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Understanding mobility patterns in a university setting: Transport mode preferences and modal shift potential

Patrones de movilidad universitaria: Preferencias de transporte y disposición al cambio modal

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KEYWORDS
Mobility Patterns; Sustainable Transport; University Community; Modal Shift; Logistic Regression

Patrones de movilidad; Transporte Sostenible; Comunidad Universitaria; Cambio Modal; Regresión Logística

ABSTRACT: This study investigates mobility patterns within the University of Cuenca community, focusing on transport mode preferences and the potential for modal shifts toward sustainable transport. Unlike previous studies that primarily examine urban transport in general contexts, this research uniquely explores a university setting in a mid-sized city in a developing country, providing insights into transport choices' demographic and behavioral determinants. An online survey with 1,253 university members reveals distinct differences between students and employees: Students predominantly use active transport modes, while employees rely on private vehicles. Logistic regression analysis highlights key factors influencing mobility preferences, such as age, gender, and income. Notably, the female students tend to prefer private vehicle use, while younger and lower-income students prefer sustainable transport options. The study also examines the willingness to adopt public and active transport modes, identifying targeted interventions, such as improving public transit safety and infrastructure. These findings contribute to understanding sustainable mobility in university communities and provide actionable insights for urban planning and policy development in comparable settings. This research establishes a pre-pandemic baseline for evaluating post-pandemic shifts in commuting behaviors. It offers a framework for advancing sustainable transport strategies in mid-sized cities of developing nations.

RESUMEN: Este estudio analiza los patrones de movilidad en la comunidad de la Universidad de Cuenca, enfocándose en las preferencias de transporte y el potencial de cambio modal hacia opciones sostenibles. A diferencia de investigaciones previas centradas en el transporte urbano en contextos generales, este trabajo aborda un entorno universitario en una ciudad intermedia de un país en desarrollo,

ofreciendo información sobre los factores demográficos y conductuales que influyen en las elecciones de transporte. Mediante una encuesta en línea a 1,253 miembros de la comunidad universitaria, se identificaron diferencias significativas: los estudiantes prefieren modos de transporte activo, mientras que los empleados dependen mayormente de vehículos privados. Un análisis de regresión logística resalta factores clave como la edad, el género y los ingresos. Las estudiantes mujeres suelen optar por vehículos privados, mientras que los jóvenes y estudiantes con menores ingresos favorecen opciones sostenibles.
Además, el estudio evalúa la disposición a adoptar transporte público y activo, señalando intervenciones específicas como mejorar la seguridad y la infraestructura del transporte público. Estos hallazgos contribuyen a comprender la movilidad sostenible en comunidades universitarias y ofrecen lineamientos prácticos para la planificación urbana y el desarrollo de políticas. Finalmente, la investigación establece una base previa a la pandemia para analizar cambios en los comportamientos de movilidad posteriores, proponiendo un marco para implementar estrategias de transporte sostenible en ciudades intermedias de países en desarrollo.

1. Introduction

Mobility patterns describe how people move regularly within specific geographic areas, the routes they take, the modes of transport they use, when they travel, and for what purpose. These patterns reveal much more than movement itself: they offer clues about how far and how often people travel, the time they spend in transit, and the reasons behind their choices. They also reflect deeper factors such as accessibility, convenience, environmental awareness, and even cultural habits that shape mobility decisions.
In recent years, sustainable transportation has become a central priority for cities worldwide. The goal is simple: people should be able to move around efficiently, fairly, and with minimal impact on the environment. Research consistently shows that encouraging walking, cycling, and public transport reduces emissions and improves quality of life in cities [1-5]. However, achieving sustainability is not only about infrastructure. People's attitudes, habits, and social expectations often determine whether greener options are actually adopted in daily life.
Universities are exciting places to study these dynamics. They function like small cities, with thousands of people commuting every day for study or work. Analyzing how students, faculty, and staff travel between their homes and campuses can reveal the effectiveness of public transportation, cycling routes, and pedestrian infrastructure. At the same time, understanding these patterns helps universities and local authorities encourage more sustainable commuting habits, reduce emissions, and enhance the overall well-being of their communities. When designed carefully, sustainable mobility strategies benefit not only universities but also the surrounding neighborhoods.
The choice of transport mode depends on a range of factors, including availability, time, cost, safety, parking, and vehicle ownership [1-5]. However, studies often overlook an important element: user satisfaction. How people feel about their current travel options strongly affects their willingness to change. Dissatisfaction with public transport, for instance, can reinforce car dependency, while positive experiences with walking or cycling can inspire change. Weather and car ownership also play a role. In Ecuador, high UV radiation can deter cycling [6],[7], and car ownership remains a strong predictor of private vehicle use [8-10]. Cultural differences between developed and developing regions further shape

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these behaviors [11-13], making it essential to study mode choice within local contexts, particularly in mid-sized cities of developing countries.

The city of Cuenca, capital of Azuay Province, offers a valuable case study. With around 361,524 inhabitants spread across 72 km², it is a mid-sized Andean city where 52.2% of residents are adults and 10% are elderly. The University of Cuenca, the city's largest and only public university, includes roughly 16,000 students, faculty, and staff [14].

This study examines whether this community relies more on private vehicles or leans toward sustainable transportation options, such as walking, cycling, and public transit. The city's first Mobility and Public Spaces Plan (2015–2025) showed a balanced distribution between active travel (31%), public transport (31%), and private vehicles (32%) [15]. Still, new data are needed to understand how these trends have evolved. Despite progress, Cuenca continues to face serious environmental challenges: vehicle emissions remain a major contributor to pollution [16], and national data from the National Institute of Statistics and Censuses (INEC) indicate that 26% of deaths in Ecuador are related to pollution [17].

Dependence on motorized transport also affects the health and productivity of university communities [17],[18]. In response, Cuenca has introduced new public transportation systems, including a tram line that connects the city's north and south, promoting walking or cycling to reach stations [19],[20]. However, the key question remains: *are members of the university community willing to adopt more active and sustainable ways of getting around?*

To answer this, transport researchers often use Stated Preference (SP) and Revealed Preference (RP) methods. SP surveys explore hypothetical choices, while RP surveys record what people actually do [22-24]. Although SP methods allow control over scenarios, they may suffer from bias or fatigue if they become too complex [25]. For this reason, this study used an RP approach to capture real commuting behaviors and assess the potential for shifting transport modes at the University of Cuenca.

The goal of this research is to analyze daily mobility patterns within the university community, identifying transport modes and opportunities for improvement. In 2018, an online RP survey collected responses from 1,253 participants, providing detailed data on commuting habits. The analysis is timely given Cuenca's evolving transport system and distinctive urban layout. Understanding how university members navigate the city can inform the development of better infrastructure and promote more sustainable practices as Cuenca continues to grow.

Logistic regression models were applied to identify the factors that influence people's willingness to change their transport mode for study or work trips. The analysis distinguishes between students and employees (faculty and staff) to highlight differences in behavior and motivation.

This study makes several contributions. It defines the modal split of the university community by gender and role, examines the willingness to shift modes, and identifies opportunities to promote sustainable transport. It also reveals contrasts between students and employees in their transport choices, offering practical insights for mobility planning.

Finally, this paper presents a pre-pandemic baseline of transport behavior within the University of Cuenca. This foundation can support future research on how the pandemic reshaped mobility preferences. The paper is organized as follows: Section 2 reviews the relevant literature, Section 3 describes the materials and methods, Section 4 presents the results, Section 5 discusses the implications, and Section 6 offers conclusions and future directions.

2. Literature Review

Figure **1**, prepared with Litmaps[1], illustrates the development of research on mobility patterns and transportation mode choices within university communities in the last two decades. Each node represents a publication: solid circles correspond to papers that were manually added to the map, while hollow circles indicate articles recommended by the system as related works. The size of each circle reflects both the number of citations and the degree of interconnection with other works, providing a visual sense of its influence within the field. Connecting lines represent citation or reference links, and the horizontal axis shows the year of publication, with links flowing from older studies on the left to newer ones on the right. In general, papers appearing farther to the right are more recent, while those placed higher on the map tend to have been cited more frequently.

In recent years, as shown in

Figure **1**, research on mobility patterns and transportation mode choices within university communities has grown significantly. This work underscores the importance of understanding the factors that influence mode choice, particularly in promoting sustainable commuting behaviors [5],[26-28]. For instance, Shannon et al. [26] analyzed commuting patterns at The University of Western Australia, finding that travel time and infrastructure limitations were significant barriers to active transport adoption. Their recommendations for subsidized public transport and expanded cycling networks set a foundation for policy interventions to reduce car dependency.

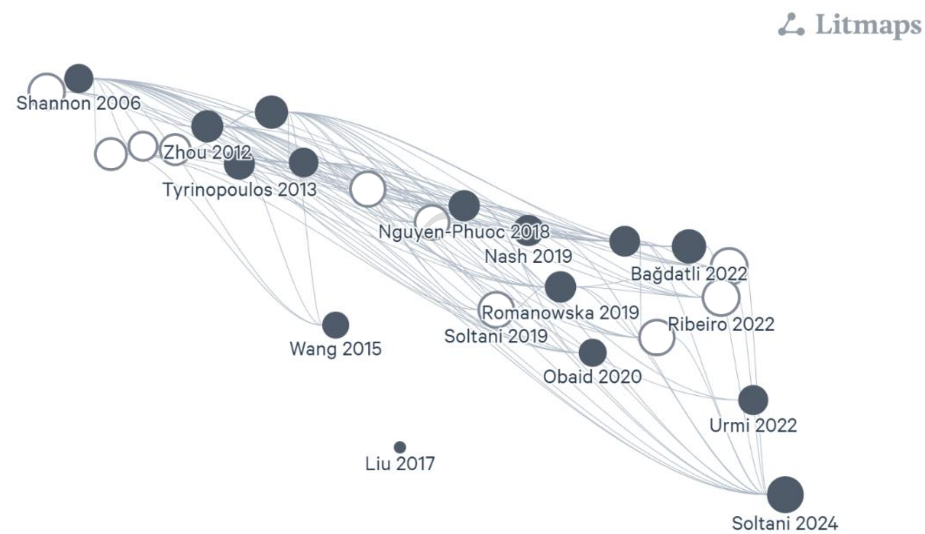


Figure 1 Scientific production and interconnections among publications on mobility patterns and transportation mode choices within university communities. Solid circles represent articles added to the map, hollow circles indicate recommended articles, and circle size reflects both citation count and degree of interconnection. Lines denote citation links, with the horizontal axis showing publication year (older on the left, newer on the right), while the vertical axis represents the number of citations received.

[1] Litmaps is a tool that empowers researchers in their literature discovery and management process, enabling every academic to find and manage papers better. https://www.litmaps.com/about/us

Recent research has continued to build on these findings. At McMaster University, Whalen et al. [5] found that many students genuinely enjoy cycling, suggesting that improving bike paths and related facilities could encourage more people to ride. Most of this work comes from universities in developed countries, showing how good infrastructure can make active travel both practical and enjoyable. However, these lessons do not always align with the realities of developing regions, where transportation needs and public systems often differ significantly.

To understand those differences, several studies have looked at mobility in developing countries [2],[4],[9],[29]. For example, Nguyen-Phuoc et al. [4] for example, studied students in Da Nang, Vietnam, and found that motorcycles are the dominant mode of transportation because public transit is unreliable. They argued that dependable and accessible transit options could motivate students to shift toward public transport. Similarly, Ribeiro et al. [9] studied the University of Minho in Portugal and found that many drivers were open to using buses or bicycles; however, poor infrastructure and long travel times deterred them from doing so. These barriers are also familiar in Cuenca, where people's preferences often clash with the city's limited mobility options.

Other research adds another layer to this picture. Nash and Mitra [20] and Soltani et al. [10] showed that neighborhood design and health concerns can strongly influence how people travel. Following the COVID-19 pandemic, Soltani et al. observed a significant shift toward private car use at Shiraz University, primarily due to concerns about hygiene and safety. Such findings are particularly relevant for Cuenca, a city that is experiencing rapid growth and change.

Despite these contributions, significant gaps remain. Few studies focus on universities in developing regions, where urban design, public transport, and economic factors intersect. This study helps fill that gap by focusing on the University of Cuenca [30]. offering insights for building more sustainable mobility in similar urban contexts.

3. Materials and Methods

This study follows a practical, synchronous, and explanatory research design, structured into three main phases, summarized in Figure 2. The research integrates quantitative data collection through a customized online survey, database development for structured storage, and multivariate statistical analysis.

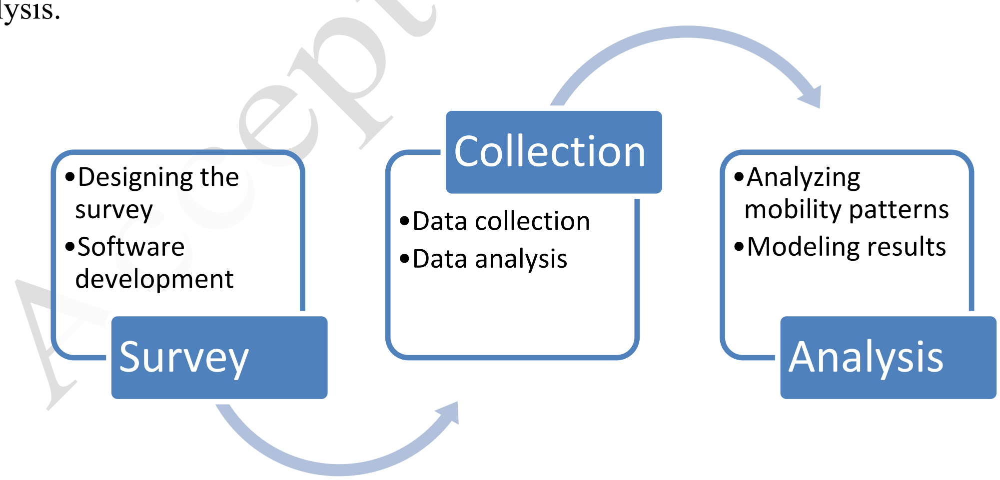


Figure 2 Overview of research strategy

Each phase of the study builds on the one before it, creating a clear and consistent connection between the conceptual design, data collection, and analysis.

3.1 Conceptual Design and Instrument Development

The first phase focused on creating and validating a mobility survey explicitly designed for the University of Cuenca. The conceptual framework guided how the survey was structured (Figure 3), ensuring that every section supported the study's main objectives: to identify how people move around the university and which transport modes they use most; to understand what motivates their transport choices and what prevents them from choosing other options; and to explore how people think about sustainability, comfort, and safety when they travel.

The survey was built on behavioral transport theory, which looks at how people make travel decisions, how satisfied they feel with those choices, and how their environmental attitudes shape their behavior [11],[31]. This framework helped ensure the questionnaire went beyond simply recording what people do when they travel; it also sought to understand the reasons behind their choices, connecting practical, emotional, and environmental aspects of mobility.

To bring these ideas to life, the questionnaire was divided into five closely related sections. The first, General Information, gathered basic details such as age, role, and place of residence to provide context for later analyses. The Travel Diary captured each participant's daily trips during a typical weekday, showing how often and how long they used each mode to identify their primary form of transport. The Purpose of Mode Choice explored why people chose a particular option, whether for economic, health, environmental, or convenience reasons. The Perception of Alternative Modes looked at why they avoided others, focusing on issues like time, safety, comfort, or limited infrastructure. Finally, the Miscellaneous Section asked about physical activity and interest in mobility topics, offering a broader view of how travel habits connect with lifestyle and awareness.

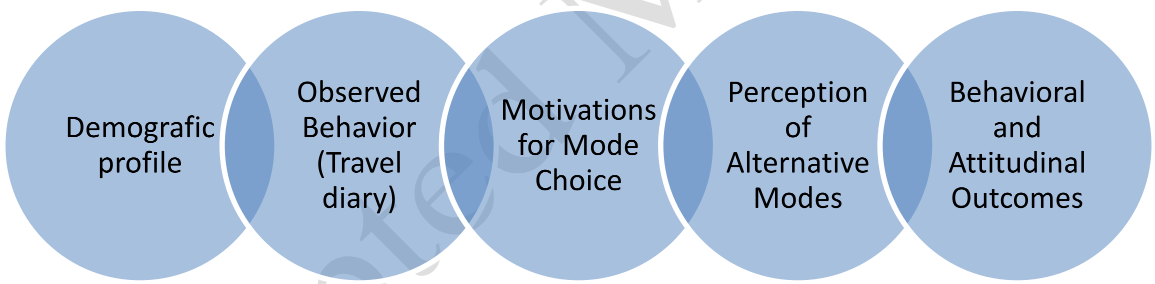


Figure 3 Conceptual design of the survey instrument

Before launching the survey, it was carefully tested to make sure the questions were clear, logical, and reliable. Some questions were repeated in different ways to check for consistency, and only complete and coherent responses were included in the analysis.

Because standard tools like SurveyMonkey [32], Google Forms, and LimeSurvey [33] could not meet the project's technical needs, the team developed a custom web application. This work allowed the survey to connect directly with university databases, verify responses automatically, and identify each participant's primary transport mode. The system was built with Java 8 for the backend, Angular 5 for the interface, and PostgreSQL for data management. After several rounds of testing with 100 pilot users, the final version was deployed at https://movilidad.ucuenca.edu.ec/encuesta, where it remained active for a limited time to collect responses.

3.2 Population and Sample

The population considered in this study comprises the entire community of the University of Cuenca, the oldest and largest university in Cuenca, Ecuador. This diverse community includes over 16,000 members, categorized as students (90.0%), faculty (6.8%), and administrative staff (3.2%) [34]. A stratified sampling method was used to ensure proportional representation of these groups, particularly given the large proportion of students.

All members of the university community were invited to participate in the online mobility survey. A random selection is made from the valid submissions to ensure that the final sample meets the established quotas for gender and university roles. This approach guarantees that each subgroup within the university is adequately represented in the study.

The sample size required for statistical validity was calculated to be a minimum of 929 participants based on a finite population, a 95% confidence level, and a 5% margin of error [35]. To ensure data reliability and minimize potential inconsistencies, the survey design incorporated redundancy in certain questions, allowing for the cross-verification of responses. Only responses that demonstrated internal consistency across all sections of the survey were deemed complete and valid, further strengthening the reliability of the collected data.

3.3 Data Collection

The survey was conducted through targeted email invitations sent to all University of Cuenca community members on June 18, 20, and 22, 2018. To maximize participation, a second round of invitations followed on July 9, 11, and 13. The survey system included a unique feature to ensure data integrity by allowing each participant to complete the survey only once, thereby preventing duplicate responses. Although the survey took an average of 15 minutes to complete, which may have felt long to respondents, this allowed for the collection of detailed information.

A comprehensive media campaign was launched alongside the invitations to encourage participation. Additionally, incentives, including prize draws for a random selection of respondents, were offered, which proved particularly effective in boosting engagement during the second wave of invitations. These strategies helped create an engaging environment that encouraged survey completion, ensuring a robust dataset for analysis.

The online format allowed for efficient data collection on complex issues, although achieving a representative sample posed challenges. Table 1 outlines the variables investigated in the survey. The survey included open-ended, closed-ended, multiple-choice questions and items using a Likert scale ranging from 1 to 4. Section 1 intentionally excluded socio-economic questions to avoid lowering the response rate, as respondents often hesitate to share personal information [36]. Section 2 focused on identifying the primary mode of transport, defined as the most frequently used mode with the longest travel time according to the displacement matrix.

Table 1 Investigated Variables List

Section	Variables	Type
1. General information	Campus	Categorical
	Role in the university	Categorical
	Age (years)	Numerical (integer)
	Gender	Categorical

	Address	Geographic
2. Trips Diary		
	Day of week	Categorical
	Start point	Categorical
	End point	Categorical
	Mean of transport	Categorical
	Departure time	Hour HH:MM
	Arrival time	Hour HH:MM
3. Level of satisfaction		
	Level of satisfaction with the current transport mean	Likert scale 1- 4 (1=detrimental, 4= very beneficial)
	Reasons for the selection of the means of transport	Multiple choices (close answer)
	Reasons why you do not select another mode of transport	Multiple choices per transport mean (close answer)
4. Willingness to shift transport mode	Willingness to shift transport mode	Dichotomous
	Main alternative	Categorical
5. Miscellaneous	Moderate physical activity	Dichotomous
	Number of times you engaged in moderate physical activity in the past week.	Numerical (integer)
	Total duration of moderate physical activity.	Hour HH:MM

3.4 Data Analysis

3.4.1 Descriptive Analysis

A descriptive analysis was conducted to summarize and highlight the critical features of the dataset collected from the online survey of 1,253 university members in 2018. The analysis focused on characterizing the sample based on variables such as gender, age, role in the university, primary mode of transportation, and the factors motivating its use. Additionally, the analysis examined participants' willingness to shift to alternative means of transport, their levels of physical activity, and their awareness of environmental issues.

All analyses were performed using the ISLR package of R software, enabling efficient data handling and the application of many descriptive statistics. This approach provides a comprehensive overview of the demographic and behavioral patterns within the university community, which is essential for understanding how university members navigate the city. This understanding is crucial for optimizing transport infrastructure and encouraging sustainable practices, considering Cuenca's evolving public transport system and unique urban layout.

3.4.2 Logistic Regression

A logistic regression model (binomial distribution, link function) was used to analyze factors influencing the willingness to switch transport modes (the dichotomous dependent variable) [37]. The model considered seven independent variables: gender, age, university role (employee/student), average travel time, primary transport mode, environmental/health concerns, and recent moderate physical activity. All categorical variables were dummy-coded with a neutral reference level. Correlation matrices were analyzed for each model to assess collinearity among the predictor variables. Pearson coefficients were calculated when both variables were metric, Phi coefficients were used for correlations between two dichotomous variables, and point-biserial correlations were computed when one variable was metric and the other dichotomous. Additionally, the analysis examined multicollinearity by estimating each variable's Variance Inflation Factors (VIF).

Pearson coefficient, r, measures the linear correlation between two continuous variables. The Pearson coefficient **r** is calculated using (1, where **n** is the number of pairs of scores, **x** are the scores for variable **x** and **y** are the scores for variable **y**.

$$r = \frac{n(\sum xy) - (\sum x)(\sum y)}{\sqrt{[n\sum x^2 - (\sum x)^2][n\sum y^2 - (\sum y)^2]}} \tag{1}$$

Phi Coefficient (ϕ) measures the association between two binary variables. ϕ is calculated using (2, where **a**, **b**, **c** and **d** are the frequency from the contingency table (Table 2):

Table 2 Contingency table.

	Variable 1=1	Variable 1=0
Variable 2=1	**a**	**b**
Variable 2=0	**c**	**d**

$$\emptyset = \frac{(\boldsymbol{ad} - \boldsymbol{bc})}{\sqrt{(\boldsymbol{a}+\boldsymbol{b})(\boldsymbol{c}+\boldsymbol{d})(\boldsymbol{a}+\boldsymbol{c})(\boldsymbol{b}+\boldsymbol{d})}} \tag{2}$$

Point-Biserial Correlation (r_{pb}) measures the correlation between a binary variable and a continuous variable. r_{pb} is calculated using (3, where M_1 is the mean of the of the continuous variable for the group with the binary variable equal to 1, M_0 is the mean of the continuous variable for the group with the binary variable equal to 0, **s** is the standard deviation of the continuous variable, **p** is proportion of cases with the binary variable equal to 1, **q** is 1-p, and **n** is the total number of cases [38].

$$\boldsymbol{r_{pb}} = \frac{M_1 - M_0}{\boldsymbol{s}}\sqrt{\frac{pq}{n}} \tag{3}$$

r, ϕ and **rpb** vary from -1 to 1. A value of 1 indicates perfect correlation, 0 means no correlation, and -1 means a perfect negative correlation, meaning that two variables move in opposite directions consistently and linearly [35],[38].

The Variance Inflation Factors (VIF) assesses how much the variance of a regression coefficient is inflated due to multicollinearity. It is calculated using (4, where R_i^2 is the coefficient of determination obtained by regressing X_i independent variable on all other independent variables [39].

$$VIF_i = \frac{1}{1 - R_i^2} \tag{4}$$

A VIF value greater than 10 typically indicates a high level of multicollinearity and that it is necessary to transform or eliminate variables of the model. If it is not possible, then a Ridge Regression is advisable. **Ridge Regression** (also known as **Tikhonov regularization**) is a regression technique used when there are issues with multicollinearity or overfitting in a linear regression model. It is a variant of linear regression that adds a penalty to the size of the model's coefficients, preventing them from becoming large and unstable. Ridge regression is often preferred when the goal is to improve the predictive performance of a linear model while addressing multicollinearity issues without completely removing variables, as is the case with **Lasso regression**.
Ridge regression incorporates an $\mathbf{L_2}$ norm penalty (the sum of the squared coefficients) to the loss function of linear regression, calculated by (5. The Ridge equation introduces a regularization term $\boldsymbol{\lambda}$ that controls the magnitude of the coefficients, where $\mathbf{y_i}$ is the observed value, $\boldsymbol{\widehat{y_i}}$ is the predicted value, $\boldsymbol{\beta j}$ are the coefficients of the predictor variables and $\boldsymbol{\lambda}$ is the regularization parameter that controls the degree of penalty [39].

$$L_2 = Minimize \sum_{i=1}^{n} (y_i - \widehat{y_i})^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \tag{5}$$

These methods offer valuable insights into the relationships between variables and the potential presence of multicollinearity within a dataset. Subsequently, the logistic regression models were established.

The model aims to evaluate the probability that a respondent is willing or unwilling to switch transport modes based on various characteristics, such as gender, age, and role in the university. This probability can be expressed in probability notation as P(willingness to switch of transport mode | gender, age, role in the university, etc.) where P will range between 0 and 1 inclusive. The logistic function to evaluate this probability is given in (6, where, **x** is the response variable, **β0** is the interceptor, and **β1, β2… βn** are the parameters for the ***n*** independent variables [40], [41].

$$\mathrm{P(X)}=\frac{e^{\beta 0+ \beta\ 1x1+\ldots\beta\ nxn}}{1+ e^{\beta 0+ \beta\ 1x1+\ldots\beta\ nxn}} \tag{6}$$

(6 can also be written as (7, where the quotient P(**x**)/(1- P(x)) is known as the odds ratio.

$$\frac{P(x)}{1- \mathrm{P(x)}} = e^{\beta 0+ \beta\ 1x1+\ldots\beta\ nxn} \tag{7}$$

Likewise, the odd ratio can take on any value between 0 and ∞. Values close to 0 indicate a very low probability. If the log function is applied to both members of (7, the logit is obtained and presented in (8, where **β0, β1, ...βn** are estimated through the maximum likelihood method.

$$ln\frac{P(x)}{1-P(x)} = \beta 0 + \ \beta\ 1x1 + \ldots \beta\ nxn \tag{8}$$

The likelihood function is represented by (9, where **β0, β1, ...βn** are chosen to maximize this likelihood function.

$$L(0, 1, \ldots n) = P(\boldsymbol{x})\ (1 - P(\boldsymbol{x})) \tag{9}$$

Once the model is established, it is essential to evaluate its performance. The Akaike Information Criterion (AIC) is used for this purpose. AIC is a metric that assesses the quality of a statistical model by considering both model fit and complexity. A lower AIC value indicates a better balance between goodness of fit and model simplicity. AIC is calculated using (10, where **k** is the number of parameters estimated in the model, and **L** is the likelihood function of the model, which reflects how well the model fits the data.

$$AIC = 2k - 2ln\ (L) \tag{10}$$

Another criterion for evaluating model performance is the Bayesian Information Criterion (BIC). Similar to the Akaike Information Criterion (AIC), the BIC assesses statistical model quality by balancing model fit with complexity, penalizing the inclusion of additional variables to avoid overfitting. However, BIC imposes a stricter penalty on more complex models than AIC, making it more conservative in selecting models with additional parameters. BIC is calculated using (11, where $\hat{\boldsymbol{L}}$ is the model's log-likelihood, **k** is the number of parameters estimated, and **n** is the number of observations in the dataset.

$$BIC = -2.\ln(\hat{L}) + k.\ln\ (n) \tag{11}$$

3.5 University of Cuenca Case Study

The University of Cuenca comprises five campuses and twelve faculties The central campus, located on the city's lower platform, is the largest and serves over 60% of the daily student population. This area has the second-highest motorization rate in the city, leading to significant congestion issues. The central campus spans 96,734 m² and accommodates a daily population of approximately 11,000 individuals, including faculty, students, and staff [34]. Despite its size and daily activity, there is currently no systematic policy to manage the travel demand to the campus, which primarily revolves around academic and work-related activities.

Accessibility at the central campus supports active and non-active transportation modes (such as walking and cycling). Well-maintained sidewalks surround the campus, and designated bike paths extend along two major avenues. A public bike station featuring twenty bicycles is conveniently situated near the rear entrance, promoting active mobility among community members. Eleven bus stops within a 500-meter radius of the campus provide access to eleven of the twenty-nine public transport lines, while a tram stop is just 600 meters away. The campus offers 471 parking spaces for faculty and administrative staff, complemented by a fee-based parking system enforced by the Cuenca's authorities on adjacent streets.

Indicators such as campus traffic congestion and high parking demand reveal a strong dependence on private vehicles, which inversely correlates with the use of active transportation modes. Consequently, the adverse effects of motorization in Cuenca are also exacerbated by the transportation habits of the university community [14],[15],[40].

4. Results

4.1 Demographic characteristics

The sample composition reveals demographic differences between employees (faculty and staff) and students. Employees represent 9.36% of the total sample. In terms of gender, employees consist of 46.0% females, while students show a higher proportion of females at 54.0%. Age distribution highlights that employees are generally older, with 25.3% aged 41-45 and 21.8% aged 36-40, while students are predominantly younger, with 55.1% in the 20-25 age group and 36.2% aged 15-19. Regarding distance to the campus, both groups exhibit similar trends, with the majority residing between 1.5-5 km from campus (52.6% of employees and 54.1% of students), followed by those living under 1.5 km (27.0% of employees and 21.7% of students), and smaller proportions living 5-10 km away (14.3% of employees and 16.2% of students). Of all the trips recorded in the sample, students account for 40% of the trips attracted to the campus, while they represent 48.4% of the trips generated from the campus. Overall, Figure 4 illustrates the age distribution within the sample, highlighting a notable age disparity between the student and employee groups.

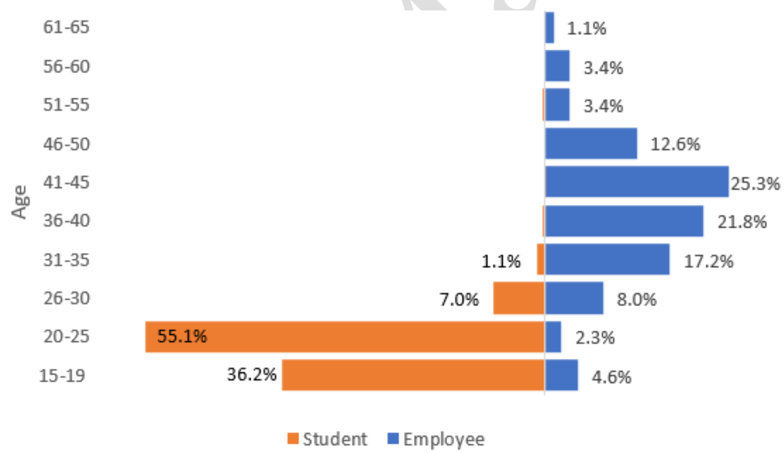


Figure 4 Age Distribution by Group.

4.2 Modal Split

The modal split in the sample is shown in Figure 5. Analyzing the modal split by gender between employees and students reveals significant similarities and differences in mobility patterns. Both groups show a notable preference for walking and using the bus; however, students exhibit a higher reliance on bus services, with 56.17% (29.45% male students and 26.72% female students) utilizing this mode compared to only 4.60% of employees. This finding suggests that students, having more flexible schedules and greater access to public transport options, depend more on bus services for their daily commutes.

On the other hand, differences in mobility become evident with the use of bicycles and motorcycles. While students use bicycles at a rate of 2.26%, employees report no usage of this mode, indicating a potential lack of adequate infrastructure or a lesser inclination towards cycling in the work environment. Motorcycle usage was significantly more prevalent among employees and was exclusively male, contrasting with a minimal mode share of 1.31% among students. This result suggests that employees may opt for motorcycles because they need faster and more flexible transport in their work routines. Finally, private vehicle usage also shows significant discrepancies between the two groups. Employees report a higher reliance on private vehicles, with 35.63% of females and 45.98% of males choosing this option. In contrast, students have a more moderate dependence on private vehicles, with 24.59% opting for this mode. These differences may reflect the varying transportation needs between the two groups, where students might be more adapted to public transport options. At the same time, employees may require greater autonomy in their commutes. Together, these data provide a clear insight into how gender and roles within the university influence the mobility choices of each group.

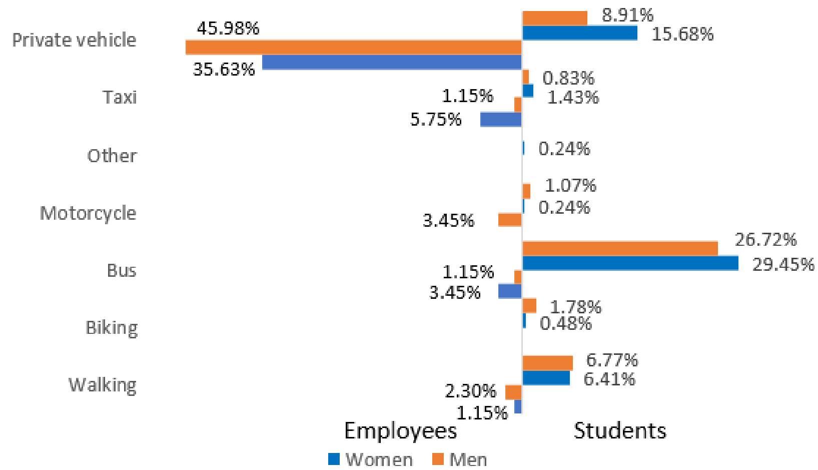


Figure 5 Modal split in the sample.

4.3 Travel Time

Travel time analysis reveals distinct modal patterns between students and employees (Table 3). Students recorded shorter mean times for walking and taxi trips. In contrast, employees report shorter travel times when using buses or private vehicles, possibly due to greater familiarity with routes or access to faster commuting options. A notable finding is that cycling was exclusively reported by students. The median bus travel time was also lower for students, suggesting less variability in their trip durations compared to employees.

Table 3 Travel time (minutes) by mode of transportation

Means of transportation	Employees			Students		
	Average	Median	Standard Deviation	Average	Median	Standard Deviation
Walking	20.00	20.00	0.00	14.33	15.00	6.50
Cycling	-	-	-	11.95	10.00	5.20
Bus	28.75	27.50	8.53	28.83	25.00	18.72
Motorcycle	20.00	20.00	0.00	17.73	20.00	5.63
Taxi	22.50	20.00	6.12	18.68	20.00	11.88
Private Vehicle	21.42	20.00	7.47	23.32	20.00	13.27

4.4 Dwell time

The dwell time reveals distinct patterns between students and employees, influenced by transportation mode. Employees who commute by taxi have the most extended stay, averaging 8 hours and 25 minutes, with a high standard deviation of nearly 3 hours, while student taxi users have a median stay of 5 hours and 52 minutes.
Dwell time is relatively similar for both employees and students who walk, with employees averaging 6 hours and 52 minutes. In comparison, students average slightly less at 5 hours and 57 minutes, both groups having a similar median of 5 hours and 15 minutes. Employees commuting by motorcycle also show more extended campus stays than students, with an average of 7 hours and 17 minutes versus 5 hours and 42 minutes. Bus commuters display less variation, as both groups show moderate stay times on campus. However, students tend to remain slightly longer, averaging 6 hours and 8 minutes, compared to 5 hours and 36 minutes for employees. These patterns indicate that the mode of transport and role within the university contribute to variations in campus engagement duration.

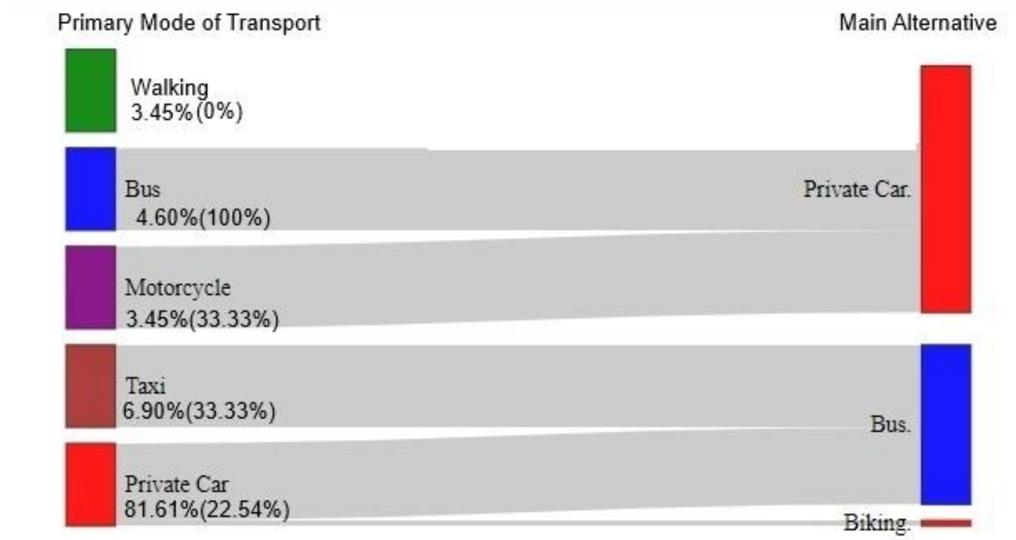
4.5 Modal Shift

At the University of Cuenca, 35.2% of respondents expressed willingness to change their transport mode. Among them, private vehicles were the preferred alternative (58.1%), followed by buses (32.7%); active modes like walking and biking were minimal (7%). Gender differences in willingness to change are minimal, with 34.5% of men and 35.9% of women expressing interest in a mode shift. However, notable variation emerges when looking at roles within the university community: students show the highest willingness to change (36.1%), while faculty and staff exhibit lower, though similar, rates at 25.4% and 28.6%, respectively.

Willingness to shift transport modes is significantly higher among motorized users (32.6%) than active travelers (2.58%). Bus users show the strongest desire to change (41.3%), followed by taxi (40%) and private vehicle users (30.6%). When examining opportunities for shifts to more sustainable options, the faculty members who currently drive, 24% wish to change modes, with 22% favoring a shift to bus and 2% to biking. Among students using private vehicles, 33.3% are willing to switch, with the majority (94.2%) leaning toward bus use. For staff, 19% of private vehicle users are interested in shifting to bus use.

In terms of threats-shifts from sustainable to less sustainable options, data indicates that all faculty and staff bus users who want to change modes prefer a private vehicle. Among students, 18% of those who walk wish to change, with 20% aiming to switch to a private vehicle. Notably, 42.3% of student bus users want to change, with 88.5% desiring to switch to private vehicles. Figure 6 summarizes the potential for modal shift, highlighting both the opportunity to adopt sustainable transport and the challenge of persistent private vehicle reliance.

a) Employees



b) Students

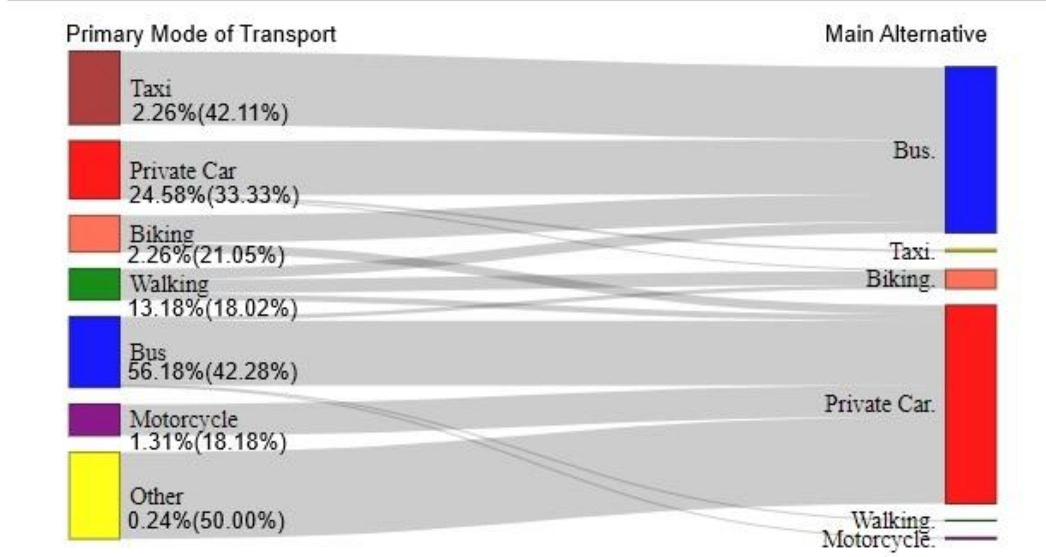


Figure 6 Modal shift and preferred alternative transport modes for (a) Employees and (b) Students, with percentages in parentheses showing the proportion of respondents considering a change from their current transport mode.

4.6 Level of satisfaction

The level of satisfaction with current transport modes highlights that individuals using active modes, such as walking and cycling, are the most satisfied with their choice. Walking, shows a high satisfaction level among both employees (mean = 4, SD = 0) and students (mean = 3.90, SD = 0.4), with students also reporting high satisfaction with cycling (mean = 3.84, SD = 0.37).

In contrast, taxi users report the lowest satisfaction levels, followed by bus users, indicating that public transport users, both individual (taxi) and mass (bus), are the least content with their current modes. Among bus users, this pattern is more pronounced for students, whose average satisfaction is 2.99 (SD = 0.76), compared to employees, who rate it slightly higher at 3.25 (SD = 0.50). These findings suggest that motorized public transport options are perceived less favorably, possibly due to factors such as comfort, reliability, or service quality. At the same time, active travelers experience higher satisfaction with their chosen modes. Table 4 presents a summary of the satisfaction level statistics for the primary mode of transport.

Table 4 Satisfaction Level with Primary Mode of Transport.

	Employees			**Students**		
Means of Transportation	**Mean**	**Median**	**Standard deviation**	**Mean**	**Median**	**Standard deviation**
Walking	4.00	4.00	0.00	3.90	4.00	0.40
Biking	-	-	-	3.84	4.00	0.37
Bus	3.25	3.00	0.50	2.99	3.00	0.76
Motorcycle	3.67	4.00	0.58	3.18	3.00	0.75
Taxi	2.33	2.50	1.21	2.58	3.00	1.02
Private vehicle	3.25	4.00	0.98	3.43	4.00	0.80

4.7 Factors Influencing Transport Mode Selection

The factors shaping transport mode choices differ noticeably between students and employees (faculty and staff) (Table 5). For students, money is the primary concern: 26.93% choose their transport mode to save costs, and 25.43% do so because they lack alternative options. Employees, on the other hand, focus more on efficiency and convenience; 17.98% select their mode to save time, while 14.61% do so to combine multiple daily activities.

Comfort and safety weigh more heavily for employees than for students. Among employees, 12.36% cite comfort and 9.74% cite safety as decisive factors, compared to 3.90% and 4.84% of students, respectively. Insecurity is a key deterrent for both groups when it comes to trying other modes, but employees express slightly greater concern (22.7%) than students (18.3%).

Table 5 Factors influencing transport mode selection.

Factors	**Employees**	**Students**
Save money	8.61%	26.93%
No other alternative	4.87%	25.43%
Less travel time	17.98%	11.63%
Multipurpose trips	14.61%	1.78%
Comfort	12.36%	3.90%
Safety	9.74%	4.84%
3.3 Reasons why you do not select another mode of transport		
Insecurity: high speed, disrespect for traffic signals, theft, etc.	22.70%	18.30%
Long travel times	13.70%	13.90%
Do not own a vehicle	2.10%	9.00%

Lack of services such as dressing rooms, lockers, secure parking spaces	8.70%	7.40%
Do not own a motorcycle	5.00%	7.70%

When asked about perceived benefits, active travelers, those who walk or cycle, rate their choices highest, with scores close to 4 on a 1-to-4 scale. Motorized transport users report lower benefits: around 3 for bus users and 3.4 for private vehicle users. Interestingly, active travelers view motorized modes less favorably; walking users rate the bus at 2.24, and cyclists at 2.26. Bus users, however, show moderate appreciation for active modes, scoring walking and cycling at around 2.76 and 2.75, respectively.
By role, faculty and staff value travel time, convenience, and comfort most. Faculty view walking most positively (3.12) but rate the bus lowest (1.83), while staff prefer private vehicles (3.43) and also rate the bus poorly (2.00). Students rate walking and private vehicles similarly (2.87), with cycling lowest (2.57). Gender differences also emerge: women rate cycling 11% lower than men, likely reflecting concerns about safety and comfort. Across all groups, barriers to modal shift persist, including limited cycling infrastructure, overcrowded buses, and cost constraints, which show that students are driven by affordability and access. At the same time, employees prioritize comfort, safety, and time.

4.8 Physical Activity

The analysis shows a majority of respondents engage in moderate exercise, with 58.7% of students and 55.2% of employees participating. Both groups reported a mean frequency of approximately 2.4 times in the past week, with a median of 2 times. Employees dedicated significantly more time to physical activity weekly (mean= 196.1 min) than students (147.4 min), with far greater variability (SD= 259.8 vs. 150.5 min). Despite this, both groups shared a median of 120 min, indicating that while some employees are far more active, the typical individual in both groups exercises similarly. (See Table 6 for a statistical summary).

Table 6 Respondent's Physical Activity Levels.

	Employees	**Students**
5.1 Moderate physical activity	55.20%	58.70%
5.2 Number of times you practiced moderate physical activity in the last week		
Mean (minutes)	2.40	2.40
Median (minutes)	2.00	2.00
Standard Deviation (minutes)	1.60	1.80
5.3 Total time of moderate physical activity		
Mean (minutes)	196.10	147.40
Median (minutes)	120.00	120.00
Standard Deviation (minutes)	259.80	150.50

4.9 Correlation Analysis

The correlation analysis between the dependent variable, Willingness to Change transport mode, and a set of independent variables indicates an overall weak or nearly negligible correlation across all tested variables (Table 7).

Using Point-Biserial correlation for the continuous variables Age and AvgTravelTime, the results show a weak relationship with Willingness to Change (r = -0.027 and r = 0.025, respectively). The Phi coefficient was applied for binary variables, such as Gender (Men), Role (Staff), Role (Faculty), Physical Activity, Concerns (Environmental/Health), and different transport modes.
The strongest correlation observed was between Willingness to Change and TransportMode(Bus), with an r value of 0.150, suggesting a very slight tendency for bus users to consider changing their mode of transport. On the contrary, slight negative correlations were noted for TransportMode(Walking) (r = -0.130) and TransportMode(Motorcycle) (r = -0.130), indicating that users of these modes may have marginally less interest in switching to another mode.
All correlations, however, remain very low, suggesting a nearly null association between Willingness to Change and independent variables. Due to this minimal correlation, further multicollinearity analysis among variables was conducted to explore potential indirect relationships and ensure robustness in interpreting the relationships among the factors affecting Willingness to Change transport modes.

Table 7 Variables and Their Correlation Coefficients.

Variable	r
Age	-0.027
AvgTravelTime	0.025
Gender(Men)	-0.010
Role(Staff)	-0.020
Role(Faculty)	-0.050
PhysicalActivity	-0.030
Concerns(Environmental/Health)	-0.060
TransportMode(Walking)	-0.130
TransportMode(Biking)	-0.040
TransportMode(Bus)	0.150
TransportMode(Motorcycle)	-0.130
TransportMode(Taxi)	0.020
TransportMode(PrivateCars)	-0.050

4.10 Collinearity

The collinearity analysis conducted for the logistic regression model revealed perfect collinearity between the variables TransportMode(Walking) and TransportMode(Motorcycle), with a correlation coefficient of r = 1. Given the low percentage of trips made by motorcycle (1.51%) compared to trips made on foot (12.27%), it was decided to exclude the TransportMode(Motorcycle) variable from the model.

Variables with VIF values above 5, namely TransportMode(Walking), TransportMode(PrivateCars), and TransportMode(Bus), showed high to very high collinearity, indicating that multicollinearity could influence the model's stability. However, these variables are essential to the study's aim to analyze willingness to shift transportation modes among users who walk, take the bus, or drive private cars.
Ridge Regression regularization was implemented to address multicollinearity without removing these essential variables. After regularization, the coefficients for TransportMode(PrivateCars) and TransportMode(Bus) were reduced from 0.355 to -0.074 and 0.777 to 0.213, respectively. This reduction

indicates that the penalty applied by Ridge Regression effectively mitigated the multicollinearity, thereby stabilizing the coefficients.

4.11 Regression Analysis

The Logistic regression and Ridge regression models showed comparable fit, achieving similar values for the AIC and BIC. This consistency suggests that Ridge regularization effectively mitigated multicollinearity without compromising model performance. With a lambda (λ) value of 0.2, the Ridge model effectively reduced the variance of specific coefficients, stabilizing the model, especially in cases of high correlation.

Both models slightly reduced the intercept and Age coefficients in the Ridge regression. This adjustment represents a modest regularization effect that smooths the influence of these variables. For transport modes, explicitly walking and motorcycle, Ridge regularization significantly reduced coefficients due to multicollinearity issues, evidenced by perfect collinearity detected between these variables in the correlation matrix. Table 8 shows the results of both regression models.

Table 8 Regression Model Coefficients.

	Logit Coefficients	**Ridge Coefficients**
(Intercept)	-0.939	-0.598
Age	0.101	-0.001
AvgTravelTime	-0.254	-0.048
Gender(Men)	0.033	-0.002
Role(Staff)	-0.458	-0.108
Role(Faculty)	-0.628	-0.170
PhysicalActivity	-0.085	-0.050
Concerns(Environmental/Health)	-0.078	-0.089
TransportMode(Walking)	-0.451	-0.271
TransportMode(Biking)	-0.235	-0.276
TransportMode(Bus)	0.777	0.213
TransportMode(Motorcycle)	NA	-0.271
TransportMode(Taxi)	0.746	0.149
TransportMode(PrivateCars)	0.356	-0.075

The Ridge Regularization was applied separately to the regression models for the Employees and Students groups, allowing for comparing their distinct patterns. Table 9 shows that the intercepts in both models are negative, with -0.535 for Students and -0.593 for Employees, indicating a similar initial offset. However, the coefficients reveal notable differences: Age positively impacts students (0.123) but has a near-neutral effect on employees (-0.014). Likewise, AvgTravelTime exerts a minor adverse effect on students (-0.034) and a substantial adverse effect on employees (-1.158), implying that travel time plays a more significant role in employees' decision-making.

Differences are also seen in how gender and physical activity correlate with willingness to change: the Gender(Men) coefficient is neutral for Students (0.000) but has a slight positive association for Employees (0.110). Meanwhile, PhysicalActivity shows a mild negative association for Students (-0.104). However, it is positively associated with Employees (0.298), indicating that Employees with higher physical activity levels may be slightly more inclined to change transport modes.

Concerning transport mode preferences, walking negatively affects both groups but is stronger among Employees (-0.517) than Students (-0.287). Likewise, the influence of biking is negative in both groups, though only reported for Students (-0.326). Notably, bus usage shows a positive correlation for both groups, especially among Employees (1.325) versus Students (0.211), indicating a stronger tendency for Employees to consider a shift when they primarily use the bus.
Motorcycle and taxi modes show a slight negative or near-neutral association in each group, while private cars have a stronger negative association among Employees (-0.309) than Students (-0.030).

Table 9 Ridge Regression Coefficients for Employee and Student Groups.

	Students	Employees
(Intercept)	-0.535	-0.593
Age	0.123	-0.014
AvgTravelTime	-0.034	-1.158
Gender(Men)	0.000	0.110
PhysicalActivity	-0.104	0.298
Concerns(Environmental/Health)	-0.089	-0.044
TransportMode(Walking)	-0.287	-0.517
TransportMode(Biking)	-0.326	
TransportMode(Bus)	0.211	1.325
TransportMode(Motorcycle)	-0.286	-0.517
TransportMode(Taxi)	0.190	0.087
TransportMode(PrivateCars)	-0.030	-0.309
Lambda_opt	0.175	0.317
AIC	1091.13	112.91
BIC	1147.96	142.5

The optimal lambda values differ for each group (0.175 for Students, 0.317 for Employees), as do the fit metrics, with lower AIC and BIC scores for Employees (112.91 and 142.5, respectively) compared to Students (1091.13 and 1147.96). These differences underscore that while some transport behaviors align between groups, Employees' transportation choices appear more sensitive to specific predictors, especially average travel time and bus usage, than those of Students.

5. Discussion

This study offers insight into how University of Cuenca community members travel and what influences their choices. Guided by its conceptual design, it combines behavioral transport theory with statistical analysis to connect people’s motivations, satisfaction, and willingness to change how they travel. This approach helps move beyond simple counts of trips or modes and offers a deeper view of why people travel the way they do.
A consistent pattern emerged between students and employees. Students, generally younger and living closer to campus, tend to walk or use public transportation. Meanwhile, employees, especially faculty, tend to rely on private vehicles, valuing comfort and time efficiency. This pattern aligns with findings from Chakrabarti [43] and Zhao et al. [44],[45], which show that age and income strongly influence mobility. From a behavioral perspective, these differences reveal that transport choices go beyond logic; they reflect lifestyle, daily routines, and personal values.

Gender also plays a defining role. Women in this study tended to rely more on private cars, whereas men were more likely to choose active or public modes of transport; a pattern also observed in Spain [46], Germany [47], and Portugal [48]. As the conceptual framework suggested, looking at factors like perception and satisfaction helped explain these differences: women often prioritize safety and comfort, while men focus on autonomy and practicality. Meeting these needs calls for infrastructure and policies that consider travel's emotional and social dimensions.

The data also reveals a pronounced contrast in the modal split between employees and students. Students make approximately 56.2% of their trips by bus, significantly higher than staff or faculty, who rely more on private vehicles. In comparison, faculty members' private vehicle usage reaches 84.7% of their total trips, consistent with findings from Van Eenoo et al. [49] and Wiersma [50], which show that higher-income individuals, such as faculty, are more car-dependent. This car dependency suggests a critical area for sustainability initiatives, like implementing carpooling incentives or increasing parking fees to discourage excessive private vehicle usage.

Regarding travel time, students generally experience shorter travel times for walking and taxi use than employees. This difference may reflect the students' closer proximity to campus, a pattern supported by other university studies that have found that campus proximity often correlates with higher active transport usage among students [51],[52]. This finding suggests that enhancing on-campus facilities and providing flexible spaces could encourage prolonged student engagement and reduce off-campus travel demand.

One of the most telling findings is how willing people are to change their mode of transport. About 35.2% of respondents said they would consider switching, but the direction of that change is telling. Many bus users would rather start driving, while fewer car users are considering moving to sustainable options. This finding echoes Allen et al. [53] and Van Lierop et al. [54] who show that frustration with public transport often pushes people toward private cars. From a conceptual standpoint, it shows how satisfaction shapes behavior: being unhappy with a service can spark change, though not always in a greener direction. Thus, improving bus reliability, comfort, and safety becomes essential to maintaining or expanding sustainable travel habits.

Satisfaction levels also follow clear trends. People walking or cycling reported the highest satisfaction, while bus users were least content, reflecting concerns about crowding and service quality; issues also noted by Minhans et al. [55] and Redman et al. [56]. Private car users are still the most resistant to change, even when they know the environmental impact [48],[52]. This trend suggests that comfort and control often outweigh environmental concerns for many commuters.

Motivations vary by role: students focus on saving money, while employees prioritize time and convenience [57]. These differences highlight how context shapes mobility choices and underscore the conceptual framework's goal of showing how perceptions and constraints influence behavior.

Recent studies have demonstrated that targeted interventions can effectively promote shifts toward sustainable mobility within university environments. For instance, investments in cycling infrastructure, such as dedicated bike lanes and secure parking facilities, as well as the implementation of university shuttle services, have been shown to significantly increase the use of active and public transport modes [10],[51],[58]. Likewise, incentive-based measures, including subsidized public transit passes, carpooling programs, and the strategic reduction of parking availability, have proven successful in encouraging behavioral change toward more sustainable commuting habits [27],[29]. In the context of mid-sized Latin American cities, even moderate investments in pedestrian and transit infrastructure, such as improved lighting, continuous sidewalks, and enhanced bus stop safety, can generate substantial benefits by reducing emissions, congestion, and travel stress [59],[60]. These examples provide practical evidence of how the study's findings can inform policy and planning decisions that align with sustainable urban growth objectives.

Overall, the study's results confirm that promoting sustainable mobility requires more than infrastructure; it needs strategies that address people's experiences, satisfaction, and willingness to change. By integrating behavioral theory with empirical analysis, the research provides a clearer picture of what drives transport choices and what might encourage a fundamental shift toward sustainability.

6. Conclusions

This study highlights how connecting a clear conceptual framework with practical methods can deepen our understanding of urban mobility in university settings. Grounded in behavioral transport theory, the research combined a tailored survey, systematic data collection, and multivariate analysis to examine how people's demographics, perceptions, and travel needs interact to shape their mobility behavior.
Three main takeaways summarize the study's contributions:

1. **From Concept to Instrument** – The survey, inspired by behavioral mobility theory, captured both the practical and emotional sides of travel decisions. Each component: demographics, satisfaction levels, and willingness to change, helped explain how people decide how to get around.
2. **From Data to Understanding** – The online survey provided a clear picture of how daily travel routines relate to personal motivations. The findings highlighted contrasts between students and employees, showing how age, income, and gender influence transport choices in mid-sized cities. Students, especially those from lower-income backgrounds and younger age groups, tended to favor sustainable modes, while employees, particularly faculty members, were more car-dependent.
3. **From Analysis to Application** – Logistic regression translated the conceptual framework into actionable insights, identifying the factors that most strongly predict a person's likelihood of changing travel modes. The analysis highlights how behavioral priorities, such as cost savings for students or time efficiency for employees, impact mobility decisions.

Together, this knowledge connect theory with practice. It shows that promoting sustainable mobility in universities requires not just better infrastructure but also targeted strategies that consider people's habits, motivations, and perceptions. Measures like incentives for active and public transport, improved walking and cycling paths, and enhanced bus services can make sustainable choices more appealing. Beyond the immediate findings, the study provides a framework for future research, which could track long-term or post-pandemic changes in travel behavior and help design more sustainable, human-centered mobility systems in universities and mid-sized cities.

Declaration of competing interest

We declare that we have no significant competing interests including financial or non-financial, professional, or personal interests interfering with the full and objective presentation of the work described in this manuscript.

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Author contributions

P. Cazorla: Conceived the project, designed the experimental work, designed the data analysis, analyzed the data, and wrote the initial and the final version of the paper. E. Avila-Ordoñez: Designed the experimental work, designed the data analysis, and wrote the final version of the paper.

Data available statement

Data associated to this paper is available under request.

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