Involving Infrastructure as a Latent Variable in Active Transportation Mode Choice: The Case Study of Baghdad City

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ABSTRACT

Infrastructural developments have been implemented with the objective of promoting active transportation as a sustainable transportation mode, including the construction of cycling and walking routes and the improvement of existing infrastructure. The impact of this factor on ridership has been a subject of research, and the incorporation of this variable into mode choice models has also been contemplated. Nevertheless, road users' perception regarding the utilization of these infrastructures has yet to be investigated. Accordingly, this research aims to examine the role of infrastructure provision for walking and cycling as a Latent Variable (LV) in the transport mode choice of high school students in Baghdad City, where this subject has not been previously addressed. A self-designed questionnaire was employed to collect the requisite data. The Integrated Choice and Latent Variable (ICLV) models have been designed and the results demonstrate that the time and cost of trips have a significant impact on the choice of transportation mode. Furthermore, the provision of walking and cycling infrastructure has a notable effect on the choice of walking and cycling for transport. The sub-models indicate that the provision of cycling fences and pedestrian bridges are the most significant variables. Consequently, it is recommended that these results be considered in the provision and improvement of cycling and walking infrastructures to promote active transportation.

Keywords-active transportation; cycling; pedestrian; walking; Latent Variables (LVs); ICLV; Multiple-Indicator Multiple-Cause (MIMIC) model

I. INTRODUCTION

The transition towards a more active transportation modal share has been identified as a key objective within the strategies of sustainable urban development. Walking and cycling are illustrative of active modes with sustainable transportation characteristics, as evidenced in [1-4]. The modal choice is typically analyzed by incorporating essential factors, such as travel costs, trip distance or time, and socio-demographic variables [5, 6]. The availability of infrastructure for active transportation is also a subject of investigation, with the aim of improving the proportion of trips made by cyclists and pedestrians. The available evidence suggests that the construction and extension of paths, along with increases in path width, reductions in grade, and the conversion from shared to exclusive paths, can all contribute to an increase in the number of trips made using active transportation modes [7, 8]. Prior research has examined the correlation between the prevalence of active transportation and the availability of dedicated infrastructure, such as cycling paths or lanes. Findings suggest that cities with longer cycling paths or lanes tend to have a higher frequency of active transportation trips [9]. Authors in [10, 11] compared the situation before and after the construction of walking and cycling infrastructures. It has been found that the frequency of trips increased due to the provision of suitable facilities. Authors in [12] examined the relationship between cycling infrastructure and cycling behavior, specifically focusing on bicycle infrastructure accessibility and bike mode choice over time in Montreal, Canada. It has been reported that an increase in the accessibility index results in a higher level of ridership. The provision of a welcoming environment and appropriate infrastructure is also a factor influencing mode choice. It has been identified as a crucial step in promoting these modes of transportation [13]. Authors in [7] investigated the influence of walking and cycling infrastructure on the choice of active transportation modes in New York City. The findings lend support to the hypothesis that the width of sidewalks, the total length of bike lanes, and the proportion of protected bike lanes influence the choice of active transportation. The findings in [14] indicate that infrastructure availability in countries with a high level of cycling infrastructure does not significantly influence the choice of active travel mode. However, it may affect attitudes towards walking and cycling. Authors in [15] examined the impact of built environment attributes, including infrastructure, on travel and mode choice behavior in Hamilton, Canada. The findings indicated a positive association between biking and walking density and the promotion of cycling and walking, respectively, as well as socioeconomic demographics. Nevertheless, recent studies have demonstrated that this correlation is influenced by additional factors, including socio-demographics, attitudes, and individual norms. This has been investigated by incorporating LVs, which represent unobserved psychological features, such as attitudes and perceptions, into utility functions and mode choice models. Authors in [16] employed a self-designed survey comprising questions based on a Likert scale, which reflected the attitudes of the student respondents towards various transportation characteristics. The findings revealed significant concerns regarding the unavailability of secure parking and the presence of unsafe infrastructure for walking and cycling.

In the study of transportation mode choice, the variables that are the subject of investigation are referred to as explanatory variables. These variables are typically classified as either objective or subjective. Objective variables are those that are directly measured, whereas subjective variables, also known as LVs, are measured by personal evaluations of specific aspects or characteristics. Subjective variables can be further classified into two categories: perceptual indicators of facilities, which assess the perception of objective characteristics, and psychological indicators, which gauge perceptions of variables that cannot be objectively measured [17]. The most straightforward approach is to integrate the variable into the utility functions associated with the choice of active transportation modes. However, this method has been shown to result in issues related to multicollinearity and efficiency loss. This issue was subsequently addressed through the use of conceptual models derived from the Theory of Planned Behavior (TPB). In recent times, the LVs have been regarded as the fundamental elements of mode choice models. The ICLV model, which combines the Structural Equation Model (SEM) and discrete choice model, is employed to identify causal relations and permit the examination of dependent relationships among multiple variables. In these models, the LVs were defined by a multiple-indicator (attitudes and perceptions) and multiple-cause (individual characteristics) (MIMIC) model [17]. A review of the literature reveals a dearth of studies in Iraq that have examined the impact of infrastructure on active transportation modes. Furthermore, there is a paucity of research that has attempted to incorporate LVs into mode choice models. To address this gap in literature, the ICLV model incorporates attitudinal variables that have been previously overlooked in the context of walking and cycling in Baghdad city. This study aims to investigate the contribution of the indicator of providing infrastructure for walking and cycling as an LV in the mode choice of secondary and high school students. The travel behavior of students commuting to educational institutions for the purpose of studying has been the subject of recent research due to its significant impact on local transportation systems and the considerable volume of daily traffic it generates [18-20]. It is most probable that pre-university students will use active transportation for their daily journeys during this phase of their lives. Therefore, they represent an appropriate population for the purposes of this research. The findings of this study can inform the development of planning and policy measures for active transportation modes in Iraq and enhance the representation of active mode choice.

II. THE CASE STUDY AND DATA COLLECTION

Baghdad City is afflicted by a significant issue of traffic congestion. The peak period for traffic congestion is during the school year, as students travel to and from their educational institutions [21-23]. In order to mitigate the adverse effects of traffic congestion, the decision-makers have put forth a series of proposals, one of which is the transition towards sustainable transportation, particularly for students. Consequently, a plan has been developed to construct infrastructure for walking and cycling. Furthermore, the practice of cycling on sidewalks has resulted in a decline in the comfort and safety of pedestrians. The street selected for this study is Ibn-Hawqal Street, which is home to a number of educational establishments. The proposal entails the construction of a walkway to facilitate the mobility of students when travelling to and from educational institutions. The street is 25 meters in width and extends for a length of 1.6 kilometers, with three lanes on either side. The street is of the collector type and experiences minimal traffic flow, allowing the implementation of enhancements. To examine mode choice behavior, a self-descriptive questionnaire was developed. The questionnaire was divided into two sections: the first pertaining to sociodemographic characteristics and the second to respondents' perceptions of infrastructure with regard to active transportation. The data set includes information on the respondents' sociodemographic profiles. With regard to trip-related parameters, the questionnaire entailed questions on mode travel time (specific to all alternatives), travel cost (specific to car and bus), the number of bicycles owned, and car ownership. Respondents were also asked about their perception of the influence of infrastructure availability. All potential respondents were informed orally about the confidentiality of their responses and were assured about secure data storage. The questionnaire consisted of nine questions on infrastructure (called indicator variables) and 16 questions on socio-demographic attributes (called predictors). The responses of the indicator variables were evaluated on a seven-point Likert scale, which facilitated a more accurate assessment of the commuter's perception of infrastructure in relation to walking and cycling. The questionnaire was revised based on feedback from the academic experts, who provided comments and suggestions that were incorporated into the final version. Following the collection of data from the study area, it was subjected to filtering using a number of statistical methods, the details of which will be discussed subsequently. To obtain reliable results in a cost-effective manner with minimal sample variability, the Central Limit Theorem technique was employed to determine the minimum requisite sample size [24]. The final sample size was determined as:

$$n = \frac{\mathrm{n}^1}{(1 + \frac{\mathrm{n}^1}{\mathrm{N}})} \quad (1)$$

where n is the final sample size, N is the population size, n^1 is the unadjusted sample size given by:

$$\frac{\mathrm{p}\,(1-\mathrm{p})}{\mathrm{s.e.}\,(\mathrm{p})^2} \quad (2)$$

where, *s.e. (p)* is the standard error given by:

$$\sqrt{\frac{(\mathrm{N}-\mathrm{n})}{\mathrm{N}} \times \frac{\mathrm{p}\,(1-\mathrm{p})}{\mathrm{n}}} \quad (3)$$

and p is the proportion of sample.

The data from the survey indicate that 50.6% and 62.8% of participants in the study area do not possess a private vehicle or bicycle, respectively. The minimum sample size required to achieve a 95% confidence level is estimated to be 363. The survey was conducted primarily via face-to-face interviews in six secondary and high schools in the study area during November 2023. Ultimately, 391 surveys were considered valid after meeting a series of criteria, including the completion of the questionnaire within an appropriate timeframe, consistency in answering all questions, and the absence of missing answers.

III. DEFINING THE ATTRIBUTES

The set of decision attributes associated with walking and cycling was defined based on an analysis of other case studies identified in the relevant literature. Such attributes include, infrastructural elements pertaining to bicycles, such as traffic signals for bicycles, parking facilities, separate bicycle fencing, and designated bicycle routes. Furthermore, walking infrastructure was encompassed, comprising traffic signals for pedestrians, wider pavements, separate pedestrian fences, pedestrian bridges, and walking paths. The authors provided visual representations of each infrastructure type and elucidated their functions to the students, thereby ensuring a comprehensive understanding prior to questionnaire completion.

IV. MODELING APPROACH

The ICLV model has been used to incorporate the predetermined attributes into the mode choices and integrate the LVs. The essential observable variables are assessed in two ways: directly, by including them in the utility functions; and indirectly, through LVs, by the SEM [25]. Subsequently, LVs are incorporated into the utility function to facilitate an understanding of their impact on mode choice. The ICLV model can be seen in [26].

A. The DCM Model

The general form of the utility function U_{nit} is:

$$U_{nit} = ASC_i + \beta_i X_{nit} + \Gamma_i LV_n + \varepsilon_{nit} \quad (4)$$

where U_{nit} is the utility of a student, n associates to a selected mode i ($i \in C_{ni}$) in the choice task t ($t \in T$). C_{ni} in the proposed model includes three modes to assess the influence of the infrastructure on active mode (walking, bicycle, and other modes). The ASC is a specific constant for all chosen modes; LV is a vector of LVs that measure the infrastructure, β is the respective vector of the coefficient, X is a vector of the essential sociodemographic characteristics related to the respondent, Γ is the effect of the LV on the utility and ε is an error term identically and independently distributed by an extreme value type1.

B. The MIMIC Model

The survey provided four and five latent indicators for cycling and walking, respectively, for each mode of transportation. As displayed in Figures 1 and 2, the MIMIC model defined these indicators, which are graded on a scale from 1 to 7. The latent indicators and constructs pertaining to mode choice were analyzed using SPSS and AMOS V.24 software. Confirmatory Factor Analysis (CFA) was employed to frame the hypothesis based on the expected inter-relationships of the variables and to subsequently analyze the path diagram in order to determine the loading of each indicator and construct.

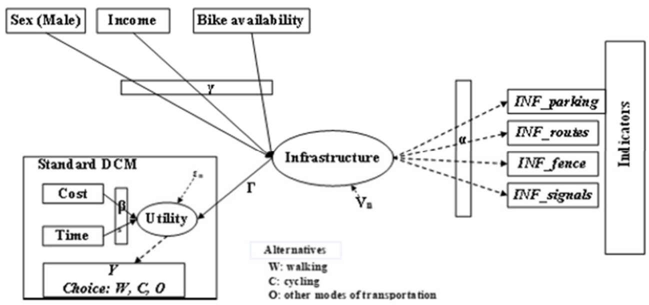

Fig. 1. The ICLV model framework (MIMIC model) for cycling.

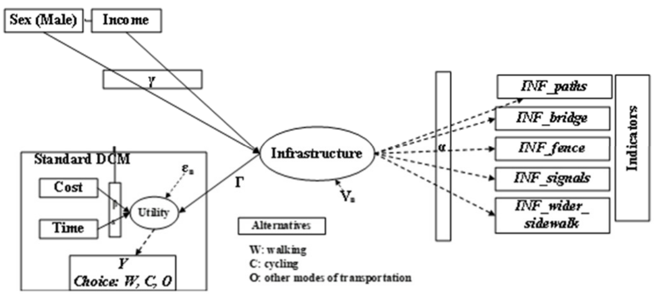

Fig. 2. The ICLV model framework (MIMIC model) for walking.

C. Structural Equation/Latent Variable Models

The structural equations were developed in two stages. First, the factor scores of all socio-demographic variables are regressed to identify the significant socio-demographic variables, which are then employed to develop the initial structural equation models. In the second step, the significance of these variables is examined by running the ICLV models. This allows the researchers to determine which variables are insignificant, and thus to drop them from the structural equation model. The ICLV models, which include a significant set of socio-demographic variables, are then run again.

$$LV_{cycling}^{\text{Infra.}} = \gamma G\ Gender + \gamma I\ Income + \gamma B\ Bicycle\ ownership + \upsilon n \quad (5)$$

$$LV_{walking}^{\text{Infra.}} = \gamma G\ Gender + \gamma I\ Income + \upsilon n \quad (6)$$

where γG, γI, γB, represent the impact of the socio-demographic variables on LV for infrastructure, and υ_n is the stochastic component of the equation [27]. The LV sub-model was constructed with three users' characteristics, which are defined as:

- *Gender* is a dummy variable that takes on the value of 1 if the user is male, and 0 otherwise.
- *Bicycle ownership* is a dummy variable that takes on the value of 1 if the user has a bicycle, and 0 if the user does not.
- *Income* is a dummy variable that takes on the value of 1 if the user has stated a household income between IQD 1,000,000 and IQD 1,500,000, and 0 otherwise.

D. Measurement Equation Model

The measurement equation reveals how the attitude towards the use of the active transportation infrastructure is loaded into LVs:

$$I_{nk}^{r} = \alpha_k^r\, LV_n^{\ r} + \eta_{nk}^{r} \quad (7)$$

where k is the number of indicators (4,5 for cycling and walking, respectively), I_{nk} is the k-th indicator for the r LV, α_k is the coefficient associated with the LV, and η_{nk} is an error term distributed normally with zero mean and standard deviation σ_η.

V. RESULTS

A. Results of the MIMIC Model

The final MIMIC model comprises five indicators and two explanatory variables for walking and four indicators and three explanatory variables for cycling, which were categorized into latent constructs, namely infrastructure. Table I presents the four categories of fitness measurement, each comprising three indices, for walking and cycling. The results of the LV sub-model, as portrayed in Table II, demonstrate that among the investigated indicators, fences are perceived as a more favorable feature when cycling on streets, while bridges are regarded as a more favorable feature when walking. The Composite Reliability (CR) was calculated as the ratio of the sum of the squared factor loadings to the sum of the squared error loadings for each construct, as a means of assessing the reliability of the models. As in [34], CR values should exceed 0.7. Validity was also assessed through the determination of convergent validity, which serves to ascertain whether the indicators of a construct converge to a greater extent, representing a larger proportion of common variance. The Average Variance Extracted (AVE) is the parameter used to assess convergent validity, with a value of >0.5 being indicative of satisfactory results [34], as illustrated in Table III. Some of the variables, such as bicycle and car parking availability and age, were deemed insignificant ($P > 0.05$), and thus removed from the analysis. Conversely, sex, bike ownership, car ownership, time for walking, cycling and other modes of travel, cost of travel for motorized modes, and income were identified as significant ($p < 0.05$), and hence retained in the model.

TABLE I. ESTIMATION OF GOODNESS OF FIT INDICES

Indices	Parameters	Value		Permissible limits	Reference
		Walking	Cycling		
Goodness-of-fit Index	Chi-Square/ DOF	3.269	1.469	< 5	[28]
Absolute-fit Indices	Goodness-of-Fit (GFI)	0.967	0.989	> 0.9	[29]
	Root Mean Square Error of Approximation (RMSEA)	0.076	0.035	< 0.08	[30]
	Root Mean Square Residual (SRMR)	0.041	0.014	< 0.09	[31]
Incremental fit Indices	Tucker-Lewis Index (TLI)	0.975	0.996	> 0.95	[31]
	Comparative Fit Index (CFI)	0.985	0.998	> 0.9	[32]
	Normed Fit Index (NFI)	0.978	0.993	> 0.9	[31]
Parsimony fit Indices	Parsimony Normed Fit Index (PNFI)	0.605	0.520	> 0.5	[33]
	Parsimony Comparative Fit Index (PCFI)	0.609	0.523	> 0.5	[33]
	Adjusted Goodness-of-Fit Index (AGFI)	0.928	0.972	> 0.9	[29]

B. Results of Regression Analysis

The following subsections present an explanation of the estimation results for the Multinominal Logit (MNL) model and the ICLV Model. The estimation of these models was conducted using the Biogeme software [35].

1) Multinominal Logit Model (MNL)

The MNL was developed with the objective of understanding the primary effect of the attributes, excluding the LVs, on mode choice. The utility functions were modeled deploying a linear approach, with no interaction between variables. With the exception of travel time and cost, all variables are considered dummies in order to control for any potential bias towards certain choices, as evidenced in Table IV.

The ICLV model, incorporates indicators of infrastructure utilization and the results are listed in Table IV. The ICLV model exhibits a markedly higher choice likelihood than the MNL model devoid of LVs. This suggests that LVs are empirically explored specifications with the potential for superior fit. The impact of each variable on the overall choice is influenced, in part, by the choice and LV sub-models.

TABLE II. RESULTS OF MEASUREMENT MODEL

Indicators	*α* Estimate	*P*-value
Walking		
INF fence	0.821	< 0.001
INF bridge	0.916	< 0.001
INF signals	0.847	< 0.001
INF paths	0.540	< 0.001
INF wider sidewalk	0.904	< 0.001
Cycling		
INF routes	0.917	< 0.001
INF fences	0.927	< 0.001
INF signals	0.860	< 0.001
INF parking	0.888	< 0.001

TABLE III. RELIABILITY AND VALIDITY CHECKS OF THE REVISED MODEL FOR PROPOSED FEEDER MODES

<table>
<tr><th>Mode of transportation</th><th>Indicators</th><th>Cronbach's Alpha</th><th>Factor loading</th><th>AVE</th><th>CR</th></tr>
<tr><td rowspan="7">Walking</td><td>INF fences</td><td rowspan="7">0.862</td><td>0.821</td><td rowspan="7">0.642</td><td rowspan="7">0.907</td></tr>
<tr><td>INF bridge</td><td>0.916</td></tr>
<tr><td>INF signals</td><td>0.847</td></tr>
<tr><td>INF paths</td><td>0.540</td></tr>
<tr><td>INF wider sidewalk</td><td>0.904</td></tr>
<tr><td>Male</td><td>0.906</td></tr>
<tr><td>Income</td><td>- 0.504</td></tr>
<tr><td rowspan="7">Cycling</td><td>INF routes</td><td rowspan="7">0.876</td><td>0.917</td><td rowspan="7">0.77</td><td rowspan="7">0.944</td></tr>
<tr><td>INF fences</td><td>0.927</td></tr>
<tr><td>INF signals</td><td>0.860</td></tr>
<tr><td>INF parking</td><td>0.888</td></tr>
<tr><td>Male</td><td>0.587</td></tr>
<tr><td>Income</td><td>- 0.516</td></tr>
<tr><td>Bicycle ownership</td><td>0.573</td></tr>
</table>

VI. DISCUSSION

The infrastructure LV for both walking and cycling is statistically significant at a 99% confidence level. The standardized coefficients of the infrastructure variable for both walking and cycling are of a considerable magnitude, thereby underscoring their pivotal role in the decision-making process regarding transport modes when compared to the objective variables. The ASC for walking in both models, MNL and ICLV, is positive and of a greater magnitude than that for cycling. This suggests that respondents prefer to walk rather than cycle, and that this preference is the result of a number of factors. Firstly, the lack of bicycle parking facilities in the vicinity of educational establishments may result in students being at risk of having their bicycles stolen. Secondly, in East Asian societies, particularly in Arab countries, such as Iraq, the use of bicycles as a means of transportation is more prevalent among males than females. The discussion about factors influencing mode choice is based on the ICLV model, which is the most comprehensive model currently available.

It is important to note that the "income" variable is included in the LV structural equation, but it is not involved in the utility models. The results indicate that the time and cost coefficients for all modes are negative. This signifies that as the expenditure and time invested by users when utilizing any mode of transportation are reduced, they are most likely to select this mode of transport. A comparison of the coefficient values indicates that the influence of cost on the decision to use motorized transportation modes is more pronounced than that on active transportation modes, as evidenced by the higher coefficient values associated with the former. Conversely, time exerts a more pronounced effect on the decision to opt for active transportation modes. This implies that individuals tend to opt for cycling and walking for shorter journeys. The positive sign of the sex coefficient indicates that males are more likely to use active transportation than females, which aligns with the anticipated patterns observed in countries with relatively low cycling and walking rates, such as Iraq.

TABLE IV. RESULTS FOR THE ESTIMATION OF THE MODELS

Variable	MNL				ICLV			
	Value	Std. err.	*t*-test	*p*-value	Value	Std. err.	*t*-test	*p*-value
ASC cycling	4.35	1.97	2.2	0.0276	36.1	12.9	2.8	0.00519
ASC walking	5.76	1.76	3.27	0.00106	57.3	17.4	3.29	0.000999
B car ownership	7.21	1.25	5.76	8.64E-09	1.37	0.633	2.17	0.0302
B cost other modes	-1.87	0.422	-4.42	9.99E-06	-18	5.66	3.19	0.00145
B sex other modes	3.72	0.965	3.86	0.000115	31.9	9.67	3.3	0.000965
B time cycling	-1.65	0.474	-3.47	0.000517	-5.07	2.13	-2.39	0.0171
B time other modes	-1.11	0.512	-2.16	0.0307	-3.39	0.929	-3.65	0.000258
B time walking	-3.53	0.634	-5.57	2.58E-08	-10.9	2.98	-3.67	0.000242
B sex walking	5.92	0.825	7.18	6.81E-13				
B sex cycling	1.56	0.342	4.55	5.43E-06				
B bike ownership	1.43	0.336	4.28	1.90E-05				
B Infr cycling					12.9	5.44	2.36	0.0182
B Infr walking					14.8	5.14	2.88	0.00397
$\bar{\rho}^{2}$ *	0.512				0.904			

* The $\bar{\rho}^2$ is not a statistical test but gives a general overview of model fit when comparing models, and it's equal to: $\bar{\rho}^2 = 1 - \frac{LL(\beta) - p}{LL(0)}$

Nevertheless, this effect is not statistically significant in the hybrid model, which may be attributed to the influence of infrastructure on their decision-making process. The positive sign of the LV coefficients indicates an increase in the propensity to walk or cycle as a result of an enhanced attitude toward the utilization of walking or cycling infrastructure. This suggests that individuals are more willing to use cycling or walking as their primary transportation mode on streets that are equipped with the necessary infrastructure. The considerable magnitude of their coefficients suggests a substantial influence of walking and cycling infrastructure on the decision to utilize active transportation modes. As anticipated, the ownership of a motor vehicle may lead to an increase in the utilization of motorized transportation modes, as evidenced by the positive and high coefficient values. The possession of a bicycle also exerts a positive influence on the decision to use cycling as a transportation mode, albeit with lower coefficient values. This implies that the ownership of a bicycle is not a primary determinant in the decision to cycle, and that it is influenced by other factors, such as the availability of safe and effective infrastructure.

VII. CONCLUSIONS

The Integrated Choice and Latent Variable (ICLV) models have been developed for secondary and high school students by incorporating Latent Variables (LVs) for cycling and walking infrastructures with other objective socio-demographic characteristics, including age, sex, income, and car ownership. The findings indicate that students tend to opt for walking over cycling, largely due to the unsafe storage of bicycles in their intended destinations or the pervasive culture of avoiding cycling, particularly among female students. In comparison to the Multinominal Logit (MNL) models, the ICLV models demonstrate a more pronounced influence of temporal and financial considerations in the selection of transportation modes. Furthermore, the analysis demonstrates the impact of implementing infrastructure that supports walking and cycling on the decision to walk or cycle for transportation. The sub-models indicate that the provision of cycling fences is the most significant variable among the others, which include traffic signals for cycling, parking for bicycles, and the provision of cycling paths. Furthermore, the results indicate that the provision of pedestrian bridges is the most significant variable among the provision of traffic signals for pedestrians, wider pavements, and the erection of separate walking fences. It is thus recommended that these results be taken into account when providing and improving infrastructure for cycling and walking, with a view to promoting active transportation. The findings of this study can be applied to other trip purposes in order to ascertain attitudes towards different transportation modes.

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