Universidade de Aveiro
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GESTÃO SUSTENTÁVEL E SEGURA DE FLUXOS DE PASSAGEIROS NO CORREDOR SUBURBANO AVEIRO – PORTO

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Dissertação apresentada à Universidade de Aveiro para cumprimento dos requisitos necessários à obtenção do grau de Mestre em Engenharia Mecânica, realizada sob a orientação científica do Doutor Jorge Filipe Marto Bandeira, equiparado a Investigador Auxiliar do Departamento de Engenharia Mecânica da Universidade de Aveiro e da Professora Doutora Marta Alexandra da Costa Ferreira Dias, Professora Auxiliar do Departamento de Economia, Gestão e Engenharia Industrial e Turismo da Universidade de Aveiro.

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Dedico este trabalho aos meus pais, avós e irmãos.

o júri

Presidente	Doutora Eloísa Catarina Monteiro de Figueiredo Amaral e Macedo, Investigadora Doutorada (nível 1), Universidade de Aveiro
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palavras-chave

Transporte de passageiros, corredores intercidades, distribuição modal, modelo logit, emissões, função de utilidade, COVID-19

resumo

Em 2019, o sector dos transportes foi responsável por 25,8% das emissões de gases com efeito de estufa (GEE) da UE-27. Embora os transportes urbanos tenham recebido muita atenção dos decisores políticos e da comunidade científica, o transporte interurbano de passageiros não tem recebido tanta atenção. Em 2019, as viagens em estradas rurais e autoestradas representaram 65% do total de quilómetros percorridos em Portugal e contribuíram para mais de 55% das emissões de dióxido de carbono (CO_2) e óxidos de azoto (NO_x). A pandemia COVID-19 afetou negativamente a mobilidade devido ao medo de infeção das pessoas e restrições e recomendações governamentais.

Os principais objetivos desta dissertação são modelar a oferta e a procura de transporte de passageiros no corredor suburbano entre Aveiro e Porto, a determinação do impacto da pandemia COVID-19 nos hábitos de deslocações e escolha de modo para diferentes níveis socioeconómicos e propósitos de deslocação e estimar as emissões e o impacto por passageiro por passageiro antes e durante a pandemia.

Um inquérito online foi concebido para compreender os hábitos e preferências de transporte, e como estes fatores mudaram durante a pandemia. O transporte foi modelado recorrendo a um modelo logit baseado nas utilidades de cada modo de transporte, que foram calculados considerando a escolha do modo, o tempo de viagem e o custo de viagem de cada alternativa. O produto desta modelação de transportes foi a distribuição modal. Os impactos considerados foram as emissões de CO_2, NO_x, $PM_{2.5}$, PM_{10}, VOC, NMVOC e CO. As emissões foram estimadas utilizando como dados as características da frota e a velocidade média.

Os resultados do inquérito mostram uma redução de 70% na frequência de deslocações durante a pandemia, sendo o teletrabalho e as aulas online as principais razões desta diminuição. Antes da pandemia, 65% das viagens eram feitas de comboio e 31% de carro. Durante a pandemia, estas percentagens mudaram para 37% e 60%, respetivamente, e 27% dos participantes deixaram de viajar. O modelo logit foi revelou-se uma ferramenta útil para a modelação de transporte. No entanto, as características da rede, a disponibilidade de modos de transporte e o tamanho da amostra limitaram a significância estatística e a precisão do modelo. Os custos da poluição atmosférica diminuíram cerca de 53% durante a pandemia, principalmente devido à diminuição da frequência de viagem.

keywords

Passenger transport, intercity corridors, modal split, logit model, emissions, utility function, COVID-19

abstract

In 2019 the transport sector was responsible for 25.8% of EU-27 greenhouse gas (GHG) emissions. While urban transport has received much attention from policy makers and the scientific community, intercity passenger transport has not received as much attention. In 2019, intercity trips accounted for 65% of the total kilometres travelled in Portugal and contributed to more than 55% of carbon dioxide (CO_2) and nitrogen oxide (NO_x) emissions. The COVID-19 pandemic has negatively affected mobility due to people's fear of infection and government restrictions and recommendations.

The main objectives of this dissertation are to model the supply and demand of passenger transport in the suburban corridor between Aveiro and Porto, determination of the COVID-19 pandemic impact on travelling behaviour and mode choice for different socio-economic levels and travel purposes and estimate the emissions and the impact per passenger before and during the pandemic.

An online survey was designed to understand travelling behaviour and preferences and how these factors changed towards the pandemic. Transport was modelled recurring to a logit model based on the utilities of each transport mode, which were calculated considering the mode choice, travel time, and travel cost of each alternative. The output of the transport modelling was the modal split. The impacts considered were CO_2, NO_x, $PM_{2.5}$, PM_{10}, VOC, NMVOC and CO emissions. The emission values were estimated using the fleet characteristics and average speed as input.

Results from the survey show a 70% reduction in travel frequency during the pandemic, with teleworking and online classes being the main reasons for this decrease. Before the pandemic, 65% of trips were made by train and 31% by car. During the pandemic, these shares shifted to 37% and 60%, respectively, and 27% of participants stopped travelling. The logit model was revealed to be a helpful tool for transport modelling. However, the network characteristics, availability of transport modes and sample size limited the statistical significance and accuracy of the model. Air pollution costs decreased by about 53% during the pandemic, primarily due to a decrease in travel frequency.

Contents

Glossary

CO_2	Carbon dioxide
EGR	Exhaust Gas Recirculation
GHG	Greenhouse gas
HDT	Heavy-duty truck
LDV	Light-duty vehicles
NO_x	Nitrogen oxides
NMVOC	Non-methane volatile organic compounds
O-D	Origin-destination
pkm	Passenger-kilometre
$PM_{2.5}$	Particulate Matter smaller than 2.5 micro-metre
PM_{10}	Particulate Matter smaller than ten micro-metres
SCR	Selective Catalytic Reduction
skm	Seat-kilometre
vkm	Vehicle-kilometre
VOC	Volatile Organic Compounds
WTW	Well-to-wheel

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1. Introduction

The introduction of this dissertation will begin by exposing the motivation behind it, followed by its objectives and structure.

1.1. Motivation

The motivation for the realization of this dissertation is based on several recurrent challenges of the transport sector, in the form of environmental impacts (1.1.1 Transport sector emissions), energy consumption (1.1.2 Transports energy consumption) and the impacts of the COVID-19 pandemic on mobility(1.1.3 Impacts of COVID-19 on mobility).

1.1.1. Transport sector emissions

Transport emissions are a significant source of air pollution, contributing to 307,000 premature deaths resulting from fine particulate matter exposure [1]. The health effects of air pollutants are the most relevant and perhaps the most analysed. However, there are other related damages, such as structural and physical damage, loss of crops and loss of biodiversity. The costs of air pollution are one of the most analysed categories of external costs. Since the 1990s, extensive studies and international research projects have been carried out, especially at the European level. In recent years, many comprehensive international studies have not covered the entire impact process, from emissions to impacts and costs [2].

The Handbook on the external costs of transport covers the emissions impacts of the following four categories of air pollutants associated with the transport sector [2]:

- Health effects: Inhaling air pollutants such as particulate matter (PM_{10}, $PM_{2.5}$) and nitrogen oxides (NO_x) increases the risk of respiratory and cardiovascular diseases, such as bronchitis, asthma, and lung cancer. These adverse health effects can lead to medical costs, reduced work productivity (due to illness), and even death in some cases.
- Crop losses: Ozone can damage crops as a secondary air pollutant (mainly through emissions of NO_x and VOC) and other acidic air pollutants (such as SO_2 and NO_x). As a result, increased ozone concentrations and other substances can reduce crop yields.
- Material and building damage: Air pollutants cause two main types of damage to buildings and other materials: contamination of building surfaces with particles and dust and corrosion caused by acidic materials such as NO_X or SO_2, process damage to facades and building materials.
- Biodiversity loss: Air pollutants can damage ecosystems. The most critical damages are a) acidification of soil, precipitation, and water (e.g., by NO_x or SO_2) and b)

eutrophication of ecosystems with nutrients (e.g., NO_x, NH_3). Damage to ecosystems can lead to a reduction in biodiversity (animals and plants).

In 2016, the transport sector was responsible for 16.2% of the global greenhouse gas emissions, as seen in Figure 1; this includes small amounts of electricity (indirect emissions) and all direct emissions from burning fossil fuels for energy transport activities. Emissions from vehicle manufacturing or other modes of transportation are not included. Road Transport accounted for 11.9% of the global emissions from the burning of petrol and diesel combustion from all forms of road transport, including cars, trucks, motorcycles, and buses. 60% of emissions from road transport come from passenger transport (cars, motorcycles, buses). The remaining 40% comes from road freight (trucks and trucks). In other words, electrifying the entire road transport sector and moving to a fully decarbonized electricity mix would reduce global emissions by 11.9%. Aviation accounted for 1.9% of the emissions; from this value, 81% corresponded to passenger travel. 1.7% were relative to Shipping of passenger and freight transportation. The share for passenger and freight rail travel emissions was 0.4%. The remaining 0.3% came from Pipelines; Fuel and raw materials (oil, gas, water, steam, etc.) often have to be transported (within or between countries) via pipelines; this requires an input of energy, which leads to emissions. Poorly designed pipelines can also leak, leading to direct methane emissions to the atmosphere, but this aspect falls under the fugitive emissions from power generation.

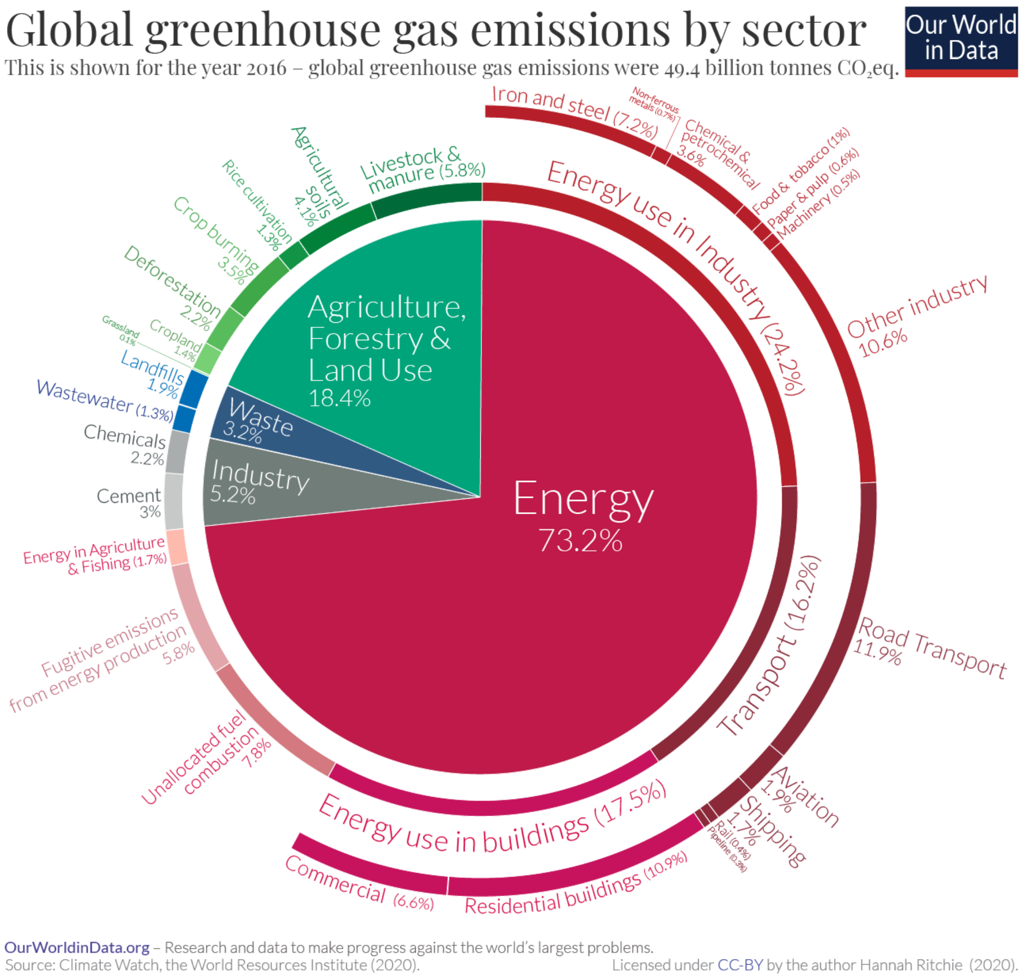

Figure 1: Global greenhouse gas emissions by sector [3].

As part of the European Green Deal, the European Union has set a binding target of reaching climate neutrality by 2050 with the European Climate Law. This target requires that greenhouse gas emissions decrease significantly over the next few decades. As an intermediate step towards climate neutrality, the EU has increased its 2030 climate target and committed to reducing emissions by at least 55% by 2030 [4].

In 2019 the transport sector was responsible for 25.8% of EU-27 greenhouse gas (GHG) emissions, as shown in Figure 2, and, according to Figure 3, since 1990, GHG emissions from other sectors have decreased, unlike the transport sector, which has increased chiefly [5].

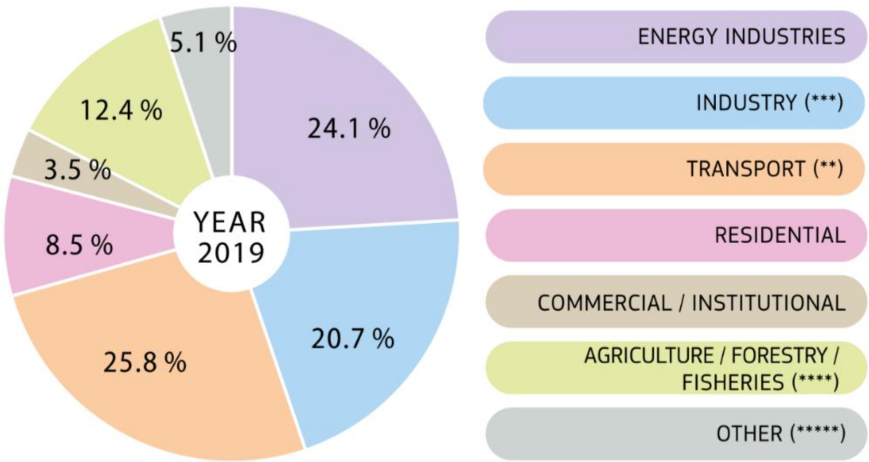

Figure 2: GHG emissions (Excluding land use, land-use change and forestry emissions) EU-27 – share by sector (million tonnes CO_2 equivalent) [5].

Domestic transport emissions from the European Union increased by 0.8% between 2018 and 2019. However, in 2020 there was a decrease of 12.7% due to a sharp decline in transport activity during the COVID-19 pandemic [6].

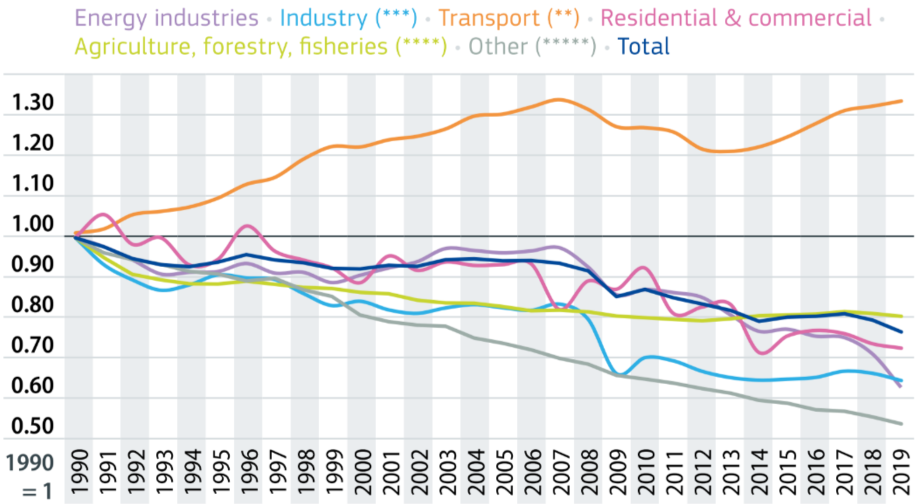

Figure 3: GHG emissions (Excluding land use, land-use change and forestry emissions) EU-27 – by sector (million tonnes CO2 equivalent) [5].

Road transport accounts for the largest share of total transport emissions, accounting for 72% of total national and international transport emissions in 2019. In the inland transport category, only domestic transport and rail have experienced a reduction in emissions since 1990. In addition, only road transport is expected to reduce emissions by 2030 [6].
One way to reduce GHG emissions from transport is to switch to low GHG-emitting and non-motorized transport modes such as walking and cycling. Figure 4 shows greenhouse gas emissions from different types of passenger transport modes. Along with air traffic, passenger cars are among the highest WTW GHG emissions per passenger-kilometre.

Therefore, switching to other modes of transport can help reduce GHG emissions from passenger transport [6].

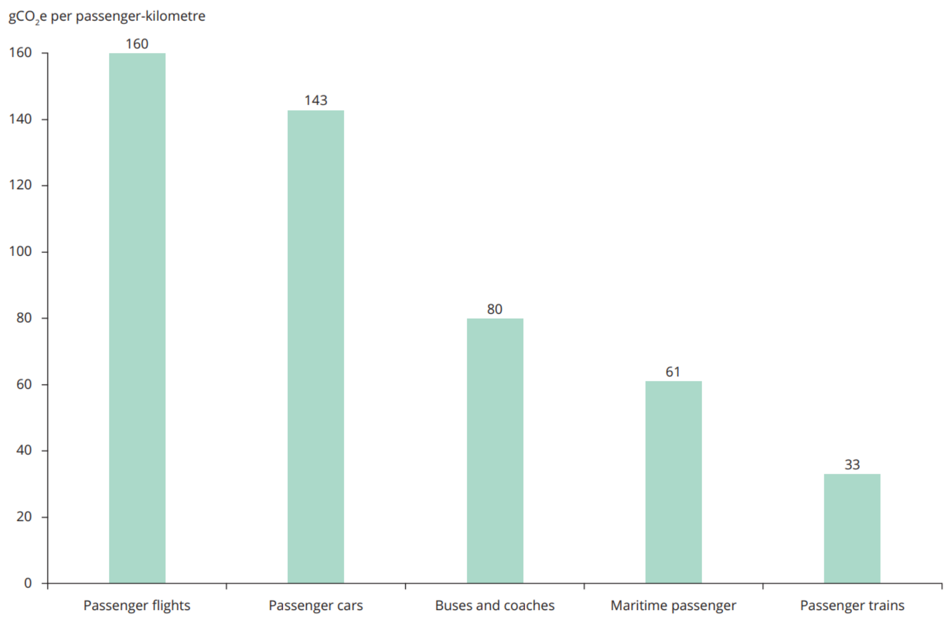

Figure 4: Average GHG emissions (gCO2e per passenger-km), well-to-wheel, for passenger transport in the EU-27, 2018 [6].

There are more than 1000 million road vehicles globally, which is expected to increase to 2000 million by 2050. In 2019 the motorisation rate was 533 cars per 1000 EU citizens [5]. As shown in Figure 5, transport and land-use planning practices have strengthened the dependence on cars and urban sprawl over the past century. This increased dependence was generally unintentional, as the full impact of these decisions was not considered. For example, when determining the number of parking spaces required for particular land use, transportation engineers probably do not consider the chaotic spreads that more generous standards bring. They are focused on ensuring drivers' convenience. Similarly, several land use impacts have been overlooked in planning decisions that affect road supply, quality of transportation services, or road prices [7].

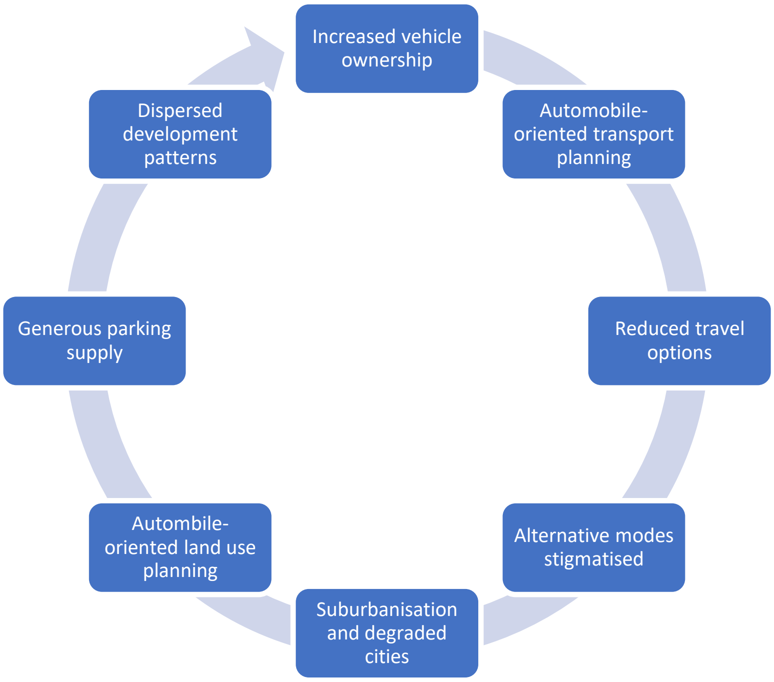

Figure 5: Self-reinforcing cycle of increased automobile dependency and sprawl [7].

In 2019, 26% of Portugal's GHG emissions were caused by the transport sector, the sector with the highest share of emissions in the country, as seen in Figure 6. Transport emissions fell by 10.4% between 2005 and 2019, but the sector's share increased by 3.3 percentage points. State plans for the sector include improving public transport by investing in fleet renewal and expanding the network to reduce personal vehicle use. The 2030 target is to reduce greenhouse gas emissions from transport by 40% compared to 2005 [8].

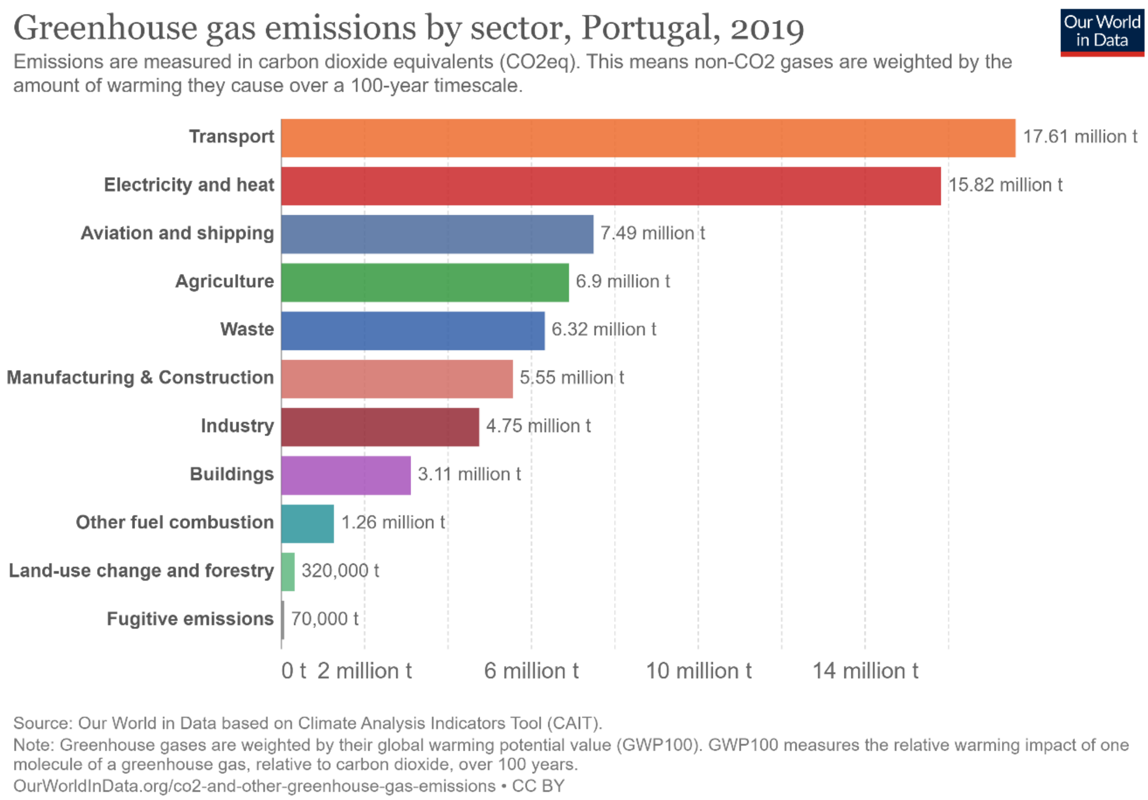

Figure 6: Greenhouse gas emissions by sector, Portugal, 2019 [3].

The road sub-sector accounts for 96% of transport emissions, while the national rail, aviation, and freight sector account for only 4%. The efficiency of these modes is relatively low, with about 1.2 passengers per private vehicle and the average occupancy rate of public transport between 17% and 24% (below the European average), leaving room for significant efficiency gains. It is also the most energy-intensive sector, with the most significant indirect contribution to primary energy imports and related energy dependence.[9].

While urban transport has received much attention from policy makers and the scientific community, long-distance passenger transport has not received as much attention. In 2019, intercity trips accounted for 65% of the total kilometres travelled in Portugal and contributed to more than 55% of the total emissions of carbon dioxide (CO_2) and nitrogen oxides (NO_x) [10].

1.1.2. Transports energy consumption

Energy consumption includes primary and energy consumption during fuel production and energy distribution (well-to-wheel). Energy consumption rates are usually expressed in kilowatt-hours (kWh) per vehicle-kilometre (vkm), passenger-kilometre (pkm) and seat-kilometre (skm). Table 1 shows European passenger transport's average energy consumption rates based on energy consumption factors such as capacity, speed, and seat occupancy. The average energy consumption rate of passenger transport by car is about three times that of bus transport. Airplanes are about 23 times less efficient than high-speed trains and 16 times less efficient than buses. Calculations of the average energy consumption of passenger cars range from low occupancy (36% in regional and intercity trains) to high occupancy (more than 60% in high-speed trains and planes). Passenger cars use 2.4 times more energy per passenger-kilometre than buses, while airplanes use 27 times more energy than rail transport [11].

Table 1: Energy consumption factors and rates for different passenger transport modes.[11]

Transport mode	**Seats**	**Average speed (km/h)**	**Occupancy (%)**	**Energy consumption**		
				kWh/vkm	kWh/pkm	kWh/skm
Regional train [12] **(RT)**	724	59	37	35.21	0.13	0.05
Intercity train [12] **(IT)**	190	71	36	6.28	0.09	0.03
Intercity Express train [12] **(IET)**	189	89	70	10.81	0.8	0.06
High-speed train [12] **(HST)**	350	160	66	17.00	0.07	0.05
Middle-class car (high-low occupation)	5	100	58-35	0.96-0.86	0.33-0.49	0.19-0.17
Standard bus (high-low occupation)	50	45	80-55	4.59-3.61	0.11-0.13	0.09-0.07
Aircraft (high-low occupation)	266	700	80-55	262.17-299.04	1.22-2.03	0.99-1.12
Train (medium-long distance)	190	100	36-31	15.70-16.82	0.23-0.28	0.08-0.09

Note: RT, IT, IET, and HST mean values are for Spain. Mean values for medium-long distance trains are for Europe.

Figure 7 compares the energy consumption of different passenger transport modes and road segments using statistical and analytical studies data. The chart shows the difference between energy consumption rates of transport modes and sectors based on occupancy level and average speed. Regional trains use more energy per passenger than intercity and high-speed trains. The chart shows the polygons on energy consumption and speed, representing different European countries' studies on energy consumption for transport. Based on data from 1990, considering the initial energy needs of the vehicle system (upstream operations are included in energy consumption estimates), diesel trains consume less than electric trains in each country. Today, the differences between train and traction technology may vary, especially if electrical conversion factors are improved and energy consumption associated with upstream operations is reduced. As a result, cars use more energy on short, low-occupancy intra-city trips than on long, high-occupancy trips. Cars use more energy than buses on long-distance trips, but less than airplanes, which use more energy for shorter distances and have fewer occupancy levels [11].

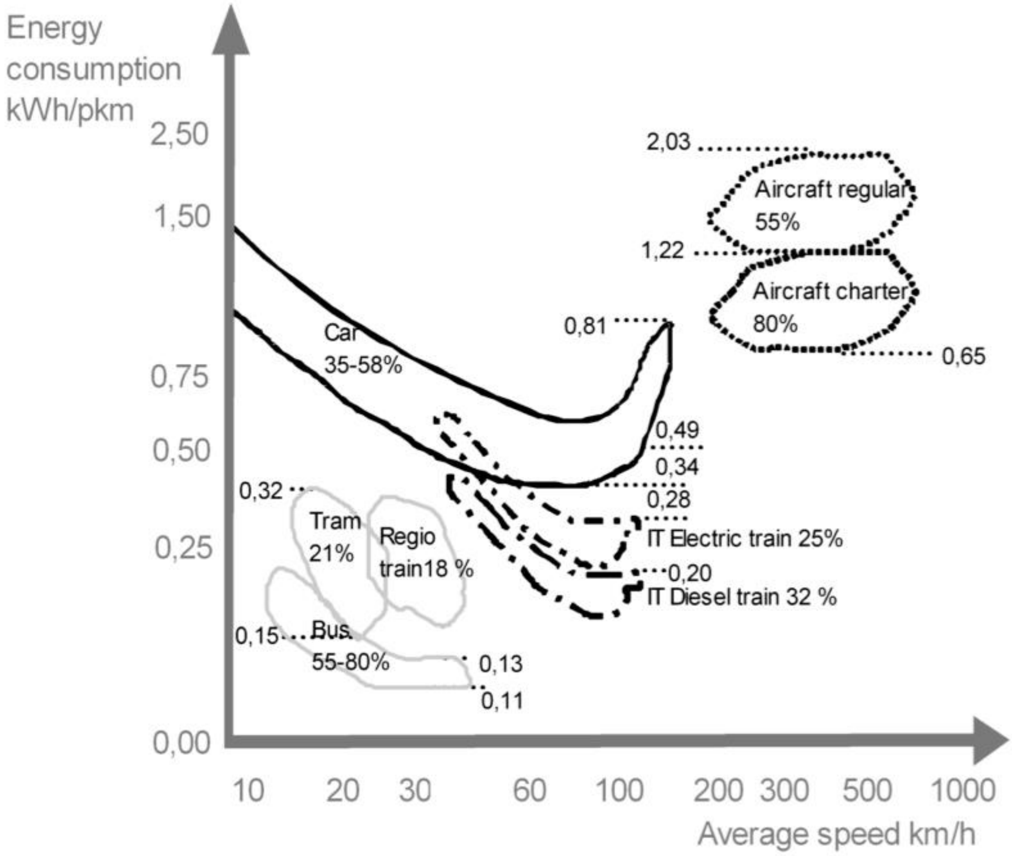

Figure 7: Energy consumption of passenger transport modes, average speed, and occupation rate. Aircraft: scheduled airlines and charter; intercity train (IT): electric and diesel tractions; regional train (electric traction), tram, bus, and car [11].

1.1.3. Impacts of COVID-19 on mobility

Travel behaviour has been dramatically affected by the COVID-19 pandemic due to restrictions and recommendations imposed by the governments. These restrictions resulted in a negative impact on all modes of transport. As seen in Figure 8, t the decrease in economic activity and restrictions have caused a significant decrease in the number of visits to various sectors in the first year of the pandemic. Work, retail, and transit-related travelling had a more medium-long-term effect [13].

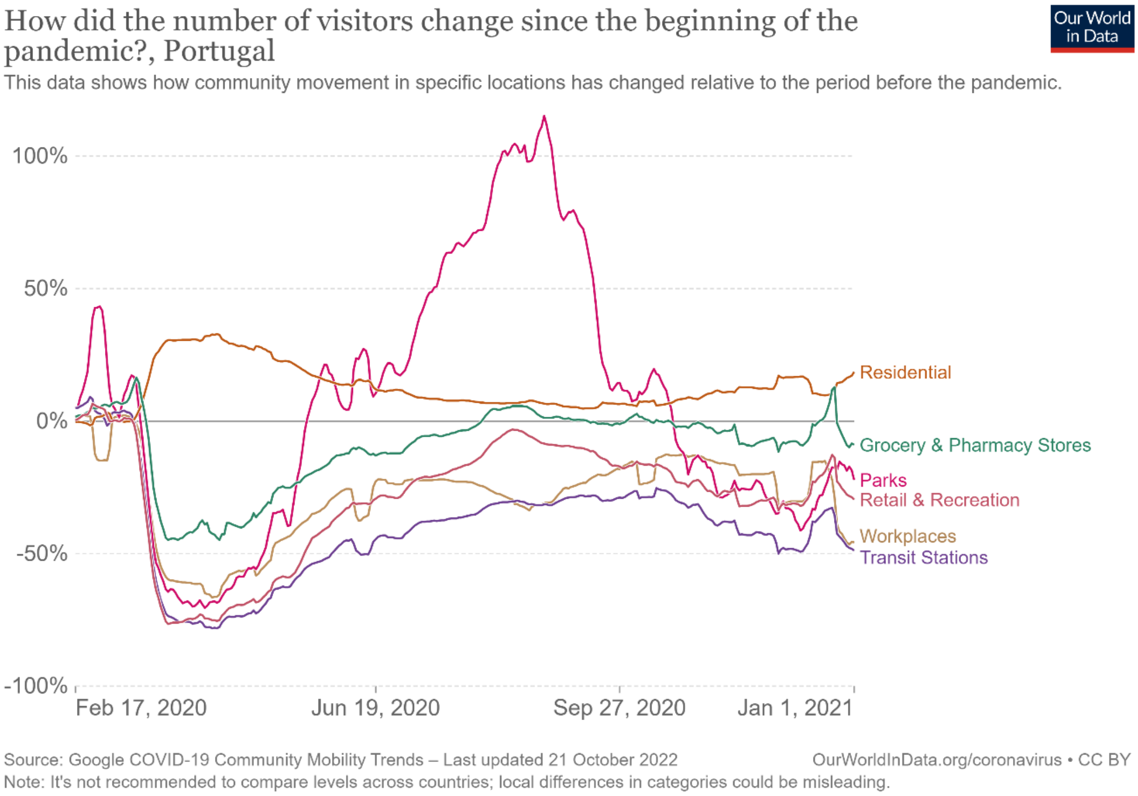

Figure 8: Changes in the number of visitors since the beginning of the COVID-19 pandemic in Portugal [14].

In Portugal, in 2020, there were decreases in the number of passengers carried by rail (-41.7%), metropolitan (-47.8%), river (-42.8%) and highway (-42.0%) after the positive variations recorded in the previous year (+18.9%, +10.6%, +4.2% and +6.7% in 2019, in the same order). Air passenger transport had the most significant impact, with a 69.4% decrease in passenger movement at national airports (+6.8% in 2019). Freight transport showed less marked decreases: in the air way (-29.4%, +12.0% in 2019), on the railway (-10.6%, -8.4% in 2019), in the maritime mode (-7.0%, -5.6% in 2019) and road transport in national vehicles (-14.8%, -2.2% in 2019) [15].

From the first quarter of 2021 to the first quarter of 2019, there was a decrease in 49% of passengers travelling in Portuguese suburban and interurban trains [15] and a 32% decrease in highway traffic between Aveiro and Porto [16].

Emissions of carbon dioxide and other greenhouse gases fell by 4.6% in 2020 as the lockdown measures restricted global mobility and hampered economic activity in the year's first half. Many hope this marks the beginning of a shift downwards in emissions; however, recent data dashed those hopes. As shown in Figure 9, annual global greenhouse gas emissions rose 6.4% last year to a record high, surpassing previous epidemic peaks as global economic activity recovered [17].

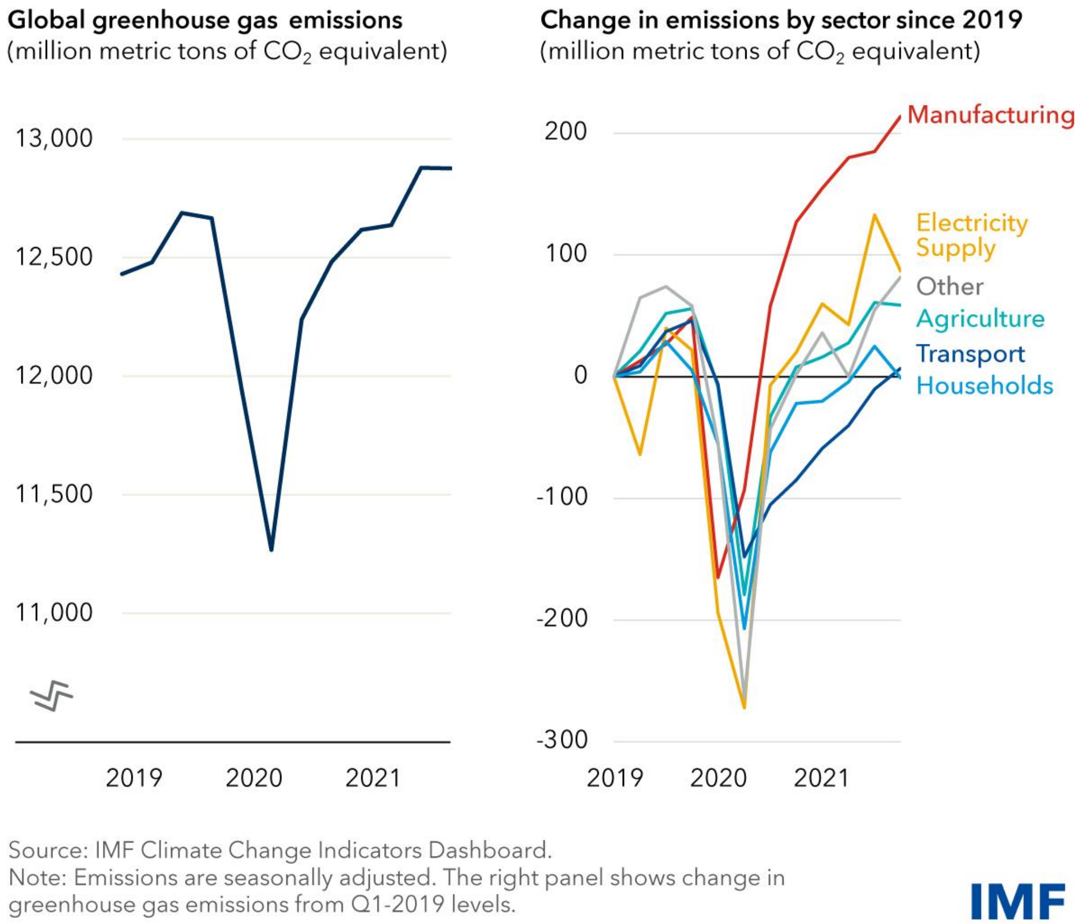

Figure 9: Global GHG emissions between 2019 and 2021 [18].

1.2. Objectives

This dissertation aims to develop tools and methodologies to implement intelligent transport search strategies to mitigate the negative externalities associated with intercity traffic in the context of the COVID-19 pandemic and returning to the new post-COVID-19 pandemic normality.

The main objectives for this work are:

- Modelling the supply and demand of the various mobility solutions in the interurban corridor of Aveiro – Porto before and during the pandemic using a logit model.
- Determination of the impact of the pandemic on the travelling behavior and transport mode choice for different socio-economic levels and travel purposes.
- Estimate the emissions and the impact per passenger on the area before and during the pandemic.

1.3. Structure

The first chapter is the introduction, dedicated to exposing this dissertation's motivation and objectives. This chapter gives an overview of the importance and impacts of the transport sector over the last few decades, particularly for passenger intercity transport.
The second chapter presents a bibliographic review of the themes discussed in this dissertation: transport modelling, emissions modelling, and the impacts of the COVID-19 pandemic on mobility.
Chapter three corresponds to the description of the methodology used in the preparation of the dissertation: the flowchart of the adopted methodology, the methods underlying the data collection, description of the area under study, transport modelling and subsequent estimation of the emissions considered as well as its associated cost.
The fourth chapter is dedicated to presenting the results and their discussion. The transport modelling results, the emissions estimation (before and during the COVID-19 pandemic), and the survey responses' outcomes are exposed.
Chapter five concludes this document with the conclusions as well as the future works regarding the subject.

2. Literature Review

The literature review aims to understand what studies have been conducted regarding how to model transport systems to reduce environmental impacts and how the COVID-19 pandemic has affected intercity travel. Therefore, this chapter comprises three sections: Transport modelling, Transport externalities and Impacts of COVID-19 on mobility.

The first Transport modelling subsection gives an overview of transport demand, what makes people travel, which factors will impact their commuting behaviour and what strategies may be used to manage it. The second subsection, Modal split, explores several factors and methods to calculate the modal distribution according to the passengers' preferences, such as a Logistic model.

The second section aims to review the impacts and analyse changes in the travel behaviour of the COVID-19 pandemic in mobility. It explains the methods used in several studies conducted in different countries and their results in changes in travel frequency, modal shifts, and perspectives for the future of mobility.

The Emissions Modelling section summarises several GHG emissions modelling methods. This section explains how these methods can be used to estimate GHG emissions and highlight the limitations, advantages, and techniques used in each.

2.1. Transport modelling

2.1.1. Transport demand

Transport demand refers to the type and quantity of transport services that the population chooses in each situation to make trips, whether for work, leisure, emergencies, etc. Figure 10 shows how users rank their travel purposes in terms of importance according to the Handbook on external transport costs. Some trips are so important that they may be taken even if the price is high, while others are of low value and only taken when the price is low. For example, when travel is cheap and convenient, people may shop around town, but when the cost of money or time increases, they may shop locally or online [19].

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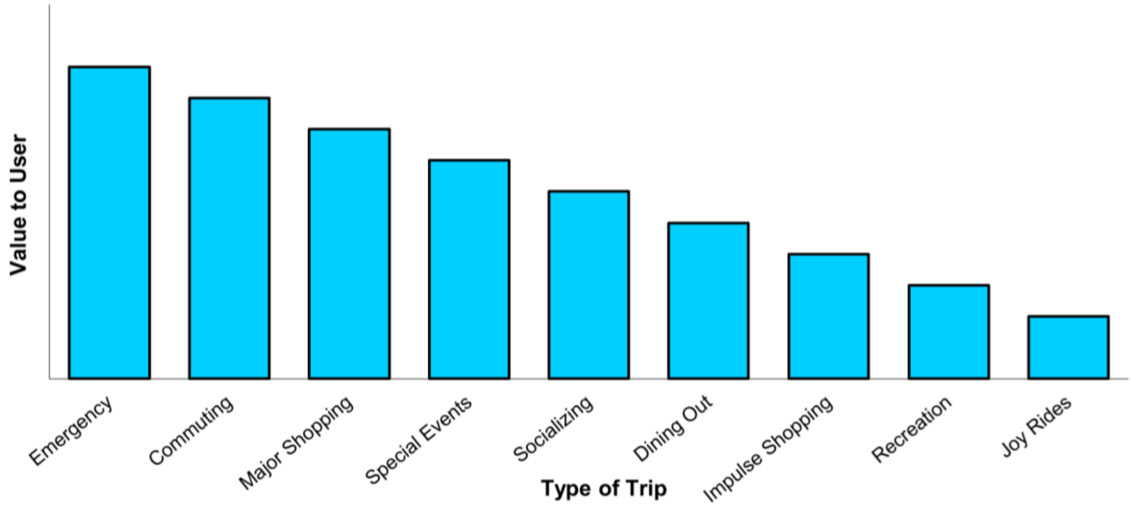

Figure 10: Travel ranked by user value [19].

Several economic, demographic, or geographical factors may influence transport demand, as shown in Table 2.

Table 2: Factors that affect transport demand [19].

Demographics	**Commercial activity**	**Transportation options**	**Land use**	**Demand management**	**Prices**
Population density	Number of jobs	Walking	Density	Road use prioritisation	Fuel prices and taxes
Employment rate	Business activity	Cycling	Mixed	Price reforms	Vehicle taxes and fees
Remuneration	Freight transport	Public transit	Walkability	Parking management	Road tolls
Ages	Tourist activity	Carpooling	Connectivity	User information	Parking fees
Lifestyles		Automobile	Transit service proximity	Promotion campaigns	Vehicle insurance
Preferences		Taxi services	Road design		Transit fares
		Telework			
		Delivery services			

A significant number of researchers are studying how changes in transport prices affect demand. Although these impacts vary greatly, it is possible to identify specific patterns to model these relationships. For example [19]:

- The impact on transportation costs may vary, such as travel type, mode, destination, route, vehicle type, and parking location. The price of one transport mode or service can affect the demand of others.
- Over time, the price impact increases and triples in the long run.
- High-value trips, such as business trips, tend to be less price-sensitive than low-value trips.
- People in good economic conditions tend to be less price-sensitive and more sensitive to the quality of service than low-income people.
- Travel tends to be price-sensitive if travellers have better travel options.
- Drivers are susceptible to tolls and parking fees.
- The advertising, structuring, and payment of fees may affect their impact.
- Drivers are more likely to accept price increases if presented as part of an integrated program with various benefits considered fair.

Transportation Demand Management, or TDM, is a general term for the strategies that increase overall system efficiency. Two paths may be taken to achieve this goal: to minimise transport demand or to improve the efficiency of existing and possible new transport modes [20].

There is some understandable scepticism regarding the idea that it is possible to change people's behaviour in order to reduce transport demand. Besides being a great indicator of success, owning a personal vehicle may be essential, considering the needs and lifestyle of a high percentage of the population. Nevertheless, attitudes may be changed [20].

It is essential to mention that, before thinking of transport demand measures, information and technologies may be excellent tools to reduce the need for travel. A good example is an increase in flexible working, both in terms of schedule and telework, which may decrease commuting. This last may increase externalities (emissions, accidents) and costs (money, time) for passengers [20].

Many suggestions for transport management measures may be applied in several scenarios, summarised in Table 3. For most of these suggestions, the role of technology is crucial since they demand some electronic tasks like organisation, monitoring and control [20].

Table 3: Examples of transport demand management strategies [20].

Improve transportation options	**Incentives to reduce driving**	**Parking and land-use management**	**Policy reforms and programs**
Alternative work schedules Bicycle improvements Bike/train transit integration Car sharing Flextime Guaranteed ride home Individual actions for efficient transport Park and ride Pedestrian improvements Carpooling Shuttle services Small-wheeled transport Taxi service improvements Telework Traffic calming Transit improvements Universal design	Walking and cycling encouragement Commuter financial incentives Congestion pricing Distance-based pricing Fuel taxes High-occupancy vehicle priority Parking pricing Pay-as-you-drive vehicle insurance Road pricing Speed reductions Street reclaiming Vehicle-use restrictions Taxi service improvements Telework Traffic calming Transit improvements Universal design	Bicycle parking Car-free districts and pedestrianised streets Clustered land use Location-efficient development New urbanism Parking management Parking solutions Parking evaluation Shared parking Thoughtful growth planning and policy reforms Transit-oriented development	Access management Campus transport Car-free planning Commute trip reduction programs Comprehensive market reforms Context-sensitive design Freight transport management Institutional reforms Least-cost planning Regulatory reform School transport management Special event management Transport demand management marketing Tourist transport management Transportation management associations

Moovit analysed millions of trip requests made by Moovit users worldwide in 2020 to gain insights into global public transport trends. These reports help discover and compare the statistics on the use of public transport and micro-mobility in several countries and the reasons and barriers to implementing public transport and micro-mobility. One of those reports aimed to understand what factors could motivate people to use public transport. The results are shown in Figure 11 [21]. Most people are concerned with total travel time (including trip time, waiting times, and walking times), the frequency of public transport vehicles, the cost fares, and the accuracy and reliability of arrival times. The crowdedness, comfort, and cleanliness are the factors that most influence the in-vehicle experience and are an excellent way to motivate users. Better accessibility for people with needs, convenient ways to purchase tickets and parking areas near the stations are also necessary improvements in some cases.

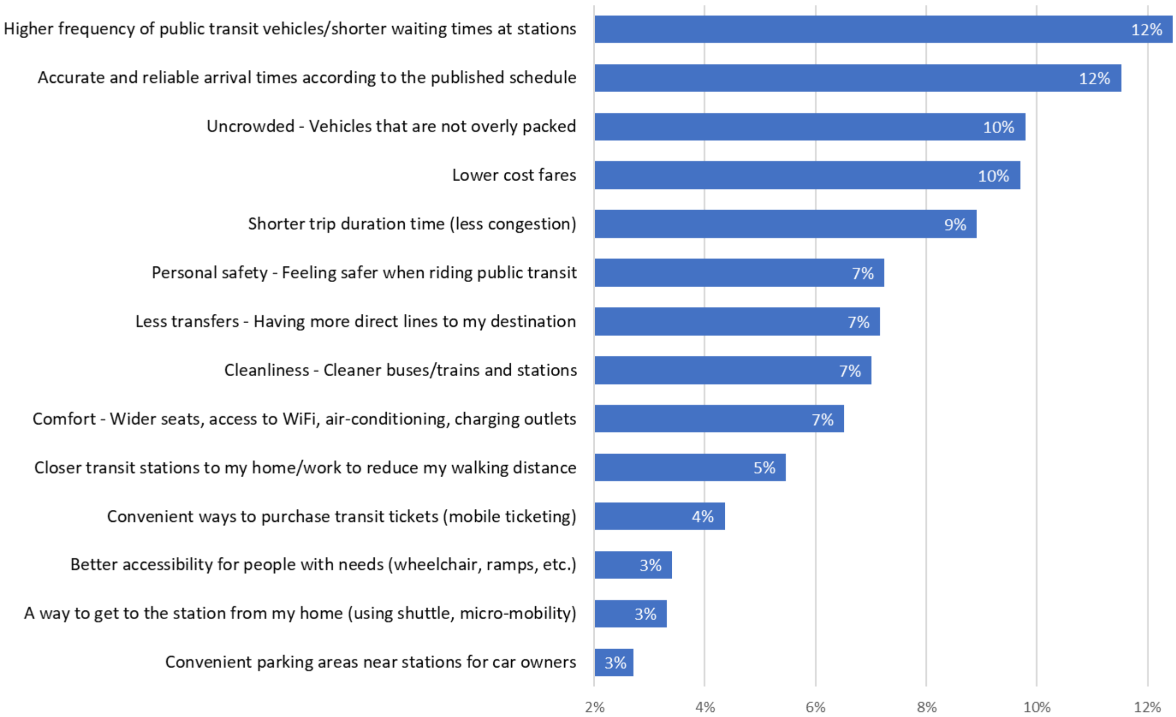

Figure 11: Public transit usage incentives [21]

2.1.2. Modal split

The choice of the mode of transport is probably one of the most critical elements in transport planning due to the vital role of public transportation in policymaking. Public transport modes use road space more efficiently than private transport and have more social benefits. If more people start using public transport, there will be less road congestion and fewer accidents. In public transport, the low cost of travel stands out. In addition, fuel is used more efficiently. The main characteristics of public transport are the specificity of its location, schedule, and frequency, unlike private vehicles, which are highly flexible and provide more comfortable and convenient travel, but at a higher cost. The question of mode choice is, therefore, probably the most crucial element in transport planning and policymaking as it affects the overall efficiency of mobility. It is then essential to develop and use models sensitive to travel attributes influencing individual transport mode choices [22].

Wu et al. brought together 19 years of literature on travel mode choice to assess current developments and trends in travel choice research and to provide potential research directions with sustainability for future research. The literature was drawn from six databases on which biometric and social network analyses are performed [23]. The top 10 cited papers were analysed in depth regarding five key elements: subject, modes of transport covered; factors of study; data collection and analysis methods; study purpose. For these ten articles, surveys were the most common data collection method, including household surveys, online surveys, and interview surveys. Discrete choice models are often used to measure the relationship between variables, i.e., binomial logit models, multinomial conditional logit models and multiple regressions [24], [25], [26]. Only two articles explicitly suggested the theoretical framework and related discretionary structures in the theoretical use section. One paper uses the theory of random utility, which assumes that individuals maximize a chosen condition's utility or net benefit. In contrast, the other paper uses the theory of planned behaviour. The purposes of these frequently cited articles also varied, with six related to policy recommendations and the remainder to increasing bus use, model development, and transportation planning [23].

Modal split, also known as modal share or mode choice, is the percentage of travellers using a particular mode of transport concerning all trips [27]. Generally, the modal split is the third of a four-step transport modelling process [28]:

- Trip generation (number of sources, destination, and transit traffic).
- Distribution of trips (routing traffic flows).
- Distribution of transport connections according to the transport used (Modal Split - distribution of transport work).
- Distribution of trips by routes and transport network sections.

Frequently, the modal distribution is determined using discrete choice models (Logit models). The most commonly used discrete choice models are multinomial (MNL) and nested (NL) logit models. Polynomial logit models include a more extensive set of options in the final data set (e.g., options may be: private vehicle, carpooling, taxi, TVDE, bicycle, walk, bus, tram, train), while nested models consist of a set of similar grouped options within a nest, where each option belongs to only one nest [29]. The general expression for the probability of choosing an alternative or element I (i= 1, 2, ... J) from a set of J options is represented in Expression 2.1.

$$P_{r(i)} = \frac{e^{V_i}}{\sum_{j=1}^{J} e^{V_j}} \qquad 2.1$$

$P_{r(i)}$ Is the probability of the decision-maker choosing alternative i?

V_j is the value of the utility of the alternative j.

The fundamental challenge of discrete mode choice analysis is to model the choice between alternatives. Utility maximization can be taken as a solution, where decision-makers choose the options with the most utility. The model consists of a parameterized utility function consisting of the independent variables estimated from the sample and the unknown parameters. The probability of choosing an alternative is the probability of obtaining the highest benefit from all possible options [30].

Economists use utility functions to understand consumer behaviour better and determine the satisfaction level of goods and services for consumers. Utility functions can also help analysts determine how goods and services will be distributed to consumers to realise total utility [31].

The most widely used mathematical formula for the utility function is the linear, additive, compensational model, following the structure of Expression 2.2. *V* refers to the total Utility, x_n is the value of factor n (travel time, for example), and a_n is the utility weight of factor *n* [32].

$$V = a_1x_1 + a_2x_2 + \cdots + a_nx_n \qquad 2.2$$

A study developed in Croatia by L. Novačko et al. aimed to estimate the utility function parameters for each transport mode based on household surveys. Generalized cost and tolerance to modes of transport were expressed using the utility function. The paper describes a method to determine the utility function for each transport alternative using the *Biogeme* software [29][33].

Another study carried out in Žilina, Slovak Republic, by M. Cingel et al. describes the parameterization of modal split calculations in a four-stage model for determining traffic forecasts. Estimating the logit function parameters is based on traffic and social studies in the Zilina region. The Biogeme software [33] is also used for the calculations. The main task was to develop a set of performance parameters of the logit function for conditions in the Zilina region. The preference for a particular mode of transport is calculated by the utility function. This function is used in a disaggregated model for individual population groups, characterized by their behaviour in the transport process. The refined model simulates individual behaviour in time and space and subsequent aggregation into the resulting local transport relationships. The transport modes were categorised taken into account: car-driver, car-passenger, public transport, bicycle and pedestrian transport [28].

Biogeme is an open-source Python package designed for general maximum likelihood estimation of parametric models, focusing on discrete selection models. It is based on a Python data analysis library package called Pandas. Biogeme was formerly a standalone software package written in C [33].

Several versions of Biogeme have been developed [33]:

- BisonBiogeme is designed to estimate parameters of predefined discrete selection models such as logit, binary probit, nested logit, cross-nested logit, multivariate maximum value models, discrete and continuous mixtures of multivariate extreme value models, models with nonlinear utility functions, models designed for panel data, and heteroscedastic models. It is based on formal and straightforward language for model specification.
- PythonBiogeme is designed for general parametric models. Specifications of models and likelihood functions are based on Python's extensions. For ease of use, several separate selection forms have been pre-coded. The package is written in C++ and is self-contained.
- PandasBiogeme is a Python package for importing Python code. It is based on the Pandas package for data processing. The syntax of the template specification is very similar to PythonBiogeme.

2.2. Impacts of COVID-19 on mobility

Governments have recommended or implemented several measures to control the spread of COVID-19. As a result of these measures, travel behaviour has been dramatically affected, although people continue to need to travel for different purposes, from groceries to work [34]. Additionally, there is evidence that voluntary social distancing has played an essential role during COVID-19, besides mandatory lockdowns. As a result, the collected data can be analysed holistically, regardless of the time of confinement in different countries [35]. Several studies analyse travel behaviour changes resulting from the COVID-19 pandemic.

Abdullah et al. collected data using an online survey that included questions about the purpose of travel, choice of travel mode, distance travelled, and frequency of travel before and during COVID-19. One thousand two hundred three responses were collected in different countries. The questionnaire consisted of three sections: socio-demographic characteristics, characteristics of primary travel before and during the COVID-19 pandemic, and factors affecting mode choice for primary travel before and during the COVID-19 pandemic. Comparative, descriptive, and quantitative analyses of the collected data have been carried out. For inferential statistical analysis, were used mainly non-parametric tests. The study examines independent and paired travel behaviour observations before and during COVID-19 [34].

A dataset was collected by Barbier et al. to identify and understand people's modal shifts and cognitive behaviour towards travel due to COVID-19 to document traffic disruptions and traffic changes due to restrictive measures implemented in ten countries, including Australia, Brazil, China, Ghana, India, Iran, Italy, Norway, South-Africa, and the United States. The first part of the survey described the use frequency of all transport modes before and while restrictions were imposed. In contrast, the second part addressed the perceived risk of contracting COVID- 19 from different modes of transport and the perceived effectiveness of travel restrictions [36].

Bhaduri et al. investigated travel behaviour changes in the Global South context. They simulated the relationship between changes in transport mode use and traveller characteristics to identify associated heterogeneity. Mathematical models were developed to estimate the effect of traveller socio-demographic characteristics on pattern-specific travel frequency before and during the early stage of COVID-19 in India. The information was collected through an online survey, and responses were received from 498 people from different cities in India. Respondents were asked about their weekly commutes and free travel habits before COVID-19 and during the first days of COVID-19 (early March 2020). The survey consists of 3 main parts: (a) transport modes and their weekly frequency of use in everyday situations; (b) Travel patterns with the frequency of weekly use in the early stages of the COVID-19 pandemic; (C) person and household level socio-demographics. In the questionnaire, respondents were asked to provide information about commuting and leisure activities [37].

Zhang et al. conducted a worldwide expert survey between the end of April and late May 2020. The survey has been distributed to WCTRS (World Congress of Transportation Research Society) members and their collaborative network. WCTRS is a platform for the exchange of ideas between researchers, managers, policymakers and educators in the field of transportation on a global scale. Its members come from more than 60 countries and regions. The survey aimed to gather views: on the impact of COVID-19 on the transport and logistics sector; how countries around the world are prepared for these public health threats; what measures were being taken during the pandemic of COVID-19; how the lives of people and communities are expected to change; how to achieve an effective recovery after the pandemic; and how to cope with previous changes in the future. Therefore, the survey aimed to seek expert advice and awareness regarding the impact of the pandemic on the transport and logistics sector, and it was composed of the following contents [38]:

- Preparedness: the existence of guidelines or contingency plans for various transport modes and facilities.
- During-pandemic measures related to the impacts:
    - Lockdown, its timings, and the type of mobility restrictions imposed.
    - Declaration and time of the state of alarm.
    - Activities/facilities prohibited to perform/use during the current COVID-19 pandemic.
    - What actions were taken against COVID-19.
    - Advice about COVID-19 for the public.
- Significant changes in the modal split during the pandemic.
- Expected long-term changes in the lifestyle and society due to the impact of COVID-19.

Li et al. studied the changes in interurban mobility in China using intercity COVID-19 pandemic data. City-wide intercity daily travel data was obtained from *Baidu Huiyan* [39], a website that publishes each city's intercity traffic index data. The intercity traffic index is a relative measure of the number of daily passenger arrivals and departures. Data estimates are based on nearly 120 billion daily service inquiries from more than 1.1 billion mobile phones. The study included five categories of explanatory variables [40]: (1) socio-economic factors such as GDP, population and urbanization ratio, (2) industry development factors that include gross product of secondary industry and tertiary industry, (3) location factors such as spatial distance and cultural distance, (4) transport factors that include data from road transport, high-speed trains and civil aviation, and (5) COVID-19 pandemic factors. The study uses the Enhanced Decision Gradient Tree algorithm proposed by Friedman [41] to study the dynamic impact of COVID-19 on intercity travel. The model combines decision trees and gradient enhancement methods to analyse travel dynamics [40].

Gu et al. also used cellular network-based datasets to study traffic changes associated with two sets of city pairs in China severely affected by COVID-19. Using spatial matching, full sample extrapolation, and lane function analysis to obtain travel volumes on intercity highways in four periods. The reliability of the source-destination matrix calculated from the cellular network dataset is demonstrated by comparing the fluctuation trend of the traffic statistics [42].

Abdullah et al. concluded that there were statistically significant differences in the purpose of travel, choice of travel method, distance travelled, and frequency of main trips before and during the pandemic. The main change is from public to private and non-motorized transport. People prioritize pandemic-related issues over general issues when choosing their situation during a pandemic. Gender, vehicle ownership, employment status, mileage, the primary purpose of travel, and possible pandemic-related factors have been essential predictors of travel choices during the pandemic [34].

Confinement campaigns, physical distancing measures in public transport and distribution, economic measures, avoidance of face-to-face social contact and online activities were the main actions against COVID-19 in the transport sector [38].

An example of the overall impact of the pandemic on travel behaviour is shown in Figure 12. Most respondents (56.6%) said they do not go to work or school because they work and study from home. About 11.4% affirmed that nothing had changed because of the COVID-19 pandemic [34].

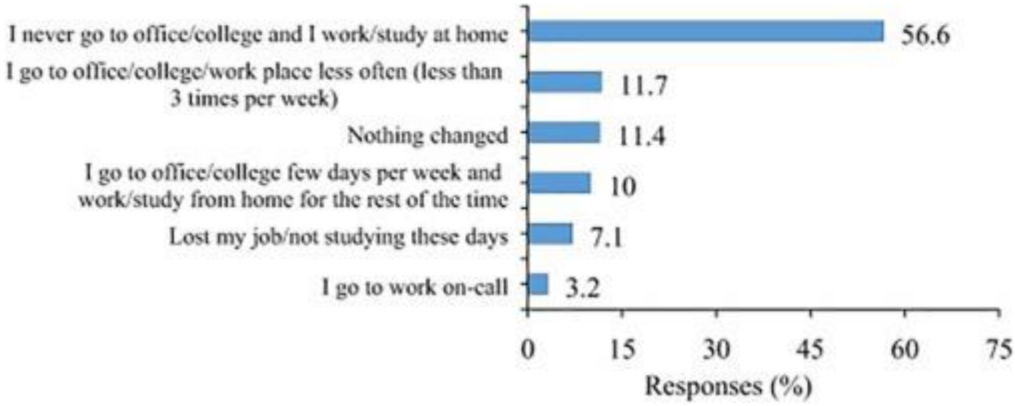

Figure 12: Change in commuting behaviours due to COVID-19 [34].

Before COVID-19, the primary purpose of travel for most respondents (58%) was work. However, during COVID-19, this was reduced to only 30% (Figure 13). On the other hand, during COVID-19, shopping became the primary travel purpose for about 44% of respondents, compared to only 4% before the pandemic [34].

Experimental research shows that traffic to the original destination and connected passenger cars on roads between Chinese cities has decreased significantly during COVID-19 [33]. It was estimated a decrease of 51.35% in intercity mobility in China from January 26 to April 7, 2020, due to COVID-19 and a series of pandemic prevention measures adopted by the Chinese government. It was also found that c. At the pandemic's beginning, the total number of confirmed cases was the most important independent variable affecting intercity mobility. With COVID-19 under control, the total number of recovered cases contributed more than the total number of confirmed cases and played the most crucial role in the study of intercity mobility. In the post-COVID-19 era, current cases have become the dominant variable [40].

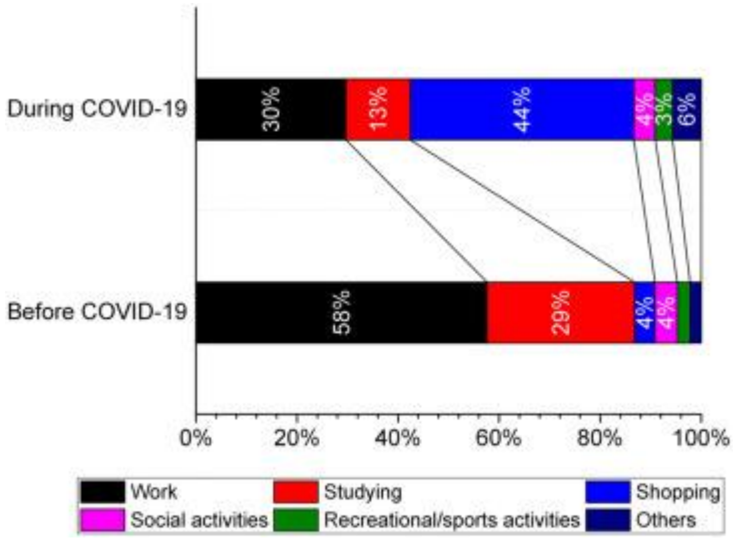

Figure 13: Primary purpose of travelling before and during the COVID-19 pandemic [34].

Statistics show that respondents have significantly reduced their travel distance during COVID-19. As shown in Figure 14, 71% of participants travelled 0 to 10 kilometres during COVID-19, compared to only 45% who travelled the same distance before COVID-19 [34].

A study carried out in Chungnam, a province of South Korea, aimed to evaluate the impact of COVID-19 on the efficiency of intercity bus operations. Results show that the operating efficiency of Chungnam intercity bus lines in 2018 and 2019 was higher than in 2017 but decreased by 15.8% in 2020, the beginning of the pandemic. Efficiency appears to be more significant when the line is operated more frequently and over longer distances, but efficiency increases at a decreasing rate as operating distance increases. Under the influence of COVID-19, the difference in efficiency according to operational distance appears to be statistically significant. The main finding is that before 2020, longer driving distances improved efficiency, but not in 2020. This may be because passengers are more concerned about getting infected with COVID-19 when driving long distances. Demand for long-distance routes has fallen following the outbreak of Covid-19, hurting the efficiency of bus companies [43].

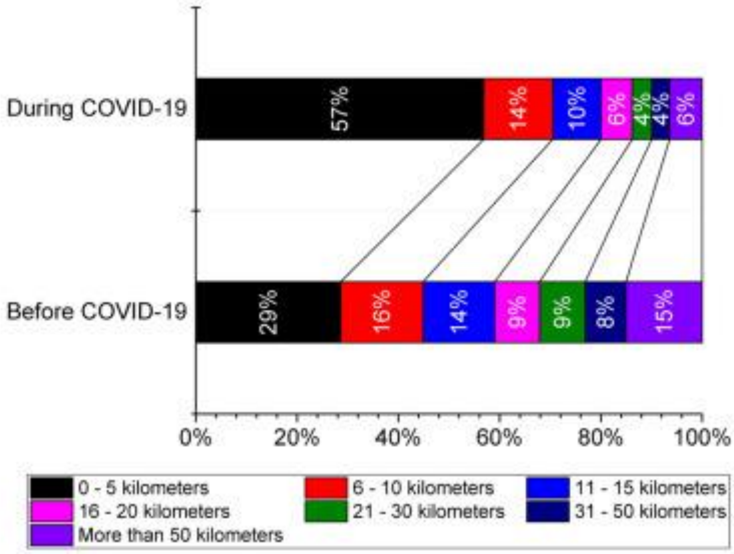

Figure 14: Distance travelled for primary outdoor trips before and during the COVID-19 pandemic [34].

Figure 15 compares the modal share for the main trips abroad before and during the COVID-19 pandemic. Most respondents (36%) said public transport was the primary mode they used to travel. A sharp drop in public transport use was seen during COVID-19, meaning only 13% of respondents used public transport. In contrast, private car use increased from 32% before COVID-19 to 39% during COVID-19 [34]. On the other hand, the authorities have suspended public transport to control the virus's spread. Thus, people tend to rely more on private modes, such as private cars or taxis, because they are safer than other alternatives [44]. Interestingly, walking (as a primary mode of transportation) also increased by 7% during COVID-19 [34].

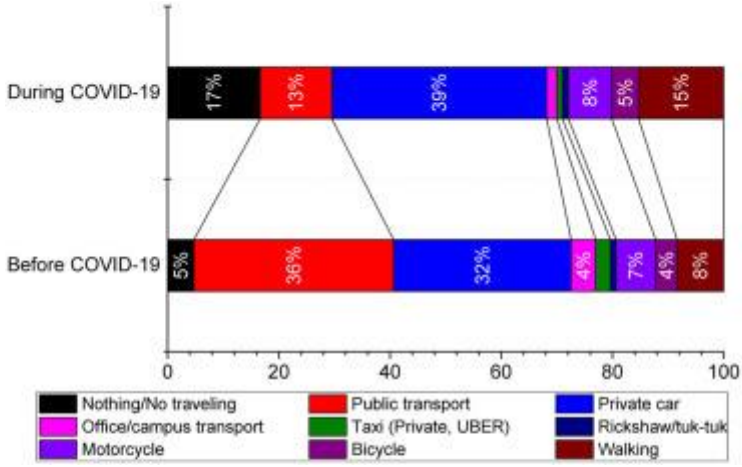

Figure 15: Mode for primary outdoor trips before and during the COVID-19 pandemic [34].

Based on the results of the expert survey, a large part of the modal shift was from public transport to other modes of transport: the most significant change was to the car (64.8%), followed by walking (42.3%), cycling (35.6%) and motorcycles (19.7%). Although the modal shift to walking and cycling is higher than to cars (mainly in Europe), more than 60% of the shift from public transport to cars has been reported (mainly in South Korea and China) [38].

Bhaduri et al. hypothesized that travellers are reasonably likely to continue using pre-COVID modes (referred to as inertia). Therefore, the level of inertia to maintain the pre-COVID-19 mode as the primary mode (the mode a person uses most during her week) was investigated. Figure 16 illustrates the inertia for commute and discretionary activities, measured in primary mode switching. The modes are grouped into five categories [37]:

- WFH - work from home and conduct discretionary activities online.
- PV - personal vehicle (car and motorbike).
- ODPV - On-demand private vehicles (auto-rickshaw, taxi, ride-hailing).
- SV - Shared vehicles (bus, rail, ride-sharing or pooled ride-hailing).
- NMT - Non-motorized transport (walk and cycle).

The "_pc" and "_ec" suffixes in Figure 16 refer to pre-COVID-19 and early COVID-19 stages, respectively. Regarding commuting, (a) it can be observed that people switched to working from home (WFH) instead of commuting, especially from low social distancing modes (SVs, ODPVs and NMT). On average, 40% of respondents switched from low social distancing modes to WFH, compared to 32% in the case of higher social distancing modes (PV). The PV inertia is high, closely following the WFH inertia. SVs and NMTs show higher inactivity than ODPVs, which can be attributed to the reluctance of long-distance travellers (mainly rail users) to use ODPVs, which may have space service coverage limitations and are more expensive. In the case of discretionary activities, Figure 16 (b), respondents tended to follow the pre-COVID-19 habit of using NMT modes rather than switching to online alternatives. Indeed, they showed a strong tendency to migrate to NMT cases, especially from modes with low levels of social distancing (SV) [37].

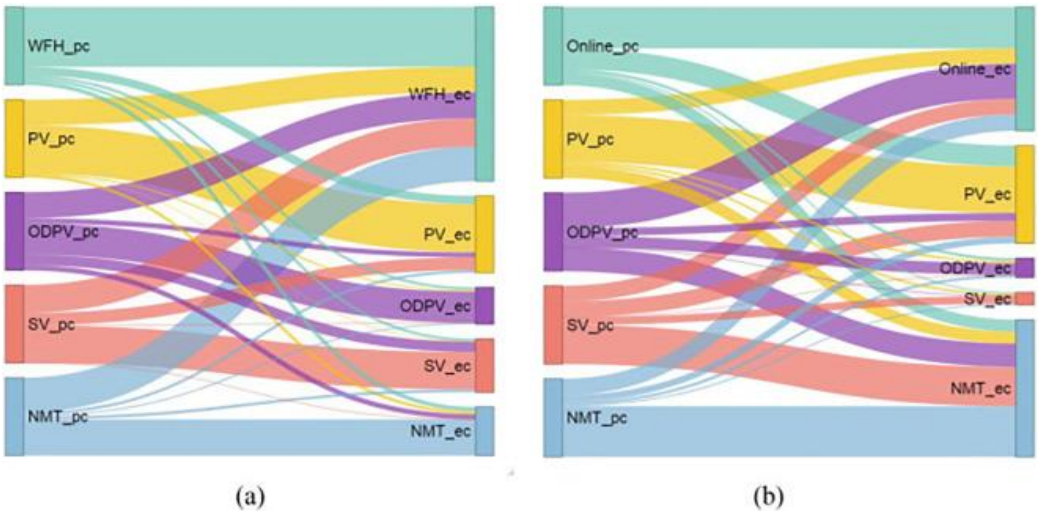

Figure 16: Inertia (measured in primary mode switching) of different mediums for (a) commute and (b) discretionary activities [37].

Regarding the long-term effects of COVID-19 on the transport sector, some experts are very concerned, on the one hand, about the possible increase in car dependence. Still, on the other hand, it is balanced by expectations of a further change of participation from physical to virtual spaces. In the context of long-term societal changes, more experts expect the changes to improve sustainability than those who show the opposite attitude [38].

As for intercity mobility of highways in China compared to origin-destination passenger car traffic, truck traffic declined significantly after the outbreak. In the event of a proper return of work and production, the movement of trucks was restored faster [42].

2.3. Emissions modelling

In order to investigate the dynamics, volume and magnitude of emissions from the transport sector, transport emissions modelling provides helpful information on emissions that can be important for the theoretical and conceptual development of a specific area [45].

Linton et al. studied several modelling methods that can be used to calculate CO_2 emissions from road transport at different scales. Several approaches were reviewed, including traffic network models (based on microsimulation), behavioural models, and Agent-based models [45].

Microsimulation provides many valuable techniques for modelling road traffic emissions, as it can analyse the effect of small network changes on traffic and the resulting emissions

[46]. The transportation demand is generated by microsimulation modelling using an origin-destination (O-D) matrix to represent individual trips in the network and the traffic assignment based on the four-stage model (1- Trip generation; 2- Trip distribution; 3- Mode split; 4- Traffic assignment) [47]. The emissions can be calculated using DRACULA (Dynamic Route Assignment Combining User Learning and microsimulAtion) or VISSIM. DRACULA measures the movement of vehicles in a given traffic network. It assumes constant consumption factors for vehicles idling or decelerating and calculates the fuel consumption of accelerating vehicles based on speed and acceleration. It is then converted to CO2, assuming the burned fuel is converted to CO2; this does not consider alternative fuel vehicles [48]. VISSIM collects data on emissions, delays, travel times etc., via the network. It requires the module plug-in "EnViVer Pro", which imports the vehicle data to calculate the CO2 emissions of the study area and output a table and graph [49.

One of the goals of transportation behaviour research is to understand how travellers use transportation infrastructure to predict demand better and improve decision-making, providing a more comprehensive view of activity [46],[47]. It captures more details about an individual's decision-making travel options and quantifies the level of transport demand, which then calculates CO_2 emissions [45].

Agent-based modelling represents a group of agents in a practice space, the modelling world in which agents interact to understand behavioural dynamics [48]. This approach captures the behavioural dynamics of the transportation system, similar to the behavioural models, and captures more flight details but understands behaviour and motivation. This modelling approach does not directly calculate road transport emissions but provides useful fuel mix information for future vehicle fleets. Such a method helps to understand future emissions from road transport and the extent to which emission reduction targets are being met through adopting alternative fuel vehicles [45].

Rito and Lopez presented a new method for modelling transport emissions using Google Maps data. The average speed can be obtained by obtaining the average travel time and the corresponding length of a section of the road. The average speed is used to determine vehicle flow in terms of Passenger Car Unit (PCU) through a speed flow curve based on Roadside Friction Index (RSFI) [49]. The analysis was performed using data generated by Google Maps available on Epifanio de los Santos Avenue (EDSA), a major road located in Metro Manila, Philippines. EDSA was divided into segments, each with an emission load account. The study determined the percentage of GHG emissions, precisely the share of atmospheric pollutants in the transport sector by different types of vehicles that travel along each road segment defined in the EDSA. The average speed of the vehicle flow was obtained by calculating the average travel time of the vehicles on a particular road section and the corresponding route length from Google Maps. Traffic flow as passenger car units (PCU) count per time was determined from speed flow curves versus a roadside friction graph [49].

Emissions can also be estimated using, for example, a macroscopic model, COPERT [10], or a microscopic instantaneous emission model, such as the vehicle-specific power (VSP) [50] methodologies. For COPERT methodology, input variables are detailed vehicle data about categories, fuel types, engine sizes, and technology/emission standards. If link-based travel time is available, it is possible to find the link-based average speed. Macedo et al. 2021 [51] propose a simplified COPERT-based model for estimating CO2 and NOX emissions of typical vehicles of the Portuguese domestic fleet, using only average speed as an input variable. The proposed approach can be mesoscopic because it considers the aggregated behaviour of different vehicles, synthesised in a single vehicle representative of a vehicle fleet. While the COPERT emission factor can be considered a group-dependent regression, this approach can be regarded as an approximation that does not explicitly consider a particular group structure. The advantage of this approach is that it allows one to determine the approximate emission factors without prior information about vehicle technology and engine capacity class [51].

2.4. Synthesis

Transport demand management aims to increase the overall sustainability of the transport sector by minimizing transport demand or improving the efficiency of existing and possible new transport modes. For most transport demand strategies, the role of technology is crucial since they demand some electronic tasks like organisation, monitoring and control. The choice of the mode of transport is probably one of the most critical elements in transport planning due to the vital role of public transportation in policymaking. Modal split refers to the percentage of travel using a particular mode of transport. Utility maximization can be taken as a solution to model the choice between alternatives, where decision-makers choose the options with the most utility. Biogeme is an open-source Python package designed for general maximum likelihood estimation of parametric models, focusing on discrete selection models.

The effects of the COVID-29 pandemic heavily impacted the transport sector and the commuting behaviour of people. Confinement campaigns, physical distancing measures in public transport and distribution, economic measures, avoidance of face-to-face social contact and online activities were the main actions against COVID-19 in the transport sector. Significant changes were verified in terms of travel purpose, mode choice, distance travelled and travel frequency. During the pandemic, many people stopped travelling to work or school because they started doing it online, and shopping became one of the primary purposes for travelling. The use of public transport was drastically reduced as people increased their use of private cars and non-motorized modes for their primary travel.

Transport emissions modelling provides helpful information on emissions which may be essential for the theoretical and conceptual development of a specific area. Other studies used several approaches, including traffic network models (based on microsimulation), behavioural models, Agent-based models, and macroscopic models, such as COPERT. A simplified version of the COPERT model can also be used for estimating emissions of the typical vehicles of a determined fleet, using only the average speed as an input variable, considering the aggregated behaviour of different vehicles, synthesised in a single vehicle representative of the fleet. The advantage of this approach is that it allows one to determine the approximate emission factors without prior information about vehicle technology and engine capacity class.

Several studies have been carried out on transport modelling, environmental impacts of transport and the impacts of COVID on mobility. Although urban transport has received much attention from policymakers and the scientific community, interurban passenger transport has not received as much attention. However, Portugal's rural roads and motorways emissions account for more than 55% of total NOX and CO2 emissions.

The present dissertation aims to cover the gap in recent studies for intercity traffic in Portugal, exploring the effects of COVID-19 on the transport sector and its emissions, focusing on the case of the suburban corridor between the cities of Aveiro and Porto.

3. Methodology

3.1. Overview

This chapter explains in detail the Case study and the adopted methodology for developing this dissertation, which consists of three main phases: Data collection, Data Analysis, Transport Characterization and Emissions modelling.

Data collection consisted of collecting data to characterise the supply of mobility solutions available and the characterization of transport demand in the corridor. This research step included searching available transport solutions on online platforms, such as vehicle occupancy, fleet data, and O-D matrices of travel cost, time, and distance. This research phase was also devoted to developing an anonymous online survey directed to the passengers of this corridor that aimed to understand their socio-economic characteristics, commuting behaviour and mode preferences.

The data obtained from the survey were subjected to descriptive and statistical analysis. The plots for the descriptive analysis were made in Microsoft Excel. For the statistical analysis, IBM SPSS was used to construct contingency tables in order to evaluate the measure of association between variables.

The observed modal split was calculated using the mode preferences data in Microsoft Excel. The travel cost, travel time and mode preferences were used to calculate the utility function parameters with the Biogeme algorithm, which were used in modelling the Modal split.

Travel time, travel distance, vehicle occupancy rates, and fleet data were the inputs to estimate the emissions of pollutants. These emissions were then converted into impact per passenger using the Handbook on the external costs of Transport [2].

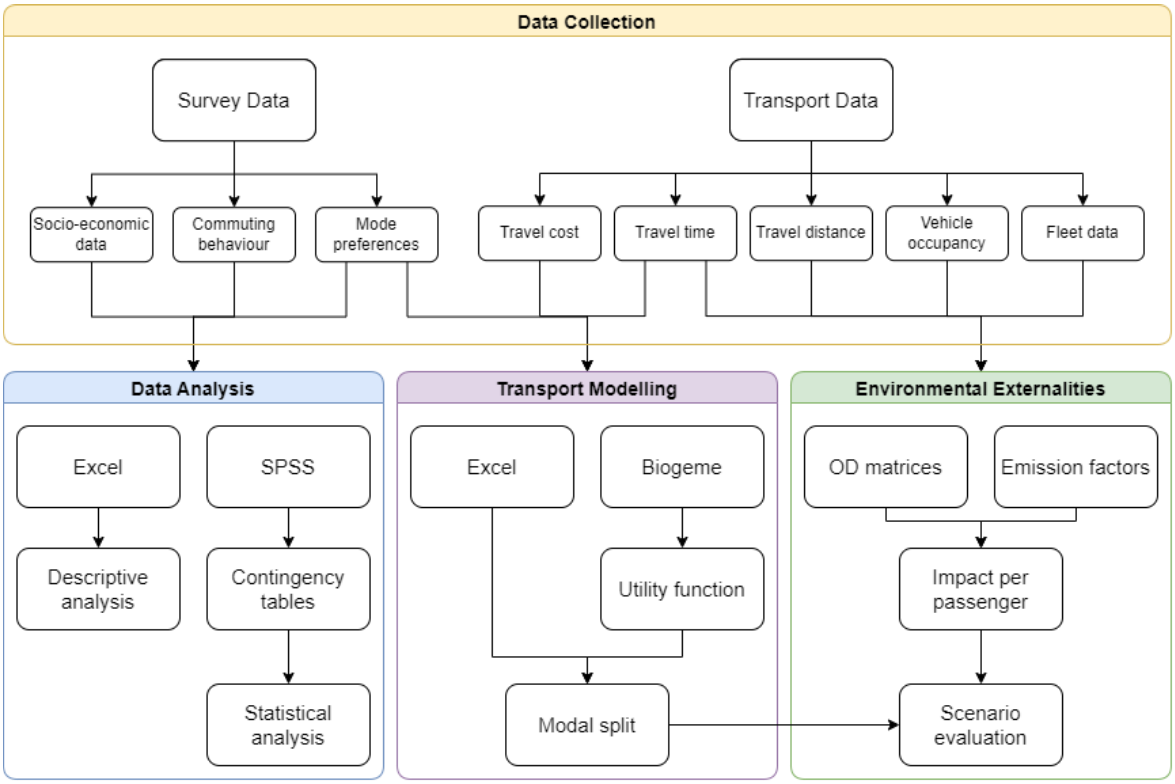

Figure 17: Methodology diagram.

3.2. Case study

The geographical area of this case study is the intercity transport corridor between the city of Aveiro and the city of Porto, which is affected by the mobility of the adjacent municipalities. Figure 18, highlighted in blue and green, represents the districts and cities of Aveiro and Porto, respectively.

The city of Aveiro is part of the Centro Region of Portugal and belongs to the sub-region called Aveiro Region. Porto belongs to the Norte Region and the sub-region of the Porto Metropolitan Area. In terms of population density, in 2020, Aveiro had an average of 401.5, while Porto counts an average of 5,232.9 habitants per km^2 [15].

Aveiro Region has a population density of 218,4 habitants per km^2. It comprises 11 municipalities: Águeda, Albergaria-a-Velha, Anadia, Aveiro, Estarreja, Ílhavo, Murtosa, Oliveira do Bairro, Ovar, Sever do Vouga and Vagos.

The Metropolitan Area of Porto has a population density of 852.5 habitants per km^2. It is composed of 27 municipalities: Arouca, Espinho, Gondomar, Maia, Matosinhos, Oliveira de Azeméis, Paredes, Porto, Póvoa de Varzim, Santa Maria da Feira, Santo Tirso, São João da Madeira, Trofa, Vale de, Cambra, Valongo, Vila do Conde and Vila Nova de Gaia [15].

Figure 18 represents the geographical area of the case study; highlighted in blue and green are the districts and cities of Aveiro and Porto, respectively.

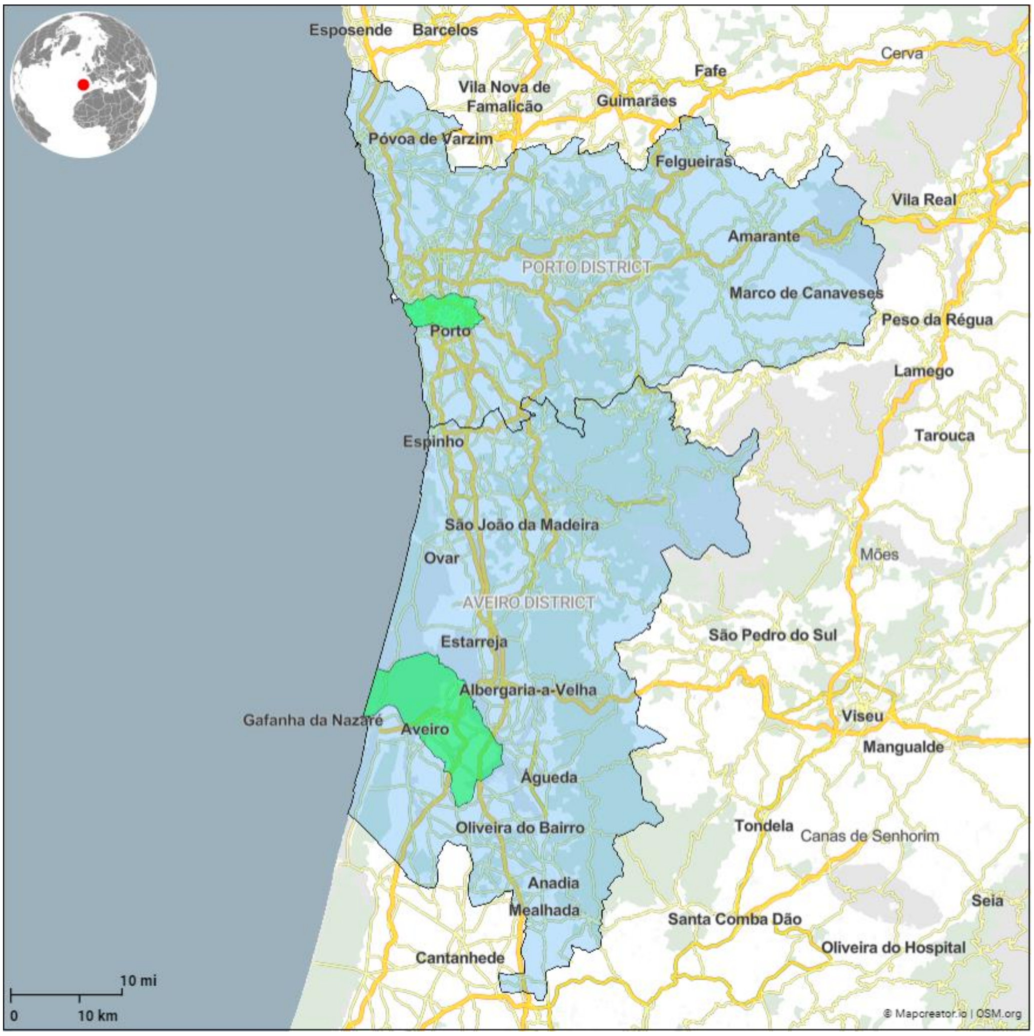

Figure 18: Map of the selected case study area [52].

3.2.1. Road mobility characterization

As the map of Figure 19 illustrates, the intercity corridor between the cities of Aveiro and Porto is, in terms of roadways, mainly composed by:

- 3 Highways:
  - A 1
  - A 29
  - A 32
- 2 Complementary Itineraries:
  - IC 1 – N109
  - IC 2 - N1

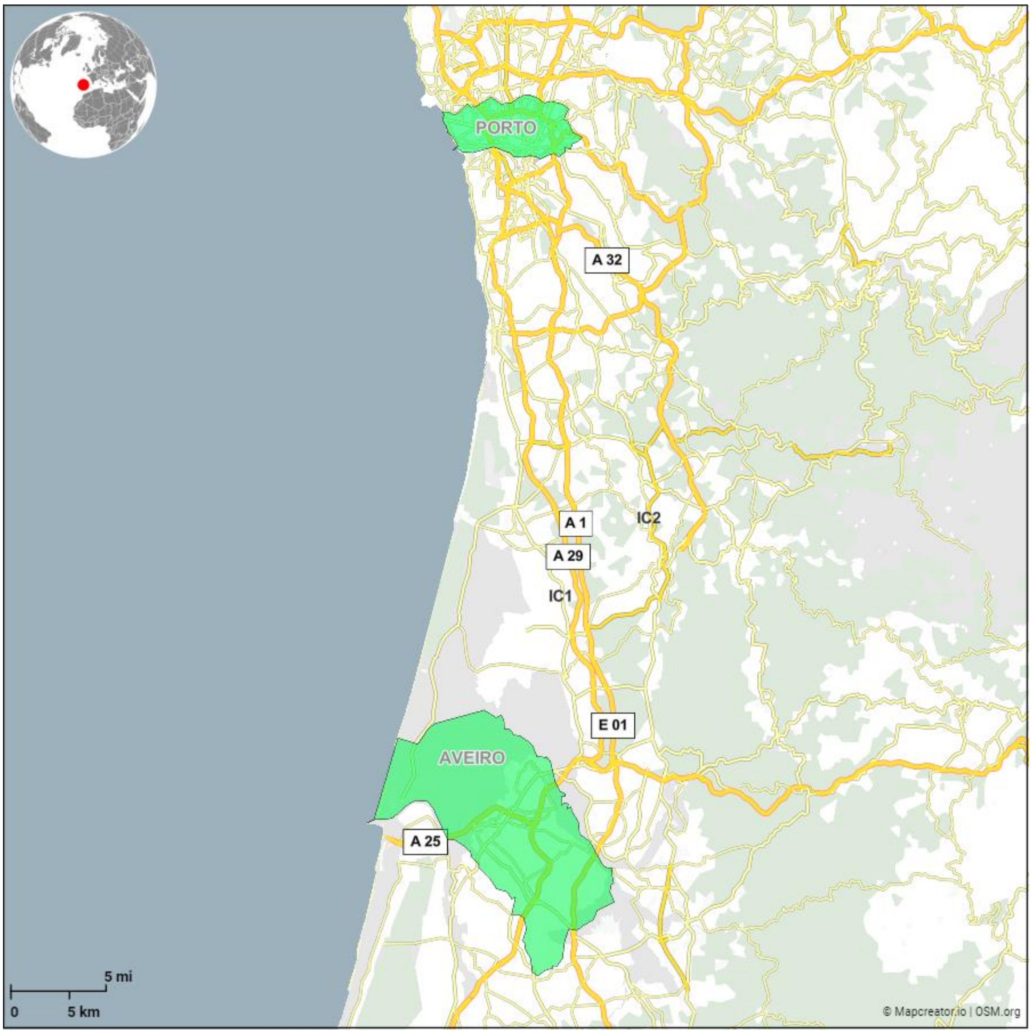

Figure 19: Highways and ICs between Aveiro and Porto [52].

Three prominent companies supply bus services to travel from Aveiro and Porto and vice versa: *Rede Nacional de Expressos* [53], *FlixBus* [54] and *Alsa* [55]. Altogether they offer around 18 travel options per business day, with a travel time between 55 minutes and 2 hours and might cost from 3€ to 18€.

In Aveiro Region, the supply of bus trips is mainly managed by the company *Transdev* [56].

The bus company that operates in Porto is STCP - *Sociedade de Transportes Coletivos do Porto, SA* [57]. There are two networks in terms of routes:

- The daytime network operates from 6 am to 12:30 am and has 58 lines, of which 36 operate throughout this period of the day, and the remaining 22 end their operation at 9 pm.
- The early morning network operates from 00:30 to 6 am, has 11 lines and operates simultaneously every day of the year.

3.2.2. Railway mobility characterization

The railway services in Portugal, Figure 20, are managed by CP (Portuguese trains) [58]. CP offers a ser of train services such as:

- High-speed (Alfa Pendular).
- Intercity (Intercidades).
- Regional and Inter-Regional.
- Lisbon Urban Trains.
- Porto Urban Trains.
- Coimbra Urban Trains..
- Celta (Porto/Vigo).

Figure 20: CP (Portuguese trains) services diagram [58].

The railway services between Aveiro and Porto, Figure 219, are part of the Linha do Norte (North Line), the leading Portuguese railway line connecting the city of Porto to the Portuguese Capital, Lisbon. CP offers an online platform where passengers can consult the available train options and buy their tickets. A passenger who wants to travel by train from Aveiro to Porto (Porto- Campanhã) has about 50 train options per business day, the prices range from 3.55€ to 20.80€, and the travel time will be between 47 and 73 minutes.

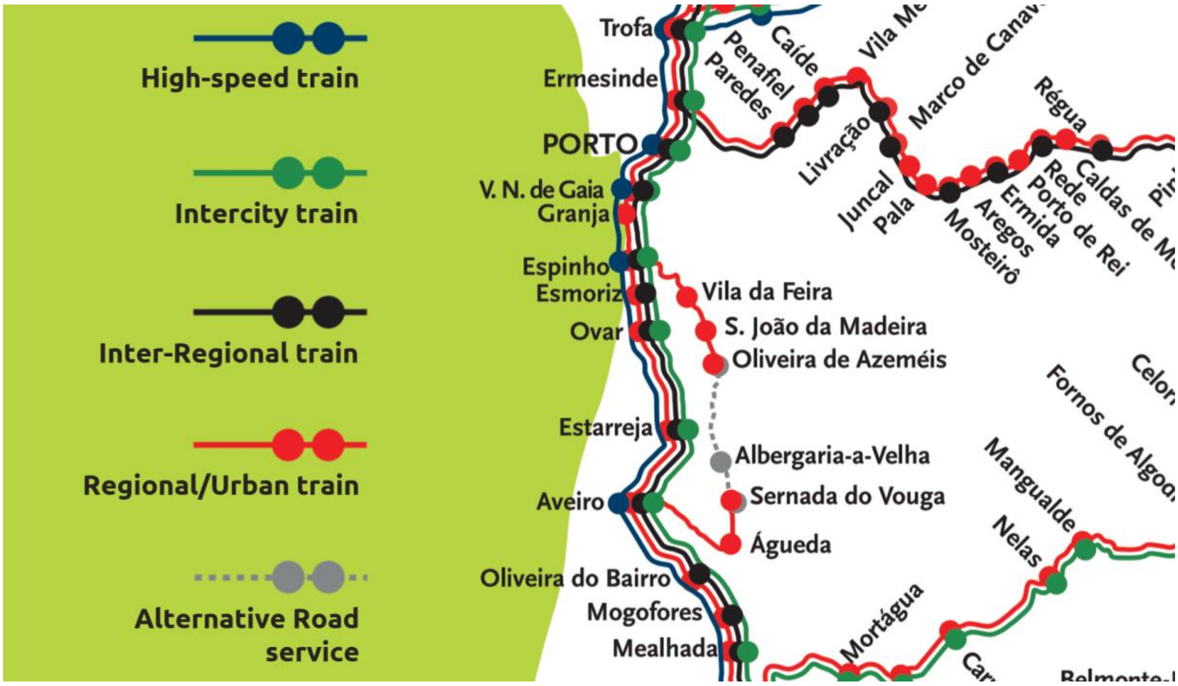

Figure 21: CP (Portuguese trains) railway services map between Aveiro and Porto [58].

3.2.3. Metropolitan Area of Porto mobility dynamics

The Mobility Survey in the Metropolitan Area of Porto and Lisboa (IMob), 2017, carried out by the National Institute of Statistics, shows that considering the population living in the Metropolitan Area of Porto aged between 6 and 84 years, it is estimated that the number of trips per day has amounted to 3.4 million. Vila Nova de Gaia (635,000 trips), Porto (419,000) and Matosinhos (359,000) were the municipalities that contributed the most, a total of 41.2%, to the total number of trips in the Metropolitan Area of Porto, based on the place of residence of the migratory population, the commuting of individuals in these municipalities corresponded, to 18.5%, 12.2% and 10.5% respectively, of the total displacement of residents in the Metropolitan Area of Porto [59].

Among the travelling population, the amount of trips/day per resident in the Metropolitan Area of Porto stood at 2.72. The highest trips/day ratios per mobile individual were calculated in the municipalities of São João da Madeira (3.00), Paredes (2.96) and Póvoa de Varzim (2.94). The municipalities of Arouca (2.26), Santo Tirso (2.47) and Gondomar (2.48) recorded the smallest values [59].

Most trips in the Metropolitan Area of Porto were performed using a private car, mainly as a driver (50.7%) and a passenger (16.9%), totalling 67.6% of the total. The use of the bus (public transport and company/school transport) accounted for 8.2% of total travel in the

Metropolitan Area of Porto, while rail transport (heavy and light) accounted for 2.8% [50]. The set designated as "soft modes" (on foot and by bike) is the second most chosen transport option, representing 18.9%. Still, the bicycle's contribution is only 0.4% of the total.

3.2.4. Aveiro Region mobility dynamics

A mobility survey was conducted in 2012 to characterize mobility in the Aveiro Region. About 6,300 residents participated, representing a sampling rate of 2.0%. In total, residents in the Region make, on average, on a working day, 712 000 trips, of which 95% are carried out within or between municipalities of the Region, which infers that the region is self-sufficient for a very significant set of activities [60].

Aveiro is the municipality that generates and attracts the most significant number of trips (28%). It is also the municipality with the most significant number of intra-municipal trips (143.000 trips), highlighting its importance as a regional business, educational and leisure centre. The following are the municipalities of Águeda and Ovar, which generate and attract about 13% of total travel, and Ílhavo (9% of the total travel) [60].

The main inter-municipal flows in the Region have as a pole of attraction the municipality of Aveiro, which confirms its importance in the regional context. The most common municipalities of origin are:

- Ílhavo: approximately 14,000 trips per direction (5% of public transport trips).
- Albergaria-a-Velha: 4,600 trips per direction (9% of trips in public transport).
- Estarreja: 4,300 trips per direction (12% of trips on public transport).
- Águeda: 4,000 trips per direction (5% of trips on public transport).

Individual transport is used in approximately 74% of the trips made in the Aveiro Region; 16% of the trips are made on foot, 4% by bicycle and 5% by public transport; such modal distribution shows a high dependence on the car for daily travel in the region [60].

Furthermore, there are essential differences in modal distribution among the eleven municipalities of the Region, mainly due to the greater or lesser weight of travel in soft modes (i.e., the weight of walking and cycling trips). As Figure 22 shows, the municipalities of Murtosa (58%), Albergaria-a-Velha (67%), Estarreja (68%) and Ovar (69%) have a lower intensity of individual transport because walking (in the cases of Albergaria-a-Velha and Ovar), by bicycle (in the case of Murtosa) or the combination of the two modes (in Estarreja) have greater expression. Also, in the municipality of Ílhavo, the share of bicycle travel is significant (13%) [60].

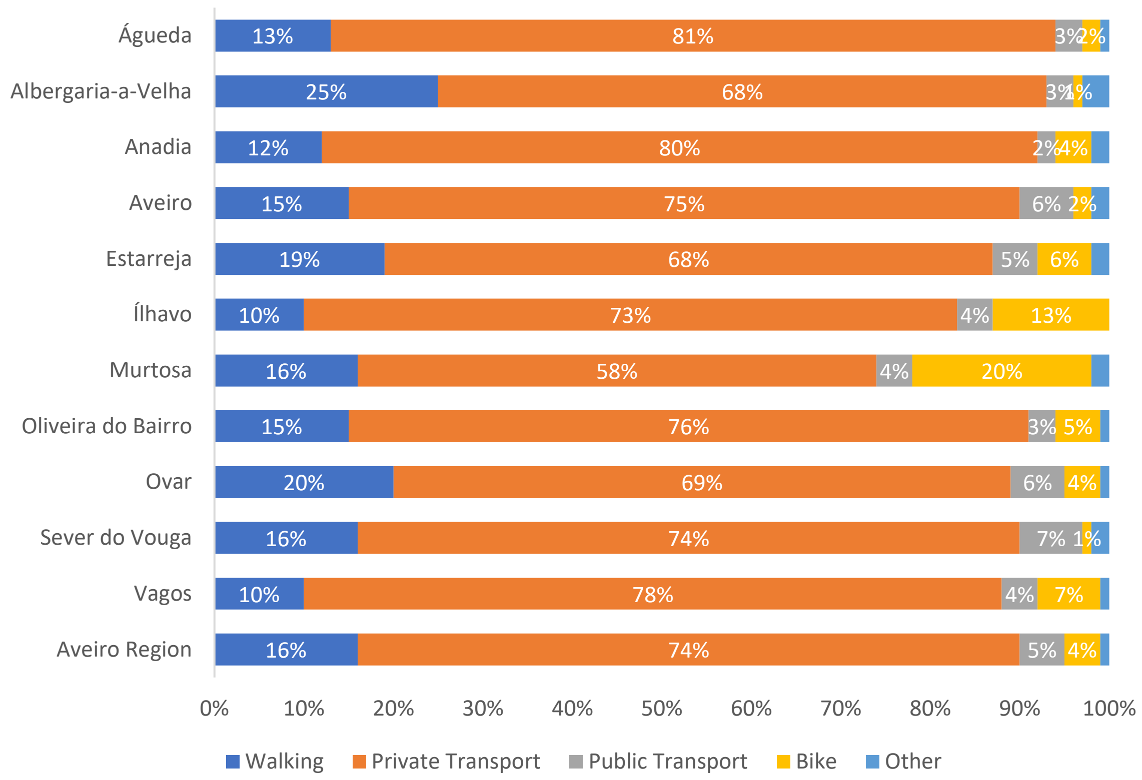

Figure 22: Modal distribution of completed trips by the municipality of Aveiro Region [60].

3.3. Data collection

The primary sources of data collection were: an online survey to estimate the commuting behaviour and transport preferences; online platforms were used to calculate the characteristics of the trips, such as travel distance, time and cost; fleet data from COPERT [10] was used to estimate the average emissions of each pollutant (PM_{10}, NO_x, VOC, NMVOC and CO_2) caused by passenger cars (Petrol, Diesel, Hybrid), LDV, HDT and buses (Diesel) relative to each trip; The marginal air pollution costs associated to rail transport, in this case, electric trains, were calculated, in €-cent per km, according to Table 20 of the Handbook on the External Costs of Transport [2].

3.3.1. Survey design

Inspired by other studies ([34],[36]), a survey was disseminated with the platform Google Forms. This survey structure is available in Appendix A. It was written in Portuguese and distributed through emails and social media channels such as Facebook and Instagram between December 29, 2020, and April 7, 2021. One hundred ninety-two (192) responses were achieved and later filtered to include only people who travelled between Aveiro and Porto before and, or during the pandemic, obtaining one hundred seventy-one (171) eligible participants. The questionnaire consisted of three sections: (1) socio-demographic characteristics, (2) primary travel frequency, reason, and destination before and during the COVID-19 pandemic, and (3) transport mode choice for primary travel before and during the COVID-19 pandemic.

Socio-demographic characteristics included gender, age, monthly household income (in Euros), vehicle ownership and employment status. The primary purpose of travel was defined as why people mainly undertake their trips. People may be able to decrease other less important trips during a pandemic. However, they may be compelled to travel for a particular primary trip purpose. Therefore, it is essential to focus on the primary purpose of travel as it determines the frequency of performed trips, distance travelled, and chosen mode.

The second section of the survey contained questions on the primary travel frequency, reason, and destination before and during the COVID-19 pandemic. The participants were asked to indicate how frequently they travelled in the intercity corridor between Aveiro and Porto and their origin and destination. Another question was addressed to know the reasons behind any changes in travel behaviour during the pandemic.

The last section of the survey intends to explore the most used transport modes and how comfortable or safe the passengers feel using each one in a pandemic scenario.

3.3.2. Transport Data

Factors like travel time, cost, distance, and average speed influence passengers' mode choices and are directly related to the environmental externalities caused by transport. The knowledge of these variables and the observation of behavioural data help explain the behaviour of passengers and, consequently, the performance and impacts generated in each mode, trip, and transport system.

Due to factors like traffic conditions and promotional rates, holidays, travel times, and costs may differ depending on the date and time of the trip. Therefore, to avoid these differences and ensure data conformity, calculations considered a trip departure at 8 am on a Wednesday. For each transport mode, the minimum travel time, in minutes, and cost, in euros, were considered for each trip, considering all possible origins and destinations. The platforms used to estimate these values were the following:

- For trips using the private vehicle, the travel time, costs and distances were calculated with the platform *ViaMichelin* [61].
- For bus trips, the travel time and costs were calculated using the following platforms: *CheckMyBus* [62], *Transdev* [56], *Omio* [63] and *Rede Expressos* [53]. The travel distance was considered the same as for the private vehicle.

- For train trips, the travel time and costs were calculated using the following platform *Comboios de Portugal* [58]; The travel distance (the rail length) was calculated using *Google Maps* [64].
- For Taxi/TVDE, the Travel costs calculated in *Rome2rio* [65], the travel time and distance were considered the same as for private car trips.
- For carpooling, travel costs were calculated using *Rome2rio* [65]; the travel time and distance were considered the same as private car trips.

3.4. Data Analysis

The data obtained from the survey were subjected to a descriptive analysis using Microsoft Excel [56] and statistical analysis using SPSS [66].

Microsoft Excel was used to construct several plots to support the descriptive analysis. The variables studied were:

- Travel purpose.
- Average trips per week.
- Average distance travelled per week.
- Modal split.
- Reasons for changes in commuting behaviour.
- Feeling of safety using each transport mode during the COVID-19 pandemic.

Data were collected before and during the pandemic for the variables, average trips per week, the average distance travelled per week and modal split. Therefore, both scenarios were compared to observe the impacts of COVID-19 on commuting behaviour.

A contingency table, also known as a cross-tabulation, describes the relationship between two categorical variables. In a contingency table, the categories of one variable define the rows of the table, and the categories of the other variables define the columns. Table cells contain the number of times a particular set of categories occurs. The last rows and columns of the tables usually contain the total number of observations for that category [67].

In order to study whether there is a significant impact of several categories in the mode choice, cross-tabulation was used to evaluate the relationship, both before and during the COVID-19 pandemic, of the following category pairs of data obtained from the survey:

- Chosen transport mode and Age (18 – 24, 25 – 44, 45 – 64 or 65+).
- Chosen transport mode and Gender (female or male).
- Chosen transport mode and professional activity (inactive, studying or working).
- Chosen transport mode and car availability (0 for true, 1 for false).
- Chosen transport mode and bus availability (0 for true, 1 for false).
- Chosen transport mode and train availability (0 for true, 1 for false).

Participants of the survey were inquired about their feeling of safety travelling by transport mode during the pandemic. The following categories were also studied using cross-tabulation to evaluate if the age of participants could have an impact on their feeling of safety relative to each mode:

- Age and Level of the feeling of safety travelling by car during the pandemic.
- Age and Level of the feeling of safety travelling by car during the pandemic.
- Age and Level of the feeling of safety travelling by car during the pandemic.

The first step is to check the asymptotic p-value of the Pearson Chi-square test to evaluate the measure of association between categories. Supposing the p-value is equal to or less than 0.05, in that case, the association is statistically significant, and the values of Cramér's V and Gamma: The cross-tabulation was generated using the software IBM SPSS Statistics [66].

- Cramér's V is the effect size measure of the Chi-square test of independence. It measures the strength to which two nominal variables are related. A value close to 1 indicates a strong association between the two variables. Values close to 0 indicate little or no association [68].
- Gamma is a symmetric measure of the association between two ordinal variables ranging from -1 to 1. A value close to the absolute value of 1 indicates a strong association between the two variables. Values close to 0 indicate little or no association [68].

3.5. Transport modelling

The choice of mode of transport (e.g., car, train, bus) depends on each passenger's preference, which is influenced by factors such as the availability of modes of transport, cost, and travel time. The factors that influence the choice of mode of transport can be divided into three groups:

- Characteristics of passengers (car ownership, possession of a driving license, domestic structure, income).
- Travel characteristics (purpose of travel - travel to work can be more accessible by public transport due to its regularity; part of the day - trips during the night, for example, are more challenging to make by public transport, etc.).
- Transport system characteristics: travel time components (travel time, wait time and walking time for each mode of transport); monetary cost components (transport ticket, tolls, fuel costs, among others); availability and parking costs; reliability of travel time and regularity of service; comfort and convenience; safety and driving protection while driving; requirements in driving skills; and opportunities to perform other activities while travelling (phone calls, reading, etc.) [69].

It is necessary to know how the transport system's characteristics influence passengers' decision-making to help understand and manage the demand for transport in a specific area. One way to estimate these choices is by deducing their utility function. In economic terms, Utility is typically used to represent the value of satisfaction a consumer derives from consuming a good or service. The utility function is a way to represent this value and allows the evaluation of a consumer's order of preferences over a set of options. In this case, the options concern modes of transport.

Economists use utility functions to understand consumer behaviour better and determine the consumer satisfaction level of goods and services. Utility functions can also help analysts determine how goods and services will be distributed to consumers to realise total utility [31].

The utility function is expressed as the quantity of a set of goods or services, usually expressed as $U(X_1, X_2, X_3, X_n)$. A utility function that describes the preference of one set of goods (X_a) over another set of goods (X_b) expressed by $U(X_a, X_b)$ [31].

The parameters of the utility functions for each mode of transport were calculated using the *Pandas Biogeme* algorithm, an open-source *Phyton* package developed for estimating the maximum probability of parametric models, more specifically, with an emphasis on discrete choice models. It is based on the *Phyton Data Analysis Library package* called *Pandas* [33].

This model considers a set of observations obtained through the survey responses to calculate the parameters of the utility functions for each mode of transport. It considers the travel time, the cost of travel, the availability associated with each transport mode for each observation, and the choice (of the transport mode) made by each passenger.

Biogeme [15] is designed to estimate the parameters of various models using maximum probability estimation and is mainly intended for discrete choice models. Five transport modes were considered: car, bus, train, carpooling and taxi. The Biogeme algorithm determined the utility function parameters for each mode of transport.

The data from the survey contains information on the time, cost of travel, availability of each mode of transport, and the alternative chosen by the participants. Each column corresponds to a specific variable, and each row corresponds to a trip.

The variables defined in the model were as follows:

- *Trip ID*: trip number.
- *T_bus*: bus travel time (in minutes).
- *T_train*: train travel time (in minutes).
- *T_car*: travel time by private car, carpooling or taxi (in minutes).
- *C_bus*: bus travel cost (in cents).
- *C_train*: cost of train travel (in cents).
- *C_car*: car travel cost (in cents).

- *C_ride*: carpooling *travel* cost (in cents).
- *C_taxi*: taxi travel cost (in cents).
- *Bus_av*: Boolean variable corresponding to 1 if bus availability is available for the route in question.
- *Train_av*: Boolean variable corresponding to 1 if there is train availability for the route in question.
- *Car_av*: Boolean variable corresponding to 1 if the passenger owns a personal car.
- *Taxi_av*: Boolean variable corresponding to 1 if Taxi or TVDE are available.
- *Ride_av*: Boolean variable corresponding to 1 if the passenger can share the car with another passenger.
- *choice_pre*: mode of transport chosen before the COVID-19 pandemic.
- *choice_pand*: mode of transport chosen during the COVID-19 pandemic.

The parameters to be estimated to define the utility function are:

- *ASC_BUS*: alternative specific constant to the bus transport mode.
- *ASC_TRAIN*: alternative specific constant to the train transport mode.
- *ASC_CAR*: alternative specific constant to the car transport mode.
- *ASC_TAXI*: alternative specific constant to the taxi transport mode.
- *ASC_RIDE*: alternative specific constant to the carpooling transport mode.
- *B_TIME*: travel time impact parameter.
- *B_COST*: travel cost impact parameter.

Utility functions, where each is associated with a mode of transport, are defined as:

- *V1 = ASC_BUS + B_TIME * BUS_T_SCALED + B_COST * BUS_C_SCALED*
- *V2 = ASC_TRAIN + B_TIME * TRAIN_T_SCALED + B_COST * TRAIN_C_SCALED*
- *V3 = ASC_CAR + B_TIME * CAR_T_SCALED + B_COST * CAR_C_SCALED*
- *V4 = ASC_TAXI + B_TIME * CAR_T_SCALED + B_COST * TAXI_C_SCALED*
- *V5 = ASC_RIDE + B_TIME * CAR_T_SCALED + B_COST * RIDE_C_SCALED*

Each mode's utility function and availability are associated with each alternative's number by a phyton dictionary.

- *V = {1: V1, 2: V2, 3: V3, 4: V4}*
- *av = {1: Bus_av, 2: Train_av, 3: Car_av, 4: Taxi_av, 5: Ride_av}*

Then, to define the model, the model logit function provides the logarithm of the probability of choosing the logit model and consists of 3 arguments:

- The dictionary that describes the utility functions (*V*).
- The dictionary that describes the conditions of availability (*av*).
- The alternative for which the probability should be calculated (*choice_pre* and *choice_pand*).

Obtaining

- *logprob = models.loglogit (V, av, choice_pre)*

- *logprob = models.loglogit (V, av, choice_pand)*

3.6. Environmental externalities

The costs associated with environmental externalities were calculated, for the road (private cars and buses) and rail transport, considering the distances and travel times between the various municipalities.

3.6.1. Road transport

The road transport emissions were calculated based on the COPERT results for the composition of the national vehicle fleet. The emission factors are determined for typical vehicle types. The least-squares fitting technique was used to find the optimal fit curve. This method can be extended to several vehicle types besides passenger cars, such as light-duty vehicles (LDVs), heavy-duty trucks (HDT) or buses. For example, the CO_2 emission factor (g/km) of a diesel passenger car can be calculated according to Expression *3.1* [51]:

$$\varepsilon_{CO_2}(s) = \begin{cases} 0.072s^2 - 7.530s + 360.424\ (R^2 = 98\%), & s \le 50km/h \\ 0.016s^2 - 2.382s + 232.506\ (R^2 = 99\%), & 50 < s \le 90km/h \\ -0.013s^2 + 4.063s + 118.640\ (R^2 = 98\%), & otherwise \end{cases} \quad 3.1$$

$\varepsilon_i = Mass\ of\ emissions\ of\ pollutant\ i\ (g)$
$s = average\ speed\ of\ the\ vehicle\ (km/h)$

Different emissions curves were computed and associated with the road type for different speed ranges. An average speed lower than 50km/h is relative to urban roads, between 50 km/h and 90 km/h for rural roads and highways for speeds above 90 km/h. Figure 23 represents the CO_2 emission curves of a diesel passenger car on urban roads, rural roads, and highways. Figure 24 compares the curve of CO_2 emissions by average speed for diesel, petrol, and hybrid cars.

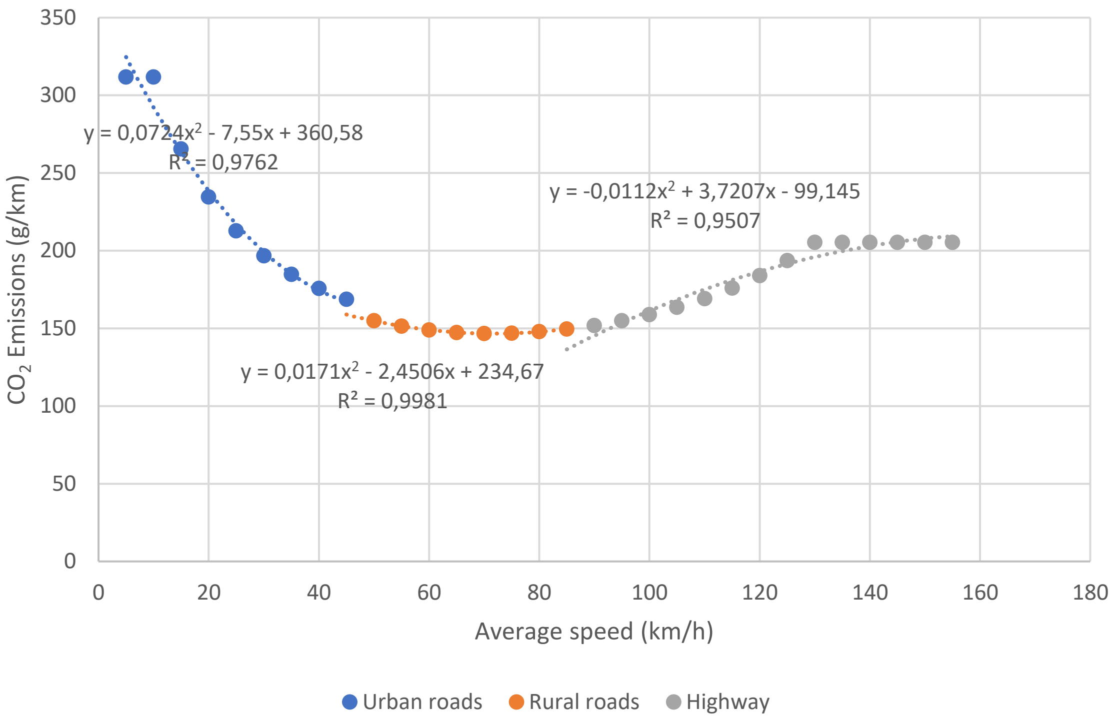

Figure 23: CO_2 emissions (g/km) for average speed (km/h) of diesel passenger cars.

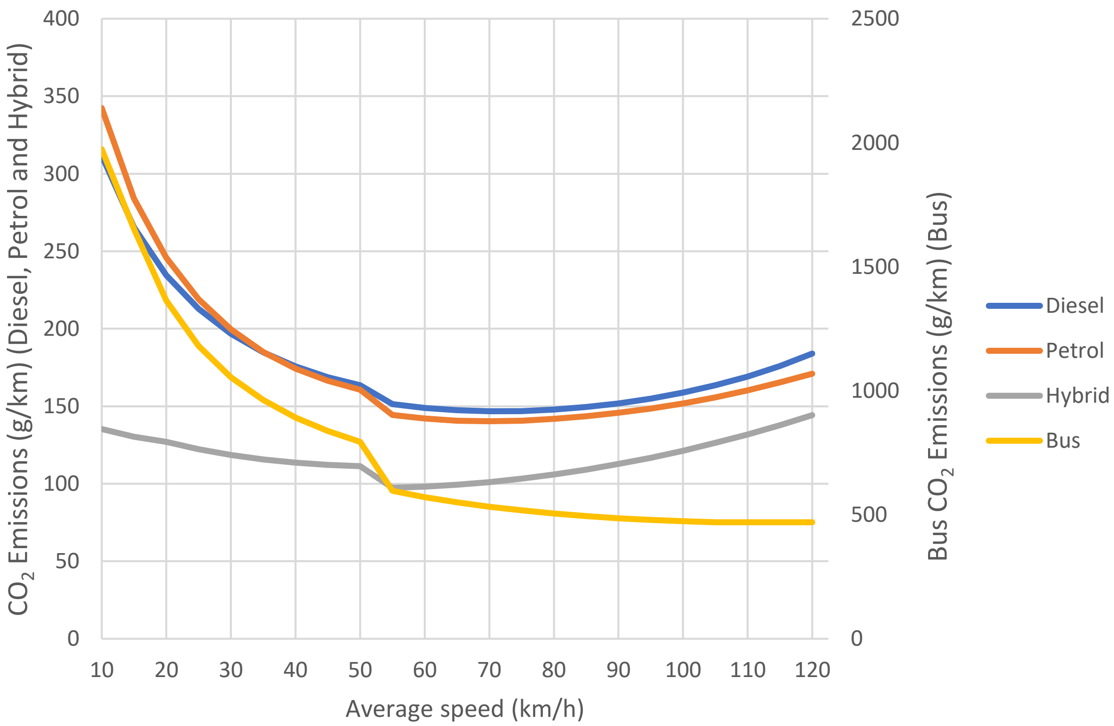

Figure 24: CO_2 Emissions by the average speed of passenger cars.

Expression *3.2* can be used as a general solution to estimate emissions of a specific pollutant.

$$\varepsilon(s) = as^4 + bs^3 + cs^2 + ds + e \quad 3.2$$

Each pollutant's emissions are represented in a different table. Table 4 is an example of the case of CO2 emissions. It contains the values of the corresponding coefficients to calculate the emissions, in grams per kilometre, depending on the fuel or vehicle category and road type. The remaining tables are available in Appendix B.

Table 4: Coefficients for CO2 emissions calculation by fuel/category and road type [10].

Fuel/Category	Road type	a	b	c	d	e
Petrol car	Urban			0.17	-14.47	477.34
	Rural			0.02	-2.36	224.54
	Highway			-0.01	3.17	-62.78
Diesel car	Urban			0.07	-7.53	360.42
	Rural			0.02	-2.38	232.51
	Highway			-0.01	4.06	-118.65
Hybrid car	Urban				-0.69	141.99
	Rural				0.39	75.36
	Highway			-0.01	3.91	-140.68
LDV	Urban			0.39	-37.04	1424.60
	Rural			0.06	-7.62	428.23
	Highway			-0.04	11.07	-437.93
HDT	Urban				-4.35	409.28
	Rural			0.04	-7.02	767.71
	Highway					485.75
Bus	Urban			0.73	-70.95	2532.70
	Rural				-3.44	783.02
	Highway		-2.00E-04	0.10	-12.78	1030.10

Knowing the estimated travel time (min), Table 5, and distance (km), Table 6, the average speed (km/h) was calculated for each trip, Table 7.

Table 5: Travel time (min) for road transport (excluding bus) [64].

Travel time (min)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	30	18	34	23	32	32	40	34	65	39	50	53	57
Águeda		22	43	32	37	42	43	40	71	48	55	58	59
Albergaria a Velha			30	22	22	30	29	29	57	37	42	46	44
Murtosa				11	24	22	30	29	58	35	42	46	44
Estarreja					16	19	23	21	50	27	34	39	45
Oliveira de Azemeis						25	9	17	37	32	34	33	37
Ovar							25	17	56	22	29	36	40
São João da Madeira								12	37	25	30	29	41
Santa Maria da Feira									43	17	23	27	26
Arouca										55	61	52	57
Espinho											19	19	28
Vila Nova de Gaia												13	14
Gondomar													18

Table 6: Travel distance (km) for road transport [64].

Travel distance (km)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	26	25	37	21	40	42	54	47	68	57	69	78	74
Águeda		16	43	29	33	47	42	49	61	63	70	83	80
Albergaria a Velha			23	16	19	37	28	38	47	52	59	69	66
Murtosa				8	23	19	31	32	52	41	56	62	59
Estarreja					16	20	25	26	45	34	49	58	56
Oliveira de Azemeis						17	9	16	30	44	48	47	50
Ovar							15	11	47	22	35	46	43
São João da Madeira								7	29	25	40	39	42
Santa Maria da Feira									35	18	30	36	34
Arouca										52	53	56	61
Espinho											17	28	24
Vila Nova de Gaia												12	9
Gondomar													15

Table 7: Road transport's average speed (in kilometres per hour).

Average speed (km/h)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	51,4	83,3	65,3	54,8	75,0	78,8	81,0	82,9	62,8	87,7	82,8	88,3	77,9
Águeda		43,6	60,0	54,4	53,5	67,1	58,6	73,5	51,5	78,8	76,4	85,9	81,4
Albergaria a Velha			46,0	43,6	51,8	74,0	57,9	78,6	49,5	84,3	84,3	90,0	90,0
Murtosa				43,6	57,5	51,8	62,0	66,2	53,8	70,3	80,0	80,9	80,5
Estarreja					60,0	63,2	65,2	74,3	54,0	75,6	86,5	89,2	74,7
Oliveira de Azemeis						40,8	60,0	56,5	48,6	82,5	84,7	85,5	81,1
Ovar							36,0	38,8	50,4	60,0	72,4	76,7	64,5
São João da Madeira								35,0	47,0	60,0	80,0	80,7	61,5
Santa Maria da Feira									48,8	63,5	78,3	80,0	78,5
Arouca										56,7	52,1	64,6	64,2
Espinho											53,7	88,4	51,4
Vila Nova de Gaia												55,4	38,6
Gondomar													50,0

Replacing *s* with the average speed in Expression *3.2* gives the estimated values for emissions of $PM_{2.5}$, PM_{10}, NO_X, VOC, NMVOC and CO_2 (g/km). For example, Table 8 represents the estimated values of CO_2 emissions for a diesel passenger’s car. The tables relative to other pollutants, vehicle classes and fuels are available in Appendix C.

Table 8: Estimated CO_2 emissions of a diesel car per each pair origin-destination (grams of CO2).

CO_2 emissions (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	3777	3574	5219	3044	5630	5941	7674	6712	9633	8267	9850	11340	10453
Águeda		2626	6130	4210	4807	6616	6011	6889	8959	8912	9866	11959	11378
Albergaria a Velha			3802	2626	2787	5203	4015	5374	8011	7456	8458	10101	9662
Murtosa				1313	3303	2787	4399	4509	7566	5761	7941	8808	8374
Estarreja					2281	2831	3527	3657	6542	4788	7075	8463	7879
Oliveira de Azemeis						2807	1283	2305	5066	6276	6890	6763	7107
Ovar							2595	1842	6941	3136	4918	6486	6073
São João da Madeira								1229	4826	3564	5672	5538	5966
Santa Maria da Feira									5922	2546	4240	5105	4807
Arouca										7485	7765	7908	8619
Espinho											2475	4073	3527
Vila Nova de Gaia												1735	1510
Gondomar													2574

The emission of air pollutants can lead to different types of damage. Most relevant and probably best analysed are the health effects due to air pollutants. However, other damages, such as building and material damages, crop losses and biodiversity losses, are also relevant. According to the air pollution costs of each pollutant for Portugal, Table 9, available in Handbook on External Costs of Transport [2], and the transport occupancy rates, the emission values were then converted into monetary costs (€-cent/passenger). It was considered an occupation rate of 1.7 passengers for private cars [70] and 33.75 for buses [11]. The air pollution costs per passenger were calculated according to *Expression 3.3*.

Table 9: Air pollution costs: average damage cost in €/kg emission, national averages for transport emissions in 2016 (excl. maritime) (All effects: health effects, crop loss, biodiversity loss, material damage) [2].

€$_{2016}$/kg	**NH_3**	**NMVOC**	**SO_2**	**NO_x city [a]**	**NO_x rural [a]**	**$PM_{2.5}$ metropole [a]**	**$PM_{2.5}$ city [a]**	**$PM_{2.5}$ rural [a]**	**PM_{10} average [b]**	**CO_2**
Portugal	4.3	0.5	4.1	2.8	1.7	292	94	39	12.3	0.1
EU28	17.5	1.2	10.9	21.3	12.6	381	123	70	22.3	0.1

Notes:

a. Rural area: outside cities; metropolitan area: cities/agglomeration with more than 0.5 million inhabitants.
b. PM_{10} cost factors can be used for the non-exhaust emission of particles PM, e.g., from brake and tyre abrasion.

$$APC_{road} = \frac{\sum_i^n \theta_i \, \varepsilon_i * 10^{-3}}{\mu_j} \quad (3.3)$$

$APC_{road} = Total\ air\ pollution\ costs\ for\ road\ traffic\ emissions\ (€/passenger)$
$\theta_i = Air\ pollution\ costs\ per\ kg\ of\ the\ pollutant\ i\ (€_{2016}/kg)$
$\varepsilon_i = Mass\ of\ emissions\ of\ pollutant\ i\ (g)$
$\mu_j = Vehicle\ occupancy\ for\ the\ vehicle\ j$

The air pollution costs for diesel cars are represented in Table 10; the tables for petrol cars, hybrid cars and diesel buses are available in Appendix D.

Table 10: Total air pollution costs ($PM_{2.5}$, PM_{10}, NO_X, VOC, NMVOC and CO_2) per passenger for diesel cars (€-cent/passenger).

Air pollution costs per passenger for diesel cars (€-cent/passenger)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	38.7	41.7	57.0	31.7	63.9	68.4	89.0	78.3	104.1	97.7	114.9	134.3	120.0
Águeda		21.0	65.4	43.7	49.7	72.8	63.7	77.8	91.8	102.6	112.6	140.7	132.1
Albergaria a Velha			29.7	21.0	28.6	58.9	42.4	61.8	59.7	87.3	99.1	120.1	114.9
Murtosa				10.5	34.8	28.6	47.3	49.4	78.4	64.3	91.8	102.1	96.9
Estarreja					24.3	30.6	38.5	41.4	67.8	54.5	83.4	100.4	89.4
Oliveira de Azemeis						22.8	13.7	24.2	38.2	73.1	80.8	79.5	82.4
Ovar							21.2	15.1	70.7	33.5	55.3	74.1	66.1
São João da Madeira								10.0	37.2	38.0	65.6	64.2	64.1
Santa Maria da Feira									44.6	27.6	48.7	59.0	55.3
Arouca										78.6	79.8	86.1	93.7
Espinho											25.6	48.2	36.1
Vila Nova de Gaia												18.1	12.4
Gondomar													19.0

3.6.2. Railway transport

Thanks to The Handbook on External Costs of Transport [2], it was possible to estimate the marginal costs of train trips due to air pollution. The trains used in the case study area are Regional, Intercity, and High-speed trains (Alfa). For each pair origin-destination, the total air pollution costs due to rail passenger transport can be calculated with Expression *3.4*.

$$APC_{rail} = \alpha * \omega \qquad 3.4$$

$APC_{rail} = Total\ air\ pollution\ costs\ due\ to\ rail\ passnger\ transport\ (€ - cent/passenger)$
$\alpha =$ Distance between origin and destination train stations (km)
$\omega = Marginal\ air\ pollution\ costs\ for\ rail\ passenger\ transport\ per\ pkm\ (€ - cent/pkm)$

Table 11 represents the Marginal air pollution costs for rail passenger transport depending on the train type (High-speed, Intercity or Regional), the traction (electric or diesel) and whether the train is equipped with EGR/SCR or not. The values of the marginal costs for diesel trains will depend on if the area is metropolitan, urban, or rural.

Table 11: Marginal air pollution costs for rail passenger transport (€-cent per pkm) [2].

Train type	Traction	Emission class	Metropolitan area	Urban area	Rural area
High-speed	Electric	n.a.	0.002	0.002	0.002
Intercity	Electric	n.a.	0.01	0.01	0.01
	Diesel	Equipped with EGR/SCR	0.47	0.38	0.23
		Not equipped with EGR/SCR	0.70	0.67	0.40
Regional	Electric	n.a.	0.02	0.02	0.02
	Diesel	Equipped with EGR/SCR	1.52	1.17	0.71
		Not Equipped with EGR/SCR	2.10	1.99	1.20

Since the use of diesel trains for passenger transport is very residual for the study area, only electric trains were considered. Table 12 represents the distance travelled by trains between each municipality train station. Albergaria a Velha, Murtosa, Arouca and Gondomar were not considered for Railway transport since there are no train stations in these municipalities.

Table 12: Railway distance between municipalities' train stations (km) [64].

Train distance (km)	Águeda	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Espinho	Vila Nova de Gaia	Porto
Aveiro	20,2	14,7	76,3	28,1	68,3	18,8	44,1	59,7	63,5
Águeda		34,9	96,5	48,3	88,5	39	64,3	79,9	120
Estarreja			61,6	13,4	53,6	48,2	29,4	45	48,8
Oliveira de Azemeis				48,2	8	13,4	32,2	47,8	51,6
Ovar					40,2	34,8	16	31,6	35,4
São João da Madeira						5,4	24,2	39,8	43,6
Santa Maria da Feira							18,8	34,4	38,2
Espinho								15,6	19,4
Vila Nova de Gaia									3,8

Applying the distance travelled by trains from Table 12 and the values of the marginal air pollution costs, from Table 11, in Expression *3.4* will provide the total air pollution costs for each trip made by regional, intercity or highspeed electric trains. The values are represented in Table 13, Table 14 and Table 15, respectively.

Table 13: Total air pollution costs for a regional electric train (€-cent/passenger).

Total air pollution costs of a regional train (€-cent/passenger)	**Águeda**	**Estarreja**	**Oliveira de Azemeis**	**Ovar**	**São João da Madeira**	**Santa Maria da Feira**	**Espinho**	**Vila Nova de Gaia**	**Porto**
Aveiro	0.40	0.29	1.53	0.56	1.37	0.38	0.88	1.19	1.27
Águeda		0.70	1.93	0.97	1.77	0.78	1.29	1.60	2.40
Estarreja			1.23	0.27	1.07	0.96	0.59	0.90	0.98
Oliveira de Azemeis				0.96	0.16	0.27	0.64	0.96	1.03
Ovar					0.80	0.70	0.32	0.63	0.71
São João da Madeira						0.11	0.48	0.80	0.87
Santa Maria da Feira							0.38	0.69	0.76
Espinho								0.31	0.39
Vila Nova de Gaia									0.08

Table 14: Total air pollution costs for an intercity electric train (€-cent/passenger).

Total air pollution costs of an intercity train (€-cent/passenger)	**Estarreja**	**Espinho**	**Vila Nova de Gaia**	**Porto**
Aveiro	0.147	0.441	0.597	0.635
Estarreja		0.294	0.450	0.488
Espinho			0.156	0.194
Vila Nova de Gaia				0.038

Table 15: Total air pollution costs for a high-speed electric train (€-cent/passenger).

Total air pollution costs of a high-speed train (€-cent/passenger)	**Vila Nova de Gaia**	**Porto**
Aveiro	0.119	0.127
Vila Nova de Gaia		0.008

4. Analysis and discussion of results

This chapter is dedicated to the analysis and discussion of results. The first section presents the estimation of the utility function parameters and the predicted modal split based on the model's results. The second section offers a descriptive analysis of the answers to the survey regarding demographics and commuting behaviour and evaluates the measure of association between the studied variables. The last section shows the results of the emissions modelling, an estimation of the air pollution costs per passenger considering the mode choices of the sample.

4.1. Data Analysis

4.1.1. Demographics

The demographic characteristics of the survey participants are summarised in Table 16. There is a bias in the sample since the survey was primarily shared on university mailing lists, which is why 64% of the sample are students. This sample must be seen, however, as representative of the university community

Table 16: Demographic characteristics of the sample.

Item	Category	Frequency	Percentage (%)
Age	18-24	110	64
	25-44	35	20
	45-64	23	13
	65+	3	2
Gender	Male	54	32
	Female	117	68
Occupation	Student	109	64
	Employee	35	20
	Student worker	14	8
	Self-employed	6	4
	Researcher	4	2
	Retired	2	1
	Unemployed	1	1
Monthly Income (Euros)	0 – 400	104	61
	401 – 680	5	3
	681 – 1100	25	15
	1101 – 1500	16	9
	1501 – 2000	9	5
	2001 – 3000	9	5
	3000+	3	2
Vehicle ownership	Yes	91	53
	No	80	47

4.1.2. Descriptive Analysis

According to Figure 25, the primary travel purpose was studying for 58% of the respondents. It was expected since students composed 64% of the sample.

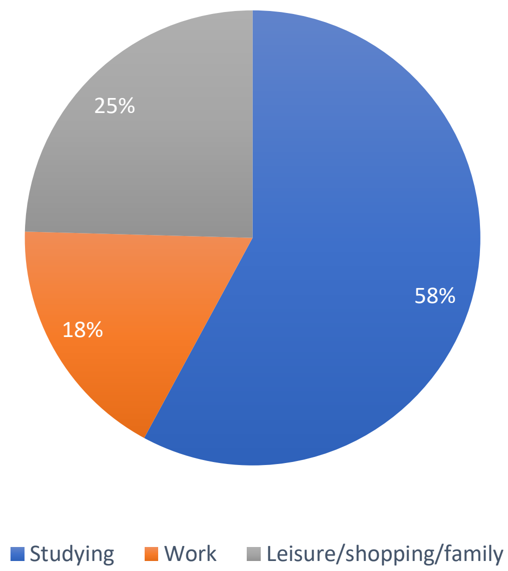

Figure 25: Travel purpose of the trips.

It is possible to observe a significant decline in travel frequency during the COVID-19 pandemic. Figure 26 shows that, on average, the participants went from 2.96 to 0.88 trips per week, meaning a decrease of nearly 70% during the pandemic. It also means an impact on the average travel distance, reduced from 327 to 105 km per week, as shown in Figure 27, meaning a decrease of almost 68%.

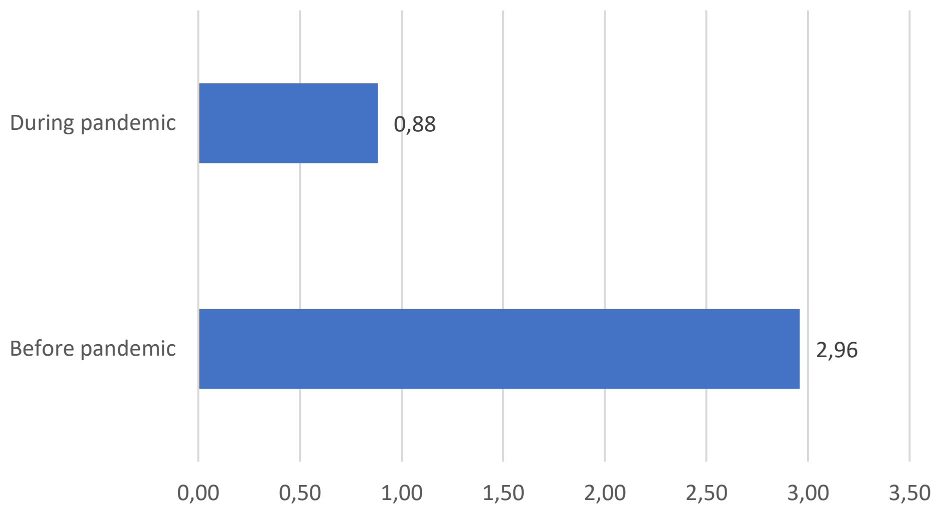

Figure 26: Average trips per week.

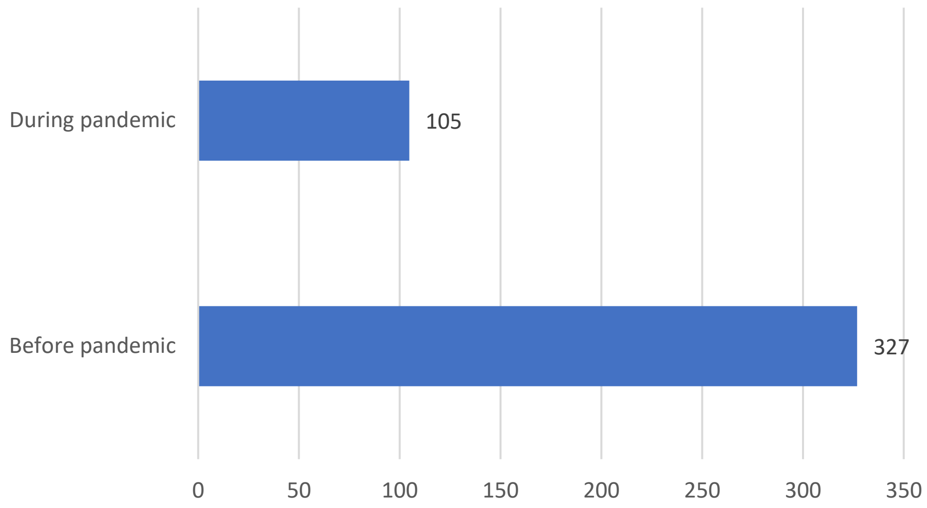

Figure 27: Average distance travelled per week (km).

Figure 28 compares the percentual use of transport modes before and during COVID-19. A decline in the use of public transport and an increase in the percentage of journeys made by private vehicles is evident. It is also relevant to point out that 27% of the respondents stopped travelling during the COVID-19 pandemic.

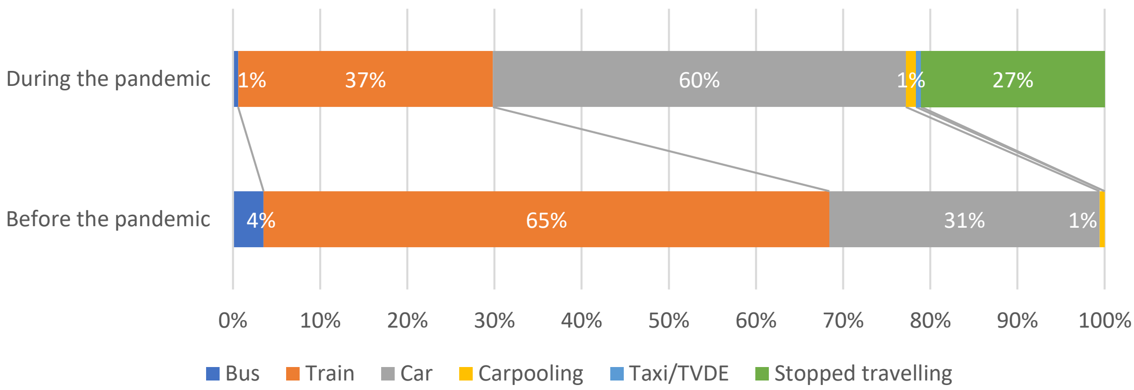

Figure 28: Modal split during and before the COVID-19 pandemic.

The survey data was collected mainly during the first quarter of 2021 (during the pandemic). During the pandemic, the total weekly trips decreased by 76% by train and 58% by private car, as seen in Table 17. Comparing the data from train passenger flows (in Portugal) [15] and highway traffic (between Aveiro and Porto) [16] of the same period (first quarter of 2021) to the first quarter of 2019 (the same quarter of the last year not affected by the pandemic) it was verified a decrease of 49% and 32% respectively. These differences between the commuting behaviour variations of the sample and the observed variations suggest that the sample is not representative of the population; however, in both cases, the decrease in train travel was higher than in the use of private cars.

Table 17: Variation of total trips per week.

Total trips per week	Before the pandemic	During the pandemic	Variation
Train	345.0	82.0	-76%
Private car	134.0	56.5	-58%

In the survey, participants were asked to explain the causes of possible changes in their commuting behaviour during the COVID-19 pandemic. As Figure 29 indicates, the respondents' most frequent reasons were the ability to work or study from home to avoid transportation. It was proven to be an effective way to prevent the spread of the virus.

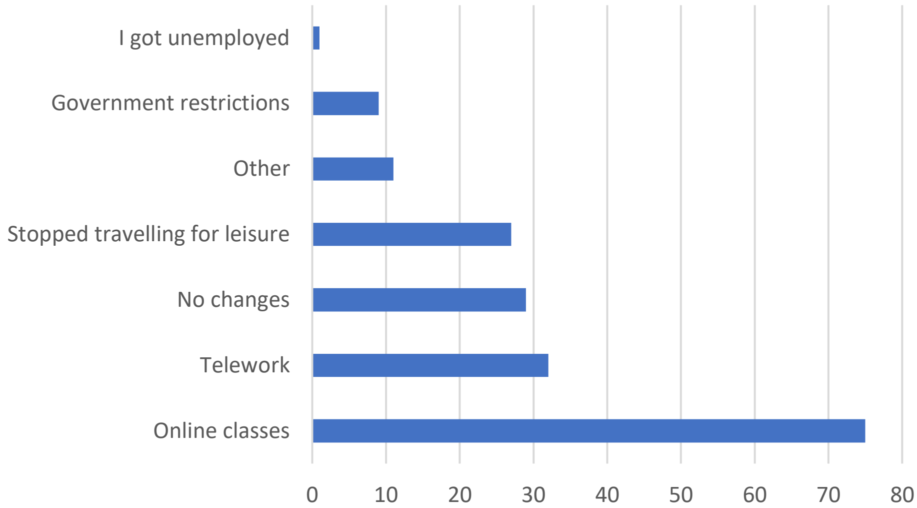

Figure 29: Reasons for changes in commuting behaviour.

People tend to avoid shared spaces outside their households during a pandemic. Consequently, passengers do not feel as safe as they used to by using travel modes shared with others. Therefore, travelling behaviour is also affected by this feeling of insecurity. Some people feel unsafe travelling at all, even with their private vehicles. On a scale of 0 to 4, Figure 30 shows the participants' feeling of safety when using each transport mode.

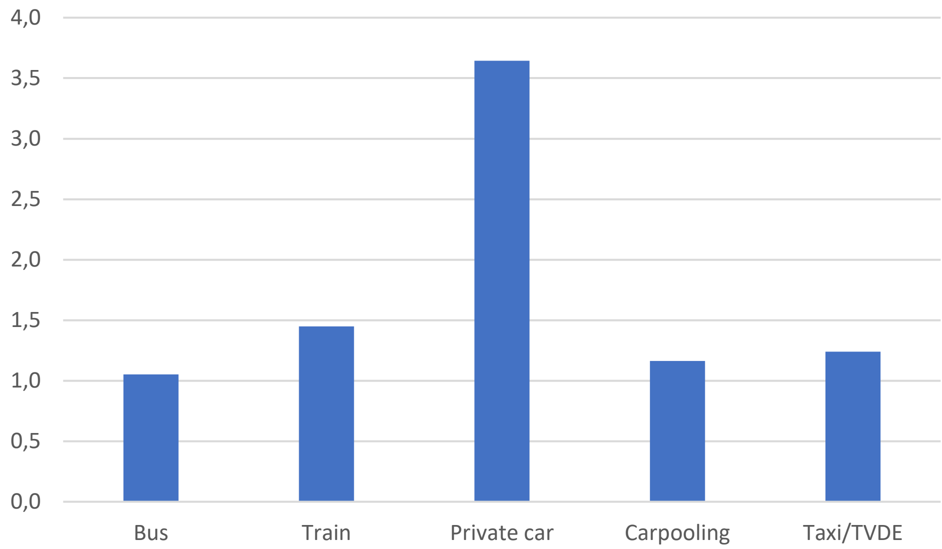

Figure 30: Feeling of safety using each transport mode during the COVID-19 pandemic.

4.1.3. Contingency tables

The association test results between the chosen transport mode and other categories such as age, gender, professional activity, and transport availability (car, bus, and train) are shown in Table 18 and Table 19.

Table 18: Results of the association tests between chosen transport modes before the COVID-19 pandemic and other categories [66].

Before the pandemic	Chi-square (p-value)	Statistically significant	Cramér's V	Association	Gamma	Association
Age	0.041	Yes	0.18	Weak	-0.185	Low
Gender	0.386	No				
Professional activity	0.003	Yes	0.198	Weak	-0,3	Moderate
Car availability	<0.001	Yes	0.607	Strong	-0.668	Strong
Bus availability	0.018	Yes	0.198	Weak	0.081	Negligible
Train availability	0.023	Yes	0.192	Weak	0.84	Very Strong

Table 19: Results of the association tests between chosen transport modes during the COVID-19 pandemic and other categories [66].

During the pandemic	Chi-square (p-value)	Statistically significant	Cramér's V	Association	Gamma	Association
Age	0.906	No				
Gender	0.622	No				
Professional activity	0.092	No				
Car availability	<0.001	Yes	0.798	Strong	-0.738	Strong
Bus availability	0.049	Yes	0.199	Weak	0.238	Low
Train availability	0.292	No				

According to the test results, gender does not seem to impact the choice of transport mode, neither before nor during the COVID-19 pandemic, since there is no statistical significance of the Chi-square value.

Before the pandemic, age revealed a weak nominal association, according to Cramér's V test, and a low ordinal association, according to the Gamma test. Figure 31 reveals that, before the pandemic, the population under 24 had higher use of trains than the private car, a tendency that started to shift for the population above 24. For the interval from 45 to 64, it is possible to notice a higher use of private cars than the train. For the results after the COVID-19 pandemic, there is no statistical significance.

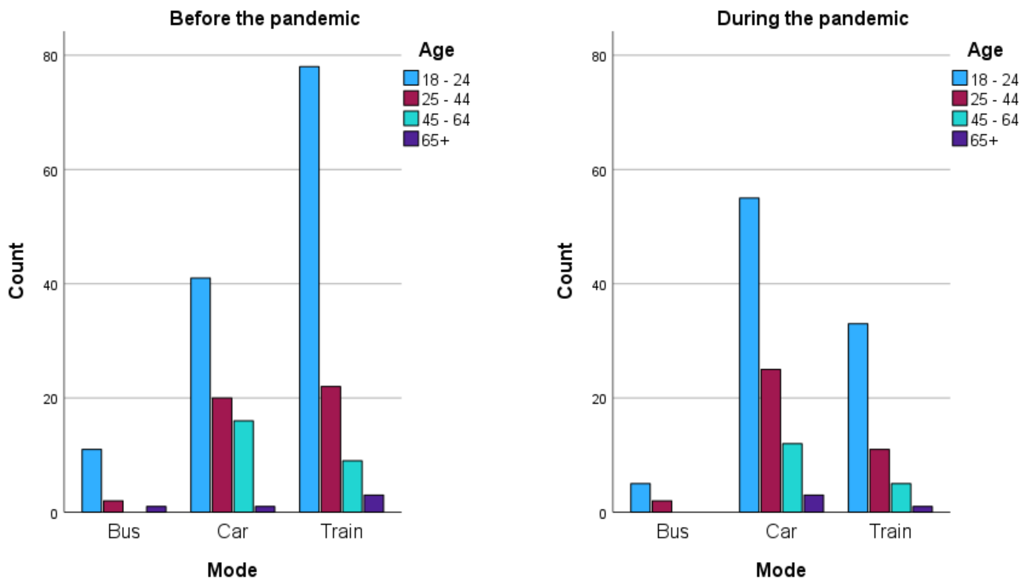

Figure 31: Mode choice by age interval [66].

Figure 23 reveals the mode choice depending on whether the person is working, studying or inactive (unemployed or retired). The trend tells that before the pandemic, there was a higher use of trains by students and professionally inactive people, but during the pandemic, the preference shifted to the private car for people working; the preference before the pandemic the private car, which intensified during the pandemic. When comparing the relationship between mode choice and professional activity, there was a statistical significance of results only before the pandemic, indicating a weak nominal and moderate ordinal association between the two categories.

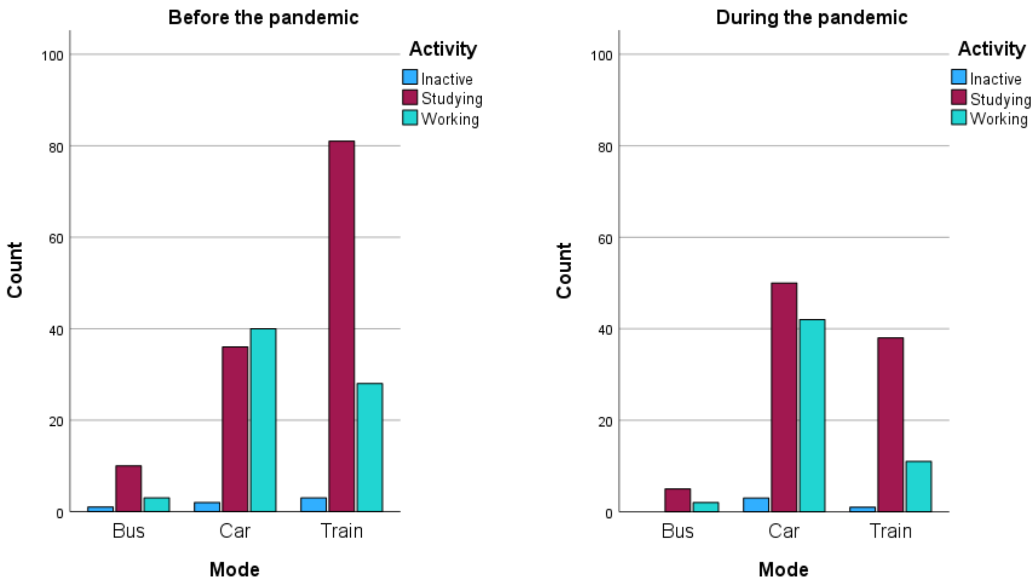

Figure 32: Mode choice by professional activity [66].

There is a strong association, both before and during the pandemic, between car availability and mode choice that is statistically significant, with a confidence level of 99%. By analysing the charts in Figure 33, it is possible to notice that people with access to a private car tend to use it more than the shared modes, a tendency intensified by the COVID-19 pandemic.

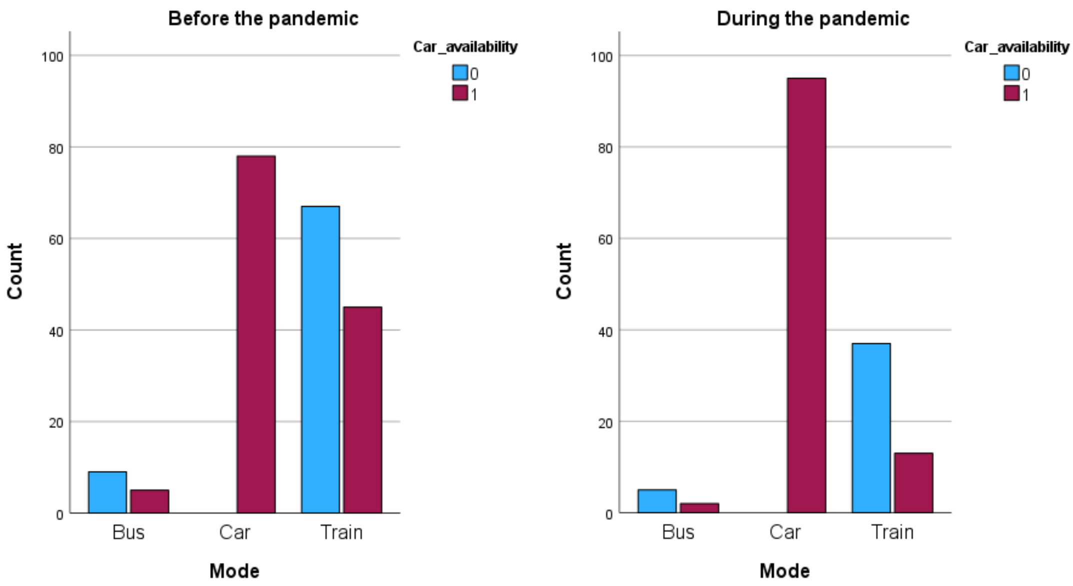

Figure 33: Mode choice by car availability [66].

The relation between mode choice and availability of the bus for specific trips was revealed to be statistically significant before and during the pandemic. The nominal association level was weak in both cases; as for the ordinal association, it was negligible before and low during the pandemic. As for the relation between train availability and mode choice, it was verified to be statistically significant, only before the pandemic, with a weak nominal association level and a very strong level of ordinal association. Figure 34 and Figure 35 reveal that before the pandemic, people with the option of travelling by bus or train tended to choose shared modes over the private car; the opposite was verified during the pandemic.

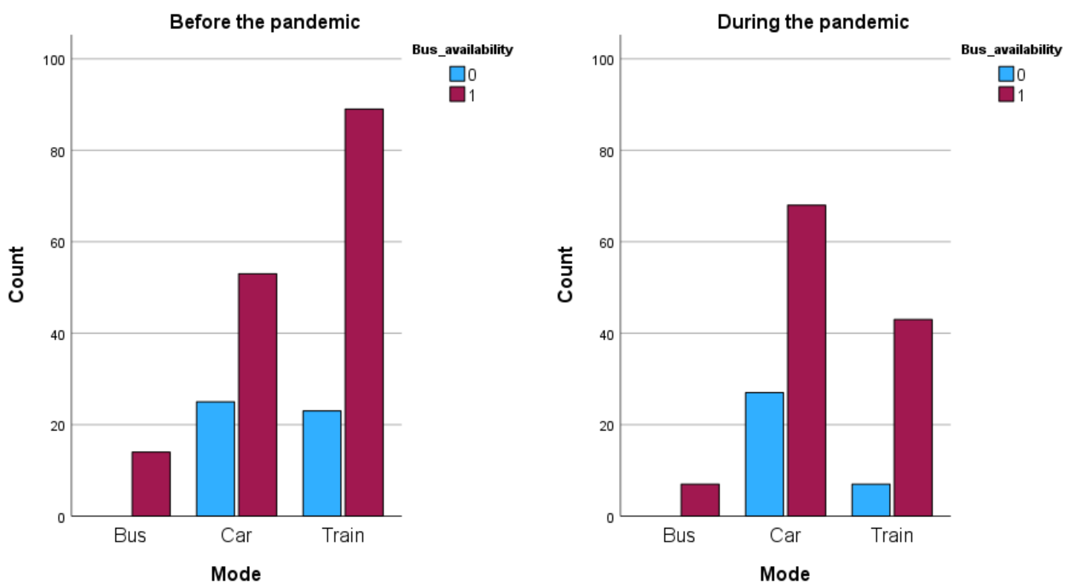

Figure 34: Mode choice by bus availability [66].

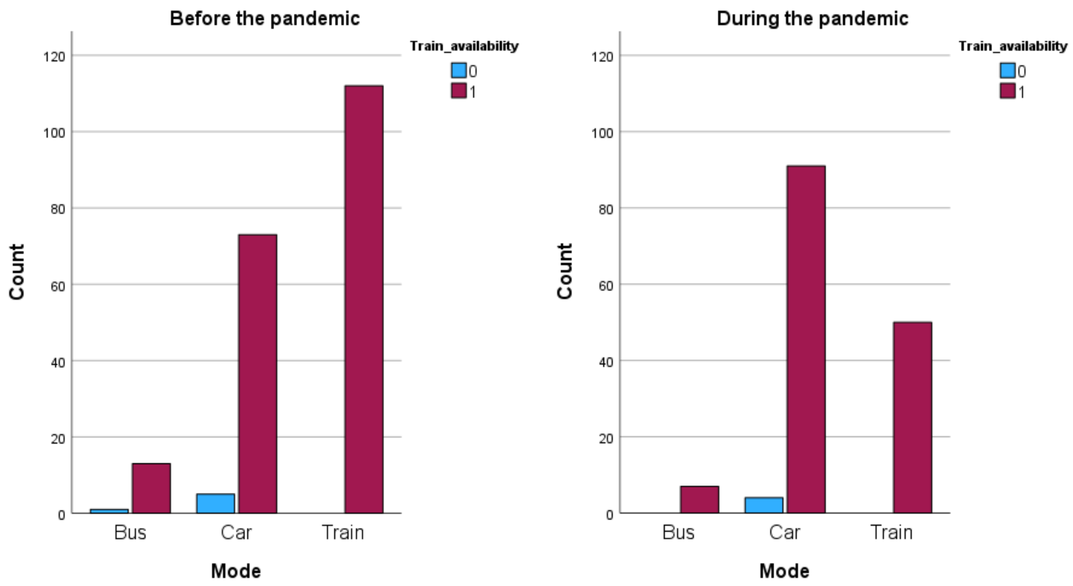

Figure 35: Mode choice by train availability [66].

Table 20 represents the association test results between the age and the feeling of safety using each transport mode. According to Table 20, there is a moderate association between age and the feeling of safety travelling by bus, which is statistically significant with a level of confidence of 99%.

Table 20: Results of the association tests between Age and feeling of safety travelling [66].

Feeling of safety	Chi-square (p-value)	Statistically significant	Cramér's V	Association	Gamma	Association
Bus	<0.001	Yes	0.241	Moderate	-0.521	Moderate
Train	0.046	Yes	0.187	Weak	-0.13	Low
Car	0.321	No				

As Figure 36 illustrates, there is a negative association between age and the feeling of safety travelling by bus. As for the train, the results are statistically significant with a 95% confidence level where the nominal association level is weak and the ordinal is low.

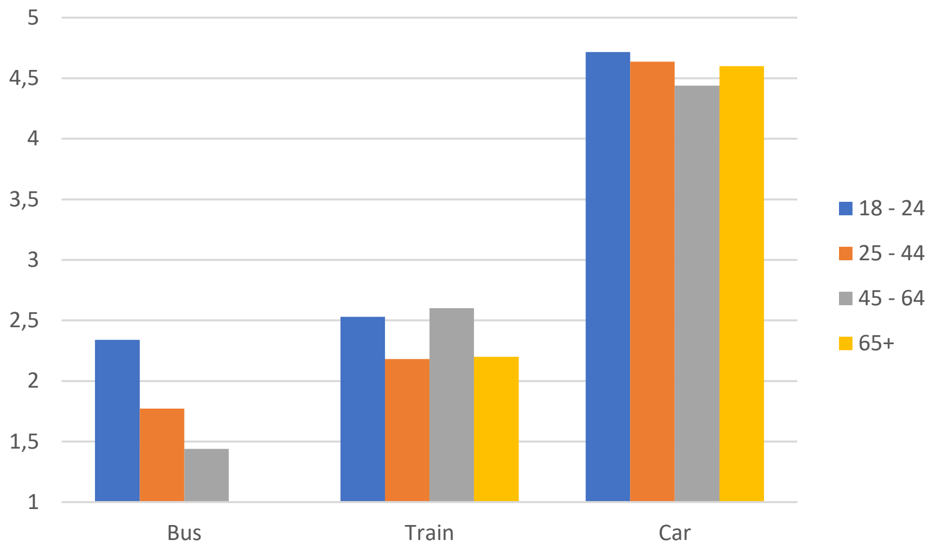

Figure 36: Average feeling of safety using each transport mode by age interval.

4.2. Transport modelling

The outputs obtained from the Biogeme algorithm are the Alternative Specific Constants for the transport modes, *ASC_BUS* and *ASC_TRAIN*, and the parameters associated with travel time and cost, *B_TIME* and *B_COST*. The alternatives of Carpooling and Taxi/TVDE were not considered when calculating the utility function's parameters since the use of these modes was residual for this sample. The results include the following for each parameter:

- The name of the parameter
- The estimated value of the parameter, β.
- The standard error (*Std err*), σ.
- The t statistics (*t-test*) calculated as $t = \frac{\sigma}{\beta}$.
- The *p-value*, calculated as $2(1 - \Phi(t))$, where $\Phi(t)$ is the cumulative distribution function of the univariate standard normal distribution.
- The robust standard error (*Rob Std err*), σ^R, of the estimate.
- The robust t statistics (*Rob. t-test*) calculated as $t^R = \frac{\beta}{\sigma^R}$.
- The robust *p-value* (*Rob. p-value*) calculated as $2(1 - \Phi(t^R))$, where $\Phi(t)$ is the cumulative density function of the univariate normal distribution.

Table 21: Results for the parameters of the Utility functions before the COVID-19 pandemic.

Parameter	Value	Std err	t-test	p-value	Rob. Std err	Rob. t-test	Rob. p-value
ASC_BUS	-3.181	0.464	-6.850	7E-12	0.454	-7.008	2E-12
ASC_TRAIN	-1.687	0.535	-3.156	0.002	0.606	-2.783	0.005
B_COST	-0.175	0.069	-2.535	0.011	0.070	-2.496	0.013
B_TIME	0.529	0.876	0.604	0.546	1.064	0.497	0.619

Table 22: Results for the parameters of the Utility functions during the COVID-19 pandemic.

Parameter	Value	Std err	t-test	p-value	Rob. Std err	Rob. t-test	Rob. p-value
ASC_BUS	-4.008	0.642	-6.243	4E-10	0.576	-6.957	3E-12
ASC_TRAIN	-2.152	0.758	-2.840	0.005	0.691	-3.113	0.002
B_COST	-0.075	0.107	-0.706	0.480	0.087	-0.865	0.387
B_TIME	-1.548	1.598	-0.968	0.333	1.451	-1.066	0.286

A result is statistically significant if it is improbable to occur based on the null hypothesis. In other words, it helps determine whether a result is likely due to chance or a factor of interest [58]. A statistical significance level of 5% was adopted for this study, which means only results with a p-value equal to or below 0.05 are considered statistically significant.

The results obtained with the Biogeme algorithm for the Utility Functions parameters before and during the pandemic (Table 21 and Table 22) show that *B_TIME* is the only parameter with no statistical significance since its p-value is above 0.05. For the pandemic scenario's results, it was impossible to obtain statistical significance either for the time or the cost parameter. The absence of statistical significance might be justified mainly by the following reasons:

- A relatively low number of observations (171 eligible participants).
- High heterogeneity in the access to own vehicle and different modes of transport
- Travel time differences between different modes of transport are less noticeable than in an urban context

It is also possible to observe that the parameter *B_COST* has a negative contribution to the Utility Function, which makes sense since the more expensive an alternative is, the less likely a passenger will be to choose it.

The results show that the *ASC_BUS* and *ASC_TRAIN* parameters are negative, meaning an inherent preference for private car use. The alternative specific constant for the private car transport mode (*ASC_CAR*) is considered zero, establishing a baseline for the other transport modes (train and bus). Therefore, the utility functions for the train and bus will be calculated for the private car. It is also essential to notice that values are even lower for the pandemic scenario. This migration might be justified by a lower feeling of safety using shared mobility, illustrated in Figure 30.

Figure 37 and Figure 38 compare the modal split according to the survey's answers and the modal split according to the calculated utility functions. The accuracy of the model results was 72% for the modal split before the pandemic and 87% during the pandemic. These results might be justified by the fact that not all utility function parameters calculated were revealed to be statistically significant, which might be explained by the small sample size. Additionally, in the pandemic context, the predictability of the choice of transport mode is higher since there are more transport restrictions.

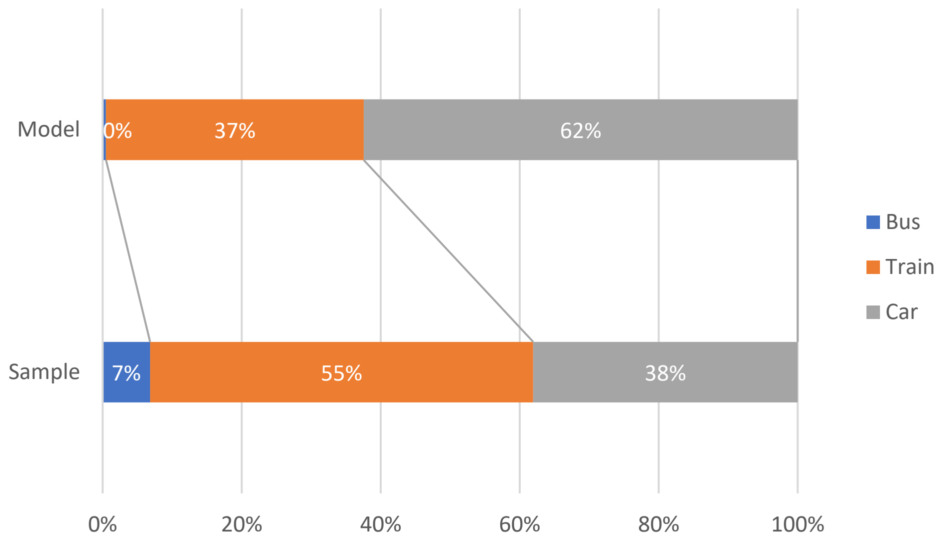

Figure 37: Modal split before the pandemic.

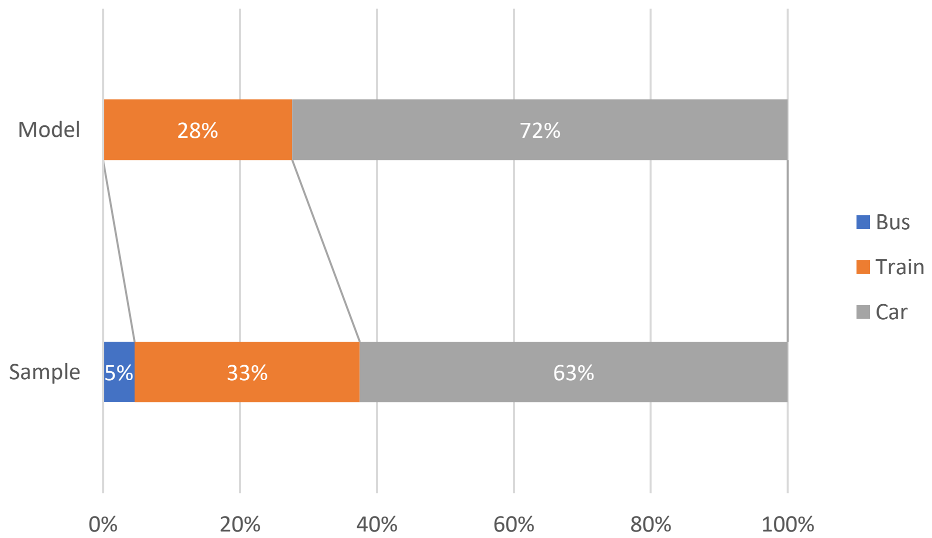

Figure 38: Modal split during the pandemic.

4.3. Environmental Externalities

For passenger cars, since there is no data on the fuel used by each passenger, it was considered an intermediate value of air pollution costs between diesel and petrol cars. In 2020, in Portugal, the type of fuel of motorised road vehicles in circulation was 65.3% for diesel, 32.1% for petrol, 0.8% for LPG and 1.7% for other types [71]. Therefore, a share of 67% of diesel vehicles and 33% of petrol cars was assumed. Since the use of fuels other than diesel or petrol is very residual, these shares were neglected.

Table 23 represents the air pollution costs (APC) caused by the trips of the population that answered the survey before and during the pandemic. The APC refers to the air pollution costs per week, considering the mode chosen by each passenger and their travelling frequency. It is possible to observe that, during COVID-19, people tend to choose transport modes with higher pollution costs. The last column represents the percentual variation of emissions after the pandemic. It is possible to observe that, during the COVID-19 pandemic, even though people tend to choose less sustainable modes, the decrease in the number of trips reduced air pollution costs by 53%.

Table 23: Air pollution costs of the sample.

Air pollution costs		**Before pandemic**	**During pandemic**	**Variation**
APC (€-cent/week)	Total	19493,5	9226,9	- 53%
	Per person	114,0	54,0	

5. Conclusions

The main objectives of this dissertation were the characterization of intercity mobility behaviour before and during the pandemic (focused on the university community) and the development of a modal split prediction tool based on a logit model. Furthermore, it was also an objective of this work to characterize the environmental impacts on inter-urban mobility as a result of behavioural changes caused by the pandemic. The results of this work were based on a survey focused on evaluating behaviour changes according to socioeconomic profile and availability of transport modes.

The survey was designed to answer the following questions: how much people travel before and during the pandemic; what their travel purpose is; what the reasons behind any changes in travel frequency were; what transport modes were used in both periods; how safe people feel using each transport mode during a pandemic; and what demographic factors might influence the choice of transport mode. The results from the survey were subjected to descriptive and statistical analysis. Transport-related data, such as travel time, cost, and distance, were collected online. A logit model was developed to support identifying key parameters that play an essential role in the mode choice. The Biogeme software was used to estimate the utility function parameters for several transport modes according to the impact of two variables (travel time and cost). The transport modes considered were bus, train, and private car. GHG emissions related to road transport were estimated for the origin-destination (O-D) matrices based on each O-D pair's average speed and distance. With these emissions, values were possible to calculate an O-D matrix with the air-pollution costs per passenger for several fuel and vehicle classes (petrol, diesel, hybrid cars, and buses). The O-D matrix of air pollution costs related to rail transport was estimated based on the travel distance and type of train. The air pollution costs applied to the modal split (before and during the pandemic) were used to estimate the COVID-19 impacts on GHG emissions in the study area.

Biogeme is a valuable tool to calculate the utility function of transport modes; however, its accuracy might be affected when dealing with relatively small sets of data (i.e., with a small number of observations). The travel cost results were statistically significant for data before the pandemic, unlike the travel time. For data during the pandemic, neither travel time nor cost was statistically significant. For the present case study sample, the result indicates a high utility of private cars for intercity trips, a preference that was intensified with the COVID-19 pandemic. Following the private car, the train's utility is also high for this area; however, it was highly affected by the pandemic. The bus was revealed to be the less used mode out of the three, something that might be explained due to the relatively low volume of services for intercity trips.

The analysis of the survey results revealed a significant reduction in the number of trips, particularly for leisure and work or study. Teleworking and online classes were the main factors contributing to the reduction in travel frequency. It was observed a widespread fear

of using shared modes. However, among public transport modes, the train was considered to be slightly safer than others.
Age, professional activity, and the availability of transport modes were revealed to significantly impact the mode choice indicated by the respondents before the pandemic. The use of trains seems to be more frequent in younger people, and as their age increases, people tend to prefer private vehicles. Students and professionally inactive people also tend to choose the train over the private car. However, people with a job tended to choose the private car. Vehicle ownership is also a factor with a strong influence on the mode choice since most people with a private car choose it over public transport. As for the data during the pandemic, only the bus and car availability was revealed to impact the mode choice significantly. Understandably, the older population expressed a higher level of insecurity when using public transport, particularly the bus.
Even though most people prefer more individual modes during the pandemic, a 53% decrease in costs related to air pollution was verified. A decrease in travelling frequency caused this reduction since nearly 27% of the sample stopped travelling during the pandemic.

Interurban traffic between Aveiro and Porto is too dependent on private cars, which has a negative impact in terms of external costs. An improvement in bus services in terms of the offer and spatial coverage could benefit the area. The attractiveness of public transport could also be improved to increase passengers' preference for these modes. The factors that most influence people's motivation towards public transport are: travel time, cost fares, service frequency, accuracy and reliability of arrival times, in-vehicle experience (comfort, crowdedness, and cleanliness), accessibility for people with needs, convenient ways to purchase tickets and parking areas near the stations since travel cost was revealed to influence mode choice strongly. Teleworking has been revealed to be an effective alternative to reducing commuting trips. Many people can still work or study from home some days or every day. Teleworking was introduced to many realities during the pandemic; therefore, not for a good reason, but the adaptation process people took created habits that now can improve transport effectiveness and sustainability.

A limitation of this study is related to the sample of survey respondents not being representative of society in general but focused mainly on the university community. The variance of trips by train and private car caused by the pandemic was compared with data obtained from the survey and data from Institute for Mobility and Transport (IMT [16]) and Statistics Portugal (INE [15]). The survey data estimated a decrease of 76% and 58% for train and private vehicle trips, respectively, while according to data from IMT and INE, the decrease was 49% for rail and 32% for highway transport.

These limitations resulted in a lack of statistical significance for some of the parameters calculated by the model. The estimation of the air pollution costs could have been more accurate if the survey collected more details, such as the type of fuel used by each vehicle and the type of train chosen by each train passenger (regional, intercity, high-speed). However, it is necessary to consider that the motivation to respond to surveys decreases if the set of information sought is too extensive. Additionally, the emission approach considers typical vehicles of the Portuguese vehicle fleet. In the survey, there was no question to find out if the participants shared a private vehicle and with how many people; this information could be helpful to calculate the environmental impact by passenger with more precision and the personal travel cost for the participant associated with that trip.

For future research, it is suggested to disclose a new survey to understand how travel behaviour and consequent environmental impact changed after the pandemic. It is recommended that this survey inquires the participants about: the type of fuel of their vehicle, the number of people they share private car trips with, the type of train they use and how many times they have been infected with COVID-19.

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Appendix A: Mobility survey

Section 1 – Socio-demographic characteristics

- Age (years):
    - (Numerical answer)

- Gender:
    - Male
    - Female
    - Other

- Occupation:
-
    - Self-employed
    - Student
    - Employee
    - Unemployed
    - Retired
    - (Other…)

- Monthly income (€):
    - 0 – 400
    - 401 – 680
    - 681 – 1100
    - 1101 – 1500
    - 1501 – 2000
    - 2001 – 3000
    - 3000+

- Do you own a personal vehicle?
    - Yes
    - No

Section 2 – Trips details

- Before the pandemic, how frequently would you travel between the regions of Aveiro and Porto? (1 trip = round trip)
    - More than a trip a day
    - One trip per day
    - One trip per weekday
    - One trip per business day

    - 2 to 4 trips per week
    - One trip per week
    - Two or fewer trips per month
    - Never
    - (Other…)

- During the pandemic, how frequently do you travel between the regions of Aveiro and Porto?
    - More than a trip a day
    - One trip per day
    - One trip per weekday
    - One trip per business day
    - Two to four trips per week
    - One trip per week
    - Two or fewer trips per month
    - Never
    - (Other…)

- What reasons made you change the frequency of the trips?
    - There were no changes
    - I am working from home
    - I got unemployed
    - I have online classes
    - I stopped travelling for leisure
    - (Other…)

- What is the trip's origin?
    - Does not apply
    - Aveiro
    - Porto
    - South from Aveiro (not listed)
    - North from Porto (not listed)
    - Águeda
    - Albergaria a Velha
    - Arouca
    - Espinho
    - Estarreja
    - Gondomar
    - Murtosa
    - Oliveira de Azemeis
    - Ovar
    - Santa Maria da Feira
    - São João da Madeira
    - Vila Nova de Gaia

- What is the trip destination?
    - Does not apply
    - Aveiro
    - Porto
    - South from Aveiro (not listed)
    - North from Porto (not listed)
    - Águeda
    - Albergaria a Velha
    - Arouca
    - Espinho
    - Estarreja
    - Gondomar
    - Murtosa
    - Oliveira de Azemeis
    - Ovar
    - Santa Maria da Feira
    - São João da Madeira
    - Vila Nova de Gaia

- What is the most frequent trip purpose?
    - Work
    - Studies
    - Leisure/shopping/family
    - (Other…)

Section 3 – Transportation mode

- From 1 to 5, where one is "never", and 5 is "always", how frequently did you use each transport mode before the pandemic?
    - Bus
    - Train
    - Car
    - Motorcycle
    - Carpooling
    - Taxi/TVDE

- From 1 to 5, where one is "never", and 5 is "always", how frequently did you use each transport mode before the pandemic?
    - Bus
    - Train
    - Car
    - Motorcycle
    - Carpooling
    - Taxi/TVDE

- From 1 to 5, where one is "not at all" and five is "totally", how comfortable/safe do you feel using each transport mode during the pandemic?
    - Bus
    - Train
    - Car
    - Motorcycle
    - Carpooling
    - Taxi/TVDE

Appendix B: Coefficients for GHG emissions calculation

Table 24: Coefficients for NO_x emissions calculation by fuel/category and road type.

Fuel/Category	Road type	a	b	c	d	e
Petrol car	Urban	-1.00E-07	1.00E-05	-5.00E-04	8.10E-03	0.22
	Rural				1.40E-03	0.13
	Highway			-4.00E-05	1.13E-02	-0.47
Diesel car	Urban			3.00E-04	-2.81E-02	1.35
	Rural			1.00E-04	-1.42E-02	1.02
	Highway			-1.00E-04	3.34E-02	-1.57
Hybrid car	Urban				9.00E-04	-1.80E-03
	Rural			-3.00E-06	6.00E-04	-7.80E-03
	Highway			2.00E-06	-5.00E-04	5.35E-02
LDV	Urban				-1.60E-02	1.68
	Rural			2.00E-04	-2.93E-02	1.82
	Highway			-2.00E-04	4.70E-02	-1.91
HDT	Urban			3.80E-03	-0.36	13.42
	Rural			4.00E-04	-7.43E-02	7.31
	Highway					4.09
Bus	Urban			9.80E-03	-0.90	27.68
	Rural				-3.30E-02	6.91
	Highway		-2.00E-06	9.00E-04	-0.12	9.16

Table 25: Coefficients for $PM_{2.5}$ emissions calculation by fuel/category and road type.

Fuel/Category	Road type	a	b	c	d	e
Petrol car	Urban		-7.00E-08	4.00E-06	-9.00E-05	1.78E-02
	Rural				-1.00E-04	2.11E-02
	Highway		-2.00E-08	8.00E-06	-1.00E-03	4.76E-02
Diesel car	Urban				-6.00E-04	8.07E-02
	Rural			8.00E-06	1.20E-03	8.38E-02
	Highway			-9.00E-06	2.70E-03	-0.13
Hybrid car	Urban		-7.00E-08	4.00E-06	-7.00E-05	1.55E-02
	Rural				-1.00E-04	1.97E-02
	Highway					8.64E-03
LDV	Urban		2.00E-06	-2.00E-04	3.00E-03	1.08E-02
	Rural			3.00E-05	-3.10E-03	0.15
	Highway			-2.00E-05	6.40E-03	-0.29
HDT	Urban			6.00E-05	-7.70E-03	0.38
	Rural				-7.00E-04	0.19
	Highway					0.13
Bus	Urban			1.00E-04	-1.53E-02	0.65
	Rural				-1.40E-03	0.23
	Highway	3.00E-09	-2.00E-06	3.00E-04	-2.97E-02	1.09

Table 26: Coefficients for PM_{10} emissions calculation by fuel/category and road type.

Fuel/Category	Road type	a	b	c	d	e
Petrol car	Urban		-1.00E-07	9.00E-06	-2.00E-04	3.17E-02
	Rural				-3.00E-04	3.98E-02
	Highway			-2.00E-07	6.00E-05	1.21E-02
Diesel car	Urban		-1.00E-07	9.00E-06	-2.00E-04	3.17E-02
	Rural				-3.00E-04	3.98E-02
	Highway			-8.00E-06	2.60E-03	-1.20E-02
Hybrid car	Urban		-1.00E-07	9.00E-06	-2.00E-04	2.94E-02
	Rural				-3.00E-04	3.84E-02
	Highway					1.47E-02
LDV	Urban		2.00E-06	-2.00E-03	2.90E-03	0.13
	Rural			3.00E-05	-3.30E-03	0.18
	Highway			-2.00E-05	6.30E-03	-0.28
HDT	Urban			6.00E-05	-7.50E-03	0.44
	Rural				-1.20E-03	0.26
	Highway					0.15
Bus	Urban			1.00E-04	-1.51E-02	0.70
	Rural				-1.80E-03	0.30
	Highway	5.00E-09	-3.00E-06	5.00E-04	-4.45E-02	1.57

Table 27: Coefficients for VOC emissions calculation by fuel/category and road type.

Fuel/Category	Road type	a	b	c	d	e
Petrol car	Urban			3.00E-04	-2.39E-03	0.99
	Rural				-1.00E-03	0.19
	Highway		-4.00E-07	1.00E-04	-1.64E-02	0.72
Diesel car	Urban			2.00E-05	-2.70E-03	0.10
	Rural				-2.00E-04	3.34E-02
	Highway		-2.00E-08	8.00E-06	-1.00E-03	5.86E-02
Hybrid car	Urban			4.00E-05	-2.10E-03	0.23
	Rural			3.00E-07	-4.00E-05	1.94E-02
	Highway			-2.00E-07	7.00E-05	1.33E-02
LDV	Urban		2.00E-06	-2.00E-04	3.60E-03	0.10
	Rural			9.00E-06	1.50E-03	0.12
	Highway			-4.00E-06	1.00E-03	5.00E-05
HDT	Urban			3.00E-04	-3.05E-02	1.01
	Rural				-2.10E-03	0.33
	Highway					0.15
Bus	Urban			5.00E-04	-5.07E-02	1.63
	Rural				-2.70E-03	0.40
	Highway		-3.00E-07	1.00E-04	-1.62E-02	0.85

Table 28: Coefficients for NMVOC emissions calculation by fuel/category and road type.

Fuel/Category	Road type	a	b	c	d	e
Petrol car	Urban			2.00E-04	-1.78E-02	0.91
	Rural				-1.00E-03	0.18
	Highway		-4.00E-07	1.00E-04	-1.64E-02	0.71
Diesel car	Urban			2.00E-05	-2.70E-03	9.84E-02
	Rural				-2.00E-04	3.20E-02
	Highway		-2.00E-08	8.00E-06	1.00E-03	5.76E-02
Hybrid car	Urban			4.00E-05	-2.10E-03	0.21
	Rural					1.73E-02
	Highway					1.73E-02
LDV	Urban		2.00E-06	-2.00E-04	3.40E-03	9.98E-02
	Rural			9.00E-06	-1.50E-03	0.12
	Highway			-4.00E-06	1.00E-03	-9.00E-04
HDT	Urban			3.00E-04	-3.05E-02	0.94
	Rural				-2.10E-03	0.30
	Highway					0.12
Bus	Urban			5.00E-04	-5.07E-02	1.54
	Rural				-2.70E-03	0.37
	Highway			2.00E-05	-4.30E-03	0.38

Table 29: Coefficients for CO emissions calculation by fuel/category and road type.

Fuel/Category	Road type	a	b	c	d	e
Petrol car	Urban			2.80E-03	-0.20	6.01
	Rural			2.00E-04	-3.44E-02	2.09
	Highway		-3.00E-05	9.80E-03	-1.13	42.81
Diesel car	Urban				-7.40E-03	0.51
	Rural				-2.30E-03	0.25
	Highway	1.00E-08	-7.00E-06	1.30E-03	-0.10	3.24
Hybrid car	Urban		2.00E-05	-9.00E-04	1.70E-02	0.37
	Rural				-4.00E-04	5.36E-02
	Highway			2.00E-06	-6.00E-04	5.42E-02
LDV	Urban				-9.60E-03	0.75
	Rural			2.00E-04	-1.77E-02	0.78
	Highway			-1.00E-04	3.51E-02	-1.68
HDT	Urban			1.10E-03	-0.11	3.64
	Rural			9.00E-05	1.61E-02	1.57
	Highway					0.88
Bus	Urban			3.30E-03	-0.29	8.15
	Rural				-8.40E-03	1.59
	Highway		-6.00E-07	3.00E-04	-3.34E-02	2.29

Appendix C: GHG emissions

Table 30: CO_2 emissions of diesel vehicles (g).

CO2 emissions of diesel vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	3949	3715	5451	3182	5867	6185	7983	6978	10065	8580	10240	11765	10884
Águeda		2703	6407	4402	5026	6907	6283	7182	9368	9277	10279	12420	11835
Albergaria a Velha			3827	2703	2914	5424	4197	5595	7713	7747	8789	10473	10018
Murtosa				1351	3452	2914	4596	4708	7911	6011	8263	9163	8713
Estarreja					2384	2958	3684	3812	6840	4989	7346	8778	8212
Oliveira de Azemeis						2942	1341	2410	4935	6525	7159	7024	7393
Ovar							2740	1943	7257	3278	5129	6757	6343
São João da Madeira								1295	4801	3725	5902	5762	6235
Santa Maria da Feira									5754	2660	4415	5312	5005
Arouca										7825	8119	8260	9003
Espinho											2587	4225	3688
Vila Nova de Gaia												1814	1594
Gondomar													2459

Table 31: CO_2 emissions of petrol vehicles (g).

CO2 emissions of petrol vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	3777	3574	5219	3044	5630	5941	7674	6712	9633	8267	9850	11340	10453
Águeda		2626	6130	4210	4807	6616	6011	6889	8959	8912	9866	11959	11378
Albergaria a Velha			3802	2626	2787	5203	4015	5374	8011	7456	8458	10101	9662
Murtosa				1313	3303	2787	4399	4509	7566	5761	7941	8808	8374
Estarreja					2281	2831	3527	3657	6542	4788	7075	8463	7879
Oliveira de Azemeis						2807	1283	2305	5066	6276	6890	6763	7107
Ovar							2595	1842	6941	3136	4918	6486	6073
São João da Madeira								1229	4826	3564	5672	5538	5966
Santa Maria da Feira									5922	2546	4240	5105	4807
Arouca										7485	7765	7908	8619
Espinho											2475	4073	3527
Vila Nova de Gaia												1735	1510
Gondomar													2574

Table 32: CO_2 emissions of hybrid vehicles (g).

CO_2 emissions of hybrid vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	2453	2698	3732	2032	4186	4457	5778	5065	6792	6248	7431	8568	7828
Águeda		1789	4248	2801	3177	4775	4127	5099	5825	6686	7363	9039	8571
Albergaria a Velha			2534	1789	1816	3858	2744	4031	5064	5631	6389	7625	7294
Murtosa				894	2250	1816	3087	3239	5011	4215	5970	6631	6300
Estarreja					1581	2001	2521	2714	4340	3566	5348	6392	5853
Oliveira de Azemeis						1934	889	1559	3250	4734	5205	5111	5352
Ovar							1756	1266	4466	2174	3628	4844	4324
São João da Madeira								824	3174	2470	4264	4168	4173
Santa Maria da Feira									3787	1803	3178	3838	3604
Arouca										5071	5073	5634	6127
Espinho											1638	3077	2291
Vila Nova de Gaia												1164	1038
Gondomar													1611

Table 33: CO_2 emissions of diesel buses (g).

CO_2 emissions of diesel buses (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	15579	12408	20660	12485	20999	21507	27234	23390	38560	27435	34372	37379	38112
Águeda		13300	24793	17282	19764	25945	24418	25977	36946	32261	36420	40472	40249
Albergaria a Velha			18831	13300	11490	19552	16344	19476	38312	25631	29089	32663	31243
Murtosa				6650	13459	11490	17661	17768	31093	22189	28436	31297	29867
Estarreja					9225	11315	13966	13713	26875	17784	23790	27609	29463
Oliveira de Azemeis						14571	5189	9420	24432	21964	23596	22984	25203
Ovar							13916	9703	28659	12685	18686	23885	24128
São João da Madeira								6627	23659	14415	20311	19711	24005
Santa Maria da Feira									28507	10160	15413	18280	17444
Arouca										30568	31994	31400	34288
Espinho											10171	13407	14546
Vila Nova de Gaia												7110	7971
Gondomar													12242

Table 34: NO_x emissions of diesel vehicles (g).

NO_x emissions of diesel vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	14.3	13.4	19.3	11.5	20.8	22.1	28.6	25.1	35.8	31.2	36.8	42.8	38.8
Águeda		11.1	22.8	15.9	18.1	24.5	22.4	25.5	34.0	33.1	36.5	44.9	42.4
Albergaria a Velha			15.9	11.1	10.6	19.2	15.0	19.9	32.7	27.9	31.7	38.3	36.6
Murtosa				5.6	12.4	10.6	16.3	16.7	28.5	21.3	29.5	32.8	31.2
Estarreja					8.5	10.5	13.1	13.5	24.7	17.7	26.6	32.0	29.1
Oliveira de Azemeis						12.0	4.8	8.6	20.8	23.4	25.8	25.4	26.5
Ovar							10.9	7.8	26.4	11.7	18.2	24.0	22.5
São João da Madeira								5.1	20.1	13.3	21.1	20.6	22.2
Santa Maria da Feira										9.4	15.7	19.0	17.8
Arouca										28.1	29.4	29.3	31.9
Espinho											9.3	15.4	13.4
Vila Nova de Gaia												6.5	6.4
Gondomar													10.4

Table 35: NO_x emissions of petrol vehicles (g).

NO_x emissions of petrol vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	5.2	6.2	8.3	4.4	9.5	10.2	13.3	11.7	15.0	14.5	17.1	19.9	17.8
Águeda		1.4	9.3	6.0	6.8	10.6	9.0	11.5	12.5	15.3	16.7	20.9	19.7
Albergaria a Velha			1.3	1.4	3.9	8.7	6.0	9.2	0.3	13.0	14.8	17.8	17.0
Murtosa				0.7	4.9	3.9	6.8	7.2	10.8	9.4	13.7	15.2	14.4
Estarreja					3.5	4.4	5.6	6.1	9.3	8.1	12.4	14.9	13.2
Oliveira de Azemeis						2.0	1.9	3.4	0.6	10.9	12.0	11.8	12.3
Ovar							2.4	1.5	9.5	4.8	8.2	11.0	9.6
São João da Madeira								1.2	1.2	5.4	9.8	9.6	9.2
Santa Maria da Feira									0.6	4.0	7.2	8.8	8.2
Arouca										11.0	10.9	12.5	13.5
Espinho											3.5	7.2	4.9
Vila Nova de Gaia												2.5	1.2
Gondomar													2.1

Table 36: NO_x emissions of hybrid vehicles (g).

NO_x emissions of hybrid vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.39	0.53	0.69	0.34	0.81	0.88	1.14	1.00	1.23	1.24	1.47	1.70	1.53
Águeda		0.60	0.75	0.46	0.52	0.89	0.72	0.98	0.92	1.31	1.44	1.79	1.69
Albergaria a Velha			0.91	0.60	0.29	0.75	0.47	0.79	2.01	1.12	1.27	1.51	1.45
Murtosa				0.30	0.39	0.29	0.55	0.60	0.82	0.80	1.18	1.31	1.24
Estarreja					0.28	0.36	0.46	0.53	0.71	0.69	1.06	1.27	1.14
Oliveira de Azemeis						0.59	0.16	0.26	1.26	0.94	1.03	1.01	1.06
Ovar							0.46	0.36	0.70	0.38	0.70	0.95	0.79
São João da Madeira								0.21	1.18	0.44	0.84	0.82	0.75
Santa Maria da Feira									1.48	0.33	0.62	0.76	0.71
Arouca										0.86	0.81	1.03	1.12
Espinho											0.27	0.61	0.36
Vila Nova de Gaia												0.19	0.30
Gondomar													0.65

Table 37: NO_x emissions of diesel buses (g).

NO_x emissions of diesel buses (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	134.1	104.1	176.1	107.2	177.5	181.2	229.0	196.3	329.3	229.1	288.5	312.0	321.4
Águeda		115.5	212.1	148.5	169.9	220.8	209.1	219.9	318.0	271.8	307.6	338.7	338.3
Albergaria a Velha			165.1	115.5	98.9	165.5	140.1	164.1	343.7	214.8	243.8	272.1	260.3
Murtosa				57.8	115.4	98.9	150.9	151.3	267.2	188.4	239.3	263.2	251.3
Estarreja					78.9	96.6	119.0	116.0	230.9	150.3	198.9	230.2	249.2
Oliveira de Azemeis						126.1	44.4	80.8	217.8	184.4	197.7	192.4	211.9
Ovar							121.6	84.1	246.8	108.5	158.3	201.7	205.8
São João da Madeira								58.1	208.6	123.3	170.9	165.8	205.2
Santa Maria da Feira									254.5	86.7	129.9	153.9	147.0
Arouca										262.2	275.2	267.8	292.5
Espinho											87.4	111.9	125.2
Vila Nova de Gaia												61.0	69.1
Gondomar													110.3

Table 38: $PM_{2.5}$ emissions of diesel vehicles (g).

$PM_{2.5}$ emissions of diesel vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.41	0.32	0.54	0.33	0.54	0.56	0.70	0.60	1.01	0.70	0.88	0.96	0.98
Águeda		0.25	0.65	0.45	0.52	0.68	0.64	0.67	0.97	0.83	0.94	1.04	1.04
Albergaria a Velha			0.35	0.25	0.30	0.51	0.43	0.50	0.69	0.66	0.75	0.83	0.80
Murtosa				0.13	0.35	0.30	0.46	0.46	0.82	0.58	0.73	0.81	0.77
Estarreja					0.24	0.30	0.36	0.36	0.71	0.46	0.61	0.71	0.76
Oliveira de Azemeis						0.27	0.14	0.25	0.44	0.57	0.61	0.59	0.65
Ovar							0.25	0.18	0.76	0.33	0.49	0.62	0.63
São João da Madeira								0.12	0.44	0.38	0.52	0.51	0.63
Santa Maria da Feira									0.52	0.27	0.40	0.47	0.45
Arouca										0.80	0.84	0.82	0.90
Espinho											0.27	0.34	0.38
Vila Nova de Gaia												0.19	0.15
Gondomar													0.22

Table 39: $PM_{2.5}$ emissions of petrol vehicles (g).

$PM_{2.5}$ emissions of petrol vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	4.28	5.98	7.26	3.64	8.75	9.57	12.61	11.20	12.96	14.28	16.42	19.67	16.71
Águeda		0.87	7.94	5.01	5.64	9.42	7.63	10.55	10.18	14.36	15.55	20.40	18.75
Albergaria a Velha			1.22	0.87	3.18	8.01	5.04	8.65	2.40	12.58	14.26	17.71	16.94
Murtosa				0.44	4.12	3.18	5.86	6.35	8.92	8.51	12.94	14.46	13.70
Estarreja					2.95	3.83	4.90	5.64	7.74	7.48	12.12	14.77	12.21
Oliveira de Azemeis						0.96	1.66	2.83	1.55	10.44	11.66	11.50	11.68
Ovar							0.89	0.63	7.73	4.06	7.44	10.25	8.36
São João da Madeira								0.42	1.52	4.62	9.24	9.08	7.89
Santa Maria da Feira									1.80	3.46	6.80	8.32	7.72
Arouca										9.24	8.91	10.91	11.82
Espinho											2.91	7.07	4.00
Vila Nova de Gaia												2.10	0.52
Gondomar													0.76

Table 40: $PM_{2.5}$ emissions of hybrid vehicles (g).

$PM_{2.5}$ emissions of hybrid vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.37	0.28	0.49	0.30	0.49	0.50	0.63	0.54	0.91	0.62	0.79	0.85	0.88
Águeda		0.23	0.59	0.41	0.47	0.61	0.58	0.61	0.89	0.74	0.84	0.92	0.93
Albergaria a Velha			0.32	0.23	0.28	0.46	0.39	0.45	0.63	0.59	0.67	0.74	0.71
Murtosa				0.11	0.32	0.28	0.42	0.42	0.74	0.52	0.66	0.72	0.69
Estarreja					0.22	0.27	0.33	0.32	0.64	0.41	0.54	0.63	0.69
Oliveira de Azemeis						0.25	0.12	0.22	0.41	0.50	0.54	0.52	0.58
Ovar							0.22	0.16	0.69	0.30	0.44	0.55	0.57
São João da Madeira								0.10	0.40	0.34	0.47	0.45	0.57
Santa Maria da Feira									0.47	0.24	0.36	0.42	0.40
Arouca										0.73	0.77	0.74	0.81
Espinho											0.24	0.30	0.35
Vila Nova de Gaia												0.17	0.13
Gondomar													0.20

Table 41: $PM_{2.5}$ emissions of diesel buses (g).

$PM_{2.5}$ emissions of diesel buses (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	4.16	2.93	5.28	3.30	5.16	5.20	6.51	5.54	9.94	6.34	8.15	8.61	9.25
Águeda		2.69	6.45	4.58	5.25	6.58	6.38	6.42	9.87	7.80	8.90	9.44	9.61
Albergaria a Velha			3.53	2.69	3.07	4.82	4.28	4.71	6.27	6.03	6.84	7.45	7.13
Murtosa				1.35	3.53	3.07	4.56	4.52	8.25	5.56	6.83	7.49	7.16
Estarreja					2.40	2.91	3.57	3.38	7.13	4.36	5.53	6.33	7.25
Oliveira de Azemeis						3.19	1.35	2.48	4.14	5.21	5.54	5.38	6.02
Ovar							3.37	2.23	7.68	3.30	4.64	5.83	6.18
São João da Madeira								1.63	4.27	3.75	4.88	4.72	6.21
Santa Maria da Feira									4.79	2.61	3.73	4.39	4.22
Arouca										8.04	8.53	8.04	8.79
Espinho											2.70	3.09	3.89
Vila Nova de Gaia												1.88	1.84
Gondomar													1.96

Table 42: PM_{10} emissions of diesel vehicles (g).

PM_{10} emissions of diesel vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	1.42	1.21	1.86	1.13	1.94	2.03	2.61	2.27	3.47	2.77	3.33	3.80	3.58
Águeda		1.09	2.23	1.57	1.80	2.34	2.20	2.39	3.38	3.05	3.39	4.02	3.86
Albergaria a Velha			1.54	1.09	1.05	1.80	1.47	1.84	3.04	2.51	2.85	3.37	3.23
Murtosa				0.55	1.21	1.05	1.59	1.60	2.82	2.02	2.70	2.99	2.85
Estarreja					0.83	1.02	1.26	1.27	2.44	1.65	2.38	2.83	2.72
Oliveira de Azemeis						1.19	0.47	0.85	1.96	2.13	2.32	2.28	2.41
Ovar							1.09	0.78	2.63	1.14	1.71	2.23	2.17
São João da Madeira								0.51	1.92	1.30	1.93	1.88	2.16
Santa Maria da Feira									2.28	0.91	1.45	1.74	1.64
Arouca										2.76	2.92	2.83	3.09
Espinho											0.92	1.36	1.33
Vila Nova de Gaia												0.64	0.64
Gondomar													0.97

Table 43: PM_{10} emissions of petrol vehicles (g).

PM_{10} emissions of petrol vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.63	0.37	0.75	0.49	0.69	0.68	0.84	0.70	1.43	0.77	1.03	1.04	1.22
Águeda		0.51	0.94	0.68	0.78	0.92	0.93	0.87	1.48	1.02	1.18	1.17	1.23
Albergaria a Velha			0.73	0.51	0.46	0.65	0.63	0.62	1.49	0.75	0.86	0.88	0.84
Murtosa				0.25	0.52	0.46	0.66	0.64	1.23	0.77	0.88	0.96	0.92
Estarreja					0.35	0.42	0.51	0.46	1.06	0.58	0.68	0.76	0.97
Oliveira de Azemeis						0.54	0.20	0.37	0.95	0.66	0.69	0.67	0.77
Ovar							0.47	0.35	1.16	0.48	0.63	0.77	0.88
São João da Madeira								0.22	0.92	0.55	0.63	0.61	0.90
Santa Maria da Feira									1.11	0.37	0.49	0.57	0.55
Arouca										1.18	1.28	1.14	1.25
Espinho											0.40	0.37	0.58
Vila Nova de Gaia												0.28	0.28
Gondomar													0.48

Table 44: PM_{10} emissions of hybrid vehicles (g).

PM_{10} emissions of hybrid vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.59	0.34	0.70	0.46	0.64	0.62	0.76	0.64	1.33	0.69	0.94	0.93	1.11
Águeda		0.47	0.88	0.64	0.74	0.86	0.87	0.80	1.40	0.93	1.08	1.05	1.12
Albergaria a Velha			0.68	0.47	0.43	0.60	0.59	0.56	1.38	0.68	0.77	0.79	0.75
Murtosa				0.24	0.49	0.43	0.61	0.59	1.16	0.71	0.81	0.88	0.84
Estarreja					0.33	0.39	0.47	0.42	1.00	0.53	0.61	0.67	0.90
Oliveira de Azemeis						0.50	0.18	0.34	0.88	0.60	0.62	0.60	0.70
Ovar							0.44	0.32	1.09	0.45	0.58	0.71	0.82
São João da Madeira								0.20	0.86	0.51	0.58	0.55	0.84
Santa Maria da Feira									1.03	0.35	0.45	0.52	0.51
Arouca										1.11	1.21	1.06	1.17
Espinho											0.38	0.33	0.55
Vila Nova de Gaia												0.26	0.26
Gondomar													0.44

Table 45: PM_{10} emissions of diesel buses (g).

PM_{10} emissions of diesel buses (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	5.22	3.65	6.60	4.14	6.43	6.47	8.10	6.89	12.43	7.86	10.13	10.67	11.51
Águeda		3.71	8.08	5.74	6.58	8.22	7.99	8.01	12.38	9.71	11.08	11.72	11.95
Albergaria a Velha			5.00	3.71	3.85	6.02	5.36	5.86	9.32	7.49	8.50	9.23	8.83
Murtosa				1.86	4.42	3.85	5.71	5.65	10.35	6.94	8.50	9.31	8.91
Estarreja					3.00	3.64	4.46	4.21	8.94	5.43	6.87	7.84	9.04
Oliveira de Azemeis						4.27	1.69	3.11	6.08	6.48	6.88	6.67	7.49
Ovar							4.30	2.91	9.64	4.13	5.79	7.26	7.73
São João da Madeira								2.06	6.13	4.70	6.07	5.87	7.78
Santa Maria da Feira									7.05	3.27	4.65	5.46	5.26
Arouca										10.07	10.70	10.05	10.99
Espinho											3.39	3.83	4.88
Vila Nova de Gaia												2.35	2.40
Gondomar													2.93

Table 46: VOC emissions of diesel vehicles (g).

VOC emissions of diesel vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.59	0.42	0.75	0.47	0.74	0.74	0.93	0.79	1.42	0.90	1.16	1.23	1.32
Águeda		0.37	0.92	0.65	0.75	0.94	0.91	0.92	1.41	1.11	1.27	1.35	1.37
Albergaria a Velha			0.48	0.37	0.44	0.69	0.61	0.67	0.85	0.86	0.98	1.06	1.02
Murtosa				0.18	0.50	0.44	0.65	0.65	1.18	0.79	0.97	1.07	1.02
Estarreja					0.34	0.42	0.51	0.48	1.02	0.62	0.79	0.90	1.03
Oliveira de Azemeis						0.44	0.19	0.35	0.56	0.74	0.79	0.77	0.86
Ovar							0.47	0.31	1.10	0.47	0.66	0.83	0.88
São João da Madeira								0.23	0.58	0.54	0.70	0.67	0.89
Santa Maria da Feira									0.65	0.37	0.53	0.63	0.60
Arouca										1.15	1.22	1.15	1.25
Espinho											0.39	0.44	0.55
Vila Nova de Gaia												0.27	0.25
Gondomar													0.27

Table 47: VOC emissions of petrol vehicles (g).

VOC emissions of petrol vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	3.5	2.7	4.6	2.8	4.6	4.7	5.9	5.0	8.6	5.8	7.4	7.9	8.3
Águeda		23.3	5.6	3.9	4.5	5.8	5.5	5.7	8.4	7.0	7.9	8.6	8.7
Albergaria a Velha			34.8	23.3	2.6	4.3	3.7	4.2	75.4	5.5	6.2	6.9	6.6
Murtosa				11.6	3.0	2.6	4.0	3.9	7.1	4.9	6.1	6.7	6.4
Estarreja					2.1	2.5	3.1	3.0	6.1	3.9	5.0	5.8	6.4
Oliveira de Azemeis						23.6	1.2	2.1	47.5	4.7	5.0	4.9	5.4
Ovar							19.4	14.8	6.5	2.8	4.1	5.2	5.4
São João da Madeira								8.9	44.6	3.2	4.4	4.2	5.4
Santa Maria da Feira									55.5	2.3	3.3	3.9	3.8
Arouca										6.9	7.3	7.0	7.6
Espinho											2.3	2.8	3.3
Vila Nova de Gaia												1.6	12.1
Gondomar													24.3

Table 48: VOC emissions of hybrid vehicles (g).

VOC emissions of hybrid vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.47	0.45	0.67	0.38	0.72	0.76	0.98	0.85	1.23	1.04	1.25	1.42	1.34
Águeda		3.38	0.78	0.53	0.60	0.85	0.76	0.89	1.11	1.14	1.27	1.51	1.45
Albergaria a Velha			4.94	3.38	0.34	0.67	0.51	0.69	10.37	0.94	1.07	1.26	1.20
Murtosa				1.69	0.42	0.34	0.56	0.58	0.94	0.74	1.01	1.12	1.07
Estarreja					0.29	0.36	0.45	0.47	0.82	0.62	0.89	1.06	1.01
Oliveira de Azemeis						3.53	0.16	0.29	6.58	0.80	0.87	0.85	0.91
Ovar							3.04	2.26	0.85	0.40	0.63	0.83	0.78
São João da Madeira								1.42	6.28	0.45	0.72	0.71	0.76
Santa Maria da Feira									7.68	0.33	0.54	0.65	0.62
Arouca										0.94	0.96	1.01	1.10
Espinho											0.31	0.51	0.44
Vila Nova de Gaia												0.22	1.85
Gondomar													3.33

Table 49: VOC emissions of diesel buses (g).

VOC emissions of diesel buses (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	6.6	4.3	8.1	5.2	7.8	7.7	9.6	8.1	15.4	9.1	11.9	12.3	13.8
Águeda		5.9	10.1	7.2	8.3	10.1	10.0	9.7	15.7	11.6	13.3	13.7	14.1
Albergaria a Velha			8.1	5.9	4.9	7.3	6.7	7.0	16.1	8.8	10.0	10.6	10.1
Murtosa				2.9	5.5	4.9	7.1	7.0	13.1	8.5	10.1	11.0	10.6
Estarreja					3.8	4.5	5.5	5.1	11.3	6.5	8.0	9.0	10.9
Oliveira de Azemeis						6.6	2.1	3.9	10.3	7.6	8.0	7.8	8.9
Ovar							6.7	4.5	12.2	5.2	7.0	8.7	9.6
São João da Madeira								3.2	10.1	5.9	7.2	7.0	9.7
Santa Maria da Feira									12.0	4.0	5.6	6.5	6.3
Arouca										12.6	13.5	12.4	13.6
Espinho											4.3	4.4	6.2
Vila Nova de Gaia												3.0	3.7
Gondomar													5.1

Table 50: NMVOC emissions of diesel vehicles (g).

NMVOC emissions of diesel vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.56	0.38	0.70	0.44	0.68	0.68	0.85	0.72	1.32	0.82	1.07	1.12	1.22
Águeda		0.30	0.86	0.61	0.70	0.87	0.85	0.85	1.32	1.02	1.17	1.23	1.26
Albergaria a Velha			0.38	0.30	0.41	0.64	0.57	0.62	0.65	0.79	0.89	0.97	0.92
Murtosa				0.15	0.47	0.41	0.61	0.60	1.10	0.74	0.90	0.98	0.94
Estarreja					0.32	0.39	0.47	0.45	0.95	0.57	0.72	0.82	0.96
Oliveira de Azemeis						0.37	0.18	0.33	0.43	0.68	0.72	0.70	0.79
Ovar							0.41	0.26	1.03	0.44	0.61	0.77	0.82
São João da Madeira								0.20	0.45	0.50	0.64	0.62	0.83
Santa Maria da Feira									0.50	0.35	0.49	0.58	0.55
Arouca										1.07	1.14	1.07	1.17
Espinho											0.36	0.40	0.52
Vila Nova de Gaia												0.25	0.22
Gondomar													0.20

Table 51: NMVOC emissions of petrol vehicles (g).

NMVOC emissions of petrol vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	3.34	2.45	4.29	2.65	4.25	4.30	5.41	4.62	8.05	5.33	6.79	7.25	7.64
Águeda		8.23	5.21	3.68	4.21	5.36	5.15	5.28	7.91	6.45	7.34	7.91	7.99
Albergaria a Velha			11.84	8.23	2.46	3.97	3.45	3.90	24.40	5.04	5.72	6.29	6.02
Murtosa				4.11	2.85	2.46	3.70	3.68	6.63	4.55	5.67	6.22	5.94
Estarreja					1.94	2.36	2.90	2.78	5.72	3.59	4.64	5.33	5.97
Oliveira de Azemeis						8.79	1.09	2.00	15.53	4.34	4.63	4.50	5.01
Ovar							7.93	5.73	6.15	2.67	3.81	4.81	5.02
São João da Madeira								3.73	14.95	3.03	4.05	3.92	5.03
Santa Maria da Feira									18.13	2.12	3.09	3.64	3.49
Arouca										6.47	6.84	6.53	7.14
Espinho											2.17	2.60	3.11
Vila Nova de Gaia												1.51	4.69
Gondomar													7.80

Table 52: NMVOC emissions of hybrid vehicles (g).

NMVOC emissions of hybrid vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.44	0.43	0.64	0.36	0.69	0.73	0.93	0.81	1.18	0.99	1.19	1.35	1.28
Águeda		3.12	0.74	0.50	0.57	0.81	0.73	0.85	1.05	1.09	1.21	1.44	1.38
Albergaria a Velha			4.56	3.12	0.33	0.64	0.48	0.66	9.61	0.90	1.02	1.19	1.14
Murtosa				1.56	0.40	0.33	0.54	0.55	0.90	0.71	0.97	1.07	1.02
Estarreja					0.28	0.35	0.43	0.45	0.78	0.59	0.85	1.00	0.97
Oliveira de Azemeis						3.25	0.16	0.28	6.09	0.76	0.83	0.81	0.86
Ovar							2.80	2.08	0.81	0.38	0.61	0.80	0.74
São João da Madeira								1.30	5.80	0.43	0.69	0.67	0.73
Santa Maria da Feira									7.11	0.31	0.52	0.62	0.59
Arouca										0.90	0.92	0.97	1.05
Espinho											0.29	0.48	0.42
Vila Nova de Gaia												0.21	1.70
Gondomar													3.08

Table 53: NMVOC emissions of diesel buses (g).

NMVOC emissions of diesel buses (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	5.8	3.5	7.0	4.6	6.5	6.4	8.0	6.7	13.4	7.4	9.8	10.0	11.5
Águeda		4.5	8.8	6.4	7.3	8.7	8.7	8.2	13.8	9.7	11.2	11.1	11.7
Albergaria a Velha			6.1	4.5	4.3	6.1	5.9	5.8	12.0	7.2	8.2	8.5	8.1
Murtosa				2.2	4.8	4.3	6.2	6.0	11.5	7.2	8.4	9.2	8.8
Estarreja					3.3	3.9	4.7	4.3	9.9	5.5	6.5	7.3	9.2
Oliveira de Azemeis						5.2	1.8	3.4	7.7	6.3	6.6	6.4	7.4
Ovar							5.4	3.6	10.8	4.5	6.0	7.3	8.2
São João da Madeira								2.6	7.6	5.1	6.0	5.8	8.4
Santa Maria da Feira									9.0	3.5	4.6	5.4	5.2
Arouca										11.1	11.9	10.7	11.8
Espinho											3.8	3.6	5.5
Vila Nova de Gaia												2.6	3.0
Gondomar													3.8

Table 54: CO emissions of diesel vehicles (g).

CO emissions of diesel vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	3.4	1.4	3.7	2.6	3.1	2.9	3.4	2.7	7.1	2.7	4.1	3.6	5.2
Águeda		3.0	4.8	3.6	4.2	4.5	4.8	3.9	8.0	4.3	5.1	4.3	5.0
Albergaria a Velha			3.9	3.0	2.5	2.9	3.2	2.6	6.7	2.9	3.3	2.9	2.8
Murtosa				1.5	2.7	2.5	3.3	3.1	6.5	3.6	3.7	3.9	3.8
Estarreja					1.8	2.1	2.5	2.0	5.6	2.6	2.5	2.6	4.3
Oliveira de Azemeis						3.5	1.0	1.9	4.5	2.6	2.6	2.5	3.1
Ovar							3.6	2.4	6.3	2.4	2.9	3.4	4.3
São João da Madeira								1.8	4.7	2.8	2.6	2.5	4.5
Santa Maria da Feira									5.2	1.9	2.1	2.3	2.3
Arouca										6.2	6.9	5.6	6.2
Espinho											2.1	1.3	3.1
Vila Nova de Gaia												1.5	2.0
Gondomar													2.1

Table 55: CO emissions of petrol vehicles (g).

CO emissions of petrol vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	21.9	15.3	25.8	16.9	25.4	26.1	33.3	28.8	48.9	34.9	42.3	47.7	46.2
Águeda		42.8	32.1	23.5	27.1	32.1	32.0	31.5	51.8	39.2	44.1	50.7	49.2
Albergaria a Velha			64.4	42.8	16.1	23.7	21.5	23.6	142.9	31.8	36.1	42.4	40.5
Murtosa				21.4	17.8	16.1	22.5	22.1	42.6	27.1	34.6	38.2	36.4
Estarreja					11.9	14.3	17.4	16.6	36.7	21.5	29.9	35.6	35.7
Oliveira de Azemeis						43.7	6.7	12.6	89.3	27.0	29.3	28.7	30.8
Ovar							37.4	27.7	40.7	16.4	22.7	28.9	30.3
São João da Madeira								17.4	83.1	18.7	24.7	24.1	30.7
Santa Maria da Feira									104.7	12.8	18.7	22.3	21.2
Arouca										40.7	44.5	39.3	43.1
Espinho											13.9	17.1	20.4
Vila Nova de Gaia												9.6	22.7
Gondomar													46.2

Table 56: CO emissions of hybrid vehicles (g).

CO emissions of hybrid vehicles (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	0.8	0.5	1.0	0.7	0.9	0.9	1.1	1.0	1.9	1.1	1.4	1.4	1.7
Águeda		17.0	1.3	0.9	1.1	1.3	1.3	1.2	2.0	1.4	1.6	1.6	1.7
Albergaria a Velha			27.5	17.0	0.6	0.9	0.9	0.8	67.3	1.0	1.2	1.2	1.2
Murtosa				8.5	0.7	0.6	0.9	0.9	1.7	1.0	1.2	1.3	1.3
Estarreja					0.5	0.6	0.7	0.6	1.4	0.8	0.9	1.0	1.3
Oliveira de Azemeis						15.7	0.3	0.5	41.1	0.9	0.9	0.9	1.1
Ovar							11.3	9.3	1.6	0.7	0.9	1.1	1.2
São João da Madeira								5.1	36.6	0.7	0.9	0.8	1.2
Santa Maria da Feira									48.5	0.5	0.7	0.8	0.8
Arouca										1.6	1.7	1.6	1.7
Espinho											0.5	0.5	0.8
Vila Nova de Gaia												0.4	7.5
Gondomar													22.1

Table 57: CO emissions of diesel buses (g).

CO emissions of diesel buses (g)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	29.9	22.3	38.7	23.8	38.5	39.1	49.3	42.1	72.5	48.8	62.0	66.4	69.5
Águeda		25.4	46.8	33.0	37.7	48.4	46.2	47.8	70.8	58.7	66.6	72.4	72.8
Albergaria a Velha			36.6	25.4	22.0	36.0	31.0	35.5	78.2	46.0	52.2	57.8	55.3
Murtosa				12.7	25.5	22.0	33.3	33.2	59.4	41.1	51.6	56.7	54.1
Estarreja					17.4	21.3	26.1	25.2	51.3	32.6	42.5	48.9	54.1
Oliveira de Azemeis						27.8	9.8	17.9	49.2	39.6	42.3	41.2	45.6
Ovar							27.4	18.7	55.0	24.0	34.5	43.7	45.2
São João da Madeira								13.2	46.5	27.2	36.9	35.7	45.2
Santa Maria da Feira									57.5	19.1	28.1	33.2	31.8
Arouca										58.1	61.2	58.8	64.3
Espinho											19.4	23.8	27.9
Vila Nova de Gaia												13.5	15.3
Gondomar													25.2

Appendix D: Air pollution costs

Table 58: Air pollution costs per passenger for diesel vehicles (€cent/passenger).

Air pollution costs per passenger for diesel vehicles (€cent/passenger)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	38.7	41.7	57.0	31.7	63.9	68.4	89.0	78.3	104.1	97.7	114.9	134.3	120.0
Águeda		21.0	65.4	43.7	49.7	72.8	63.7	77.8	91.8	102.6	112.6	140.7	132.1
Albergaria a Velha			29.7	21.0	28.6	58.9	42.4	61.8	59.7	87.3	99.1	120.1	114.9
Murtosa				10.5	34.8	28.6	47.3	49.4	78.4	64.3	91.8	102.1	96.9
Estarreja					24.3	30.6	38.5	41.4	67.8	54.5	83.4	100.4	89.4
Oliveira de Azemeis						22.8	13.7	24.2	38.2	73.1	80.8	79.5	82.4
Ovar							21.2	15.1	70.7	33.5	55.3	74.1	66.1
São João da Madeira								10.0	37.2	38.0	65.6	64.2	64.1
Santa Maria da Feira									44.6	27.6	48.7	59.0	55.3
Arouca										78.6	79.8	86.1	93.7
Espinho											25.6	48.2	36.1
Vila Nova de Gaia												18.1	12.4
Gondomar													19.0

Table 59: Air pollution costs per passenger for petrol vehicles (€cent/passenger).

Air pollution costs per passenger for petrol vehicles (€cent/passenger)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	24,9	23,4	34,4	20,1	37,0	38,9	50,2	43,9	63,5	53,9	64,4	73,9	68,5
Águeda		17,7	40,4	27,7	31,7	43,6	39,6	45,3	59,0	58,4	64,7	78,0	74,5
Albergaria a Velha			25,5	17,7	18,4	34,2	26,5	35,2	53,1	48,7	55,3	65,7	62,9
Murtosa				8,8	21,8	18,4	29,0	29,7	49,9	37,9	52,0	57,7	54,8
Estarreja					15,0	18,7	23,2	24,0	43,1	31,4	46,1	55,1	51,7
Oliveira de Azemeis						18,9	8,5	15,2	33,7	41,0	45,0	44,1	46,5
Ovar							17,5	12,4	45,7	20,7	32,3	42,6	40,0
São João da Madeira								8,3	32,2	23,5	37,1	36,3	39,3
Santa Maria da Feira									39,4	16,8	27,8	33,4	31,5
Arouca										49,3	51,2	52,1	56,8
Espinho											16,3	26,5	23,2
Vila Nova de Gaia												11,4	10,2
Gondomar													17,0

Table 60: Air pollution costs per passenger for hybrid vehicles (€cent/passenger).

Air pollution costs per passenger for hybrid vehicles (€cent/passenger)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	16.0	17.0	24.0	13.2	26.6	28.2	36.5	32.0	43.7	39.3	46.9	53.8	49.7
Águeda		11.8	27.4	18.2	20.7	30.6	26.7	32.5	38.0	42.4	46.8	56.9	54.2
Albergaria a Velha			16.7	11.8	11.8	24.6	17.8	25.5	33.5	35.5	40.3	47.8	45.7
Murtosa				5.9	14.6	11.8	19.9	20.8	32.6	26.9	37.8	41.9	39.9
Estarreja					10.2	12.9	16.2	17.3	28.2	22.7	33.6	40.1	37.2
Oliveira de Azemeis						12.7	5.7	10.1	21.5	29.9	32.8	32.2	33.8
Ovar							11.5	8.3	29.2	14.0	23.1	30.8	27.8
São João da Madeira								5.4	21.0	16.0	27.0	26.4	26.9
Santa Maria da Feira									25.0	11.6	20.2	24.3	22.8
Arouca										32.9	33.1	36.2	39.4
Espinho											10.7	19.3	14.9
Vila Nova de Gaia												7.6	6.8
Gondomar													10.6

Table 61: Air pollution costs per passenger for diesel buses (€cent/passenger).

Air pollution costs per passenger for diesel buses (€cent/passenger)	Águeda	Albergaria a Velha	Murtosa	Estarreja	Oliveira de Azemeis	Ovar	São João da Madeira	Santa Maria da Feira	Arouca	Espinho	Vila Nova de Gaia	Gondomar	Porto
Aveiro	6.5	5.1	8.6	5.2	8.7	8.9	11.2	9.6	16.1	11.2	14.1	15.3	15.7
Águeda		5.4	10.3	7.2	8.3	10.8	10.2	10.7	15.5	13.3	15.0	16.6	16.6
Albergaria a Velha			7.7	5.4	4.8	8.1	6.8	8.0	15.5	10.5	11.9	13.4	12.8
Murtosa				2.7	5.6	4.8	7.4	7.4	13.0	9.2	11.7	12.9	12.3
Estarreja					3.8	4.7	5.8	5.7	11.2	7.3	9.8	11.3	12.2
Oliveira de Azemeis						6.0	2.2	3.9	9.9	9.0	9.7	9.4	10.4
Ovar							5.8	4.0	12.0	5.3	7.7	9.9	10.0
São João da Madeira								2.8	9.6	6.0	8.4	8.1	10.0
Santa Maria da Feira									11.5	4.2	6.4	7.5	7.2
Arouca										12.8	13.4	13.1	14.3
Espinho											4.3	5.5	6.1
Vila Nova de Gaia												3.0	3.3
Gondomar													4.9