and End Time</td></tr>
<tr><td>Laborer</td><td>qt_t1a_l_Oct18.rds
qt_t2a_l_Oct18.rds</td></tr>
</table>

B. Data Assembly:

After familiarization with the data, a complete record of events (Figure 2) is necessary to start forming the sequential activity and travel pattern for each participating respondent for each person in the two groups surveyed. The first step was creating a “unique ID” that is attached to each record while continuing to maintain the IDs of their household.

This ID allows the same people to match up when joining different data sets. A new, empty data frame is created to combine all the necessary previous data. The total number of household residents and laborer respondents is 30,708 and 1,047, respectively. Of these, only 19,445 household members and 993 laborers traveled on their reporting day. Household members are synonymous with residents throughout this thesis. After data cleaning, 19,444 household residents and 992 laborers were kept for sequence analysis. The excluded two persons had missing data that could not be recovered. The start and stop times for both activities and trips were determined using the travel and activity forms. These were then placed in sequential order, unique to each traveler.

Figure 2: Example R Data Frame Sequence of a Traveler

TUCASEID	travel_id	starttime	stoptime	States
010318-14Q066-FA066-44-3	1	180	405	H_PersonalAct
010318-14Q066-FA066-44-3	2	405	420	T_School
010318-14Q066-FA066-44-3	3	420	540	NH_InClass
010318-14Q066-FA066-44-3	4	540	600	NH_Eating
010318-14Q066-FA066-44-3	5	600	675	NH_InClass
010318-14Q066-FA066-44-3	6	675	720	T_Home
010318-14Q066-FA066-44-3	7	720	840	H_Eating
010318-14Q066-FA066-44-3	8	840	960	H_Study
010318-14Q066-FA066-44-3	9	960	1140	H_PersonalAct
010318-14Q066-FA066-44-3	10	1140	1200	H_Eating
010318-14Q066-FA066-44-3	11	1200	1619	H_PersonalAct

C. Methodology

Reading these files in R resulted in several different raw data frames created to better group together characteristics. Each contains the alphanumeric sample unit identification that is different for each household (and person within a household) and each laborer. Laborers are, in essence, single persons not considered to be living in households in Qatar even when they share the same housing unit. When needed, data from one database, such as places visited and activities, are combined, and new variables are computed in R. The travel and activity files contain only those who made more than one trip on their report date. Each file is named to address the data in a more condensed fashion. The basic file naming (ex. "qt_p_h_Oct18.rds") reflects the longer format of (Location-Data Type-Group Surveyed-Date.rds) as shown in Table 1. An inventory of the files used in this thesis is provided in Table 2.

The objective is to create sequences that will allow the representation of daily travel behavior and activity allocation in Qatar. Behavioral factors that will play a role in the sequence analysis include the number of trips taken, duration of trips, travel mode, and activity types. In this thesis, a profile that contains 1440 minutes in a day is needed to describe a person's daily pattern. Each minute represents a specific state that an individual is in as described by their travel diary following the procedures created in GeoTrans (McBride et al., 2019; Goulias et al., 2020; McBride et al., 2020a; Su et al., 2021b). The next step creates the sequential ordering of the duration during each activity. This step includes running a "for loop" through each of the "unique IDs," storing them in a temporary data frame, and from the original trip and activity data, the "place" value and "arrive mins" are added to the new data frame. This step takes the original activity each respondent starts their day with at 03:00 (180 mins) and puts their unique schedule into order with each activity and sequential time listed until the end of the day at 23:59 (1619 mins). Trips can be defined as a "continuous sequence of stages between two activities" up to this point (Axhausen, 2007). Activities are "a continuous interaction with the physical environment, a service or person, within the same socio-spatial environment, which is relevant to the sample/observation unit.

It includes any pure waiting (idle) times before or during the activity" (Axhausen, 2007). Trips and activities are now grouped and renamed "states." The other meaningful columns "unique id," "arrive mins," and "leave mins" are renamed to reflect the start and stop times while keeping the individual Id's connected to each person.

D: Data Cleaning and Activity Episodes:

Some survey responses are long and repetitive. Renaming and grouping responses is more effective for modeling and analysis. An example is shown in Table 3 below as variations of studying and exercise are condensed. The state represents the activity being conducted, while frequency shows the number of instances that state occurred in the minute-by-minute data.

Table 3: Renaming States Example

State	Freq
Home Sports & Exercise (sports, jogging, bicycling, gym)	19
Exercise & Sports at home	699
Study / schoolwork	2926
Study / schoolwork Personal activities (internet, sleeping, personal care, leisure, watch TV, housework etc.)	1
Home Study / schoolwork	4
Home In school / classroom / lectures	9

→

State	Freq
H_Exercise	718
H_Study	2940

The state names were condensed into four main categories. Those that start with (H_...) indicate states where participation is done at home. Those with (NH_...) are states that are accomplished away from the home. These would include shopping or working. Starting with (T_...) indicates travel of any mode or duration and includes picking up or dropping off passengers. Lastly, "Other" represents all other unspecified states as selected in the survey by respondents. The revised state names fall from 110 to 29 for the household residents and 41 to 12 for the laborers. These become the number of states used in analysis later and can be viewed in Table 4 below. The problem with too many states is the difficulty of viewing when examining the sequence analysis representation later. With the removal of incorrect start times and missing data, the data combining step has been completed, and the results are shown in Table 4. The trips taken by respondents show the most frequent options included in the survey. The modes by which respondents traveled are shown in Table 7. These remain unchanged from the original survey. Not home working (i.e., working at a place outside the home), traveling home, and personal activities conducted at home rank among the most popular states from the main categories within the survey.

Table 4: Household Residents and Laborer States

Household Resident

State	Freq
H_Eating	21258
H_Entertainment	1178
H_Exercise	700
H_HostingVisitors	445
H_PersonalAct	57465
H_Prayer	10
H_ShoppingO	294
H_SocialVisits	6
H_Study	2914
H_Working	290
NH_ChangeMode	109
NH_Cruising	260
NH_Eating	5642
NH_Exercise	1110
NH_HealthCare	503
NH_InClass	6048
NH_PersonalBusiness	508
NH_Prayer	2115
NH_Shopping	3650
NH_SocialVisits	2158
NH_Working	13373
Other	520
T_Home	25912
T_Mosque	1415
T_Other	14614
T_PickupDropoff	4003
T_RetailMall	3078
T_School	4792
T_Work	9944
<NA>	0
Total	184314

Laborer

State	Freq
H_Eating	1107
H_Other	52
H_PersonalAct	1765
NH_AllOther	48
NH_ChangeMode	16
NH_Eating	384
NH_Shopping	75
NH_Working	1392
T_AllOther	412
T_Home	1061
T_PickupDropoff	148
T_Work	982
<NA>	0
Total	7442

E: Summary of Tables and Descriptive Sample Characteristics

Although previewed in Table 2, a more in-depth view of the person characteristics used for analysis can be found in Table 5. Since both household residents and laborers were given identical surveys, the possible response answers are the same for each.

Table 5: Descriptive Statistics of the Household Members in ABHHI

Variable	Definition	Subgroup	Household Residents (n = 30708)	Laborer (n = 1047)
Age	Respondent Age Group	0 – 4 Years Old	12.07%	N/A
		5 - 11 Years Old	12.61%	N/A
		12 – 15 Years Old	5.67%	N/A
		16 – 18 Years Old	3.23%	N/A
		19 - 24 Years Old	5.71%	15.47%
		25 - 34 Years Old	24.13%	44.32%
		35 - 44 Years Old	20.85%	27.70%
		45 - 54 Years Old	10.54%	10.51%
		55 - 64 Years Old	4.17%	1.81%
		65 - 74 Years Old	0.80%	0.19%
		75 + Years Old	0.22%	N/A
Sex	Respondent's Sex: Male or Female	Male	53.33%	100%
Monthly Income	Respondent's Monthly income	No Income	0.02%	N/A
		Less than or equal to QAR 1,000/month	0.90%	33.72%
		QAR 1,001 - 3,000/month	6.64%	61.32%
		QAR 3,001 - 6,000/month	5.90%	2.87%
		QAR 6,001 - 10,000/month	8.98%	0.48%
		QAR 10,001 - 15,000/month	7.50%	0.19%
		QAR 15,001 - 20000/month	4.56%	N/A
		QAR 20,001 - 35,000/month	4.35%	N/A
		QAR 35,001 - 50,000/month	1.68%	N/A
		QAR 50,001 - 75,000/month	0.69%	N/A
		QAR 75,001 - 100,000/month	0.16%	N/A
		More than QAR 100,000/month	0.12	N/A
		Confidential	2.21%	0.19%
		N/A	56.28%	N/A

Table 5: Descriptive Statistics of the Household Members in ABHHI (Cont.)

Variable	Definition	Subgroup	Household Residents (n = 30708)	Laborer (n = 1047)
As Driver	**Respondent's Status as Driver**	Always	33.06%	10.60%
		Never	61.26%	89.21%
		Sometime	3.49%	0.19%
		N/A	2.19%	N/A
As Passenger	**Respondent's Status as Passenger**	Always	49.89%	69.15%
		Never	25.97%	17.86%
		Sometime	22.95%	12.99%
		N/A	2.19%	N/A
Educational Attainment	**Respondent's Educational Attainment**	Doctorate (Ph.D)	0.65%	N/A
		Masters Degree (MSc/MA)	6.28%	1.0%
		Graduate (BA/BS/Other)	30.17%	7.64%
		High School	12.57%	33.32%
		Secondary	2.30%	37.35%
		Primary	1.45%	14.14%
		Nursery	2.09%	6.11%
		Other	9.40%	0.96%
		N/A	35.10%	0.19%
Main Occupation	**Respondent's Job Category**	Full-time employed	43.01%	99.81%
		Full-time student	24.85%	N/A
		Full-time student and Part-time work	0.03%	N/A
		Full-time work and Part time student	0.04%	N/A
		Part-time employed (< 5 hours/day)	0.39%	N/A
		Part-time work and Part time student	0.02%	N/A
		Part-time student	0.19%	N/A
		Self Employed	0.23%	N/A
		House person	29.32%	0.10%
		Retired	1.0%	N/A
		Looking for Job	0.77%	0.10%
		Disabled/Sick	0.06%	N/A
		Other	0.09%	N/A

Table 5: Descriptive Statistics of the Household Members in ABHHI (Cont.)

Variable	Definition	Subgroup	Household Residents (n = 30708)	Laborer (n = 1047)
Report Day of the Week	**Respondent's Day Recorded**	Monday	14.11%	11.46%
		Tuesday	15.50%	20.63%
		Wednesday	13.70%	16.52%
		Thursday	10.42%	11.75%
		Friday	12.52%	12.42%
		Saturday	4.67%	1.43%
		Sunday	16.99%	25.79%
		N/A	12.08%	N/A
Nationality	**Most Frequent Respondents' Nationalities**	Qatar	14.05%	0%
		India	29.22%	39.733%
		Egypt	11.32%	0.478%
		Philippines	9.73%	8.405%
		Sudan	4.37%	0%

Household Residents

The household residents in this survey detail a composition of 137 countries spanning from Afghanistan to Zimbabwe. These countries reflect the population composition of Qatar, with over 2.4 of their 2.7 million people coming from many foreign nations. As Xiang et al. (2019) showed, the survey is inconsistent regarding nationality composition with the synthetic population. The descriptive statistics show a heavy concentration in middle-aged groups of 25 to 54 years old, with just over half of the respondents being male. Nearly a quarter of all respondents are full-time students. All respondents within a household are recorded, including younger children, with answers provided by their parents.

Laborers

Laborers are a unique group of people consisting of single, working-age males who have immigrated to Qatar on a temporary worker status. The descriptive statistics for laborer data have fewer non-applicable responses than household residents. Males of working age represent the entirety of the laborer data. They are exclusively foreign to Qatar and mostly come from nearby countries such as India (29.22%), Egypt (11.32%), and the Philippines (9.73%). Laborers are the reflection of recruited blue-collar workers focusing on construction (the survey year predates the construction and completion of major facilities to host an international sports event and the completion of the Doha subway). The patterns derived later (clusters) will detail the longer working conditions that laborers endure compared to household residents. The monthly income in Table 4 gives the first glimpse into the disparity between the household residents and laborers. The survey provides income using the national currency, Qatari Riyal. Roughly 3,641 Qatari Riyal equates to $1,000 USD at the current exchange. Most Laborers make less than the United States equivalent of $1,000 a month, whereas most household members (residents) make well over double that amount. Lower education levels are common among the laborers versus their counterparts, with the majority attaining secondary and high school levels of class.

F: Time Allocation of Activities

Table 6 below describes the average state duration by type of state. These durations were first computed for the total 19,444 travelers (persons that made at least one trip on the interview day) from the household resident data set. The calculated mean, standard deviation, and median are purposeful in determining the skewness of an observed state. For instance, in

Table 6, home working (H_Working) has a mean duration of 4.23 hours and a median of 3.98 hours, indicating right skewness and probable outliers among the respondents. These numbers can be verified by observing the standard deviation of 4.18 hours, indicating more dispersion among the survey answers. When computing the same duration for people employed full-time, the mean and median durations of H_Working are 4.61 hours and 2.67 hours, respectively.

These statistics will become more prominent in explaining the grouping done later. The travel mode and duration by which all respondents traveled are recorded in Table 6. The episodes defined here are for each instance of a trip. The episodes mean one person could have several repeated episodes using one mode of transportation or a mix throughout the day depending on how they traveled (i.e., company bus for work and car driver for other activities of the day). Nearly 50% of travelers are drivers of personal vehicles, the highest percentage in Qatar. Passengers follow farther behind at the second-highest percentage of 16%. The low percentage of non-motor transportation (i.e., walking or biking) illustrates the vehicle-dominated city of Doha and the weather, which limits non-motor transportation. Those using a personal vehicle have a trip average of 31 minutes, whereas passengers on a school bus have a trip average of 39 minutes. These durations describe a city where most people live further from their jobs and school. Another transportation mode that is less frequent in this dataset is the use of public ride-hailing as the taxi service, public bus, public transit, and Uber/Careem (Careem is a taxi service similar to Uber in Doha) only make up just over 1% of the data.

Table 6: Overall Average State Duration by State

	States	Episodes	Percent	Average Duration (Hours)	Standard Deviation (Hours)	Median (Hours)
1	**H_Eating**	21258	11.53	1.22	1.45	1.00
2	**H_Entertainment**	1178	0.64	2.69	1.94	2.17
3	**H_Exercise**	700	0.38	1.46	0.98	1.00
4	**H_HostingVisitors**	445	0.24	2.54	1.93	2.00
5	**H_PersonalAct**	57465	31.18	4.65	3.39	3.98
6	**H_Prayer**	10	0.01	0.72	0.4	0.62
7	**H_ShoppingO**	294	0.16	1.55	0.82	1.00
8	**H_SocialVisits**	6	0	1.51	0.69	1.92
9	**H_Study**	2914	1.58	2.35	1.57	2.00
10	**H_Working**	290	0.16	4.23	4.18	2.79
11	**NH_ChangeMode**	109	0.06	0.21	0.37	0.08
12	**NH_Cruising**	260	0.14	2.2	2.40	1.50
13	**NH_Eating**	5642	3.06	1.02	0.94	1.00
14	**NH_Exercise**	1110	0.6	1.87	1.39	1.50
15	**NH_HealthCare**	503	0.27	1.80	2.06	1.25
16	**NH_InClass**	6048	3.28	5.00	2.23	6.00
17	**NH_PersonalBusiness**	508	0.28	0.92	1.45	0.48
18	**NH_Prayer**	2115	1.15	0.97	1.21	0.58
19	**NH_Shopping**	3650	1.98	1.52	1.23	1.17
20	**NH_SocialVisits**	2158	1.17	2.87	2.28	2.33
21	**NH_Working**	13373	7.26	5.52	3.04	5.00
22	**Other**	520	0.28	2.54	3.81	0.75
23	**T_Home**	25912	14.06	0.51	0.43	0.50
24	**T_Mosque**	1415	0.77	0.14	0.33	0.08
25	**T_Other**	14614	7.93	0.64	1.21	0.42
26	**T_PickupDropoff**	4003	2.17	0.24	0.78	0.08
27	**T_RetailMall**	3078	1.67	0.5	0.97	0.33
28	**T_School**	4792	2.6	0.61	0.42	0.50
29	**T_Work**	9944	5.4	0.54	0.52	0.50

Table 7: Average Trip Duration by Mode

	Transportation Mode to Occupation	Episodes	Percent	Average Duration (Mins)	Standard Deviation (Mins)	Median (Mins)
1	**Bike**	68	0.11	31.06	76.36	17.5
2	**Car / Van / Truck Driver**	31228	48.98	30.49	41.91	25.0
3	**Car / Van / Truck Passenger**	10254	16.08	31.90	41.59	30.0
4	**Company Bus**	2216	3.48	38.52	39.96	30.0
5	**Karwa Taxi**	549	0.86	33.74	57.21	29.0
6	**Motorcycle / Scooter / Moped**	12	0.02	30.83	22.04	25.0
7	**Other**	104	0.16	31.95	32.06	24.5
8	**Other Non-Motorized (skateboard, etc.)**	14	0.02	27.14	15.78	20.0
9	**Other Private Transit**	543	0.85	36.95	44.68	30.0
10	**Private Vehicle**	4	0.01	35.00	28.68	39.0
11	**Private Shuttle (employer, hotel, etc.)**	1253	1.97	33.00	28.52	30.0
12	**Public Bus**	140	0.22	45.71	43.95	30.0
13	**Public Transit Shuttle (airport shuttle etc.)**	29	0.05	59.83	62.10	40.0
14	**Rental Vehicle**	453	0.71	29.47	23.40	30.0
15	**School Bus**	6748	10.58	38.68	36.03	30.0
16	**Uber/Careem**	577	0.90	26.06	26.35	20.0
17	**Undisclosed Transport**	8017	12.57	30.41	66.30	20.0
18	**Walk**	1546	2.42	20.55	46.46	10.0
19	**Wheelchair / Mobility Scooter**	3	0.00	10.00	8.66	5.0

III. Daily Activity Patterns:

A. Methods for Sequences

Sequence analysis offers a way to compare different travel behaviors among population segments in the same country (aka Qatar) and other countries for which similar data are available (McBride, 2020a). The first step after data cleaning is sequence analysis and daily time allocation cluster identification and visualization. The method is called sequence alignment, in which one first identifies different types of activities and travel in a daily schedule. Then, it compares the sequence of activities and travel to all other respondents. Then, a score of dissimilarity is assigned among all the sequences. Finally, using these dissimilarities, groupings are created using any appropriate clustering method, as explained later. Sequence analysis was selected based on its successful usage in similar studies (McBride, 2020a). Sequence analysis is the preferable method since it can jointly include the activities, trips, durations, and their order into a condensed pattern for analysis (McBride, 2020a). The method uses TraMineR, a package "for mining, describing and visualizing sequences of states or events, and more generally discrete sequence data" (Gabadinho et al., 2009). Next, a minute-by-minute character string is created that will allow the start time and stop time to be further divided for analysis. Sequences are created with the time axis of 180-1619 mins. A more detailed look at sequences is shown below in Table 8, with two examples.

Table 8: Examples of Sequences

Person	(State, Duration in Mins)	Pattern
Household Resident	(Personal Activities, 225)…(Trip to School, 15) …(In Class, 120)…(Eating, 60)…(In Class, 75)…(Trip to Home, 35)…(Eating, 120)…(Studying, 120)…(Personal Activities, 180)…(Eating, 60)…(Personal Activities, 419)	(H_PersonAct)…(T_School)…(NH_Inclass)…(NH_Eating)…(NH_InClass)…(T_Home)…(H_Eating) …(H_Study)…(H_PersonalAct)…(H_Eating)…(H_PersonalAct)
Laborer	(Trip to work, 210)…(Working, 330)…(Eating, 30)…(Working, 300)…(Trip to home, 60)…(Eating, 30)…(Personal Activities, 509)	(T_Work)…(NH_Working)…(NH_Eating)…(NH_Working)…(T_Home)…(H_Eating)…(H_PersonAct)

We identify missing data by creating the substitution cost matrix and dissimilarity matrix and remove such missing data from the analysis. The "alphabet" is then run to specify states and limit unassigned or missing states. In this case, it reflects the state names listed in Table 3.

Two sequences can be made identical by using the Hamming distance, which is defined as the minimum number of substitutions (substitution cost) required to make them the same (Hamming, 1950; Su et al., 2021b). Hamming distance is most useful for sequences of equal lengths, whereas optimal matching could be used for unequal sequences (Gabadinho et al., 2011). The Hamming distance is then used to create the dissimilarity matrix comprised of dissimilarity scores (Bookstein et al., 2002; Hamming, 1950; Su et al., 2021b). These dissimilarity scores for every sequence form a dissimilarity matrix (Table 9). Substitution cost enables the computation of dissimilarity scores. Su et al. (2021b) best summarize Gabadinho et al. (2011) substitution cost as,

"*EQ 1:* $SC\ Sp,Sq = 2 - P\ Sp|Sq - P(Sq|Sp)$

*where SC(Sp , Sq) is the substitution cost between states Sp and Sq with a value between 0 and 2; P(Sp |Sq), the transition rate from state Sq to state Sp, is the probability of observing state Sp at time t + 1 given that state Sq has been observed at time t. If the transition rate from state Sq to state Sp has a value close to 1, it means that a person in a given state Sq at time t has a great probability to transition to state Sp at time t + 1. Notice that P(Sp |Sq)is not equal to P(Sq |Sp). The idea is to set a high cost when changes between Sp and Sq are not observed often and lower cost when they are frequent" (*Su *et al., 2021b).*

The resulting dissimilarity matrix reflects the number of states represented, in the case of laborers 12. A sample of 10 sequences was extracted from the laborer data to show a computation of the matrix and the dissimilarity scores in Table 9. The diagonal zeros are because the dissimilarity between a sequence and itself is zero. Similar patterns only have a difference of a few hundred points, while values in the thousands represent a considerable cost necessary to change the sequence. In the example shown below (Table 9) the unique ID 080418-I4D029-FA027-11-L-1 (Row 1) has a similar sequence to 177080418-I4D029-FA027-8-L-1 (Column 6) with a substitution cost of only 177.16 but a largely different sequence than 177080418-I4D029-FA027-7-L-1 with a dissimilarity value of 2158.95 (Column 5).

Table 9: Dissimilarity Matrix Example

	080418-I4D029-FA027-11-L-1	**080418-I4D029-FA027-12-L-1**	**080418-I4D029-FA027-4-L-1**	**080418-I4D029-FA027-5-L-1**	**080418-I4D029-FA027-7-L-1**	**080418-I4D029-FA027-8-L-1**	**080418-I4D029-FA027-9-L-1**	**080418-I4D036-FA005-10-L-1**	**080418-I4D036-FA005-3-L-1**	**080418-I4D036-FA005-4-L-1**
080418-I4D029-FA027-11-L-1	0.0000	1798.1773	558.9301	277.3472	2158.9536	177.1629	898.2582	1076.5850	1277.8979	1137.2584
080418-I4D029-FA027-12-L-1	1798.1773	0.0000	1638.8832	1857.1926	688.7826	1857.1727	1797.8912	1594.5462	1547.3274	1556.4812
080418-I4D029-FA027-4-L-1	558.9301	1638.8832	0.0000	498.7077	1928.4303	617.9844	979.1349	1197.0052	1228.5829	1258.3274
080418-I4D029-FA027-5-L-1	277.3472	1857.1926	498.7077	0.0000	2158.9711	218.2929	1057.1336	1175.8548	1366.9328	1157.3259
080418-I4D029-FA027-7-L-1	2158.9536	688.7826	1928.4303	2158.9711	0.0000	2158.9487	2158.4387	1916.4208	1828.1438	1858.3754
080418-I4D029-FA027-8-L-1	177.1629	1857.1727	617.9844	218.2929	2158.9487	0.0000	957.2584	1115.9185	1317.2314	1137.2584
080418-I4D029-FA027-9-L-1	898.2582	1797.8912	979.1349	1057.1336	2158.4387	957.2584	0.0000	795.3944	617.4514	836.0487
080418-I4D036-FA005-10-L-1	1076.5850	1594.5462	1197.0052	1175.8548	1916.4208	1115.9185	795.3944	0.0000	1095.2381	876.6554
080418-I4D036-FA005-3-L-1	1277.8979	1547.3274	1228.5829	1366.9328	1828.1438	1317.2314	617.4514	1095.2381	0.0000	348.7781
080418-I4D036-FA005-4-L-1	1137.2584	1556.4812	1258.3274	1157.3259	1858.3754	1137.2584	836.0487	876.6554	348.7781	0.0000

B. Clustering

The matrix of dissimilarities is then used to derive an optimal number of clusters among all the sequences analyzed. Using hierarchical clustering, named agglomerative nesting clustering method (AGNES) determines the optimal number of clusters by grouping low in-group variance while maximizing the difference in large out-of-group variance. This clustering method was chosen based on similar analysis in McBride (2020a) and Shi (2022). This computation results in four laborer and six household resident clusters. Each cluster is then appropriately labeled. These labels include a count of the unique individuals in each cluster and the title describing the cluster. Once the matrices have been reordered, ggplot displays the grouped daily sequences. Each representation uses a color palette that best expresses the difference in the four main states (H_..., NH_..., T_..., Other). Figures 3 and 4 display the output below. A more in-depth look at each cluster's state averages is listed below in a summary of tables.

Figure 3: Household Resident Cluster Analysis

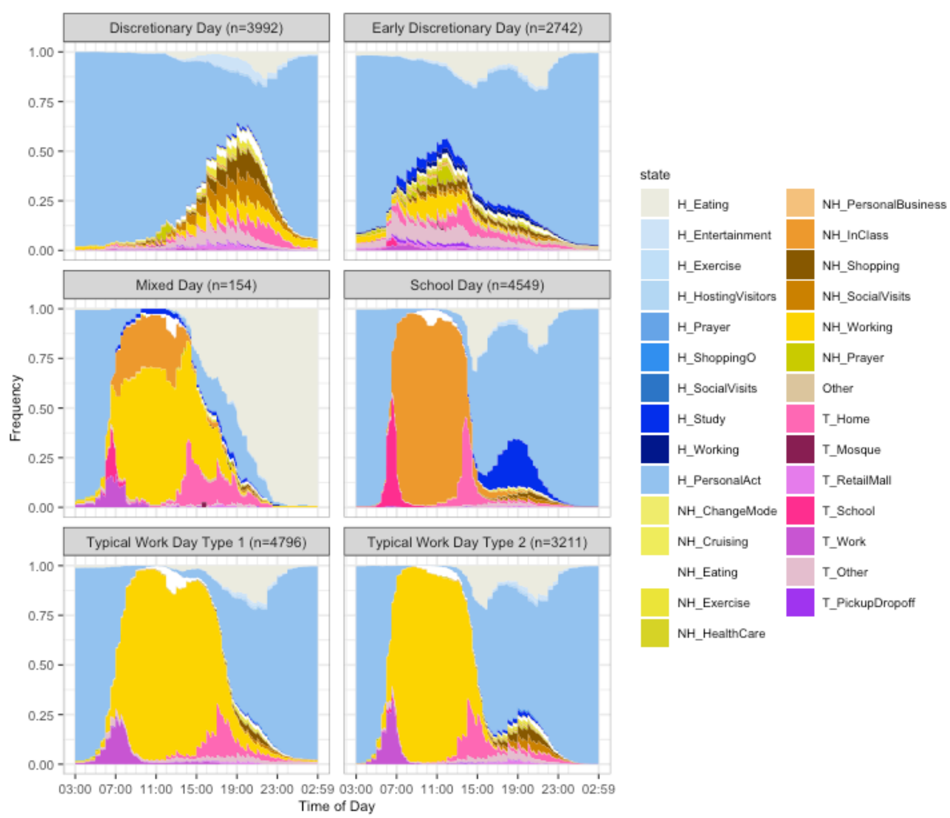
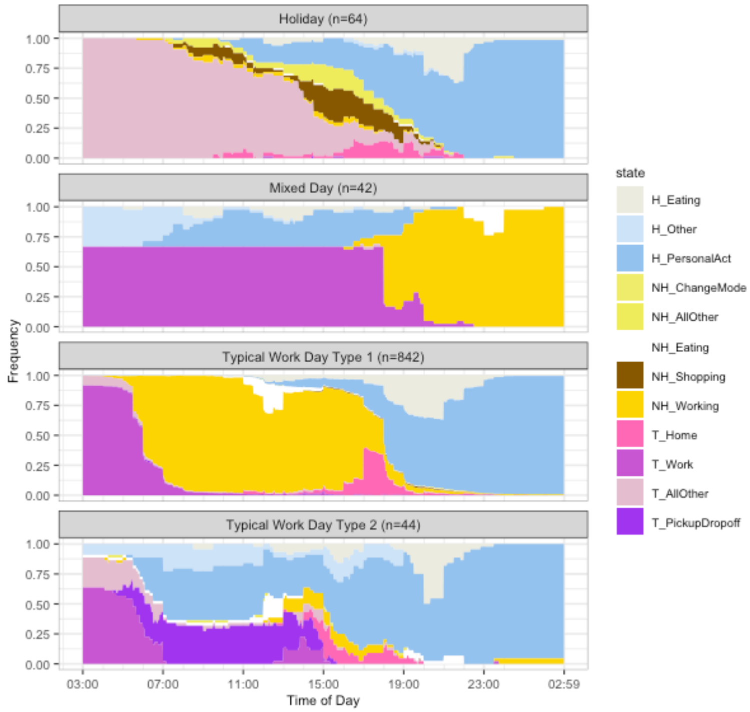


Figure 4: Laborer Cluster Analysis



C. Sequence Comparisons and Summary of Tables: State Statistics by Cluster

Table 10. Typical Workday Type 1

	States	Episodes	Percent	Average Duration (Hours)	Standard Deviation (Hours)	Median (Hours)
1	H_Eating	4936	10.49	1.03	0.59	1.00
2	H_Entertainment	175	0.37	2.17	1.19	2.00
3	H_Exercise	224	0.48	1.24	0.82	1.00
4	H_HostingVisitors	103	0.22	2.04	1.05	2.00
5	H_PersonalAct	13706	29.11	3.89	2.16	3.98
6	H_Prayer	2	0	0.83	0.59	0.83
7	H_ShoppingO	136	0.29	1.48	0.67	1.00
8	H_Study	69	0.15	1.71	1.00	1.00
9	H_Working	28	0.06	1.68	1.27	1.25
10	NH_ChangeMode	35	0.07	0.15	0.17	0.08
11	NH_Cruising	34	0.07	1.34	1.51	1.00
12	NH_Eating	1747	3.71	0.93	0.64	1.00
13	NH_Exercise	214	0.45	1.38	0.96	1.08
14	NH_HealthCare	72	0.15	1.04	0.79	0.75
15	NH_InClass	21	0.04	2.42	1.38	2.00
16	NH_PersonalBusiness	114	0.24	0.56	0.68	0.25

Table 10. Typical Workday Type 1 (Cont.)

	States	Episodes	Percent	Average Duration (Hours)	Standard Deviation (Hours)	Median (Hours)
17	**NH_Prayer**	344	0.73	0.81	0.87	0.50
18	**NH_Shopping**	643	1.37	1.00	0.76	0.83
19	**NH_SocialVisits**	210	0.45	2.02	1.82	1.50
20	**NH_Working**	7457	15.84	5.81	3.24	5.00
21	**Other**	124	0.26	0.64	0.6	0.5
22	**T_Home**	6532	13.88	0.53	0.38	0.5
23	**T_Mosque**	163	0.35	0.12	0.16	0.08
24	**T_Other**	3165	6.72	0.59	0.82	0.48
25	**T_PickupDropoff**	907	1.93	0.13	0.34	0.08
26	**T_RetailMall**	543	1.15	0.40	0.31	0.25
27	**T_School**	10	0.02	0.58	0.36	0.50
28	**T_Work**	5362	11.39	0.55	0.48	0.50

In Table 10, the average duration of working outside the home is 5.81 hours in a day (with a median of 5 hours) and motivates the naming of this group of daily patterns as Typical Workday.

Table 11: Typical Workday Type 2

	States	Episodes	Percent	Average Duration (Hours)	Standard Deviation (Hours)	Median (Hours)
1	**H_Eating**	3841	11.65	1.03	0.65	1.00
2	**H_Entertainment**	133	0.4	2.63	1.74	2.00
3	**H_Exercise**	136	0.41	1.44	0.91	1.00
4	**H_HostingVisitors**	88	0.27	2.00	1.08	2.00
5	**H_PersonalAct**	10258	31.11	3.89	2.56	3.50
6	**H_Prayer**	1	0	0.20	NA	0.20
7	**H_ShoppingO**	73	0.22	1.78	0.98	2.00
8	**H_SocialVisits**	3	0.01	1.94	0.05	1.92
9	**H_Study**	130	0.39	2.12	0.89	2.00
10	**H_Working**	24	0.07	1.71	1.46	1.00
11	**NH_ChangeMode**	26	0.08	0.19	0.48	0.08

Table 11: Typical Workday Type 2 (Cont.)

	States	Episodes	Percent	Average Duration (Hours)	Standard Deviation (Hours)	Median (Hours)
12	NH_Cruising	40	0.12	1.29	1.14	0.84
13	NH_Eating	920	2.79	0.96	0.81	1.00
14	NH_Exercise	148	0.45	1.55	1.02	1.25
15	NH_HealthCare	81	0.25	1.52	0.92	1.33
16	NH_InClass	43	0.13	2.18	1.36	2.00
17	NH_PersonalBusiness	80	0.24	0.62	0.65	0.41
18	NH_Prayer	333	1.01	0.60	0.78	0.42
19	NH_Shopping	569	1.73	1.34	1.00	1.00
20	NH_SocialVisits	339	1.03	2.18	1.47	2.00
21	NH_Working	4068	12.34	5.74	2.50	6.50
22	Other	58	0.18	1.26	1.42	0.63
23	T_Home	4705	14.27	0.52	0.38	0.50
24	T_Mosque	224	0.68	0.11	0.12	0.08
25	T_Other	2236	6.78	0.5	0.61	0.33
26	T_PickupDropoff	712	2.16	0.16	0.46	0.08
27	T_RetailMall	476	1.44	0.45	0.56	0.33
28	T_School	116	0.35	0.67	0.47	0.58
29	T_Work	3117	9.45	0.52	0.32	0.50

In Table 11, the average duration of working outside the home is 5.74 hours in a day (with a median of 6.5 hours) and motivates the naming of this group of daily patterns as Typical Workday Type 2 to distinguish it from the first type. This pattern has a more peaked shape and starts later than the Typical Workday Type 1 cluster. It also has more variety of after-work activity participation.

Table 12: School Day

	States	Episodes	Percent	Average Duration (Hours)	Standard Deviation (Hours)	Median (Hours)
1	**H_Eating**	6031	14.22	1.00	0.55	1.00
2	**H_Entertainment**	132	0.31	2.03	1.20	2.00
3	**H_Exercise**	190	0.45	1.62	0.94	1.00
4	**H_HostingVisitors**	48	0.11	3.08	2.80	2.00
5	**H_PersonalAct**	14056	33.13	4.19	2.75	3.50
6	**H_ShoppingO**	23	0.05	1.44	0.59	1.00
7	**H_Study**	2292	5.4	2.14	1.30	2.00
8	**H_Working**	6	0.01	1.06	0.68	1.00
9	**NH_ChangeMode**	6	0.01	0.51	0.98	0.12
10	**NH_Cruising**	23	0.05	2.36	1.88	2.00
11	**NH_Eating**	1251	2.95	0.79	0.50	1.00
12	**NH_Exercise**	128	0.3	1.50	0.77	1.50
13	**NH_HealthCare**	44	0.1	1.34	1.13	1.00
14	**NH_InClass**	5768	13.6	5.10	2.19	6.00
15	**NH_PersonalBusiness**	34	0.08	0.78	1.25	0.25
16	**NH_Prayer**	147	0.35	0.81	1.17	0.27
17	**NH_Shopping**	269	0.63	1.62	1.24	1.33
18	**NH_SocialVisits**	180	0.42	2.64	1.98	2.00
19	**NH_Working**	42	0.1	2.36	1.59	2.00
20	**Other**	40	0.09	1.23	1.53	0.75
21	**T_Home**	5409	12.75	0.58	0.34	0.50
22	**T_Mosque**	100	0.24	0.12	0.14	0.08
23	**T_Other**	1295	3.05	0.57	0.87	0.33
24	**T_PickupDropoff**	236	0.56	0.12	0.44	0.03
25	**T_RetailMall**	237	0.56	0.46	0.62	0.33
26	**T_School**	4359	10.28	0.61	0.38	0.5
27	**T_Work**	77	0.18	0.59	0.51	0.5

In Table 12, the average duration of in-class outside the home is 5.10 hours a day (with a median of 6 hours) and motivates the naming of this group of daily patterns as the School Day. Noticeable is also the narrow and high peak of arrivals at schools and departures from schools.

Table 13: Mixed Day

	States	Episodes	Percent	Average Duration (Hours)	Standard Deviation (Hours)	Median (Hours)
1	H_Eating	448	33.01	8.33	3.48	8.17
2	H_Exercise	3	0.22	1.00	0.00	1.00
3	H_HostingVisitors	3	0.22	1.83	0.76	2.00
4	H_PersonalAct	238	17.54	3.10	1.44	3.00
5	H_ShoppingO	2	0.15	1.5	0.71	1.50
6	H_Study	14	1.03	3.14	2.31	2.00
7	H_Working	1	0.07	1.00	NA	1.00
8	NH_Cruising	1	0.07	3.00	NA	3.00
9	NH_Eating	36	2.65	0.86	0.61	1.00
10	NH_Exercise	6	0.44	1.28	0.41	1.12
11	NH_InClass	51	3.76	5.45	2.05	6.33
12	NH_PersonalBusiness	3	0.22	0.92	0.98	0.67
13	NH_Prayer	8	0.59	0.83	0.9	0.50
14	NH_Shopping	10	0.74	0.83	0.58	0.75
15	NH_SocialVisits	3	0.22	1.63	0.33	1.50
16	NH_Working	147	10.83	6.12	3.00	6.50
17	Other	7	0.52	2.71	2.78	2.00
18	T_Home	173	12.75	0.98	1.46	0.50
19	T_Mosque	4	0.29	0.5	0.00	0.50
20	T_Other	35	2.58	0.48	0.41	0.42
21	T_PickupDropoff	8	0.59	0.07	0.07	0.03
22	T_RetailMall	7	0.52	0.77	0.94	0.50
23	T_School	45	3.32	0.7	0.34	0.67
24	T_Work	104	7.66	0.59	0.71	0.50

In Table 13, the average duration of working outside the home is 6.12 hours a day (with a median of 6.50 hours). The average duration of in-class outside the home for this group is 5.45 hours in a day (with a median of 6.33 hours), motivating the naming of this group of daily patterns as mixed work and school activity.

Table 14: Discretionary Day

	States	Episodes	Percent	Average Duration (Hours)	Standard Deviation (Hours)	Median (Hours)
1	**H_Eating**	2503	7.84	1.11	0.97	1.00
2	**H_Entertainment**	577	1.81	3.00	2.22	2.60
3	**H_Exercise**	54	0.17	1.57	1.40	1.00
4	**H_HostingVisitors**	110	0.34	3.30	2.37	2.83
5	**H_PersonalAct**	10140	31.75	6.88	4.96	5.00
6	**H_Prayer**	5	0.02	0.88	0.35	1.00
7	**H_ShoppingO**	22	0.07	1.24	0.71	1.00
8	**H_SocialVisits**	2	0.01	1.46	0.65	1.46
9	**H_Study**	96	0.30	2.33	1.44	2.00
10	**H_Working**	45	0.14	3.19	2.28	2.67
11	**NH_ChangeMode**	22	0.07	0.16	0.19	0.08
12	**NH_Cruising**	99	0.31	2.50	2.59	1.5
13	**NH_Eating**	1164	3.64	1.32	1.25	1.00
14	**NH_Exercise**	415	1.30	2.38	1.68	2.00
15	**NH_HealthCare**	139	0.44	1.89	2.77	1.17
16	**NH_InClass**	95	0.30	2.70	1.61	2.25
17	**NH_PersonalBusiness**	116	0.36	1.21	1.69	0.50
18	**NH_Prayer**	545	1.71	1.03	0.81	0.83
19	**NH_Shopping**	1446	4.53	1.83	1.35	1.50
20	**NH_SocialVisits**	1153	3.61	3.42	2.53	2.93
21	**NH_Working**	851	2.66	4.66	2.89	4.25
22	**Other**	111	0.35	2.06	3.00	0.75
23	**T_Home**	4922	15.41	0.45	0.34	0.42
24	**T_Mosque**	427	1.34	0.14	0.15	0.08
25	**T_Other**	4361	13.65	0.63	0.84	0.50
26	**T_PickupDropoff**	590	1.85	0.47	1.25	0.08
27	**T_RetailMall**	1228	3.84	0.49	0.37	0.50
28	**T_School**	76	0.24	0.52	0.34	0.46
29	**T_Work**	625	1.96	0.47	0.33	0.50

In Table 14, the average duration of home entertainment is 3.00 hours a day (with a median of 2.60 hours), and the average duration of personal activities for this group is 6.88 hours a day (with a median of 5.00 hours), motivating the naming of this group of daily patterns as a discretionary or entertainment day.

Table 15: Early Discretionary Day

	States	Episodes	Percent	Average Duration (Hours)	Standard Deviation (Hours)	Median (Hours)
1	H_Eating	3499	12.26	1.25	1.57	1.00
2	H_Entertainment	161	0.56	2.71	1.91	2.00
3	H_Exercise	93	0.33	1.63	1.11	1.00
4	H_HostingVisitors	93	0.33	2.46	1.87	2.00
5	H_PersonalAct	9067	31.77	4.94	3.39	4.48
6	H_Prayer	2	0.01	0.46	0.06	0.46
7	H_ShoppingO	38	0.13	1.63	1.05	1.25
8	H_SocialVisits	1	0.00	0.33	NA	0.33
9	H_Study	313	1.1	4.04	2.42	3.00
10	H_Working	186	0.65	5.31	4.68	4.00
11	NH_ChangeMode	20	0.07	0.32	0.28	0.3
12	NH_Cruising	63	0.22	2.71	2.97	1.58
13	NH_Eating	524	1.84	1.28	1.61	1.00
14	NH_Exercise	199	0.7	1.84	1.35	1.67
15	NH_HealthCare	167	0.59	2.32	2.18	1.50
16	NH_InClass	70	0.25	2.34	2.04	1.92
17	NH_PersonalBusiness	161	0.56	1.15	1.86	0.50
18	NH_Prayer	738	2.59	1.19	1.63	0.58
19	NH_Shopping	713	2.5	1.47	1.3	1.00
20	NH_SocialVisits	273	0.96	2.25	1.83	1.95
21	NH_Working	808	2.83	2.67	1.95	2.5
22	Other	180	0.63	4.84	5.1	2.00
23	T_Home	4171	14.61	0.46	0.6	0.33
24	T_Mosque	497	1.74	0.15	0.53	0.08
25	T_Other	3522	12.34	0.82	2.01	0.42
26	T_PickupDropoff	1550	5.43	0.26	0.86	0.08
27	T_RetailMall	587	2.06	0.70	2.03	0.33
28	T_School	186	0.65	0.72	0.94	0.50
29	T_Work	659	2.31	0.65	1.25	0.50

In Table 15, the average duration of social visits is 2.25 hours a day (with a median of 1.95 hours), and the average duration of prayer for this group is 1.19 hours a day (with a median of 0.58 hours), motivating the naming of this group of daily patterns.

IV. Membership in Each Daily Pattern

A. Household Members

Table 16: Household Members Age

Age	Typical Workday Type 1	Typical Workday Type 2	School Day	Early Discretionary Day	Discretionary Day	Mixed Day	Total
0 - 4 Years old	0 (0.0%)	0 (0.0%)	2 (50.0%	2 (50.0%)	0 (0.0%)	0 (0.0%)	4 (100.0%)
5 - 11 Years old	5 (0.2%)	66 (2.0%)	2491 (77.0%)	227 (7.0%)	422 (13.0%)	23 (0.7%)	3234 (100.0%)
12 - 15 Years old	2 (0.1%)	31 (2.1%)	1103 (76.0%)	109 (7.5%)	196 (13.5%)	11 (0.8%)	1452 (100.0%)
16 - 18 Years old	2 (0.3%)	14 (1.8%)	571 (73.5%)	75 (9.7%)	106 (13.6%)	9 (1.2%)	777 (100.0%)
19 - 24 Years old	157 (14.8%)	139 (13.1%)	279 (26.3%)	150 (14.2%)	329 (31.0%)	6 (0.6%)	1060 (100.0%)
25 - 34 Years old	1823 (37.7%)	930 (19.2%)	41 (0.8%)	742 (15.3%)	1258 (26.0%)	41 (0.8%)	4835 (100.0%)
35 - 44 Years old	1676 (36.4%)	1089 (23.7%)	40 (0.9%)	807 (17.5%)	957 (20.8%)	34 (0.7%)	4603 (100.0%)
45 - 54 Years old	834 (34.3%)	685 (28.2%)	16 (0.7%)	392 (16.1%)	479 (19.7%)	23 (0.9%)	2429 (100.0%)
55 - 64 Years old	267 (29.9%)	238 (26.6%)	6 (0.7%)	181 (20.2%)	195 (21.8%)	7 (0.8%)	894 (100.0%)
65 - 74 Years old	28 (21.1%)	17 (12.8%)	0 (0.0%)	46 (34.6%)	42 (31.6%)	0 (0.0%)	133 (100.0%)
75+	2 (8.7%)	2 (8.7%)	0 (0.0%)	11 (47.8%)	8 (34.8%)	0 (0.0%)	23 (100.0%)
Total	4796 (24.7%)	3211 (16.5%)	4549 (23.4%)	2742 (14.1%)	3992 (20.5%)	154 (0.8%)	19444 (100.0%)

Over 40% of the Qatari household residents surveyed are between the ages of 25 and 44. These working ages make up nearly 69% of all the working clusters. While those ages 5 to 15 make up the highest percentage of school days. The youngest bracket of ages (0-4) doesn’t tend to leave the house, as shown by the overall four cases of sequences. These numbers are an additional reason for the difference in those surveyed versus those who traveled since these young ages make up over 12% of the entire household residents. The 25–34-year-olds make up the largest number of discretionary days.

Table 17: Household Members Education Attained

Education Attained	Typical Workday Type 1	Typical Workday Type 2	School Day	Early Discretionary Day	Discretionary Day	Mixed Day	Total
Doctorate (Ph.D)	60 (35.7%)	52 (31.0%)	5 (3.0%)	27 (16.1%)	23 (13.7%)	1 (0.6%)	168 (100.0%)
Masters Degree (MSc/MA)	726 (44.9%)	414 (25.6%)	9 (0.6%)	169 (10.5%)	285 (17.6%)	13 (0.8%)	1616 (100.0%)
Graduate (College)	3151 (41.8%)	1885 (25.0%)	70 (0.9%)	988 (13.1%)	1371 (18.2%)	80 (1.1%)	7545 (100.0%)
High School	614 (25.6%)	525 (21.9%)	268 (11.2%)	407 (17.0%)	563 (23.5%)	20 (0.8%)	2397 (100.0%)
Primary	23 (11.3%)	25 (12.3%)	14 (6.9%)	68 (33.3%)	74 (36.3%)	0 (0.0%)	204 (100.0%)
Secondary	81 (22.0%)	101 (27.4%)	2 (0.5%)	111 (30.1%)	74 (20.1%)	0 (0.0%)	369 (100.0%)
Nursery	4 (5.1%)	13 (16.5%)	3 (3.8%)	34 (43.0%)	25 (31.6%)	0 (0.0%)	79 (100.0%)
Other	115 (8.0%)	88 (6.1%)	882 (61.2%)	152 (10.5%)	179 (12.4%)	26 (1.8%)	1442 (100.0%)
<NA>	22 (0.4%)	108 (1.9%)	3296 (58.6%)	786 (14.0%)	1398 (24.9%)	14 (0.2%)	5624 (100.0%)
Total	4796 (24.7%)	3211 (16.5%)	4549 (23.4%)	2742 (14.1%)	3992 (20.5%)	154 (0.8%)	19444 (100.0%)

Those with higher education degrees are concentrated on either of the Typical Workdays. Household residents with their highest education levels as Primary are mainly included in Discretionary Days. Those with a college degree make up over 38% of the data. Less than one percent didn’t attain an education level beyond nursery school. Over 28% of all respondents didn’t provide a response for their education attained.

Table 18: Household Members Monthly Income

Monthly Income (QAR)	Typical Workday Type 1	Typical Workday Type 2	School Day	Early Discretionary Day	Discretionary Day	Mixed Day	Total
Confidential	241 (42.1%)	193 (33.7%)	3 (0.5%)	53 (9.3%)	79 (13.8%)	3 (0.5%)	572 (100.0%)
No Income	0 (0.0%)	1 (25.0%)	0 (0.0%)	1 (25.0%)	2 (50.0%)	0 (0.0%)	4 (100.0%)
Less than or equal to QAR 1,000/month	60 (39.5%)	28 (18.4%)	2 (1.3%)	28 (18.4%)	31 (20.4%)	3 (2.0%)	152 (100.0%)
QAR 1,001 - 3,000/month	436 (37.8%)	194 (16.8%)	4 (0.3%)	292 (25.3%)	221 (19.2%)	7 (0.6%)	1154 (100.0%)
QAR 3,001 - 6,000/month	770 (47.6%)	392 (24.2%)	16 (1.0%)	178 (11.0%)	245 (15.1%)	17 (1.1%)	1618 (100.0%)
QAR 6,001 - 10,000/month	1078 (43.5%)	683 (27.5%)	22 (0.9%)	291 (11.7%)	383 (15.4%)	23 (0.9%)	2480 (100.0%)
QAR 10,001 - 15,000/month	942 (44.7%)	572 (27.1%)	18 (0.9%)	252 (12.0%)	305 (14.5%)	19 (0.9%)	2108 (100.0%)
QAR 15,001 - 20000/month	535 (42.1%)	369 (29.0%)	14 (1.1%)	136 (10.7%)	205 (16.1%)	13 (1.0%)	1272 (100.0%)
QAR 20,001 - 35,000/month	482 (40.8%)	354 (30.0%)	5 (0.4%)	140 (11.9%)	189 (16.0%)	10 (0.8%)	1180 (100.0%)
QAR 35,001 - 50,000/month	156 (32.7%)	179 (37.5%)	1 (0.2%)	51 (10.7%)	80 (16.8%)	10 (2.1%)	477 (100.0%)
QAR 50,001 - 75,000/month	50 (26.5%)	78 (41.3%)	0 (0.0%)	30 (15.9%)	30 (15.9%)	1 (0.5%)	189 (100.0%)
QAR 75,001 - 100,000/month	13 (31.0%)	16 (38.1%)	0 (0.0%)	7 (16.7%)	6 (14.3%)	0 (0.0%)	42 (100.0%)
More than QAR 100,000/month	10 (31.2%)	12 (37.5%)	0 (0.0%)	3 (9.4%)	7 (21.9%)	0 (0.0%)	32 (100.0%)
<NA>	23 (0.3%)	140 (1.7%)	4464 (54.7%)	1280 (15.7%)	2209 (27.1%)	48 (0.6%)	8164 (100.0%)
Total	4796 (24.7%)	3211 (16.5%)	4549 (23.4%)	2742 (14.1%)	3992 (20.5%)	154 (0.8%)	19444 (100.0%)

At the current 2023 exchange rate $1,000 USD equates to 3,641 Qatari Riyal, the national currency of Qatar. Most respondents earn from 6,001 to 10,000 Qatari riyal a month. Over 8,000 people didn’t report their monthly income. A reason for so many unanswered incomes is the structure of Qatari households. A typical household is often larger than a Western country and can include generations of families, and children will often stay until marriage. Extended households are common in Middle Eastern countries (Al-Ammari, 2016). Until the recent past and a rise in globalization, women didn’t have the same labor opportunities as men, creating an inability to generate more household income (Al-Ammari, 2016). Disregarding those who didn't answer, those falling into a workday of either type have the highest monthly income. The majority of those who earn less than 3,000 Qatari Riyal also fall into one of the workdays. There is evidence of a disparity in jobs among those who work, as some make less than average income.

Table 19: Household Members Main Occupation

Main Occupation	Typical Workday Type 1	Typical Workday Type 2	School Day	Early Discretionary Day	Discretionary Day	Mixed Day	Total
Disabled/Sick	0 (0.0%)	0 (0.0%)	0 (0.0%)	2 (100.0%)	0 (0.0%)	0 (0.00%)	2 (100.0%)
Full-time employed	4739 (42.6%)	3043 (27.3%)	82 (0.7%)	1417 (12.7%)	1745 (15.7%)	107 (0.96%)	11133 (100.0%)
Full-time student	11 (0.2%)	120 (2.1%)	4443 (76.2%)	445 (7.6%)	768 (13.2%)	46 (0.79%)	5833 (100.0%)
Full-time student and Part-time work	0 (0.0%)	0 (0.0%)	5 (62.5%)	2 (25.0%)	1 (12.5%)	0 (0.00%)	8 (100.0%)
Full-time work and Part time student	2 (18.2%)	5 (45.5%)	0 (0.0%)	1 (9.1%)	3 (27.3%)	0 (0.00%)	11 (100.0%)
House person	3 (0.2%)	5 (0.3%)	10 (0.5%)	703 (35.5%)	1257 (63.5%)	1 (0.05%)	1979 (100.0%)
Looking for Job	3 (2.5%)	4 (3.3%)	0 (0.0%)	46 (38.3%)	67 (55.8%)	0 (0.00%)	120 (100.0%)
Other	1 (8.3%)	0 (0.0%)	0 (0.0%)	6 (50.0%)	5 (41.7%)	0 (0.00%)	12 (100.0%)
Part-time employed (< 5 hours/day)	17 (20.2%)	20 (23.8%)	1 (1.2%)	27 (32.1%)	19 (22.6%)	0 (0.00%)	84 (100.0%)
Part-time student	0 (0.0%)	0 (0.0%)	6 (40.0%)	1 (6.7%)	8 (53.3%)	0 (0.00%)	15 (100.0%)

Table 19: Household Members Main Occupation (Cont.)

Main Occupation	Typical Workday Type 1	Typical Workday Type 2	School Day	Early Discretionary Day	Discretionary Day	Mixed Day	Total
Part-time work and Part time student	1 (33.3%)	0 (0.0%)	1 (33.3%)	0 (0.0%)	1 (33.3%)	0 (0.00%)	3 (100.0%)
Retired	0 (0.0%)	3 (1.6%)	1 (0.5%)	78 (41.7%)	105 (56.1%)	0 (0.00%)	187 (100.0%)
Self Employed	19 (33.3%)	11 (19.3%)	0 (0.0%)	14 (24.6%)	13 (22.8%)	0 (0.00%)	57 (100.0%)
Total	4796 (24.7%)	3211 (16.5%)	4549 (23.4%)	2742 (14.1%)	3992 (20.5%)	154 (0.79%)	19444 (100.0%)

Usurpingly, full-time employees make up most of typical workdays while students show the same results for school days. An interesting observation is the large proportion of discretionary days made up by a "house person." A house person could be categorized as someone who performs house duties in place of working on a job location outside the home or going to school. We see those looking for a job and are retired, absent from the Typical Workdays, which can validate data quality. The main occupation data also describes the discretionary days full-time employees participate in on their days off.

Table 20: Household Members Transport to Occupation

Mode Choice	Typical Workday Type 1	Typical Workday Type 2	School Day	Early Discretionary Day	Discretionary Day	Mixed Day	Total
Bike	14 (60.9%)	2 (8.7%)	0 (0.0%)	3 (13.0%)	4 (17.4%)	0 (0.00%)	23 (100.0%)
Car / Van / Truck Driver	3234 (39.9%)	2191 (27.0%)	252 (3.1%)	1108 (13.7%)	1249 (15.4%)	81 (1.00%)	8115 (100.0%)
Car / Van / Truck Passenger	398 (10.4%)	449 (11.8%)	1941 (50.9%)	356 (9.3%)	639 (16.8%)	31 (0.81%)	3814 (100.0%)
Company Bus	419 (51.0%)	186 (22.7%)	27 (3.3%)	63 (7.7%)	120 (14.6%)	6 (0.73%)	821 (100.0%)
Karwa Taxi	100 (49.3%)	32 (15.8%)	3 (1.5%)	28 (13.8%)	39 (19.2%)	1 (0.49%)	203 (100.0%)
Motorcycle / Scooter / Moped	1 (33.3%)	2 (66.7%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.00%)	3 (100.0%)
Other	6 (21.4%)	4 (14.3%)	1 (3.6%)	8 (28.6%)	7 (25.0%)	2 (7.14%)	28 (100.0%)
Other Non-Motorized (skateboard, etc.)	3 (75.0%)	0 (0.0%)	0 (0.0%)	1 (25.0%)	0 (0.0%)	0 (0.00%)	4 (100.0%)
Other Private Transit	42 (21.4%)	34 (17.3%)	68 (34.7%)	17 (8.7%)	31 (15.8%)	4 (2.04%)	196 (100.0%)
Private Shuttle (employer, hotel, etc.)	224 (50.0%)	70 (15.6%)	50 (11.2%)	36 (8.0%)	63 (14.1%)	5 (1.12%)	448 (100.0%)
Private Vehicle:	1 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.00%)	1 (100.0%)
Public Bus	25 (51.0%)	11 (22.4%)	4 (8.2%)	7 (14.3%)	1 (2.0%)	1 (2.04%)	49 (100.0%)
Public Transit Shuttle (airport shuttle etc.)	7 (53.8%)	2 (15.4%)	0 (0.0%)	1 (7.7%)	3 (23.1%)	0 (0.00%)	13 (100.0%)
Rental Vehicle	34 (20.9%)	29 (17.8%)	54 (33.1%)	14 (8.6%)	31 (19.0%)	1 (0.61%)	163 (100.0%)
School Bus	10 (0.4%)	85 (3.2%)	2077 (78.0%)	186 (7.0%)	288 (10.8%)	17 (0.64%)	2663 (100.0%)
Uber/Careem	87 (47.8%)	31 (17.0%)	14 (7.7%)	22 (12.1%)	27 (14.8%)	1 (0.55%)	182 (100.0%)
Walk	182 (44.7%)	65 (16.0%)	41 (10.1%)	60 (14.7%)	56 (13.8%)	3 (0.74%)	407 (100.0%)
Wheelchair / Mobility Scooter	0 (0.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (100.0%)	0 (0.00%)	1 (100.0%)
<NA>	9 (0.4%)	18 (0.8%)	17 (0.7%)	832 (36.0%)	1433 (62.0%)	1 (0.04%)	2310 (100.0%)
Total	4796 (24.7%)	3211 (16.5%)	4549 (23.4%)	2742 (14.1%)	3992 (20.5%)	154 (0.79%)	19444 (100.0%)

The use of private cars appears to be dominant in Qatar workdays, making up over 32% of the mode chosen by the total population of travelers. The school bus is mainly used on school days but shows an interesting trend in being in service for discretionary days. Possible explanations for use on non-school days could be school extracurriculars or dual usage for religious purposes. The use of bikes and walking are limited and can be explained by the severe heat that discourages time spent outside.

Table 21: Household Members As Driver

	Typical Workday Type 1	Typical Workday Type 2	School Day	Early Discretionary Day	Discretionary Day	Mixed Day	Total
Always	3173 (36.4%)	2183 (25.1%)	204 (2.3%)	1504 (17.3%)	1573 (18.1%)	74 (0.8%)	8711 (100.0%)
Never	1357 (14.0%)	838 (8.7%)	4205 (43.5%)	1055 (10.9%)	2138 (22.1%)	71 (0.7%)	9664 (100.0%)
Sometime	154 (21.9%)	135 (19.2%)	32 (4.6%)	151 (21.5%)	227 (32.3%)	4 (0.6%)	703 (100.0%)
N/A	112 (30.6%)	55 (15.0%)	108 (29.5%)	32 (8.7%)	54 (14.8%)	5 (1.4%)	366 (100.0%)
Total	4796 (24.7%)	3211 (16.5%)	4549 (23.4%)	2742 (14.1%)	3992 (20.5%)	154 (0.8%)	19444 (100.0%)

The importance of including driving status reflects how mode choice is selected in Qatar. Most responses indicate that respondents do not drive. This question does not discriminate amongst ages, although a significant proportion may be too young to drive. The minimum age to obtain a driving license in Qatar is 18 (Shaaban, 2012). The driving age means over 24% of the household residents aren’t legally allowed to drive. Over 92% of those who attend school reported never driving themselves.

Table 22: Household Members As Passenger

	Typical Workday Type 1	Typical Workday Type 2	School Day	Early Discretionary Day	Discretionary Day	Mixed Day	Total
Always	1110 (14.0%)	731 (9.2%)	3352 (42.3%)	897 (11.3%)	1774 (22.4%)	57 (0.7%)	7921 (100.0%)
Never	2453 (37.4%)	1573 (24.0%)	291 (4.4%)	1082 (16.5%)	1103 (16.8%)	53 (0.8%)	6555 (100.0%)
Sometime	1119 (24.3%)	850 (18.5%)	803 (17.4%)	734 (15.9%)	1062 (23.1%)	39 (0.8%)	4607 (100.0%)
N/A	114 (31.6%)	57 (15.8%)	103 (28.5%)	29 (8.0%)	53 (14.7%)	5 (1.4%)	361 (100.0%)
Total	4796 (24.7%)	3211 (16.5%)	4549 (23.4%)	2742 (14.1%)	3992 (20.5%)	154 (0.8%)	19444 (100.0%)

Passenger status indicates that over 40% of household residents are always passengers. Driver and passenger status reflect each other quite well, indicating School Day respondents do not drive themselves and workday respondents are never passengers. An interesting distinction can be found in the “sometime” response, which increases across all clusters.

Table 23: Household Members Report Day of Week

Report DOW	Typical Workday Type 1	Typical Workday Type 2	School Day	Early Discretionary Day	Discretionary Day	Mixed Day	Total
Sunday	1137 (29.4%)	746 (19.3%)	1050 (27.1%)	486 (12.5%)	425 (11.0%)	29 (0.8 %)	3873 (100.0%)
Monday	861 (26.9%)	626 (19.6%)	914 (28.6%)	382 (11.9%)	390 (12.2%)	28 (0.9%)	3201 (100.0%)
Tuesday	994 (28.1%)	646 (18.3%)	986 (27.9%)	454 (12.8%)	416 (11.8%)	38 (1.1%)	3534 (100.0%)
Wednesday	948 (30.6%)	537 (17.3%)	842 (27.2%)	346 (11.2%)	383 (12.4%)	45 (1.5 %)	3101 (100.0%)
Thursday	585 (24.0%)	526 (21.6%)	648 (26.6%)	229 (9.4%)	442 (18.1%)	8 (0.3%)	2438 (100.0%)
Friday	84 (3.4%)	66 (2.7%)	69 (2.8%)	654 (26.7%)	1575 (64.3%)	2 (0.1%)	2450 (100.0%)
Saturday	183 (21.9%)	62 (7.4%)	40 (4.8%)	188 (22.5%)	360 (43.0%)	4 (0.48%)	837 (100.0%)
N/A	4 (40.0%)	2 (20.0%)	0 (0.0%)	3 (30.0%)	1 (10.0%)	0 (0.0%)	10 (100.0%)
Total	4796 (24.7%)	3211 (16.5%)	4549 (23.4%)	2742 (14.1%)	3992 (20.5%)	154 (0.8%)	19444 (100.0%)

Most respondents (3873, that is 20% of the total) reported their data on Sunday. Around 48.7% of Sunday respondents report a typical workday of either Type 1 or 2, which verifies the start of a new workweek. Friday is primarily a day of prayer, and Saturday is seen more as a discretionary day. The School Days match up the same for most students, and a majority of the students responded on the first day after their weekend. Having the lowest response rates for Saturday (837) confirms a more discretionary day where household residents are participating in less predictable states compared to the work week.

B. Laborers

Table 24: Laborers Age

Age	Typical Workday Type 1	Typical Workday Type 2	Holiday	Mixed Day	Total
19 - 24 Years old	137 (87.3%)	2 (1.3%)	9 (5.7%)	9 (5.7%)	157 (100.0%)
25 - 34 Years old	380 (85.0%)	15 (3.4%)	29 (6.5%)	23 (5.1%)	447 (100.0%)
35 - 44 Years old	217 (82.2%)	22 (8.3%)	17 (6.4%)	8 (3.0%)	264 (100.0%)
45 - 54 Years old	91 (87.5%)	5 (4.8%)	7 (6.7%)	1 (1.0%)	104 (100.0%)
55 - 64 Years old	16 (88.9%)	0 (0.0%)	1 (5.6%)	1 (5.6%)	18 (100.0%)
65 - 74 Years old	1 (50.0%)	0 (0.0%)	1 (50.0%)	0 (0.0%)	2 (100.0%)
Total	842 (84.9%)	44 (4.4%)	64 (6.5%)	42 (4.2%)	992 (100.0%)

Due to the harsh living conditions and discrimination that laborers face, they often come by themselves, choosing to send remittances back to their home countries and families. These circumstances lead to an almost entirely working-aged male industry of labor. There wasn't a traveling laborer surveyed under 19, and only 2% of those surveyed were over 55. The majority of those interviewed were between the ages of 25 and 34. Those older than 54 seemed to report almost always on working days, whereas the opposite is true for the younger age groups for the most part.

Table 25: Laborers Education Attained

Education Attained	Typical Workday Type 1	Typical Workday Type 2	Holiday	Mixed Day	Total
Masters Degree (M.Sc)	1 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (100.0%)
Graduate	59 (81.9%)	4 (5.6%)	7 (9.7%)	2 (2.8%)	72 (100.0%)
High School	271 (82.9%)	21 (6.4%)	24 (7.3%)	11 (3.4%)	327 (100.0%)
Secondary	329 (87.7%)	7 (1.9%)	16 (4.3%)	23 (6.1%)	375 (100.0%)
Primary	123 (85.4%)	5 (3.5%)	11 (7.6%)	5 (3.5%)	144 (100.0%)
Nursery	51 (83.6%)	5 (8.2%)	4 (6.6%)	1 (1.6%)	61 (100.0%)
Other	8 (80.0%)	2 (20.0%)	0 (0.0%)	0 (0.0%)	10 (100.0%)
<NA>	0 (0.0%)	0 (0.0%)	2 (100.0%)	0 (0.0%)	2 (100.0%)
Total	842 (84.9%)	44 (4.4%)	64 (6.5%)	42 (4.2%)	992 (100.0%)

Unskilled labor doesn't require extensive amounts of education. Laborers primarily accomplish secondary and high school levels of education before entering the workforce. Around 7% of the laborers graduate from higher education compared to the over 47% of household residents that do the same. Around 6% of all traveling laborers' highest level of education is nursery school. This number jumps to nearly 21%, with the addition of primary school being the extent of their education. These numbers detail the lack of educational emphasis on unskilled laborers in Qatar.

Table 26: Laborers Monthly Income

Monthly income	Typical Workday Type 1	Typical Workday Type 2	Holiday	Mixed Day	Total
Less than or equal to QAR 1,000/month	285 (85.1%)	9 (2.7%)	27 (8.1%)	14 (4.2%)	335 (100.0%)
QAR 1,001 - 3,000/month	514 (84.5%)	34 (5.6%)	34 (5.6%)	26 (4.3%)	608 (100.0%)
QAR 3,001 - 6,000/month	25 (86.2%)	1 (3.4%)	1 (3.4%)	2 (6.9%)	29 (100.0%)
QAR 6,001 - 10,000/month	5 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	5 (100.0%)
QAR 10,001 - 15,000/month	2 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	2 (100.0%)
<NA>	11 (84.6%)	0 (0.0%)	2 (15.4%)	0 (0.0%)	13 (100.0%)
Total	842 (84.9%)	44 (4.4%)	64 (6.5%)	42 (4.2%)	992 (100.0%)

As opposed to the household residents, laborers make far less money each month, even with more hours worked. Most laborers make less than the equivalent of $1,000 USD per month. Only 7 of the 992 traveling laborers make more than $1,648 monthly, less than 1%. The difference is over 40% of household resident travelers that make more than that. Laborers in Qatar are alienated and often segregated from the household residents of Qatar (Mohammad, 2016). Although the foreign population in Qatar is large, foreign household residents and laborers are not synonymous. Laborers often live in labor camps, group together, experience poor living conditions, and participate in manual labor jobs. The foreign household residents have more established careers, often better education, and experience in skilled labor. An informal labor market known as the "labor mundy" is present in city centers where laborers look for jobs daily to generate an income (Mohammad & Sidaway, 2016). The informal market leads to unpredictable monthly incomes and increased working hours for jobs obtained.

Table 27: Laborers Main Occupation

	Typical Workday Type 1	Typical Workday Type 2	Holiday	Mixed Day	Total
Full-time employed	842 (85.1%)	44 (4.4%)	62 (6.3%)	42 (4.2%)	990 (100.0%)
House person	0 (0.0%)	0 (0.0%)	1 (100.0%)	0 (0.0%)	1 (100.0%)
Looking for Job	0 (0.0%)	0 (0.0%)	1 (100.0%)	0 (0.0%)	1 (100.0%)
Total	842 (84.9%)	44 (4.4%)	64 (6.5%)	42 (4.2%)	992 (100.0%)

This table serves to validate the working-dominated laborer group. Less than 1% of those laborers who traveled weren't full-time employees. These numbers are compared to the over 57% of household resident travelers who are full-time employees.

Table 28: Laborers Transport to Occupation

Mode Choice	Typical Workday Type 1	Typical Workday Type 2	Holiday	Mixed Day	Total
Bike	1 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (100.0%)
Car / Van / Truck Driver	82 (78.8%)	14 (13.5%)	6 (5.8%)	2 (1.9%)	104 (100.0%)
Car / Van / Truck Passenger	59 (88.1%)	1 (1.5%)	3 (4.5%)	4 (6.0%)	67 (100.0%)
Company Bus	389 (84.4%)	18 (3.9%)	42 (9.1%)	12 (2.6%)	461 (100.0%)
Karwa Taxi	1 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (100.0%)
Motorcycle / Scooter / Moped	1 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (100.0%)
Other Non-Motorized (skateboard, etc.)	1 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (100.0%)
Private Shuttle (employer, hotel, etc.)	136 (87.7%)	0 (0.0%)	10 (6.5%)	9 (5.8%)	155 (100.0%)
Public Transit Shuttle (airport shuttle etc.)	1 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (100.0%)
School Bus	1 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	1 (100.0%)
Walk	170 (86.3%)	11 (5.6%)	1 (0.5%)	15 (7.6%)	197 (100.0%)
<NA>	0 (0.0%)	0 (0.0%)	2 (100.0%)	0 (0.0%)	2 (100.0%)
Total	842 (84.9%)	44 (4.4%)	64 (6.5%)	42 (4.2%)	992 (100.0%)

The increase in walking for laborers compared to the household residents is interesting in Table 31. The environment is not conducive to walking outdoors, although low incomes can't afford private vehicles. The company bus and private shuttle comprise over 62% of the laborer transport modes. Even on Holidays, these two transportation modes are used by laborers. Holidays can be better viewed as a free day.

Table 29: Laborers As Driver

	Typical Workday Type 1	Typical Workday Type 2	Holiday	Mixed Day	Total
Always	83 (78.3%)	15 (14.2%)	7 (6.6%)	1 (0.9%)	106 (100.0%)
Never	757 (85.6%)	29 (3.3%)	57 (6.4%)	41 (4.6%)	884 (100.0%)
Sometime	2 (100.0%)	0 (0.0%)	0 (0.0%)	0 (0.0%)	2 (100.0%)
Total	842 (84.9%)	44 (4.4%)	64 (6.5%)	42 (4.2%)	992 (100.0%)

The low-income generation and driving laws make obtaining a driving license harder for laborers. These restrictions are shown in many laborers who never drive. Those who do drive could be using company vehicles or sharing amongst laborers.

Table 30: Laborers As Passenger

	Typical Workday Type 1	Typical Workday Type 2	Holiday	Mixed Day	Total
Always	582 (85.7%)	16 (2.4%)	45 (6.6%)	36 (5.3%)	679 (100.0%)
Never	142 (79.3%)	18 (10.1%)	16 (8.9%)	3 (1.7%)	179 (100.0%)
Sometime	118 (88.1%)	10 (7.5%)	3 (2.2%)	3 (2.2%)	134 (100.0%)
Total	842 (84.9%)	44 (4.4%)	64 (6.5%)	42 (4.2%)	992 (100.0%)

The presence of the informal labor market could explain why travelers do not drive or ride as a passenger. The cost of transportation dramatically increases the farther from city centers the laborers reside. These high prices cause the informal markets to set up camps close to city centers and readily be available for work.

Table 31: Laborers Report Day of Week

Day of Week	Typical Workday Type 1	Typical Workday Type 2	Holiday	Mixed Day	Total
Monday	97 (83.6%	4 (3.4%)	3 (2.6%)	12 (10.3%)	116 (100.0%)
Tuesday	186 (86.5%)	19 (8.8%)	3 (1.4%)	7 (3.3%)	215 (100.0%)
Wednesday	162 (95.3%)	6 (3.5%)	1 (0.6%)	1 (0.6%)	170 (100.0%)
Thursday	113 (92.6%)	6 (4.9%)	3 (2.5%)	0 (0.0%)	122 (100.0%)
Friday	34 (39.5%)	3 (3.5%)	49 (57.0%)	0 (0.0%)	86 (100.0%)
Saturday	14 (93.3%)	0 (0.0%)	1 (6.7%)	0 (0.0%)	15 (100.0%)
Sunday	236 (88.1%)	6 (2.2%)	4 (1.5%)	22 (8.2%)	268 (100.0%)
Total	842 (84.9%)	44 (4.4%)	64 (6.5%)	42 (4.2%)	992 (100.0%)

Like the household residents, laborers reported much of their responses on their first day back from their weekend. Free time is infrequent among laborers, and their working days are long. Limited responses on Saturday could be explained by the fewer survey workers working this day. It is worth noting that there seems to be a drop in reporting on Monday, either from the inactivity of survey workers or laborer input.

C: Discussion of Sequences for Household Members

Typical Workday Type 1

Making up most clusters with nearly 25% (4796) persons, the Typical Workday Type 1 encompasses a standard workday. These persons leave in the morning around 6:00-7:00 a.m., with the most duration of their daytime states consisting of working before leaving to return home. Much of the time before and after their workday is spent conducting personal activities (H_PersonAct), including internet, sleeping, and leisure. One reason two different workday sequences are shown in the observable lunch break where a decrease in work, an increase in travel, eating, and mid-day prayer occurs at roughly 12:30 p.m. for the Type 1.

Another differentiation from a Type 2 Workday is the lack of diverse states conducted after work in Type 1. These differences are evident by a sizeable singular spike in eating at home and limited duration in other states, occurring from 5:00 p.m. to 11:00 p.m.. Unsurprisingly, 98.8% of Typical Workday Type 1 household residents are full-time employees. Most respondents are between 25 and 54 years old, and over 82% of Type 1 respondents have a college degree or greater. The highest percentage reporting day coincides with the first day after their weekend, Sunday. Some inaccuracies or anomalies can be spotted in the data as there are seven people 5-15 years old who participate in this sequence.

Typical Workday Type 2

Ending the workday earlier than a Type 1 Workday, the Typical Workday Type 2 illustrates some significant differences. Taking fewer trips at lunch details a more pronounced two meals, one occurring right after work and another after activity participation. A larger occurrence of after-work shopping and other activities takes place from around 6:00 p.m. to 9:00 p.m. when compared to the Typical Workday Type 1. The workday is shorter than Type 1, although it begins first. The day starts with a large increase in work at 6:30 a.m. and continues to 3:00 p.m. versus the Type 1 Workday starting around 6:00 a.m. and continuing until, in some cases, past 5:00 p.m. These times show the clear differentiation between the two workdays, with one structured to focus mainly on going to work, working, and then coming home (Workday Type 1) versus the same with the addition of after-work activities. Like the Type 1 Workday, the cluster is comprised of mainly full-time employees with an interesting addition of students. Less than 1% of Typical Workday Type 1 respondents are full-time students, but nearly 4% are students in the Type 2 Workday. These numbers could be one explanation as to the differing variation of after-work activities to include studying.

School Day

The School Day is typical and closely related to a Western country (McBride et al., 2020a). Both School Days show a consistent trip to work, attending school most of the day, returning home, or participating in activities. Over 97% of Qatar School Day respondents are full-time students aged 5-24. Students start the day with personal activities before leaving their homes around 6:00 a.m. to go to school, with 45.6% taking the school bus. This transportation mode is in clear contrast to the students in the United States, who are usually driven to school in private cars (McBride et al., 2020a). These survey numbers connect well with other variables in the data since 92.4% of students never drive. After a defined period of 7:00 a.m. to 1:00 p.m. of attending class, students travel back home to either participate in other activities or, for a majority, start studying. A defined lunch time at around 10:00-11:00 a.m. is followed by an after-school meal at 2:00 p.m., and what appears to be dinner at 7:00 p.m. Personal activities finish off the day.

Mixed Day

The Mixed Day illustrates some possibly errored data. The day includes the smallest sample of only 154 and incorporates a mix of work and school days. The times and separation of activities are plausible, but the abnormalities occur after completing either their school or workday. Data input reflects an implausible amount of time allocated to eating at home. Further analysis of the data sequences shows an inconsistency in the input of some of these select individuals with home eating durations lasting over half a day. This cluster was kept because it highlights two important factors. One is the ability of sequence analysis to determine and model the inconsistency for further analysis. Secondarily, it shows the imperfection of the data without altering it. These errors in data are most likely caused by human error in either collection or data reconfiguration.

Early Discretionary Day

As the name suggests, the Early Discretionary Day starts earlier at around 6:00 a.m. Early Discretionary Day best illustrates a typical weekend or errand day packed with many different states. An Early Discretionary Day makes sense as most people report on Friday, the first day of their weekend, and are comprised of roughly the same major age range as a Typical Workday. This cluster is unique in showing the few occurrences where breakfast is eaten. For the most part, the data shows that most respondents first meal is lunch, anywhere from 11:00 a.m. to 1:00 p.m. This cluster has occurrences starting from the start of the day where people are eating and is the only cluster where this stays constant throughout the day.

Discretionary Day

The days in Qatar can reach extreme temperatures and make midday outdoor activities unfeasible in the summer months. This data was mainly collected throughout the winter months. Most activities take place near or after the sun sets, and this is highlighted in Discretionary Day. A prominent peak in activity happens around 7:00 p.m. and continues late into the night. This time could also better explain why the early discretionary days drop off when the day is at its hottest around 2:00 p.m. The most visible presence of the entertainment state (H_Entertainment) better defines this cluster as discretionary. This cluster includes the greatest number of retired persons and those looking for a job.

Non-Travelling Day

The last pattern, implicitly determined through sequence analysis, illustrates those whose daily pattern doesn't involve traveling. These people primarily stay in their homes and are often comprised of house persons, women, and very young children. Descriptive statistics indicate many undisclosed answers as information with this group, but most are house persons who stay at home. In the regression analysis that follows, this is further expanded.

D: Discussion of Sequences for Laborers

Typical Workday Type 1

Starting early in the morning, a Typical Workday Type 1 shows laborers starting their day before the survey commences. Starting work nearly 2 hours earlier than the household residents, laborers look to have a standard workday from 5:00 a.m. to 6:00 p.m. This cluster outnumbers the entirety of the other clusters combined with 842 persons. An earlier lunch takes place around 11:30 a.m., and dinner from 6:00 p.m. to 10:00 p.m. illustrates a dinner window. Most respondents fall between 25-34 years old and primarily reported at the beginning of their workweek, Sunday through Tuesday. Although 100% of all respondents are full-time employees, 33.8% make less than 1,000 Qatari Riyals a month, the equivalent of less than $275 USD per month. Private shuttles, company buses, and walking dominate the mode choice used by laborers, amassing 82.5% of all respondents. The Typical Workday Type 1 holds the greatest number of people with a higher education degree.

Typical Workday Type 2

In contrast to a Type 1 Workday, the Typical Workday Type 2 highlights an important travel component. The ride shares or pick up/drop off passengers are highlighted in this cluster. Another explanation could be the presence of personal drivers who start early in the morning and drive throughout the day. This cluster starts around 5:00 a.m. and extends until 3:00 p.m.; this group size is 44. The activity participation at home differs from a Type 1 Workday with an uptake in home other activities. This group tends to be slightly older than the Type 1 Workday group, with 50% of persons aged 35-44.

Mixed Day

Another illustration of possible data inconsistencies, the Mixed Day details data irregularities captured by sequence analysis that highlight improbable workdays. The late work can be explained by the long commute among the 42 persons in this cluster. This long commute might be caused by the 35.7% of respondents that walk, the highest percentage among all four laborer clusters.

Holiday

The Holiday cluster is likely an off day for the worker-dominated laborer data. The presence of trips to other places and an apparent shopping state validates this weekend day. The most compelling argument can be seen in the 78.1% of respondents who answered on Friday or Saturday. The highest percentage of respondents were 25-34, similar to a Type 1 Workday. Although a free day, the company bus is used most of the time, indicating its dual usage for laborers.

V. Distinction of Household Types in Travel Behavior

Another way to study membership in each of the patterns explored here is to analyze membership in each cluster using multivariate regression. In this case, a categorical variable is created, signifying the type of daily pattern a person conducts. Then, person and household characteristics are used as explanatory variables of the membership in a cluster. The analysis here is complementary to the cross-tabulations reported above and confirmatory of the significance of a person's characteristics in explaining daily pattern choices. By including ethnicity and demographic variables as explanatory factors of the membership regression function, the sampling biases are accounted for here. The multivariate regression tool used is the Multinomial Logit Model (MNL).

In this analysis, all the data of the residents are used jointly (i.e., the persons staying at home on the entire interview day and the six daily patterns of the persons that made at least one trip outside their home). Interpretation of the regression's coefficient is relative to the option used as reference (i.e., the stay-at-home day). Below is a similar composition of descriptive statistics as used in Table 4, shortened to only the top three percentages for each characteristic for a broad overview. Children too young to respond on their own were answered for by their parents.

Table 32: Composition of the Stay-at-Home All Day Respondent Group/Cluster

Variable	Definition	Subgroup	Non - Travelers (n = 11263)
Age	**Respondent Age Group**	0 – 4 Years Old	32.87%
		25 - 34 Years Old	22.87%
		35 - 44 Years Old	15.98%
Sex	**Respondent's Sex: Male or Female**	Male	34.88%
Monthly Income	**Respondent's Monthly income**	QAR 1,001 - 3,000/month	7.87%
		QAR 3,001 - 6,000/month	5.90%
		N/A	80.96%
As Driver	**Respondent's Status as Driver**	Always	12.78
		Never	81.22
		Sometime	3.28
As Passenger	**Respondent's Status as Passenger**	Always	62.97%
		Never	12.60%
		Sometime	21.68%
Educational Attainment	**Respondent's Educational Attainment**	Graduate	15.26%
		High School	12.99%
		N/A	45.76%

Table 32 Composition of the Stay-at-Home All Day Respondent Group/Cluster (Cont.)

Variable	Definition	Subgroup	Non - Travelers (n = 11263)
Main Occupation	**Respondent's Job Category**	Full-time employed	18.41%
		Full-time student	15.97%
		House person	62.37%
Report Day of the Week	**Respondent's Day Recorded**	Friday	12.39%
		Sunday	11.94%
		Undisclosed	32.84%
Nationality	**Respondent's Nationality**	Qatar	13.11%
		India	28.86%
		Philippines	11.50%

Note: Only top three percentages shown for each characteristic. Total of present and missing percentages equate to 100%. All data subgroups are the same as Table 4.

In the following tables, a positive regression coefficient means a person of a specific characteristic used as an explanatory variable is more likely to be in that daily pattern when compared to the stay-at-home day and negative the opposite. Also, when one includes dummy variables (i.e., an indicator taking the value 1 for a category of a variable and 0 otherwise), assuming one divides the original variable into n dummies, in the regression model, n-1 dummies can be used. The interpretation of the coefficient value on the probability of belonging in one of the daily patterns is relative to the dummy used as the base.

In what follows, the first table (Table 33) shows an MNL with all the observations combined, and then two tables for households with and without children are Tables 34 and 35, respectively. In this way, one can identify the impact of children on daily schedules that we know have a major impact on the time allocation of their parents and, in Qatar, the time allocation of domestic in-home workers.

A. Multinomial Logit Model Comparisons

Table 33: Multinomial Logit Model for All Household Members

(MNL reference is the Stay-at-Home Day)

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Base: 0-54 Years old						
55 - 64 Years old	0.118 (0.113)	-0.228** (0.106)	0.061 (0.419)	0.321 (0.45)	0.227* (0.127)	-0.210* (0.125)
65 - 74 Years old	0.172 (0.211)	-0.529** (0.207)	-7.618 (55.764)	-7.239 (38.126)	-0.21 (0.35)	-0.227 (0.324)
75+	-0.069 (0.391)	-1.357*** (0.42)	-3.066 (23.77)	-5.172 (29.911)	0.492 (1.112)	0.065 (1.282)
Base: QAR 20,001/month – more than 100,000/month						
Less than or equal to QAR 1,000/month	-0.183 (0.257)	-0.357 (0.24)	0.676 (0.664)	0.241 (0.857)	-0.487* (0.274)	-0.201 (0.239)
QAR 1,001 - 3,000/month	0.027 (0.145)	-0.167 (0.139)	-0.462 (0.505)	0.098 (0.648)	-0.162 (0.152)	-0.319** (0.138)
QAR 3,001 - 6,000/month	0.408*** (0.142)	0.358*** (0.132)	0.118 (0.363)	1.280*** (0.418)	0.267** (0.129)	0.129 (0.123)
QAR 6,001 - 10,000/month	0.307** (0.123)	0.268** (0.115)	-0.05 (0.32)	1.112*** (0.388)	0.310*** (0.112)	0.052 (0.108)
QAR 10,001 - 15,000/month	0.337*** (0.13)	0.253** (0.123)	-0.06 (0.331)	1.155*** (0.404)	0.265** (0.117)	0.135 (0.114)
QAR 15,001 - 20000/month	0.193 (0.151)	0.304** (0.138)	0.072 (0.366)	1.327*** (0.425)	0.215 (0.131)	0.091 (0.129)
Base: Female						
Male	0.377*** (0.079)	0.272*** (0.067)	0.145 (0.237)	0.206*** (0.069)	0.229** (0.097)	0.688*** (0.102)
Base: Saturday						
Sunday	0.499*** (0.107)	-0.387*** (0.092)	1.903*** (0.539)	3.330*** (0.186)	2.327*** (0.156)	1.729*** (0.119)
Monday	0.386*** (0.111)	-0.311*** (0.094)	2.077*** (0.541)	3.420*** (0.189)	2.274*** (0.158)	1.648*** (0.122)
Tuesday	0.565*** (0.109)	-0.265*** (0.093)	2.337*** (0.533)	3.354*** (0.187)	2.332*** (0.158)	1.788*** (0.121)
Wednesday	0.300*** (0.112)	-0.363*** (0.094)	2.454*** (0.528)	3.404*** (0.19)	2.051*** (0.159)	1.566*** (0.121)
Thursday	0.276** (0.122)	0.207** (0.096)	1.213* (0.619)	3.461*** (0.195)	2.498*** (0.163)	1.655*** (0.129)
Friday	0.367*** (0.103)	0.625*** (0.081)	-1.595* (0.869)	-0.474** (0.215)	-0.864*** (0.192)	-1.676*** (0.154)
Undisclosed Day of Week	-4.865*** (0.588)	-7.230*** (1.006)	-71.800*** (0)	-21.835*** (0)	-2.085*** (0.731)	-1.356** (0.595)

Table 33: Multinomial Logit Model for All Household Members (Cont.)

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Base: Disabled/Sick, Full-time student and Part-time work, Full-time work and Part time student, Other, Part-time student, Part-time work and Part time student						
Full-time Student	0.769* (0.425)	-0.004 (0.34)	4.609 (4.813)	2.410*** (0.504)	3.596*** (1.374)	-0.785 (1.05)
Part time Employee	0.619 (0.497)	-0.289 (0.452)	-3.09 (23.843)	-2.747** (1.169)	4.837*** (1.397)	1.911* (1.053)
Full-time Employee	0.393 (0.417)	-0.073 (0.339)	4.217 (4.801)	-1.753*** (0.57)	6.120*** (1.365)	3.517*** (1.004)
Looking for a Job	0.361* (0.196)	0.388** (0.168)	-4.601 (42.82)	-6.124 (32.094)	2.404*** (0.605)	2.136*** (0.719)
Retired	0.315* (0.191)	0.704*** (0.168)	-6.001*** (0.004)	1.023 (1.076)	1.486** (0.691)	-4.118 (17.468)
Self Employed	0.409 (0.566)	-0.281 (0.516)	-1.815 (20.28)	-8.838 (42.469)	5.063*** (1.428)	2.585** (1.071)
Base: Doctorate (Ph.D), Other, Undisclosed						
Graduate	-0.081 (0.078)	-0.059 (0.066)	1.001** (0.412)	-0.303 (0.232)	0.058 (0.126)	0.286** (0.123)
Highschool	-0.371*** (0.085)	-0.214*** (0.072)	0.212 (0.365)	-0.669*** (0.121)	-0.327** (0.134)	-0.262** (0.134)
Masters Degree (M.Sc)	-0.223* (0.124)	0.039 (0.105)	0.797 (0.498)	-0.37 (0.402)	0.225 (0.153)	0.395*** (0.148)
Nursery	-0.343 (0.236)	-0.381 (0.236)	-12.618*** (0)	-0.533 (0.91)	-0.455 (0.411)	-1.283** (0.59)
Primary	-0.21 (0.177)	0.072 (0.159)	-10.002*** (0.0001)	-0.594 (0.468)	-0.656** (0.291)	-0.823*** (0.301)
Secondary	-0.344** (0.145)	-0.670*** (0.153)	-14.549*** (0)	-1.879** (0.801)	-0.484** (0.197)	-0.714*** (0.203)
Base: Sometimes Driver						
Always Driver	0.430*** (0.119)	0.192* (0.108)	0.028 (0.551)	0.31 (0.299)	0.238 (0.157)	0.122 (0.154)
Never Driver	-0.829*** (0.113)	-0.324*** (0.096)	0.285 (0.602)	-0.356 (0.283)	-0.359** (0.161)	-0.124 (0.163)
Undisclosed Driver Status	-0.863*** (0.228)	-0.442** (0.192)	0.179 (0.71)	0.068 (0.352)	-0.256 (0.255)	-0.203 (0.241)
Base: Undisclosed						
Car Driver	-0.053 (0.423)	0.439 (0.345)	1.251 (4.741)	3.847*** (0.591)	0.191 (1.335)	3.569*** (1.077)
Car Passenger	0.502 (0.424)	0.674** (0.341)	0.681 (4.746)	4.523*** (0.577)	0.528 (1.339)	3.255*** (1.075)
Private and Public Rides	0.711 (0.433)	1.084*** (0.351)	0.988 (4.749)	4.546*** (0.589)	0.673 (1.34)	3.736*** (1.076)

Table 33: Multinomial Logit Model for All Household Members (Cont.)

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Nonmotor	0.294 (0.454)	0.541 (0.375)	0.604 (4.78)	4.352*** (0.641)	0.255 (1.348)	3.558*** (1.082)
School Bus	0.756* (0.432)	0.772** (0.347)	0.705 (4.751)	4.987*** (0.58)	1.099 (1.347)	2.458** (1.127)
Base: Three+ Cars						
Zero Cars	0.074 (0.146)	-0.078 (0.123)	0.191 (0.553)	-0.516** (0.219)	0.008 (0.171)	0.25 (0.166)
One Car	0.058 (0.087)	0.116 (0.075)	0.203 (0.361)	-0.168 (0.114)	0.0001 (0.105)	0.151 (0.109)
Two Cars	0.218*** (0.081)	0.148** (0.071)	0.632* (0.342)	0.003 (0.107)	0.116 (0.099)	0.159 (0.106)
Base						
One Adult, Zero Children	-0.049 (0.161)	0.005 (0.152)	0.149 (0.521)	-0.152 (0.444)	-0.126 (0.186)	0.113 (0.184)
One Adult, youngest 0-4	-0.367 (0.48)	-0.691 (0.5)	-6.192 (28.704)	0.338 (0.568)	-0.703 (0.651)	-0.685 (0.607)
One Adult, youngest 12-15	0.126 (0.51)	0.183 (0.493)	-5.758 (23.297)	-0.830* (0.494)	-1.069 (0.884)	-0.707 (0.77)
One Adult, youngest 5-11	0.238 (0.346)	-0.698* (0.417)	-6.723 (29.358)	-0.225 (0.355)	0.544 (0.515)	0.373 (0.576)
Two+ Adults, Zero Children	-0.304** (0.128)	0.003 (0.117)	-0.33 (0.479)	-0.398** (0.202)	-0.128 (0.161)	0.081 (0.165)
Two+ Adults, youngest 0-4	-0.011 (0.125)	0.313*** (0.113)	-0.101 (0.458)	0.487*** (0.154)	0.145 (0.16)	-0.036 (0.165)
Two+ Adults, youngest 12-15	0.016 (0.143)	0.281** (0.129)	0.051 (0.517)	0.354** (0.169)	0.278 (0.182)	-0.037 (0.191)
Two+ Adults, youngest 5-11	0.155 (0.126)	0.169 (0.116)	0.301 (0.456)	0.597*** (0.152)	0.473*** (0.164)	0.079 (0.171)
Base: 132 Countries						
Qatar	-0.242*** (0.091)	0.104 (0.077)	-0.692* (0.373)	-0.133 (0.107)	0.398*** (0.105)	-1.212*** (0.127)
Phillipines	-0.084 (0.096)	-0.261*** (0.087)	-0.069 (0.297)	-0.622*** (0.142)	-0.311*** (0.109)	0.282*** (0.097)
India	-0.124* (0.064)	-0.103* (0.057)	-0.048 (0.224)	-0.207** (0.092)	-0.164** (0.078)	0.329*** (0.071)
Sudan	-0.129 (0.124)	-0.021 (0.106)	-0.033 (0.399)	-0.349** (0.145)	0.385*** (0.139)	-0.383** (0.153)
Egypt	-0.226** (0.091)	-0.105 (0.078)	0.205 (0.271)	0.18 (0.11)	0.296*** (0.103)	0.181* (0.1)
Base: Fellow worker, Other, Other relative, Parents/Grandparents, Sibling, Son/Daughter						
Head of Household	1.044*** (0.109)	0.730*** (0.095)	0.382 (0.357)	-0.466 (0.291)	0.752*** (0.11)	0.675*** (0.105)

Table 33: Multinomial Logit Model for All Household Members (Cont.)

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Spouse/Partner	0.544*** (0.106)	0.473*** (0.083)	-0.316 (0.415)	0.136 (0.241)	0.519*** (0.124)	0.222* (0.128)
Live in Driver	1.276*** (0.156)	0.041 (0.17)	-12.047*** (0.00004)	-1.864* (1.13)	-2.075*** (0.329)	-4.049*** (0.6)
Live in Maid	-0.919*** (0.188)	-0.989*** (0.148)	-28.055*** (0)	-10.897 (44.339)	-5.931*** (1.015)	-3.700*** (0.375)
Constant	-2.046*** (0.205)	-1.339*** (0.176)	-10.688*** (1.389)	-8.396*** (0.471)	-8.438*** (0.42)	-8.413*** (0.488)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 34: Multinomial Logit Model for Household Members and their Children

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Base: 0-54 Years old						
55 - 64 Years old	0.147 (0.174)	-0.327* (0.169)	0.207 (0.636)	0.207 (0.637)	0.241 (0.202)	-0.197 (0.214)
65 - 74 Years old	0.177 (0.394(	-0.842** (0.418)	-9.399*** (0.001)	-10.940*** (0.00001)	-0.443 (0.603)	-0.46 (0.599)
75+	-1.816 (1.112)	-2.327*** (0.867)	-2.23 (41.643)	-7.727*** (0.0004)	-7.041*** (0.0004)	-3.327 (56.066)
Base: QAR 20,001/month – more than 100,000/month						
Less than or equal to QAR 1,000/month	0.18 (0.331)	-0.302 (0.328)	-12.469*** (0.0001)	0.633 (1.158)	-0.114 (0.38)	0.071 (0.371)
QAR 1,001 - 3,000/month	-0.193 (0.212)	-0.319 (0.205)	-13.470*** (0.002)	0.562 (1.02)	-0.087 (0.289)	-0.531* (0.298)
QAR 3,001 - 6,000/month	0.647*** (0.204)	0.601*** (0.19)	-0.536 (0.603)	1.529*** (0.582)	0.480** (0.186)	0.336* (0.186)
QAR 6,001 - 10,000/month	0.282* (0.162)	0.334** (0.15)	-0.556 (0.431)	1.559*** (0.502)	0.371** (0.146)	0.043 (0.146)
QAR 10,001 - 15,000/month	0.332** (0.164)	0.277* (0.154)	-0.163 (0.39)	1.332** (0.532)	0.287* (0.147)	0.166 (0.146)
QAR 15,001 – 20,000/month	0.418** (0.194)	0.555*** (0.179)	0.176 (0.428)	2.116*** (0.525)	0.515*** (0.17)	0.329* (0.172)
Base: Female						
Male	0.285*** (0.095)	0.318*** (0.08)	-0.201 (0.278)	0.200*** (0.074)	0.358*** (0.134)	0.444** (0.175)
Base: Saturday						
Sunday	0.555*** (0.129)	-0.457*** (0.109)	1.961*** (0.626)	3.404*** (0.193)	2.768*** (0.221)	1.974*** (0.171)
Monday	0.410*** (0.133)	-0.454*** (0.113)	2.196*** (0.623)	3.418*** (0.195)	2.661*** (0.224)	1.813*** (0.175)
Tuesday	0.572*** (0.13)	-0.416*** (0.111)	2.347*** (0.617)	3.361*** (0.193)	2.722*** (0.223)	1.966*** (0.174)
Wednesday	0.320** (0.136)	-0.423*** (0.113)	2.173*** (0.623)	3.465*** (0.197)	2.475*** (0.225)	1.849*** (0.174)
Thursday	0.389*** (0.147)	0.242** (0.115)	1.159 (0.739)	3.552*** (0.202)	2.939*** (0.23)	1.966*** (0.185)
Friday	0.331*** (0.124)	0.671*** (0.095)	-34.176*** (0)	-0.428* (0.22)	-0.487* (0.263)	-1.591*** (0.234)
Undisclosed Day of Week	-5.173*** (0.719)	-19.489*** (0)	-37.765*** (0)	-14.929*** (0.00001)	-2.311** (1.03)	-1.061 (0.7)

Table 34: Multinomial Logit Model for Household Members and their Children (Cont.)

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Base: Disabled/Sick, Full-time student and Part-time work, Full-time work and Part time student, Other, Part-time student, Part-time work, and Part time student						
Full-time Student	1.442** (0.634)	-0.008 (0.421)	4.68 (7.632)	2.391*** (0.563)	5.091*** (1.898)	-1.777 (1.106)
Part time Employee	0.863 (0.729)	-0.292 (0.582)	-3.196 (52.894)	-2.627** (1.256)	6.188*** (1.932)	1.083 (1.167)
Full-time Employee	0.73 (0.631)	-0.157 (0.429)	4.827 (7.641)	-1.988*** (0.702)	7.387*** (1.893)	2.910*** (1.067)
Looking for a Job	0.338 (0.283)	0.460* (0.241)	-4.594 (59.403)	-10.544*** (0.00001)	2.445*** (0.824)	3.112*** (0.934)
Retired	0.533* (0.286)	0.910*** (0.249)	-2.469 (39.661)	1.768 (1.107)	1.447 (1.096)	-8.629*** (0.002)
Self Employed	0.025 (0.973)	0.308 (0.718)	-2.024 (50.896)	-14.738*** (0.00002)	6.433*** (1.997)	2.293* (1.21)
Base: Doctorate (Ph.D), Other, Undisclosed						
Graduate	-0.12 (0.096)	-0.101 (0.081)	0.865 (0.528)	-0.331 (0.28)	-0.004 (0.168)	0.066 (0.173)
Highschool	-0.356*** (0.103)	-0.301*** (0.088)	0.054 (0.416)	-0.693*** (0.13)	-0.408** (0.178)	-0.462** (0.193)
Masters Degree (M.Sc)	-0.169 (0.153)	0.087 (0.129)	0.441 (0.653)	-0.283 (0.467)	0.211 (0.203)	0.16 (0.204)
Nursery	-0.111 (0.274)	-0.262 (0.275)	-9.124*** (0.006)	-0.351 (0.952)	-0.208 (0.466)	-0.964 (0.622)
Primary	-0.314 (0.214)	-0.154 (0.196)	-10.767*** (0.0001)	-0.882* (0.473)	-0.866** (0.389)	-2.026*** (0.65)
Secondary	-0.501*** (0.191)	-0.766*** (0.199)	-11.202*** (0.001)	-2.752** (1.088)	-0.794*** (0.268)	-0.910*** (0.305)
Base: Sometimes Driver						
Always Driver	0.534*** (0.14)	0.249* (0.131)	0.363 (0.763)	0.042 (0.354)	0.211 (0.194)	0.189 (0.199)
Never Driver	-0.996*** (0.131)	-0.382*** (0.114)	0.49 (0.822)	-0.395 (0.328)	-0.343* (0.199)	-0.08 (0.217)
Undisclosed Driver Status	-1.074*** (0.27)	-0.490** (0.223)	0.709 (0.883)	-0.013 (0.392)	-0.550* (0.32)	-0.342 (0.313)

Table 34: Multinomial Logit Model for Household Members and their Children (Cont.)

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Base: Undisclosed						
Car Driver	-0.553 (0.636)	0.336 (0.433)	0.909 (7.609)	3.753*** (0.663)	-1.038 (1.859)	4.500*** (1.206)
Car Passenger	0.034 (0.635)	0.678 (0.426)	0.135 (7.6)	4.349*** (0.645)	-0.7 (1.859)	4.095*** (1.2)
Private and Public Rides	0.212 (0.648)	1.015** (0.442)	0.405 (7.609)	4.363*** (0.657)	-0.849 (1.863)	4.496*** (1.206)
Nonmotor	-0.346 (0.678)	0.165 (0.489)	0.902 (7.633)	4.293*** (0.715)	-1.027 (1.882)	4.495*** (1.227)
School Bus	0.318 (0.639)	0.805* (0.428)	0.126 (7.603)	4.789*** (0.647)	-0.28 (1.863)	3.550*** (1.265)
Base: Three+ Cars						
Zero Cars	0.094 (0.2)	-0.335* (0.176)	0.283 (0.781)	-0.509** (0.237)	-0.34 (0.271)	0.032 (0.273)
One Car	0.115 (0.106)	0.143 (0.093)	0.335 (0.43)	-0.107 (0.121)	0.017 (0.134)	0.109 (0.151)
Two Cars	0.243** (0.096)	0.148* (0.085)	0.629 (0.399)	0.029 (0.113)	0.081 (0.122)	0.168 (0.141)
Base: One Adult, Youngest 16-18; Two+ Adults, Youngest 16-18						
One Adult, youngest 0-4	-0.386 (0.487)	-0.681 (0.507)	-10.121*** (0.0001)	0.295 (0.565)	-0.549 (0.655)	-0.744 (0.617)
One Adult, youngest 12-15	0.139 (0.512)	0.217 (0.501)	-10.912*** (0.0002)	-0.862* (0.494)	-1.049 (0.885)	-0.785 (0.77)
One Adult, youngest 5-11	0.256 (0.352)	-0.608 (0.422)	-10.962*** (0.0001)	-0.231 (0.357)	0.65 (0.521)	0.334 (0.595)
Two+ Adults, youngest 0-4	0.008 (0.127)	0.320*** (0.115)	-0.025 (0.465)	0.466*** (0.155)	0.118 (0.163)	-0.017 (0.169)
Two+ Adults, youngest 12-15	0.026 (0.144)	0.277** (0.13)	0.028 (0.519)	0.332* (0.17)	0.255 (0.183)	-0.057 (0.194)
Two+ Adults, youngest 5-11	0.17 (0.128)	0.157 (0.118)	0.326 (0.462)	0.571*** (0.153)	0.450*** (0.167)	0.09 (0.174)
Base: 132 Countries						
Qatar	-0.300*** (0.11)	0.164* (0.093)	-0.937** (0.426)	-0.147 (0.114)	0.337*** (0.13)	-1.128*** (0.162)

Table 34: Multinomial Logit Model for Household Members and their Children (Cont.)

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Phillipines	-0.183 (0.123)	-0.273** (0.11)	-0.603 (0.461)	-0.678*** (0.149)	-0.383** (0.151)	0.366** (0.142)
India	-0.205*** (0.078)	-0.097 (0.069)	-0.152 (0.274)	-0.261*** (0.097)	-0.309*** (0.102)	0.326*** (0.099)
Sudan	-0.295** (0.148)	-0.06 (0.126)	-0.259 (0.462)	-0.455*** (0.151)	0.219 (0.171)	-0.431** (0.196)
Egypt	-0.259** (0.104)	-0.128 (0.09)	0.107 (0.317)	0.144 (0.116)	0.231* (0.127)	0.229* (0.129)
Base: Fellow worker, Other, Other relative, Parents/Grandparents, Sibling, Son/Daughter						
Head of Household	1.159*** (0.153)	0.798*** (0.131)	-0.113 (0.494)	-0.416 (0.354)	0.891*** (0.159)	0.777*** (0.17)
Spouse/Partner	0.647*** (0.139)	0.509*** (0.107)	-0.84 (0.542)	-0.18 (0.301)	0.688*** (0.174)	-0.099 0.203
Live in Driver	1.675*** (0.21)	0.283 (0.22)	-6.713 (70.652)	-1.661 (1.325)	-1.668*** (0.411)	-3.380*** (0.653)
Live in Maid	-0.464** (0.226)	-0.620*** (0.179)	- 11.498*** (0.0002)	- 16.024*** (0.00001)	-5.617*** (1.044)	-3.672*** (0.493)
Constant	-2.052*** (0.238)	-1.306*** (0.201)	- 10.147*** (1.532)	-8.168*** (0.523)	-8.973*** (0.515)	-8.652*** (0.672)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 35: Multinomial Logit Model for Household Members Without Children

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Base: 0-54 Years old						
55 - 64 Years old	0.112 (0.154)	-0.166 (0.138)	0.05 (0.57)	0.238 (0.661)	0.206 (0.167)	-0.192 (0.157)
65 - 74 Years old	0.25 (0.258)	-0.339 (0.243)	-9.623*** (0.005)	-9.143*** (0.004)	-0.062 (0.432)	-0.07 (0.387)
75+	0.343 (0.436)	-0.933* (-0.486)	-8.337*** (0.001)	-6.688*** (0.0004)	0.896 (1.124)	0.407 (1.284)
Base: QAR 20,001/month – more than 100,000/month						
Less than or equal to QAR 1,000/month	-0.854* (0.436)	-0.600* (0.358)	1.608* (0.829)	-0.325 (1.403)	-1.054** (0.412)	-0.513 (0.32)
QAR 1,001 - 3,000/month	0.086 (0.213)	-0.222 (0.203)	0.363 (0.684)	-0.293 (0.929)	-0.369* (0.206)	-0.347* (0.183)
QAR 3,001 - 6,000/month	0.157 (0.209)	0.109 (0.194)	0.805 (0.586)	1.046 (0.64)	-0.036 (0.19)	-0.065 (0.172)
QAR 6,001 - 10,000/month	0.279 (0.193)	0.155 (0.182)	0.761 (0.564)	0.165 (0.716)	0.136 (0.178)	0.025 (0.164)
QAR 10,001 - 15,000/month	0.373* (0.215)	0.217 (0.206)	0.234 (0.658)	1.006 (0.655)	0.244 (0.196)	0.118 (0.184)
QAR 15,001 - 20000/month	-0.101 (0.247)	-0.061 (0.227)	-0.012 (0.742)	-6.113 (15.922)	-0.288 (0.213)	-0.235 (0.2)
Base: Female						
Male	0.564*** (0.152)	0.098 (0.126)	1.472** (0.632)	-0.156 (0.325)	0.058 (0.148)	0.716*** (0.138)
Base: Saturday						
Sunday	0.411** (0.199)	-0.181 (0.173)	1.966* (1.073)	1.875** (0.832)	1.792*** (0.23)	1.490*** (0.176)
Monday	0.346* (0.206)	0.063 (0.176)	1.735 (1.108)	2.920*** (0.83)	1.863*** (0.235)	1.540*** (0.182)
Tuesday	0.575*** (0.205)	0.135 (0.177)	2.419** (1.068)	2.653*** (0.829)	1.914*** (0.236)	1.672*** (0.182)
Wednesday	0.291 (0.201)	-0.185 (0.174)	2.976*** (1.035)	1.929** (0.83)	1.594*** (0.232)	1.341*** (0.177)
Thursday	0.053 (0.221)	0.17 (0.177)	1.435 (1.168)	2.261*** (0.85)	1.960*** (0.238)	1.322*** (0.189)
Friday	0.422** (0.186)	0.546*** (0.155)	-0.289 (1.234)	-1.218 (1.102)	-1.362*** (0.293)	-1.821*** (0.214)
Undisclosed Day of Week	0.796 (1.564)	0.333 (1.476)	-4.200*** (0.014)	-0.859 (51.586)	1.3 (1.639)	0.258 (1.634)

Table 35: Multinomial Logit Model for Household Members Without Children (Cont.)

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Base: Disabled/Sick, Full-time student and Part-time work, Full-time work and Part time student, Other, Part-time student, Part-time work and Part time student						
Full-time Student	-0.2 (0.672)	-0.22 (0.631)	-1.528 (37.809)	1.897 (1.213)	1.059 (2.263)	1.099 (1.732)
Part time Employee	0.177 (0.737)	-0.514 (0.755)	-2.984 (48.321)	-20.838*** (0)	2.829 (2.239)	2.855* (1.68)
Full-time Employee	-0.194 (0.613)	-0.105 (0.59)	4.389 (13.088)	-1.775 (1.196)	4.341** (2.18)	4.264*** (1.621)
Looking for a Job	0.496* (0.286)	0.279 (0.241)	-1.672 (2.305)	-8.070*** (0.001)	2.254** (0.935)	1.157 (1.175)
Retired	0.397 (0.269)	0.674*** (0.235)	0.261 (72.004)	-9.334*** (0.0002)	1.443 (0.968)	-14.902*** (0)
Self Employed	0.177 (0.764)	-1.036 (0.842)	-2.327 (48.314)	-20.512*** (0)	3.148 (2.256)	3.025* (1.701)
Base: Doctorate (Ph.D), Other, Undisclosed						
Graduate	-0.022 (0.142)	0.036 (0.117)	8.111 (30.082)	0.027 (0.481)	0.161 (0.196)	0.525*** (0.178)
Highschool	-0.371** (0.158)	-0.036 (0.13)	7.393 (30.083)	-0.443 (0.385)	-0.151 (0.21)	-0.021 (0.191)
Masters Degree (M.Sc)	-0.312 (0.218)	-0.025 (0.183)	8.333 (30.085)	-0.443 (0.86)	0.267 (0.241)	0.654*** (0.22)
Nursery	-0.849* (0.498)	-0.561 (0.475)	-2.135 (1.763)	-10.577*** (0.0001)	-1.466 (0.956)	-20.330*** (0)
Primary	0.043 (0.331)	0.605** (0.283)	-2.249 (3.65)	1.4 (1.149)	-0.188 (0.463)	0.008 (0.398)
Secondary	-0.167 (0.237)	-0.447* (0.245)	-3.52 (3.603)	-0.012 (1.134)	-0.02 (0.296)	-0.413 (0.279)
Base: Sometimes Driver						
Always Driver	0.263 (0.234)	0.15 (0.196)	-0.468 (0.85)	0.79 (0.592)	0.252 (0.278)	0.004 (0.251)
Never Driver	-0.258 (0.231)	-0.177 (0.183)	-0.382 (0.98)	-0.861 (0.592)	-0.331 (0.284)	-0.139 (0.261)
Undisclosed Driver Status	-0.207 (0.443)	-0.348 (0.381)	-8.852 (68.789)	-0.259 (1.483)	0.263 (0.447)	0.076 (0.406)
Base: Undisclosed						
Car Driver	1.038 (0.633)	0.809 (0.605)	4.434 (20.51)	4.223*** (1.387)	1.916 (2.182)	2.591 (1.638)
Car Passenger	1.388** (0.639)	0.823 (0.607)	4.378 (20.512)	5.133*** (1.386)	2.176 (2.186)	2.276 (1.641)
Private and Public Rides	1.462** (0.646)	1.236** (0.614)	4.587 (20.51)	4.466*** (1.502)	2.537 (2.186)	2.759* (1.641)

Table 35: Multinomial Logit Model for Household Members Without Children (Cont.)

	Early Discretionary Day	Discretionary Day	Mixed Day	School Day	Typical Workday Type 2	Typical Workday Type 1
Nonmotor	1.346** (0.675)	1.012 (0.643)	3.496 (20.536)	-1.949 (24.076)	2.126 (2.194)	2.629 (1.647)
School Bus	0.576 (0.998)	-1.173 (1.199)	-7.965*** (0.045)	6.769*** (1.471)	3.278 (2.235)	1.479 (1.773)
Base: Three+ Cars						
Zero Cars	-0.295 (0.238)	0.047 (0.195)	-0.062 (0.985)	-0.422 (0.783)	0.126 (0.259)	0.309 (0.234)
One Car	0.035 (0.156)	0.11 (0.135)	0.113 (0.737)	-0.827* (0.429)	0.052 (0.176)	0.228 (0.164)
Two Cars	0.151 (0.159)	0.146 (0.139)	0.778 (0.732)	-0.341 (0.386)	0.196 (0.18)	0.092 (0.173)
Base						
One Adult, Zero Children	-0.811*** (0.145)	-0.492*** (0.125)	-7.631 (11.859)	-2.226*** (0.599)	-2.672*** (0.251)	-2.640*** (0.243)
Two+ Adults, Zero Children	-0.974*** (0.12)	-0.489*** (0.099)	-7.942 (11.856)	-2.826*** (0.455)	-2.659*** (0.238)	-2.688*** (0.232)
Base: 132 Countries						
Qatar	-0.037 (0.167)	-0.015 (0.143)	0.058 (0.866)	0.099 (0.39)	0.547*** (0.185)	-1.350*** (0.217)
Philippines	0.094 (0.159)	-0.242* (0.144)	0.69 (0.444)	-0.406 (0.687)	-0.205 (0.164)	0.270* (0.138)
India	0.058 (0.117)	-0.05 (0.103)	0.106 (0.405)	0.259 (0.413)	0.128 (0.125)	0.427*** (0.107)
Sudan	0.292 (0.236)	0.19 (0.2)	0.579 (0.804)	0.607 (0.609)	0.801*** (0.251)	-0.164 (0.259)
Egypt	-0.17 (0.196)	0.014 (0.168)	0.417 (0.534)	0.183 (0.479)	0.427** (0.188)	0.171 (0.173)
Base: Fellow worker, Other, Other relative, Parents/Grandparents, Sibling, Son/Daughter						
Head of Household	0.942*** (0.163)	0.570*** (0.143)	0.879* (0.529)	-0.486 (0.629)	0.621*** (0.158)	0.545*** (0.141)
Spouse/Partner	0.314* (0.188)	0.333** (0.14)	1.064 (0.806)	0.863* (0.468)	0.382* (0.195)	0.489*** (0.183)
Live in Driver	0.868*** (0.269)	-0.165 (0.296)	-10.258*** (0.0003)	-12.321*** (0.0003)	-17.516*** (0)	-18.533*** (0)
Live in Maid	-1.838*** (0.446)	-1.831*** (0.338)	-12.851*** (0.00005)	-8.35 (28.62)	-15.712*** (0.00001)	-3.906*** (0.748)
Constant	-1.786*** (0.226)	-0.981*** (0.181)	-15.572 (23.712)	-5.052*** (0.835)	-5.332*** (0.469)	-5.328*** (0.459)

Note: *p<0.1; **p<0.05; ***p<0.01

The Multinomial Logit Model results above explain the composition of the patterns. This model is equivalent to comparing the means of the cross-tabulation tables shown earlier but in a multivariate way, accounting for the impact of many other variables. As mentioned earlier, the models contain the six membership clusters of the household members while holding the seventh cluster as the reference category in the seven-category dependent variable used here. This seventh cluster contains all other household members who did not travel in the survey, and they are 11,263 respondents.

The purpose of holding the non-travel category as a reference shows the significance of some variables to certain traveling cluster membership. Some variables are not significantly different from zero, and this may be due to either a sample of the data that is too small or a similar value to the reference category and base variables. In this analysis, the laborer data are not used because they are less statistically interesting in comparison to the household residents since the overall main pattern was going to work, working, and returning home with slight variations. There is not enough diversity in social and economic characteristics to derive correlations between daily patterns and other factors.

As mentioned, three MNL models have been constructed to compare travel behavior among households with and without children. The first MNL model has all variables for everyone in the household resident's dataset (n=30,707). The next MNL model has the same variables for all household residents who have children or are children themselves (n=22,722). Children are defined as any person 18 years old or younger. The final model also continues showing the same variables for households with no children (n=7,985).

These models contain added characteristics of individuals and households to the earlier cross-tabulations. Household structure has been added to summarize families' sizes with or without children. Household structure is the only variable that differs between the with or without children models. The model containing children removes all household structures without children, and the model without children does the opposite. The number of vehicles per household at the individual level has also been included. Nationality and relation status have also been added. Only the five most populous nationalities are included to have a sufficient number of observations in the regression models. Creating dummy variables allows for each variable to be tested for significance, and removing insignificant variables becomes the base of that variable. The coefficients in Table 33 and Table 34 show similar estimates since most of the overall sample comprises members from households with children. The exclusion of children in Table 35 shows different patterns and coefficients of lower significance. Below is a breakdown of each variable and its significance within each model.

The age variable in younger ages is not statistically significant from zero due to correlation with other variables or similar patterns throughout all three regression models in Tables 33, 34, and 35, except for older age groups. Preliminary specifications of all the models included the younger ages (0-55), and they did not present a statistically significant difference from zero. These groups are removed to illustrate patterns of 55-year-old through 75+ years old. Older adults do not appear to travel that much, and Table 34 and Table 35 show a significant negative coefficient for School Days.

Income as a variable is more complicated in this model. The negative coefficients with significance do not correspond to higher relative frequency because of their correlation to other variables in the model, such as the number of cars in the household. There are other explanations for significance in the very low-income households that can be explained through the informal market that creates unpredictable work patterns and limited money for transportation to jobs. Some people who do not have enough money to purchase transportation may have a more difficult time finding work. The overall table (Table 33) and household members and their children (Table 34) show strong positive coefficients for making 3,000 to 15,000 Qatari Riyal monthly on school days. Most of the incomes of household members without children (Table 35) are not significantly different from zero in contrast to Table 33 and Table 34. The exception is the lowest income category, indicating those members without children are working for very little income. The lower income could be a driving force for the absence of children.

Gender is a positive and significant variable in all the patterns except Mixed Day for Table 33 and Table 34. Overall, the positive coefficients throughout all the models indicate a simple pattern of travel behavior in Qatar. That is, men are more likely to leave the home and are more likely to have more typical workdays. A Typical Workday Type 1 is more likely than a Typical Workday Type 2 to occur throughout all the models. An absence of children in the households in Table 35 shows males are less likely to be in the Mixed Day pattern or stay at home. They are, however, more likely to participate in Typical Workday Type 1 than either the overall table (Table 33) or the household members and their children (Table 34).

The days of the week are different than those of a Western country. As mentioned, Sunday starts the work week in Qatar and continues through Thursday. Friday is primarily a day of religion, while Saturday is a more typical weekend or free day. The models confirm some of these patterns, as Sunday marks a large positive and significant coefficient for school and workdays while having a negative and significant coefficient for early discretionary days. There appears to be a group of people who participate in early discretionary days on Sundays and the rest of the work week throughout each of the models.

Monday through Thursday follow a similar trend, showing this typical work week. The overall table (Table 33) and the table for household members and their children (Table 34) show Thursdays to be like a Western country's Fridays. Work and school visits still take place, but a significant uptake in discretionary days is in this sample on Thursdays. Friday illustrates the opposite as the pattern's coefficient has switched from positive to negative, and now discretionary days are seen as significantly positive. There are less significant coefficients throughout the week for both discretionary days in the table for household members without children (Table 35) except for Friday. The findings on Friday indicate even childless households still use this day as a 'weekend' or day of religious activity. This variable provides evidence for the typical work week of Qatar and the use of discretionary days on what is classified as 'weekends' in Qatar.

The findings indicate full-time employees are most frequent in typical workdays across all models. In contrast, full-time students show a higher propensity to participate in School Day patterns, except for Table 35. This exception makes sense as the absence of children in Table 35 has significantly fewer members participating in school. The full-time students in Table 33 and Table 34 also indicate a positive and significant coefficient in Typical Workday Type 2, which could mean that some students work outside of school. Self-employed and retired individuals still have statistically significant workdays across all the models.

Education attained is more closely associated with workdays, while lower education is not. Survey participants with graduate and master's degrees are also more likely to have a Typical Workday Type 1 instead of a Type 2 Workday in all the tables. This variable is correlated with income and age, creating confounding results.

Driving status is not statistically significant from zero in households without children (Table 35). Table 33, with the entire sample and Table 34, for the household members and their children, indicate a higher likelihood to participate in Early Discretionary Days if the respondent is the driver. Those who never drive appear to leave the house less often and do not participate in the six traveling patterns. Those who are never drivers, including children, are less likely to participate in either Discretionary Day, and they are less likely to participate in Typical Workdays Type 2.

Mode of transportation answers the 'how' question of travel behavior. Car drivers and car passengers are more likely to go to school or have a Typical Workday Type 1. Those respondents who use private or public ride-hailing are very similar, with a greater likelihood of having a discretionary day. The overall table (Table 33) and household members and their children (Table 34) have positive and significant coefficients in School and Workdays for non-motor and private and public ride-sharing. These results show that some daily time allocation patterns are more suitable for alternative forms of transportation, including walking or taking the bus. The household members without children (Table 35) indicate positive coefficients in nonmotorized travel for Early Discretionary Days and Typical Workday Type 1.

One of the more interesting details of the models in this study includes the use of family structure. Modeling the family structure by the number of parents and the age of the youngest child shows a lack of significance when compared to the United States (Hui et al., 2022). It appears the structure of the household does not have an impact on the membership of a certain pattern in Table 33. Table 34 indicates a higher likelihood of School Days, which is expected of a household with younger children. Table 35 tells a story of very little travel with negative and significant coefficients for all the daily patterns, indicating those without children do not travel as much as those with children. The travel is further discussed later in the Travel Time Ratio section. For specific ethnic groups, family structures in Qatar are much different than those in the United States, with more members per household on average. The average household size in this dataset of household residents is just over 3.28 people per household. This size is substantially larger than that of the 2.60 average size of the United States and the 2.92 average size of California (United States Census Bureau 2017-2021 data).

A new set of explanatory factors about travel behavior is shown through nationality or place of origin. The models indicate that certain nationalities, in this case, the five most populous of the datasets, have similar daily patterns to one another. The overall table (Table 33) illustrates similar patterns among Qataris, Sudanese, and Egyptians. Each of these nationalities is likelier to participate in a Typical Workday Type 2 and less likely to participate in a Typical Workday Type 1. The Philippines and India have opposite daily patterns as they have positive and significant coefficients for Typical Workday Type 1 and negative and significant for Typical Workday Type 2. The household members and their children (Table 34) show that people from the Philippines, India, and Sudan are less likely to have School Days.

Relation status describes the individuals' relationship to their household. The head of the household is often a male. Both heads of households and spouses have similar patterns, and it appears they do not stay home all day. Both groups are more likely to have Typical Workdays or Discretionary Days. Domestic help includes live-in maids and live-in drivers. Live-in maids do not appear to leave the house and have negative and significant coefficients in all the patterns. Live-in drivers are similar except for Early Discretionary Days, where they are more likely to travel (e.g., chauffeurs on weekends).

VI. Travel Time Ratio

The patterns of household travelers separated by the status of children and patterns of ethnicity presented in this thesis are novel for both sequence analysis and the study of travel behavior in Middle Eastern countries, specifically Qatar. Travel Time Ratio (TTR) is used as an indicator of the amount of time spent traveling versus time spent on activities and can be used as an indicator of spatial reach (Dijst and Vidakovic, 2000) and as another indicator of transportation system performance (McBride at al., 2020a). In this thesis, two Travel Time Ratios are presented. The first is calculated as the total travel time in the interview day divided by the amount of time spent in activities outside of the home plus travel. These are designated as the "TTR" columns in the tables below. The second, TTR not home (NH), is calculated similarly as the sum of all travel time in the day divided by the activities conducted outside the home, not including travel, and is presented as "TTR NH" below. A second table has been created for the duration of travel and out-of-home activity. Like the multinomial logit models, one of each table (TTR and durations) has been made for the three characterizations of the data, one for the overall data of household residents (Table 36), and the other two are split up for households with (Table 37) and without children (Table 38).

Table 36: Travel Time Ratio for All Households (Overall)

Daily Pattern	Mean TTR	SD TTR	Mean TTR NH	SD TTR NH
Typical Workday Type 1	0.154	0.094	0.316	8.085
School Day	0.170	0.087	0.322	4.854
Typical Workday Type 2	0.169	0.088	0.221	0.225
Early Discretionary Day	0.524	0.342	41.663	115.333
Discretionary Day	0.365	0.277	15.279	66.644
Mixed Day	0.190	0.175	10.508	72.939

Table 37: Durations for All Households (Overall)

	Mean Travel Duration (Hours)	SD Travel Duration (Hours)	NH Mean Activity Duration (Hours)	NH SD Duration (Hours)
Typical Workday Type 1	1.806	1.281	9.783	2.072
School Day	1.475	0.941	7.030	1.578
Typical Workday Type 2	1.740	1.120	8.280	1.792
Early Discretionary Day	2.270	2.971	2.740	3.424
Discretionary Day	1.552	1.472	3.699	3.087
Mixed Day	1.864	1.722	8.209	2.480

Overall, of the six traveling patterns, the respondents in Early Discretionary Days experience the most time spent traveling with the highest TTR. This TTR can be interpreted as roughly 52% of the time is spent traveling against conducting out-of-home activities, including travel on an early discretionary day. The durations table confirms this, as Early Discretionary Days are the only pattern where travel is over 2 hours on average. Since most people are doing many activities, including shopping and attending a Mosque, this pattern makes sense to have the most traveling on average. Although travel durations are the highest, the activity durations are the lowest for Early Discretionary Days, indicating many stops for short amounts of time as this pattern is the only one with under three hours spent participating in out-of-home activities. The lowest TTR is a Typical Workday Type 1, where only around 15% of the time is spent traveling. The durations table indicates, however, that the most time spent conducting activities out of the home takes place on Typical Workday

Type 1 with an average of over nine hours per day. These activities are mainly composed of work. The Typical Workday Type 2 is very similar to the Type 1 Workday with a slightly higher TTR and the second-highest duration of out-of-home activities. It is worth reiterating that the Type 2 Workday consists of traveling to work, working, returning home, and then going out again for activities after work.

The TTRs for households with children (Table 38) minimally increase as the addition of children overall increases the amount of travel conducted in a day on average. The activity duration out of the home doesn't change drastically as the amount of work, school, or discretionary activities doesn't appear to be affected by the presence of children. The households with children comprise most of the overall data and, as expected, have similar patterns to the overall sample.

Households without children (Tables 40 and 41) tend to show an interesting trend in travel behavior compared to households with children. In every pattern except School Day, the households without children have lower TTRs on average, indicating they travel less of the time than participate in activities. The duration table confirms this with the same or lower travel durations for households without children. School Days illustrate an interesting finding in the data. Households without children tend to travel more to get to school. The comparison of travel durations shows over a 15-minute increase in travel for School Days among households without children versus households with children.

Table 38: Travel Time Ratio for Households With Children

Daily Pattern	Mean TTR	SD TTR	Mean TTR NH	SD TTR NH
Typical Workday Type 1	0.164	0.098	0.463	11.746
School Day	0.169	0.086	0.323	4.916
Typical Workday Type 2	0.174	0.088	0.230	0.254
Early Discretionary Day	0.563	0.348	46.146	111.598
Discretionary Day	0.373	0.279	16.103	70.287
Mixed Day	0.219	0.200	15.482	88.463

Table 39: Durations for Households With Children

	Mean Travel Duration (Hours)	SD Travel Duration (Hours)	NH Mean Activity Duration (Hours)	NH SD Duration (Hours)
Typical Workday Type 1	1.930	1.369	9.632	2.198
School Day	1.468	0.937	7.027	1.548
Typical Workday Type 2	1.786	1.136	8.189	1.784
Early Discretionary Day	2.294	2.925	2.524	3.366
Discretionary Day	1.551	1.484	3.546	2.947
Mixed Day	2.061	1.935	7.580	2.440

Table 40: Travel Time Ratio for Households Without Children

Daily Pattern	Mean TTR	SD TTR	Mean TTR NH	SD TTR NH
Typical Workday Type 1	0.144	0.088	0.184	0.167
School Day	0.201	0.103	0.275	0.192
Typical Workday Type 2	0.160	0.086	0.205	0.160
Early Discretionary Day	0.433	0.310	31.208	123.041
Discretionary Day	0.347	0.270	13.210	56.456
Mixed Day	0.131	0.076	0.161	0.124

Table 41: Durations for Households Without Children

	Mean Travel Duration (Hours)	SD Travel Duration (Hours)	NH Mean Activity Duration (Hours)	NH SD Duration (Hours)
Typical Workday Type 1	1.695	1.185	9.919	1.942
School Day	1.758	1.053	7.144	2.485
Typical Workday Type 2	1.657	1.084	8.445	1.796
Early Discretionary Day	2.213	3.076	3.244	3.507
Discretionary Day	1.555	1.440	4.083	3.384
Mixed Day	1.455	1.063	9.517	2.024

VII. Summary of Findings and Conclusions

Qatar provided a unique and previously unexplored study area for travel behavior. A rarely available place-based activity-travel diary database is used to identify daily patterns in time allocation in Qatar. The data collection mimicked surveys in the United States, allowing the use of techniques and pattern analysis using similar methods. The data analysis here uses 30,708 person days in a country of approximately 2.7 million residents.

The predominantly Islamic country has a majority immigrant population that works within the country. The many ethnic groups in Qatar make for a novel opportunity to examine their differences in travel behavior. The presence of children in households was also undertaken, detailing the mostly higher travel durations for households with children. These distinct travel behavior clusters were generated using sequence analysis and cluster analysis jointly. The membership of each cluster of daily activity and travel patterns was then studied using MNLs. In this thesis, four research questions were answered. Each question is restated and summarized below.

The ability to jointly look at activities, trips, durations, and their ordering for individuals makes sequence analysis the preferable method in this thesis (McBride, 2020a). The data analysis started with raw R data frames being converted into a workable sequence for each respondent (Figure 2). Each minute of the day (1440) is then accounted for by an activity or trip (called a state) the individual did in each minute. Of the total respondents, 19,444 and 992 traveled on their reporting day for the household residents and laborers, respectively. These responses were then used in sequence analysis while the remaining respondents created the stay-at-home cluster. A substitution cost matrix was calculated for each traveling respondent. The value between these sequences was then used to generate a dissimilarity score using the Hamming distance designed for sequences of equal length. The classification of the optimal number of clusters is then calculated based on the matrix of dissimilarities. Considering this analytical summary, answers to the four key research questions follow.

I. What are the daily time allocation and travel behavior patterns in Qatar?

Data analysis, jointly with cluster analysis, revealed seven patterns for household residents and four patterns for laborers. For the household residents, two typical workdays were determined. The Type 1 Workday illustrates a work-focused day with limited activities after returning home in the evening. The Type 2 Workday shows a slightly shorter workday focusing on more activity participation after work. The Discretionary Day reflects a typical free day absent of work where diverse activity participation can be found later into the evening. In contrast, the Early Discretionary Day contains a variety of activities occurring earlier in the day. The School Day is representative of a large portion of all students in the survey that drive or ride to school, attend school, and then participate in activities. The final pattern is found for respondents who do not travel outside the home during the day.

The laborers have four major patterns. The Typical Workday Type 1 reflects a workday of driving to work and then working before driving back home. In comparison to the household members, the laborers are working longer hours with minimal activity participation after work. The Typical Workday Type 2 also shows traveling to work, working, and traveling home. This pattern also highlights laborers who are personal drivers. This pattern differs from Type 1 in that it focuses mainly on ridesharing for laborers to get to and from work. Age was the most important determinant in the Beckman and Goulias study, where younger immigrants make longer commutes to work (Beckman & Goulias, 2008). The limited ages of the laborers see a more similar commuting pattern for all of them absent their age.

Due to their social and economic status in the country, laborers have more constrained daily schedules, leading to their limited travel patterns compared to household residents. We found that household residents have a wider variety of travel and more participation in activities outside of work. With the barriers to assimilation, laborers will continue to have travel patterns with limited ability to change them in the future (Nagy, 2006). Limited incomes and employer-provided housing situate laborers closer to work locations (Nagy, 2006); this could perpetuate the need to focus on work-related travel to increase income primarily. The patterns of discretionary days indicate travel for various activities among groups of children and adults, which likely creates more complex schedules (McBride et al., 2020a).

II. Are there major differences among the variety of nationalities residing in Qatar?

It was determined that there are major differences among nationalities in Qatar. In addition to Qatar, the four most populous immigrant-originating countries are used in the MNLs to compare membership in each cluster. The countries included were India, Egypt, the Philippines, and Sudan. Nationalities among household residents show differences in which typical workday is statistically significant from zero. We expected differences in travel patterns for immigrant nationalities compared to native-born Qatari (Nagy, 2006) but found more similarities than expected in the household residents' data. Qatar, Sudan, and Egypt, in contrast to the Philippines and India, are more likely to participate in a Typical Workday Type 2 instead of Type 1. Respondents from Qatar, India, and Egypt are less likely to participate in early discretionary days. School Day participation is significantly different than zero and negative for the Philippines, India, and Sudan, indicating they are less likely to participate in this cluster.

If travel assimilation is to take place in Qatar, the findings here show that it is more likely to be at a different pace for each of the various ethnic groups. Nationalities with patterns and religious practices similar to Qatari citizens have the best prospects for assimilation. The MNL results indicate that people from Egypt and Sudan could have the best chance of assimilating into Qatar. However, a complete sense of belonging for nationalities with similar patterns to Qatar will be difficult (Soudy, 2013). Among the rare group of naturalized citizens of Qatar, they are often perceived as non-Qatari (Nagy, 2006). Even if a child is second generation Qatari from immigrant parents, they are not treated as natural Qatari, and the same partial acceptance can be seen in children of mixed marriages (Nagy, 2006).

III. What are some differences in daily behavior among different household types in Qatar?

Households were divided into two categories: those that contained children and those that did not. Households that contain children have significantly more participants in School Days. They also tend to travel longer than households without children, with a minimal increase in overall TTR. The households without children have lower TTRs on average, indicating they participate longer in activities than traveling. An exception is found in the School Day cluster, where it is likely transportation other than the children's parents are taking the children to school.

This increase in travel for households with children was expected and reflected similarly to other household types studied in the United States (McBride et al., 2020a; McBride et al., 2020b). More complex daily travel patterns are observed for households with children within the United States (McBride et al., 2020a). The more complex travel patterns are a direct result of participating in many different activities in a day and the required travel to each activity (McBride et al., 2020a). With the added responsibilities for households with children in Qatar (i.e., transporting children to activities), we find higher TTRs, on average, for households with children.

IV. Do we find similarities and differences with published daily patterns in the United States?

Sequence analysis derives six distinct daily patterns, of which two represent typical workdays, one represents a typical school day, one pattern captures recording errors with a mix of school and work, two discretionary/leisure daily patterns, and one separate pattern of people staying at home all day. These are all very similar patterns (typical workdays and school days) that are found in California using CHTS and NHTS (McBride et al., 2020a; McBride et al., 2020b; Shi et al., 2022) and a more recent nationwide analysis (Shi et al., 2023). Considering the social and ethnic composition of Qatar, the findings here are an indication of worldwide similarities and typical routine work schedules (with the caveat of earlier start times in Qatar and the switching of days of the week with Sunday becoming the first work day of a week), children going to school with similar fixity of time schedules, large proportion of the population staying at home all days (with the addition of domestic workers in Qatar), and then the discretionary days with a variety of activities after sunset. However, the Qatar patterns do not have a few patterns found in California characterized by either people coming back from an out-of-the-region travel (with an overnight stay elsewhere than home) or leaving home and staying away for the day of the interview (McBride et al., 2020a).

Comparing the travel and activity distribution in Qatar to that in California shows higher Travel Time Ratios for household residents in Qatar (McBride et al., 2020a). These higher TTRs could be explained as the result of underperforming land use-transportation systems that have forced people into more private car usage over longer distances. Presumably, lower oil and gas prices sustain this practice. However, recent reports from Qatar address a move to more sustainable futures (see https://www.euronews.com/2023/05/17/how-qatar-is-putting-sustainability-at-the-heart-of-its-economy). Qatar is not as different from western countries as one would expect based on media reports and other misconceptions about Islam based country constitutions. Of the daily patterns determined in California, several closely match those of Qatar. These include two Typical Workdays and Discretionary Days. In addition, through similar studies conducted in California, it was determined that School Days in Qatar are like school days in the United States. McBride et al. (2020a) state that the most populous of clusters is the "Home Day," which is categorized as spending most of the day at home. This same trend can be seen in Qatar, where the most populous daily pattern is a stay-at-home day.

The other patterns closely resemble one another on typical days. These follow a simplified pattern of waking up, going to work or school, working or studying before returning home, or participating in after-work/school activities. The discretionary days, mirrored by the "Errands Type 1/2" day in the California patterns, also illustrate a pattern of participating in a more mixed day of activities before returning home at night to conduct more personal activities (McBride et al., 2020a). There is the presence of some patterns in California that are not seen in Qatar. These mainly include travel days where respondents travel out of the data collection region (McBride et al., 2020a).

Some limitations presented in this study are the data gathered before the construction of major infrastructure in the city of Doha, which included a metro and tram (Goulias, 2023). The data was also completed before the 2022 FIFA World Cup hosted by Qatar, which saw many people contribute to the country in both construction for the World Cup and tourism to see the events. Another limitation is the absence of historical population data in Qatar to see trends over time. With the economic developments of the country, there is still little historical data for comparison between immigrant travel behavior of the present and past.

The next steps include taking the accessibility indicators determined by Goulias (2023) and correlating them with the patterns found in this thesis. This correlation will enable us to determine if local land use plays a significant role in the activity and travel daily allocation and the use of private cars. The determination of the most optimal clustering method is still in the early stages, and further research could focus on doing similar studies with differing clustering methods and different numbers of clusters to test the robustness of the analytical techniques used here. While looking at the MNL models, only the five most populous nationalities in Qatar were examined for their membership in each cluster. An expansion to cover more of the 137 countries represented in Qatar could give more insight into the role nationalities have in determining travel behavior. The household types are currently split between the presence of children or their absence. A more in-depth breakdown of the household structure could provide more data significantly different from zero in the

MNLs. We could also gather a better understanding of the TTR and travel duration for households of different sizes and children of different ages.

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