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The Impact of Socio-Economic, Land Use, and Travel Related Variables on Escort and Non-Escort Intermediate Stops on Work Tours

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Abstract

Stop frequency prediction model is one of the components of the activity-based travel demand models. Most of the previous studies have considered stops during commutes regardless of their purposes. This approach does not yield the contribution of the explanatory variables to the likelihood of making stops of different purposes. Besides, most of the former studies have been conducted in larger metropolitan areas. This study attempts to cover these gaps by using 2012 travel data of Fargo-Moorhead medium-sized US metropolitan area and classifying stops on work tours into escort, non-escort, and a combination of all stops. The results of logit models indicate that personal characteristics of the commuters do not contribute to the escort stop participation likelihood. In addition, household size variables have a large impact on the likelihood of participating in escort stops and participating in the combined stops on the outbound leg of the commutes. Contrary to several previous studies, the significance and sign of the coefficient of income level vary for different stop purposes. Commuters seemed to be more likely to make more than one non-escort stop close to their workplace on the outbound legs of their commutes. The general results suggest separating the stop purposes yields more illustrative results rather than using one model for the combined stops.

Keywords

Activity Based Models, Work Tour, Stop Frequency, Escort Stop, Non-Escort Stops

1. Introduction

Travel demand model (TDM) is a critical tool used by transportation planners in making transportation investment decisions (Pereira, et al., 2022; Garus, Alonso, Raposo, Ciuffo, & dell'Olio, 2022). Tour and activity-based models are relatively newer classes of TDMs and are at the forefront of TDM research. The models allow for a more nuanced analysis and for the analysis of complex policies including demand management, equity, carpooling, parking studies, and tolling. Tours are defined as trips that start and end at homes. If travelers make a tour or trip chain with more than one stop out of their home location, it is known as a complex tour (Ye, Pendyala, & Gottardi, 2007) and as the number of these stops increases, the complexity of that tour increases as well. One of the reasons for making complex trip chains is to improve the efficiency of a journey through sequencing the required trips (Schmocker, Su, & Noland, 2010). There is a large body of literature in which the role of different variables contributing to tour complexities has been investigated. Some authors have addressed if a tour is complex (Paleti, Pendyala, Bhat, & Konduri, 2011; Yang, Wang, Chen, Wan, & Xu, 2007) and some others discussed the tours degree of complexity by predicting the number of trips or stops carried out throughout a journey (Shi, 2017; Yang, Hu, & Wang, 2018).

To shed deeper light on the formation of complex tours and realization of the interaction of travelers with time and space constraints, tours can be analyzed within different segments. Given that a tour is an activity that starts from and ends at home, it might be segmented into three parts including the trips made from home to a primary destination known as outbound leg, trips made at the primary destination as a sub-tour of that destination, and trips made from the primary destination to home known as the inbound leg. Due to different factors, such as personal and household characteristics, the occurrence or the number of the trips or stops made on each of the mentioned segments may vary. Prediction of stop frequency or stop occurrence is usually a part of activity-based travel demand models as it deals with the behavior and the perception of travelers towards making stops on a tour; based on their personal or household needs as well as their time and space constraints. In the case of a work tour, where work is the primary destination of the tour, the stops are usually considered as activities with lower priorities compared to work. These stops could be categorized based upon their purposes as mentioned in the previous studies. Picking up/dropping off a passenger, shopping, social/recreation, eating out, personal business, work, and school related stops are some of the common stops to or from a workplace (Currie & Delbosc, 2011; Hatcher & Mahmassani, 1992; Chu, 2003, 2005).

In the previous studies, most of the explanatory variables used in tour complexity or stop frequency modeling are classified into personal and household demographic variables (Chu, 2003, 2005; Bhat & Singh, 2000; Chowdhury & Scott, 2018; Daisy, Liu, & Millward, 2018; Schneider et al., 2021; Verma, Verma, Sarangi, Yadav, & M, 2021); environmental or land use related variables (Chu, 2003, 2005, 2022; Chowdhury & Scott, 2018; Daisy, Liu, & Millward, 2018; Daisy, Millward, & Liu, 2018; Zhu & Guo, 2022); activity related variables such as arrival/departure time; activity duration (Chu, 2003, 2005; Bhat & Singh, 2000; Chowdhury & Scott, 2018; Xianyu, 2013); transportation related attributes such as mode choice (Chu, 2003; Chowdhury & Scott, 2018; Daisy, Millward, & Liu, 2018; Xianyu, 2013; Liu, 2013), and travel time or distance (Bhat & Singh, 2000; Daisy, Millward, & Liu, 2018; Xianyu, 2013; Liu, 2013; Zhu & Guo, 2022; Chu, 2022).

As the decision of making stops on different legs of a tour might be jointly correlated, in some studies such as in (Chu, 2004; Wu & Ye, 2008; Xian-Yu et al., 2011), an interdependence of stop making behavior among different legs of a tour was observed. Using activity participation time and travel time leading to that activity, different stop purposes on a tour were simulated for tours with at least two stops (Garikapati, 2014) and then the stops were located before and after the primary activity of the tour using a binary logit model (Garikapati, 2014). However, the role of land use on the probability of participating in different stop purposes was not discussed in (Garikapati, 2014).

Even though former studies have investigated the contributing factors to trip chaining, stop frequency, and interdependence of stop making behavior within a tour, less attention has been paid to how combining all the stop purposes without distinguishing them based on stop purpose may yield unsuitable results of the model parameters. As the nature of different stop purposes vary, the stop frequency or stop occurrence models may yield unrealistic results in case stops with different purposes are combined. Among different stop purposes, picking a child up from school could be a routine stop (Hatcher & Mahmassani, 1992) for some travelers, whereas other stops such as shopping or a personal business might not be a routine activity and the variables contributing to the prediction of these stops could vary especially if they constitute a large portion of the stops in a region. While an escort trip could be considered a maintenance activity (Castiglione, Bradley, & Gliebe, 2015), in some other studies such as in (Chu, 2004), it was separate from maintenance activities. In the past, some studies investigated the likelihood of escorting children to school by household members or by other means (He, 2013; He & Giuliano, 2017).

Most of the previous studies on stop frequency and tour complexity are conducted in larger metropolitan areas such as in (Chu, 2003, 2005; Bhat & Singh, 2000; Daisy, Millward, & Liu, 2018; Liu, 2013; Commission, 2012; Wang, 2015; Kun, Zhicai, & Jie, 2009) and stop occurrence or frequency within a tour has gained less attention in smaller metropolitan areas. Large metropolitan areas have different trip making behaviors in comparison to small metropolitan areas. Transferring coefficients from these models as a typical practice to smaller metropolitan areas, where there is no local data, could lead to erroneous outputs. Hence, the objective of this study is to develop stop making models within a tour in a medium-sized US metropolitan area separately for escort stops, non-escort stops, and all stops combined. Predicting stop occurrence or frequency could yield more informative results in case these activities are separated into different groups based on their purposes for each leg of a tour.

2. Data

In general, household surveys are conducted to collect information with respect to the study objectives (Toh, Angwafo, Ndam, & Antoine, 2018; Chu, 2003). The data used in this study is from a travel survey conducted in 2012 in Fargo-Moorhead metropolitan area. The data used to develop the models was only considered for the internal-internal trips. In this study, work tours as the unit of analysis are defined as activities with the primary purpose of work starting and ending at the anchor location which is home. The work purpose as the primary activity was determined from the survey by assuming that if a trip maker reports a work or work-related activity as the out of home activity, it is considered as the primary destination of the tour. As the coordinates of the household locations and trips origins and destinations were reported with a 500 feet tolerance in the survey, some of these data points were located in other surrounding Traffic Analysis Zones (TAZs) instead of their actual TAZ, in particular if they are close to the boundary of a TAZ. To account for this deficiency, an arbitrary 1-mile buffer was developed in GIS around the centroid of each TAZ. Then, the attributes of all the TAZs that fully or partially fall into this buffer were summed up. These new attributes are assigned to the TAZ whose centroid was used to develop the buffer. Thus, the TAZs that are discussed and used in this study are modified TAZs whose new attributes were assigned to the home locations and to the trips' origins and destinations. The variables used in this study to predict the occurrence or the frequency of stops on the outbound and inbound legs of a commute are classified into four groups including personal, household, land use, and tour-related ones. **Table 1** displays the explanatory variables used in the modeling process. Also, the mean and standard deviation of the variables are shown in this table. For example, the average age of the respondents is 50.77, and 25% of the respondents hold a post graduate work/advanced degree.

The database shows that for the outbound leg of the work tours, there are a total of 169 stops among which, 67 stops belong to escort purpose and 102 stops belong to non-escort stops. Moreover, for the inbound leg of the work tours, there are a total of 307 stops among which 60 stops are escort stops and 247 stops are of the non-escort stops category. The escort stops include pick-up and drop-off, and non-escort stops include maintenance, discretionary stops as well as school or volunteer activities. The data show that escort stops comprise around 40 and 20 percent of the whole stops for outbound and inbound legs of tours respectively. Similar to some of the previous studies (Chu, 2003, 2004, 2005; Kitamura & Susilo, 2006), the percentage of escort stops is considerably higher on the outbound legs of the commute tours compared to those on the inbound leg of the tours. Moreover, the percentage of escort stops in this study seems to be higher on the both inbound and outbound legs compared to those

Table 1. Variables used in the models and their definition.

Variable Categories	Explanations and statistics		
	Explanations	Mean	Standard deviation
Personal			
Male	If the traveler is male, it takes value 1, otherwise 0, a binary variable	0.5	0.5
Age	Age of the traveler, a continuous variable	50.77	11.85
Post graduate work/advanced degree (education level), (PGD)	If the traveler has the stated academic degree, it takes value 1, otherwise 0, a binary variable	0.25	0.43
Household			
Household size, (HH2)-(HH3) and (HH ≥ 4)	Several binary variables including: 1 person household (base), 2-person household, 3-person household, 4 or more than 4-person household	HH1 = 0.11 HH2 = 0.42 HH3 = 0.17 HH ≥ 4 = 0.29	HH1 = 0.31 HH2 = 0.49 HH3 = 0.37 HH ≥ 4 = 0.45
Income level of more than $65K, (Inc65K)	If the traveler's household income is more than $65K annually, it takes value 1, otherwise 0, a binary variable	0.62	0.48
Number of driver's license holders in the household, (DLHH)	A continuous variable	2.11	0.69
Land Use			
Total jobs density in the home TAZ, (JDH)	A continuous variable (1,000 employees per square mile)	1.27	1.26
Total jobs density in the work TAZ, (JDW)	A continuous variable (1,000 employee per square mile)	2.78	1.75
Tour			
Number of work tours, (NWT)	Number of work tours that a traveler makes during a day, a continuous variable	1.28	0.49
Tour starting time from home, (TS)	A one-hour period during which the work tour starts. For example: TS78am means the tour starts between 7 and 8 a.m., several binary variables	TS67AM = 0.13 TS78AM = 0.39 TS89AM = 0.14	TS67AM = 0.34 TS78AM = 0.48 TS89AM = 0.35
Tour ending time, (TE)	A one-hour period during which the work tour ends. For example: TE45pm means the traveler arrives back at home between 4 and 5 p.m., several binary variables	TE23PM = 0.03 TE34PM = 0.07 TE45PM = 0.17 TE56PM = 0.26 TE67PM = 0.10 TE78PM = 0.04 TE89PM = 0.05	TE23PM = 0.18 TE34PM = 0.25 TE45PM = 0.37 TE56PM = 0.44 TE67PM = 0.30 TE78PM = 0.20 TE89PM = 0.22

in (Chu, 2003, 2004, 2005; Kitamura & Susilo, 2006).

3. Methodology

According to the varying number of stops on a tour, different econometric models have been proposed to predict tour complexity or stop frequency. Some studies used ordered probit models to account for the ordered nature of the data (Chu, 2003; Kun, Zhicai, & Jie, 2009; Daisy, 2018; Noland & Thomas, 2007). In other studies negative binomial regression model (Liu, 2013; Noland & Thomas, 2007) and multinomial logit model (Commission, 2012; Wen & Koppelman, 1999) were used. For escort stops in the Fargo-Moorhead metropolitan area, there were few number of observations with more than one escort stop. Hence, binary variables for the escort stops for each leg of the work tours were defined. This variable takes value 1 if the traveler participated in at least one escort stop and takes 0 if there was no escort stop. Thus, two binomial logit models were developed for the escort stops of work tour legs to estimate the probability of making at least one escort stop on the tour legs. For non-escort stops and escort and non-escort stops combined, which include all the stops, the data were separated into 0, 1, and more than 1 stops per tour leg respectively. As Multinomial Logit Models (MNL) yielded better fit compared to ordered probit and Poison regression, they were used to analyze the data for each leg of the commutes for non-escort and combined stops.

The general form of a logit model is as follows:

$$U_i\left(\text{alternative } j\right) = \beta_j x_{ij} + \varepsilon_j \quad (1)$$

where U is the random utility of choosing alternative j by person i, β is the vector of estimated coefficients by the maximum likelihood method, x is the vector of independent variables and ε is the error term or the unobserved part of the utility function. In the multinomial form of the model, the error term is assumed to be identically and independently distributed across the utilities leading to the independence from irrelevant alternatives, IIA, property. IIA property specifies that the ratio of the probability of choosing each pair of alternatives is independent from the availability or the attributes of the other alternatives (Train, 2009). According to IIA feature, the probability of choosing alternative j by person i is:

$$P_i\left(\text{alternative } j\right) = Prob\left(U_{ij} > U_{in}\right), \ \forall n \neq j \quad (2)$$

$$P_i\left(\text{alternative } j\right) = \frac{e^{\beta_j x_{ij}}}{\sum_{j=0}^{J} e^{\beta_j x_{ij}}}, \ \ j = 0, 1, \cdots, J \quad (3)$$

In the binomial logit model, Equation (3) is written as:

$$P_i\left(y = 1\right) = \frac{e^{\beta x_i}}{1 + e^{\beta x_i}} \quad (4)$$

$$P_i\left(y = 0\right) = \frac{1}{1 + e^{\beta x_i}} \quad (5)$$

which yield the probabilities that person i chooses alternative 1 and alternative 0 respectively. Hence, the design and analysis method in this research is defined in this order: 1) Data collection through a travel survey in the Fargo-Moorhead metropolitan area, 2) Defining personal, household, land use, and tour-related variables using the survey results, 3) Defining two stop purposes of escort and non-escort stops on the work tours besides a combination of all stops purposes on the work tours, 4) Applying binary logit models to escort stops and multinomial logit models to non-escort and combined stops separately for outbound and inbound legs of commutes, 5) and Evaluating the impact of the explanatory variables on the stops making of the travelers.

4. Results and Discussion

The results of two binary logit models and four multinomial logit models are reported in **Table 2** and the significant coefficients at 5% are shown in bold. Zero stop is considered as the reference outcome for all the models. The results of this study are discussed based on the role of explanatory variables on different stop purposes next.

4.1. Personal Characteristics

The socioeconomic demographics for each traveler were analyzed to evaluate how they impacted stops within work tours. According to **Table 2**, women were found to be significantly associated with a higher likelihood of participating in more than one stop for non-escort stops and more than one stop for combined stops on the inbound leg of a work tour. This is in line with the results of previous studies conducted in the New York metropolitan area (Chu, 2003, 2004, 2005). For example, previous authors have shown that women appeared to be positively associated with engaging in stops on the morning and evening commutes as they are expected to undertake the major maintenance responsibilities of a household (Chu, 2003, 2004, 2005; Bhat & Singh, 2000). Similarly, females were found to be associated with a higher likelihood of making complex commute tours than males in studies conducted in larger metropolitan areas in China (Xianyu, 2013) and across the US (Liu, 2013), and more complex trip chains involving maintenance and discretionary activities in a study in Adelaide, Australia (Primerano, Taylor, Pitaksringkarn, & Tisato, 2008). However, gender did not play a significant role in the prediction of stops on the outbound leg of commutes in the Fargo-Moorhead area.

An increase in the age of the commuters only significantly contributes to an increase in the likelihood of engaging in one non-escort stop and one combined stop on the outbound leg of a commute. Similar to this result, travelers older than 40 were shown to be more likely to take part in the activities on the morning legs of their commutes in the previous studies in New York (Chu, 2003, 2004, 2005). Although an increase in age increases the utility of making non-escort stops and combined stops on the outbound leg of the commutes, its impact is not

Table 2. The results of the logit models.

Stop Purpose	Outbound Leg					Inbound Leg				
	Escort	Non-Escort		Combined		Escort	Non-Escort		Combined	
Stop Frequency	1+	1	2+	1	2+	1+	1	2+	1	2+
Variables	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.	Coef.
Constant term	−1.884	**−5.734**	**−4.897**	**−3.821**	−2.367	−1.584	**−2.123**	−0.121	−0.797	−0.275
Personal										
Male	0.178	0.062	−1.090	0.303	−0.771	−0.254	−0.255	**−1.288**	−0.292	**−1.208**
Age	−0.024	**0.054**	0.036	**0.031**	0.020	−0.019	0.023	0.003	0.008	0.005
PGD	0.079	**0.637**	0.301	0.475	0.522	0.208	0.081	0.561	0.218	0.529
Household										
HH2	−0.847	0.756	−0.219	0.486	0.177	−0.344	−0.280	0.813	−0.255	0.969
HH3	**2.785**	1.411	1.325	**1.508**	**2.478**	**2.613**	−0.531	1.153	0.047	**1.659**
HH ≥ 4	**3.712**	**1.668**	1.442	**2.399**	**2.931**	**2.498**	−0.056	0.147	0.468	1.266
Inc65K	0.319	0.586	−0.835	**0.710**	−0.486	0.706	0.180	**−0.723**	0.297	−0.446
DLHH	**−1.726**	**−0.833**	0.092	**−1.055**	**−0.849**	**−1.000**	−0.162	0.403	**−0.395**	**−0.657**
Land Use										
JDH	0.191	−0.094	−0.299	−0.083	−0.016	−0.341	0.014	−0.107	−0.057	−0.130
JDW	−0.030	0.092	**0.381**	0.030	0.225	−0.106	0.052	−0.011	0.050	0.041
Tour										
NWT	−0.677	0.327	−0.424	0.186	−1.044	−0.531	**−0.567**	**−1.076**	**−0.544**	**−1.063**
TS67AM	**2.181**	0.219	−1.324	0.334	−0.536					
TS78AM	**2.783**	−0.433	**−2.967**	0.588	−1.043					
TS89AM	**2.414**	0.337	−0.929	0.425	−0.001					
TE23PM						**2.167**	0.671	1.163	**1.313**	1.146
TE34PM						**2.195**	0.494	0.863	**1.463**	0.949
TE45PM						1.228	0.246	−0.667	0.640	−0.724
TE56PM						**1.543**	0.583	−0.414	**0.770**	−0.083
TE67PM						0.682	**0.866**	−0.083	**1.011**	0.078
TE78PM						**1.684**	**2.057**	**1.057**	**1.699**	**1.654**
TE89PM						**2.108**	**1.503**	**1.566**	**1.376**	**1.486**
Log likelihood function	−120.9	−230.81		−327.6		−133.1	−419.9		−468.8	
Restricted log likelihood	−194.9	−259.02		−376.0		−183.1	−471.5		−523.1	
McFadden Pseudo R-squared	0.38	0.10		0.13		0.27	0.11		0.10	
Observation	644	644		644		644	644		644	

significant for the inbound leg of the commutes. This shows it might be more convenient for older workers in the study area to return home after work and then make non-work tours in case they need to take part in other activities.

Commuters with a post graduate work or with an advanced degree were found to be associated with an increased likelihood of making one non-escort stop on the outbound leg of a commute. In the previous studies, the likelihood of making stops on a tour or tour complexity were found to increase by an increase in the level of education of the traveler in the studies conducted across the US (Liu, 2013; Wang, 2015) and a study conducted in Germany (Scheiner & Holz-Rau, 2017). In the Fargo-Moorhead metropolitan area, higher education is not significantly associated with stop making propensity on the inbound leg of the work tours. As the results of this study reveals, personal characteristics of the commuters in this study do not significantly contribute to escort stop making probability.

4.2. Household

In the initial models developed for this study, a degree of multi-collinearity was observed between the number of children under 18 and the household size of four or more. Using household size yielded better models with higher McFadden R-squared in comparison to models that used number of children in a household.

Travelers from households with a greater number of residents were more likely to participate in at least one escort stop on both outbound and inbound legs of commutes. As household size was highly correlated with the number of children, this suggests that travelers from households with more children were more likely to take part in a commute with at least one escort stop on each leg of the tour. Additionally, travelers from larger households were associated with an increased likelihood of engaging in one non-escort stop on the outbound leg of the tour and an increased likelihood of engaging in at least one combined stop for the outbound leg. It is notable that for the inbound legs, only the three-person household variable appeared to be significant in predicting more than one combined stop. These results show that household size plays a more significant role in the stop prediction for the outbound legs of the work tours. When the number of children under 18 in a household was used in the models in the initial runs instead of household size, travelers were similarly found to be associated with higher likelihood of participating in stops on both legs of the commutes. These results are in line with the previous studies in which the presence of children in a household contributed to the participation of a worker in the morning commute activity in New York (Chu, 2003, 2004, 2005) or to the more complexity of a work tour in studies across the US (Wang, 2015) and in northern California (Cao, Mokhtarian, & Handy, 2008).

With the household income more than $65K, the probability of a commuter making more than one non-escort stop decreases, however this decrease is significant only in the inbound model. This shows that commuters in the Fargo-Moorhead area with a higher income level do not tend to make more than one non-escort stop such as maintenance and discretionary. This could be the result of short commute trips. Commuters from households with higher incomes can afford to go back home before embarking on other trips, whereas lower income households tend to trip chain more with their work trips. However, it is notable that in larger metropolitan areas, the association between higher income level and stop engagement on the evening commutes can be positive as shown in New York (Chu, 2003, 2004, 2005) and in the Boston and Bay metropolitan areas (Bhat & Singh, 2000). In the Fargo-Moorhead area, commuters from households with more than $65K are only significantly associated with a higher likelihood of making one combined stop on the outbound leg of their commutes and this could be the result of combining escort and non-escort stops.

As the number of driver's license holders increases in a household, the likelihood of engaging in escort stops on both legs of a commute decreases and the magnitude of the coefficient of this variable is larger for the outbound escort stop model. This variable is also associated with a decreased likelihood of making one non-escort stop and at least one combined stop on the outbound leg of the commutes. In addition, as the number of driver's license holders increases in a household, the likelihood of making at least one combined stop for a commuter from that household significantly decreases on the inbound leg of the commute. These results show more independent trips and mode choices of the commuters from those households with a higher driver's license ownership as the commuters do not need to provide rides to the other household members who can drive. Moreover, when combined stops are considered, the results suggest that with more drivers in a household, travelers tend to share household chores with other members who are capable of driving. In the past studies, more number of employed adults (Chu, 2003, 2005) or more adults in a household (Liu, 2013; Wang, 2015) were associated with a lowered likelihood of stop making during a commute and the reason for the lowered stop making likelihood was suggested to be sharing the household responsibilities with other members (Liu, 2013). It is notable that for smaller metropolitan areas that are very car-centric, most households own a car, and most work trips are made using cars. It has been shown that compared to other regions in the US, the Midwest has the highest number of vehicles per household (Thakuriah & Liao, 2005). Thus, a higher driver's license ownership can be linked to more independent drivers and consequently fewer escort stops.

4.3. Land Use

Job density variables were insignificant for all the models of this study except for the model of non-escort stop on the outbound leg of the work tours. The results indicate that an increase in the number of employees in the work location TAZ of the commuters is associated with an increase in the likelihood of making more than one non-escort stop on the outbound leg of a commute. As the job density variable at the residence of the commuters has a negative coefficient for more than one non-escort stop, this suggests that more than one non-escort stop on the outbound leg of their commute is probably more likely to occur around the workplace of the commuters rather than their residence. However, in two previous studies conducted in New York (Chu, 2003, 2004), higher employment density around commuters' households appeared to be more encouraging for the commuters to make intermediate stops on the morning and evening legs of their commutes around their residence rather than their work place. Generally, higher employment density whether at residence (Cheng, Chen, & Yang, 2016; Chu, 2003, 2004) or at work location (Chu, 2003, 2004) was shown to be a significant factor in the stop making propensity of commuters in larger metropolitan areas. However, in the Fargo-Moorhead area, employment density does not play such a role for most of the stops. These differences could be related to the available opportunities around the residence and the workplace of the commuters in the Fargo-Moorhead area leading to one of the differences of trip patterns between a small and a large metropolitan area in terms of stop frequency on a work tour.

4.4. Tour

The results for the parameters in the tour section indicate that an increase in the number of work tours during a day is associated with a lowered likelihood of making at least one non-escort stop and at least one combined stop on the inbound leg of the commutes. This shows that people with multiple jobs and people who commute to their workplace more than one time such as the ones who go home for lunch typically have a lower probability of adding the mentioned stops to their tours. This is perhaps due to the time constraints on going from one job to another one or going home during the lunch breaks. However, this variable does not significantly affect the likelihood of making stops on the outbound leg of the commutes and the likelihood of making escort stops on the inbound leg of the commutes.

Arrival and departure time to and from work and their contribution to stop making propensity on a commute have been studied in the past by several researchers (Chu, 2003, 2004, 2005; Bhat & Singh, 2000; Xian-Yu et al., 2011; Kun, Zhicai, & Jie, 2009). In this study, tour start and ending time variables were used to reveal how the stop making propensity changes for escort stops, non-escort stops, and combined stops for different time intervals in the Fargo-Moorhead stop frequency models. The results show that commuters who start their work tour between 6 a.m. to 7 a.m., 7 a.m. to 8 a.m. or 8 a.m. to 9 a.m. have a high likelihood of participating in at least one escort stop on the outbound leg of the commutes. Schools usually open between 7 a.m. to 9 a.m. and early birds may provide rides to other household members reason why the tour starting time variable between 6 a.m. to 7 a.m. is significantly positive. Commuters who start their work tour between 7 a.m. to 8 a.m. have the least probability of making more than one non-escort stop on the outbound leg of the commutes. This means that commuters in the Fargo-Moorhead area during that time interval are not inclined to make several non-escort stops on the morning leg of their commute. In fact, commuters do not need to make numerous stops for non-escort purposes during this time interval which makes sense as they are mostly leaving to work, or they may make escort stops. Combining the escort and non-escort stops on the outbound leg of work tours makes the tour start time variables insignificant.

The commuters whose work tour ends between 3 p.m. to 4 p.m. have the highest likelihood of participating in an escort stop on the inbound leg of their commutes. The positive and significant contribution of the variable of tour ending time between 2 p.m. to 3 p.m., 3 p.m. to 4 p.m. is probably because during these time intervals many schools ends. The tour ending time variables of 5 p.m. to 6 p.m., 7 p.m. to 8 p.m. and 8 p.m. to 9 p.m. are positive and significant indicating that commuters whose work tours end during these time intervals have a higher likelihood of participating in an escort stop in the Fargo-Moorhead area. Commuters whose work tour ends between 7 p.m. to 8 p.m. and 8 p.m. to 9 p.m. have a higher likelihood of making at least one non-escort stop on the inbound leg of their work tours. When combined stops are considered, commuters whose work tour ends between 7 p.m. to 8 p.m. have the highest likelihood of making at least one stop on the inbound leg of the commute. In general, it is notable that the commuters whose work tour ends after 7 p.m. are significantly associated with a higher likelihood of making more than one stop of different purposes.

According to the results, in case the escort and non-escort stops are combined with each other, making inferences about the impact of tour start and ending time can be misleading and it cannot reveal the real impact of these variables on the likelihood of making stops of different purposes. For example, if a work tour ends between 3 p.m. and 4 p.m., the commuter is more likely to participate in at least one escort stop but this variable is insignificant in non-escort stops model. This shows that combing these stops and reporting them as a general stop regardless of the purpose of the stop will not yield the real contribution of the tour start and ending time variables leading to an invalid inference of the estimated model parameter.

As a summary, higher education is not significantly associated with the likelihood of escort stop making of the travelers in their work tours. The household size variables are of the most influential variables on the stop making behavior of the travelers, particularly on the outbound leg of the commutes. The significance of the land use variable appeared to be associated with the non-escort stops on the outbound leg of the commutes as displayed in **Table 2**. Moreover, among the tour-related variables, the work tours beginning between 7 a.m. to 8 a.m. are associated with the highest likelihood of making escort stops on the outbound leg of the commutes.

5. Conclusion

This study addressed the stop making behavior within work tours in a medium-sized metropolitan area in the US. In addition, how each explanatory variable may contribute to the stops of different purposes for such areas was another addressed gap using the data of a trip survey conducted in the Fargo-Moorhead metropolitan area.

The role of personal variables including gender, age and education level appeared to be varying in magnitude and significance for different models of this study. These variables did not significantly contribute to the escort stop making probability on the outbound and inbound legs of the commutes.

For the escort stops, household size of more than two residents had the highest impact on the likelihood of stop making for both outbound and inbound legs of a commute among all the variables. One of the main differences between the results of this study and those of the previous researches conducted in larger metropolitan areas was that in the previous studies, variables such as gender or income had a high impact on the likelihood of making stops on the commute, whereas in this study household size variables played this role. In this study, household size variable proxied the number of children and using household size yielded better models rather than using the number of children in terms of model predictive power determined by McFadden Pseudo R-squared. Furthermore, more individuals holding driver's license in a household significantly contributed to a lowered likelihood of making escort stops by commuters.

Another outcome of this study showed that as opposed to the previous studies in larger metropolitan areas, employment density as the land use variable did not play a significant role in contributing to the stop generation in most of the models. However, in case commuters have more than one non-escort stop on the outbound leg of their commutes, they are probably more likely to make that stop close to their workplace location rather than their home.

Tour starting and ending time for different stop purposes revealed the highest likelihood of making escort stops on the outbound leg of commutes is when commuters start the tour between 7 a.m. to 8 a.m. Commuters who start their commute in this time interval besides the time interval of 8 a.m. to 9 a.m. are associated with an increased likelihood of participating in escort stops and this could be because many schools open during these time intervals.

Generally, the difference between the magnitude and significance of the explanatory variables for escort, non-escort, and combined stops prediction for both outbound and inbound leg of the work tours showed that classifying stops on a commute into different stop purposes could yield more realistic results with respect to the stop purposes and it could increase the accuracy of prediction and result in better inferences from the model parameters. The results of this study could be used by policy makers and planners to address different land use, parking, and demand management questions depending on their study objective, especially in smaller metropolitan areas. For example, if a new transportation mode or service is desired, the households with larger sizes might be targeted for further studies to investigate their willingness or unwillingness to switch to a new transportation mode in the early morning instead of escorting others or being escorted by the household members.

Although this study was an attempt to cover the gaps in the field of stop analysis on the work tours, there are still more grounds on which more research can be conducted. The stops were classified only into two categories of escort and non-escort in this study due to the few observations for non-escort stops. In case there are enough data, this research can be conducted for more non-escort stop purposes such as shopping, recreation, and personal business. Also, for land use variables, if more categories of job density corresponding to different stop purposes were available, then it could reveal a better correlation between different stop purposes and land use variables. It is noteworthy that land use variables that were used in this study were modified as described in the paper due to the data collection method.

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Conflicts of Interest

The author declares no conflicts of interest regarding the publication of this paper.

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