INTERNATIONAL JOURNAL OF SUSTAINABLE TRANSPORTATION
2020, VOL. 14, NO. 10, 788–805
https://doi.org/10.1080/15568318.2019.1628327

Analyzing the impact of neighborhood safety on active school travels

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ABSTRACT

Childhood obesity has become a serious public health challenge during the past few decades, calling for policies to incorporate physical activity into students' routines. This study is an effort to contribute to the current literature of school travels by analyzing how improving safety of different neighborhoods in Chicago, Illinois would encourage students toward shifting to active modes, and how this interrelationship is affected by the severe weather conditions during the cold winters of the region. The results are complemented by multiple sensitivity analyses to quantify how these shifts would help different students burn extra walking calories (i.e. the extra calories each student burns due to walking more). We estimate multiple discrete continuous extreme value models to understand how flexible a student is in combining his/her most preferred transportation mode with other choices. Various sources of inter-personal heterogeneity are also captured by using a latent-classification framework as well as differentiating the before-school from after-school trip chains to consider the behavioral distinction, explicitly. Several explanatory variables are incorporated into the models, including socio-demographics of students and their household, land-use, crime prevalence, and seasonal/weather conditions. Per the results, improving safety of Chicago from its current condition to the national median, would encourage students to be up to 40% more active. This extra active travel demand would provide obese students aged 14–18 with 18% of the calorie burn they need to lose weight to the obesity cutoff and 13% of the calorie burn required for losing weight from the obesity cutoff to overweight.

ARTICLE HISTORY
Received 26 May 2018
Accepted 2 June 2019

KEYWORDS
Active travel; crime rate; Latent-class MDCEV; neighborhood safety; school mode choice

1. Introduction

There is alarming evidence suggesting childhood obesity as a major health priority worldwide. In the United States, percentage of obese children aged 12–19 has doubled since 1980s (Ogden et al., 2016) and percentage of under-12 students with an extreme obesity diagnosis has significantly raised (Ogden et al., 2016). Obesity can result in immediate physical and psychological damage in children as well as long-term health conditions by, inter alia, increasing cardiovascular risks and diabetes in adulthood (Griffiths, Parsons, & Hill, 2010; Jelalian & McCullough, 2012; Must, Hollander, & Economos, 2006; Puhl & Luedicke, 2012). Weight gain/loss and energy balance are multi-parametric factors, especially for children,[1] as studied by a profound portion of the public health literature (Anderson & Butcher, 2006; Davison & Birch, 2001).

Important action plans have been proposed accordingly. The Institute of Medicine Committee on Prevention of Obesity in Children and Youth has developed a plan emphasizing on prevention as a key strategy to reduce childhood obesity in the United States (Kraak, Liverman, & Koplan, 2005). Nutrition assistance programs, broad areas of research, agricultural policies, highway design and safety regulations, state and community grant programs, and multidisciplinary surveillance systems are the core critical elements of this action plan to prevent obesity as a national priority. Plan of Action for the Prevention of Obesity in Children and Adolescents (PAHO) also highlights a multi-sectoral life-course approach for increasing intake of nutritious foods and improving physical activity (Plan of Action for the Prevention of Obesity in Children & Adolescents, 2014). Furthermore, the Safe Routes to School (SRTS) is a national-level program designed to encourage students to engage in active school travels by enforcement tools, incentives, and/or addressing the barriers of walking/biking for children. A key dimension of SRTS is to promote incorporation of physical activities into the daily routines of children (Hill, Wyatt, & Peters, 2012; Spiegelman & Flier, 2001).

Active school commutes among the various types of physical activity have received special recognition in the literature due to the broad range of children being involved in such activity (Bond Brill, Perry, Parker, Robinson, & Burnett, 2002; Jáuregui, Medina, Salvo, Barquera, & Rivera-Dommarco, 2015; Larouche, Faulkner, Fortier, & Tremblay, 2014; Services, 2008). According to the Center of Disease

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[1]Many behavioral, socio-economic, genetic, and metabolic aspects, among others, are argued to be of significant effect.

Control and Prevention (CDC), such commutes provide equal opportunities, in the sense that even students with limited athletic inclinations and those who cannot afford gyms are encouraged to be physically active (Services, 2008).

The present article focuses on the transportation-behavior aspects of active school commutes, to further analyze how the public tendency towards such commutes could be manipulated by the city officials. We focus on obesity of children aged 6–12 and 12–18, as two groups of the society calling for effective, immediate, and long-term plans to guarantee a healthy future life. Although children are by nature attracted to physical activities such as walking, biking, and running, it still remains a challenge to promote active school trips among them (Services, 2000). Various factors are believed to be influential, among which safety concerns—of the children and their parents—stand out. In fact, not only would not walking/biking to school be attractive in an unsafe setting, but also it might not be taken as a feasible action at all. Following is a brief review of the different aspects of school travel safety as discussed in the literature.

The major attention in the literature is focused on the safe interactions between students and the conflicting traffic vehicular flow (Deka & Von Hagen, 2015; Hopkins & Mandic, 2017; Kerr et al., 2006; Moniruzzaman & Farber, 2018; Rodríguez & Vogt, 2009). Such interactions mostly take effect from urban settings (e.g., street connectivity indices) and are well-studied to this point. In addition, a stream of research is triggered recently, defining school trip safety in terms of crime prevalence and supporting the significance of accounting for it (Kamargianni, Dubey, Polydoropoulou, & Bhat, 2015; Ma, Xiong, Wang, & Xie, 2018; Woldeamanuel, 2016).

Our main focus in the present article is to have a closer look into the role of crime prevalence in the context of the Chicago metropolitan area, Illinois. Regarding the safety challenges of the region, recent data released by the Uniform Crime Reporting Program (Federal Bureau of Investigation) shows that the city of Chicago is among the least safe cities nationwide. The city is less safe than 89% of American cities. Furthermore, violent crime rate in the city stands at 9.08 (per 1000 residents), as compared to the national median crime rate of 3.8 ("Chicago Crime Rates and Statistics - NeighborhoodScout," 2017). We also account for the safety challenges caused by the drastic weather conditions during the winter period. Our empirical evidence supports the significant role of the weather conditions, as well.

Adopting advanced statistical modeling approaches, we explore how critical it could be to accommodate policies to increase the *crime safety* in the residence of students. The main hypothesis is that children living in unsafe neighborhoods are generally more reluctant towards active travel. In more details, we explore how children's active school travels is a function of violent-crime prevalence in the neighborhood where they reside and how this relationship is affected by the weather conditions. Using the weight-for-age charts proposed by CDC, we also explore how policies for improving safety of Chicago to the national median, contributes to the students' energy balance in the form of *extra walking* calorie burns (i.e. the extra calories burned due to walking more) for *each student*.

Two key terms need especial attention in the above statement: *extra walking* calorie burn and *each student*. We limit the scope of the present research to the *extra walking* calories (as compared to the full calorie burn), for the sake of availability of a comprehensive-enough dataset. The full entanglement of the relationship requires a longitudinal dataset that contains detailed information on the household-level transportation behavior of the children and their families, weather conditions and crime records, the socio-demographics like age, gender, income, membership in gyms, and not least, genetic factors, weight, height, metabolic factors, the attitudes towards playing indoor versus outdoor in play grounds, etc. Limiting scope of the research helps us legitimately assume that putting aside all the individual-specific factors mentioned above does not harm the validity of our results, since those factors all cancel out when focusing on *each student separately* and looking *merely into the extra energy* that he/she consumes while having the peace of mind to walk for longer distances in the neighborhood.

Remainder of this article is organized as follows. Next section reports on a comprehensive review of the literature conducted to understand the context and to choose proper analysis methods. As discussed in that section, we adopt the multiple discrete continuous extreme value (MDCEV) (Bhat, 2008) econometrics modeling approach to account for the satiation effects (i.e. students loose interest towards, for example, walking as they walk for longer distances). Next, in Section 3, we discuss the different sources of data we used in this study. The econometrics modeling approach is elaborated in detail in Section 4, and the model specification and the estimation results are reported in Section 5. Readers interested mostly in our results can skip these two sections and reach Section 6 where we discuss the immediate findings of the study. In Section 7, we take a step forward and simulate the outcome of policies to make Chicago safer, in the forms of: (1) extra active travels before and after school, and (2) the individual-level extra walking calorie burns discussed above. The article concludes in Section 8 with summarizing findings of the study.

2. Literature review

A comprehensive review of the literature helped us gain insight on the context, find the gaps, and adopt a suitable analysis method. This section is dedicated to a brief discussion on the take-aways from the previous studies in two fields: (1) transport mode choice behavior and (2) Childhood obesity as a major health priority.

2.1. Transport mode choice

Selected studies in the transport mode choice literature are summarized in Table 1. Studies in this table are chosen to cover a wide range of analysis features, focusing on the mode choice.

Regarding the choice set formation, we noted that a majority of studies on school travels have either developed models on a limited subset of modes and studied the rest through descriptive analyses (Helbich, 2017; Johansson, Laflamme, & Hasselberg, 2012; Larsen et al., 2009; Leslie, Kremer, Toumbourou, & Williams, 2010; Rodríguez & Vogt, 2009; Van Dyck, De Bourdeaudhuij, Cardon, & Deforche, 2010), or merely focused their attention on active modes as a binary choice (Broberg & Sarjala, 2015; Deka & Von Hagen, 2015; Mitra, Buliung, & Roorda, 2010). Another dimension of the problem, which often-times is ignored, is the interrelationships between accompaniment and mode in a school trip. Parents are expected to have less safety concerns while escorting their child to school, especially when it comes to younger students' travels. Although the limited choice set in most of the studies cited above is an intrinsic challenge of GPS tracking data used by them, we have more freedom in the present research, thanks to using travel diaries. In this sense, the models developed in this article recognize:

- Three accompaniment styles (i.e., alone, having one accompany, and having more than one accompany), as well as
- Four modes of travel (i.e., active, transit, auto, and school bus) to form a comprehensive choice set.

With regards to the statistical modeling approach, we used the MDCEV model (Bhat, 2008), despite majority of school trip studies that stick to single-discreteness choice models such as Multinomial Logit (MNL) and Nested logit (NL). As a principle of the utility theory (Seager, 1917), people generally get less inclined towards waking, biking, taking a bus, etc., as they go farther distances by the mode. This principal behavioral concept is also referred to as the *satiation effects* and is the main driver behind choosing different alternatives at the same time. Put differently, in such choice situations, a rational decision maker oftentimes chooses a bundle of alternatives instead of sticking to one insatiably. Conventional choice models like MNL are mainly proposed to model situations of single-discreteness where only one alternative is being selected. Relaxing this limitation, the novel closed form formulation of MDCEV allows for analyzing how flexible a student is in combining his/her most-preferred mode with other choices.

Also, we used a latent classification framework to endogenously capture the potential heterogeneity in mode choice behavior of students (Greene & Hensher, 2003). The mode choice decision is generally argued to be subject to considerable degrees of heterogeneity (Shabanpour, Golshani, Derrible, Mohammadian, & Miralinaghi, 2017; Vij, Carrel, & Walker, 2013). In the context of students' mode choice, however, few studies could be found taking the heterogeneity into account explicitly in a unified model structure. Inspiring from literature, also, travels to and from school are analyzed separately (Mitra et al., 2010; Schlossberg, Greene, Phillips, Johnson, & Parker, 2006; Wilson, Marshall, Wilson, & Krizek, 2010; Yarlagadda & Srinivasan, 2008). These two portions of a student's daily travel pattern are argued to be fundamentally different in nature; commute to school is, by definition, a travel towards a mandatory activity with inflexible start time, while getting back home is a travel towards a more enjoyable activity which probably provides the student with more peace of mind and flexibility.

We incorporate into the models a set of different predictors including socio-demographic characteristics of students and their households, land-use, crime safety, and seasonal/weather conditions. Age, grade, gender, household composition indices (e.g., presence or number of siblings), vehicle and license ownership, and household income are among the most recognized socio-demographic variables in the context (Kamargianni et al., 2015; Mitra et al., 2010; Sidharthan, Bhat, Pendyala, & Goulias, 2011; Wen et al., 2008; Zhang, Yao, & Liu, 2017). Furthermore, frequently used land-use variables, can be categorized into home-school distance (either with respect to the mileage of travel or the travel time), street connectivity measures (e.g., intersection density, road density), population or residential density, and urbanicity (Helbich, 2017; Johansson et al., 2012; Mitra et al., 2010; Woldeamanuel, 2016; Zhang et al., 2017). Safety indices of the student's pathway to school are also commonly recognized as influential variables in their mode choice behavior (Johansson et al., 2012; Kamargianni et al., 2015; Rodríguez & Vogt, 2009; Wen et al., 2008).

2.2. Childhood obesity as a major health priority

Mounting previous evidence, 22 million children under 5 years of age are overweight internationally (Deckelbaum & Williams, 2001). Much research has been devoted to assessing the impacts and comorbidities of childhood obesity. Previous evidence suggests that childhood obesity is a risk factor of future chronic diseases (e.g., high blood pressure, hyperlipidemia, or elevated insulin levels; Freedman, Dietz, Srinivasan, & Berenson, 1999). Hence, there is rising concern to control childhood obesity by providing easy and accessible strategies in community level (e.g., active school trips, nutrition improvement, and physical activities) and improving social media focusing on the issue.

Obesity is a multifactorial health issue affected by genetic background, nutrition, age, gender, parents' lifestyles, and school policies. In this sense, there is no consensus on defining childhood obesity. Underwater weighing (densitometry), multi-frequency bioelectrical impedance analysis (BIA), and magnetic resonance imaging (MRI) are methods to measure body fat percentage for research applications. In clinical environment, anthropometrics aids gain an indirect estimate of body fat. Reviewing the literature, BMI and weight-for-age are two important anthropometric parameters that could be used in our research. Different studies suggested diverse BMI cutoff points for defining obesity among youth (Flodmark, Lissau, Moreno, Pietrobelli, & Widhalm, 2004; Ghosh, 2014; Nawab, Khan, Khan, & Ansari, 2014). Yet, BMI is believed to be an inaccurate estimate of child obesity, due to physiologic changes during the growth period.

Another strategy to gain a more robust view of childhood obesity is to use weight-for-age charts released by CDC. As reported by previous research, the 90th and 75th percentiles are appropriate cutoffs to define children as obese or overweight, respectively (Gamliel, Ziv-Baran, Siegel, Fogelman, & Dubnov-Raz, 2015). We adopted this metric.

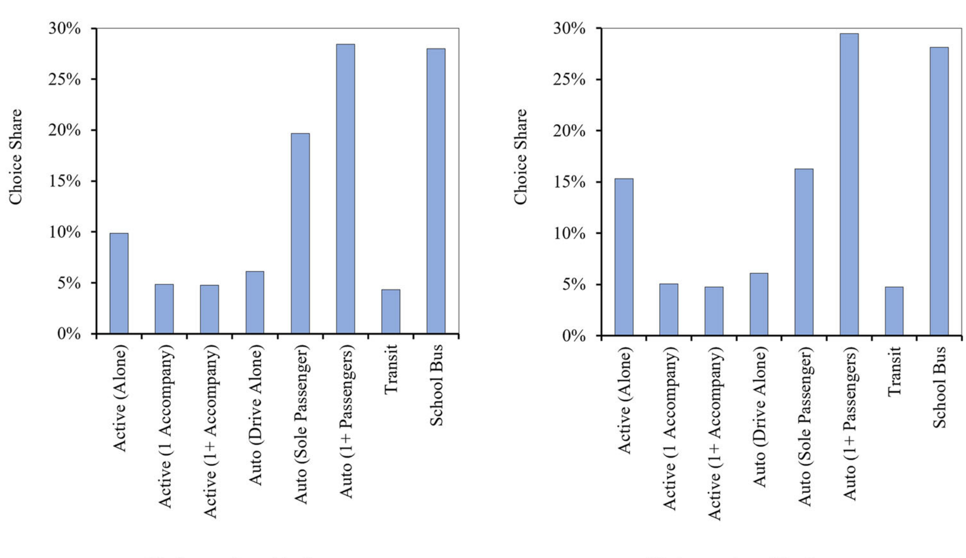
Three prevention strategies can be implemented to lower childhood obesity. Primordial prevention mainly focuses on maintaining healthy lifestyle (weight-for-age $<$ 75th percentile). Primary prevention helps avoiding at risk population to become obese (weight-for-age 75th to 90th percentile) and secondary prevention aims to reduce comorbidities of obesity (weight-for-age $>$ 90th percentile). The present research focuses on the last two categories.

3. Data preparation and sample formation

The main source of data used in this study is the Travel Tracker Survey, hosted by Chicago Metropolitan Agency for Planning. The survey gathers travel information of 23,808 individuals in 10,552 households, among which around 10% are school children aged 6–18. After extensive data cleaning, the final sample used for the analysis contains information of 2703 students in this age range. This sample is, then, enriched by adding built-environment data at the census tract level to reflect land-use settings in students' residential areas.

Although the survey includes diverse demographic attributes and travel information, it does not explicitly collect travel distance information (instead, straight line distances are computed and reported as proxies). To obtain more accurate proxies, we have employed Google Maps' Distance Matrix API ("Distance Matrix API", 2018). Distance Matrix API is a service provided by Google Maps that facilitates systematic route choice queries. The API responds to queries of origin–destination with details of the best route. We developed a computer code in Python 3 to go over the trip legs of students in the sample, query each record from the API, and extract the corresponding travel time and distance. Using a similar approach, we also extract from the API the walking distances between students' home and school locations based. That is, this variable is generated for a hypothetical walking travel from home directly to school, choosing the route suggested by the Google Maps Distance Matrix API. Origin and destination of 6.3% of the trip legs are reported to be the same in the survey, resulting in zero travel distances returned by the API. In such cases, the corresponding travel distances are imputed using the method of stochastic regression (Little & Rubin, 2014), incorporating other travel- and individual-level information as predictors of the regression. The variables used for imputation include time of day, the straight-line distances as reported in the raw dataset, and socio-demographics, among others.

The final estimation sample is formed by aggregating different mode-escort combinations into eight choice alternatives, namely active but alone, active with one companion, active with more than one companion, drive alone, being the only passenger of a car, being part of a carpool, taking transit, or riding school bus. Figure 1 presents the percent of students who have chosen each mode-escort alternative in their travel to/from school. The figure reveals that carpooling and school bus constitute more than 50% of the chosen modes in both before-school and after-school tours. Another insight from this Figure is that students are more likely to walk from school to home than when heading to school. To add more perspective, Figure 2 depicts the distribution of active transport mileages of traveling to/from school. Accordingly, students are also more likely to walk for longer distances when they are heading back home compared to when they are going to school. In Section 2.1, we provided evidence from the literature regarding the distinction between before- and after-school chains. Figures 1 and 2 also provide further insight on the importance of testing the



(a) Before school (b) After school

Figure 1. Percent of students who have chosen each mode-escort alternative.

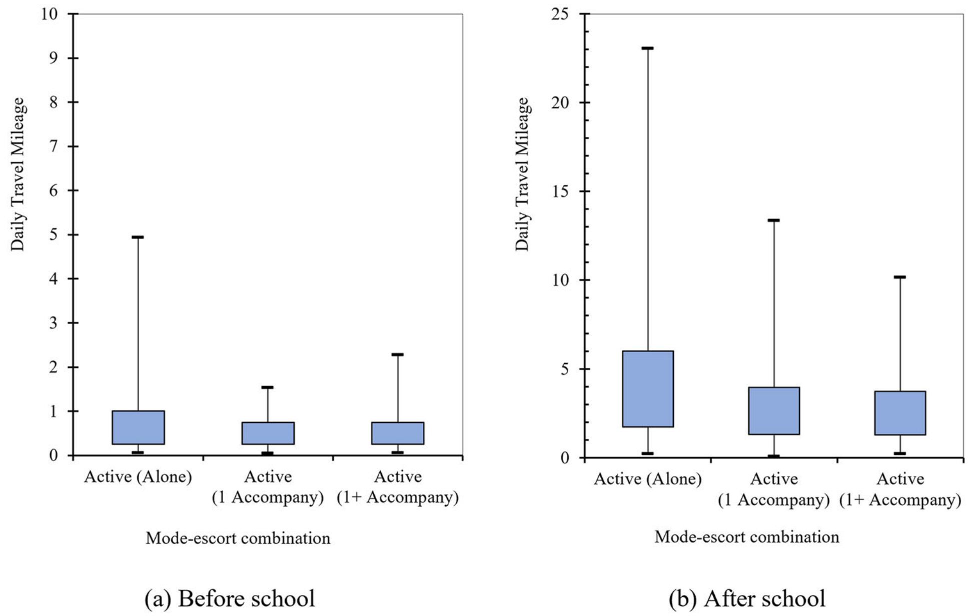


Figure 2. Distribution of active travel mileage in before-school versus after-school travels.

distinction, specifically, for our dataset. Such tests are conducted in Section 5. Please refer to that section for more details.

4. Methodology for transport mode choice modelling

This article adopts the latent-class modeling approach (Greene & Hensher, 2003; Sobhani, Eluru, & Faghih-Imani, 2013) to control for the potential heterogeneity among students in their decisions regarding active travels. In this framework, students are endogenously assigned to specific classes, and for each class, a separate MDCEV (Bhat, 2008) model is estimated.

4.1. Latent-Classification model

Let H_{is} denote the probability distribution function associated with individual i being a member of class s. A detailed discussion on different H_{is} formulations can be found in Greene and Hensher (2003). Following Sobhani et al. (2013), we adopt the multinomial logit form in Equation (1), where y_i is a vector containing various attributes associated with individual i, and δ_s is the vector of segment-specific coefficients corresponding to y_i.

$$H_{is} = \frac{\exp(\delta_s y_i)}{\sum_{k=1}^{S} \exp(\delta_k y_i)} \tag{1}$$

Also, let $P_{ij}|\mathrm{s}$ denote the likelihood that individual i demonstrates choice pattern j, given being a member of class s. Having the class-membership and within-class choice probabilities specified, the overall likelihood of individual i choosing a choice pattern j can be written as:

$$L = \sum_{k=1}^{S} H_{ik} \times P_{ij}|\mathrm{s} \tag{2}$$

4.2. MDCEV model

In some choice situations, the consumer demands for multiple goods given a limited budget, instead of an insatiable desire on selecting one. Choosing among different modes of travel is an example—one may imperfectly substitute one mode for another. A student might be given a ride by his/her parent to a safe zone close to school and walk rest of the way. In this case, total mileage that the student travels from home to school (or vice versa) is the budget, which is split among auto and walk.

One popular method of analyzing such situations is through applying Kuhn-Tucker (KT) conditions (Bhat, 2008; Wales & Woodland, 1983). This method can be traced back to the work of Wales and Woodland (1983) where the authors proposed a likelihood function of multivariate normal integrals, resulting in computational difficulties that prevented the model from getting prevailing at the time (Bhat, 2008). Kim, Allenby, and Rossi (2002) advanced this approach by incorporating a translated CES (i.e., Constant Elasticity of Substitution) utility function, and employing a simulation approach to approximate the integrals. Few other studies have also applied similar approaches (see, e.g., Phaneuf, Kling, & Herriges, 2000; von Haefen, Phaneuf, & Parsons, 2004). Bhat (2005) developed a novel closed-form formulation, MDCEV, which was further enhanced by the same author in 2008 (Bhat, 2008). Different specifications have been proposed for each version of the model. Following literature Castro, Eluru, Bhat, and Pendyala (2011), Eluru, Pinjari, Pendyala, and Bhat, (2009), Pinjari and Bhat, (2010a), and Rajagopalan, Pinjari, and Bhat, (2009), we adopt the γ-profile specification of the 2008 version for the present study.

Let C_k denote the mileage traveled by mode k, and $U(C)$ denote the total utility that a student gains from choosing a particular chain of modes (e.g., having someone give them a ride, then walking for the last quarter mile). Then, the

γ-profile for $U(C)$ is suggested as:

$$U(C) = \sum_{k=1}^{K} \gamma_k \psi_k ln\left(\frac{C_k}{\gamma_k} + 1\right) \quad (3)$$

where γ_k is the translation parameter, which also alters for satiation effects. Furthermore, ψ_k is the baseline marginal utility (at the point of zero consumption), which by definition, needs to be positive for all students. Equation 4 guarantees the positivity condition.

$$\psi_k = \exp(\beta Z + \varepsilon_k) \quad (4)$$

here, Z denotes the vector of explanatory variables, β is the corresponding vector of coefficients, and ε_k denotes the error term, which is assumed to follow an iid extreme value distribution within each latent class.

4.3. Estimation technique

Expectation maximization (EM) is the technique mostly used in previous studies to overcome estimation difficulties of a discrete choice model with mixed error terms (Train, 2009). EM starts by estimating the original log-likelihood by a simple-to-optimize function (i.e., the Expectation function) and continuous to find its maximum in each iteration. Then, the algorithm moves forward to ultimately find a point sufficiently close to a stationary point in the log-likelihood function. However, this method has two main drawbacks: First, convergence rate of the method is very slow, and second, it increases the chance of trapping in a local optimum (Bhat, 1997; Zhang, Kuwano, Lee, & Fujiwara, 2009).

To account for these concerns, inspiring from Bhat (1997), we have used a simplified version of the HELPME algorithm (Shamshiripour & Samimi, 2017). The algorithm starts by generating 15 random initial solutions around estimation results of the corresponding basic MDCEV (the single-class model), which are allowed to randomly fluctuate in the domain of $[-2 \times \beta$ to $2 \times \beta]$ for the baseline marginal utility parameters and $[0.4 \times \gamma$ to $1.5 \times \gamma]$ for the translation parameters. In addition to avoiding local optima, this technique has also helped us to impose no restrictions to any of the β parameters.

5. Transport mode choice model: Specification

We tested two different approaches for capturing the distinction between students' travel behavior before and after school. First, a model is developed for the entire home-to-home trip chain. In this model, the distinction between before- and after-school tours is recognized by introducing a dummy variable into the latent-segmentation component. The distinction of before- from the after-school trips is confirmed by the t-test conducted for the dummy variable's coefficient in the model. This model is then compared against separate models for before-school and after-school trip chains. The latter approach is found to offer more stable and more accurate results; thus, the home-to-home model is not reported. The distinction between before- and after-school trips is also supported by these models, using the likelihood ratio test.

Table 2 summarizes definition of various explanatory variables incorporated into the models, as well as their average and standard deviation in the final estimation sample.

Also, number of classes is set to 3 based on the stability of the results, and AIC and BIC indices. AIC and BIC values are outlined in Tables 4 and 5. Per these values, the model with three latent classes is superior to the 2-class model for before-school and after-school trip chains. Similarly, the 4-class model structure is superior to the 3-class structure per the AIC results. However, the 4-class structure is not considered a good model specification as it leads to unstable results, in terms of both magnitude and sign of the coefficients.

Table 3 outlines results of the latent-segmentation models, setting Class 1's utility function as the base. The segment-specific models developed for before-school and after-school trip chains are respectively reported in Table 4 and Table 5. The last column of these tables outlines average parameter estimates calculated using the Bayesian formula (Greene & Hensher, 2003). The reader may note that the average values are not reported for translation parameters.

Table 2. Description of the explanatory variables used in this study.

Variable name	Variable definition	Avg.	St. Dev.
Student's age	Student's age in years	11.98	3.63
Student's age: 6 to 12	1: If the student is 6 to 12 years old/ 0: Otherwise	0.53	0.49
Student's gender: male	1: If the student is a male/ 0: Otherwise	0.51	0.49
HH income: \$100k+	1: If the household's annual income is more than \$100,000/ 0: Otherwise	0.42	0.48
HH structure: # students	Number of students in the household	2.35	1.05
HH structure: # workers	Number of workers in the household	1.79	0.79
HH structure: # not student/worker	Number of individuals in the household who are neither a student nor a worker	0.15	0.87
HH mobility: # vehicles per driver	Number of vehicles div. by number of driving license holders in the household	0.97	0.40
Urbanicity: Chicago	1: If the household resides in the city of Chicago/ 0: Otherwise	0.24	0.43
Built Env.: intersection density	Intersection density[†] of the Census Tract of household's residence	1.57	0.80
Built Env.: youth population density	Population density[††] of 5 to 19 yo people in Census Tract of household's residence	0.49	0.54
Built Env.: crime density	Density of crime[†††] records in Census Tract of household's residence, div. by 1000	0.02	0.05
Built Env.: walking distance	Natural logarithm of walking distance between student's home and school assuming the shortest path	3.43	1.18
Weather: spring	1: if the student is surveyed during April or May/ 0: Otherwise	0.11	0.31
Weather: winter	1: if the student is surveyed during December, January, or February/ 0: Otherwise	0.17	0.38

[†]Defined as the number of intersections per the unit area of the Census Tract.
[††]Defined as the population per the unit area of the Census Tract.
[†††]Defined as the number of criminal activities (homicide, weapon-violation, and theft) per the unit area of the Census Tract.

Table 3. Estimation results: latent classification model for before-school and after-school chains.

Independent Variables Used for Latent-Classification	Coefficient in Each Latent Class's Utility Function†		
	Latent Class 1	Latent Class 2	Latent Class 3
Home to School			
Alternative Specific Constant	*Comparison basis*	−0.074	−0.091*
Student's Age: 6–12		−0.117*	–
HH Income: $100k+		–	−0.112**
Urbanicity: Chicago		–	−1.968***
Student's Gender: male		0.118**	–
Weather: spring		−0.086**	–
School to Home	*Comparison basis*		
Alternative Specific Constant		0.664***	0.545***
Student's age: 6–12		0.258**	–
HH Income: $100k+		–	−0.168**
Urbanicity: Chicago		–	−2.013***
Student's Gender: male		−0.204***	–
Weather: spring		−0.443***	–

†*, **, and *, respectively, mean 95%, 90%, and 85% level of statistical confidence.

We avoid reporting the values to underline the fact that those values are subject to enormous variations among classes, making an average value lose its meaning.

6. Transport mode choice model: Discussion

This section is structured to elaborate on the results outlined in Tables 3, 4, and 5, with an emphasis on the transportation behavior. We first go over our findings regarding the individual preferences in terms of baseline marginal utility variables. The findings include the roles of socio-demographic variables, urban settings, and seasonal effects. After that, we explain the modal satiation effects and marginal utilities specific to each mode and class. At the end, the discussions in this section conclude with a simple simulation to further disentangle the effects of the latent classification variables and study how they eventually affect the preferences towards active modes of travel.

6.1. Baseline marginal utility variables

The influence direction of socio-demographics (except household-structure indicators), urban settings and land-use variables, and seasonal effects are found to be consistent in sign across different classes as well as for before- and after-school chains. These variables are discussed first, starting with the student's age. In addition to latent segmentation model, this variable is also found to significantly influence the mode choice behavior. Per results, students tend to walk or bike alone to/from school as they age. This effect is specifically observed for the second and third classes. Older students of the third class are also found to lose interest in accompanied active modes. Notably, students become more inclined toward shifting to the drive-alone mode, as they age. Number of vehicles per licensed driver in a household is also confirmed to be influential. As the results show, students in households owning more vehicles are less likely to walk (or bike) alone (observed for first and second classes) or take transit (observed only for the second class).

Previous studies have concluded different results regarding structure of the student's household (McDonald, 2008; Mitra et al., 2010). We found household-structure coefficients to be subject to variations in sign across different classes, and in some instances, between before- and after-school chains. The average Bayesian estimates are presented in Tables 4 and 5 to gain a general sense of these variables' influence direction. Per the average results, number of students in a household positively affects the probability of a carpooling trip to school. In case of after-school chains, though, the relationship holds in the opposite direction. Furthermore, students who have more student siblings are found to be more interested in active travels with more than one companion. The reader may note that this effect is consistent across different classes, and before-school versus after-school chains. Although McDonald (2008) reported similar results regarding influence of number of siblings, Mitra et al. (2010) found no significant associations to students' tendency to walk. Per our results, also, students of households with more workers are less likely to have someone give them a ride from home to school, while being more likely to do so for getting back home. Number of non-students in the household who do not work is another indicator of the household structure. The effect of this variable is observed to be consistent among before- and after-school chains. As number of such individuals increases in a household, it becomes more probable that a student of the household takes an active journey to school while being accompanied by others.

Coping with active modes of travel is also found to be under influence of various urban settings, by previous research (Johansson et al., 2012; Kamargianni et al., 2015; Nelson, Foley, O'Gorman, Moyna, & Woods, 2008; Schlossberg et al., 2006) and the current study. Intersection density is an instance. Neighborhoods with higher intersection densities provide more safe zones (per unit of area) for students to pass the street and, thereby, have a more flexible route choice experience and safer journey to/from school (Helbich et al., 2016; Schlossberg et al., 2006). In line with this expectation, our results indicate that higher intersection densities encourage students to have more walking/biking school travels, either while they are alone (observed for first and third classes) or when they are being accompanied by a companion (observed only for the first class). Crime density is another safety indicator considered in this study. Students

Table 4. Estimation results: class-specific MDCEV models for before-school chains.

Coefficients of Independent Variables in Each Dependent Variable's Baseline Marginal Utility Function	Coefficients Specific to Each Latent Class†			
	Latent Class 1	Latent Class 2	Latent Class 3	Bayesian Avg.
Dependent variable: Active (Alone)				
Alternative Specific Constant	−2.538 ***	9.579 ***	0.880 *	2.664
Student's Age	–	1.491 ***	0.393 ***	0.633
HH Mobility: # vehicles per driver	−0.077 *	−6.023 ***	–	−2.187
Built Env.: intersection density	0.834 ***	–	0.708 ***	0.504
Built Env.: walking distance	–	−8.925 ***	−2.615 ***	−3.856
Built Env.: crime density	–	–	−3.587 ***	−3.587
Dependent variable: Active (1 Accompany)				
Alternative Specific Constant	−1.790 ***	−1.311 ***	−4.394 ***	−2.276
Student's Age	–	–	−0.287 *	−0.287
HH Structure: # not student/worker	0.440 ***	−1.297 ***	2.183 ***	0.258
Built Env.: intersection density	0.540 ***	–	–	0.540
Dependent variable: Active (1+ Accompany)				
Alternative Specific Constant	−2.060 ***	−8.575 ***	−7.615 ***	−5.796
HH Structure: # students	0.377 ***	2.560 ***	0.472 **	1.183
Built Env.: youth population density	–	–	6.719 ***	6.719
Dependent variable: Auto (Drive Alone)				
Alternative Specific Constant	−11.760 ***	−50.679 ***	−46.872 ***	−34.563
Student's Age	0.536 ***	2.600 ***	2.756 ***	1.836
Dependent variable: Auto (Sole Passenger)				
Alternative Specific Constant	−0.623 ***	3.155 ***	−2.957 ***	0.140
HH Structure: # workers	0.224 **	0.305 ***	−0.842 *	−0.016
Weather: winter	0.756 ***	–	–	0.756
Dependent variable: Auto (1+ Passengers)				
Alternative Specific Constant	0.133	1.615 ***	−5.078 ***	−0.652
HH Structure: # students	−0.203 *	1.229 ***	0.588 ***	0.510
Weather: winter	1.347 ***	–	–	1.347
Dependent variable: Transit				
Alternative Specific Constant	−1.958 ***	7.510 **	−10.072 **	−0.617
HH Mobility: # vehicles per driver	–	−11.907 ***	–	−11.907
Weather: winter	–	2.434 ***	–	2.434
Built Env.: crime density	1.614 ***	–	–	1.614
Dependent variable: School Bus	*Comparison basis*			
Translation Parameters				
Active (Alone)	1.624 ***	3.155 ***	6,800.551 ***	–††
Active (1 Accompany)	57,833.802 ***	0.245 ***	0.080 ***	–††
Active (1+ Accompany)	76,323.453 ***	0.961 ***	0.229 ***	–††
Auto (Drive Alone)	0.849 ***	0.002 **	2,951.339 ***	–††
Auto (Sole Passenger)	31.664 ***	74.136 ***	0.671 ***	–††
Auto (1+ Passengers)	23.105 ***	15.176 ***	0.783 ***	–††
Transit	163.319 ***	2,403.223 ***	19.954 ***	–††
School Bus	84,962.36 ***	72,809.124 ***	81,914.325 ***	–††
Scale Parameter	1.000 ^{f}	1.000 ^{f}	1.000 ^{f}	–††
Number of non-missing observations		2,703		
Log-likelihood at convergence		−4771.398		
Bayesian Information Criterion (BIC)				
Best 2-segment model		−11,801.046		
Best 3-segment model		−10,151.260		
Best 4-segment model		−10,194.446		
Akaike Information Criterion (AIC)				
Best 2-segment model		−11,399.702		
Best 3-segment model		−9,696.796		
Best 4-segment model		−9,592.430		

†***, **, and *, respectively, mean 95%, 90%, and 85% level of statistical confidence; *f* indicates a fixed parameter.
††These values are not reported due to their corresponding class-specific values being subject to enormous variations.

living in neighborhoods with higher crime densities are found to be considerably less likely to go to/from school by walking or biking when they are alone. This finding is consistent with results of previous studies (McDonald & Aalborg, 2009; Schlossberg et al., 2006; Woldeamanuel, 2016). Schlossberg et al. (2006), for instance, report significant relationships between parents' fear of potential dangers from strangers and their tendencies for allowing the child for having an active school travel.

Per the results, students living in neighborhoods with more individuals in their age (who are very likely to be students too) also show more tendencies towards home-school active travels with more than one accompanies. We believe this is a significant finding, showing how influential social networks could be in encouraging students to be more active. Per this result, students having more opportunities to socialize with their neighbor fellows are also of higher potentials of coping an active lifestyle. The results also confirm the intuitive expectation that students get less inclined towards walking (or biking) to/from school when they live farther from school. Per the results, walking and biking are also less expected during December, January, or

Table 5. Estimation results: class-specific MDCEV models for after-school chains.

Coefficients of Independent Variables in Each Dependent Variable's Baseline Marginal Utility Function	Coefficients Specific to Each Latent Class[†]			
	Latent Class 1	Latent Class 2	Latent Class 3	Bayesian Avg.
Dependent variable: Active (Alone)				
Alternative Specific Constant	−4.789 ***	2.565 ***	7.091 ***	0.846
Student's Age	–	0.282 ***	0.563 ***	0.243
HH Mobility: # vehicles per driver	−1.286 ***	−1.826 ***	–	−1.154
Built Env.: intersection density	1.401 ***	–	1.106 ***	0.825
Built Env.: walking distance	–	−1.236 ***	−5.471 ***	−1.825
Built Env.: crime density	–	–	−4.655 ***	−4.655
Dependent variable: Active (1 Accompany)				
Alternative Specific Constant	−2.162 ***	−2.399 ***	−2.857 ***	−2.422
Student's Age	–	–	−0.228 *	−0.228
HH Structure: # not student/worker	0.548 ***	−0.572 *	1.085 ***	0.283
Built Env.: intersection density	0.927 ***	–	–	0.927
Dependent variable: Active (1+ Accompany)				
Alternative Specific Constant	−2.857 ***	−2.887 ***	−68.063 ***	−19.348
HH Structure: # students	0.067	1.041 ***	10.832 ***	3.136
Built Env.: youth population density	–	–	28.571 ***	28.571
Dependent variable: Auto (Drive Alone)				
Alternative Specific Constant	−80.768 ***	−26.942 ***	−115.215 ***	−70.205
Student's Age	4.471 ***	1.634 ***	7.269 ***	4.163
Dependent variable: Auto (Sole Passenger)				
Alternative Specific Constant	−0.079 *	0.419 *	−3.992 ***	−0.890
HH Structure: # workers	−0.745 **	0.435 ***	0.651 **	0.030
Weather: winter	0.657 *	–	–	0.657
Dependent variable: Auto (1+ Passengers)				
Alternative Specific Constant	0.901 ***	0.008 **	−1.692 *	−0.074
HH Structure: # students	−0.597 ***	0.799 ***	−1.225 *	−0.256
Weather: winter	1.117 ***	–	–	1.117
Dependent variable: Transit				
Alternative Specific Constant	−2.052 ***	2.558 ***	−14.909	−3.651
HH Mobility: # vehicles per driver	–	−5.903 ***	–	−5.903
Weather: winter	–	0.975 **	–	0.975
Built Env.: crime density	2.505 ***	–	–	2.505
Dependent variable: School Bus	*Comparison basis*			
Translation Parameters				
Active (Alone)	8.732 ***	13.913 ***	63,923.5 ***	–[††]
Active (1 Accompany)	26.736 ***	0.932 ***	0.284 ***	–[††]
Active (1+ Accompany)	3,729.412 ***	16.719 ***	20,360.17 ***	–[††]
Auto (Drive Alone)	70,288.517 ***	39.763 ***	34.741 ***	–[††]
Auto (Sole Passenger)	19.908 ***	22.262 ***	26.560 ***	–[††]
Auto (1+ Passengers)	22.415 ***	22.901 ***	43,590.46 ***	–[††]
Transit	81,786.5 ***	91,801.217 ***	4,733.122 ***	–[††]
School Bus	577.498 ***	41,307.267 ***	33,959.320 ***	–[††]
Scale Parameter	1.000 [f]	1.000 [f]	1.000 [f]	–[††]
Number of non-missing observations		2,703		
Log-likelihood at convergence		−5774.837		
Bayesian Information Criterion (BIC)				
Best 2-segment model		−14,169.836		
Best 3-segment model		−12,158.140		
Best 4-segment model		−12,168.860		
Akaike Information Criterion (AIC)				
Best 2-segment model		−13,768.492		
Best 3-segment model		−11,703.674		
Best 4-segment model		−11,566.844		

[†]***, **, and *, respectively, mean 95%, 90%, and 85% level of statistical confidence; f indicates a fixed parameter.
[††]These values are not reported due to their corresponding class-specific values being subject to enormous variations.

February when the weather gets severe. This relationship is in line with results of Kamargianni et al. (2015) that argued that students are more likely to be active in a sunny weather.

6.2. Tendency to combine modes

Students' tendencies to combine a mode-accompaniment option with other options (i.e., Satiation effects) are summarized in Figure 3, separating before-school from after-school chains. This figure is drawn for a hypothetical student of each class, setting his/her baseline marginal utility to unity. To produce comparable depictions, travel mileage and total utility axes are shown, respectively, up to 20 miles and 50 units for all active, and 100 miles and 200 units for all non-active modes. As can be seen, most alternatives are subject to considerable satiation variations across different classes. For instance, for active travels with one accompany, an almost-linear utility profile is estimated for the first class, while the third class is assigned with a highly satiated profile. Such variations, indeed, underline importance of accounting for the existing heterogeneity in mode choice behavior of students.

According to Figure 3, furthermore, school bus and transit users are the least probable students to combine their current choices with other modes (that could potentially be walking or biking). This finding is not so surprising for the school bus, as it can be thought of as a door-to-door mode which eliminates the potentially active accesses and aggresses. The transit network, on the other hand, has long been argued to provide considerable potentials of encouraging users to adopt an active life style, due to the access/egress portions which are often conducted by walk or bike (Woldeamanuel, 2016). In this sense, this finding is worth underscoring, since it indeed indicates that most student users of the transit system are those who are not willing to combine it with other modes, including walking and biking (i.e., their origin and destinations are probably close to a station). There are still considerable potentials of shifting students living not-so-close to the transit stations to use this mode, as well.

6.3. Latent classification variables

At the first glance, the results of latent classification variables indicate that mode choice behavior of students aged less than 12 is different from older students. Also, we found gender as a significant predictor of the latent classification component. Living in high income households and living in the city of Chicago are also found as sources of significant behavioral variations. The results also confirm that students behave differently during April and May, compared to other times of school year.

These findings only serve as indications of influence, but they are barely informative on the direction of the influence. We calculate the pseudo elasticity values to determine how, eventually, these variables would influence students' tendencies towards active travels to/from school. Pseudo elasticity of a dummy variable is defined as the percentage change in the *total* active-commute mileage (either alone, or with one or more accompany) as a result of changing state of the variable from 0 to 1 (Train, 2004). The pseudo elasticity estimates are calculated numerically using the prediction algorithm which was originally proposed by Pinjari and Bhat (2010b) for a simple MDCEV model and was later expanded by Sobhani et al. (2013) for latent-class MDCEV models. The algorithm is set to iterate 1000 times, each time with a different set of simulated IID Extreme Value error terms, and the results are averaged over the 1000 simulations. Then, the elasticity values are calculated for each of the latent classification variables based on the average predictions, and the results are depicted in Figure 4.

Figure 4 shows elasticity estimates for home to school and school to home tours. The results suggest that students who live in the city of Chicago are about 16% (10%) more active in their travels to (from) school compared to those living in suburban areas. This finding is in line with the literature that evidences the higher vehicle ownership by households living in suburban areas (Alemu & Tsutsumi, 2011) and the more sprawl development of the suburban areas as compared to urban settings (Kuang, Chi, Lu, & Dou, 2014). In accordance to the literature, our results also depict that students who are members of higher-income families are potentially less active in their travels between home and school (McMillan, 2007). This could be attributed to higher rates of automobile ownerships among higher income households.

The elasticities further reveal that during April and May students are slightly more active in home-school travels. This distinction is probably attributed to both pleasant weather conditions and scenery in spring, which provides a suitable walking environment. It is argued in the literature that attractiveness of a walking pathway has a significant potential of convincing people to walk instead of drive (Broberg & Sarjala, 2015; Kerr et al., 2006).

The discussions in Section 6.1 reveal that older students are more inclined towards both active (alone) and drive modes for traveling to/from school. Therefore, the coefficients alone cannot explicitly identify whether older students are more likely to choose active modes or driving. The sensitivity analyses in this section further add that as younger students (6–12 years old) age they become slightly more active (i.e., about 2% increase in active mode mileage for traveling from home to school and 3% increase in traveling from school to home). This could be either due to the vulnerability of younger students to safety threats, or their lack of tolerance for walking high distances, which diminishes as they grow older. On the other hand, the trend reverses after the age of 12 (i.e., elasticity values are about −5% and −6% for before-school and after-school travels) possibly due to the capability of obtaining a driver's license. These results in fact underline the importance of promoting active living lifestyle among younger students to reduce the potential of shifting to non-active school modes as they reach the legal age of obtaining a driver's license.

7. Policy implication: Enhancing safety in Chicago

In order to enhance the city of Chicago's safety to reach the national median, the violent crime rate should be reduced by about 60%. This is while, per the results reported in Section 6.1, students who are living in less safe neighborhoods are significantly less likely to go on active school commutes. This section of the article is devoted to quantifying how the 60% improvement of crime density in the city of Chicago would affect active school commute behavior of its student residents. Also, we derive a linkage between daily commutes and some health indicators to provide more tangible takeaways.

7.1. Active travel mileages

The prediction algorithm discussed in Section 6.1 is used again to predict active travel mileages associated with 13 scenarios: the base condition (i.e., do nothing) and 12 improvement scenarios. Each improvement scenario assumes enhancement of the previous state by a 5% reduction in crime density. That is, the first scenario assumes that the crime density is reduced to 95% of the base condition, the

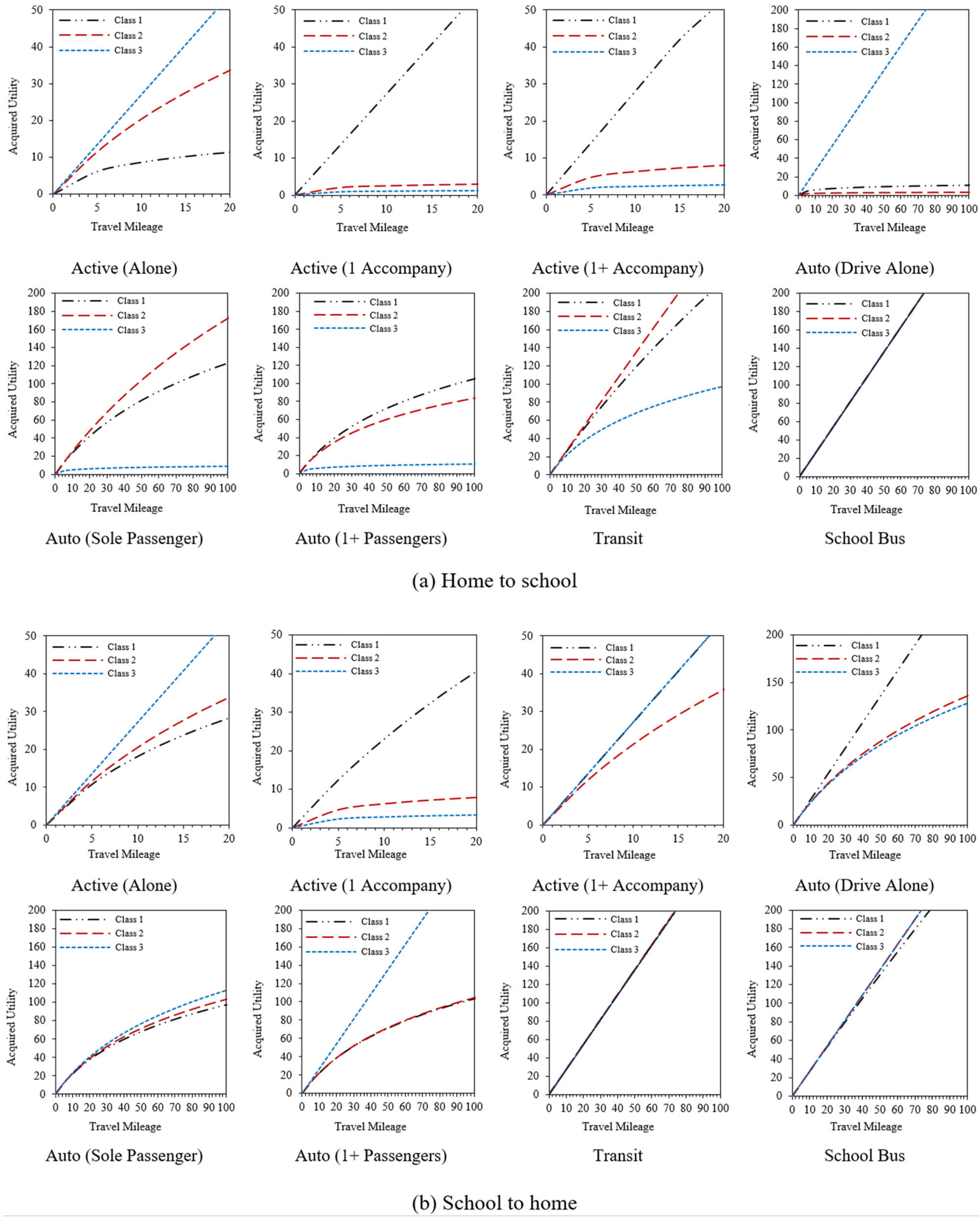


Figure 3. Satiation curves associated with each mode.

second scenario assumes it is reduced to 90% of the base condition, and so on. Our analyses show distinct travel patterns for residents of different parts of the city, and for different seasons. These distinctions are taken into account by dividing students into eight different groups depending on the month of travel and the base condition's crime density (i.e., the do-nothing scenario). The base condition's crime density (i.e., defined as number of criminal activities per the unit area) is divided into four groups: extremely low crime density (less than 0.05), low crime density (0.05–0.10), high crime density (0.10–0.15), and extremely high crime density (0.15 and above). These groups respectively constitute

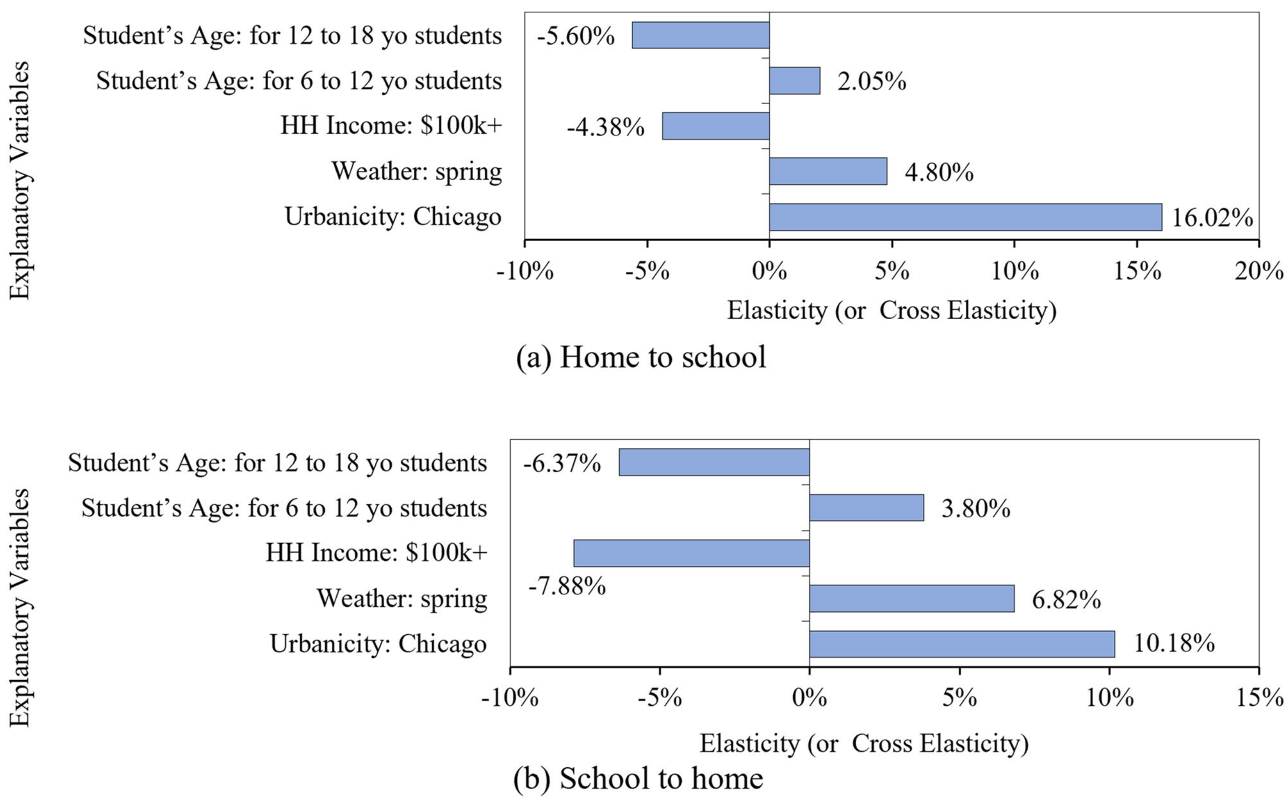


Figure 4. Sensitivity of active-commute mileage to variables of the latent classification model.

83.0%, 7.5%, 5.3%, and 4.2% of the whole sample. Also, the school year is divided into two sections as suggested by the model specification: during December, January, or February (the winter period), and rest of the year (non-winter). Figure 5 depicts the percentage change in the overall active travels for each group.

In overall, this figure reveals a growing pattern of increase in the students' propensities towards active modes as a result of safety improvements. This trend is observed to the point of a 55% improvement of crime densities. Further safety improvements, however, would be associated with lower rates of encouragement towards active travels. According to this Figure, furthermore, students' tendencies towards active modes are considerably less sensitive to crime density during December to February as compared to warmer months of the school year. This is understandable given the severe weather conditions during these months. The severe weather conditions during December to February would result in such a strong disutility that could overcome the disutility caused by safety concerns. This pattern is especially observed in regions of the city that are flagged as extremely low or low crime density, and understandably diminishes in higher crime-density regions.

Per Figure 5(a), moreover, residents of extremely low crime density regions (83% of the society) are more or less inelastic to making the city safer—especially during the winter. Such an inelasticity makes sense given the fact that such areas of the city are already safe enough to provide necessary peace of mind to their residents. Reducing the crime density of these neighborhoods would barely increases students' active-mode distance traveled by approximately 1.5%. However, the safety improvements would considerably affect the other 17% of the student society. It is estimated that by improving safety of the city of Chicago from its current conditions to the national-level median, around 4% of the students (i.e., those who live in areas with extremely high crime density) would become 40% more active in terms of daily travel distance, while the whole 17% of students would become at least 14% more active. Equivalently, the change would result in an increase in daily walking times of about 21 minutes for about 4% of the students, and at least 8 minutes for the whole 17% of students (assuming an average walking speed of 3 miles per hour).

7.2. Extra walking calorie burn

In the previous section, we presented the policy implication results in terms of the extra distances for which each student would walks if Chicago were made safer. In this section, we transformed those changes into the extra walking calories on the individual basis. That is, for each and every student in our sample, we first simulate the extra walking distance associated with each safety-improvement scenario (as explained in the previous section). Then, we use the weight-for-age charts proposed by CDC to transform the extra walking distance into the extra walking calorie, for overweight and obese students. In accordance to the literature (Gamliel et al., 2015), we assume the obesity and overweight cutoffs to be, respectively, the 75th and 90th weigh-for-age percentiles. Before moving on to more details, it should be kept in mind that the results in this section should not be

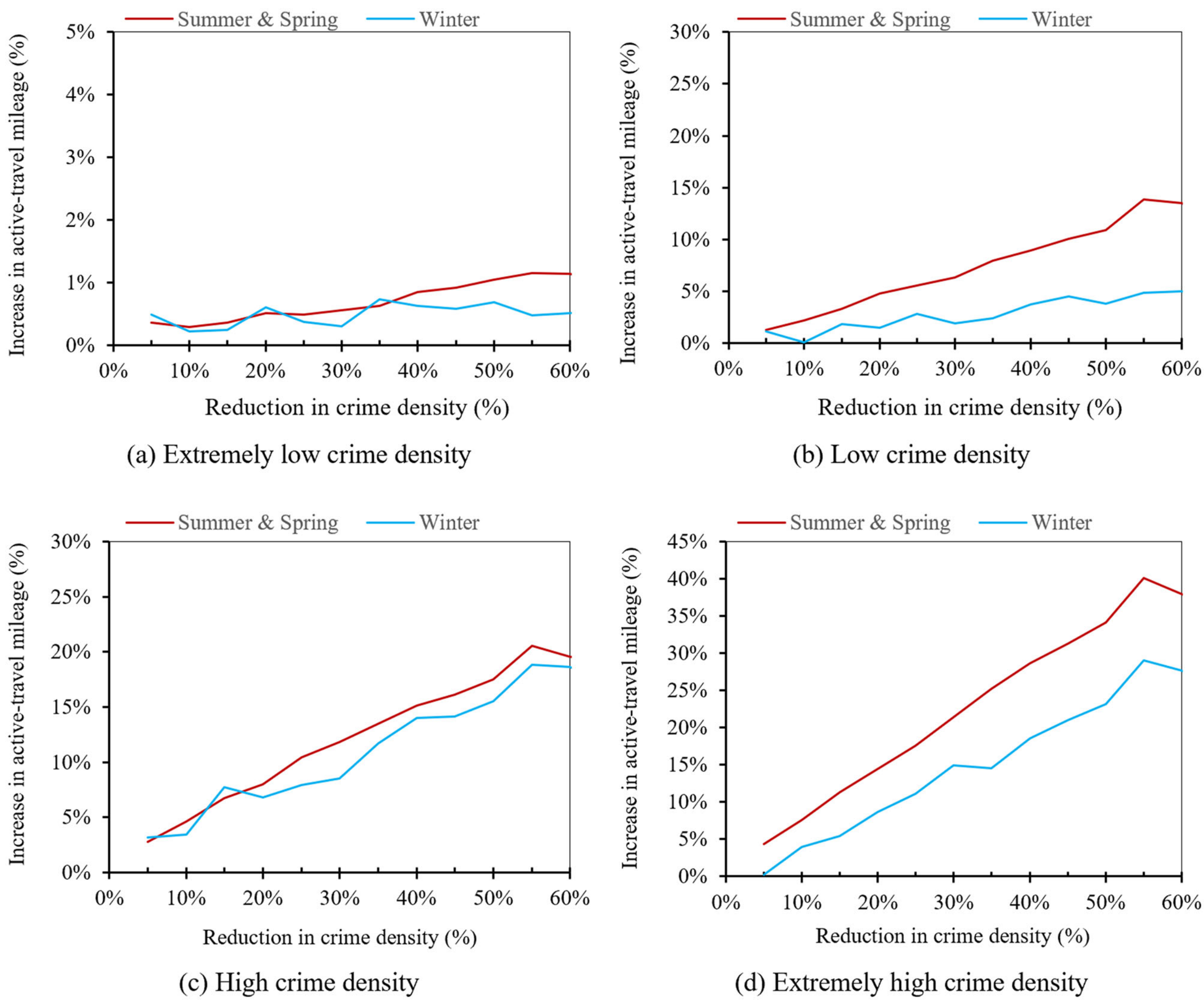


Figure 5. Percentage change in the overall active travels.

interpreted as a representation of the whole pattern of calorie burn (which is also a function metabolic and genetic factors, among the many others) of the students. We merely derive a good proxy for how much more calorie each student burns while walking for the extra distance.

The calculations are designed to replicate the annual values. Walking calorie depends on speed and duration of the walk, weight of the student, and the pathway's grade (Glass, Dwyer, Medicine, & Of, 2007; Margaria, Cerretelli, Aghemo, & Sassi, 1963). We assume all active travels are walking; walking speed of students is on average 3 miles per hour; and all sidewalks are level. The calorie burns are calculated accordingly (Glass et al., 2007) for six classes of students (three age categories and three weight categories) living in each of the four neighborhood types discussed in the previous section. The results are depicted in Figure 6.

According to Figure 6a, b, a 60% safety improvement is not expected to be of great calorie burn benefits for residents of neighborhoods with low or extremely low crime densities. However, this would not be the case for neighborhoods with higher rates of crime prevalence. As can be seen, for neighborhoods with extremely high (high) crime rates, the safety improvement results in an annual energy consumption of 7900 calories (5800 calories), for an obese student aged 14–18.

Health professionals suggest a steady pattern of losing a pound (or equivalently 3,500 calories) per week to achieve a more sustainable lose-weight plan ("Healthy Weight | CDC.GOV," 2017). Using this, we can also calculate how the extra walking calories depicted in Figure 6 would contribute to a sustainable plan of losing weight. The contributions are outlined in Table 6. As can be seen, the extra walking calorie burn can provide a student who is 14–18 years old on the 95th weight-for-age percentile, with approximately 18% of the energy he/she needs to sustainably lose weight to the obesity cut off. Similarly, the extra walking calorie burn provides the student with approximately 13% of the energy needed to lose weight from the obesity cutoff to overweight.

8. Conclusions

In this study, we adopt latent-class MDCEV models to investigate students' overall tendencies toward combining

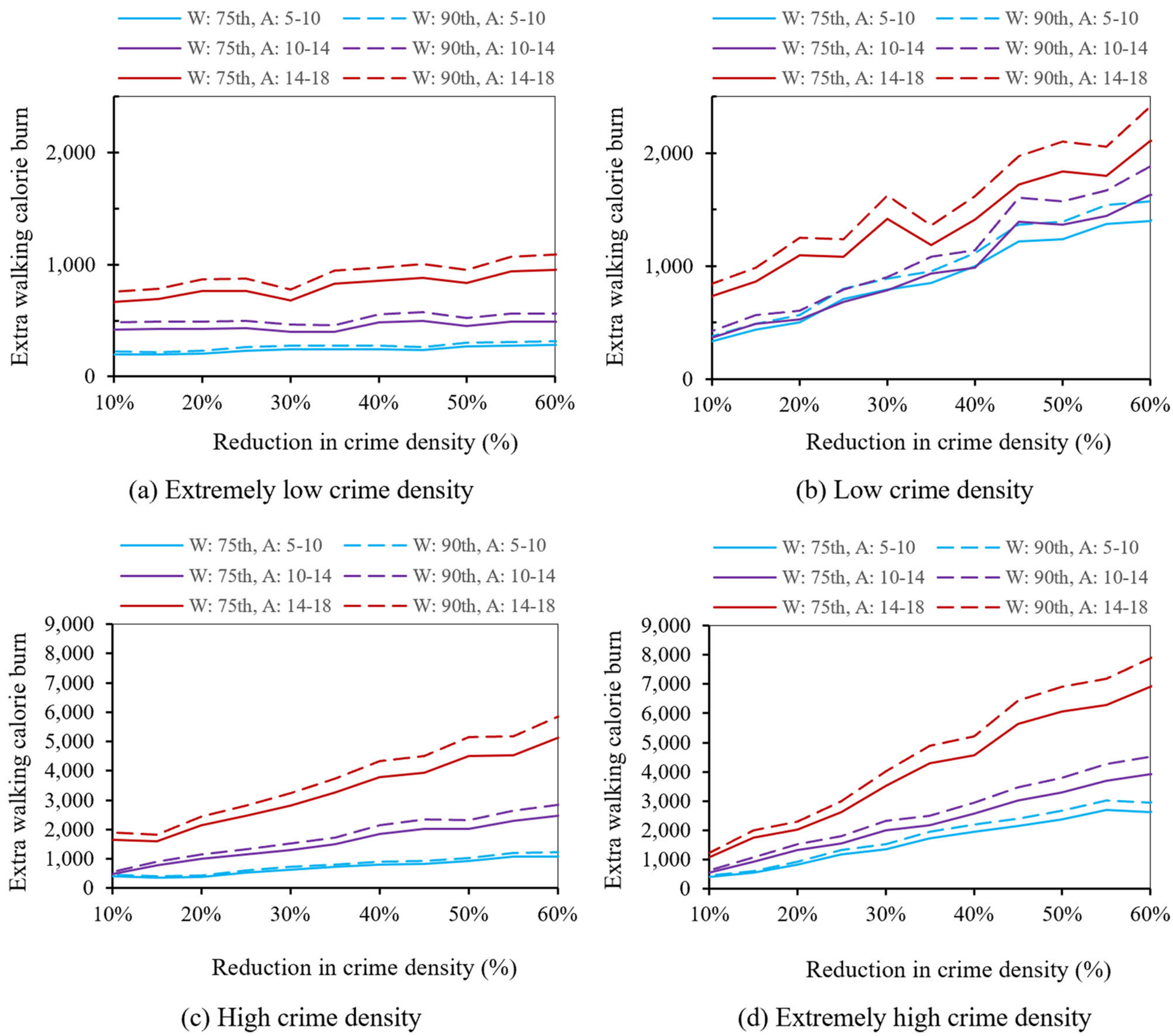


Figure 6. Extra walking calorie burn in a typical school year.

Table 6. Contribution of extra walking calorie burn (%) to a sustainable lose-weight plan.

		Current weight					
		A: 5–10		A: 10–14		A: 14–18	
Contribution of extra walking calorie burn (%)	Target weight	W: 90th	W: 95th	W: 90th	W: 95th	W: 90th	W: 95th
High crime density neighborhoods	90th	–	7%	–	8%	–	13%
	75th	5%	3%	6%	4%	9%	6%
Extremely high crime density neighborhoods	90th	–	16%	–	13%	–	18%
	75th	11%	7%	9%	6%	13%	8%

their most preferred choice bundle of *mode-accompaniment style* with other options, in school commutes. In addition, the models provide opportunity of directly predicting the daily active-commute mileage of each student, which can easily be transformed into public health indices such as daily calorie burns. The model is sensitive to prevalence of violent-crime in different geographical locations, providing us with the opportunity to predict health implications of testing different safety-improvement policies. The models also encompass household structure, auto ownership, urbanicity (i.e., living in city of Chicago or somewhere else), built environment (e.g., intersection density and youth population density), and weather conditions among other explanatory variables to prevent the omitted variable bias.

The results confirm a significant relationship between students' tendencies to choose active modes and violent crime prevalence. Per the results, making city of Chicago as safe as half of American cities would encourage students, for up to 40%, to shift from non-active modes. The induced demand of active-travel would provide obese students aged 14–18 with up to 18% of the calorie burn they need to achieve a healthy pattern of weight loss to the obesity cutoff and 13% of the calorie burn required for losing weight from the obesity cutoff to overweight. The results also show that, while adopting a safety-improvement strategy, different neighborhoods should be prioritized based on the violent-crime rates and number of students there.

The current study also has certain limitations that need to be addressed in future studies. First, we only studied the effects of crime prevalence in the neighborhood where students reside. Future research can take a leap to also analyze the behavior in terms of safety of the school's environment and, not least, safety of the routes chosen between home and school. Also, an important stream of research for the future would be to scrutinize the policy making aspects of the subject, aiming at tailoring proper action plans for making Chicago safer, step by step. Future studies might also assess how short- to mid-term remedies (e.g., providing patrols to alleviate the safety concerns in certain times of day for certain pathways) could encourage students and their parents to go on active travels. Improving safety of a neighborhood requires long-term plans to achieve sustainable states.

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