Understanding and Modeling the Activity-Travel Behavior of University Commuters at a Large Canadian University

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Abstract: This paper examines the daily activity-travel behavior of undergraduate students, graduate students, faculty, and staff at a large university to better understand their activity travel demands for automobile, active transportation (AT), and transit trips. The data were derived from the first university-based activity travel diary survey [Environmentally Aware Travel Diary Survey (EnACT)] conducted in spring 2016 at Dalhousie University, Canada. Results show that students reside nearer to the campus than faculty and staff, and their trip length from home to school is significantly shorter. Zero-inflated negative binomial (ZINB) models show that if housing tenure is less than 1 year, it is more likely that the traveler will make more AT trips but fewer automobile trips. It indicates that individuals living far from the campus will produce fewer transit trips than those who live nearer. Interestingly, the mean number of AT trips per day for the overall sample is more than one trip, whereas for automobile trips and transit trips it is less than one. The behavioral analysis and empirical models provide useful insights that can be utilized to represent university populations in regional travel demand models, as well as to develop campus-based travel demand management (TDM) strategies. **DOI: 10.1061/(ASCE)UP.1943-5444.0000442.** *© 2018 American Society of Civil Engineers.*

Introduction

Enrollment in postsecondary education is increasing rapidly for various reasons, such as population growth, growing numbers of educational institutes, and growing desire for higher education. The increase in university populations leads to an increase in the overall number of university commuters. Consequently, university campus authorities need to estimate and manage high volumes of automobile traffic and higher demand for on-campus parking. In addition, empirical data on travel demand are required to improve university travel demand management (TDM) strategies in order to reduce on-campus traffic and establish sustainable transportation on campus (Toor and Havlick 2004; Black et al. 1999; Balsas 2003). However, despite the substantial effect of university populations on regional travel demand models, only a few studies to date have been carried out to understand the activity-travel behavior of university populations (Axhausen and Garling 1992; Bowman and Ben-Akiva 2001; Bhat et al. 2004). Notably, understanding the activity-travel behavior of university populations is more vital for cities, such as Halifax, Canada, where one or more large universities are major trip generators of travel demand.

Metropolitan planning organizations and transportation engineers recommended that university populations should be considered as a subpopulation with special travel behavioral characteristics in regional travel demand models. Recent travel demand models are more focused in disaggregated modeling such as activity-based models. This study aims to model the activity-travel behavior of students, staff, and faculty at a large Canadian university using a disaggregated modeling approach.

Though the importance of studying the activity-travel behavior of university populations has been increasingly recognized in the past decade, mostly in American universities for finer regional travel demand models, there has not been any travel diary survey conducted for a university population in Canada. The current study is also unique in analyzing the results of the first university-based travel diary survey across Canada. According to Statistics Canada (2015), postsecondary enrollment increased 1.2% in the 2013–2014 academic year and there are now more than 2 million students enrolled in postsecondary education, which is more than 5% of the total population of Canada. The student population in the province of Nova Scotia is higher than the national average, at 5.90%, which suggests the need for greater attention to understand their activity-travel behavior. Unfortunately, the latest General Social Survey (GSS) of Canada conducted in 2010 captured samples of only 538 students with student status and 293 students with full- or part-time employment across Canada, and the numbers for Nova Scotia are only 26 and 16, respectively. These small samples are inadequate for many purposes, and may indicate underrepresentation of university students in the regional travel surveys. This may result from using landline or mailed tools to reach survey respondents because university students are more frequent users of mobile phones (Wang et al. 2012). Hence, the current study contributes to the literature by providing a rich data set on activity travel behavior of a large Canadian university population at Dalhousie University that can be used in regional travel demand models of Nova Scotia. Hence, the Environmentally Aware Travel Diary Survey (EnACT) was conducted among Dalhousie University commuters in spring 2016. Dalhousie University is the largest university in the Maritime Provinces of Canada and it is one of the main trip generators in the province of Nova Scotia.

To date, travel demands of university students have not been properly modeled in regional travel demand models in Nova Scotia.

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Most often, travel demand models consider trip rates with socioeconomic information (e.g., household size, household income, car ownership) generated for the general population, which do not appropriately reflect the travel behavior of the university population (Wang et al. 2012). Broadly, university campuses comprise mixed land uses with vibrant built environment characteristics, and offer more opportunities to participate in different types of activities within an accessible distance. These unique features distinguish university travel behavior from the general population, and require special consideration for travel demand management strategies. The data of this study were collected through a unique online-based travel diary survey among all four Dalhousie University campuses in spring 2016. The insights from this study will inform travel demand management strategies and trip generation modeling for university-oriented cities like Halifax, Nova Scotia, where university populations affect traffic volumes and travel patterns significantly. Results obtained from this study are expected to be incorporated within the activity-based travel demand model for Halifax Regional Municipality (HRM), Nova Scotia, which is currently under development.

Literature Review

University communities can be assumed to be an underrepresented group in travel surveys even though they represent a significant portion of the total population. Previous studies confirm underrepresentation of university communities or student population in national travel surveys (Wang et al. 2012; Volosin et al. 2014). There are few peer-reviewed articles on university populations, and those discussing their inclusion in regional travel models are even fewer. There are, however, several studies that have been focused on university-related commuting mode choices (Balsas 2003; Rodríguez and Joo 2004; Akar et al. 2012). For instance, Rodríguez and Joo (2004) studied the relationship between mode choices and spatial characteristics among University of North Carolina at Chapel Hill commuters. Akar et al. (2012) predicted mode choices for home-to-campus trips by Ohio State University (OSU) populations based on a travel survey conducted in 2011. The results of the study revealed that it is more likely that students will use the biking and transit modes for home-to-campus trips compared with faculty members and staff. In another study, Kamruzzaman et al. (2011) utilized trip diary information to investigate out-of-home travel and activities by university students. Another study by Balsas (2003) focused on the development of on-campus sustainable transport systems through policy actions at eight American universities. This study examined policy actions aimed at nonmotorized transport and showed that such actions produced significant changes in modes of travel for the commute to school.

A school-day activity-travel diary survey was conducted at North Carolina State University to explore university travel behavior characteristics (Eom 2007). Results showed that undergraduate students and graduate students who are living on campus participate more in out-of-home activities than students who are living off campus. Similarly, a 1-week travel diary survey conducted at a Thailand university examined the activity travel patterns of university students at a rural university (Limanond et al. 2011). Another 1-week travel diary survey conducted at the University of Western Australia was utilized to study the commuting patterns of students and staff, and the study examined the on-campus zones of car driving, walking, and biking (Shannon et al. 2006). The Virginia Department of Transportation sponsored two sets of web-based surveys in 2009 and 2010 to study university students' travel behavior. In 2009, the travel diary survey was conducted for four universities (i.e., University of Virginia, Virginia Commonwealth University, Old Dominion University, and Virginia Polytechnic Institute and State University). This study identified differences between student populations and general populations by comparing the collected data with the National Household Travel Survey (NHTS). The results showed that university students are a relatively lower income segment of the population and they have atypical travel behaviors (Khattak et al. 2011). The study found significant differences between urban residents and students, where students from urban campuses were found to participate in more out-of-home activities than the general population.

Despite the presence of the preceding few studies on university populations, there exists no activity-travel behavior study on a university population in the context of Canadian universities. Thus, this study aims to fill this gap in knowledge by exploring the activity-travel characteristics of population groups at Dalhousie University, the largest university in the Maritime Provinces of Canada. It is expected that results of the empirical models of this study can be utilized to quantify trip generation for university populations throughout Canada, and can be incorporated into the regional travel demand model for Nova Scotia.

Modeling Approach

A count data modeling approach is appropriate for modeling the trip frequency because it shows the characteristics of a discrete distribution that is nonnegative and has integer values (W. Greene, "Accounting for excess zeros and sample selection in Poisson and negative binomial regression models," Working Paper EC-94-10, Stern School of Business, New York Univ., New York; Jang 2005). The Poisson model has been utilized in several studies for trip frequency modeling because trips occur randomly and independently over time (Bhat et al. 1998; Misra 1999; Ma and Goulias 1999; Wallace et al. 1999; Jang 2005; Habib and Daisy 2013). However, the Poisson model postulates the equidispersion theorem in which the conditional variance of the dependent variable is equal to the conditional mean. Mullahy (1997) claimed that if there is overdispersion in the data, then a negative binomial (NB) model should be utilized instead of the Poisson model. A number of studies have utilized zero-inflated negative binomial (ZINB) models for modeling trip frequencies when there is overdispersion and excess zeros in the data set (e.g., Jang 2005; Khattak et al. 2011; Xu et al. 2015). Thus, this study also employs a ZINB model for empirical analysis because there are excess zeros and overdispersion in the data. The model is utilized to report and analyze trip frequencies of automobile, active transportation (AT), and transit trips. In this study, AT includes both walking and biking trips.

For frequency analysis, because the dependent variables are nonnegative and integers, alternative modeling approaches are the negative binomial model, zero-inflated model, and Poisson regression model. According to the Poisson regression model, the probability $P(y_k)$ of having y_k number of trips by a given mode for observation k can be written as

$$P(y_k) = \frac{\exp(-\lambda_k)\lambda_k^{y_k}}{y_k!} \quad (1)$$

where λ_k = Poisson parameter for observation k; and y_k = expected number of trips by the mode.

The mean and variance for the number of trips is assumed to be equal (i.e., $E[y_k] = \mathrm{Var}[y_k]$) in the Poisson model. If the expected mean number of trips is not equal to the variance, then the data are assumed to be underdispersed or overdispersed. In such situations, parameter estimation with the Poisson regression model will be incorrect (Lambert 1992; W. Greene, "Accounting for excess zeros and sample selection in Poisson and negative binomial regression models," Working Paper EC-94-10, Stern School of Business, New York Univ., New York). To address this overdispersion or underdispersion, the NB form can be utilized because it adds a random error term in the parameter estimation. Hence, the form of λ_k calculation for NB can be written as follows:

$$\lambda_k = \exp(\beta X_k + \varepsilon_k) \tag{2}$$

However, in the case of trip made by a specific mode, there exist zero and nonzero values among the observations. This dual-state process requires dual-state count models, such as the ZINB model or the zero-inflated Poisson (ZIP), which explicitly separate the true zero-state process and count data process and allow explanatory variables to affect both occurrences. Thus, $1 - p_k$ is estimated as the probability that an individual actually makes zero automobile or AT or transit trips and follows a NB distribution. Given this

$$y_k \begin{cases} = 0 & \text{with probability } p_k + (1 - p_k)\left[\dfrac{\theta}{\theta + \lambda_k}\right]^{\theta} \\ = K & \text{with probability } (1 - p_k)\left[\dfrac{\Gamma(\theta + K)u_k^{\theta}(1 - u_k)^K}{\Gamma(\theta)K!}\right] \end{cases} \tag{3}$$

where K = number of trips made by an individual k by automobile or AT or transit; $\theta = 1/\alpha$, with α being the dispersion parameter; $u_k = \theta/(\theta + \lambda_k)$, with λ_k being the mean; and $\Gamma(\cdot)$ = gamma function.

In the NB model, the Poisson assumption requires the mean to be equal to the variance by letting $\mathrm{Var}[y_k] = E[y_k]\{1 + \alpha E[y_k]\}$, that is, relaxed by the parameter estimation of α. And for ZINB, the dispersion $\mathrm{Var}[y_k]$ follows the following equation:

$$\mathrm{Var}[y_k] = U[y_k]\left\{1 + \frac{p_k}{1 - p_k}U[y_k]\right\} \tag{4}$$

Thus, for the ZINB model, $p_k/(1 - p_k)$ can be interpreted as α. Regarding the zero-inflated model application, there arises the problem of distinguishing whether the NB or Poisson distribution is the source of overdispersion. The probability density function (PDF) for the random variable y_k is

$$P(y_k) = (1 - p_k)\left[\frac{\Gamma(\theta + k)u_k^{\theta}(1 - u_k)^K}{\Gamma(\theta)K!}\right] + Z_k p_k \tag{5}$$

where

$$y_k \begin{cases} = 0 & \text{when } Z_k = 1 \\ \neq 0 & \text{when } Z_k = 0 \end{cases}$$

The application of the indicator variable Z_k is utilized for the maximization of the log-likelihood function, where the log-likelihood function can be written as follows:

$$\sum_k \log(p(y_k)) \tag{6}$$

However, for identifying a better fitted distribution, Vuong (1989) proposed the Vuong test, which provides proper power using count data (W. Greene, "Accounting for excess zeros and sample selection in Poisson and negative binomial regression models," Working Paper EC-94-10, Stern School of Business, New York Univ., New York). The Vuong statistic is calculated as follows:

$$G = \frac{\bar{q}\sqrt{R}}{S_q} \tag{7}$$

where $\bar{q}$ = mean with $q = \log[f_1(\cdot)/f_2(\cdot)]$, where $f_1(\cdot)$ indicates the distribution function of the ZINB distribution and $f_2(\cdot)$ indicates the distribution function of the parent NB distribution; S_q = standard deviation; and R = sample size.

The ZINB model better represents the data where the value of G is greater than 1.96 (the 95% confidence level in the t-test). On the other hand, a value of G less than −1.96 favors the parent NB. The next section continues with a description of the survey and descriptive statistics.

Travel Diary Survey

Dalhousie EnACT Survey

The Transportation and Environmental Simulation Studies (TESS) group at Dalhousie University conducted an online web-based 1-day travel diary survey, EnACT, in spring 2016 across the entire population of Dalhousie University commuters. The survey covered all Dalhousie commuters, comprising undergraduate students, graduate students, faculty members, and staff from all four campuses. After designing the survey, a pilot study was conducted to understand the fill-out timing, understanding of questions, and user friendliness. Following receipt of feedback and comments, the survey was modified. Through the cooperation of the university administration, a survey link was circulated to all students, faculty members, and staff. The EnACT survey included six sections: (1) household information, (2) individual information, (3) environmental attitudes and behavior, (4) attitudes toward transportation, (5) use of information and communications technology (ICT), and (6) 24-h travel log.

The typology of the survey was consistent with the GSS of Canada (Statistics Canada 2011) and the Halifax Space-Time Activity Research (STAR) survey (Millward and Spinney 2011), for comparison purposes, and so findings and results from this survey can be utilized for disaggregated regional travel demand modeling. Following survey data collection, and after rigorous cleaning, error checking, and geocoding, the survey yielded a sample of 346 fully completed 24-h travel logs with demographic and socioeconomic information for the city campuses [see Hafezi et al. (2018b) for more details]. The sample demographic characteristics were compared with those of the total university population (using the annual Dalhousie sustainability and commuter survey and the data from Dalhousie Analytics) to investigate the representativeness of the sample. It was found that the EnACT sample is roughly representative with respect to age, employment status, gender, travel mode, and commute time in comparison with the Dalhousie University population (Hafezi et al. 2018a). However, women are slightly overrepresented and higher age individuals are slightly underrepresented. The current study used the sample directly obtained from the survey without sample weighting or population synthesis. Future studies will include matching with the entire university population and expanding the sample size using population synthesis technique. A comprehensive explanatory analysis of all six sections of the EnACT survey can be found in Liu et al. (2016).

Summary Statistics of Variables

Only the three Dalhousie University campuses located in HRM were considered for this study, because one campus (Truro) has different campus and locational characteristics. The sample consists

Table 1. Summary Statistics of Variables Used in the Empirical Model

Variable	Description	Mean	Standard deviation	Minimum	Maximum
Dependent variable					
AT trips	Number AT trips per day	1.2	1.49	0	7
Automobile trips	Number automobile trips per day	0.87	1.28	0	6
Transit trips	Number transit trips per day	0.56	0.94	0	5
Independent variable					
AGE	Age of the respondent	30.96	12.08	18	72
FEMALE	Gender of respondent (dummy, 1 if the respondent is a female, 0 otherwise)	62.42%	—	—	—
LESS15K	Annual personal income (dummy, 1 if the income is less than $15,000 per year, 0 otherwise)	38.44%	—	—	—
BT50T75K	Annual personal income (dummy, 1 if the income is between $50,000 and $75,000 per year, 0 otherwise)	9.54%	—	—	—
Q6HHSIZE	Household size	2.88	1.42	1	7
STAFF	Staff (dummy, 1 if the respondent belongs to staff segment of the population, 0 otherwise)	19.36%	—	—	—
FACULTY	Faculty (dummy, 1 if the respondent belongs to faculty segment of the population, 0 otherwise)	6.94%	—	—	—
GRAD	Graduate student (dummy, 1 if the respondent belongs to graduate student segment of the population, 0 otherwise)	36.42%	—	—	—
UNGRAD	Undergraduate student (dummy, 1 if the respondent belongs to undergraduate student segment of the population, 0 otherwise)	37.28%	—	—	—
HIGHFLEX	Highly flexible (dummy, 1 if the school or work schedule of the respondent is flexible, 0 otherwise)	21.68%	—	—	—
ABV10YR	More than 10 years of living (dummy, 1 if the respondent is living in the current house for more than 10 years, 0 otherwise)	16.47%	—	—	—
Q9HHCAR	Number of automobiles at household	1.02	0.95	0.00	6.00
DRVLNS	Driving license (dummy, 1 if the respondent has a driver's license, 0 otherwise)	88.73%	—	—	—
HOMOWN	Home ownership (dummy, 1 if the respondent owns a house, 0 otherwise)	33.24%	—	—	—
DISTHW	Total home-to-campus distance	7.06	14.22	0.18	114.74

of 37.28% undergraduate students, 36.42% graduate students, 6.94% faculty members, and 19.36% staff members. Summary statistics of the response variables are shown in Table 1. It is encouraging that the mean number of AT trips per day for the sample is more than 1.0 trip per person, whereas the automobile mode has a mean of less than 1.0 trip. The transit mode, perhaps surprisingly, is used much less than either AT or automobile. The high standard deviations for all three modes, along with zero trips per day as the minimum, explains the overdispersion or underdispersion of the data. The mean number of automobiles per household is 1.02 and the mean household size is 2.88.

Characteristics of Daily Travel Behavior

This study aimed to investigate similarities and dissimilarities of activity-travel characteristics between different segments of the university sample. To that end, Table 2 shows the travel mode shares of undergraduate students, graduate students, faculty members, and staff by trip purpose. The highest mode share percentage for the undergraduate and graduate student segments is for the walk mode, whereas for faculty and staff segments the most used mode is automobile (driver). For work- and school-related trips, the most used modes for graduate students are walk, automobile (driver), and transit, whereas for undergraduate students they are walk and automobile (driver). For faculty members, the most used modes for work and school are automobile (driver) and walk. In contrast, staff members choose automobile (driver), automobile (passenger), and walk modes more than other modes.

For shopping activities, the most used mode is automobile driver for graduate students, undergraduate students, and staff, whereas faculty members preferred the walk mode for shopping. This may be explained by the neighborhood built environments and the presence or absence of shopping opportunities close to home. However, each sample segment makes significant numbers of walk and transit trips, which is consistent with findings from other university-based studies (Miller 2012). For entertainment-, sports-, and hobbies-related activities, all segments prefer automobile (driver). Presumably, this occurs due to convenience and comfort, and the preference to travel in company with friends or team mates.

Table 3 presents the mean trip travel times, trip distances, and trip rates by trip purpose for each university sample segment. Among all segments of the Dalhousie community, the mean travel time for a trip is approximately 24 min, which is consistent with other studies (Volosin et al. 2014). However, there is variation among different segments in terms of mean trip durations: the faculty mean trip travel time is slightly shorter than others, whereas the staff mean trip travel time is highest among all segments. In contrast, the mean trip travel time for paid work is longer for both faculty members and staff compared with student segments. Overall, staff segment trip duration is higher for most of the activities compared with other sample segments. Furthermore, trip travel time for graduate students is longer than for undergraduate students.

Trip rates are estimated by dividing the total number of trips by the number of respondents in respective segments, which implies that zero-trip makers are being considered as well. From the mean total number of trips per day, it is found that undergraduate students

Table 2. Mode Share in Percent by Trip Purpose for Various University Market Segments

Market segment	Purpose	Automobile (driver)	Automobile (passenger)	Walk	Transit (bus or ferry)	Bicycle	Total
Graduate students	Household-related works	0.0	25.0	25.0	25.0	25.0	100.0
	Paid work	26.3	0.0	38.6	26.3	8.8	100.0
	Entertainment-related activities	45.0	5.0	20.0	15.0	15.0	100.0
	Organizational, voluntary, and religious activity	0.0	25.0	25.0	12.5	37.5	100.0
	Personal care-related activities	14.7	0.0	47.1	17.6	20.6	100.0
	School- and education-related activities	17.2	4.1	39.1	32.0	7.7	100.0
	Shopping activities	44.2	4.7	30.2	18.6	2.3	100.0
	Caregiving activities	100.0	0.0	0.0	0.0	0.0	100.0
	Sports and hobbies	35.7	0.0	21.4	28.6	14.3	100.0
	All activities	23.7	3.7	36.3	26.3	10.0	100.0
Undergraduate students	Household-related works	50.0	0.0	33.3	16.7	0.0	100.0
	Paid work	26.8	0.0	39.3	23.2	10.7	100.0
	Entertainment-related activities	41.7	0.0	33.3	25.0	0.0	100.0
	Organizational, voluntary, and religious activity	0.0	0.0	85.7	14.3	0.0	100.0
	Personal care-related activities	18.2	9.1	68.2	0.0	4.5	100.0
	School- and education-related activities	24.3	4.1	49.1	18.9	3.6	100.0
	Shopping activities	35.3	20.6	35.3	8.8	0.0	100.0
	Sports and hobbies	42.9	28.6	28.6	0.0	0.0	100.0
	All activities	27.1	5.5	46.2	17.2	4.0	100.0
Faculty	Paid work	35.3	3.9	29.4	15.7	15.7	100.0
	Entertainment-related activities	100.0	0.0	0.0	0.0	0.0	100.0
	Organizational, voluntary, and religious activity	50.0	0.0	50.0	0.0	0.0	100.0
	Personal care-related activities	66.7	0.0	33.3	0.0	0.0	100.0
	School- and education-related activities	100.0	0.0	0.0	0.0	0.0	100.0
	Shopping activities	0.0	0.0	100.0	0.0	0.0	100.0
	Sports and hobbies	36.4	0.0	18.2	27.3	18.2	100.0
	All activities	40.8	2.6	28.9	14.5	13.2	100.0
Staff	Household-related works	33.3	33.3	33.3	0.0	0.0	100.0
	Paid work	30.8	5.6	30.1	24.5	9.1	100.0
	Entertainment-related activities	14.3	42.9	14.3	0.0	28.6	100.0
	Media and communication	0.0	0.0	100.0	0.0	0.0	100.0
	Organizational, voluntary, and religious activity	71.4	0.0	0.0	0.0	28.6	100.0
	Personal care-related activities	85.7	0.0	14.3	0.0	0.0	100.0
	School- and education-related activities	0.0	50.0	50.0	0.0	0.0	100.0
	Shopping activities	62.5	0.0	18.8	6.3	12.5	100.0
	Caregiving activities	100.0	0.0	0.0	0.0	0.0	100.0
	Sports and hobbies	46.7	0.0	33.3	13.3	6.7	100.0
	All activities	37.4	6.8	27.7	18.4	9.7	100.0

make the fewest trips compared with other population segments. In contrast, faculty members have the highest mean trip rate, at 2.92 trips. For student population segments, the trip rates for school- and education-related purposes is more than 1, whereas for faculty and staff segments, the paid work trip rates are more than 1.

For trip distance, the overall mean trip distance is highest for faculty members (7.51 km), whereas graduate students had the shortest mean travel distance (3.84 km). On average, faculty members and staff travel 13.81 and 16.55 km, respectively, for paid work, whereas undergraduate students and graduate students travel only 4.32 and 7.81 km, respectively, for work or school trips. Clearly, students live nearer to the campus compared with faculty members and staff. Even though faculty members travel longer distances and have higher trip rates, their travel time is lower compared with other groups. This suggests that faculty members use faster modes of travel to reach the activity locations.

Fig. 1 presents the activity participation behavior of Dalhousie University community sample segments. Across all segments, the highest activity duration per day is allocated for personal care–related activities. Much of this is accounted for by sleep, meals, and grooming. As expected, the second longest activity duration for undergraduate students and graduate students is school- and education-related activities, whereas paid work is the second longest activity duration for faculty members and staff. Compared with all the segments, staff spend the shortest time on entertainment-related activities, whereas undergraduate students spend the shortest time on sports- and hobbies-related activities.

Model Results

Parameter estimation results of the maximum likelihood estimation of the Poisson, NB, and ZINB models described in "Modeling Approach" are presented in Tables 4–6. For all the modes, including daily automobile trips, AT trips, and transit trips, the ZINB specification best describes the underlying two-state process. The Poisson and NB models provide very similar coefficients for both daily AT and automobile trip models. The overdispersion parameter α in the NB model is greater than 1.0 for all models, indicating that there is significant overdispersion in the data. The ZINB estimates for daily automobile trips, AT trips, and transit trips shown in Tables 4–6 have Vuong statistics much greater than 1.96; the values of 3.56, 5.11, and 3.1 for automobile, AT, and transit, respectively, indicate that there is a higher probability that a two-state process is

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Table 3. Mean Trip Travel Times, Distances, and Trip Rates for Various Activity Types

Variable	Activity type	Undergraduate students	Graduate students	Faculty	Staff
Trip rate per day	Household-related works	0.05	0.03	0	0.04
	Paid work	0.44	0.47	1.96	2.01
	Entertainment-related activities	0.19	0.17	0.08	0.1
	Media and communication	0	0	0	0.01
	Organizational, voluntary, and religious activity	0.06	0.07	0.08	0.1
	Personal care-related activities	0.17	0.28	0.23	0.1
	School- and education-related activities	1.34	1.4	0.08	0.06
	Shopping activities	0.27	0.36	0.08	0.23
	Caregiving activities	0	0.01	0	0.04
	Sports and hobbies	0.06	0.12	0.42	0.21
	All trips	2.58	2.89	2.92	2.9
Trip duration (min/day)	Household-related works	30.83	17.5	0	36.67
	Paid work	21.96	19.47	25.49	30.77
	Entertainment-related activities	23.75	26.5	27.5	45
	Media and communication	0	0	0	30
	Organizational, voluntary, and religious activity	37.14	18.13	15	22.86
	Personal care-related activities	20.45	25.59	22.5	24.29
	School- and education-related activities	20.83	23.55	20	28.75
	Shopping activities	23.24	24.3	10	21.25
	Caregiving activities	0	10	0	18.33
	Sports and hobbies	27.14	32.14	26.36	24
	All trips	25.67	21.91	20.98	28.19
Trip distance (km)	Household-related works	4.08	2.17	0	7.67
	Paid work	5.4	4.2	13.81	16.55
	Entertainment-related activities	10.4	4.96	8.52	6.27
	Media and communication	0	0	0	2.4
	Organizational, voluntary, and religious activity	2.37	1.86	11.57	2.08
	Personal care-related activities	2.83	2.55	7.03	6.44
	School- and education-related activities	4.32	7.81	4.4	4.58
	Shopping activities	4.47	4.37	4.75	3.21
	Caregiving activities	0	1.36	0	2.03
	Sports and hobbies	5.68	4.72	2.49	6.19
	All trips	4.94	3.84	7.51	5.74

present. Thus, ZINB is the best estimator of the zero-trip and non-zero-trip states, with plausible signs.

From the ZINB model for automobile trips presented in Table 4, it is found that the respondent's gender is a significant factor. The sign for female gender is negative, which shows that male respondents are more likely to use automobile trips than female students. If the respondent's duration of living in the current residence is less than 1 year, then it is more likely the respondent would make fewer automobile trips compared with those who are staying longer. As expected, more automobiles in the respondent's household is related to a higher probability that the respondent will make automobile trips. Similarly, having a driver's license has a positive coefficient, showing that the respondent is more likely to make automobile trips per day. It is also found that household size has a positive sign, indicating that respondents in larger households will make more automobile trips compared with those from smaller households. Similarly, individuals that own a home are likely to undertake more automobile trips in comparison with others.

From the parameter estimates for AT trips per day reported in Table 5, it is more likely that younger commuters will undertake more AT trips per day compared with older ones. In contrast, gender is not a significant variable in the model. Among other socio-demographic characteristics, it is evident that if the annual income is lower than \$15,000, then the probability of making AT trips increases. This would apply primarily to students. Also, housing tenure of less than 1 year has a positive coefficient value, indicating the transient student groups who change housing with each new academic year are more likely to make AT trips. Among the four university segments, staff members are less likely to employ AT trips compared with others. Also, if the daily school or work schedule is flexible, then it can be expected that the individual will make more AT trips. The coefficient values for faculty members and staff have negative signs, whereas for graduate students the sign is positive. These variables have been retained in the final model, with the assumption that if the sample size were larger these variables would have been significant.

Table 6 also shows the ZINB parameter estimates for transit trip frequencies. The ZINB model for transit trips shows that the number of daily automobile and AT trips have significant negative effect on daily transit trip frequencies. Among the personal characteristics variables, age of the individual has a negative sign, which indicates that younger individuals will undertake more transit trips compared with older ones. The coefficient for annual income less than \$15,000 is positive, but negative for annual income between \$15,000 and \$25,000. This shows that individuals who make less than \$15,000 will undertake more transit trips per day than those with an annual income of more than \$15,000. It is also found that individuals with no flexibility in work will undertake more transit trips than others. In addition, the distance between home and work has a negative coefficient value, showing that individuals living far from the campus employ fewer transit trips than those who live nearer.

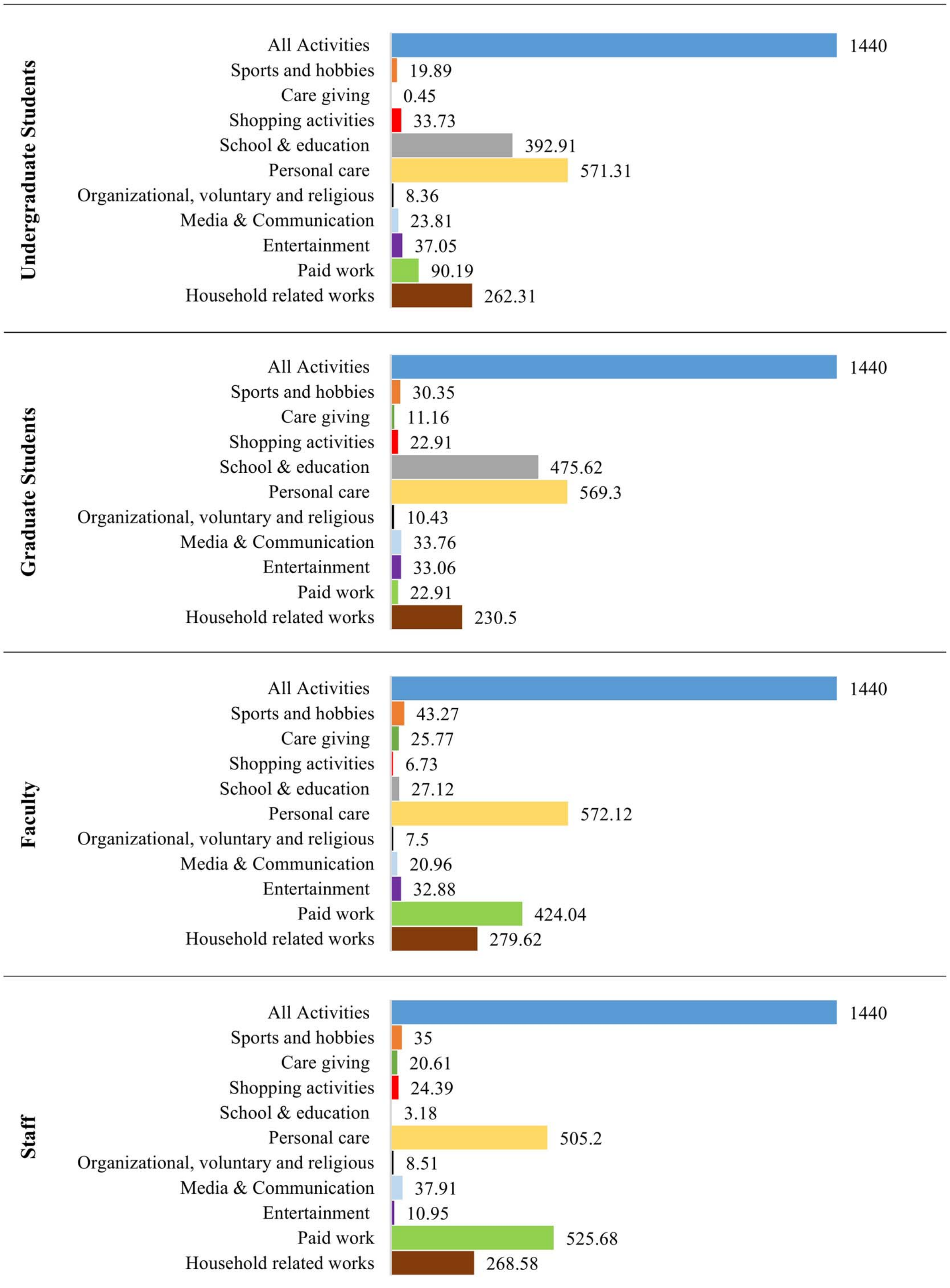

Fig. 1. Activity participation segment (minutes)

Conclusions

This paper explored the trip characteristics, activity characteristics, and travel behavior of students and workers at the largest university in the Maritime Provinces of Canada. The target population comprised undergraduate students, graduate students, faculty members, and staff at Dalhousie University, which is a significant generator of travel demand in HRM. This is the first study of activity-travel behavior for a large Canadian university. The findings of this paper provide insights that can be employed in TDM strategies at other large urban campuses, and empirical data that can be utilized to represent university populations in regional travel demand models.

The paper presented a detailed tabulation of travel mode share, trip characteristics, trip duration, trip length, and activity duration by purpose. Staff members reside farther away from campus and they travel a longer distance for home-to-work commuting, which is consistent with previous findings (Volosin 2014). In contrast, students reside nearer to the campus and their mean trip length from home to school is significantly shorter than those of faculty members and staff. Although faculty members, on average, travel a

Table 4. Parameter Estimation Results of Trip Frequency Models for Dalhousie University Population for Automobile Trips

Variable	Poisson		NB		ZINB	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant	−1.1	−2.3	0.67	1.98	1.21	**2.41**
AT	−1.00	−4.65	−1.00	−6.07	−1.00	**−7.34**
BUS	−1.36	−3.08	−1.36	−3.68	−1.36	**−4.87**
FEMALE	−0.22	−1.36	−0.21	−1.18	−0.33	**−2.15**
LES1YR	−0.30	−2.59	−0.30	−1.37	−0.30	**−2.24**
ABV10YR	0.42	1.91	0.42	1.38	0.42	1.21
Q9HHCAR	0.32	1.03	0.25	1.31	0.41	**2.01**
DRVLNS	0.46	1.85	0.46	2.51	−0.46	**2.42**
STAFF	−0.42	−1.19	−0.42	−1.72	−0.42	−1.48
UNGRAD	0.08	1.67	0.08	1.31	0.08	1.26
HIGHFLEX	−0.17	−1.32	−0.20	−1.1	−0.27	−1.58
Q6HHSIZE	0.06	1.49	0.06	1.26	0.06	**2.18**
HOMOWN	0.13	1.39	0.13	1.15	0.13	**2.09**
Dispersion parameter						
Alpha	—	—	0.2	2.52	0.51	**3.26**
Tau	—	—	—	—	−1.11	**−3.31**
Log-likelihood (null)	−505.17		−505.17		−505.17	
Log-likelihood (full)	−471.11		−411.23		−401.55	
Vuong statistic			3.56			

Note: Bold values represents the significant parameters at 99% confidence level (P-value < 0.01); AGEGRP = age of the respondents; AT = number of active transport trips per day; BT15T25K = annual individual income (dummy, if the income is between 15K to 25K, 0 otherwise); BUS = number of transit trips per day; CAR = number of Automobile trips per day; LES1YR = less than 1 year of living (dummy, if the respondent is living in the current house for less than 1 year, 0 otherwise); NOFLEX = no flexibility (dummy, if the work or schedule of the respondent is not flexible, 0 otherwise).

Table 5. Parameter Estimation Results of Trip Frequency Models for Dalhousie University Population for AT Trips

Variable	Poisson		NB		ZINB	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant	0.30	1.89	0.31	1.54	0.67	**2.11**
BUS	−0.76	−2.15	−0.76	−2.81	−0.76	**−4.15**
CAR	−0.86	−2.27	−0.86	−3.70	−0.86	**−4.72**
FEMALE	−0.54	−1.35	−0.01	−1.43	−0.01	−1.37
AGE	−0.21	−0.55	−0.11	−0.16	−0.21	**−2.14**
LESS15K	0.20	1.09	0.43	1.43	0.55	**2.53**
BT50T75K	−0.23	1.50	0.23	1.58	0.23	1.50
LES1YR	0.46	2.29	0.46	1.16	0.46	**2.06**
STAFF	−0.43	−1.56	−0.43	−1.18	−0.43	**−1.84**
FACULTY	−0.10	−1.70	−0.10	−1.79	−0.10	−1.62
HIGHFLEX	0.14	−1.29	−0.21	−1.11	−0.32	**−2.09**
Dispersion parameter						
Alpha	—	—	1.21	1.86	0.63	**2.51**
Tau	—	—	—	—	−0.31	−1.68
Log-likelihood (null)	−587.12		−587.12		−587.12	
Log-likelihood (full)	−556.71		−534.01		−498.34	
Vuong statistic			5.11			

Note: Bold values represents the significant parameters at 95% confidence level (P-value < 0.05); AT = number of active transport trips per day; BT15T25K = annual individual income (dummy, if the income is between 15K to 25K, 0 otherwise); BUS = number of transit trips per day; CAR = number of Automobile trips per day; LES1YR = less than 1 year of living (dummy, if the respondent is living in the current house for less than 1 year, 0 otherwise); NOFLEX = no flexibility (dummy, if the work or schedule of the respondent is not flexible, 0 otherwise).

longer distance, they use faster modes of travel and therefore experience shorter trip durations per trip. In general, the most used mode for undergraduate and graduate students is walking, whereas for faculty and staff segments the most used mode is automobile (driver). For entertainment-related activities and sports and hobbies, all four sample segments choose automobile (driver). Also, the mean number of AT trips per day for the overall sample is more than 1.0 trip, whereas automobile has less than 1.0 trip. These are encouraging findings for promoting active transportation for commuting trips in the case of the university population. Discouragingly, however, transit usage was lower than for automobile usage, even for the student groups.

Statistical analysis showed the existence of overdispersion and excess zeros among the dependent variables, thus suggesting the use of a zero-inflated negative binomial structure for modeling activity travel demands. The ZINB model for AT trips per day suggests that the number of AT trips per day is positively associated with older age commuters, annual income below $15,000, housing tenure less than 1 year, and highly flexible school and work schedules. In contrast, the ZINB model for automobile trips suggests that the frequency of automobile trips per day is negatively associated with female respondents, housing tenure less than 1 year, and larger household size, and positively associated with household automobile ownership and having a driver's license. The ZINB model

Table 6. Parameter Estimation Results of Trip Frequency Models for Dalhousie University Population for Transit Trips

Variable	Poisson		NB		ZINB	
	Coefficient	t-stat	Coefficient	t-stat	Coefficient	t-stat
Constant	0.04	1.11	0.10	1.51	0.43	**1.85**
AT	−0.96	−4.80	−0.96	−4.07	−0.96	**−5.13**
CAR	−1.44	−3.16	−1.44	−3.71	−1.44	**−4.14**
FEMALE	−0.15	−2.50	0.00	−1.39	0.00	−1.08
AGEGRP	−0.27	−1.41	−0.23	−1.29	−0.27	**−2.13**
HOMOWN	−0.23	−1.59	−0.23	−1.60	−0.23	−1.76
LESS15K	0.25	1.85	0.20	1.90	0.31	**2.35**
BT15T25K	−0.10	−1.35	−0.12	−1.18	−0.14	**−2.11**
UNGRAD	−0.20	−1.95	−0.20	−1.57	−0.20	−1.38
NOFLEX	0.16	1.24	0.16	1.13	0.21	**2.12**
DISTHW	0.20	1.58	−0.13	−1.69	−0.17	**−1.86**
Dispersion parameter						
Alpha	—	—	0.43	1.37	0.71	**2.30**
Tau	—	—	—	—	−0.21	**−1.98**
Log-likelihood (null)	−452.27		−452.27		−452.27	
Log-likelihood (full)	−411.31		−393.41		−376.33	
Vuong statistic			3.1			

Note: Bold values represents the significant parameters at 95% confidence level (P-value < 0.05); AT = number of active transport trips per day; BT15T25K = annual individual income (dummy, if the income is between 15K to 25K, 0 otherwise); BUS = number of transit trips per day; CAR = number of Automobile trips per day; LES1YR = less than 1 year of living (dummy, if the respondent is living in the current house for less than 1 year, 0 otherwise); NOFLEX = no flexibility (dummy, if the work or schedule of the respondent is not flexible, 0 otherwise).

suggests that the number of daily transit trips is positively associated with annual income less than $15,000 and with no flexibility in work schedule, whereas the number of daily automobile trips, number of daily AT trips, age of the individual, annual income between $15,000 and $25,000, and home to work or school distance are negatively associated with the daily transit trips.

In summary, data collected through the EnACT survey provide a rich data set on a large Canadian university population, which can be considered as one of the major trip generators that affect regional traffic. The empirical model presented in this paper can improve disaggregated regional travel demand models with more accuracy and better precision. This study analyzes and compares the activity travel demand for all four university population segments, which have received very limited attention in the literature.

The analysis shows that there exists significant heterogeneity among different market segments of the university population, which needs more attention from transportation planning. Further studies will investigate the association between built environment, land use, and mode choice across the different university segments using econometric modeling and *ArcGIS*. The findings on university population segments can assist the development and implementation of more practical and strategic planning solutions to promote a walking- and biking-friendly environment near and on campus, and enhance management of on-campus travel demand. The results of this paper are expected to be incorporated within the activity-based travel demand model, Scheduler for Activities, Locations and Travel (SALT), for HRM, Nova Scotia, Canada, which is currently under development.

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