Research instruments and data analysis for mode choice in travel within the university environment

Instrumentos de pesquisa e tratamento de dados para escolha modal no ambiente universitário

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ABSTRACT
This article reviews recent literature on data collection and analysis procedures regarding modal choice in university travel. The review method included the search, selection, and critical analysis of studies published in indexed journals in the bibliographic databases between 2018 and 2023. While most studies utilized online questionnaires, there was some adherence to in-person surveys. Strategies such as social media promotion and prize incentives have been employed. Regarding analysis tools, it was observed that most studies employ quantitative approaches, including statistical tests, discrete choice models, and integrated and latent variable models. In addition to commonly used variables such as socioeconomic or behavioral factors, there has been an inclusion of variables that explain the effect of the global pandemic scenario on the travel behavior of the academic community.

Keywords: mobility, university environment, university travel, mode choice, data collection instrument, choice models.
RESUMO
Este artigo revisa a literatura recente sobre procedimentos de coleta e análise de dados relativos à escolha modal em viagens universitárias. O método de revisão incluiu a busca, seleção e análise crítica de estudos publicados em periódicos indexados nas bases de dados bibliográficas entre 2018 e 2023. Embora a maioria dos estudos tenha utilizado questionários on-line, houve alguma adesão aos questionários presenciais. Estratégias como a promoção nas redes sociais e o incentivo com prêmios têm sido empregadas. Em relação aos instrumentos de análise, observou-se que a maioria dos estudos emprega abordagens quantitativas, incluindo testes estatísticos, modelos de escolha discreta e modelos de variáveis integradas e latentes. Além das variáveis comumente utilizadas, como fatores socioeconômicos ou comportamentais, houve a inclusão de variáveis que explicam o efeito do cenário pandêmico global sobre o comportamento de viagem da comunidade acadêmica.

Palavras-chave: mobilidade, ambiente universitário, viagens universitárias, escolha modal, instrumento de coleta de dados, modelos de escolha.

1 INTRODUCTION
Mobility within the university environment is a significant part of the urban context and has been a concern for researchers worldwide. There is a growing interest in understanding and explaining people’s travel behavior within this setting. This is evident in the increasing number of research papers published in recent years. Several motivations drive the studies conducted, including barriers and opportunities for sustainable mobility, first and last-mile issues, transport demand management, university mobility plans, and the effects of the pandemic, among others.

The diversity of modes used for traveling to campus is more significant when compared to urban trips. Some studies use these campuses as an observatory to help understand the travel behavior patterns adopted in urban areas (SULTAN; KATAR; AL-ATROUSH, 2021). Different groups carry out the trips, including students, professors, and other staff members. University students, for example, can be considered an essential and novel population as they still form their values and beliefs, making them more receptive to potential changes in their travel choices (CHEN et al., 2022). Most research focuses on the travel patterns of the student community (CHEN et al., 2022; HASNINE; CHUNG; NURUL HABIB, 2022; TUVERI et al., 2020). Many researchers study the travel choice
patterns of students and staff members (FRASZCZYK; WEERAWAT; KIRAWANICH, 2019; LOGAN et al., 2020; HAMAD; HTUN; OBAID, 2021; DEWEESE; RAVENSBERGEN; EL-GENEIDY, 2022).

This study focuses on the type of data collection instruments and the methods of data treatment and analysis adopted in recent years. A review of these two aspects will provide an overview of how the pattern of university travel has been addressed in various parts of the world while also providing insights for researchers who wish to conduct studies in this field.

This article is structured into five sections. The first section provides an elucidation of the adopted methodology. Following that, a brief contextualization is supplied regarding the motivations of the reviewed studies. Sections 3 and 4 present the results and discussions, exploring the authors’ different methodological approaches, focusing on the data collection instrument and data analysis, respectively. Finally, the conclusions and contributions obtained are presented.

2 METHODOLOGY

Firstly, a search was conducted in three online databases: Science Direct, Scielo, and Scopus. Publications between 2018 and 2023 were considered. The keyword pairs “mode choice” and “university” as well as “mode choice” and “campus” were utilized. For the selection stage, titles, abstracts, and keywords were read to assess the works’ relevance to this study’s theme.

Two aspects were the focus of evaluation: i) how authors collect travel data within university environments, and ii) how these data are treated and analyzed concerning the research objective. All selected publications were reviewed and analyzed based on these two questions. The information extracted from the articles was used to construct this review.

To facilitate the discussion, the results were divided into three parts. The first part addresses the motivation behind the studies presented in the articles. The second part discusses the characteristics of data collection instruments. The final part examines the treatment and analysis of the collected data. Throughout these discussions, some results obtained from the studies are presented.
3 MOTIVATION FOR THE STUDIES

Eighty studies addressing the topic of mode choice in university travel were found. After selecting and filtering, 70 studies were obtained and considered for this review. The main objective of these studies was to investigate the mode choice behavior of academic community groups in trips to and from the university. Etminani-Ghasrodashti et al. (2018) investigated travel behavior among Iranian university and college students. Mohammadzadeh (2020) examined the choices of students from the University of Auckland, which is located in one of the most car-dependent cities in the world.

Saitluanga and Hmangaihzela (2022) investigated the travel behavior of university students from other cities to study at colleges in Aizawl, a rapidly growing hilly town in India. More general modal choice studies also appear at the University of Science and Technology in Vietnam (NGUYEN-PHUOC et al., 2018), at the University of Minho, Portugal (RIBEIRO; FONSECA; MEIRELES, 2020), at the University of Lausanne, in Switzerland (RÉRAT, 2021), and at the State University of Campinas in Brazil (MAIA et al., 2020).

Other studies have presented action plans for developing sustainable university mobility plans in European universities (PAPANTONIOU et al., 2020), including Sapienza University in Italy (SGARRA et al., 2022). Hamad, Htun, and Obaid (2021) investigated the differences among traveler groups to the Sharjah University City campus in the United Arab Emirates.

3.1 BARRIERS AND OPPORTUNITIES

Many reviewed studies follow this trend when there is a more significant environmental concern. They are focused on analyzing barriers and opportunities for mode shift towards more sustainable and efficient transportation options. The studies are presented below in chronological order of publication.

Rybarczyk (2018) searched to understand the potential for a modal shift to active modes among the resident university population throughout Southeast Michigan, USA. Pike and Lubell (2018) analyzed the effects of social influence on travel mode choice at the University of California in the city of Davis. Orozco-Fontalvo et al. (2018) sought to identify the factors influencing modal choice at
Francisco de Paula Santander University Ocaña (Colombia) by introducing cycling as a travel alternative. De Paepe et al. (2018) studied university students' perceptions in Ghent, Belgium, regarding how travel behavior changed during the transition from secondary to higher education. This research fits within the broader framework of mobility biographies, where travel behavior is analyzed throughout one's life, considering certain life events.

The University of Toronto in Canada developed a project called Student-MoveTo (2023). It is a partnership between ten colleges and universities and four government and community organizations in Greater Toronto and Hamilton. The travel patterns of students were investigated using various approaches (ANOVAR et al., 2019; HASNINE et al., 2018; HASNINE; CHUNG; NURUL HABIB, 2022; MONIRUZZAMAN; FARBER, 2018).

Mehdizadeh, Zavareh, and Nordfjærn (2019) conducted a study in Norway to investigate the effects of environmental norms and beliefs, as well as situational characteristics, on the use of "green" transportation modes (multimodal and monomodal) and cars during university trips in winter and summer. The research was conducted at the Dragvoll and Gløshaugen campuses in Trondheim. On the same campuses, Nordfjærn, Egset, and Mehdizadeh (2019) evaluated the relative roles of the norm activation model, transport priorities, and situational constraints, considering spatial heterogeneity in university travel behavior among students during the winter season. Soltani et al. (2019) aimed to clarify the differences in travel behaviors of students in Australia and China, examining associations with environmental attitudes. Bayas Aldaz and Sandoval Hamon (2019), for example, analyzed the perception and attitudes of student representatives from Spanish universities regarding sustainable transportation on their campuses, considering the geographical location. Yan, Levine, and Zhao (2019) investigated travelers' adherence to an integrated public transportation system proposed at the University of Michigan. Peer (2019) explored the determinants of cycling in a scenario involving relocating one of Austria’s most prominent universities.

The changes in travel choices and habits of university students at Cardiff University in the United Kingdom were studied by Haggar, Whitmarsh, and Skippon (2019). Pinto et al. (2019) investigated the motivations for choosing the
carpooling system at the University of Lavras in Brazil. In Thailand, Fraszczyk, Weerawat, and Kirawanich (2019) surveyed students and staff from Mahidol University, who were considered potential users of a planned subway line nearby, to ascertain their willingness to switch to this mode.

Papu Carrone et al. (2020) analyzed how individuals value features of car-sharing services and the choice patterns between using this service and traditional modes of transport in Copenhagen. Cadima, Silva, and Pinho (2020) examined the commuting habits of students and investigated their interrelationships, as well as the main barriers and motivations that affect the travel decisions of students from the Faculty of Engineering at the University of Porto. Dzisi et al. (2020) studied the dissemination and use of ride-sharing among young people at a university in Ghana.

Tuveri et al. (2020) aimed to identify ways to promote a sustainable culture and improve public transportation services at Roma Tre University. In Lebanon, Sfeir, Abou-Zeid, and Kaysi (2020) investigated the potential market demand for shared taxi and public transportation services designed to serve members of organizations in densely urbanized areas at the American University of Beirut. Henning, Schubert, and Maciel (2020) evaluated the factors influencing the choice of active transportation modes at a university in Joinville, Brazil.

Teuber and Sudeck (2021) tested personal motivators and barriers for active mode usage at the University of Tübingen in Germany. Attard et al. (2021) sought to understand better the determinants of pedestrian and cyclist mobility at the University of Malta in Europe. Sultan, Katar, and Al-Atroush (2021) conducted a study to examine travel patterns in Riyadh at Prince Sultan University, focusing on the quality of the pedestrian environment around the campus. The characteristics of profiles for car users who are less willing to switch to a sustainable mode were outlined by Beria et al. (2021) at the Polytechnic University of Milan.

Dzisi and Lugada (2021) sought to understand the underlying factors influencing bicycle usage and developed models to explain the potential shift from motorcycle taxis to bicycles. Two Chilean universities, Lizana, Tudela, and Tapia (2021), highlighted the processes behind bicycle mode choice decisions, incorporating pro-bicycle attitudes and habits. Vahedi, Shams, and Mehdizadeh
(2021) studied variables’ direct and indirect effects relative to active commuting on university trips at Isfahan University in Iran. De Angelis, Mantecchini, and Pietrantoni (2021) aimed to identify passenger groups based on their modal choice in a large higher education institution in Italy. They also compared these groups regarding sociodemographic and psychosocial variables.

Ribeiro and Fonseca (2022) assessed the potential for changing the mode choice of students at the University of Minho in Portugal towards more sustainable modes, as well as analyzing carbon emissions. Hidalgo-González, Rodríguez-Fernández, and Pérez-Neira (2022) analyzed travel behavior at the University of Leon in Spain, along with the environmental implications generated and the main barriers to implementing a modal shift, according to professional affiliation and gender. Trček and Mesarec (2022) aimed to identify the factors influencing the mode choice of students and employees to understand weaknesses, strengths, and opportunities for improving sustainable mobility at the University of Maribor in Slovenia.

3.2 FIRST AND LAST-MILE ISSUES

Some studies have examined patterns of university travel within the scope of micro-mobility or alternatives for first/last-mile transportation. Sanko (2020) investigated modal choices for accessing/departing from various campuses of Kobe University in Japan and railway stations. In this case, topographical factors play an essential role.

Vich et al. (2021) studied the effect of the distance to the nearest railway station on the decision to use public transportation to travel to the main campus of the Autonomous University of Barcelona. A pilot test with e-bikes was organized by Ton and Duives (2021) at the Delft University of Technology in the Netherlands. Studies on using e-scooters were carried out at the University of Portland in the United States (McQueen; Clifton, 2022) and the Aristotle University of Thessaloniki in Greece (Nikiforiadis et al., 2023). The level of perception regarding the need for motorcycle ride-sharing services among university students in Indonesia was evaluated by Irawan et al. (2021).
In China, Chen et al. (2022) examined the usage behavior of the free-floating bicycle-sharing service on the Huai’yin Institute of Technology campus and Jiageng et al. (2022) explored potential factors influencing the usage behavior of the shared bicycle system at Henan Polytechnic University. Crotti et al. (2022) investigated the relationship between proximity to public transportation and sustainable commuting based on a survey conducted at the Bizzozero Campus of the University of Insubria, located in a peripheral area of the city of Varese in Italy.

### 3.3 TRANSPORTATION DEMAND MANAGEMENT

Some studies investigated aspects related to demand management policies. Sweet and Ferguson (2019) described and estimated the extent to which available TDM (Transportation Demand Management) tools at McMaster University in Hamilton (Canada) lead to travel reductions. Yan, Levine, and Marans (2019) analyzed the influence of parking policies at the University of Michigan in Ann Arbor.

Dell’olio et al. (2019) proposed a methodology to estimate the importance of different variables in users’ mobility choices by simulating their response to policies, such as introducing new modes of transportation or parking charges on campus. Logan et al. (2020) investigated the influence of travel demand management initiatives on the travel habits of students and staff at the University of Aberdeen in Scotland. Hamad and Obaid (2022) aimed to test solutions, strategies, and alternative policies in Sharjah University City.

### 3.4 THE EFFECTS OF THE PANDEMIC

The COVID-19 pandemic, which started in 2020, motivated some authors to analyze aspects related to university travel, including the pre-pandemic situation, the lockdown period, and the return to in-person activities. (CAULFIELD et al., 2021; DEWEESE; RAVENSBERGEN; EL-GENEIDY, 2022; MALJAAE; KHADEM SAMENI, 2022; VERSTEIJLEN; VAN WEE; WAL, 2021).

Caulfield et al. (2021) aimed to identify the factors influencing mode choice and workplace choice among students and staff at Trinity College Dublin when the campus fully reopens (post-pandemic period). Versteijlen et al. (2021) studied
mode choice and the decision among students at Avans University of Applied Sciences in the Netherlands to go to campus or study online.

DeWeese et al. (2022) examined modal shifts and quantified greenhouse gas emissions during three periods (pre-pandemic, early pandemic, and post-pandemic) at McGill University in Canada. Maljaee and Sameni (2022) searched for factors affecting subway use by surveying students at the Iran University of Science and Technology in the capital city of Iran before and after the pandemic outbreak.

3.5 NEW APPROACHES

New approaches, such as the influence of other variables on choice or the use of alternative analysis methods, also motivated researchers in their investigations. For example, Gokasar and Bakioglu (2018) examined the travel choice behavior of individuals at Istanbul Technical University using real-time traffic information obtained through various traffic apps.

Sarangi and Manoj (2020) explored escorting decisions and mode choice among members of an urban university in India, comparing sociodemographic impacts, travel characteristics, and attitudinal factors. Faboya et al. (2020) investigated factors influencing mode choice decisions to and from the University of Nottingham in the UK. Additionally, they examined changes in choice patterns in response to policy interventions related to the identified factors and the influence of traveler interactions.

The influence of perceived safety on mode choice was assessed at the University of São Paulo in Brazil (CAPASSO DA SILVA; RODRIGUES DA SILVA, 2020) and Utah State University in the United States (RAHMAN; POUDEL; SINGLETON, 2021). To understand the reasons that affect mode choice and how the use of information and communication technologies, along with opinions and attitudes, influence the decision-making process of individuals commuting to the University of Utrecht in the Netherlands was the motivation behind the study by Van Lierop and Bahamonde-Birke (2021).

Yaghoubi, Rassafi et al. (2022) sought to understand the factors influencing students’ demand and travel behavior at a university in Iran. Kim and Lee
(2023) examined mode choice among individuals at the University of Illinois, focusing on the role of attitude variables. The following sections will delve deeper into the discussion of these studies, focusing on data collection instruments and the treatment and analysis of data.

4 DATA COLLECTION INSTRUMENTS

Most of the studies conducted adopted online questionnaires as the data collection instrument. In the case of the works analyzed here, it was observed that this approach gained even greater adherence after the resumption of in-person academic activities, which had been halted due to the city-wide lockdown. Nonetheless, some researchers opted for in-person surveys to increase response rates and obtain a more representative sample (CADIMA; SILVA; PINHO, 2020; DZISI et al., 2020; ETMINANI-GHASRODASHTI; PAYDAR; HAMIDI, 2018; FABOYA et al., 2020; FRASZCZYK; WEERAWAT; KIRAWANICH, 2019; JIAGENG; LANLAN; XIANGHONG, 2022; MAIA et al., 2020; MEHDIZADEH; ZAVAREH; NORDFJAERN, 2019; MOHAMMADZADEH, 2020; NORDFJÆRÑ; EGSET; MEHDIZADEH, 2019; PAPANTONIOU et al., 2020; SARANGI; MANOJ, 2020; VAHEDI; SHAMS; MEHDIZADEH, 2021; VERSTEIJLEN; VAN WEE; WALS, 2021).

Etminani-Ghasrodashti et al. (2018), Sarangi and Manoj (2020), and Jiageng, Lanlan, and Xianghong (2022) maintained a focus on conducting in-person questionnaires. Other authors conducted face-to-face interviews (DZISI et al., 2020; MOHAMMADZADEH, 2020; VAHEDI; SHAMS; MEHDIZADEH, 2021), researched other databases (CADIMA; SILVA; PINHO, 2020), and carried out on-site surveys (PINTO et al., 2019) to complement the data. Maia et al. (2020) and Fraszczyk, Weerawat, and Kirawanich (2019) adopted the strategy of online and paper questionnaires. Versteijlen et al. (2021) and Orozco-Fontalvo et al. (2018) organized their research through focus groups. Faboya et al. (2020) also utilized the strategy of focus groups and online and paper questionnaires. Papantoniou et al. (2020) employed the Brainstorming approach with students and staff from several European university campuses. Mehdizadeh, Zavareh, and
Nordfjærn (2019) and Nordfjærn, Egset, and Mehdizadeh (2019) sought to organize lectures for dissemination and respondent recruitment.

The data collection instrument can have various structures and formats depending on the research objective. In the case of questionnaires, the decision to use either a Stated Preference or Revealed Preference survey will guide the choice of form, particularly regarding the types of questions and responses. Some authors mentioned using Stated Preference (2023; 2018; 2020; 2020), while others mentioned using Revealed Preference Surveys (LIZANA; TUDELA; TAPIA, 2021; YAN; LEVINE; MARANS, 2019). Some authors utilized both types of survey (SANKO, 2020; SWEET; FERGUSON, 2019; YAN; LEVINE; ZHAO, 2019). For example, the form can be created on various platforms such as Survey Monkey (2022) or Google Forms (2020). The following topics describe the characteristics of the research instruments regarding the methods of survey dissemination and application, type of respondents, and sample.

4.1 SURVEY DISSEMIMATION AND APPLICATION

Regarding the application, in-person surveys were administered by a trained team at strategic locations within and outside the university. As for online survey distribution, the majority were sent via email. Some authors mentioned using the university's database as an official means of contacting respondents (CAPPASSO DA SILVA; RODRIGUES DA SILVA, 2020; HENNING; FERREIRA SHUBERT; CECCATO MACIEL, 2020; MCQUEEN; CLIFTON, 2022; RIBEIRO; FONSECA, 2022; SOLTANI et al., 2019; TEUBER; SUDECK, 2021).

To increase the visibility of the research and reach more responses, one strategy that has been adopted involves using communication channels on social media platforms such as Facebook, Instagram, LinkedIn, and WhatsApp groups, among others. The research was disseminated through Facebook groups (HAGGAR; WHITMARSH; SKIPPON, 2019; 2019); various social media platforms (ATTARD; CAÑAS; MAAS, 2021; IRAWAN et al., 2021; 2022); email, Facebook posts (TEUBER; SUDECK, 2021); promotional campaigns using flyers at university gathering points (HAGGAR; WHITMARSH; SKIPPON, 2019; SOLTANI et al., 2019; TEUBER; SUDECK, 2021); the university portal (DE ANGELIS;
Authors promoted reminders, posters, and stories in the media to grab the attention of students (ANOWAR et al., 2019; HASNINE et al., 2018; HASNINE; CHUNG; NURUL HABIB, 2022; MONIRUZZAMAN; FARBER, 2018). Sgarra et al. (2022) organized lectures, workshops, meetings, and short informative texts to disseminate the research and sent reminders.

Regarding the survey duration, it was observed that the data collection time varies, ranging from a few days (DELL’OLIO et al., 2019; TUVERI et al., 2020), a few weeks (CADIMA; SILVA; PINHO, 2020; HAGGAR; WHITMARSH; SKIPPON, 2019; JIAGENG; LANLAN; XIANGHONG, 2022; MCQUEEN; CLIFTON, 2022; RYBARCZYK, 2018; SWEET; FERGUSON, 2019; TEUBER; SUDECK, 2021) to a few months (CHEN et al., 2022; NORDFJÆRN; EGSET; MEHDIZADEH, 2019; RAHMAN; POUDEL; SINGLETON, 2021; RIBEIRO; FONSECA; MEIRELES, 2020). For example, DeWeese et al. (2022) conducted their survey during three distinct periods: a pre-pandemic period in January 2020, the onset of the pandemic in April 2020, and a post-pandemic period in September 2020. Some universities, such as Logan et al. (2020) conducted periodic surveys to understand changes occurring over the years, whose survey was conducted every two years between 2006 and 2016, and Rérat (2021) completed their survey every year from 2005 to 2017. Some authors did not mention the duration of the data collection.

4.2 TYPE OF RESPONDENT

Regarding the types of survey respondents, some authors limited themselves to evaluating the travel behavior of the student community. Some studies considered undergraduate students (MEHDIZADEH; ZAVAREH; NORDFJAERN, 2019; NORDFJÆRN; EGSET; MEHDIZADEH, 2019; PINTO et al., 2019). Tuveri et al. (2020), for example, exclusively focused on undergraduate students from the Transportation Engineering program at Roma Tre University. Other works assessed undergraduate and postgraduate students (ANOWAR et al., 2019; CHEN et al., 2022; ETMINANI-GHASRODASHTI; PAYDAR; HAMIDI, 2018; HASNINE et al., 2018; HASNINE; CHUNG; NURUL HABIB, 2022;
Mohammadzadeh, 2020; Moniruzzaman; Farber, 2018). Bayas Aldaz and Sandoval Hamon (2019) specifically examined the group of student representatives from 44 Spanish universities.

Many authors also included staff members in their research, in addition to students (Beria et al., 2021; Capasso da Silva; Rodrigues da Silva, 2020; Caulfield et al., 2021; Crotti; Grechi; Maggi, 2022; De Angelis; Mantechini; Pietrantoni, 2021; Dell’Olio et al., 2019; Deweese; Ravensbergen; El-Geneidy, 2022; Faboya et al., 2020; Fraszczyk; Weerawat; Kirawanich, 2019; Gokasar; Bakioglu, 2018; Hamad; Htun; Obaid, 2021; Hamad; Obaid, 2022; Hidalgo-González; Rodríguez-Fernández; Pérez-Neira, 2022; Lizana; Tudela; Tapia, 2021; Logan et al., 2020; Orozco-Fontalvo et al., 2018; Papantoniou et al., 2020; Papucarrone et al., 2020; Rahaman; Poudel; Singleton, 2021; Rérat, 2021; Ribeiro; Fonseca; Meireles, 2020; Rybarczyk, 2018; Sfeir; Abou-Zeid; Kaysi, 2020; Sgarra et al., 2022; Sultan; Katar; Al-Atrash, 2021; Sweet; Ferguson, 2019; Ton; Duives, 2021; Trček; Mesarec, 2022; Vich et al., 2021; Yan; Levine; Zhao, 2019). For example, Sarangi and Manoj (2020) focused only on married professors, staff, and students in their work. Yan, Levine, and Marans (2019), Van Lierop and Bahamonde-Birke (2021), and Kim and Lee (2023) investigated the behavior of professors and staff members. Finally, Attard et al. (2021) aimed their research toward the entire university community and other individuals interested in the Sustainable Urban Mobility Plan at the University of Malta.

4.3 SAMPLE

While many authors do not mention the type of sampling used in their studies, a significant portion of academic papers utilized simple random selection, where all elements in a population have an equal chance of being selected for the sample. Rybarczyk (2018) set a random sample of 15% of the students for their survey. Some authors (Anowar et al., 2019; Dzisi et al., 2020; Hasnine et al., 2018; Hasnine; Chung; Nurul Habib, 2022; Moniruzzaman;
FARBER, 2018; YAGHOUBI; RASSAFI; MIRZAHOSSEIN, 2022), adopted stratified random sampling.

Other researchers have employed convenience sampling, a non-probabilistic sampling, as it utilizes readily available results for data collection (NORDFJÆRN; EGSET; MEHDIZADEH, 2019; TEUBER; SUDECK, 2021; VAHEDI; SHAMS; MEHDIZADEH, 2021). Quota sampling was employed in the studies conducted by Etminani-Ghasrodashti et al. (2018) and Henning, Schubert and Maciel (2020). Pike and Lubell (2018) chose the snowballing method. In part of their research, Papu Carrone et al. (2020) also employed this sampling method and simple random sampling.

Regarding sample size, Attard et al. (2021) mentioned the participation of 34 individuals in the conducted activities. The focus groups organized by Versteijlen et al. (2021) involved 56 students. Surveys that utilized questionnaires generally had larger sample sizes. However, discussing response rates rather than just the absolute number of participants is preferable for a better understanding the sample size. Some studies mentioned the achieved response rates. In the case of surveys conducted periodically, the rates varied between 16% and 34% (2020) and between 17.5% and 16.8% (RÉRAT, 2021). Table 1 summarizes other studies that mentioned response rates obtained through questionnaire administration. It can be observed that some authors present response rates per respondent group (RYBARCZYK, 2018; SGARRA et al., 2022; SWEET; FERGUSON, 2019). Among them, Sweet and Ferguson (2019) achieved the highest rate (41%) among the employees at the University of Sapienza in Italy. Regarding overall response rates, Caulfield et al. (2021) reported the highest rate (12.5%) obtained at Trinity College Dublin (Ireland).

4.4 DISCUSSION

Table 2 summarizes the data collection instruments used in the reviewed studies, categorized by research motivation. It can be observed that many studies employed questionnaires, both online and printed. The primary method of distribution was email. Additionally, there is a noticeable increase in the use of social media to disseminate university research.
Table 1: Some response rates from the reviewed studies

<table>
<thead>
<tr>
<th>Case Study</th>
<th>Application</th>
<th>Response</th>
<th>Response Rate</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>University of Michigan (USA)</td>
<td>Online and printed</td>
<td>520</td>
<td>22% students; 24% teachers; 28% employees</td>
<td>(RYBARCZYK, 2018)</td>
</tr>
<tr>
<td>Universities in Toronto (Canada)</td>
<td>Online</td>
<td>3208</td>
<td>2%</td>
<td>(HASNINE et al., 2018)</td>
</tr>
<tr>
<td>Universities in Toronto (Canada)</td>
<td>Online</td>
<td>8903</td>
<td>5%</td>
<td>(MONIRUZZAMAN; FARBER, 2018)</td>
</tr>
<tr>
<td>McMaster University (Canada)</td>
<td>Online</td>
<td>2279</td>
<td>5% students; 11% teachers; 14% employees</td>
<td>(SWEET; FERGUSON, 2019)</td>
</tr>
<tr>
<td>State University of Campinas (Brazil)</td>
<td>Online and printed</td>
<td>1179</td>
<td>Almost 3%</td>
<td>(MAIA et al., 2020)</td>
</tr>
<tr>
<td>University of São Paulo (Brazil)</td>
<td>Online</td>
<td>244</td>
<td>2.60%</td>
<td>(CAPASSO DA SILVA; RODRIGUES DA SILVA, 2020)</td>
</tr>
<tr>
<td>University of Minho (Portugal)</td>
<td>Online</td>
<td>1482</td>
<td>7%</td>
<td>(RIBEIRO; FONSECA; MEIRELES, 2020)</td>
</tr>
<tr>
<td>University of Bologna (Italy)</td>
<td>Online</td>
<td>8093</td>
<td>8.94%</td>
<td>(DE ANGELIS; MANTECCHINI; PIETRANTONI, 2021)</td>
</tr>
<tr>
<td>Trinity College Dublin (Ireland)</td>
<td>Online</td>
<td>2653</td>
<td>12.50%</td>
<td>(CAULFIELD et al., 2021)</td>
</tr>
<tr>
<td>Sharjah University City (United Arab Emirates)</td>
<td>Online</td>
<td>1928</td>
<td>10%</td>
<td>(HAMAD; HTUN; OBAID, 2021; HAMAD; OBAID, 2022)</td>
</tr>
<tr>
<td>University of Minho (Portugal)</td>
<td>Online</td>
<td>686</td>
<td>5.15%</td>
<td>(2022)</td>
</tr>
<tr>
<td>University of Sapienza (Italy)</td>
<td>Online</td>
<td>14719</td>
<td>students 14%; teachers 41%</td>
<td>(SGARRA et al., 2022)</td>
</tr>
<tr>
<td>Iran University of Science and Technology (Iran)</td>
<td>Online</td>
<td>379</td>
<td>Greater than 5%.</td>
<td>(MALJAEE; KHADEM SAMENI, 2022)</td>
</tr>
<tr>
<td>Universities in Toronto (Canada)</td>
<td>Online</td>
<td>15226</td>
<td>8.70%</td>
<td>(HASNINE; CHUNG; NURUL HABIB, 2022)</td>
</tr>
<tr>
<td>Portland State University (USA)</td>
<td>Online</td>
<td>1968</td>
<td>9.90%</td>
<td>(MCQUEEN; CLIFTON, 2022)</td>
</tr>
</tbody>
</table>

Source: The authors.
Table 2: Types of instruments (to be continued)

<table>
<thead>
<tr>
<th>Motivation</th>
<th>Type of Instrument</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Barriers and opportunities</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Workshop</td>
<td>(ATTARD; CANAS; MAAS, 2021)</td>
<td></td>
</tr>
<tr>
<td>Focal groups/interviews</td>
<td>(OROZCO-FONTALVO et al., 2018)</td>
<td></td>
</tr>
<tr>
<td>Smartphone App</td>
<td>(TUVERI et al., 2020)</td>
<td></td>
</tr>
<tr>
<td>Questionnaire</td>
<td>(BAYAS ALDÁZ; SANDOVAL HAMON, 2019;\n BERIA et al., 2021; DZISI; LUGADA, 2021)</td>
<td></td>
</tr>
<tr>
<td>Printed questionnaire / interviews</td>
<td>(VAHEDI; SHAMS; MEHDIZADEH, 2021)</td>
<td></td>
</tr>
<tr>
<td>Printed questionnaire</td>
<td>(CADIMA; SILVA; PINHO, 2020; DZISI et al., 2020; MEHDIZADEH; ZAVAREH; NORDFJÆRN, 2019; NORDFJÆRN; EGENSET; MEHDIZADEH, 2019)</td>
<td></td>
</tr>
<tr>
<td>Printed and online questionnaire</td>
<td>(FRASZCZYK; WEERAWAT; KIRAWANICH, 2019; RYBARCZYK, 2018)</td>
<td></td>
</tr>
<tr>
<td>Online questionnaire / research in loco</td>
<td>(PINTO et al., 2019)</td>
<td></td>
</tr>
<tr>
<td>Motivation</td>
<td></td>
<td></td>
</tr>
<tr>
<td>The Effects of the pandemic</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Focal groups</td>
<td>(VERSTEIJLEN; VAN WEE; WALS, 2021)</td>
<td></td>
</tr>
<tr>
<td>Online questionnaire</td>
<td>(CAULFIELD et al., 2021; DEWEES;\n RAVENBERGEN; EL-GENEIDY, 2022; MALJAAE; KHADEM SAMENI, 2022)</td>
<td></td>
</tr>
<tr>
<td>Transportation demand management</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Online questionnaire</td>
<td>(DELL’OLIO et al., 2019; LOGAN et al., 2020; SWEET; FERGUSON, 2019; YAN; LEVINE; MARANS, 2019)</td>
<td></td>
</tr>
<tr>
<td>First and last mile issues</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Printed questionnaire</td>
<td>(JIAGENG; LANLAN; XIANHONG, 2022)</td>
<td></td>
</tr>
<tr>
<td>Online questionnaire</td>
<td>(CHEN et al., 2022; CROTTI; GRECHI; MAGGI, 2022; IRAWAN et al., 2021; MCQUEEN; CLIFTON, 2022; NIKIFORIADIS et al., 2023; SANKO, 2020; TON; DUIVES, 2021; VICH et al., 2021)</td>
<td></td>
</tr>
<tr>
<td>New Approaches</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Focal groups / Printed and online</td>
<td>(FABOYA et al., 2020)</td>
<td></td>
</tr>
<tr>
<td>questionnaire</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Questionnaire</td>
<td>(GOKASAR; BAKIOGLU, 2018)</td>
<td></td>
</tr>
<tr>
<td>Printed questionnaire</td>
<td>(SARANGI; MANOJ, 2020; YAGHOUBI; RASSAFI; MIRZAHOSSEIN, 2022)</td>
<td></td>
</tr>
<tr>
<td>Online questionnaire</td>
<td>(CAPASSO DA SILVA; RODRIGUES DA SILVA, 2020; KIM; LEE, 2023; RAHMAN; POUDEL; SINGLETON, 2021; VAN LIEROP; BAHAMONDE-BIRKE, 2021)</td>
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</table>
Regarding the sample size, preference surveys only sometimes reach a representative sample. As a result, inferences become limited, given that the patterns obtained may not represent the patterns of the population. This constitutes a limitation of this type of research. One of the strategies to encourage public participation in this type of research is the random drawing of prizes among respondents (Peer, 2019; Sweet; Ferguson, 2019; Irawan et al., 2021; Vahedi; Shams; Mehdizadeh, 2021; Van Lierop; Bahamonde-Birke, 2021). The reviewed studies reported overall response rates ranging from 2% (Hasnine et al., 2018) to 34% (Logan et al., 2020).

Most of the surveys aimed to investigate the behavior of the student community, considering that it constitutes much of the university population. Many authors also analyzed the travel patterns of staff members. Examining the behavior of various user groups enables understanding potential differences and identifying the specific needs of each group. Consequently, the adopted policies can be appropriately tailored, leading to more efficient results for the involved community.

5 DATA PROCESSING AND ANALYSIS

From the collected data, variables that explain the analyzed phenomenon are constructed. The variables represent socioeconomic characteristics (e.g., age, gender, income), travel-related factors (e.g., distance and travel time), and mode-related factors (e.g., comfort and cost). Some authors included variables of a behavioral and psychological nature, such as habits, attitudes, and

<table>
<thead>
<tr>
<th>Motivation</th>
<th>Type of Instrument</th>
<th>Reference</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel in general</td>
<td>Questionnaire</td>
<td>(Nguyen-Phuoc et al., 2018)</td>
</tr>
<tr>
<td></td>
<td>Printed questionnaire</td>
<td>(Etminani-Ghasrodashti; Paydar; Hamidi, 2018)</td>
</tr>
<tr>
<td></td>
<td>Printed questionnaire / interviews</td>
<td>(Mohammadzadeh, 2020)</td>
</tr>
<tr>
<td></td>
<td>Printed and online questionnaire</td>
<td>(Maia et al., 2020)</td>
</tr>
<tr>
<td></td>
<td>Online questionnaire</td>
<td>(Rerat, 2021; Ribeiro; Fonseca; Meireles, 2020; Saitluanga; HamangaiHZela, 2022)</td>
</tr>
<tr>
<td>Mobility Plans</td>
<td>Brainstorming</td>
<td>(Papantoniou et al., 2020)</td>
</tr>
<tr>
<td></td>
<td>Online questionnaire</td>
<td>(Hamad; Htun; Obaid, 2021; Hamad; Obaid, 2022; Sgarra et al., 2022)</td>
</tr>
</tbody>
</table>

Source: The authors.
awareness (FABOYA et al., 2020; KIM; LEE, 2023; LUAN et al., 2021; TEUBER; SUDECK, 2021). Maia et al. (2018) explored the variables used in this type of study in publications before 2017.

With the COVID-19 pandemic, which started in 2020, research has also been conducted to assess the effects of this health crisis on individuals' behavior in university travel. Thus, other variables were included in modal choice studies, such as the degree of importance given to social distancing and the availability of hand sanitizer (DEWeese; RAVENsBERGEN; EL-GENEiDY, 2022; LUAN et al., 2021; MALJAEE; KHADEM SAMENI, 2022; MANGRUM; NIEKAMP, 2022).

The reviewed studies mention various types of data treatment and analysis with different degrees of complexity. They were classified as quantitative and qualitative to describe and discuss the kinds of analyses.

5.1 QUANTITATIVE ANALYSIS

The quantitative analyses were subdivided into the following categories: statistical study, regression models, discrete choice models, structural equation models, and integrated approaches.

5.1.1 Statistical Analysis

DeWeese et al. (2022) utilized descriptive statistics and observed that reductions in travel led to lower greenhouse gas emissions. Some statistical tests showed that TDM initiatives themselves do not substantially influence a shift to sustainable modes (LOGAN et al., 2020); they determined differences among traveler groups, for example, regarding gender (HAMAD; HTUN; OBAID, 2021); indicated that the degree of importance given to barriers for public transportation use varies among different campus populations (RIBEIRO; FONSECA; MEIRELES, 2020); aided in inferring that young people are more likely to choose to carpool due to convenience and cost advantage compared to conventional taxis (DZISI et al., 2020); demonstrated that the pandemic scenario affected mode choice priorities (MALJAEE; KHADEM SAMENI, 2022), and resulted in a significant willingness of respondents to switch to the subway mode (FRASZCZYK; WEERAWAT; KIRAWANICH, 2019).
In addition to statistics, some authors also employed complementary analyses in their studies. These include the construction of a conceptual model to relate students' travel patterns with the built environment, demographics, and environmental awareness (SOLTANI et al., 2019); The use of Rasch modeling revealed students' perception of the need for motorcycle ride-sharing services for first and last-mile trips (IRAWAN et al., 2021); Evaluation of the pedestrian environment quality indicated influencing factors in the choice of walking mode and highlighted barriers that may hinder the transition to sustainable mobility (SULTAN; KATAR; AL-ATROUSH, 2021); Thematic analysis of qualitative data identified factors that influence students’ mode choice, such as car accessibility and attitude variables (MOHAMMADZADEH, 2020). Analysis of indicators and scenario building revealed differences in habits among observed user groups (HIDALGO-GONZÁLEZ; RODRÍGUEZ-FERNÁNDEZ; PÉREZ-NEIRA, 2022).

Spatial analysis tools were also employed with statistical analyses, primarily to examine the influence of spatial variations on travel patterns, highlighting potential differences among traveler groups (CAULFIELD et al., 2021; 2021; HIDALGO-GONZÁLEZ; RODRÍGUEZ-FERNÁNDEZ; PÉREZ-NEIRA, 2022; TRČEK; MESAREC, 2022). Other studies applied decision tree techniques to investigate relationships between variables (CADIMA; SILVA; PINHO, 2020; CAPASSO DA SILVA; RODRIGUES DA SILVA, 2020). For instance, Capasso da Silva and Rodrigues da Silva (2020) explored the relationships between user experiences, the characteristics of their routes to campus, and the decision to use sustainable modes using this technique.

5.1.2 Regression Models

Regression models were also applied in some analyses. Among them, factor analyses and hierarchical block regressions revealed associations between cycling, perceived study environment, motivators, and personal barriers among students (TEUBER; SUDECK, 2021); multiple regression models and conditional process modeling confirmed the hypothesis of habit discontinuity among students (HAGGAR; WHITMARSH; SKIPPON, 2019); Multivariate regression model and importance-performance analysis identified essential
attributes of free-floating bicycle sharing services (CHEN et al., 2022). Anowar et al. (2019) employed a random utility framework and random regret decision to examine mode and departure time choices. Rybarczyk (2018) utilized exploratory spatial data analysis, ordinary least squares, and geographically weighted regression.

Some studies applied logistic regression models. De Paepe et al. (2018) developed a conceptual framework followed by descriptive data analysis. They also employed hierarchical binary logistic regressions to analyze car use in mandatory and leisure activities. Ton and Duives (2021) used chi-square tests, independent sample t-tests, and a binary logistic regression model to observe the adherence of students and employees to e-bike use; Dzisi and Lugada (2021) conducted an exploratory factor analysis and binary logistic regression analysis, through which they discovered factors with implications for cycling, such as safety and demographic characteristics.

Rérat (2021) employed multivariate binary logistic regressions and observed, for example, that mode choice can be explained by the effects of gender, age, income, the territorial context, and values associated with mode importance. It is worth noting that this research focuses on factual elements and does not inquire individuals about the reasons for their mode choice. Descriptive statistics, mixed-effects binary logistic regression models, modal choice fitting predictions, and survival analysis through Cox regression were used in Vich et al.’s study (2021). This enabled an understanding of the effect of distance on the mode choice of non-captive public transport passengers. A specific profile based on distance thresholds and choice was developed to support efficient transportation policies.

5.1.3 Discrete Choice Models

Discrete choice models have also been adopted. The use of multinomial logit models showed the influence of real-time public transportation information provision on traveler behavior (GOKASAR; BAKIOGLU, 2018) revealed the importance of investing in improvements in non-motorized transportation services (SWEET; FERGUSON, 2019) and indicated that mode choices are influenced by
interconnected factors, including socioeconomic and demographic background, mode availability, and residential location (SAITLUANGA; HMANGAIHZELA, 2022). Applying descriptive statistics and multinomial logit models together indicates, in Saranji and Manoj (2020) work, that even though families perceive the university environment as safe and secure, they have a higher dependence on private vehicles, especially among mothers. Crotti, Grechi, and Maggi (2022) study also shows the crucial role of proximity to public transportation in subway use among students and employees.

Using spatial analysis with the application of multinomial logit models showed variation in students’ travel behavior (MONIRUZZAMAN; FARBER, 2018) and aimed at identifying possible missing spatial variables (BERIA et al., 2021). An analysis using descriptive statistics, residual inclusion model, and multinomial logit model demonstrated the variation in the strength of social influence according to travel distances and costs (PIKE; LUBELL, 2018). Hasnine, Chung, and Nurul Habib (HASNINE; CHUNG; NURUL HABIB, 2022) utilized a multinomial logit model in constructing an econometric model that could simultaneously model three choices: housing arrangement choice, distance between home and university, and mode choice.

In addition to multinomial logit models, other variations have also been applied. Descriptive statistics and conditional logit regression models demonstrated impact variables on students’ choice decision (NGUYEN-PHUOC et al., 2018); the use of nested logit models indicated travelers’ response tendencies to parking policies (YAN; LEVINE; MARANS, 2019) and identified variables significantly associated with the probability of choosing bikeshare and e-bikeshare (JIAGENG; LANLAN; XIANGHONG, 2022); the application of mixed logit models allowed inferences about the influence of demand management measures on car-use choices (DELL’OLIO et al., 2019) and generated attitudinal indices to control mode perception (MCQUEEN; CLIFTON, 2022). It also revealed intense competition between floating car-sharing, public transportation, and bicycle trips (PAPU CARRONE et al., 2020). A binomial logit model, exploratory analysis, and bivariate associations identified the variables that most influence students’ choice of bicycle (HENNING; FERREIRA SHUBERT; CECCATO MACIEL, 2020).
Some authors opted for the combination of logistic models. Orozco-Fontalvo et al. (2018) combined multinomial logit models with systematic variations, panel-effect multinomial and mixed logit models, and Hasnine et al. (2018) used multinomial logit, nested logit, and cross-nested logit models to show the differences between models regarding goodness of fit and variable relationships. The application of multinomial and binary logit models provided insights, for example, that time value varies between pedestrians and bus passengers on uphill sections (SANKO, 2020). The use of multinomial and mixed logit models indicated that the main difficulties in using MTransit are additional transfers and boardings (YAN; LEVINE; ZHAO, 2019) and brought to light the factors influencing the demand and travel behavior of students living in university residences (YAGHOUBI; RASSAFI; MIRZAHOSSEIN, 2022). Using different logit models allowed for discovering evidence that past cycling times are a reference point for future mode choice decisions (PEER, 2019).

5.1.4 Structural Equation Models and Integrated Approaches

Some authors adopted structural equation models. Confirmatory factor analysis and structural equation modeling showed that safety concerns systematically vary among users of different modes and demographic groups (RAHMAN; POUDEL; SINGLETON, 2021). Vahedi, Shams, and Mehdizadeh (2021) employed confirmatory factor analysis, statistical parameters, and structural equation models, highlighting that students who reported more positive attitudes and were satisfied with walking and cycling were more likely to engage in active modes of transportation. The combination of the theory of lazy user and partial least squares structural equation modeling was the approach used by Pinto et al. (2019). The results showed that this theory could not fully explain carpooling behavior at the university, suggesting that cultural elements play an essential role.

Other authors adopted an integrated modeling approach between discrete choice models and structural models of latent variables. Etminani-Ghasrodashti et al. (2018) used an integrated process combining a multinomial logit model and structural equation modeling. The results showed that cultural and educational contexts encourage a preference for driving among young adults in Shiraz.
Furthermore, restrictions on gender interaction in public places and public transportation in religious cultures, such as Iran, also contribute to young adults’ preference for private cars, which differs from those in developed countries. Sfeir, Abou-Zeid, and Kaysi (2020) adopted a multinomial distribution and latent variable model (likelihood function), demonstrating the advantages of using weekly decisions in modeling choices, ensuring better prediction accuracy, and obtaining a time value estimate closer to other local estimates for the study area using the complete enumeration method. Lizana, Tudela, and Tapia (2021) used the theory of expectancy-value, Verplanken's frequency, and an integrated choice and latent variable model, confirming the importance of attitude in explaining travel behavior.

The application of principal component analysis along with an integrated choice and latent variable model was the approach used by Van Lierop and Bahamonde-Birke (2021), showing strong correlations between the types of mobile applications used by individuals and their attitudes towards travel, personal characteristics, and mode of transportation. Kim and Lee (2023) applied an integrated choice and latent variable model, revealing, for example, that pro-car attitudes that reduce the utilities of buses, bicycles, and walking are significantly associated with gender, university affiliation, and income level.

Hybrid choice models (HCM) were developed by Nikiforiadis et al. (2023). These authors observed that time and cost variables can significantly affect stated preferences. Mehdizadeh, Zavareh, and Nordfjærn (2019) tested the norm activation theory and demographic, socio-economic, and situational data to explain mode choice. Nordfjærn, Egset, and Mehdizadeh Campo (2019) also used mixed linear models to test the norm activation theory. The authors observed, for instance, that a campus in a rural area was associated with higher car and public transportation use and lower active transportation use compared to a campus in an urban area.

Simulation techniques were also developed in the analyses. Faboya et al. (2020) conducted an agent-based simulation study, demonstrating how a theory-based framework can be used with survey data in numerical experiments to explore real-life scenarios to develop actions to promote behavioral changes.
Hamad and Obaid (2022) research made a significant contribution by integrating a demand forecasting model based on trips with a university, considering the entire transportation network, detailed traffic microsimulation, and an emissions assessment model.

5.2 QUALITATIVE ANALYSIS

Some studies proceeded with a qualitative analysis of the data. Papantoniou et al. (2020) evaluated the contributions of promoted brainstorming and proposed an action plan for creating a sustainable mobility plan. Sgarra et al. (2022) also defined the objectives of a mobility plan for the university through descriptive data analysis and assessment of municipal and national community policy guidelines. Bayas Aldaz and Sandoval Hamón (2019) analyzed statements from student representatives. They identified differences in travel behavior between those studying in intermediate city campuses and those in major urban center campuses. Attard et al. (2018) assessed and spatially distributed perceived walkability and bike-ability around the campus, presenting the results on a participatory electronic map.

Versteijlen et al. (2021) conducted a qualitative analysis of the discussions held in focus groups and observed, for example, that Dutch students tend to choose more sustainable modes of transportation to commute to the university. Tuveri et al. (2020) classified the collected trips according to the primary purpose, travel time, the mode used, and user attributes. One of the main contributions of this work is to analyze voluntary behavior changes of students regarding the mode of travel before and after implementing an informative measure. Ribeiro and Fonseca (2022) classified groups of students based on their potential for shifting to more sustainable modes of transportation and constructed scenarios based on carbon-emission savings.

5.3 DISCUSSION

Table 3 provides a general summary of the methodological approaches used in the reviewed studies. Most of the research applied discrete choice modeling. The multinomial logit model was the most adopted model by the authors.
However, it has limitations, such as assuming identical cross-elasticities among alternatives. As a result, studies are emerging that apply other more complex models, such as Mixed Logit (DELL’OLIO et al., 2019) and Cross-Nested Logit (HASNINE et al., 2018), to overcome these limitations and compare the effects of different variables on mode choice.

Indeed, the approach using structural equation modeling has been adopted by some authors. This choice was mainly due to its ability to identify constructs with non-normalized data and explore the influence of latent variables on travel behavior (PINTO et al., 2019; VAHEDI; SHAMS; MEHDIZADEH, 2021) and relationships between exogenous variables and latent variables (RAHMAN; POUDEL; SINGLETON, 2021). Notably, structural equations include the utility function used in discrete choice models. Another approach used is the integrated modeling between integrated choice and latent variable models (KIM; LEE, 2023; LIZANA; TUDELA; TAPIA, 2021; VAN LIEROP; BAHAMONDE-BIRKE, 2021) or between discrete choice models and structural equation models (ETMINANI-GHASRODASHTI; PAYDAR; HAMIDI, 2018; NIKIFORIADIS et al., 2023). Latent variables have been used in discrete choice modeling to incorporate heterogeneity in the model specification related to concepts that cannot be directly measured but only observed through their impact on attitudinal questions.

Descriptive statistics or statistical tests are reported in a considerable portion of the reviewed studies. In this case, the authors aim to provide an initial description of the data or infer the relationships between variables that explain travel patterns. Alongside the statistical analyses, spatial analysis tools, conceptual models, indicator evaluation, and qualitative data analysis have also been adopted. One of these studies implemented the Rasch model and statistical tests (IRAWAN et al., 2021). In this case, the Rasch model was used as a tool to measure the perceived need by students and the barriers inherent to motorcycle ride-sharing services. The Rasch model, extensively used in fields such as psychology and economics, is gaining traction in transportation studies to assess difficulties in using specific modes of travel and the ability to overcome them.
The qualitative analysis of the data was carried out in several studies aiming to understand the effects of the pandemic on mode choice (VERSTEIJLEN; VAN WEE; WALS, 2021); identify barriers and opportunities for the use of more sustainable modes (ATTARD; CAÑAS; MAAS, 2021; BAYAS ALDAZ; SANDOVAL HAMÓN, 2019; 2022; TUVERI et al., 2020) or develop action plans for the university's mobility strategies (PAPANTONIOU et al., 2020; SGARRA et al., 2022). The decision to use this approach was mainly driven by data availability for analysis. In this case, it included statements, perceptions, opinions, and travel records of groups of individuals from the academic community.

Table 3: Data analysis approaches (to be continued)

<table>
<thead>
<tr>
<th>Approaches</th>
<th>Reference</th>
</tr>
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<tbody>
<tr>
<td>Qualitative Analysis</td>
<td>(TUVERI et al., 2020; PAPANTONIOU et al., 2020; SGARRA et al., 2022; BAYAS ALDAZ; SANDOVAL HAMÓN, 2019; ATTARD; CAÑAS; MAAS, 2021; VERSTEIJLEN; VAN WEE; WALS, 2021; 2022)</td>
</tr>
<tr>
<td>Qualitative Analysis; Statistical tests</td>
<td>(MOHAMMADZADEH, 2020)</td>
</tr>
<tr>
<td>Qualitative Analysis; Statistical tests; Spatial Analysis</td>
<td>(CAULFIELD et al., 2021)</td>
</tr>
<tr>
<td>Descriptive statistics</td>
<td>(DEWEESE; RAVENSBERGEN; EL-GENEIDY, 2022)</td>
</tr>
<tr>
<td>Descriptive statistics; indicators</td>
<td>(HIDALGO-GONZALEZ; RODRIGUEZ-FERNANDEZ; PÉREZ-NEIRA, 2022; SULTAN; KATAR; AL-ATROUSH, 2021)</td>
</tr>
<tr>
<td>Statistical tests</td>
<td>(DZISI et al., 2020; HAMAD; HTUN; OBAID, 2021; LOGAN et al., 2020; MALJAEE; KHADEM SAMENI, 2022; RIBEIRO; FONSECA; MEIRELES, 2020)</td>
</tr>
<tr>
<td>Statistical tests; Conceptual Model</td>
<td>(SOLTANI et al., 2019)</td>
</tr>
<tr>
<td>Statistical tests; Rasch Model</td>
<td>(IRAWAN et al., 2021)</td>
</tr>
<tr>
<td>Statistical tests; Spatial Analysis</td>
<td>(DE ANGELIS; MANTECCHINI; PIETRANTONI, 2021; MAIA et al., 2020; TRČEK; MESAREC, 2022)</td>
</tr>
<tr>
<td>Econometric model</td>
<td>(ANOWAR et al., 2019)</td>
</tr>
<tr>
<td>Regression Models</td>
<td>(CHEN et al., 2022; HAGGAR; WHITMARSH; SKIPPON, 2019; TEUBER; SUDECK, 2021)</td>
</tr>
<tr>
<td>Spatial Regression</td>
<td>(RYBARCZYK, 2018)</td>
</tr>
<tr>
<td>Binary logistic regressions</td>
<td>(DE PÆPE et al., 2018; DZISI; LUGÁDA, 2021; RERAT, 2021; TON; DUIVES, 2021; VICH et al., 2021)</td>
</tr>
<tr>
<td>Decision tree model</td>
<td>(CÁDIMA; SILVA; PINHO, 2020; CAPASSO DA SILVA; RODRIGUES DA SILVA, 2020)</td>
</tr>
</tbody>
</table>
Some authors also adopted regression models. One study chose to utilize a spatial regression model (GWR) in its analysis, aiming to incorporate spatial variations of the phenomenon (RYBARCZYK, 2018). These variations highlight the importance of localized interventions based on the specifics of the region where the campus is located, as well as coordinated efforts between the university and the surrounding community. There has also been an increasing use of logistic regressions as a data analysis tool. This type of regression offers several advantages over the commonly used multiple regressions. One advantage is its suitability for modeling binary or categorical dependent variables, for example. In the case of Dzisi and Lugada (2021), binary logistic regression proved to be the ideal approach for constructing an appropriate model when predicting the probability of students switching their mode of transportation from motorcycles to bicycles.

More unique data analysis techniques were also found. One of them involves decision tree models. This data mining technique was adopted due to its non-parametric approach, allowing several types of variables and not relying on significant mathematical assumptions (CAPASSO DA SILVA; RODRIGUES DA SILVA, 2020). Cadima et al. (2020) also highlight the advantage of working with

<table>
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<tr>
<th>Approaches</th>
<th>Reference</th>
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<tbody>
<tr>
<td>Logit Models</td>
<td>(BERIA et al., 2021; CROTTI; GRECHI; MAGGI, 2022; DELL’OLIO et al., 2019; GOKASAR; BAKIOGLU, 2018; HENNING; FERREIRA SHUBERT; CECCATO MAGIEL, 2020; JIAGENG; LANLAN; XIANGHONG, 2022; MCQUEEN; CLIFTON, 2022; MONIRUZZAMAN; FARBER, 2018; NGUYEN-PHUOC et al., 2018; PAPU CARRONE et al., 2020; PIKE; LUBELL, 2018; SAILLUANGA; HMANGAIHZELA, 2022; SARANGI; MANOJ, 2020; SWEET; FERGUSON, 2019; YAN; LEVINE; MARANS, 2019)</td>
</tr>
<tr>
<td>Structural equation models</td>
<td>(PINTO et al., 2019; RAHMAN; POUDEL; SINGLETON, 2021; VAHEDI; SHAMS; MEHDIZADEH, 2021)</td>
</tr>
<tr>
<td>Integrated modeling</td>
<td>(ETMINANI-GHASRODASHTI; PAYDAR; HAMIDI, 2018; HASNINE; CHUNG; NURUL HABIB, 2022; KIM; LEE, 2023; LIZANA; TUDELA; TAPIA, 2021; MEHDIZADEH; ZAVAREH; NORDFJAERN, 2019; NIKIFORIADIS et al., 2023; NORDFJÆRN; EGSET; MEHDIZADEH, 2019; SFEIR; ABOU-ZEID; KAYSI, 2020; VAN LIEROP; BAHAMONDE-BIRKE, 2021)</td>
</tr>
<tr>
<td>Agent-based simulation</td>
<td>(FABOYA et al., 2020)</td>
</tr>
<tr>
<td>Traffic simulation</td>
<td>(HAMAD; OBAID, 2022)</td>
</tr>
</tbody>
</table>

Source: The authors.
small samples. Another example of unique analysis can be seen in Hamad and Obaid (2022) work, which significantly contributed by integrating a demand forecasting model with a microsimulation of traffic, considering the entire transportation network. This integration also allowed for the evaluation of pollutant emission scenarios.

The agent-based simulation had limited usage in the analyzed studies. Fáboya et al. (2020) conducted a study applying this type of simulation and demonstrated how a theory-based framework could be used in numerical experiments to explore actual travel choice behaviors. Following this approach, Pinto et al. (2019) incorporated the Theory of the Lazy User into the structural equation model. This theory posits that all individual decisions can be explained by the principle of least effort, considering four concepts: money availability, time availability, and physical and mental effort.

6 CONCLUSIONS

The purpose of this literature review was to gather and discuss academic works published in recent years that focused on the analysis of modal choice in university travel. Out of the 80 papers found, 70 were selected for analysis. Firstly, a description was provided regarding the motivation behind these studies, revealing a predominant trend in investigating barriers and opportunities for using specific modes. This indicates a significant concern with promoting changes in the travel behavior of the university population, aiming for more sustainable mobility.

The data collection instruments and analysis tools were the main focus of this review. Most authors mentioned the use of online research instruments. However, a significant adherence to in-person surveys was observed. One limitation regarding preference studies relates to the sample. Researchers have been employing strategies such as utilizing social media and offering prizes as a reward to encourage public participation.

Regarding data analysis tools, some studies applied a qualitative approach. However, most studies employed a quantitative analysis approach, utilizing both traditional and more complex methods. Some studies adopted a mixed
approach, incorporating theory-based structures into numerical experiments to explore choice behaviors. New types of tools and additional variables have emerged in recent studies. In addition to the commonly used socioeconomic and behavioral variables, variables explaining the effects of the global pandemic scenario on university travel behavior were observed.

One of the limitations encountered during the development of this review pertains to the level of detail provided in the conducted research. Some studies omit crucial information necessary for method replication or result comparison.

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