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Effects of the built environment on the share of transportation modes in Bratislava

Bachelor Thesis

Spatial Planning and Design

Michal Bartek S4784987
Supervisor: Samira Ramezani

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Contents

1 Abstract

The topic of the effects of the built environment (BE) on the share of different modes of transport has been extensively studied in the context of sustainable development goals pursued by countries and cities globally. This study on the effects of the built environment on transportation modes in Bratislava focuses on the Eastern European context, taking car ownership into account. The study utilizes both secondary and primary data sources and employs multiple linear regressions to analyze the effects of the BE on the share of transportation modes. BE factors studied include Population density, cycling network density, road density and public transportation stop density. Results indicate that while in Bratislava the mentioned BE factors do not have a statistically significant effect on the share of transportation modes on their own, they enhance the explanatory power of models for car and public transportation modes. Subsequently, in order to evaluate the effects at the district level, six reference districts were analyzed using descriptive statistics. Car ownership emerged as a significant variable, highly correlated with the share of different transportation modes on one hand and with the effects of the built environment on the other. Policy makers and spatial planners in Bratislava and other Eastern European cities should consider the impact of BE features on transportation mode prevalence when creating policies for more targeted interventions in the field of urban mobility. Additionally, they should take into account other factors such as sociodemographic variables and car ownership, which were controlled for in the research with significant effects. Future studies could examine the city at the neighborhood level to uncover more nuanced results.

Keywords: Built environment factors, share of transportation modes, Sustainability, Bratislava, Car ownership, Trip characteristics, Sociodemographic factors, Preferences and attitudes

2 Introduction

2.1 *Background*

Over the past three decades, car ownership has been steadily increasing across most European countries (European Commission A, 2021), counter to the sustainable transportation goals set by the European Union. Initiatives within the Urban Mobility Framework, such as free transport tickets, parking fees, and congestion charges, aim to mitigate this trend by reducing the number of cars on the road, thereby addressing air pollution and congestion issues (Rye&Hrelja, 2020). European cities have taken proactive measures to promote sustainable transportation, including public transit, cycling, and walking.

However, while some major Western European cities and countries have seen success in these efforts, certain regions of Eastern Europe have experienced a significant increase in car ownership in recent years. For instance, in Bratislava, there are 759 cars per 1000 inhabitants (Statistical Office of the SR, 2021), compared to 371 in geographically close Vienna (Frey et al., 2023), 376 in Budapest (Bucsky, 2020) or 281 in Zurich (Menendez & Ambühl, 2022). The car ownership strongly correlates with higher car usage (Laviolette et al., 2021), thus rise in car ownership raises questions about the dynamics of transportation mode choice, particularly in light of the EU's active promotion of alternative forms of transport. The transportation mode choice is frequently linked to built environment (BE) factors; however, the impacts of these factors can vary significantly across different contexts (Yin et al., 2022). As a result, such concepts remain untested in Eastern European contexts. Furthermore, there has been no identified passenger mobility survey conducted in Slovakia to provide a deeper understanding of this phenomenon (European Commission et al., 2022).

Transportation mode choice is a crucial factor in the multiple realms of human society. It significantly influences population health and well-being by affecting physical activity levels. Active transportation and public transit usage are associated with healthier lifestyles, contributing to overall physical health (Adkins et al., 2012; Mueller et al., 2015; Herreros-Irarrázabal et al., 2021). Furthermore, transportation mode choice can have an effect on climate change and emission production (Ana Luiza Ferrer&Tavares, 2023). European cities have been pioneers in addressing air pollution and combating climate change, with global organizations like the World Bank stressing the importance of reducing motorization in urban areas to tackle these challenges. Air pollution, linked to 500,000 premature deaths worldwide, including in European cities, poses severe health risks (WHO, 2017; European Environment Agency, 2023; Nieuwenhuijsen, 2016).

Furthermore, transportation mode choice influences physical health, with frequent car use strongly correlating with increased obesity rates (Frank et al., 2007). Initiatives aimed at decreasing car dependency and promoting effective urban transport systems seek to address these issues (European Commission B, 2021). These efforts promote safer, environmentally friendly transportation modes, enhancing physical health and overall life satisfaction (Yin et al., 2020). Furthermore, active transportation initiatives are expected to generate over 435,000 additional jobs in 56 European cities (WHO, 2017).

Additionally, these transportation modes are more environmentally friendly and sustainable compared to individual motorized options (Xia et al., 2013). Hence, numerous organizations advocate reducing reliance on individual motorized transport in urban areas, prompting many cities to implement initiatives favoring active transportation while reducing car usage.

For instance, Vienna managed to significantly decrease the share of car trips between 1993 and 2014 (Buehler et al., 2016) with a mix of policies including land-use policies making car trips unattractive and improving conditions for walking, cycling, and public transport. On the other hand the geographically close city Bratislava has seen a rise in motorization rates and car ownership (Horňák et al., 2013).

This trend underscores the challenges in promoting sustainable transportation modes in certain regions. In Bratislava alone, the number of cars has more than doubled from 198 thousand in the year 2000 to 414 thousand in 2020 (Statistical Office of the SR, 2021). One of the significant factors influencing car usage and transportation mode choice in general is the Built environment as also seen in the Vienna example. Given the significant influence of the built environment (BE) on transportation mode choice (Handy et al., 2006), it is essential to examine the applicability of the BE effects on mode transportation choice in various geographical and cultural contexts. Study at hand focuses on Eastern Europe, particularly Bratislava, to assess whether and to what extent built environment characteristics affect transportation choices in this region.

2.2 *Research problem*

The research aims to investigate how specific built environment features influence transportation modes in different districts of Bratislava while controlling for sociodemographic factors, preferences and trip distance influencing the share of modes of transport. The modes of transport included in the study are the car as the transportation mode, public transportation and active forms of transport (cycling and walking). Furthermore the research examines the car ownership role in this dynamic. In order to research these concepts in Bratislava a research question has been developed as following:

- What aspects of the Built environment influence the share of specific transportation modes in the city districts of Bratislava and what is the role of car ownership in this dynamic?

With the subquestions stated as following:

- How does the BE affect car ownership in Bratislava?
- How does car ownership influence the share of transportation modes in Bratislava?
- How does the BE and infrastructure in different districts of Bratislava affect the share of different mode choices?

3 Theoretical framework

The influence of the built environment on transportation mode choice is a well-established concept within urban planning and transportation research. Scholars (Handy et al., 2006; Yin et al., 2020) have developed theories emphasizing how elements of the built environment shape people's transportation behaviors. These findings suggest that factors such as land use patterns or access to transportation infrastructure can significantly impact individuals' decisions regarding how they travel within urban areas.

However, before implementing policies related to the built environment, it's essential to study its effects within specific contexts, such as in the case of the study at hand - Eastern European cities. Despite initial trends favoring public transport in Central and Eastern European countries during the early 1990s, this trend has not been sustained (Horňák et al., 2013). Cities like Bratislava have experienced increases in car ownership, raising questions about the influence of the built environment on transportation choices in local contexts.

Assessing the effects of the BE on share of transportation mode choice in the Eastern and Central European context, particularly in Bratislava, is critical. Therefore, a literature review was conducted to examine the influential built environment factors affecting transportation mode choice. Following this, a theoretical framework was developed.

3.1 *Density*

Density strongly influences transportation mode choice, as indicated by research (Cervero, 2002). In densely populated urban areas, there is a tendency for people to opt for public transport, walking, and cycling as primary modes of transportation rather than car usage (Gascon et al., 2020; Stefansdottir et al., 2019). The proximity of amenities, workplaces, and transit options in densely populated areas reduces the reliance on cars, making alternative modes more convenient and desirable for the population. This concept underlines how density shapes transportation preferences, leading to more sustainable and active forms of travel within urban environments.

3.2 *Cycling infrastructure*

The density of a cycling infrastructure network significantly influences transportation mode choice, as highlighted by research (Fosgerau et al., 2023). Studies suggest that well-developed networks of bicycle lanes increase the number of people who choose cycling as their dominant mode of transportation (Ton et al., 2019). Areas with extensive cycling infrastructure provide safer and more convenient options for cyclists, encouraging more individuals to adopt cycling for commuting or short-distance travel. The accessibility and connectivity of cycling infrastructure contribute to its effectiveness in promoting cycling as a viable alternative to driving, therefore reducing traffic congestion, emissions, and promoting healthier lifestyles.

3.3 *Public transportation stops network*

The network of public transportation stops significantly influences transportation mode choice, as highlighted by research (Ingvardson & Nielsen, 2018; Gascon et al., 2020). The availability and accessibility of transportation infrastructure, including well-connected transit systems and convenient access to stations, play crucial roles in encouraging public transport ridership. Areas with extensive transit networks and stations located within convenient distances tend to attract more transit users (Rao & Pafka, 2021), as they offer efficient travel options compared to driving. Research indicates that a distance of 300-400 meters to stops is particularly influential (Stojanovski, 2019), as it ensures accessibility and convenience for potential users. This close proximity reduces the usability barriers and encourages individuals to opt for public transportation over individual vehicles, contributing to a more sustainable and efficient transportation system overall.

3.4 *Car ownership*

Car ownership is strongly correlated with the built environment, particularly density (Karjalainen et al., 2021), access to public transportation stops and cycling infrastructure as important variables in the effects of BE on mode choice of transport dynamic (Ding et al., 2017). In densely populated areas with limited parking space, individuals may rely more on public transit and cycling lanes, reducing their need for cars. The availability and proximity of public transportation stops offer convenient alternatives, while well-developed cycling infrastructure promotes healthier and environmentally friendly transportation option. Contrary, in less densely populated areas with limited public transit options, car ownership tends to be higher. The design and infrastructure of the built environment significantly influence the car ownership rates and influence mode choices for transportation. In the most prominent example of this relationship: increased car ownership leads to higher car usage (Laviolette et al., 2021).

3.5 *Trip characteristics (Distance, time and costs)*

Studies often overlook how factors like trip duration and costs influence mode choice (Cervero, 2002). The duration of urban trips, along with factors such as destination and expenditure, significantly impacts transportation mode selection (Le & Teng, 2023; Axhausen, 2007). Shorter urban trips tend to favor walking or cycling (Ek et al., 2021), while longer ones may lean towards public transport or driving. Understanding these dynamics is essential for designing effective urban transportation policies and infrastructure that helps to study diverse travel needs and preferences of the population.

3.6 *Sociodemographic factors*

Sociodemographic factors are a crucial factor when it comes to influence on share of different mode choices and are included within the study at hand. Age is a significant factor when it comes to selection of the preferred mode choice (Abdullah et al., 2021) as younger people tend to prefer public transport (Brown et al., 2016; Şimşekoğlu et al., 2015). Gender is also a highly influential factor (Lindström, 2003) as females tend to spend less time travelling with active modes of transportation then males (Ek et al., 2021). Demographic with the trouble-free access to various modes of transportation has been shown to be a significant factor in multiple studies. Individuals with discounted or prepaid cards are more likely to use public transportation compared to those who purchase single tickets (Abrate et al., 2009). Similarly, access to a bicycle increases the likelihood of using active modes of transportation (Biassoni et al., 2023), while access to a car does not lead to increased time spent traveling by car (Tiikkaja & Liimatainen, 2021).

3.7 *Preferences and attitudes*

Personal attitudes and preferences play a significant role in individual mode choice (Choo & Mokhtarian, 2004; Vredin Johansson et al., 2006). Key factors influencing this choice include environmental considerations, flexibility, convenience, and comfort, all of which affect transportation mode selection (Vredin Johansson et al., 2006). A value system is also influential; for instance, individuals who prioritize status and power often value ownership and might prefer car usage (Şimşekoğlu et al., 2015; Paulssen et al., 2013).

Those who prioritize environmental aspects tend to use public transportation or active modes of transport (van Lierop & Bahamonde-Birke, 2021). Individuals who prioritize convenience are more likely to travel by car (Jaime Sierra Muñoz et al., 2024). Those who value comfort and flexibility also tend to prefer traveling by car (Şimşekoğlu et al., 2015). Finally, individuals who acknowledge the quality of a specific transportation mode are inclined to use that particular mode (Luan et al., 2022).

3.8 Conceptual Model

The conceptual model works with factors and dependent variables embodied in the share of different modes of transportation. Factors are the characteristics of the Built environment that will be tested in the context of Bratislava. These are population density, cycling network density, public transportation network coverage (in % per district) and road density. These BE factors jointly with the sociodemographic factors, preferences, attitudes, trip specifications will be tested whether they have a significant effect in the context of Bratislava. While societal factors, preferences and trip characteristics are influential, the research at hand focuses primarily on the effects of the built environment. Therefore, the change in the importance and significance of BE coefficients will be investigated more thoroughly. The study prioritizes the core of understanding how urban infrastructure shapes transportation behaviors and takes the rest of the factors into account as a control variables for better understanding of local modal choices in Bratislava. The direct relationship and influence of these factors on modes of transport has been described in the theoretical framework and will be investigated in the research. The indirect link connects to the eminent problem of Bratislava mentioned in the research background and that is the rising number of motor vehicles in the city and therefore has been tested independently of the sociodemographic factors for a focused and more nuanced review. As the relationship between household car ownership and travel mode choice has been proven in general (Ding et al., 2017), it will be tested in the context of Bratislava.

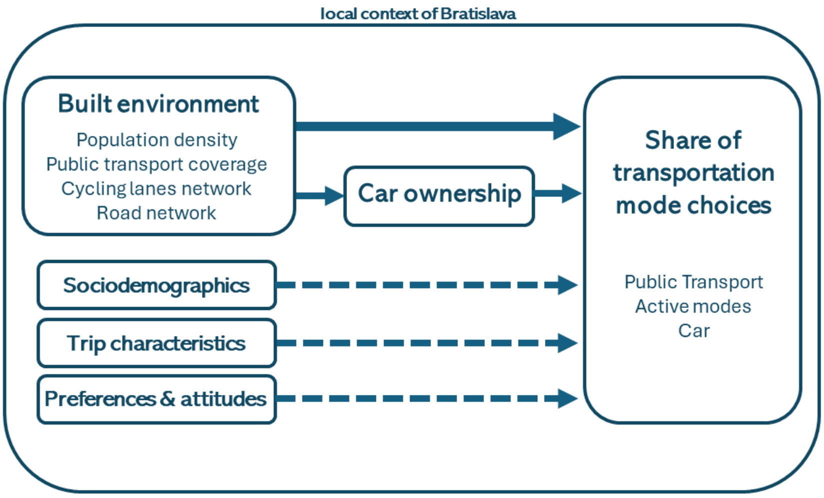

Figure 1: Conceptual model

3.9 *Hypothesis*

Based on the literature discussed in the theoretical framework and the conceptual model, the following hypotheses have been formulated:

- Increase in population density results in increase of share of active modes of transport, public transportation and decrease in car usage and ownership.
- There is a positive relationship between the Public Transportation network coverage and share of public transport usage in Bratislava.
- There is a positive relationship between the density of the cycling lanes network and active transportation usage in Bratislava and negative relationship with car usage and car ownership.
- There is a negative relationship between car ownership rate and active transport or public transport usage in Bratislava and a positive relationship with the car mode transportation choice.
- Car ownership as the mediator in this dynamic is influenced by the BE characteristics.

4 Methodology

4.1 *Research method*

A quantitative method was chosen to identify patterns based on a larger dataset, which allows for robust statistical analysis and findings that can be generalized. This approach allows for comparability across the districts of Bratislava with meaningful insights. By using quantitative methods, the study can apply broader concepts to the city of Bratislava with larger reliability and objectivity, supporting evidence-based spatial policy-making.

4.2 *Study area*

The administrative division of the Slovak capital consists of counties of approximately 100,000 inhabitants, further subdivided into city districts, which serve as the primary source of the data on the official administrative division basis. In the majority of the cases, the districts represent distinct characteristics shaped by their history of development and generally reflect the neighborhoods within them. In the research, the focus is on the whole city of Bratislava. For more detailed descriptive statistical analysis six districts of Bratislava with a sufficient number of respondents from the questionnaire were chosen (Fig. 2). Districts differ in their BE characteristics and nature (Fig. 4 BE factors). Respondents of different backgrounds and ages from all districts were asked to provide valuable entries for the dataset and analyzing the concepts stated in the theoretical framework.

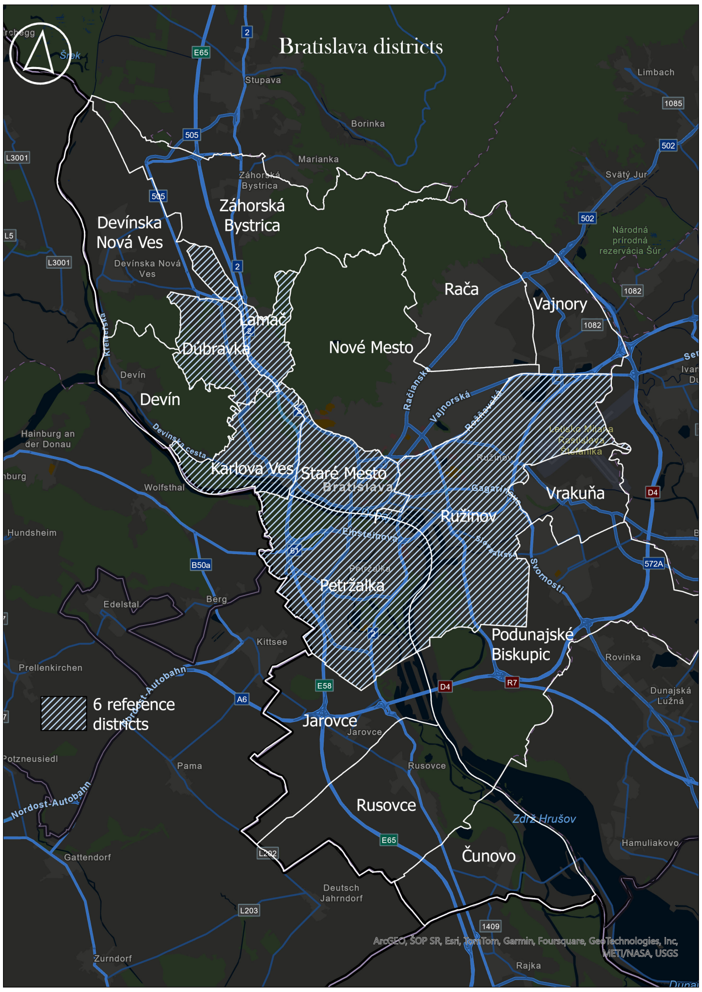

Figure 2: Bratislava districts and reference districts

4.3 *Data*

The key aspect of the data used in the study lies in utilizing a combination of primary and secondary data. Existing secondary datasets were used mostly to analyze the built environment, while primary data to fill in gaps where research and quality data was lacking or unavailable. Variables using the secondary data available were population density, the network of public transportation stops, and the network of cycling lanes density and road density. Primary data about the sociodemographic, preferences, trip characteristics factors were collected to gain more insights and explanatory power. Car ownership statistics was also sourced from the primary data collection to grasp car ownership rates in the districts separately from each other, but also on the individual level prediction basis. Overview of all the variables is available in Appendix 1.

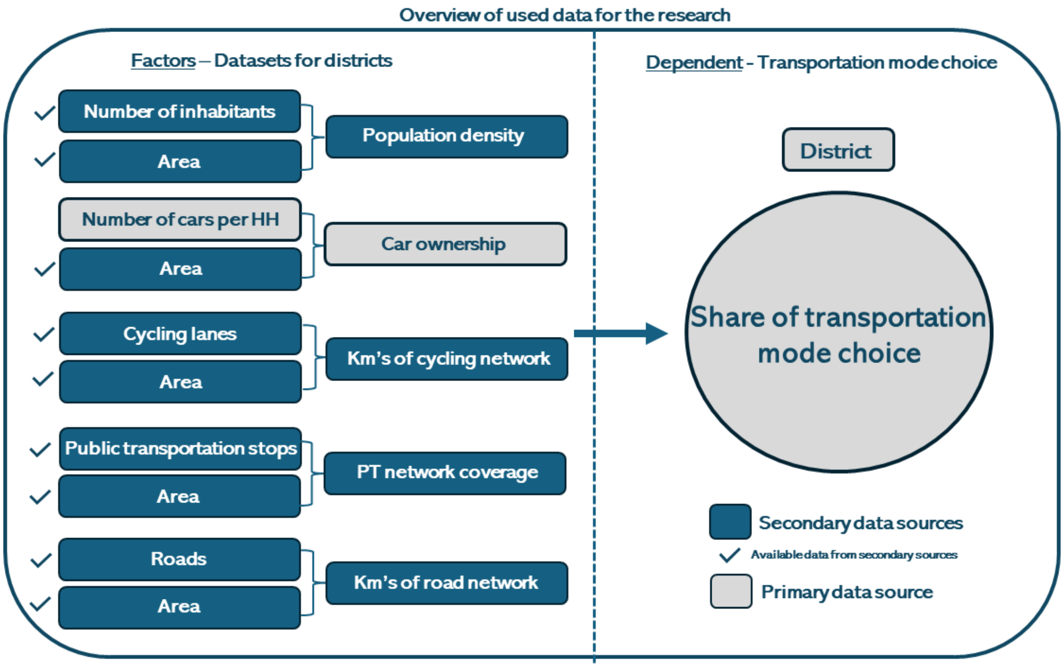

Figure 3: Data sources

4.3.1 *Questionnaire*

The data from the survey was collected over the period of one month and includes more than 300 respondents. The survey can be divided into three main themes. First theme concerned sociodemographic factors such as age, gender or education used to predict the share of modes of transport. The second theme concerned the trip specific data like the distance, home district and most importantly the main dependent variable the share of different modes of transport in Bratislava. The respondents indicated for each mode average daily time spent with that mode in minutes. Thirdly the preferences& attitudes of the respondents about BE and different modes of transportation were asked to help in explaining the dependent variable. Respondents indicated on the ordinal scale (Likert-scale) from 1-7 (strongly disagree - strongly agree) their attitude towards the statements about the different modes of transport. The questionnaire was in Slovak language for the convenience of the respondents, however also the translated version is provided in Appendix 2.

4.3.2 *Sample selection*

The sample was collected primarily but not exclusively from respondents living in 6 districts for the detailed analysis, containing various demographics. Questions in the survey focused on the respondents time spent on different mode choices as well as socio demographic information, trip characteristics or preferences and attitudes. Approximately normal distribution over sociodemographics was the important aim of the sample selection for the meaningful conclusions. For the sufficient sample size and desired normality of the dataset, multiple layers of recruiting of the respondents have been conducted.

Via social networks

Most of the recruiting was achieved through a combination of targeting close contacts and further reaching out through the social network using the snowball sampling method with which up to 200 respondents were recruited. These respondents have been invited to fill out the questionnaire via social media and group chats.

Via letterbox invites

Letterbox recruiting was employed to ensure representatives of the sample from the districts that the snowball method had little success in. Contacting more of the possible respondents living in these areas was done by random sampling and distributing flyers with QR code to the survey (Appendix 2). Around 100 flyers were distributed to post boxes around these districts. Estimated 10 responses were achieved from this method, presenting a relatively low response rate.

Via online platforms

The link to the online questionnaire was sent into the various online social groups within the city of Bratislava. The link was then further circulated online where members and inhabitants of various communities and social media groups could respond. Up to 100 responses were achieved from this method.

4.3.3 *GIS analysis*

GIS analysis was conducted in order to evaluate the BE factors in the districts of Bratislava. Formatting of the different datasets was conducted in Python software coding language (Appendix 3) before it was used in ArcGIS for handling spatial analysis. In ArcGIS, Population density was assessed by dividing the population by the area of each district. The road and cycling density datasets were intersected and spatially joined for the sum of them for each district. The network density was finalized by dividing the sum by the area for representative measure. Subsequently, the Public transportation network variable was computed by creating a buffer of 300 meters from the public transportation stops as it deemed the distance people are willing to reach (Stojanovski, 2019). The buffers were dissolved into one coherent layer and intersected again by the boundaries of city districts. The accessible PT area for each district was divided by the total area of the district for the proportional public network coverage of all districts. The total of 4 BE factors were established for all 17 districts of Bratislava (Fig. 4).

District	PTcoverage (percent)	Population	Population Density	ShapeArea (m2)	Cycling Density	Road Density
Čunovo	13,72	1770,00	95,03	18626006,43	586,06	769,30
Devín	21,46	2071,00	147,85	14007472,62	741,35	1163,85
Devínska Nová Ves	27,50	17067,00	704,76	24216913,61	751,33	1314,57
Dúbravka	51,00	35572,00	4112,98	8648714,66	551,41	4228,48
Jarovce	6,09	3016,00	141,44	21323848,69	363,97	576,37
Karlova Ves	59,28	34942,00	3190,77	10950957,94	958,45	4148,16
Lamač	43,16	7827,00	1196,37	6542271,55	411,98	3642,63
Nové Mesto	38,39	45342,00	1209,66	37483277,01	1300,52	2052,20
Petržalka	43,18	112794,00	3936,49	28653415,76	1753,54	4949,79
Podunajské Biskupic	13,63	23276,00	547,92	42480936,64	361,95	1129,74
Rača	31,32	26214,00	1107,93	23660327,23	750,11	2261,32
Rusovce	7,73	4468,00	174,82	25557198,60	612,08	399,85
Ružinov	46,55	82483,00	2076,93	39713823,02	821,45	4611,68
Staré Mesto	93,29	47375,00	4940,48	9589147,91	3335,84	11754,81
Vajnory	33,11	6038,00	446,14	13533896,37	975,03	2159,58
Vrakuňa	31,42	20221,00	1964,00	10295800,94	594,01	1643,71
Záhorská Bystrica	10.22	7564.00	234.20	32297348.08	166.85	1012.31

Figure 4 (BE factors in the 17 districts of Bratislava)

4.3.4 *Data analysis*

The initial step in the data analysis process involved examining correlations between the built environment (BE) and the share of various modes of transportation across the entire dataset for Bratislava. To assess the strength and direction of these relationships. Spearman's rho correlation test was employed for examining the variables.

The first round of correlations aimed to evaluate the initial assumptions regarding the relationships between BE factors and the share of transportation modes. Following that, the car ownership variable was correlated with these variables to assess its relationship with BE factors and share of transportation modes in this analysis (see Fig. 12). Spearman's rho was used due to its suitability for non-normally distributed data and the limited sample size in this research.

Subsequently, two sets of multiple linear regressions were conducted to determine the influence of BE factors on the share of different transportation modes. In the initial set of regressions (one for each mode of transport, totaling three), the transportation modes were predicted without considering the BE factors. In the second set of regressions, the BE factors were incorporated into the model to examine any changes in significance and explained variance. The primary objective was set to examine whether the inclusion of BE factors improved the models or had an insignificant impact.

The formula for multiple linear regression used is given by:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_p X_p + \epsilon$$

where:

$$\begin{aligned} Y &\text{ is the dependent variable of time travelled by the transportation mode,} \\ \beta_0 &\text{ is the intercept,} \\ \beta_1, \beta_2, \ldots, \beta_p &\text{ are coefficients for the independent variables (factors) } X_1, X_2, \ldots, X_p \text{ respectively,} \\ X_1, X_2, \ldots, X_p &\text{ are the independent variables (factors),} \\ \epsilon &\text{ is the error term (residuals).} \end{aligned}$$

- β_0: The intercept represents the expected value of Y when all independent variables ($X_1, X_2, \ldots, X_p$) are zero.
- $\beta_1, \beta_2, \ldots, \beta_p$: Coefficients indicate the change in Y associated with a one-unit change in each independent variable ($X_1, X_2, \ldots, X_p$)
- $X_1, X_2, \ldots, X_p$: These are the independent variables (predictors) in the regression model.
- ϵ: The error term represents the variability in Y that is not explained by the model.

4.4 *Ethical Considerations*

Ethical considerations in utilizing secondary data are addressed within Slovakia's framework as a member of the European Union, adhering to GDPR regulations. Official data sources strictly comply to these regulations. For primary data obtained through surveys, ensuring respondent anonymity was prioritized. All collected primary data were fully anonymyzed, preventing any individual respondent from being traced back to their answers. The survey primarily focused on gathering information such as the geographical location of residents' districts, socioeconomic status, preferences, and the prevalent mode of transport used for commuting. Detailed personal information collected was handled in an aggregated manner during statistical analysis, thus safeguarding individual respondents' identities and ensuring their privacy.

5 Results

5.1 *Introduction*

In the following section, the results of the data analysis will be presented. The main research question and subquestions will be addressed. As previously discussed, the relationship between the three indicators of the district built environment and the share of different modes of transport in Bratislava will be explored. In the descriptive statistics, a comparative approach will be applied to six reference districts, focusing on car ownership and the share of various transport modes.

In the following section, car ownership and its correlations with built environment factors in Bratislava will be assessed at the whole sample level.

Lastly, two multiple linear regression models are examined for each transportation mode. These regressions are structured in pairs, each corresponding to a different category of transportation mode (car, public transport, and active modes). As previously mentioned, the **first set** (model A) was conducted **excluding built environment factors**, while the **second set included these factors** (model B). In the multiple linear regression analysis, the significance level and r-squared value are evaluated for each test.

In multiple linear regression, the coefficient of determination (R^2) is calculated as:

$$R^2 = \frac{SSR}{SST}$$

where:

$$SSR = \sum_{i=1}^{n} (\hat{Y}_i - \bar{Y})^2$$
$$SST = \sum_{i=1}^{n} (Y_i - \bar{Y})^2$$

- SSR is the Regression Sum of Squares, which measures the explained variation by the regression model ($\hat{Y}_i$) and the mean of the dependent variable ($\bar{Y}$).

- SST is the Total Sum of Squares, which represents the total variation in the dependent variable Y ($\bar{Y}$).

It is important to note that correlation does not always imply causation. Given that the compared districts are seemingly quite similar and the dataset is not extensive, the threshold for a p-value of 0.1 (90% confidence interval) will be considered meaningful in the analysis. This slightly higher threshold allows to account for the similarities between the districts, providing a more detailed understanding of the relationships between built environment factors and transport modes without being overly rigid in the interpretation. In the figures the BE factors are reported as well as the significant values of other explanatory factors. Complete SPSS outputs with all the variables are included in the Appendix 4.

5.2 *Descriptive statistics*

The first figure (Fig. 4) presents the complete table for the built environment (BE) factors of the districts of Bratislava, allowing for a comparison of the selected districts. The included maps (Fig. 5, Fig. 6) show the density of the districts and the Public transportation coverage per district for better understanding of the context.

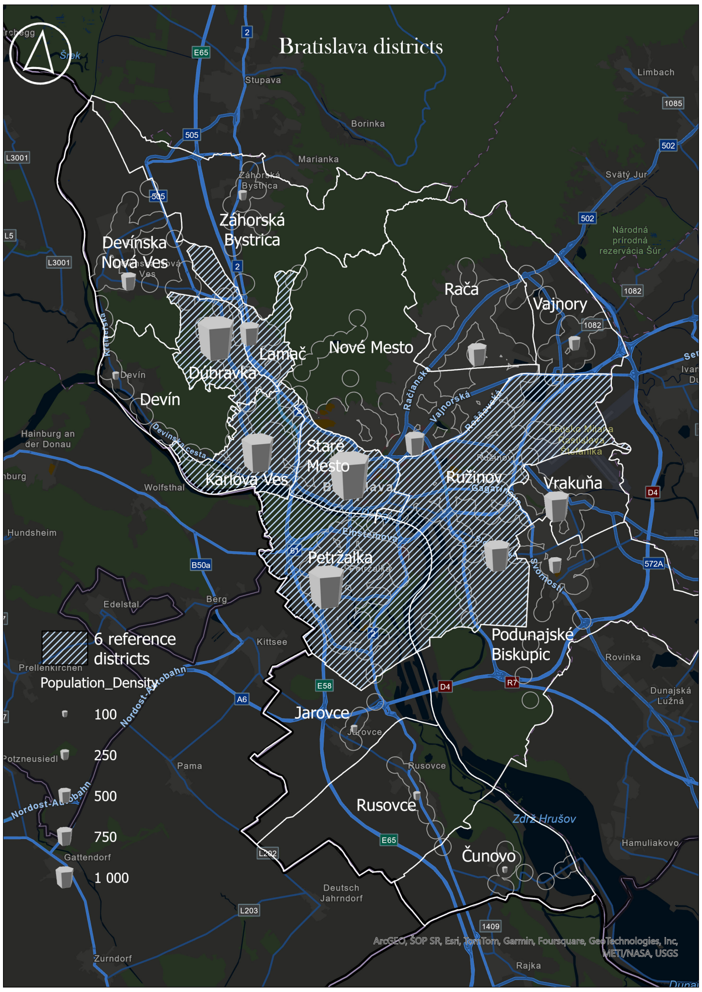
Bratislava districts
Devínska Nová Ves
Záhorská Bystrica
Rača
Vajnory
Nové Mesto
Lamač
Dúbravka
Devín
Staré Mesto
Karlova Ves
Ružinov
Vrakuňa
Petržalka
Podunajské Biskupic
Jarovce
Rusovce
Čunovo
6 reference districts
Population_Density
100
250
500
750
1 000

Figure 5

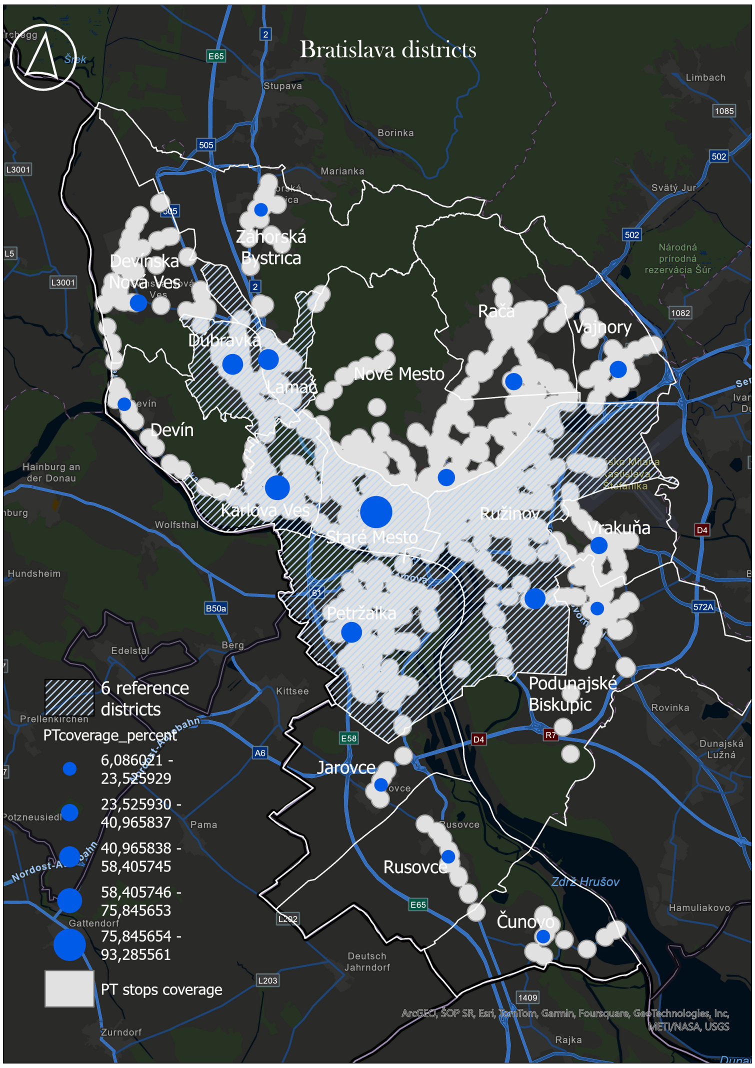

Figure 6

In the third figure (Fig. 7), the mean number of cars per household in six reference districts is shown alongside the count of respondents who answered this question. There are no significant discrepancies in the average number of cars per household across the districts of Bratislava. However, the Old Town (Stare Mesto) and the nearby modernistic neighborhood of Petržalka have the lowest average number of cars per household. This could be attributed to their proximity to the city center and higher density which is in line with the findings of Karjalainen et al. (2021). In contrast, the less densely populated and more distant district of Lamač has the highest number of cars per household.

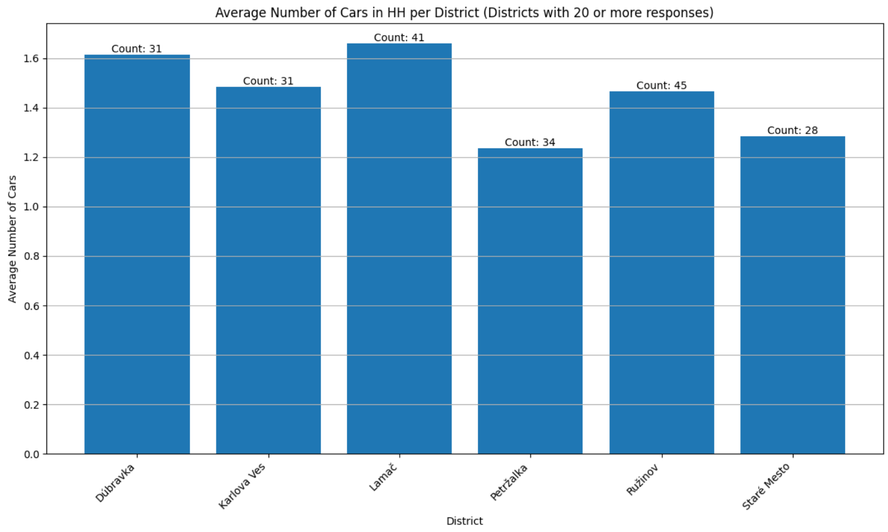

Figure 7 ,Cars ownership in Districts

Examining the share of car mode of transport (Fig. 8), the highest mean number of minutes traveled by car is seen in Lamač, confirming theories that this district's distance from the city center and lower population density contribute to higher car usage and vice versa (Gascon et al., 2020; Stefansdottir et al., 2019). Surprisingly, Ružinov exhibits high car usage despite its relatively high density and proximity to the city center, likely due to the diversity within its neighborhoods.

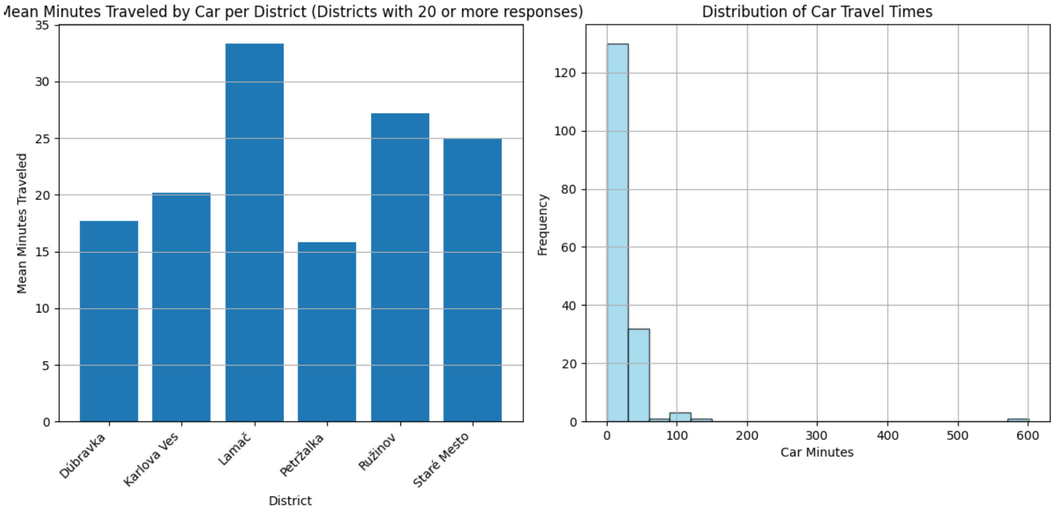

Figure 8, Car usage

Public transportation usage is highest in Dubravka and Karlova Ves (Fig. 9), as these districts are well-connected by tram lines to the city center supporting findings of Rao & Pafka (2021). Other districts show similar figures, except for Stare Mesto with lower public transportation utilization (in terms of time). This can be explained by the fact that most activities in the city occur in the city center, therefore its residents have no necessity to travel extensively or they use active modes of transportation.

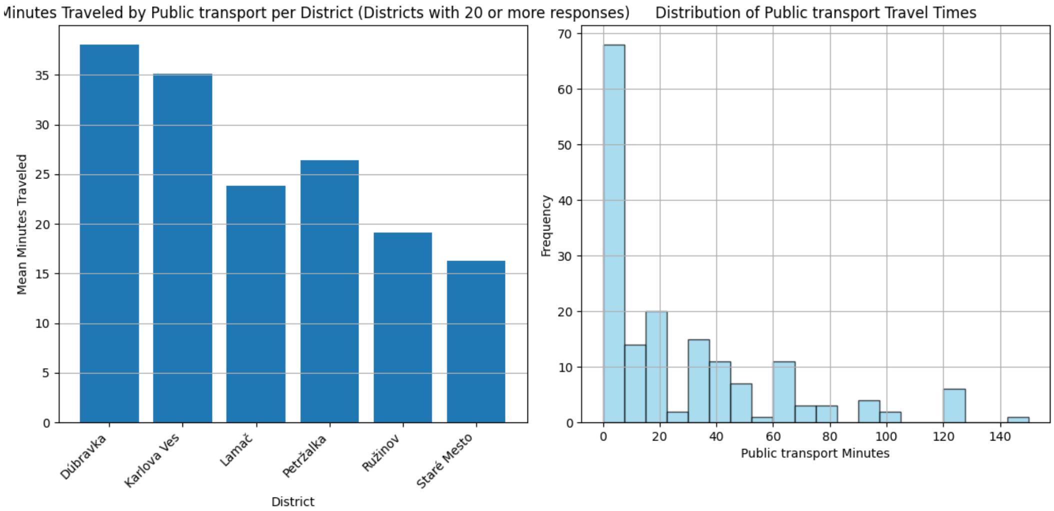

Figure 9, Public Transportation usage

Active modes were analyzed separately for more detailed insights. As shown in the figure (Fig. 10), walking exhibits relatively uniform trends, whereas cycling varies significantly between districts. The lowest level of cycling (Fig. 11) was recorded in Lamač, which has poor cycling infrastructure, supporting theories that cycling is more popular where infrastructure is available (Ton et al., 2019). Highest recorded mean cycling value was in Karlova Ves, which has an important cycling highway in its boundaries most likely embracing these figures.

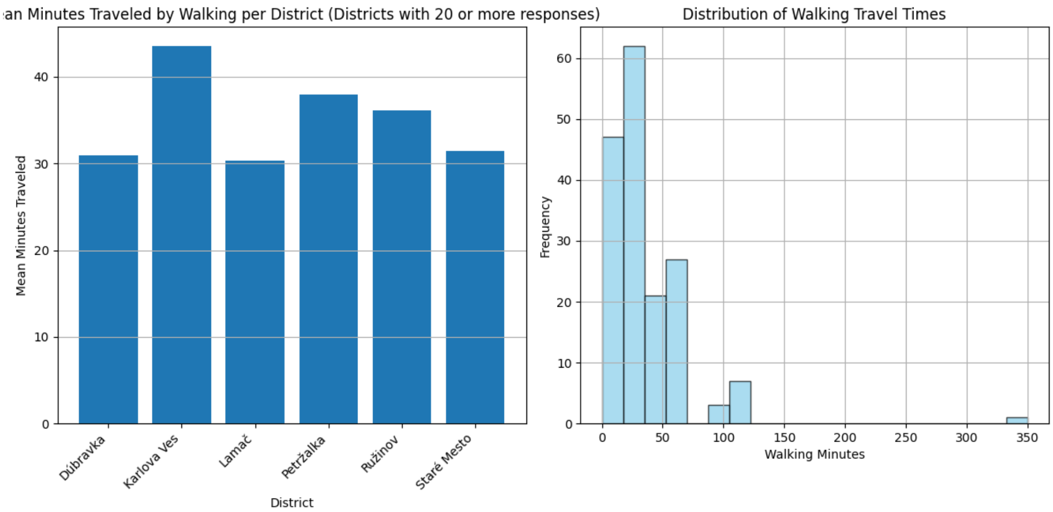

Figure 10, Walking transportation

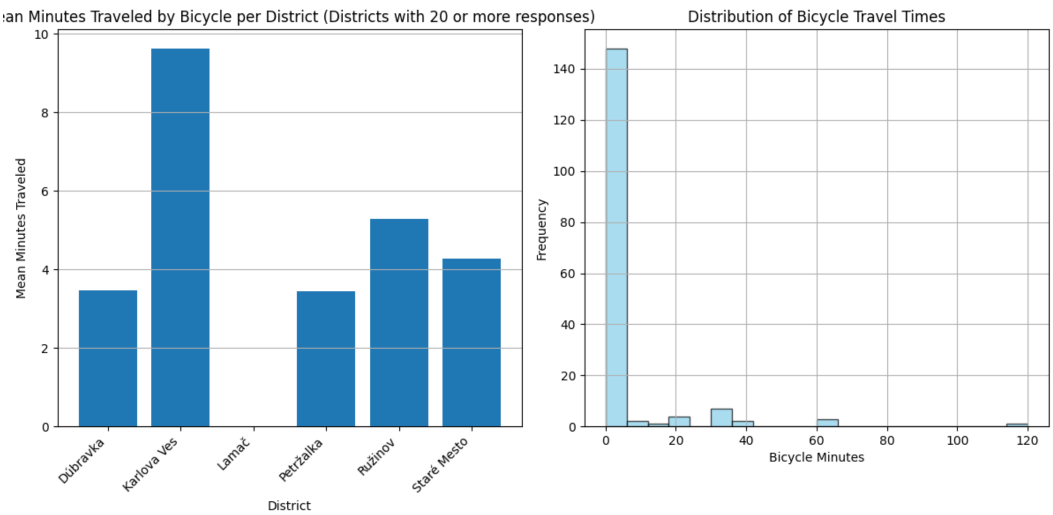

Figure 11, Bicycle transportation

5.3 *Car ownership*

In the following segment, the correlations between car ownership and built environment factors are tested. As shown in the figure below (Fig. 12), three out of four built environment factors coefficients were significant at the 90% confidence level, with two factors reaching the 95% confidence level. Population density and cycling network density exhibited the highest correlations coefficients with car ownership, and the relationships were negative meaning the car ownership declines as they increase. This aligns with the theories that car ownership declines as population density increases (Karjalainen et al., 2021), although the strength of the correlation coefficient is relatively weak (below 0.3). Car ownership also has a significant and moderately positive (0.3 - 0.5) correlation with the minutes spent on car as a mode of transport underpinning the theories of Laviolette et al. (2021).

Correlations

			Number of cars in HH	Car	Public Transport	AT_Cycling + Walking	Population_Density	CyclingDensity	PTcoverage_percent	RoadDensity
Spearman's rho	Number of cars in HH	Correlation Coefficient	1,000	,328**	-,125*	-,003	-,102	-,149*	-,040	-,119
		Sig. (2-tailed)	.	<,001	,043	,955	,098	,015	,516	,053
		N	264	264	264	264	264	264	264	264

Figure 12, Car ownership Spearman's rho correlation

5.4 *Car Mode Analysis*

Null Hypothesis: In the population, there is no linear relationship between time spent using a car as a mode of transportation on one hand and all the independent variables on the other.

First Regression Model: In the initial regression model, the results were not significant with the p-value at 0.388 and R^2 value of 8.8%, indicating that we failed to reject the null hypothesis. This suggests there is no linear relationship between car usage and the independent variables. Only the three preference statements showed significance in their coefficients, implying that personal preferences play a role in car usage independent of the variables tested.

Comfort was found to be significant factor in individual mode choice for car. The Q1 on preference was found significant with negative Beta about the statement praising costs above comfort, suggesting that those who prefer comfort, travel more with car. Similarly Q2 statement uplifting comfort above other factors such as costs or environmental aspects had positive Beta meaning people valuing comfort travel more with car supporting findings of Şimşekoğlu et al. (2015). Convenience was found significant in Q7 statement about the distance to PT stop being a barrier where positive Beta was found , implying that the those who found the public transportation inconvenient to access, travel more with car underpinning that convenience is valued high by car users (Jaime Sierra Muñoz et al., 2024).

Table 1: Regression Performance, Car mode - model A

Model	R	R^2	Adjusted R^2
Model 1	0.297	0.088	0.005

Table 2: ANOVA Table for Multiple Linear Regression

Source	Sum of Squares	df
Regression	42402.602	20
Residual	437749.4817	220
Total	480152.083	240
F-statistic	**1.066**	
p-value	**0.388**	

Table 3: Coefficients

	Unstandardized Coefficients	Standardized Coefficients	
Model	B	Beta	Sig
Q1	−3.724	−0.137	0.071
Q2	3.788	0.149	0.040
Q7	3.943	0.128	0.062

*Q1 I choose the transportation mode more based on costs than on comfort and wellbeing.

Q2 Advantages associated with the ownership of car (time and comfort) outweight the disadvantages (environment implicaitons, costs, maintenance).

Q7 The distance from my home to the Public Transportation stop prevents me from using Public Transportation.

Set of figures 13, First regression on car mode

Second Regression Model with BE Factors: In the second regression model, which included built environment (BE) factors, the desired p-value of 0.1 was not reached (0.301) , resulting in a failure to reject the null hypothesis. However, the inclusion of BE factors improved the model's significance and explanatory power (R^2) from 8.8% to 11.3%. This indicates that while the overall relationship was not statistically significant, the BE factors did enhance the model's ability to predict time spent using a car mode of transportation.

The coefficients for the BE factors closest to significance (population density and cycling lanes density) were negative, supporting the theories that increased population density leads to decreased car usage (Gascon et al., 2020; Stefansdottir et al., 2019). Although the results were not significant, the improvement in the models R^2 suggests that BE factors play a role in influencing car usage, even if they do not produce a strongly significant relationship. The preferences remained significant.

Table 4: Regression Performance, Car mode - model B

Model	R	R^2	Adjusted R^2
Model 1	0.335	0.113	0.014

Table 5: ANOVA Table for Multiple Linear Regression

Source	**Sum of Squares**	**df**
Regression	54021.325	24
Residual	426130.758	216
Total	480152.083	240
F-statistic	**1.141**	
p-value	**0.301**	

Table 6

	Unstandardized Coefficients	Standardized Coefficients	
Model	B	Beta	Sig
Q1	−3.766	−0.139	0.068
Q2	4.204	0.165	0.024
Q7	4.458	0.145	0.038
Population Density	−0.005	−0.153	0.169
PT coverage	0.576	0.242	0.222
Cycling network	−0.010	−0.188	0.192
Road network	0.001	0.087	0.730

Set of figures 14, Second regression on car mode

5.5 *Public Transportation mode analysis*

Null hypothesis: In the population, there is no linear relationship between time spent using Public Transportation as a mode of transportation on one hand and all the independent variables on the other.

First Regression Model: The first model for public transportation was highly significant (p-value ¡ 0.001) and showed relatively high explanatory power compared to other models, both in with R^2 and adjusted R^2 (both between 20% and 30%). In this model, the coefficient for age was significant and negative, indicating that with each additional year of age, the average time spent traveling by public transport decreased by approximately one-third of a minute which further supports findings of Abdullah et al.(2021) and Brown et al. (2016). Another highly significant factor, with a positive effect, was the possession of public transportation subscription cards. On average, holders of these cards traveled 22 minutes more than non-holders supporting the research of Abrate et al.(2009).

Table 7: Regression Performance, Public transportation mode - model A

Model	R	R^2	Adjusted R^2
Model 1	0.533	0.284	0.223

Table 8: ANOVA Table for Multiple Linear Regression

Source	**Sum of Squares**	**df**
Regression	63192.738	19
Residual	159307.962	223
Total	222500.700	242
F-statistic	**4.656**	
p-value	**0.001**	

Table 9: Coefficients

	Unstandardized Coefficients	Standardized Coefficients	
Model	B	Beta	Sig
Age	−0.331	−0.185	0.018
PT discount/prepaid	22.469	0.371	<001
Q3	2.499	0.125	0.077

**Q3 I am willing to endure longer travel time if I save on costs*

.

Set of figures 15, First regression on PT mode

Second Regression Model:

Including built environment (BE) factors in the MLR notably improved the overall model and its explanatory power, with R^2 and adjusted R^2 values of 30.1% and 22.8%, respectively. It can be assumed the BE factors add to the power of the model although, the coefficients of the BE factors are not significant on their own. Cycling infrastructure density BE factor is the closest to significance, with slight positive effect. Public transportation card access and age remained the most important variables in terms of explanatory power and with high significance (pvalues of ¡0.001 and 0.02).

Table 10: Regression Performance, Public transportation mode - model B

Model	R	R^2	Adjusted R^2
Model 1	0.549	0.301	0.228

Table 11: ANOVA Table for Multiple Linear Regression

Source	Sum of Squares	df
Regression	67059.415	23
Residual	155441.284	219
Total	222500.700	242
F-statistic	**4.108**	
p-value	**0.001**	

Table 12: Coefficients

	Unstandardized Coefficients	Standardized Coefficients	
Model	B	Beta	Sig
Age	−0.328	−0.183	0.020
PT discount/prepaid	22.936	0.378	<001
Q3	2.033	0.102	0.158
Population Density	0.002	0.078	0.424
PT coverage	0.273	0.167	0.322
Cycling network	−0.006	−0.182	0.144
Road network	0.000	−0.041	0.850

**Q3 I am willing to endure longer travel time if I save on costs*

.

Set of figures 16, Second regression on PT mode

5.6 *Active modes of transport analysis*

Null hypothesis: In the population, there is no linear relationship between time spent using active modes of transportation as a mode of transportation on one hand and independent variables on the other.

First Regression Model: The first model predicting active modes of transportation was significant (p=0.021), indicating a rejection of the null hypothesis and suggesting the linear relationship exists. However, the R^2 value was relatively low at 14.3%, indicating that the model explains only a small portion of the variability in the dependent variable. The analysis of coefficients revealed that the number of cars in a household and access to a bicycle significantly affect the dependent variable. Specifically, the time spent using active modes of transport decreases by more than 5 minutes on average for each additional car in the household. Conversely, having access to a bicycle increases the time spent using active modes by 14 minutes. Additionally, within the 90% confidence interval, gender was a significant factor, with females traveling on average 8 minutes less than males using active modes of transportation.

Table 13: Regression Performance, Active transportation modes - model A

Model	R	R^2	Adjusted R^2
Model 1	0.378	0.143	0.064

Table 14: ANOVA Table for Multiple Linear Regression

Source	**Sum of Squares**	**df**
Regression	34611.299	20
Residual	208167.440	218
Total	242779.040	238
F-statistic	**1.812**	
p-value	**0.021**	

Table 15: Coefficients

	Unstandardized Coefficients	Standardized Coefficients	
Model	B	Beta	Sig
Cars in HH	−5.306	−0.148	0.043
Access to bike	14.593	0.197	0.005
Gender Females	−8.629	−0.132	0.053
Q3	3.070	0.145	0.065

**Q3 I am willing to endure longer travel time if I save on costs*

.

Set of figures 17, First regression on active modes

Second Regression Model with BE Factors: In the second regression mode the explanatory power slightly increased (R^2 = 14.8%). Due to the adjusted threshold for the target p-value, the model remained significant under the 90% confidence interval, allowing for an analysis of the coefficients, which showed little change from the first model. None of the BE factors proved to be significant in relation to active modes of transport. However, the density of cycling infrastructure was the closest to being significant. This may be due to the combined consideration of cycling and walking, where cycling infrastructure might have a more substantial impact if cycling were analyzed separately.

Table 16: Regression Performance, Active transportation modes - model B

Model	R	R^2	Adjusted R^2
Model 1	0.385	0.148	0.053

Table 17: ANOVA Table for Multiple Linear Regression

Source	**Sum of Squares**	**df**
Regression	35947.195	24
Residual	206831.844	214
Total	242779.040	238
F-statistic	**1.550**	
p-value	**0.055**	

Table 18: Coefficients for Active Transportation Model B

	Unstandardized Coefficients	Standardized Coefficients	
Model	B	Beta	Sig
Cars in HH	−5.205	−0.148	0.043
Access to bike	14.593	0.197	0.007
Gender Females	−8.629	−0.132	0.053
Q3	3.070	0.145	0.117
Population Density	0.002	0.078	0.493
PT coverage	−0.079	−0.047	0.809
Cycling network	−0.005	−0.126	0.373
Road network	0.001	0.124	0.617

**Q3 I am willing to endure longer travel time if I save on costs*

.

Set of figures 18, Second regression on active modes

6 Conclusions

In this study, the effects of the built environment (BE) on the share of different transport mode choices were investigated. Particular emphasis was placed on car ownership dynamics in the context of Bratislava. Findings underscore the significance of car ownership as a key variable in this dynamic, revealing its correlation with BE factors and its negative effect on public transportation and active modes of transport in the conducted analyses. The regression analysis conducted in this study highlights the different degrees of influence that BE factors have on different modes of transportation in Bratislava. Although the inclusion of BE factors generally enhanced the explanatory power of the models, their individual significance levels were quite low and cannot be taken as a decisive argument supporting the assumption that BE factors have significant effect on share of different modes of transport in Bratislava. From the limited BE factors effects, the population density and cycling infrastructure emerged as consistently the most influential factors, supporting arguments that higher density and better infrastructure tend to diminish car usage while promoting alternative modes of transport. However, it's important to note that the observed significance levels did not reach a high threshold in the context of Bratislava, indicating a nuanced relationship between BE characteristics and transportation behaviors in the city.

Furthermore, the comparison of neighborhoods based on descriptive statistics provided valuable insights into the prevailing transport dynamics across different districts of Bratislava. This analysis helped in the understanding of the complex interplay between BE characteristics and transportation mode choices in the districts of Bratislava. In the display of the descriptive statistics, the theories were much more visible with higher usage of cars and decrease in alternative modes in remote less dense districts and vice versa. Based on this evidence the BE effects on share of transportation mode choice in Bratislava can be observed, however they were not proven by the statistical analysis in statistically significant matter.

In conclusion, the study contributes to a deeper understanding of how the built environment influences transport mode choices in Bratislava. The dynamics of relationships between BE factors, car ownership dynamics, and transportation behaviors was explored, providing valuable insights for policymakers and spatial planners aiming to create a more sustainable and accessible built environment in the city of Bratislava and in the Eastern European context. Understanding the effects of factors such as BE, sociodemographics, preferences, and trip characteristics allows policymakers to more efficiently target policies aimed at influencing transportation mode choices towards more sustainable options.

6.1 *Limitations*

The use of both secondary and primary data sources in this study is accompanied by certain limitations. While secondary data provide a robust base for the research, the sources are rigid and cannot be altered according to the needs of this particular study. The limited significance of the built environment (BE) factors can be attributed to the scale of the administrative division of Bratislava, where only 17 districts are available for analysis. Some of these districts vary greatly in size, making it challenging to compare nuances such as BE characteristics and share of different modes of transport within them. Furthermore, the similarity between certain districts in terms of BE may diminish their individual effects when aggregated into the total sample of all the respondents. Ideally, a finer division into smaller neighborhoods would be an ideal setting for such research, which connects to the next limitation of the absence of the data.

In the context of Bratislava, data for smaller administrative divisions is not available, and therefore the study was conducted at the district level, which might undermine the possible statistical significance of the relationships in the context of the city. Reliance on official sources additionally narrows down the BE factors that can be calculated for meaningful analysis, resulting in a limited inclusion of BE factors in this study.

Limitations with primary data lie in the representativeness of the sample and whether respondents correlate with the demographics and travel patterns of the entire district. With some districts overrepresented and some underrepresented, the statistical results can be questioned. Descriptive statistics serve as a valuable supporting way of analysis. Another limitation connected to the sampling of the primary data are the outlying data possibly from the respondents that have misunderstood the question asked and enter disproportional values. In such a small study setting, these factors can have negative influence if they are indeed entered incorrectly.

The study might be missing additional contexts that were not included in the analysis, such as the influence of cultural preferences or more nuanced factors of modes of transport. Exploring these additional contexts such as division of Public transportation into more subcategories could provide a more comprehensive understanding of the complex relationships between the built environment and transportation behaviors in districts of Bratislava. Moreover, studying the role of emerging technologies, such as ridesharing services or electric vehicles, could help in examining the trends in mobility and BE.

6.2 *Further research*

The study of Bratislava provides replicable tools that can be followed in similar studies in other cities. While specific factors and approaches are tailored to the Eastern European context and focus on factors like car ownership, preferences etc., the methodology—employing multiple regressions and emphasizing built environment, offers a template for assessing transportation behaviour elsewhere. Policymakers and planners can adapt these approaches to their local contexts, though considerations of urban structure, cultural context and preferences will influence the approach. Further research at neighborhood levels could improve these insights for broader applicability.

Additionally, research could delve deeper into the nuanced relationships between the built environment (BE) and modes of transportation in Bratislava. Specifically, future studies could consider collecting more precise data by asking respondents about the precise locations of their homes and commuting destinations. This approach could provide a stronger basis for analyzing how specific BE characteristics, such as proximity to public transportation stops or cycling infrastructure, influence individuals' transportation choices.

Additionally, future research could explore the temporal aspects of transportation behaviors, considering factors such as time of day, day of the week, and seasonal variations that can be seen with active forms of transport. Understanding how transportation patterns fluctuate over different time periods would be a valuable insight into the dynamics of transport behaviors in Bratislava.

Moreover, qualitative research methods, such as interviews, could support quantitative analyses by providing in-depth insights into the perceptions, attitudes, and preferences of residents regarding transportation and the built environment. This qualitative approach could help uncover more hidden and detailed factors driving transport behaviors and be a source for more targeted interventions aimed at promoting sustainable modes of transportation in Bratislava.

By exploring these ideas for future research, there can be an understanding of the complex dynamics between the built environment and transportation modes in Bratislava, eventually contributing to the development of more effective strategies for creating sustainable and accessible cities.

7 Appendices

7.1 *Appendix 1 - Overview of the variables*

	Question SK	Variable name EN	Type of variable	Number of categories	Mode in analysis	Note	TFW (theroreical framework)
				BE factors			
GIS analysis	Population Density	Population Density	ratio		All		BE factors
	PT coverage	PT coverage	ratio		All		BE factors
	Road Density	Road Density	ratio		All		BE factors
	Cycling network density	Cycling network density	ratio		All		BE factors
				Sociodemographic factors			
Survey – Primary data source	Otazka 1	Age	Ratio	-	All		Sociodem.
	Otazka 2	Gender	Nominal	3	All	*Dummy F = 1 M= 0*	Sociodem.
	Otazka 3	Education	Nominal /Ordinal	1-5	All	*Dum - master*	Sociodem.
	Otazka 4	Job	Nominal	5 + other	All		Sociodem.
	Otazka 5	Home District	Nominal	17 districts	-	*Only for grouping*	
	Otazka 6	Access to Bike	Nominal	2	Active	*D Yes = 1*	Sociodem.
	Otazka 7	Prepaid PT	Nominal	2	PT	*D Yes = 1*	Sociodem.
	Otazka 8	Access to Car	Nominal	2	Car	*D Yes = 1*	Sociodem.
				Trip specifications			
	Otazka 9	Most Common Mode	Nominal	4 + does not commute	-		Not used
	Otazka 10	Commute distance	Nominal /Ordinal	5 + does not commute	All	Distance to daily destination	Trip specifications
	Otazka 11	Commute district	Nominal	17	-		Not used
	Otazka 12a_1	Car (minutes daily)	Ratio		Dependent		
	Otazka 12a_2	PT(minutes daily)	Ratio		Dependent		
	Otazka 12a_3	Cycling (minutes daily)	Ratio		Dependent		
	Otazka 12a_4	Walking (minutes daily)	Ratio		Dependent		
	Sum of 3 and 4	Active modes	Ratio		Dependent		
	Otazka 12b_1	Car weekend (min daily)	Ratio				Not used
	Otazka 12b_2	PT weekend (min daily)	Ratio				Not used
	Otazka 12b_3	Cycling weekend (min daily)	Ratio				Not used
	Otazka 12b_4	Walking (minutes daily)	Ratio				Not used
	Otazka 13	Car Ownership in HH	Ratio		All		Car ownership
				Preferences and Attitudes			
	QID21_1	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	All		comfort
	QID21_2	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	Car		comfort
	QID21_3	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	All		convenience
	QID21_4	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	PT		propensity
	QID21_5	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	Car		propensity
	QID21_6	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	All		environment
	QID21_7	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	PT, Car		convenience
	QID21_8	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	Car		status
	QID21_9	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	Active forms		propensity
	QID21_10	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	Active forms		propensity
	QID21_11	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	Active forms		convenience
	QID21_12	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	PT		convenience
	QID21_13	Translation under the figure	Ordinal	1-7 (1disagree, 7 agree)	Active forms		propensity

QID21_1 I choose the mode trip more based on costs than on comfort and wellbeing

QID21_2 Advantages associated with the ownership of car (time, comfort) outweight the disadvantages (environment implicaitons, costs, maintenance)

QID21_3 I am willing to endure longer travel time if I save on costs.

QID21_4 Public Transport is a comfortable mode of transportation

QID21_5 Car is a comfortable mode of transportation

QID21_6 I am willing give up on some of the comfort for the sake of more environmentally friendly mode.

QID21_7 The distance from my home to the Public Transportation stop prevents me from using PT.

QID21_8 Car embodies the symbol of status, freedom and independency

QID21_9 I consider active forms of transport (bike, walking) more pleasant and more stress relieving than car

QID21_10 I am satisfied with the quality of the cycling infrastructure in my surroundings.

QID21_11 The quality of cycling infrastructure in my surroundings motivates me to consider bike as a mode of transportation

QID21_12 I consider travelling with Public transportation as a meaningfully spent time (interactions, being productive, listening to music, reading)

QID21_13 Active modes of transport (Cycling and Walking) positively effect my physical health and well-being.

7.2 *Appendix 2 - Flyer with the QR code and Questionnaire*

Flyer used to reach respondents in reference districts with not sufficient amount of responses (and English translation).

BT_Vplyvy infraštruktúry na výber formy dopravy v Bratislave

My name is Michal Bartek and I am a third-year undergraduate student in Spatial Planning and Design at the University of Groningen in the Netherlands. I am working on a bachelor's thesis investigating the impacts of infrastructure on transportation modes in Bratislava. Please help me by filling out the relevant questionnaire to obtain a representative sample of the residents of our city. The questionnaire is anonymous, and the data will be included in aggregate with other respondents. The questionnaire is short, with only a few simple questions, and should take no more than 5 minutes to complete. Thank you very much for your participation.

If needed, please contact me at the following email address: m.bartek@student.rug.nl

I agree that my data will remain anonymous and will be used solely for research purposes.

- ○ I agree (1)

Question 1: What is your age (as of the day you are filling out the questionnaire)?

____

Question 2: Gender

- ○ Male (1)
- ○ Female (2)
- ○ Other/I wish not to say (3)

Question 3 What is your highest educational level achieved?

- ○ Elementary School (1)
- ○ High School (2)
- ○ Bachelor's Degree (3)
- ○ Master's Degree (4)
- ○ Doctoral Degree (5)

Question 4 Employment status
▢ Employed (1)
▢ Unemployed (2)
▢ Part-time Job (3)
▢ Student (4)
▢ Retired (5)
▢ Other (please specify) (6) ____

Question 5: In which district of Bratislava do you live?

◯ Staré Mesto (1)

◯ Petržalka (2)

◯ Lamač (3)

◯ Ružinov (4)

◯ Karlova Ves (5)

◯ Nové Mesto (6)

◯ Vrakuňa (7)

◯ Podunajské Biskupice (8)

◯ Rača (9)

◯ Vajnory (10)

◯ Dúbravka (11)

◯ Devín (12)

◯ Devínska Nová Ves (13)

◯ Záhorská Bystrica (14)

◯ Jarovce (15)

◯ Rusovce (16)

◯ Čunovo (17)

Question 6 Do you have access to a bicycle?

◯ Yes (1)

◯ No (2)

Question 7 Do you have a prepaid Public transportation subscription?

- Yes (1)
- No (2)

Question 8 Do you have access to a car?

- Yes (1)
- No (2)

Question 9 What mode of transportation do you most frequently use to reach your daily (commute) destination?
*The term "daily destination"/ “commute destination” refers to your place of employment/school, or any other routine, frequently visited destination.

- Car (1)
- Public Transportation (2)
- Bicycle (3)
- Walking (4)
- I do not commute (5)

Question 10 How long is the distance to your daily destination from your place of residence?
*The term "daily destination"/ “commute destination” refers to your place of employment/school, or any other routine, frequently visited destination.

- Less than 2km (1)
- 2-5km (2)
- 5-10km (3)
- 10-15km (4)
- More than 15km (5)
- I do not commute (7)

Question 11 In which district of Bratislava is your daily destination located?
(If you don't commute, please skip this question)

- Staré Mesto (1)
- Petržalka (2)
- Lamač (3)
- Ružinov (4)
- Karlova Ves (5)
- Nové Mesto (6)

- ◯ Vrakuňa (7)
- ◯ Podunajské Biskupice (8)
- ◯ Rača (9)
- ◯ Vajnory (10)
- ◯ Dúbravka (11)
- ◯ Devín (12)
- ◯ Devínska Nová Ves (13)
- ◯ Záhorská Bystrica (14)
- ◯ Jarovce (15)
- ◯ Rusovce (16)
- ◯ Čunovo (17)

Question 12a How much time do you spend commuting on average on a typical workday using the following modes of transportation? (Please provide an approximate estimate in minutes)

- ◯ Car (1) ____
- ◯ Public transportation (2) ____
- ◯ Bicycle (3) ____
- ◯ Walking (4) ____

Question 12b How much time do you spend commuting on average on a typical weekend day using the following modes of transportation? (Please provide an approximate estimate in minutes)

- ◯ Car (1) ____
- ◯ Public transportation (2) ____
- ◯ Bicycle (3) ____
- ◯ Walking (4)

Question 13 How many cars is there in your household?

____

Please fill in your preferences regarding transportation modes in Bratislava. (last part of the questionnaire)

Strongly Disagree (1) Disagree (2) Somewhat Disagree (3) Neutral (4) Somewhat Agree (5) Agree (6) Strongly Agree (7)**

1. I choose my mode of transportation based more on price than on comfort and convenience.

o o o o o o o

2. The benefits associated with owning a car (comfort, time...) outweigh the drawbacks (costs, maintenance, environmental impact...).

o o o o o o o

3. I am willing to endure a longer travel time if it saves on costs.

o o o o o o o

4. Public transportation is a comfortable mode of transportation.

o o o o o o o

5. Traveling by car is a comfortable mode of transportation.

o o o o o o o

6. I am willing to sacrifice some comfort for the sake of sustainability (environmental protection).

o o o o o o o

7. The distance from my home to the bus stop discourages me from choosing public transportation.

o o o o o o o

8. A car represents a symbol of status, freedom, and independence.

o o o o o o o

9. I consider cycling and walking to be more pleasant and efficient forms of transportation for reducing stress than driving a car.

o o o o o o o

10. I am satisfied with the quality of cycling infrastructure in my area.

o o o o o o o

11. The quality of cycling infrastructure in my area motivates me to consider cycling as a mode of transportation.

o o o o o o o

12. I perceive traveling by public transportation as time well spent (social interactions, performing productive activities, reading, or listening to music).

o o o o o o o

13. Active forms of transportation (walking, cycling) positively affect my physical health and well-being.

o o o o o o o

End of the questionnaire. Thank you for your time! If you have the opportunity, please pass the questionnaire along, it would greatly help me.
If you have any comments, please write them here.

____

7.3 *Appendix 3 - Python data formatting*

In Appendix 3, the code for formatting of the data in PyCharm (Python coding language) software is shown.

```
import pandas as pd
import pyreadstat
#reading into dataframe
BT_df = pd.read_csv('BT_337_csv.csv', low_memory=False)
#merging responses to the BE factors by ID
GIS_df_excel = pd.read_excel('GIS_BE_Stats2.xlsx')
ID_survey_column = GIS_df_excel['ID_survey']
GIS_df = pd.DataFrame({'ID_survey': ID_survey_column})

GIS_df[['MC_LABEL_1', 'ID_survey', 'SUM_Cycle_Length',
        'SUM_Road_Length', 'PowerPT_total',
        'PTcoverage_percent', 'Population',
        'Population_Density', 'Shape__Area',
        'CyclingDensity', 'RoadDensity']] = GIS_df_excel
GIS_df['ID_survey'] = GIS_df['ID_survey'].astype(str)

#Merging based on District (Otazka 5)
merged_df = pd.merge(BT_df, GIS_df, left_on='Otázka 5', right_on='ID_survey', how='left')

merged_df.to_excel('Final_xlsxBT.xlsx', index=False)
merged_df.to_csv('Final_csvBT.csv', index=False)
```

```
import pandas as pd
import pyreadstat

df = pd.read_excel('Final_xlsxBT_zeroFloat.xlsx')

#replacing spaces in column names with underscores
df.columns = [col.replace(' ', '_') for col in df.columns]
# Removing columns
df = df.drop(columns=['Mail:_m.bartek@student.rug.nl'])
df = df.drop(columns=['Duration_(in_seconds)'])

#illegal characters in column names for spss
illegal_chars = set(r'[]/\;,><&*:%=+@!#^()|?^' + '"')
illegal_columns = [col for col in df.columns if any(char in illegal_chars for char in col)]
if illegal_columns:
    print("Illegal characters found in column names:", illegal_columns)
else:
    spss_file = 'Final_spss.sav'


    pyreadstat.write_sav(df, spss_file)
```

```python
import pandas as pd
import matplotlib.pyplot as plt
BT_df = pd.read_csv('BT_338csv_text.csv', low_memory=False)
#needed columns
relevant_columns = ['Otázka 5', 'Otázka 12a_1', 'Otázka 12a_2', 'Otázka 12a_3', 'Otázka 12a_4']
filtered_data = BT_df[relevant_columns].copy()
filtered_data.columns = ['District', 'Car', 'Public transport', 'Bicycle', 'Walking']
modes_columns = ['Car', 'Public transport', 'Bicycle', 'Walking']
filtered_data[modes_columns] = filtered_data[modes_columns].apply(pd.to_numeric, errors='coerce')
filtered_data.dropna(inplace=True)
#districts with 20 or more responses
district_counts = filtered_data['District'].value_counts().reset_index()
district_counts.columns = ['District', 'Response Count']
selected_districts = district_counts[district_counts['Response Count'] >= 20]['District']
filtered_data = filtered_data[filtered_data['District'].isin(selected_districts)]
#mean minutes traveled for each mode per district
avg_minutes_per_district = filtered_data.groupby('District')[modes_columns].mean().reset_index()
for mode in modes_columns:
    plt.figure(figsize=(12, 6))
    plt.subplot(1, 2, 1)
    plt.bar(avg_minutes_per_district['District'], avg_minutes_per_district[mode])
    plt.xlabel('District')
    plt.ylabel('Mean Minutes Traveled')
    plt.title(f'Mean Minutes Traveled by {mode} per District (Districts with 20 or more responses)')
    plt.xticks(rotation=45, ha='right')
    plt.grid(True, axis='y')
    #Histogram
    plt.subplot(1, 2, 2)
    plt.hist(filtered_data[mode], bins=20, color='skyblue', edgecolor='black', alpha=0.7)
```

```python
for mode in modes_columns:
    plt.figure(figsize=(12, 6))
    plt.subplot(1, 2, 1)
    plt.bar(avg_minutes_per_district['District'], avg_minutes_per_district[mode])
    plt.xlabel('District')
    plt.ylabel('Mean Minutes Traveled')
    plt.title(f'Mean Minutes Traveled by {mode} per District (Districts with 20 or more responses)')
    plt.xticks(rotation=45, ha='right')
    plt.grid(True, axis='y')
    #Histogram
    plt.subplot(1, 2, 2)
    plt.hist(filtered_data[mode], bins=20, color='skyblue', edgecolor='black', alpha=0.7)
    plt.xlabel(f'{mode} Minutes')
    plt.ylabel('Frequency')
    plt.title(f'Distribution of {mode} Travel Times')
    plt.grid(True)

    plt.tight_layout()
    plt.show()
```

7.4 *Appendix 4 - SPSS output*

Car mode

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,297[a]	,088	,005	44,60684

a. Predictors: (Constant), Q8_AccessCar_YES, Q10_Distance5_10km, PrimaryEd, Q2_GendOther, PhD, QID21_8, QID21_3, BachEd, QID21_7, QID21_2, Q2_GendFem, Distance15+km, QID21_5, HighSchEd, Q10_Distance10_15km, QID21_6, QID21_1, Number of cars in HH, Q10_Distance2_5km, Age

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	42402,602	20	2120,130	1,066	,388[b]
	Residual	437749,481	220	1989,770		
	Total	480152,083	240			

a. Dependent Variable: Car

b. Predictors: (Constant), Q8_AccessCar_YES, Q10_Distance5_10km, PrimaryEd, Q2_GendOther, PhD, QID21_8, QID21_3, BachEd, QID21_7, QID21_2, Q2_GendFem, Distance15+km, QID21_5, HighSchEd, Q10_Distance10_15km, QID21_6, QID21_1, Number of cars in HH, Q10_Distance2_5km, Age

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-6,022	27,179		-,222	,825
	Age	,216	,247	,081	,872	,384

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-6,022	27,179		-,222	,825
	Age	,216	,247	,081	,872	,384
	Q2_GendFem	-,297	6,564	-,003	-,045	,964
	Q2_GendOther	-19,666	47,362	-,028	-,415	,678
	PrimaryEd	-1,697	22,302	-,005	-,076	,939
	HighSchEd	3,753	8,401	,038	,447	,655
	BachEd	3,974	13,638	,020	,291	,771
	PhD	-10,351	9,067	-,082	-1,142	,255
	Q10_Distance2_5km	-3,551	9,616	-,032	-,369	,712
	Q10_Distance5_10km	-7,361	8,466	-,076	-,869	,386
	Q10_Distance10_15km	-4,297	9,468	-,038	-,454	,650
	Distance15+km	-,993	11,501	-,007	-,086	,931
	Number of cars in HH	-,645	4,159	-,013	-,155	,877
	QID21_1	-3,724	2,053	-,137	-1,814	,071
	QID21_2	3,788	1,835	,149	2,064	,040
	QID21_3	1,810	2,327	,062	,778	,438
	QID21_5	-1,357	2,441	-,041	-,556	,579
	QID21_6	-,048	2,276	-,002	-,021	,983
	QID21_7	3,943	2,106	,128	1,872	,062
	QID21_8	-,983	1,849	-,037	-,532	,595
	Q8_AccessCar_YES	13,893	10,457	,110	1,329	,185

a. Dependent Variable: Car

model A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,335[a]	,113	,014	44,41652

a. Predictors: (Constant), RoadDensity, BachEd, Q2_GendFem, QID21_1, QID21_2, Q10_Distance5_10km, QID21_7, QID21_8, PhD, PrimaryEd, Q2_GendOther, Q8_AccessCar_YES, QID21_5, HighSchEd, Distance15+km, QID21_6, Q10_Distance10_15km, QID21_3, Number of cars in HH, Q10_Distance2_5km, Age, Population_Density, CyclingDensity, PTcoverage_percent

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	54021,325	24	2250,889	1,141	,301[b]
	Residual	426130,758	216	1972,828		
	Total	480152,083	240			

a. Dependent Variable: Car

b. Predictors: (Constant), RoadDensity, BachEd, Q2_GendFem, QID21_1, QID21_2, Q10_Distance5_10km, QID21_7, QID21_8, PhD, PrimaryEd, Q2_GendOther, Q8_AccessCar_YES, QID21_5, HighSchEd, Distance15+km, QID21_6, Q10_Distance10_15km, QID21_3, Number of cars in HH, Q10_Distance2_5km, Age, Population_Density, CyclingDensity, PTcoverage_percent

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-24,290	30,831		-,788	,432
	Age	,266	,248	,100	1,070	,286
	Q2_GendFem	-,816	6,562	-,009	-,124	,901
	Q2_GendOther	-15,957	48,010	-,023	-,332	,740
	PrimaryEd	-1,237	22,652	-,004	-,055	,957
	HighSchEd	4,978	8,410	,050	,592	,555
	BachEd	6,229	13,810	,032	,451	,652
	PhD	-12,972	9,175	-,102	-1,414	,159
	Q10_Distance2_5km	-2,125	9,633	-,019	-,221	,826
	Q10_Distance5_10km	-6,658	8,670	-,069	-,768	,443

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients		
		B	Std. Error	Beta	t	Sig.
1	(Constant)	-24,290	30,831		-,788	,432
	Age	,266	,248	,100	1,070	,286
	Q2_GendFem	-,816	6,562	-,009	-,124	,901
	Q2_GendOther	-15,957	48,010	-,023	-,332	,740
	PrimaryEd	-1,237	22,652	-,004	-,055	,957
	HighSchEd	4,978	8,410	,050	,592	,555
	BachEd	6,229	13,810	,032	,451	,652
	PhD	-12,972	9,175	-,102	-1,414	,159
	Q10_Distance2_5km	-2,125	9,633	-,019	-,221	,826
	Q10_Distance5_10km	-6,658	8,670	-,069	-,768	,443
	Q10_Distance10_15km	-,103	9,795	-,001	-,011	,992
	Distance15+km	1,417	11,809	,010	,120	,905
	Number of cars in HH	-1,640	4,210	-,032	-,390	,697
	QID21_1	-3,766	2,053	-,139	-1,834	,068
	QID21_2	4,204	1,853	,165	2,269	,024
	QID21_3	2,215	2,372	,075	,934	,351
	QID21_5	-1,682	2,437	-,051	-,690	,491
	QID21_6	,124	2,333	,004	,053	,958
	QID21_7	4,458	2,133	,145	2,090	,038
	QID21_8	-,968	1,841	-,036	-,526	,600
	Q8_AccessCar_YES	15,224	10,561	,120	1,442	,151
	Population_Density	-,005	,003	-,153	-1,381	,169
	PTcoverage_percent	,576	,470	,242	1,225	,222
	CyclingDensity	-,010	,007	-,188	-1,309	,192
	RoadDensity	,001	,004	,087	,346	,730

a. Dependent Variable: Car

model B

Public transportation mode

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics: R Square Change	F Change	df1	df2	Sig. F Change
1	,533[a]	,284	,223	26,72799	,284	4,656	19	223	<,001

a. Predictors: (Constant), QID21_12, Age, Distance15+km, Q2_GendOther, BachEd, Q2_GendFem, Q10_Distance10_15km, QID21_7, PrimaryEd, Average number of cars in HH, PhD, QID21_6, Q10_Distance2_5km, QID21_1, Q7_PTcard_YES, QID21_3, QID21_4, HighSchEd, Q10_Distance5_10km

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	63192,738	19	3325,934	4,656	<,001[b]
	Residual	159307,962	223	714,385		
	Total	222500,700	242			

a. Dependent Variable: Public Transport

b. Predictors: (Constant), QID21_12, Age, Distance15+km, Q2_GendOther, BachEd, Q2_GendFem, Q10_Distance10_15km, QID21_7, PrimaryEd, Average number of cars in HH, PhD, QID21_6, Q10_Distance2_5km, QID21_1, Q7_PTcard_YES, QID21_3, QID21_4, HighSchEd, Q10_Distance5_10km

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	21,344	12,970		1,646	,101
	Age	-,331	,139	-,185	-2,376	,018
	Q2_GendFem	-5,040	3,837	-,081	-1,314	,190
	Q2_GendOther	-14,534	27,971	-,031	-,520	,604
	PrimaryEd	-21,396	13,451	-,100	-1,591	,113
	HighSchEd	1,217	5,099	,018	,239	,812
	BachEd	,425	8,139	,003	,052	,958
	PhD	6,928	5,432	,080	1,275	,204
	Q7_PTcard_YES	22,469	4,347	,371	5,169	<,001
	Q10_Distance2_5km	2,668	5,794	,035	,460	,646
	Q10_Distance5_10km	7,757	5,465	,118	1,419	,157
	Q10_Distance10_15km	9,119	5,923	,117	1,540	,125
	Distance15+km	-3,259	6,930	-,033	-,470	,639
	Average number of cars in HH	-,479	2,253	-,014	-,213	,832
	QID21_1	,748	1,244	,041	,601	,548
	QID21_3	2,499	1,408	,125	1,774	,077
	QID21_4	-,898	1,479	-,046	-,607	,544
	QID21_6	-1,491	1,348	-,073	-1,106	,270
	QID21_7	,000	1,238	,000	,000	1,000
	QID21_12	-,203	1,311	-,012	-,155	,877

model A

Model Summary

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,549[a]	,301	,228	26,64165

a. Predictors: (Constant), Q7_PTcard_YES, Population_Density, BachEd, Q2_GendOther, PrimaryEd, Distance15+km, QID21_7, PhD, Q10_Distance10_15km, Q2_GendFem, QID21_6, HighSchEd, QID21_1, Q10_Distance2_5km, Number of cars in HH, QID21_12, QID21_3, QID21_4, Age, CyclingDensity, Q10_Distance5_10km, PTcoverage_percent, RoadDensity

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	67059,415	23	2915,627	4,108	<,001[b]
	Residual	155441,284	219	709,778		
	Total	222500,700	242			

a. Dependent Variable: Public Transport

b. Predictors: (Constant), Q7_PTcard_YES, Population_Density, BachEd, Q2_GendOther, PrimaryEd, Distance15+km, QID21_7, PhD, Q10_Distance10_15km, Q2_GendFem, QID21_6, HighSchEd, QID21_1, Q10_Distance2_5km, Number of cars in HH, QID21_12, QID21_3, QID21_4, Age, CyclingDensity, Q10_Distance5_10km, PTcoverage_percent, RoadDensity

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	12,993	14,736		,882	,379
	Population_Density	,002	,002	,078	,802	,424
	CyclingDensity	-,006	,004	-,182	-1,466	,144
	RoadDensity	,000	,002	-,041	-,190	,850
	PTcoverage_percent	,273	,275	,167	,993	,322
	Age	-,328	,140	-,183	-2,338	,020
	Q2_GendFem	-5,179	3,842	-,084	-1,348	,179
	Q2_GendOther	-11,482	28,369	-,024	-,405	,686
	PrimaryEd	-19,489	13,645	-,091	-1,428	,155
	HighSchEd	1,700	5,095	,025	,334	,739

Coefficients[a]

Model		Unstandardized Coefficients B	Std. Error	Standardized Coefficients Beta	t	Sig.
1	(Constant)	12,993	14,736		,882	,379
	Population_Density	,002	,002	,078	,802	,424
	CyclingDensity	-,006	,004	-,182	-1,466	,144
	RoadDensity	,000	,002	-,041	-,190	,850
	PTcoverage_percent	,273	,275	,167	,993	,322
	Age	-,328	,140	-,183	-2,338	,020
	Q2_GendFem	-5,179	3,842	-,084	-1,348	,179
	Q2_GendOther	-11,482	28,369	-,024	-,405	,686
	PrimaryEd	-19,489	13,645	-,091	-1,428	,155
	HighSchEd	1,700	5,095	,025	,334	,739
	BachEd	2,344	8,209	,017	,286	,776
	PhD	6,905	5,507	,080	1,254	,211
	Q10_Distance2_5km	1,985	5,803	,026	,342	,733
	Q10_Distance5_10km	5,768	5,554	,088	1,039	,300
	Q10_Distance10_15km	8,881	6,088	,114	1,459	,146
	Distance15+km	-4,165	7,101	-,043	-,587	,558
	Number of cars in HH	-,679	2,268	-,020	-,300	,765
	QID21_1	,497	1,246	,027	,399	,691
	QID21_3	2,033	1,435	,102	1,417	,158
	QID21_4	-,933	1,486	-,048	-,628	,531
	QID21_6	-,932	1,383	-,046	-,674	,501
	QID21_7	,443	1,254	,022	,353	,724
	QID21_12	-,150	1,309	-,009	-,115	,909
	Q7_PTcard_YES	22,936	4,374	,378	5,244	<,001

a. Dependent Variable: Public Transport

model B

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,378[a]	,143	,064	30,90140

a. Predictors: (Constant), QID21_13, QID21_3, Q10_Distance5_10km, PhD, Q2_GendOther, PrimaryEd, QID21_10, BachEd, Q2_GendFem, Q6_AccessBikeYES, Distance15+km, HighSchEd, Average number of cars in HH, Q10_Distance10_15km, QID21_6, QID21_1, Q10_Distance2_5km, QID21_9, QID21_11, Age

b. Dependent Variable: Cycling + Walking

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	34611,599	20	1730,580	1,812	,021[b]
	Residual	208167,440	218	954,897		
	Total	242779,040	238			

a. Dependent Variable: Cycling + Walking

b. Predictors: (Constant), QID21_13, QID21_3, Q10_Distance5_10km, PhD, Q2_GendOther, PrimaryEd, QID21_10, BachEd, Q2_GendFem, Q6_AccessBikeYES, Distance15+km, HighSchEd, Average number of cars in HH, Q10_Distance10_15km, QID21_6, QID21_1, Q10_Distance2_5km, QID21_9, QID21_11, Age

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	9,475	17,404		,544	,587
	Average number of cars in HH	-5,306	2,522	-,148	-2,103	,037
	Q6_AccessBikeYES	14,593	5,176	,197	2,819	,005
	Age	-,021	,169	-,011	-,124	,902
	Q2_GendFem	-8,629	4,391	-,132	-1,965	,051
	Q2_GendOther	-48,308	32,675	-,098	-1,478	,141
	Q10_Distance2_5km	6,867	6,658	,087	1,031	,304
	Q10_Distance5_10km	3,846	6,157	,056	,625	,533
	Q10_Distance10_15km	-3,116	6,796	-,039	-,459	,647
	Distance15+km	-11,616	8,013	-,112	-1,450	,149
	PrimaryEd	-2,696	15,410	-,012	-,175	,861
	HighSchEd	1,873	5,923	,026	,316	,752
	BachEd	-6,794	9,466	-,048	-,718	,474
	PhD	9,847	6,244	,109	1,577	,116
	QID21_1	-,742	1,444	-,038	-,514	,608
	QID21_3	3,070	1,658	,145	1,852	,065
	QID21_6	-1,557	1,663	-,073	-,937	,350
	QID21_9	,978	1,771	,048	,552	,581
	QID21_10	-,873	1,765	-,040	-,495	,621
	QID21_11	2,334	1,839	,109	1,269	,206
	QID21_13	1,362	2,042	,053	,667	,505

a. Dependent Variable: Cycling + Walking

model A

Model Summary[b]

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate
1	,385[a]	,148	,053	31,08865

a. Predictors: (Constant), PTcoverage_percent, QID21_13, Q2_GendFem, BachEd, QID21_1, Q10_Distance5_10km, Q2_GendOther, PhD, QID21_10, PrimaryEd, Q6_AccessBikeYES, Average number of cars in HH, Distance15+km, QID21_6, HighSchEd, Q10_Distance2_5km, QID21_3, Q10_Distance10_15km, QID21_9, QID21_11, Age, CyclingDensity, Population_Density, RoadDensity

b. Dependent Variable: Cycling + Walking

ANOVA[a]

Model		Sum of Squares	df	Mean Square	F	Sig.
1	Regression	35947,195	24	1497,800	1,550	,055[b]
	Residual	206831,844	214	966,504		
	Total	242779,040	238			

a. Dependent Variable: Cycling + Walking

b. Predictors: (Constant), PTcoverage_percent, QID21_13, Q2_GendFem, BachEd, QID21_1, Q10_Distance5_10km, Q2_GendOther, PhD, QID21_10, PrimaryEd, Q6_AccessBikeYES, Average number of cars in HH, Distance15+km, QID21_6, HighSchEd, Q10_Distance2_5km, QID21_3, Q10_Distance10_15km, QID21_9, QID21_11, Age, CyclingDensity, Population_Density, RoadDensity

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	8,987	19,734		,455	,649
	Average number of cars in HH	-5,205	2,558	-,145	-2,035	,043
	Q6_AccessBikeYES	14,259	5,260	,193	2,711	,007
	Age	-,027	,172	-,014	-,156	,876
	Q2_GendFem	-8,631	4,436	-,132	-1,946	,053
	Q2_GendOther	-42,437	33,461	-,086	-1,268	,206
	Q10_Distance2_5km	6,394	6,726	,081	,951	,343
	Q10_Distance5_10km	3,226	6,395	,047	,504	,614
	Q10_Distance10_15km	-3,174	7,108	-,039	-,447	,656
	Distance15+km	-11,666	8,337	-,112	-1,399	,163
	PrimaryEd	,055	15,810	,000	,003	,997
	HighSchEd	2,196	5,995	,031	,366	,714
	BachEd	-6,392	9,660	-,045	-,662	,509
	PhD	10,003	6,382	,111	1,567	,119
	QID21_1	-,888	1,462	-,046	-,607	,544
	QID21_3	2,710	1,720	,128	1,575	,117
	QID21_6	-1,084	1,740	-,051	-,623	,534
	QID21_9	1,049	1,786	,051	,587	,558
	QID21_10	-,871	1,784	-,040	-,488	,626
	QID21_11	2,172	1,889	,101	1,150	,251
	QID21_13	1,151	2,069	,045	,556	,579
	RoadDensity	,001	,003	,124	,501	,617
	CyclingDensity	-,005	,005	-,126	-,894	,373
	Population_Density	,002	,002	,078	,687	,493
	PTcoverage_percent	-,079	,325	-,047	-,242	,809

a. Dependent Variable: Cycling + Walking

model B

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