MODELING ANTICIPATED INTEGRATION OF BIKESHARE WITH TRAVEL MODES

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ABSTRACT

This paper presents a comprehensive investigation of anticipated bikeshare integration with available travel modes in an urban setting. The key objective of the research is to enhance our understanding of the factors affecting choice of different potential integration types that include (a) transit-bikeshare, (b) auto-bikeshare, (c) walk-bikeshare, (d) other modes-bikeshare, and (e) no integration with bikeshare, if a public bikeshare system is available. This paper uses data collected from a bikeshare survey conducted in Halifax, Canada, in 2011. The web-based survey included questions regarding the system's potential usage in respondents' daily activities, the frequency of usage, and the anticipated integration with their existing travel mode choices. A latent class choice model is used in the study, which accounts for unobserved heterogeneity often ignored in traditional choice modeling. One of the unique features of the modeling approach taken in this paper is that observed attitudinal factors determine class membership probabilities. The results suggest that the latent class logit model outperforms the conventional logit model in terms of model fit. Several socio-economic characteristics, accessibility measures, and neighborhood characteristics are found to explain different types of integration. Moreover, it is found that considerable latent heterogeneity exists among sampled household. The research offers significant behavioral insights that could be potentially useful in planning for bikeshare implementation.

Keywords: Public Bikeshare System, Integration, Travel Modes, Latent Class Choice model

INTRODUCTION

This paper presents the findings of a latent class logit model that examines how individuals might integrate bikeshare with currently available travel modes. Bikesharing programs are increasingly being adopted by many cities, facilitating the integration of cycling with other transportation modes (such as transit or walking), and encouraging the usage of bicycles as a travel mode choice on a daily basis (Shaheen et al., 2010). By providing access to readily-available and affordable bicycles in central business districts, bikesharing programs are viewed as innovative ways of alleviating traffic congestion and reducing pollution in inner city areas (Lin and Yang, 2011). Opportunities for combining different transportation modes offer a wider range of travel choices, and simultaneously facilitate more flexible, multi-modal travel options around the city (Bachand-Marleau et al., 2011). Public bicycle systems (PBS) could, for example, extend the accessibility of transit to final destinations, which reduces the need for private vehicles. Many European cities, in particular, have already implemented successful public bicycle systems. The recent adoption of bikesharing in cities such as Montreal, Toronto, and Washington, D.C., and plans for program implementation in New York and Los Angeles, show that interest in public bicycle systems is growing outside of Europe (Rojas-Rueda et al., 2011). Previous studies have investigated measures that facilitate the integration of cycling with transit. However, little is known about the demand for various integration measures beyond a general roadmap (Bachand-Marleau et al., 2011). As a matter of fact, no study has yet examined how individuals might integrate bikesharing with their current daily travel modes. This research attempts to fill the gap, specifically by investigating all possible modal integration options: transit-bikeshare, auto-bikeshare, walk-bikeshare, other modes-bikeshare, and no integration at all.

A random utility-based choice modeling approach is utilized to examine the determinants of each integration type choice. A latent class logit model is estimated using a dataset obtained from a bikeshare survey administered in Halifax, Canada. The main motivation of using a latent class model structure is that it offers flexibility in order to allow variations in parameters, which captures unobserved heterogeneity, such as attitudes, perceptions and awareness. One of the unique features of the model proposed in this study is that observed attitudinal factors determine class membership probabilities.

The rest of the paper is organized as follows: first, a review of the literature is provided. This is followed by a discussion of the modeling approach used in the study. The next section describes the data used in the empirical application, followed by a discussion of model results. The paper concludes by providing a summary of contributions and future research directions.

LITERATURE REVIEW

Bicycling is widely recognized as a healthy and environmentally friendly mode of transportation (Wardman et al., 2007). Bicycles offer a range of advantages for short-distance trips in urban areas, including lower investment requirements for cycling infrastructure than for cars (deMaio and Gifford, 2004; Martens, 2007; Pucher and Buehler, 2008). It can also act as a feedering mode to other transportation modes (Shaheen et al., 2010). Non-motorized modes of transportation, such as cycling, are often viewed as key elements of a sustainable transportation system and offer a means of reducing automobile commuting, congestion and greenhouse gas emissions, while simultaneously adding health benefits (Rietveld and Daniel, 2004; Noland and Kunreuther, 1995). Bikeshare programs offer additional opportunities to existing and new cyclists to access on-demand and affordable rental bicycles within city centers, facilitating better movement around the urban core. Despite growing interest in public bicycle systems, research focusing on bikesharing is limited in the existing literature.

Several studies investigate cycling trends and successful policies that promote the use of bicycles (Noland and Kunreuther, 1995; Pucher and Dijkstra, 2000; Rietveld and Daniel, 2004; Pucher and Buehler, 2008). Pucher and Dijkstra (2000) compare cycling policies between Europe and North America. In a Dutch study, Rietveld and Daniel (2004) argue that simultaneously reducing cycling costs and making competing modes more expensive can better promote the choice of this mode for daily travel. In recent years, numerous successful public bicycle programs have been implemented, predominantly in Europe. Bikesharing programs are gaining attention in North American and Asian cities as well. Shaheen et al. (2011) identify that as of March 2011, there were over 135 PBS in 160 cities around the world, with more than 235,000 shared bicycles. Studies have shown that PBS can significantly increase cycling rates: in Lyon, bicycle usage increased by 44% within the first year of the implementation of the Velo'v program (Buhrmann, 2007), and Paris experienced a 70% increase after the launch of Vélib' (Shaheen et al., 2010).

Existing bikeshare studies tend to focus predominantly on understanding usage patterns, bicycle distribution, and activity cycles of registered users of PBS, such as Bicing in Barcelona and the Barclays Cycle Hire (BCH) scheme in London (Froehlich et al., 2008; Kaltenbrunner et al., 2010; Lathia et al.,2012). Studies in London attempt to understand the travel patterns of users and how these trips are integrated into the broader public transport system (Noland and Ishaque, 2006). Another study investigates the personal and area-level characteristics of users which act as the main predictors of the scheme usage (Ogilvie and Goodman, 2012). It reveals that female users constituted only one-third of all registered users for the BCH scheme in London and made fewer trips than men. Recently, Shaheen et al. (2011) analyzed the early adoption and behavioral response to the implementation of the Guangzhou Public Bicycle service in China, providing insight into the opportunities for expanding membership both locally, and in other bikesharing cities. However, several studies suggest that further research is required to explore the extent of possibilities that bikesharing can offer (Fuller et al., 2011).

Public bicycle systems can effectively promote bike-transit integration (deMaio and Gifford, 2004). By acting as a 'feedering mode', these programs may provide potential solutions to the problem of accessing transit stops and stations from origins and destinations of trips. An added advantage of bikesharing programs is that they could facilitate one-way trips, and reduce the need to bring bicycles onto public transit during peak hours (Lin and Yang, 2011). A recent study in Montreal offers a notable contribution in the study of transit-bike integration. It uses a factor-cluster market segmentation analysis to identify different groups of bicycle and transit integrators (Bachand-Marleau et al., 2011). However, a review of the literature suggests that no research has yet examined the potential integration of bikeshare with all types of travel modes. This paper aims to fill the gap in the existing literature, particularly by adding to our understanding on how individuals anticipate integrating bikeshare with the available travel modes in an urban setting.

A growing body of cycling research argues that the choice of cycling as a travel mode depends on many factors, including cost, flexibility, personality traits, and attitudinal factors (Johansson et al., 2006). Several studies show that most bike-and-ride trips are undertaken for the purpose of work and school (Martens, 2004). Density is also found to be a contributing factor to cycling. Those living in compact urban areas are more likely to utilize bicycles as part of their daily commute than those living in suburban locations (Dill and Voros, 2007). Other notable factors identified in previous studies include income, access to a vehicle, and residential location (Dill and Voros, 2007; Pucher et al., 1999; Stinson and Bhat, 2005). It is argued that the social values and attitudes may be better suited to explain cycling levels than socio-economic factors alone (Heinen et al., 2010). Similarly, choice of bike-transit integration is argued to be determined by the attitudinal factors that cut across socio-demographic lines (Bachand-Marleau et al., 2011). But psychological factors, such as attitudes, perceptions, and awareness, are rarely used in choice modeling, because they are not straightforward to measure or analyze, and may not comprehensively capture all relevant attitudes if measured (Mokhtarian and Cao, 2008). Therefore, in modeling multiple types of bikeshare integration choices, this paper takes an innovative approach utilizing a latent class modeling structure, which is flexible enough to allow for the representation of variations for unobserved (latent) heterogeneity (due to unobserved perceptions, attitudes and awareness). At the same time, the observed attitudinal factors can be used to identify the (latent) class membership probabilities. The model structure used in this study is presented in the next section.

MODELING APPROACH

In modeling the integration of bikeshare with different travel modes, this paper considers five plausible choice scenarios obtained through a survey administered in Halifax, Canada: (1) transit-bikeshare integration, (2) auto-bikeshare integration, (3) walk-bikeshare integration, (4) other modes-bikeshare integration, and (5) no integration with bikeshare. The choice model can be formulated following a random utility-based discrete choice modeling approach. The underlying assumption is that individuals will maximize their utility by choosing an alternative within the choice set, and the utility of choosing an alternative is composed of two components: systematic utility and random utility. The systematic utility (V) is considered linear in the parameter function of covariates (X) and corresponding parameters (β). Assuming that the random utility is independent and identically distributed (IID) with a Gumbel (type I extreme value) distribution, a multinomial logit model (MNL) is given by (McFadden, 1974):

$$P_j(i \mid \beta) = \frac{e^{V_{ij}}}{\sum_{k=1}^{K} e^{V_{ij}}} = \frac{e^{\beta X_{ij}}}{\sum_{k=1}^{K} e^{\beta X_{ij}}} \tag{1}$$

where $P_j(i \mid \beta)$ represents the probability of individual j choosing alternative i in a given choice context. X_{ij} is a vector of observed attributes of the alternative i and individual j. K represents the number of alternatives considered in the choice set.

Although the MNL model has been widely used for many years in choice modeling, there is a growing body of research exploring alternative formulations for variety of reasons, including addressing problems with latent (unobserved) heterogeneity. The unobserved heterogeneity may exist due to taste variations as well as attitudinal factors, often unknown to the analyst. The effects of taste variations could be incorporated within the MNL model by using observed socio-economic characteristics or via interaction variables. Latent heterogeneity may well remain despite the use of only the observable attributes of individuals (Greene and Hensher, 2003). On the other hand, assessing unobserved attitudinal variations across individuals is challenging, and often ignored in conventional models (Handy et al., 2005). When latent heterogeneity exists and the homogeneity assumption is imposed in choice models, it results in inconsistent estimates of model parameters and even more severe inconsistent estimates of choice probabilities (Bhat, 2000). Recent advances in behavioral choice modeling offer a relaxation of assumptions in the MNL model, leading to continuous mixture logit models as well as latent class logit models. A relative advantage of the latent class model (LCM) over continuous mixture models is that it does not require the analyst to make specific assumptions about the distributions of parameters across individuals (Greene and Hensher, 2003). Instead, the LCM implicitly sorts groups of individuals into discrete classes to reflect latent heterogeneity through a class membership allocation model. The LCM model further appears to be advantageous because the class allocation model can be specified using observed attitudinal factors, which is rarely considered in such models. As such, this paper examines a latent class model for modeling the anticipated integration of bikeshare with travel modes. Let $P_j(i \mid \beta_m)$ be the probability of individual j choosing alternative i conditional on individual j being sorted into m classes. Hence, the unconditional choice probability can be written as:

$$P_j(i \mid \beta_1, ...\beta_M) = \sum_{m=1}^{M} \phi_{jm} P_j(i \mid \beta_m) \qquad (2)$$

where ϕ_{jm} represents the probability of individual j falling into class m. Although individuals are grouped into classes based on this probability, class membership of a particular individual remains unknown.

Some studies restrict the class membership probabilities (ϕ_{jm}) to be constant across individuals (e.g., Greene and Hensher, 2003). The real flexibility, however, arises when ϕ_{jm} does not simply represent constants, but when a class membership model is used to link these probabilities to individuals' characteristics (Hess et al., 2011). In general, socio-demographic attributes are used to represent such probabilities in existing literature (Gupta and Chintagunta, 1994). In contrast, this paper utilizes observed attitudinal factors, such as awareness of the bikeshare experiences, and support for the implementation of a bikeshare program in defining class membership probabilities. Although various functional forms have been proposed for the class membership model, this paper adopts a logit form that is consistent with several recent studies (Zhang et al., 2009). Thus, the class membership probability can be expressed as:

$$\phi_{jm} = \frac{e^{\alpha_m + \theta_m z_j}}{\sum_{s'=1}^{S} e^{\alpha_m + \theta_m z_j}} \tag{3}$$

Here, Z_j represents attitudinal factors considered in the utility function for the class membership model, and θ_m is a vector of associated parameters to be estimated. In addition, α_m represents latent class-specific constants. To secure identification of the model, α_m and θ_m parameters are fixed to zero for a particular class, which is considered as the reference latent class.

The class membership parameter vectors (α_m and θ_m) for $M-1$ classes, and class-specific parameter vectors (β_m) for M classes, are obtained through a maximum likelihood estimation. Combining the individual contribution of individual j to the likelihood function (based on equation 2), the log-likelihood for all individuals can be written as:

$$\ln L = \sum_{j=1}^{N} \ln \left[\sum_{m=1}^{M} \phi_{jm} \left(\prod_{i} P_j(i \mid \beta_m) \right)^{\delta_{ij}} \right] \tag{4}$$

where δ_{ij} represents a dummy being equal to 1 when the alternative i is chosen by the individual j, and 0 otherwise. N is the number of observations. The expectation-maximum (EM) algorithm is used to estimate the model. The asymptotic covariance matrix for the full set of parameter estimators is obtained by inverting the analytic second derivatives matrix of the above-mentioned log-likelihood function (see Greene, 2011, for details). Note that no simulation is required, unlike other approaches of incorporating latent heterogeneity (such as continuous mixture models), reducing computation burdens during estimation.

DATA USED IN THE EMPIRICAL APPLICATION

Halifax Bikeshare Survey

The data source for estimating the models is a bikeshare survey, administered in Halifax, Canada in 2011 as a part of the bikeshare feasibility study. The main objective of the study was to evaluate the feasibility of implementing a public bicycle system in Halifax. The survey was specifically designed to collect information on various aspects of individuals' current travel behavior, and the anticipated usage of the system, including willingness-to-pay, possible usage of bikeshare by trip purposes, and the potential integration of bikeshare with the currently available modes of transportation. Participants were also asked to provide information regarding socio-economic characteristics, locational information (such as home and work locations), and awareness of, and attitudes towards, public bicycle systems. A web-based survey instrument was used to collect the data through Dalhousie University's licensed on-line survey system. To reach a broader spectrum of the public, various survey distribution methods were used, including web media, radio interviews, email newsletters, and list-serv invitations via major employers in Halifax, elected representatives, public officials, and private and non-profit organizations. A list of the survey distribution partners, detailed description of the survey design, and an exploratory analysis of the dataset, are available in Rad (2011). In total, 360 completed responses were obtained. After cleaning for missing information (such as residential location/income), 337 responses were retained for further analysis. To verify the dataset, aggregate statistics of several socio-economic characteristics of the sample were compared against Census data for Halifax. The younger population, for instance, is found to be slightly over-represented, which is possibly due to the use of the web-based survey. In general, the sample's aggregate statistics are within the range of a few percentage points of that of the entire population. For example, the percentage of employed individuals in the sample is 69.17, whereas it is 64.50% for the population for the Halifax Census Metropolitan Area. Hence, it can be considered a representative sample of the Halifax population.

Data Preparation for Modeling

The data preparation phase involved several steps. First, a database with all relevant attributes was created. Second, employment and home locations were geocoded using the online service BatchGeo™. Third, utilizing these geocoded home and work locations, as well as known locations for transit stops, the central business district, and major shopping centers, accessibility measures were derived using ArcGIS. The ArcGIS Network Analyst tool was employed to calculate road network distances for home to employment, home to nearest transit stop, home to the CBD, and home to nearest major shopping center. Fourth, neighborhood characteristics were derived by means of the spatial join function in ArcGIS to combine the respondents' residential locations with dissemination area (DA) data from the 2006 Canadian census. Joined data included, for example, average household income, average number of rooms, total number of dwelling, and average dwelling value. Population and dwelling densities were further derived by normalizing the respective fields with the DA area. Finally, GIS-based land use information was used to generate land use indices. For example, a land-use mix measure, proposed by Bhat and Gossen (2004) was used in the empirical analysis, which ranges from 0 to 1, with 1 indicating perfect land use heterogeneity and 0 indicating perfect homogeneity.

DISCUSSIONS OF RESULTS

The exploratory analysis of the sample reveals that the distribution of anticipated bikeshare integration types are as follows: transit-bikeshare (9.4%); auto-bikeshare (9.2%); walk-bikeshare (18.1%); other modes-bikeshare (21.7%); and (5) no integration with bikeshare (41.7%). Note that 'other modes-bikeshare' integration encompasses modes such as carshare and taxi, as well as a combination of two or more transportation modes. Further details of the descriptive statistical analysis are presented in Rad (2011).

As explained earlier, a latent class logit model is used to explore determinants of each integration type. Several types of explanatory variables are tested during model estimation, including socio-economic characteristics, trip attributes, accessibility, land use, and neighborhood characteristics. Table 1 shows the summary statistics of the independent variables retained in the final model specification. For a broad illustration of the effects of the variables, a conventional multinomial logit model (MNL) is estimated using the same variables retained in the latent class model (see Table 2).

Results of the Multinomial Logit Model

The parameter estimates of the MNL model suggest that, generally, socio-economic variables, such as age and income, are strong factors in explaining the choice of each type of integration. However, accessibility and land use measures are also found to influence the stated choice of different types of bikeshare integration: for example, land use mix in case of transit-bikeshare integration, and the distance to the central business district (CBD) in cases of transit-bikeshare, auto-bikeshare, and other modes-bikeshare integration.

In the case of transit-bikeshare integration, a dummy representing the age category under 24 years is found to have the strongest effect in the MNL model. The results suggest that this age group intends to integrate bikeshare with transit more in comparison to the other age groups. Land use mix, distance to CBD, and distance to nearest major shopping destination also influence the probability of transit-bikeshare integration. For instance, a negative relationship is found for the distance from respondents' home to the nearest major shopping center, indicating that relatively higher distance to the nearest shopping center reduces the probability of integrating bikeshare with transit for the individuals.

For auto-bikeshare integration, a positive relationship is found with a dummy representing individuals in the 50-64 age category. In contrast, individuals earning below $48,000 are less likely to integrate auto and bikeshare. This is arguably the case since lower incomes indicate more limited access to vehicles due to the cost of car-ownership. A positive, yet weak, relationship is found between being a student and this form of integration. Population density is also a factor for auto-bikeshare integration. The variable that most strongly impacts auto-bikeshare integration is the distance to the CBD, indicating that the further people live from the CBD, the more likely it is that they will combine auto with bikeshare. On the other hand, distance from a major shopping center is a weak predictor of auto-bikeshare integration. The model also suggests that individuals making occasional trips on the Peninsula (1-2 per week) are likely to integrate bikeshare with auto.

Again, the probability of integrating walking and bikeshare increases if an individual belongs to the 50-64 year age group. The contribution of this variable is higher for walk-bikeshare integration (1.15) than for auto-bikeshare integration (0.70). Similarly, being a student positively influences the integration of bikeshare with walking (more so than with auto). Living on the Halifax Peninsula positively affects walk-bikeshare integration as distances between home and work, or home and various services, are relatively short. There is a positive, yet relatively weak, relationship between income and walk-bikeshare integration. Unlike transit- and auto-bikeshare integration, the distance to a major shopping center indicates a positive relationship.

Factors affecting the integration of bikeshare with other modes (e.g. carshare, taxi, mix of modes) includes age, income, gender, employment status, distance to CBD and major shopping centers, and population density. The age category between 25 and 34 years shows a negative relationship between other modes and bikeshare integration. Additionally, the variables representing males, full-time workers, density, and distance to nearest major shopping center exhibit negative relationships for the other modes-bikeshare integration alternative.

The model results reveal that the probability of not integrating bikeshare with any type of available modes is lower for younger, working population groups (i.e., 25-34 years old), compared to other age groups. Males and individuals with an income between $48,000 and $96,000 are less likely to use bikeshare (i.e. no integration) in comparison to their respective counterparts. Conversely, the model shows that the higher the dwelling density in the neighborhood, the less likely it is that there will be no integration. Finally, individuals living in a neighborhood with higher average rooms per household would exhibit a lower probability of integration all else being equal.

The goodness-of-fit statistics of the MNL model (i.e. an adjusted pseudo R-square) is 0.10436. On the other hand, the latent class model exhibits a higher adjusted pseudo R-squared value (0.24859). It can reasonably be concluded that the latent class model (LCM) outperformed the MNL in terms of the model fit. Moreover, the LCM accounts for latent heterogeneity, allowing parameter variations for latent classes. Hence, this paper considers LCM as a better model than the conventional logit model. The following section presents a discussion of the LCM results.

Latent Class Model

Table 2 shows the parameter estimates of all the variables retained in the latent class model. The majority of the variables exhibit statistical significance at least at the 95% confidence interval (t-statistic greater than 1.96). In some cases, the t-statistic is less than the threshold value; however, those variables are retained in the final model since they offer important behavioral insights, with an assumption that if a larger dataset were available, these parameters might show statistical significance.

The LCM results suggest that significant heterogeneity exists among the sampled individuals. The model is assumed to follow two latent classes. Also, few variables are assumed to be fixed across the sample. However, the majority of the variables show considerable variations both in terms of parametric values and relationships.

For transit-bikeshare integration, the dummy representing the age category of under 24 years shows a similar positive relationship for the individuals that were implicitly sorted into latent Class 2 (the reference class), as found in the MNL model. However, it shows an opposite relationship for those who belong to Class 1. The parameter value of this variable in Class 2 is three times higher than that found in the MNL model. It implies that some individuals who might be within this sub-group of the population would have a higher tendency to integrate bikeshare with transit. In addition, population density, as well as the distance to the CBD, is found to positively influence transit-bikeshare integration in both latent classes. The distance to CBD variable, however, is assumed to be class independent (i.e. fixed). This positive parameter value implies that as distance increases for individuals, the probability of integrating transit with bikeshare increases. This result corresponds to the a priori hypothesis, as suggested by Keijer and Rietveld (2000), that multi-modal trips are most appealing when people have to travel long distances. Faster types of transit (such as MetroLink, a bus rapid transit service available in Halifax) tend to attract people from further distances due to potential time savings, and cycling provides an attractive access mode to final destinations.

Additionally, the distance to the nearest major shopping center has a negative impact on transit-bikeshare integration. Interestingly, a very strong, negative relationship exists between the land use mix and transit-bikeshare integration in Class 1, as indicated by a coefficient value of -5.81 (more than quadruple that of the value in the MNL model). Land use mix is higher in downtown areas, where people prefer taking one mode for shorter distance, and do not necessarily need to combine two modes of transportation. This is similar to the distance variable – the farther the distance from the CBD, the more likely it is that transit-bikeshare integration will occur. However, Class 2 exhibits considerable difference in the effect of land use mix, showing a positive parametric value for transit-bikeshare integration.

In case of auto-bikeshare integration, a dummy representing age between 50 and 64 years shows a positive sign, as expected. The variable distance to the CBD from respondents' homes indicates a similar effect for both classes. Individuals with an income below $48,000 and students, however, are less likely to integrate bikeshare with auto presumably due to the high cost of auto ownership as indicated earlier. This kind of negative relationship is also exhibited by the distance to the closest major shopping center variable. Population density is found to be a strong predictor of auto-bikeshare integration in Class 2, whereas variation exists in case of Class 1. Taking occasional trips on the Peninsula (1-2 trips per week) also positively affects auto-bikeshare integration in Class 1, with a statistically significant coefficient value of 4.20. It shows an opposite effect for Class 2.

For walk-bikeshare integration, dummy variables representing the 50-64 age category, income in the range of $48-96k, and student status consistently show the same positive relationship for both latent classes. However, the effect of being a student is approximately nine times greater for Class 2 than for Class 1. The results also suggest that individuals living in the Halifax urban core have a higher probability of walk-bikeshare integration if they belong to Class 2. Similarly, the distance to the nearest major shopping center shows a negative sign for Class 2. In addition, average household income in the neighborhood also marginally influences walk-bikeshare integration.

The model results for other modes-bikeshare integration indicates that individuals between the age of 25 and 34 are less likely to engage in this type of integration, irrespective of class membership. Other factors that explain other modes-bikeshare integration includes distance to the CBD, distance to the nearest major shopping center, population density, and dummy variables representing other socio-economic characteristics. For example, the results indicate that full-time workers are less likely to integrate other modes (such as taxi, carshare, and mix of modes) with bikeshare, in the case that they are sorted into Class 1. Presumably, full-time employment entails a fixed routine and demands reliable transportation, such as a private vehicle or transit. On the other hand, for Class 2 it exhibits a positive sign. This group might resemble those who anticipate combining multiple modes for daily travel.

Consistent with the MNL model results, it is found (in both latent classes) that the probability of not integrating bikeshare is lower for younger population groups (25-34 years) relative to other age groups. Individuals within this age group tend to be more aware of transportation alternatives, be more environmentally conscious, and often live closer to their workplace, all resulting in willingness to consider integrating bikeshare into their daily travel. Other variables, such as frequent trips on the Halifax Peninsula (i.e. urban core) and dwelling density in the neighborhood, are found to influence the probability of integrating bikeshare with reasonable statistical significance.

Overall, Class 2 results tend to exhibit stronger relationships between the explanatory variables and the integration type of interest. Generally, strong coefficient values in one class show weaker relationships in the other class and vice versa. Some of the variables show profound differences in terms of both the nature of the relationship and their relative contributions (for example, DENSITY in auto-bikeshare integration, and HFXCORE in walk-bikeshare integration). It suggests that significant heterogeneity exists within the sampled population when evaluating the anticipated integration of bikeshare with available travel modes in Halifax.

Several other variables were considered during model estimation, but could not be included in the final model specification due to various reasons, including unexpected signs and poor statistical significance. For example, some neighborhood attributes, such as labor market participation rate, and average number of children, yielded counter-intuitive results. On the other hand, distance to nearest transit stops is hypothesized to be a critical factor in explaining transit-bike integration. However, the variable consistently shows weak statistical significance. Additional efforts have been made, for instance, to generate dummies for different distance bands (such as 500 m, 1 km) in order to test possible non-linear relationships; however, the resulting model does not yield reasonably acceptable statistical significance. Thus, those hypotheses could not be confirmed in this latent class model.

As indicated earlier, although most studies assume a constant class probability across the sample, this paper examines observed attitudinal factors in the class allocation component of the model. Three dummies, indicating individuals who support implementation of bikeshare in Halifax, are not willing to use bikeshare, and are aware of bikeshare practices, are found to be statistically significant (above 95% confidence level) in the class allocation model (see Table 2). The results intuitively suggest that Class 1 membership might include individuals who generally do not support the implementation of bikeshare in peninsular Halifax, would not use it, but are generally aware of the program. On the other hand, Class 2 can be broadly characterized by individuals who would support implementation of the program, will likely use it where possible, but are generally unfamiliar with the bikesharing programs. Generally speaking, several variables demonstrate intuitive relationships with the dependent variable (i.e. integration type) across both Class 1 and Class 2. For example, in case of transit-bikeshare integration, the dummy representing the under 24 age group shows an intuitive relationship. Respondents that fall into the under 24 age category who do not support bikeshare, are unwilling to use it, and are generally aware of the program, are less likely to integrate transit with bikeshare. The results for the respondents within this age category who support bikeshare and indicate that they are willing to use it (but are unaware of the program) show that the probability of integrating transit with bikeshare is higher. Similarly, the variables population density and land use mix exhibit intuitively reasonable differences between latent classes. However, such inferences could not always be corroborated. As a matter of fact, the direct inference of variations that is found among latent classes could be tricky, since multiple domains of contrasts exist in such models (Greene and Hensher, 2003). This paper assumes two latent classes in modeling bikeshare integration types, which provides some relative advantage in this regard, but could be far more challenging if several class membership possibilities are required for consideration in accounting for unobserved heterogeneity in other applications. Further research is required to gain additional understanding about how to deal with such models in travel behavior research.

CONCLUSION

This paper presents a comprehensive modeling framework for investigating bikeshare integration. Particularly, it offers an in-depth behavioral understanding of how individuals anticipate integrating bikeshare with available travel modes. The contribution of this paper is two-fold: first, it sheds light on the integration of bikeshare with all plausible travel options, a much expected outcome that has hitherto not been studied. Second, it proposes a flexible latent class modeling (LCM) approach in which observable attitudinal factors can be used to explain class membership probabilities. This method is particularly suitable for bicycling research, since bicycle usage is often thought to be associated with personality traits, attitudes and perceptions.

The model results suggest that the latent class logit model outperforms the conventional logit model in terms of model fit. Additionally, the latent class model accounts for unobserved heterogeneity by allowing parameters to be varied across classes. The findings of the latent class logit model used in this study suggest that mainly socio-economic characteristics, accessibility measures, land use, and neighborhood attributes explain the anticipated bikeshare integration with different types of travel modes in Halifax. In general, socio-economic characteristics are found to be the most significant contributors in explaining each type of bikeshare integration. Accessibility and neighborhood characteristics are also noteworthy factors. For example, in the case of transit-bikeshare integration, distance to CBD, distance to nearest shopping center, population density, and land use mix are found to influence the probability of this type of integration. It is found that the higher the population density in the neighborhood where an individual lives, the higher the probability of integrating bikeshare with transit, and vice versa. Similarly, the further an individual lives from the CBD, the higher the probability of integrating transit with bikeshare. The same positive effect is found for auto-bikeshare integration. However, considerable variation of the effects of the variables is observed across latent classes. Some of the variables show profound differences in both the nature of the relationship, and relative contributions. It can be concluded that significant heterogeneity exists among the sampled individuals when evaluating anticipated bikeshare integration with other modes.

One of the key features of the proposed model in this paper is that it attempts to utilize observed attitudinal factors to identify class membership probabilities that are mostly assumed to be constant across classes in the existing literature. The results of the class allocation component of the LCM suggest that intuitively, one of the classes can be recognized as a sub-group of individuals who generally do not support the implementation of bikeshare in Halifax, would not use it if available, but are generally aware of bikeshare practices. The second class represents the opposite group. Several variables demonstrate reasonable inferences regarding the nature of the relationship between the dependent variable and the independent variables. However, this is not always the case, despite the use of a simple two-class LCM structure. It is anticipated that as the number of classes in an

LCM increases, direct inference regarding the implication of variables used in a class allocation model will become increasingly challenging. Further research is required in this area, particularly where multiple domains of contrast exist in choice modeling. Bikeshare integration research could also take different future paths, for example, examining the actual observed integration of bikeshare by trip purposes in cities where PBS are already operating. Additionally, anticipated and actual choices can be investigated in cities where these bikeshare programs are being planned and where implementation will soon occur. A bigger sample size could also be utilized to explore the latent class modeling approach proposed in this paper.

This paper significantly contributes to both bikeshare research and behavioral modeling literature. The latent class model application is unique in the existing literature. The paper also offers an in-depth understanding of the factors that affect different types of integration, including transit-bikeshare, auto-bikeshare, and walk-bikeshare. Such behavioral insights will be useful in informing policy-makers on how to better promote bikeshare programs, in particular the design of the programs in order to offer a range of plausible options for their integration into the wider transportation network.

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TABLE 1 Summary Statistics of Explanatory Variables used in the Bikeshare Integration MNL model and LCM

Variable	Description	Mean / Proportion	St. Dev.	Min.	Max.
Socio-Economic Characteristics					
AGEBL24	Respondent under 24 years of age (dummy)	18%	-	-	-
AGE25_34	Respondent between age of 25 and 34 (dummy)	33%	-	-	-
AGE50_64	Respondent between age of 50 and 64 (dummy)	17%	-	-	-
INC0_12	Respondent income less than $12,000/year (dummy)	20%	-	-	-
INC0_48	Respondent income less than $48,000/year (dummy)	52%	-	-	-
INC48_96	Respondent income between $48,000 and $96,000/year (dummy)	36%	-	-	-
STUDENT	Employment status - Student (dummy)	24%	-	-	-
FTWRK	Employment status – Full-time (dummy)	62%	-	-	-
MALE	Gender - Male (dummy)	52%	-	-	-
Trip Characteristics					
POCCOMM	Occasional peninsular commuter - (dummy, '1' if 1-2/week, '0' otherwise)	10%	-	-	-
PFQTRIP	Frequent intra-peninsular trips < 5km (dummy, '1' if >10/week, '0' otherwise)	36%	-	-	-
PNOTRIPS	No intra-peninsular trips < 5km (dummy, '1' if 0/week, '0' otherwise)	14%	-	-	-
Accessibility and Land Use Characteristics					
CBDDIST	(Log) distance from home to CBD (in meters)	8.22	0.935	5.15	11.03
SHOPDIST	(Log) distance from home to nearest major shopping center (in meters)	7.72	0.802	5.15	10.85
HFXCORE	Resides in the urban core of the peninsula (dummy)	54%	-	-	-
LUMIX	Land use mix index	0.19	0.175	0.00	0.67
Neighborhood Characteristics					
DENSITY	Population density (log) in home DA (ppl/sq-km)	7.61	1.582	1.1	10.8
DWELDENS	Dwelling density (log) in home DA (dwelling units/sq-km)	6.84	1.669	0.2	10.2
AVHHINC	Average annual household income of home DA ($)	66120.10	30678.50	20235	276008
AVROOMS	Average rooms per household in home DA	5.93	1.510	3.0	11.3
Attitudinal Characteristics					
AWARBS	Bikeshare awareness - (dummy, '1' if familiar, '0' otherwise)	76%	-	-	-
SUPPBS	Support implementation of a public bikeshare system in Halifax urban core (dummy, '1' if support, '0' otherwise)	86%	-	-	-
NOUSEBSW	Willingness to use bikeshare system in the winter (dummy, '1' if not willing, '0' otherwise)	39%	-	-	-
NOUSEBSS	Willingness to use bikeshare system in the summer (dummy, '1' if not willing, '0' otherwise)	18%	-	-	-

TABLE 2 Parameter Estimation Results from Bikeshare Integration MNL model and LCM

	MNL		**LCM**			
			Class 1		Class 2	
	coefficient	*t-stat*	*coefficient*	*t-stat*	*coefficient*	*t-stat*
Transit-Bikeshare Integration						
AGEBL24	1.273116	2.666**	-1.497698	-0.748	3.560869	5.569**
DENSITY	0.534973	1.907*	0.187474	0.796	1.676370	3.826**
CBDDIST	1.217202	2.804**	1.067292	2.857**	1.067292	2.857**
SHOPDIST	-0.497547	-1.203	-1.341715	-3.169**	-1.341715	-3.169**
LUMIX	-1.333882	-0.933	-5.813869	-1.908*	0.923054	0.594
PNOTRIP	0.967663	1.828*	3.728309	3.830**	-19.910142	-0.006
Auto-Bikeshare Integration						
AGE50_64	0.694055	1.404	0.576594	1.118	0.576594	1.118
INC0_48	-1.171989	-2.071**	-19.531551	-0.009	-0.161388	-0.303
STUDENT	0.094215	0.106	-1.558868	-1.548	-1.558868	-1.548
DENSITY	0.046467	0.231	-0.475313	-2.02**	1.187306	2.872**
CBDDIST	1.322876	3.222**	1.107095	3.074**	1.107095	3.074**
SHOPDIST	-0.444201	-1.266	-0.748711	-2.032**	-0.748711	-2.032**
POCCOMM	1.146248	2.317**	4.197403	3.347**	-0.416961	-0.690
Walk-Bikeshare Integration						
AGE50_64	1.147721	2.705**	2.176365	3.823**	2.176365	3.823**
INC48_96	0.477610	1.198	0.483057	0.862	9.894789	2.959**
STUDENT	0.808004	2.048**	0.968663	1.530	10.083920	3.254**
HFXCORE	0.460192	1.232	-0.947819	-1.646*	15.724859	4.331**
SHOPDIST	0.018076	0.068	0.291244	1.192	-2.762560	-3.131**
AVHHINC	0.000002	0.319	-0.000002	-1.126	0.000137	3.375**
Other Modes-Bikeshare Integration						
AGE25_34	-0.502668	-1.466	-0.189645	-0.323	-1.037205	-2.104**
INC0_12	0.215382	0.488	-1.039598	-1.252	15.479472	4.464**
MALE	-0.475865	-1.521	-2.177269	-2.727**	0.356356	0.793
FTWRK	-0.036301	-0.098	-1.907095	-2.635**	15.929828	4.513**
CBDDIST	0.341755	1.239	0.902931	2.548**	-0.510502	-1.285
SHOPDIST	-0.213691	-0.722	-0.385848	-1.115	-0.385848	-1.115
DENSITY	-0.134298	-0.892	-0.162502	-0.730	0.661027	1.722*
No Integration with Bikeshare						
AGE25_34	-0.386504	-1.273	-0.897970	-1.665*	-0.582395	-1.090
INC48_96	0.233186	0.745	0.426549	1.138	0.426549	1.138
MALE	0.275752	1.004	1.282074	2.260**	-3.162429	-4.528**
PFQTRIP	0.678547	2.473**	0.838194	1.460	3.140234	4.970**
NOUSEBSW	1.376920	5.375**	3.700392	5.346**	-1.404717	-2.786**
DWELDENS	-0.049945	-0.356	-0.365816	-2.039**	1.699998	3.982**
AVROOMS	0.148845	1.285	0.438716	2.042**	0.328157	1.778*
Constants (Reference = No integration)						
Transit-Bikeshare	-10.796872	-2.105**	-	-	-	-
Auto-Bikeshare	-8.017937	-1.945*	-	-	-	-
Walk-Bikeshare	-0.567038	-0.232	-	-	-	-
Other Modes-Bikeshare	1.034718	0.427	-	-	-	-

Class Membership Allocation Model						
Constant	-	-	1.293286	1.487	-	-
SUPPBS	-	-	-1.928570	-2.344**	-	-
NOUSEBSS	-	-	1.246589	2.206**	-	-
AWARBS	-	-	1.050978	2.772**	-	-
LL (constant only)	-489.508			-489.5075		
LL (at convergence)	-426.389			-389.1079		
Adjusted R-sq	0.10436			0.24859		

** 95 % confidence interval; * 90 % confidence interval