electronics

Article

Assessing Urban Mobility Resilience: An Exploratory Approach Using Hazard-Based Duration Models

Luís A. P. Jardim Gonçalves [1], Sara Ferreira [2] and Paulo J. G. Ribeiro [1,*]

[1] CTAC—Centre for Territory Ambient and Construction, School of Engineering, University of Minho, 4800-058 Guimarães, Portugal; goncalves.luis1993@gmail.com
[2] CITTA—Centre for Territory, Transports and Environment, Faculdade de Engenharia da Universidade do Porto, Rua Dr Roberto Frias s/n, 4200-465 Porto, Portugal; sara@fe.up.pt
* Correspondence: paulo.ribeiro@civil.uminho.pt

Abstract: Urban systems are vulnerable to disturbances from both natural and human origins, which can disrupt their normal functioning. Evaluating the resilience of these systems, particularly the main transportation networks and their usage levels, is crucial and innovative for understanding the impacts of such disturbances. Thus, this work aims to assess resilience in urban mobility through the probability of a particular journey using a specific mode: "surviving" through critical travel time. To achieve this, a methodology was developed based on the Weibull model with gamma heterogeneity (hazard-based duration models), which was applied to a medium-sized Portuguese municipality. Eighteen groups representing active populations were set and compared. The results indicated that using the bus and cycling are the most resilient modes of transport, whereas walking is the least resilient. Additionally, a specific group was identified as having lower mobility resilience, making them more vulnerable to disruptions in the transport system. Finally, the findings of this study demonstrate the practical application of this methodology, which relies on travel time to assess resilience and, thus, guide political attention and actions to the less resilient mode. Future research should aim to develop a comprehensive framework that incorporates several variables to fully describe the complex nature of transport systems and their resilience.

Keywords: urban mobility; resilience; travel time; hazard-based duration models; Weibull model

check for updates

Citation: Jardim Gonçalves, L.A.P.; Ferreira, S.; Ribeiro, P.J.G. Assessing Urban Mobility Resilience: An Exploratory Approach Using Hazard-Based Duration Models. *Electronics* **2024**, *13*, 4220. https://doi.org/10.3390/electronics13214220

Academic Editors: Faheim Sufi and Alam Edris

Received: 22 August 2024
Revised: 16 October 2024
Accepted: 18 October 2024
Published: 28 October 2024

1. Introduction

A problem that society has been facing for several years is the growth of large cities and metropolitan areas, with an even more significant increase predicted in the coming decades [1,2]. This growth undermines the functioning of some urban systems, such as transportation and mobility, due to the intensive increase in demand for transportation given the growing mobility needs of the resident population [3]. Associated with the increase in travel resulting from urban growth and mobility patterns dominated by the use of private cars, there has been an increase in motorized traffic volumes in cities, causing mobility problems such as congestion, environmental pollution, noise, and accidents [4]. However, the urbanization process is a key phenomenon in the economic development of cities, regions, and even countries [5].

Traffic congestion directly affects the quality of urban mobility, contributing to reducing accessibility and urban mobility levels. In addition to increasing time wasting and energy expenditure [6], pollution, and stress [7,8], it also decreases productivity and increases the cost of living for society [9]. However, urban transport systems are always exposed to other types of disturbances that can affect system functioning, such as natural disasters, like hurricanes, floods, and fires, or human-origin events, like terrorist attacks, cultural events, strikes, and failures in urban systems caused by human error or mismanagement [10–14]. Thus, the concept of resilience concerning transport and urban mobility systems arises. According to the transportation literature, resilience relies on the system's ability to resist, reduce, and absorb the impacts of a disturbance while maintaining an acceptable level of service (static resilience) and restoring regular and balanced operation within a reasonable time and cost (dynamic resilience) [15]. In this sense, government entities need to assess the resilience of transport and mobility systems to properly plan transport networks and control traffic movements to ensure and mitigate mobility-related problems [4,16,17].

In urban mobility studies, travel demand modeling is typically associated with the perspective that transport demand is derived from a specific set of purposes, such as work, shopping, personal business, and recreational activities, along with their characteristics. Therefore, travel time associated with activities has been widely used as a measure to identify factors that significantly affect transport demand [18]. However, the analysis of travel times requires studying a complex decision-making process that deals with activity and trip generation, mode choice, and route options, which can be modeled to estimate travel times for specific travelers on a given urban transport network. Over the years, in order to study travelers' complex decisions and develop models capable of predicting travel times (time to destination) resulting from variations in transport networks and socioeconomic characteristics of the population, urban models have been built based on the traditional four-step model (trip generation, trip distribution, modal split, and traffic assignment) and have incorporated activity-based models and dynamic urban network models [19].

As an alternative to an extensive urban transportation modeling system, a more simplistic approach to gain insights into the factors determining individual travel times is to model travel times directly (implicitly including the complex decision-making related to destination, route, activity, and time of day). For this purpose, [19]) investigated the relationships between travel time (origin–destination) and various influential factors such as socioeconomic characteristics, income, demographics, and mode of transportation.

However, there is a gap in the literature regarding studies that analyze the resilience of the transportation and mobility system considering its different modes. Therefore, it becomes essential for entities managing the road network to develop transportation models that allow them to analyze traffic congestion phenomena [20].

Therefore, for a transportation and urban mobility system to be considered resilient, it should have the capacity to resist, maintain or recover, adapt, or transform in the face of disturbances resulting from scenarios that limit the balanced operation of the system. For this purpose, resilience assessment tools in the transportation and urban mobility system should be able to identify key risks related to actions of natural or anthropogenic origin that may block the circulation and mobility of the population in an urban area and should be able to assess the impact of these disturbances on the overall functioning of the system in terms of the main transportation networks and their respective levels of utilization per transport mode. Indeed, we hypothesized that resilience varies depending on the mode of transport used. Consequently, the objective of this work is to evaluate resilience in urban mobility through the probability of a particular journey, using a specific mode, "surviving" through the application of hazard-based duration models, using the travel time as the dependent variable. This novel approach contributes to the resilience evaluation as follows:

- Providing a quantitative indicator for measuring resilience based on critical travel time;
- The proposed methodology is supported by a robust model, i.e., hazard-based duration model, allowing the modeling of travel time and the analysis of factors that may affect this variable;
- The proposed resilience framework is based on a revealed-preference survey conducted by a government statistical office and following the guidelines of the statistical office of the European Union (Eurostat), which seeks to provide harmonized and comparable statistics throughout the European territory. Therefore, this proposed

methodology can be applied to several cities using the same kind of information and providing a reliable comparison.

This work follows the following structure: in Section 1, the introduction is presented, indicating the main causes of interruptions in transportation and mobility systems, the hypothesis and research, and the objectives. In Section 2, a state-of-the-art discussion of the applicability of hazard-based duration models in the transportation and mobility sector is presented. Section 3 describes the methodology developed and subsequently applied in this work. Section 4 presents the case study and the description of the variables used in the models. In Section 5, the developed methodology is applied to the case study, presenting the development of the Weibull model with heterogeneity and the interpretation of its results, resilience assessment, and discussion of the results. In Section 6, the discussion of the results obtained from applying the methodology is presented. Finally, in Section 7, the main conclusions of this research are presented.

2. Literature Review

Over the past decade, several studies applying hazard-based duration models have been developed to study various problems in the field of transportation, with time as the dependent variable. Many works apply hazard-based duration models to situations where disruptive events impair the normal lives of populations and the normal functioning of transportation systems, such as natural disasters, road accidents, and congestion. For instance, [21] developed a random-parameter hazard-based model to understand hurricane evacuation time. Other authors present hazard-based duration models to investigate various relevant aspects of transportation, such as factors affecting road safety, including cyclist and motorcyclist safety [22], motorcyclist behavior during overtaking maneuvers [23], examining the survival risk of accident injuries regarding road environmental factors [24], accident duration prediction [25], investigating the distance traveled by a vehicle in an off-road accident [26], comparing braking profiles of young drivers [27], examining the influence of various factors affecting the duration of various types of road incidents [3], and evaluating the time it takes to detect/report, respond to, and clear road incidents [28]. Another topic investigated using hazard-based duration models is congestion duration. [29] present a hazard-based duration model for the accurate prediction of congestion duration for urban rail transit (URT) passenger flow. Meanwhile, [30] proposed an approach to estimate congestion duration on a particular road segment and the probability that, given its onset, congestion will end during the subsequent time period.

On the other hand, some research has focused on issues related to waiting time and travel time in public transportation, specifically investigating the tolerance of public transport users during unplanned service disruptions and identifying the factors affecting their behaviors [31], predicting railway transportation delays [32], estimating the duration of commercial vehicle stops in urban areas [33], and evaluating the effects of mixed traffic flow on bus operation times at bus stops [34]. Other authors apply hazard-based duration models to identify factors influencing the travel times and duration of social activities for transport network users, specifically analyzing how the duration of social activities is influenced by the characteristics of the social activity [35], investigating explanatory factors affecting the travel behavior of the elderly [36], studying determinants of travel time to destination in urban areas [19], exploring factors leading some individuals to spend a significant amount of time traveling [37], and examining how congestion status, traffic demand, road variables, and weather conditions impact travel time performance [38]. Conversely, other authors have developed a set of panel survival analyses to describe the phenomenon that individuals' emotional well-being may worsen after traveling for a certain period [39].

In contrast, travel distance has recently been gaining more attention in environmental impact research and due to the increasing demand for new modes of transportation powered by alternative energies, such as electric vehicles [40]. However, the application of the hazard-based duration modeling approach using travel distance is still limited. This is because travel distance is typically considered as an outcome of the trip rather than a process, and, therefore, the duration dependency is often ignored [41]. Some studies have been developed applying hazard-based duration models using the time variable to identify important factors determining activity-based travel distance in urban areas [18,41], to explore the spatial dimension of new types of alternative energy-powered public transportation use (electric and natural gas-powered modes), to reduce environmental pollution and improve mobility and safety in urban areas [42], to study the prediction of daily car travel distances using socioeconomic variables, weather conditions, and vehicle characteristics [40], and to analyze the sociodemographic and built environment effects on travel distances [41].

As one can conclude, despite the extensive literature on transportation using hazard-based duration models, there are no studies applied to resilience.

Regarding the model used, it is observed in the transportation literature that the log-logistic model belonging to hazard-based duration models presents a better fit to the data for studies of congestion duration (see [23,29,30]). On the other hand, when studying the factors influencing travel time (distance), the model that best fits the data is the Weibull model with gamma heterogeneity (see [18,19,28,42]).

3. Methodology

Theorical Framework to Evaluate the Resilience in Urban Mobility

Through the analysis of the literature, it was found that there is a gap in the literature regarding the assessment of resilience in urban mobility. Therefore, the resilience assessment will be based on population data that can be obtained from mobility surveys, which, along with other socioeconomic information of the population, will allow us to define hazard-based duration models as a function of a cost function, which in this work will be based on travel time, to evaluate the acceptance thresholds for maintaining or changing the mode of transportation for the main daily trips.

From a practical standpoint, the contribution of the assessment associated with hazard-based duration models that reflect the behavior of a population, either individually or by population groups, regarding the use of various modes of transportation comprising a mobility system will be challenging to achieve in a very disaggregated (individual) manner. This is because it would require a vast amount of information about all individuals or about a significant sample of population groups.

In this context, it is assumed that for trips with travel times (T_{travel}) shorter than the critical threshold ($T_{50\%}$), there is no change in the mode of transportation, and the system, from the perspective of users' behavior in that mode of transportation, is resilient. This means that they contribute to the stability of the system, as it can be considered that they absorb the impact of hazards and represent the initial phase of the resilience process, embodying the robustness of the mobility system. This can be calculated as follows:

- Ttravel $\leq T_{50\%}$—+Resilient
- Ttravel $> T_{50\%}$—−Resilient

The critical threshold $T_{50\%}$ will be determined assuming the probability of 50% of a trip "surviving", i.e., of ending. This threshold is a mathematical choice and can be considered for comparison purposes for other samples (i.e., cities).

In Figure 1, a synthesis of the methodological process for evaluating resilience associated with the behavioral component at the level of population mobility is presented based on their mobility patterns, modal choice, and, more specifically, the robustness of the trips.

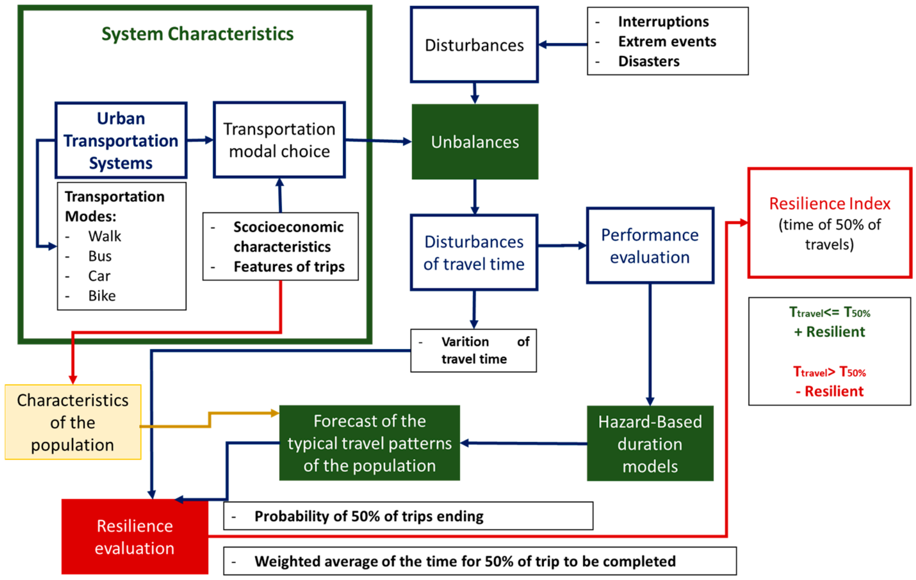

Figure 1. Resilience theoretical framework.

Thus, concerning travel time, an approach that includes the assessment of the risk associated with a given hazard makes it possible to assess the conditional probability that a trip ends up taking place in a given mode after a certain time, δ; that is, the trip in a mode under study does not end until time δ. In the Weibull model, the hazard function is given by the following expression [43]:

$$h(\delta) = f(\delta)/[\mathbf{1} - \boldsymbol{F}(\delta)] \tag{1}$$

where $\boldsymbol{F}(\delta)$ is the cumulative distribution function and $f(\delta)$ is the density function of travel times.

- The risk function given by expression (1) allows us to obtain the rate at which trips will end in time δ, given that they lasted until time δ. Thus, the risk function can be interpreted as follows [43]: dh(δ)/d δ > 0; this suggests that the conditional probability that the trip ends soon (given it has not ended yet) increases as time increases (i.e., the function slopes upwards as time increases);
- (dh(δ)/dδ < 0); this suggests that the conditional probability that the trip will end soon decreases as time increases (i.e., risk function slopes downwards);
- (dh(δ)/dδ = 0); this suggests that the conditional probability of the trip ending soon is independent of the trip time (hazard function is constant as time increases).

To assess the effect of the explanatory variables in the hazard-based models, a proportional hazards approach can be used, where the explanatory variables act in a multiplicative way in a base risk function (or baseline), resulting in [43] the following:

$$h(\,\delta|\boldsymbol{X}) = h_0(\delta)\exp(\boldsymbol{\beta X}) \tag{2}$$

where $\boldsymbol{X}$ is the vector of explanatory variables, $\boldsymbol{\beta}$ is the vector of estimated parameters, and $h_0(\delta)$ is the baseline hazard that indicates the risk when all elements of the vector of explanatory variables are zero. In estimating Equation (2), a common approach considers various parametric forms of the base risk function. It is also possible not to make any parametric assumptions, but this will make inferences related to risk probabilities difficult as they change over time [43].

In the specific case of the Weibull model, it is possible to uniformly increase or decrease (monotonically) the hazard functions (which implies that the probability of a trip ending can increase or decrease the longer the trip time). Taking into account the parameters $\lambda > 0$ and $P > 0$, the Weibull distribution has the following density function [43]:

$$f(\delta) = \lambda \boldsymbol{P}(\lambda\delta)^{P-1} \exp(-\lambda\delta)^{P} \tag{3}$$

The hazard is given by the following:

$$h(\delta) = \lambda \boldsymbol{P}(\lambda\delta)^{P-1} \tag{4}$$

where P and λ are the parameters to be estimated by the model. As indicated in Equation (4), if the Weibull parameter is $P > 1$, the risk is uniform, increasing travel time; if it is $P < 1$, the risk is uniform, decreasing travel time; and if $P = 1$, the risk is constant regardless of travel time.

Equally flexible, the Weibull model with gamma heterogeneity is less restrictive regarding the assumption that the hazard function must be homogeneous across observations. Thus, all variation in travel time "survivability" is no longer considered to be captured by the variable vector $\boldsymbol{X}$. This is important because unobserved factors that cannot be included in $\boldsymbol{X}$ can influence travel time survival. However, this unobserved heterogeneity can lead to specification errors, which, in turn, can lead to wrong inferences about the shape of the hazard function (hazard) and inconsistent parameter estimates. [44,45]. If ω represents the heterogeneity, $g(\omega)$ represents its gamma distribution in the population with a mean of 1, a variance of θ, and $S(\delta|w)$ being the conditional survival function. The unconditional survival function is given by the following [43]:

$$S(\delta) = \int_0^\infty S(\delta|w)g(w)dw = \left[1 + \theta(\lambda\delta)^P\right]^{-1/\theta} \tag{5}$$

resulting in the following hazard function:

$$h(\delta) = \lambda P(\lambda\delta)^{P-1}[S(\delta)]^{\theta} \tag{6}$$

If $\theta = 0$, the risk is reduced for the Weibull model and heterogeneity is not present.

Based on the Weibull model, it then becomes possible to determine the time for which a trip has a certain probability of ending [19,23,28,29,36].

4. The Case Study and Description of the Data

The data used in this model are from the "Mobility Survey in the Metropolitan Areas of Porto and Lisbon." [46], which is an official data set collected by the National Statistical Institute of Portugal (INE). It aims to obtain statistical information for transport and mobility following the guidelines of the statistical office of the European Union (Eurostat), seeking to provide harmonized and comparable statistics throughout the European territory. In this revealed-preference survey, the respondents were asked to reveal the previous day's trip and their personal and household characteristics and identification. The data were collected between October and December of 2017.

From the data, 4064 trips were selected considering the socioeconomic characteristics of the population residing in the municipality of Póvoa de Varzim and its surroundings (Figure 2). [46]. This municipality includes 7 parishes with a total of 64,320 inhabitants. The urban city center is represented in red in Figure 2. The municipality is part of the Porto metropolitan area, the second largest metropolitan area of Portugal.

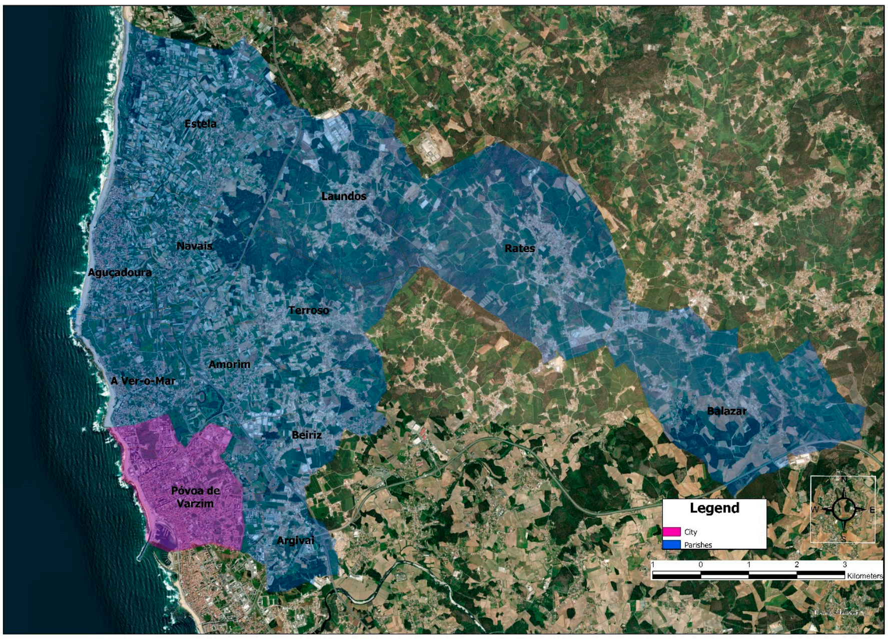

Figure 2. Map of the area of Póvoa de Varzim, Portugal (Source: Bing Maps).

In this sense, in order for the model to faithfully convey the characteristics of trips made by the active population, taking into account variations in travel time, some variables characterizing the population were selected.

Therefore, the socioeconomic information includes gender, age, level of education, driver's license, purpose of the trip, and mode of transportation. Gender is classified into two categories: male and female. Age is classified as follows: age equal to or less than 14 years, age between 15 and 24 years, age between 25 and 44 years, age between 45 and 64 years, and age equal to or greater than 65 years. The level of education is classified as follows: none or incomplete first cycle, complete basic education (first cycle, second cycle, or complete third cycle), complete secondary education, and complete higher education. Driver's license is divided into two categories: has a driver's license or does not have a driver's license. The purpose of the trip is classified into the following categories: commuting to/from work, commuting to/from school or school-related activities, take/pick up/accompany family members or friends, leisure and sports, and purchase of goods and services. Finally, the modes of transportation are car, bus, walking, and bicycle. Table 1 lists the descriptive statistics of the selected variables, and Figure 3 presents the histogram of travel times.

Table 1. Descriptive statistics of the selected variables.

Variables	Sample (or %)	Mean	Minimum	Maximum
Travel time (min)	4064	20.5	0.97	120
Gender (1 Male, 0 Female)	48.7%		0	1
Age 14 years old or less	10.5%		0	1
Age between 15 and 24 years	10.3%		0	1
Age between 25 and 44 years	32.1%		0	1
Age between 45 and 64 years	32.9%		0	1
Age 65 years or older	14.2%		0	1
None or incomplete 1st cycle	6.6%		0	1
Basic education	49.2%		0	1
Secondary education	19.7%		0	1

Table 1. *Cont.*

Variables	Sample (or %)	Mean	Minimum	Maximum
Higher education (Bachelor's, Master's, Doctorate, Higher Professional Technical Course)	24.5%		0	1
Driving license (1 Yes, 0 No)	71.5%		0	1
Go/return from work	43.5%		0	1
Going to/from school or school activities	13.4%		0	1
Take/pick up/accompany family or friends	11.8%		0	1
Leisure activity and sport	20.3%		0	1
Purchase of goods and services	11.0%		0	1
Transportation mode—Car	74.3%		0	1
Transportation mode—Bus	5.3%		0	1
Transportation mode—Walk	19.4%		0	1
Transportation mode—Bike	1.1%		0	1

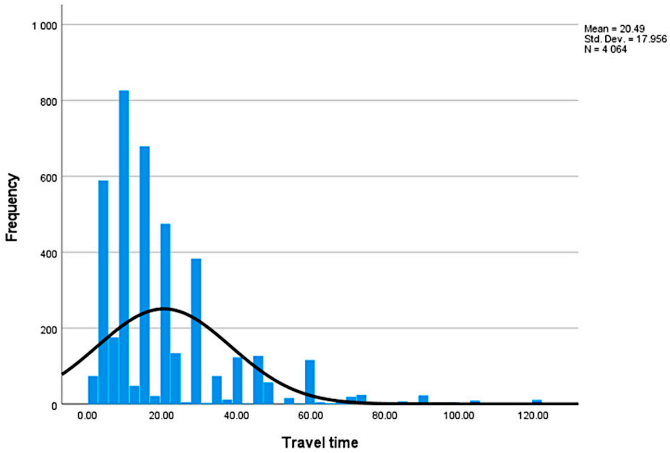

Figure 3. Histogram of travel times(min) (Mean = 20.49; Std. Dev. = 17.956; N = 4064) (Source: IBM SPSS 28).

5. Application of the Methodology to the Case Study

5.1. Results of the Weibull Model with Heterogeneity

According to the literature, the Weibull model with gamma heterogeneity is the one that best fits the data for estimating travel time. Therefore, Table 2 presents the parameter estimates of the hazard model estimated through the selected variables. Note that the negative sign of a parameter affects the duration and not the risk. Thus, the explanatory variables are defined to represent all factors that likely affect travel time.

The obtained results show that the parameter P of the Weibull model with gamma heterogeneity is positive and greater than 1 (indicating a uniformly increasing function). Figure 4 shows the density function corresponding to the Weibull distribution function (the first derivative of the cumulative distribution concerning time). In addition, according to Figure 5, the risk is not constant over the duration. It can be observed that the probability of travel time (calculated between 0 and 1) being 1 min is approximately 1, while the probability of travel time being greater than 100 min is almost 0. On the other hand, the hazard function is not uniform—it increases until the travel time reaches about 15 min and then decreases (Figure 6).

Table 2. Parameter estimates of the hazard model.

Variables	**Weibull Model with Gamma Heterogeneity**	
	Independent Variables	
	Coefficients	**Standard Error**
Constant	2.68853 ***	0.0471
Gender (male)	0.1151 ***	0.02441
Age less than or equal to 14 years	−0.23406 ***	0.06452
Age between 15 and 24 years	0.11109 **	0.05035
Age between 45 and 64 years	0.08556 ***	0.03053
Age 65 years or older	0.2914 ***	0.04128
None or incomplete 1st cycle	−0.11419 **	0.05360
Secondary education	0.15716 ***	0.03441
Higher education (Bachelor's, Master's, Doctorate, Higher Professional Technical Course)	0.42754 ***	0.03195
Driving license (Yes)	−0.10214 ***	0.03949
Going to/from school or school activities	−0.01981	0.05140
Take/pick up/accompany family or friends	−0.24173 ***	0.04019
Leisure activity and sport	−0.11907 ***	0.03350
Purchase of goods and services	−0.07384	0.04213
Transportation mode—Bus	0.41798 ***	0.05966
Transportation mode—Walk	−0.23182 ***	0.03340
Transportation mode—Bike	0.22835	0.16849
Note: ***, **, * ==> Significance at 1%, 5%, 10% level.		
Teta	0.74291 ***	0.06312
Density parameters underlying the significance of the data:		
Parameter	Estimated	
Lambda	0.06252	
P	2.08162	
Median	15.26001	

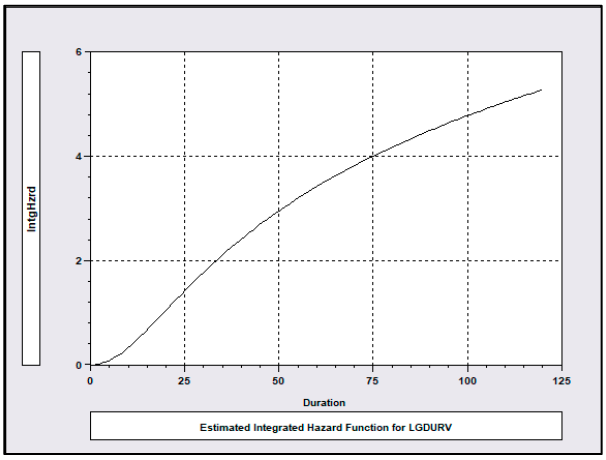

Figure 4. Density function–travel time (Source: NLOGIT 5 software).

From Table 2, an analysis of the relationship between variables and travel time can be conducted based on the estimated parameters. It is observed that socioeconomic characteristics affect the duration of trips. Male users have slightly longer travel times than female users. Users aged 65 and over have the longest travel time, indicating a distinct travel pattern for this age group. On the other hand, users aged 14 or younger have the shortest travel time. This is because it is the population segment that is most dependent, consisting of babies, preschool-age children, and children attending basic education, where schools are typically located close to the residential area.

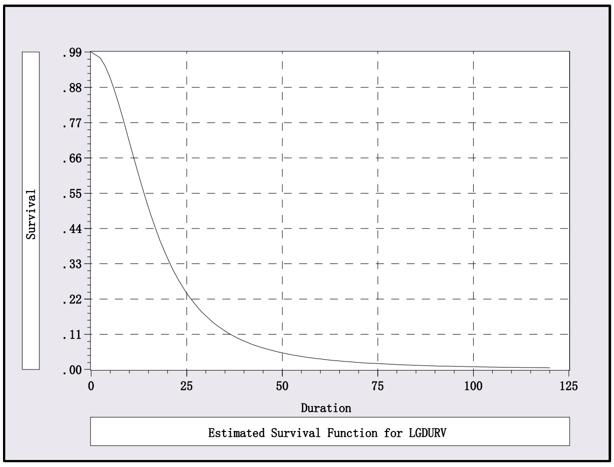

Figure 5. Survival function–travel time (Source: NLOGIT 5 software).

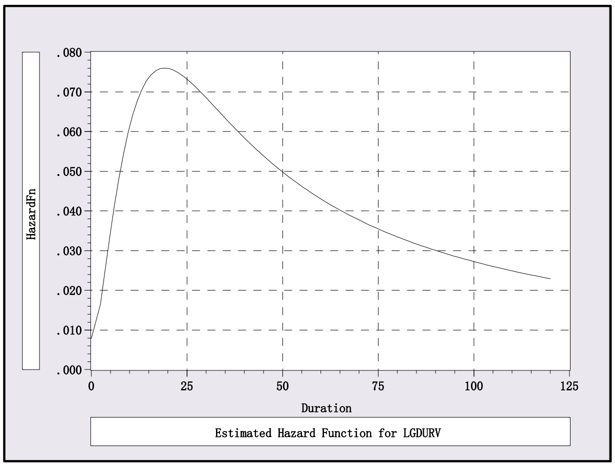

Figure 6. Hazard function–travel time (Source: NLOGIT 5 software).

The education level of individuals affects travel time linearly. Individuals with no education or incomplete primary, secondary, or tertiary education have the shortest travel time. This may be associated with the type of professional activity of these individuals. On the other hand, individuals with higher education have the longest travel time. This may be because this segment of the population has access to professional activities associated with executive positions in companies or government, which are often associated with longer commutes. Finally, individuals with completed secondary education and those with completed basic education have the second and third longest travel times, respectively. These two segments of the population are mainly composed of the working class, where most work near their residential area.

Regarding the driver's license, individuals who are licensed to drive motor vehicles have shorter travel times than those who do not have this license.

In terms of trip attributes, it is observed that trips with the purpose of "Commute to/from work" have longer travel times. This is because a significant portion of this population usually spends some time in traffic congestion to travel to work as they typically commute during rush hours. Trips with the purpose of "Accompanying/fetching friends or family" have the shortest travel times. These trips typically involve accompanying someone to the doctor, taking children to school, or picking someone up from work. Trips for "Leisure and sports" have the second shortest travel times. These trips are usually made in the vicinity of the residential area and often involve active modes of transportation (walking or cycling), resulting in shorter and less time-consuming trips (avoiding traffic congestion). Trips for "Shopping for goods and services" have the third longest travel times. This is because individuals tend to travel away from their residential area to go to a particular supermarket, hospital, or public service, which are usually located in the city center. Lastly, trips for "Commute to/from school or school-related activities" have the second longest travel times. This is due to the centralization of schools, where primary schools and lower and upper secondary schools are mainly located in city centers, requiring students to travel longer distances.

Regarding the transportation mode variables of the trip, the pedestrian mode has the shortest travel times. This is because this mode of transportation is used for short-distance trips with short durations. The bus mode is the transportation mode with the longest travel times. This is because this mode of transportation makes several stops (bus stops) along its route to pick up or drop off passengers and has a lower circulation speed compared to the car mode, dealing with the same congestion issues. The bicycle mode has the second longest travel times. This is because individuals who opt for this mode of transportation tend to take longer trips than walking, often as long as bus and car trips, resulting in longer travel durations.

5.2. Determination of Critical Threshold ($T_{50\%}$) and Resilience Analysis

After defining the hazard-based duration model (Weibull with gamma heterogeneity), and in order to better understand how population characteristics influence travel over time, several typical users of the transportation and mobility system were selected. These users characterize the active population in the municipality of Póvoa de Varzim and its surroundings, as they represent the fraction of the population that most frequently uses the transportation and mobility system, typically exhibiting the same travel patterns. Therefore, Table 3 presents the eighteen main characteristic users of this population group in order to subsequently assess the resilience, more specifically the characteristic of robustness, associated with a potential change in the mode of transportation, namely car, when traveling from home to work.

Table 3. Main types of individuals belonging to the active population.

User	Variables											
	Gd	**A1**	**A2**	**A4**	**A5**	**EL1**	**EL2**	**EL3**	**DL**	**PT2**	**PT3**	**PT4**	**PT5**
Man 1	1	0	1	0	0	0	1	0	1	0	0	0	0
Man 2	1	0	1	0	0	0	0	1	1	0	0	0	0
Man 3	1	0	1	0	0	0	0	0	1	0	0	0	0
Man 4	1	0	0	0	0	0	1	0	1	0	0	0	0
Man 5	1	0	0	0	0	0	0	1	1	0	0	0	0
Man 6	1	0	0	0	0	0	0	0	1	0	0	0	0
Man 7	1	0	0	1	0	0	1	0	1	0	0	0	0
Man 8	1	0	0	1	0	0	0	1	1	0	0	0	0
Man 9	1	0	0	1	0	0	0	0	1	0	0	0	0
Woman 1	0	0	1	0	0	0	1	0	1	0	0	0	0
Woman 2	0	0	1	0	0	0	0	1	1	0	0	0	0
Woman 3	0	0	1	0	0	0	0	0	1	0	0	0	0
Woman 4	0	0	0	0	0	0	1	0	1	0	0	0	0
Woman 5	0	0	0	0	0	0	0	1	1	0	0	0	0
Woman 6	0	0	0	0	0	0	0	0	1	0	0	0	0
Woman 7	0	0	0	1	0	0	1	0	1	0	0	0	0
Woman 8	0	0	0	1	0	0	0	1	1	0	0	0	0
Woman 9	0	0	0	1	0	0	0	0	1	0	0	0	0

Gd—Gender (1 is male, 0 is female); A—Age, in which A1 is an age less than or equal to 14 years, A2 is an age between 15 and 24 years, A4 is an age between 45 and 64 years, A5 is an age of 65 years or older; EL—education level in which EL1 is none or an incomplete first cycle; EL2 is basic education; EL3 is secondary education (Bachelor's, Master's, Doctorate, Higher Professional Technical Course); DL—driver license (1 is with driver license, 0 otherwise); PT—purpose of the trip (PT2 is commuting to/from school or school-related activities, PT3 is take/pick up/accompany family members or friends, PT4 is leisure and sports, and PT5 is purchase of goods and services.

As can be concluded from Table 3, we defined population groups assuming both genders and all ages, all education levels, and both alternatives for driving licenses, therefore covering most of the population characteristics of the municipality.

The analysis of the travel time was applied for these eighteen population groups, allowing for a comparison between the groups and providing the computation of a weighted average of the travel time.

Considering the various types of users from the active population presented in Table 3, the probability of a trip ending after a certain time was analyzed based on the results obtained from the Weibull model with gamma heterogeneity. Therefore, Figure 7 depicts the variation of the probability of a trip ending over time for different modes of transportation, considering the characteristics of the selected users. Figure 7 is in line with the tendency of the survival function shown in Figure 6, as the longer the travel time, the higher the probability that it has already ended.

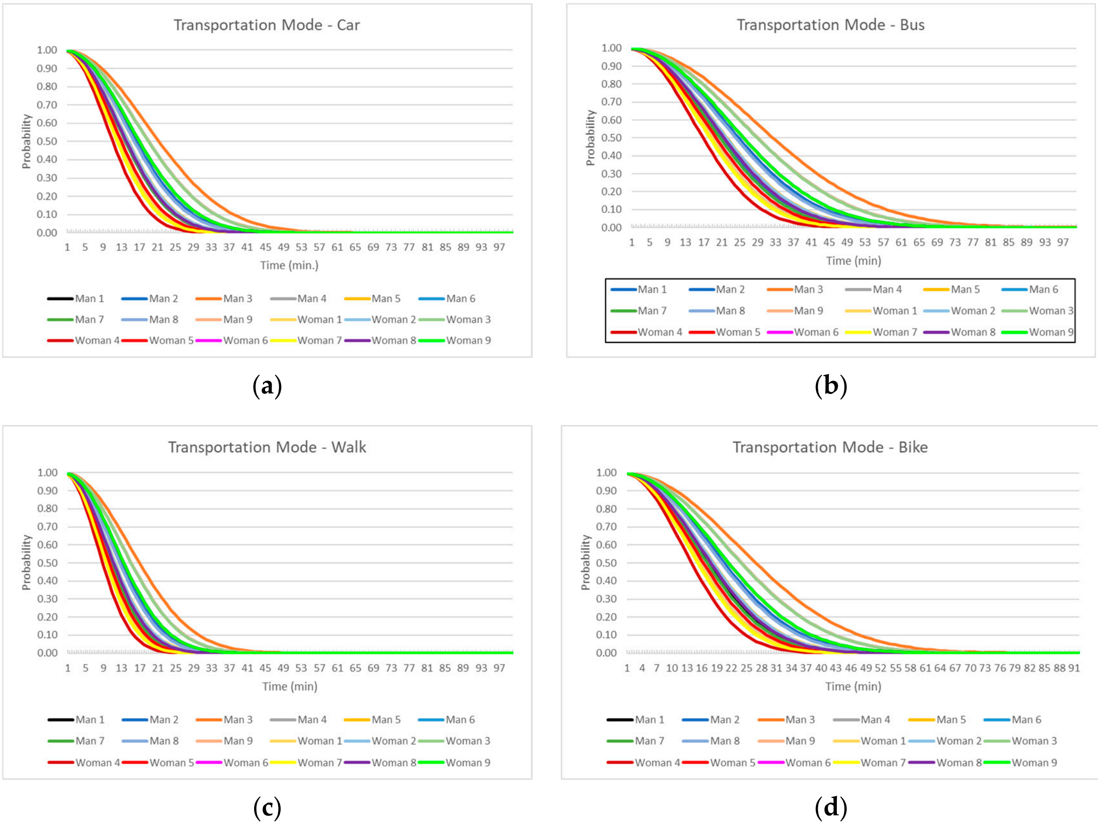

Figure 7. Probability of a trip ending based on travel time for (**a**) car, (**b**) bus, (**c**) walk, and (**d**) bicycle considering the eighteen population groups (SOURCE: Excel 2023).

From the results obtained in Figure 7, the critical times (Tc) (P = 50%) for trip survival were calculated for each mode of transportation.

Subsequently, considering the travel time of each group of individuals (Table 4), the critical time (Tc) of the network was determined by the mode of transportation for each population group. Finally, in order to obtain a unique value per transport mode, the weighted average (average time) of the critical time for a given mode was calculated by the percentage of individuals from each group in the total sample, as shown in Table 4.

Table 4. Critical travel time for modes of transportation.

Gender	Man									Woman								
Age	**15–24 Years**			**25–44 Years**			**45–64 Years**			**15–24 Years**			**25–44 Years**			**45–64 Years**		
Education Level	**EL2**	**EL3**	**EL4**	**EL2**	**EL3**	**EL4**	**EL2**	**EL3**	**EL4**	**EL2**	**EL3**	**EL4**	**EL2**	**EL3**	**EL4**	**EL2**	**EL3**	**EL4**
Sample Percentage (%)	4.0	2.1	0.3	8.2	6.2	11.0	12.9	5.0	5.9	7.0	1.7	1.6	4.0	6.8	10.6	9.5	3.5	9.3
Mode	Car																	
Time (min)	14.0	16.3	21.3	12.5	14.6	19.1	14.0	16.0	19.1 (b)	12.5	14.6	19.0	11.1 (a)	13.0	17.0	12.1	14.1	17.0
Average time (min)	16.6																	
Mode	Bus																	
Time (min)	21.1	24.7	32.4 (b)	19.0	22.1	29.0	20.6	24.1	29.0	19.0	22.0	29.0	17.0 (a)	19.7	26.0	18.4	21.5	26.0
Average time (min)	25.1																	
Mode	Walk																	
Time (min)	11.0	13.0	17.0 (b)	9.9	11.6	15.1	11.0	12.6	15.1	9.9	11.6	15.1	9.0 (a)	10.3	13.5	9.6	11.3	13.5
Average time (min)	13.1																	
Mode	Bike																	
Time (min)	17.5	20.4	27.0 (b)	15.6	18.3	24.0	17.0	20.0	24.0	15.6	18.3	24.0	14.0 (a)	16.4	21.5	15.3	17.8	21.5
Average time (min)	20.7																	

(a) Minimum value; (b) maximum value.

Table 4 shows that there is a common population group with the lowest time for all transport modes, which represents women between 25 and 44 years old with secondary education. According to our criteria, this group is the least resilient in all kinds of transport modes, being, for that reason, the first group to be affected by a disruptive event. In contrast, men between 15 and 24 years old with higher education are the most resilient group when traveling by bus, bicycle, or walking. In the case of traveling by car, the most resilient group is described as men between 25 and 44 years old with higher education.

In addition, from the results presented in Table 4, it can be observed that the general critical times, based on the weighted average, for the various modes of transportation are as follows: for the car, it is 16.6 min; for the bus, it is 25.1 min; for pedestrian, it is 13.1 min; and for bicycle, it is 20.7 min. Therefore, according to the methodology, resilience associated with potential modal changes (the robustness of trips) will be evaluated based on this critical time, reflecting the characteristics of the active population of the municipality of Póvoa de Varzim, as identified in Table 4.

After defining the critical time, the percentages of resilient trips were analyzed for each mode of transportation (Table 5).

Table 5. Percentage of resilient trips by mode of transportation.

Mode	Critical Time (min)	Resilient Trips
Car	16.6	1793 (59.4%)
Bus	25.1	126 (58.9%)
Walk	13.1	413 (52.4%)
Bike	20.7	28 (63.6%)

Indeed, we can observe that the mode of transportation with the highest percentage of robust trips is the bicycle, at 63.6%. However, due to the small sample size, its influence on the population is limited. Note that the bus has the highest critical time (in weighted average) followed by the bicycle, denoting that the trips made by bus and bike have the highest probability of surviving. The car mode presents the second highest percentage of robust trips, at around 59.4%. This indicates that approximately 40.6% of trips have a strong possibility of transitioning to another mode of transportation, such as the bus or bicycle, in the case of a critical event. Next, the mode with the third highest percentage of robust trips is the bus, at around 58.9% of trips. It is also noticeable that the percentages of robust trips in the car and bus modes are very close. Finally, the mode with the lowest percentage of robust trips is the pedestrian mode (52.4%). Also, walking is associated with the lowest critical time in the weighted average, representing the lowest probability of surviving. This indicates that walking is the least resilient mode of transportation for the average active population. This finding suggests that in a medium-sized city, with a city center where there is a high density of inhabitants contrasting to the neighboring parishes but with low job opportunities, walking does not fulfill the needs of an active population.

6. Discussion

The travel time per transport mode has been widely used as a measure to identify factors that significantly affect transportation demand. Several studies in this area have investigated the relationships between travel time and various influencing factors using risk-based analysis. However, a gap was observed in the literature regarding mobility resilience, which is known as the ability of travel to withstand, recover from, and adapt to disruptions. Therefore, the purpose of this work was to assess resilience in urban mobility, more specifically the characteristic of robustness, using the municipality of Póvoa de Varzim, Portugal, as a study case to explore the proposed novel methodology by applying risk-based duration models for travel time, the Weibull model with gamma heterogeneity.

Several key factors have played an important role in determining travel duration over time. The factors that showed differences in travel duration were the age group of individuals (<=14 years, 15–24 years, 25–44 years, 45–64 years, and >= 65 years), the gender of individuals (male and female), the educational level of individuals (none or incomplete 1st cycle, completed basic education, completed secondary education, completed higher education, and education level not applicable), driving license (yes and no), the purpose of the trip (going to/from work, going to/from school or school-related activities, leisure and sports, and purchase of goods and services), and the mode of transportation (traveling by bus, car, walking, or bicycle)

Based on the critical time value (Tc) calculation, trips were evaluated considering that users will remain in the mode for trips with a duration shorter than the critical value, demonstrating high resilience. Trips with a duration longer than the Tc value were considered less resilient than those with a lower value and, therefore, had a high potential for transformability.

By reproducing these trip characterizations, it was possible to analyze the resilience of travel patterns in urban mobility concerning time in the municipality of Póvoa de Varzim and its surroundings (active population), more specifically the robustness of travel. It is concluded that as the duration of trips increases, their robustness tends to decrease because the longer the trip in a particular mode of transportation, the higher the probability of it undergoing a modal change. The assumption is that short trips under a transport mode are more robust. Note, however, that the definition of "short" may vary depending on the transport mode and population characteristics, as shown in this study case, but also on urban context (i.e., transport infrastructure, urban morphology, etc.), which was not analyzed in the present study.

Consequently, considering the results, we can conclude that the mode of transportation with the highest percentage of robust trips is the bicycle, at 63.6%, but the bus is the transport mode associated with the highest critical time followed by the bicycle. The car mode presents the second highest percentage of resilient trips, at around 59.4%. Next, the mode with the third highest percentage of resilient trips is the bus, with approximately 58.9% of trips. Finally, the mode with the lowest percentage of robust trips is the pedestrian mode. Also, walking is associated with the lowest critical time in the weighted average, representing the lowest probability of surviving. These findings were based on the weighting considering the eighteen groups representing the active population. When comparing these groups, we found that women between 25 and 44 years old with secondary education are the traveling group with the least resilience in all kinds of transport modes. In contrast, men between 15 and 24 years old with higher education are the most resilient group when traveling by bus, bicycle, or walking. When traveling by car, the most robust is the group described as men between 25 and 44 years old with higher education.

Finally, a comparative analysis is conducted on the critical times of various modes of transportation in the case study, comparing them with average travel times obtained in other countries in urban contexts. Therefore, Table 6 presents travel times in some cities worldwide.

Table 6. Average travel time by mode of transportation in some cities/countries.

City/Country	Transportation Mode—Average Travel Time (min)				Author(s)
	Car	Bus	Bike	Walk	
Randstad/Netherlands	44.2	68.5	21.7	21.5	[47]
-/Singapura	30	37	30	8	[48]
Nanjing/China	31	40.3	21.8	13.2	[49]
Tarnow/Poland	15.6	21.2	14.3	13.4	[50]
-/United Kingdom	27.8	38.7	25.8	14.5	[51]
Case Study—Critical Time	16.6	25.1	20.7	13.1	

The examples presented show that the critical times calculated in the case study (see Table 5) are significantly lower than the average travel times practiced in other cities/countries worldwide in almost all cases. It is worth noting that the scale of the case study is much smaller than the examples presented in Table 6. Also, the methodology used in each study to compute the travel time is distinct from ours.

7. Conclusions

The objective of this work was to assess resilience in urban mobility, more specifically the characteristic of robustness, using the municipality of Póvoa de Varzim, Portugal, as a case study. The proposed novel methodology was explored by applying hazard-based duration models for travel time, including the Weibull model with gamma heterogeneity across different transport modes (bus, car, walking, and bicycle).

The resilience assessment framework for urban mobility proposed in this study was developed by evaluating the "survival" probability of trips for each transport mode and considering various groups of the active population. The study measures resilience by calculating a "critical time" (Tc), which indicates when a trip using a specific mode has less than a 50% chance of being completed. Trips shorter than Tc are considered more resilient, while longer ones are deemed less resilient. Bicycles had the highest percentage of resilient trips (63.6%), followed by cars (59.4%) and buses (58.9%). Walking showed the lowest resilience. The least resilient group was women aged 25–44 with secondary education, while the most resilient group was men aged 15–24 with higher education. A comparison of critical times revealed that Póvoa de Varzim's travel times were generally lower than the average travel times in other cities, although factors like city size and methodology varied.

It should be noted that the findings about resilience are only supported by the assessment of one variable—travel time. Urban mobility and its resilience are very complex concepts, and aspects such as transport infrastructure and transport mode characteristics (e.g., car depends on fuel or other source of energy in contrast to walking) may be affected differently depending on the type of disruption of the system. Therefore, a comprehensive framework is needed to embrace several variables. In addition, the study is based on a revealed-preference survey, which the government office conducted for national statistics of Portugal with distinct purposes from the present study. Other variables not included in the study, such as annual average daily traffic (AADT), weather, and infrastructure characteristics, may affect the mode choice and therefore, may be relevant to the resilience analysis.

Nevertheless, the present study empirically illustrates the applicability of the proposed innovative methodology based on calculating risk based on travel time using hazard-based duration models to assess resilience in urban mobility, more specifically the robustness of trips and, consequently, the transportation system. It is expected that this proposed methodological approach and the research results will assist future research to better understand travel behavior in urban environments and future assessments of the resilience capacity of the system.

Author Contributions: Conceptualization, P.J.G.R. and L.A.P.J.G.; methodology, P.J.G.R., L.A.P.J.G. and S.F.; formal analysis, L.A.P.J.G., S.F. and P.J.G.R.; investigation, L.A.P.J.G., S.F. and P.J.G.R.; data curation, L.A.P.J.G., S.F. and P.J.G.R.; writing—original draft preparation, L.A.P.J.G., S.F. and P.J.G.R.; writing—review and editing, L.A.P.J.G., S.F. and P.J.G.R.; supervision, P.J.G.R. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: Data are contained within the article.

Conflicts of Interest: The authors declare no conflicts of interest.

References

1. Grimm, N.B.; Faeth, S.H.; Golubiewski, N.E.; Redman, C.L.; Wu, J.; Bai, X.; Briggs, J.M. Global Change and the Ecology of Cities. *Science* **2008**, *319*, 756–760. [CrossRef]
2. Jedwab, R.; Christiaensen, L.; Gindelsky, M. Demography, Urbanization and Development: Rural Push, Urban Pull and . . . urban Push? *J. Urban Econ.* **2017**, *98*, 6–16. [CrossRef]
3. Tavassoli Hojati, A.; Ferreira, L.; Washington, S.; Charles, P. Hazard Based Models for Freeway Traffic Incident Duration. *Accid. Anal. Prev.* **2013**, *52*, 171–181. [CrossRef]
4. Farahani, R.Z.; Miandoabchi, E.; Szeto, W.Y.; Rashidi, H. A Review of Urban Transportation Network Design Problems. *Eur. J. Oper. Res.* **2013**, *229*, 281–302. [CrossRef]
5. Madlener, R.; Sunak, Y. Impacts of Urbanization on Urban Structures and Energy Demand: What Can We Learn for Urban Energy Planning and Urbanization Management? *Sustain. Cities Soc.* **2011**, *1*, 45–53. [CrossRef]
6. Ko, Y.; Jang, K.; Radke, J.D. Toward a Solar City: Trade-Offs between on-Site Solar Energy Potential and Vehicle Energy Consumption in San Francisco, California. *Int. J. Sustain. Transp.* **2017**, *11*, 460–470. [CrossRef]
7. Bigazzi, A.Y.; Figliozzi, M.A.; Clifton, K.J. Traffic Congestion and Air Pollution Exposure for Motorists: Comparing Exposure Duration and Intensity. *Int. J. Sustain. Transp.* **2015**, *9*, 443–456. [CrossRef]
8. Bastos, J.; Marques, P.; Batterman, S.A.; Freire, F. Environmental Impacts of Commuting Modes in Lisbon: A Life-Cycle Assessment Addressing Particulate Matter Impacts on Health. *Int. J. Sustain. Transp.* **2019**, *13*, 652–663. [CrossRef]
9. Rao, A.M.; Rao, K.R. Measuring Urban Traffic Congestion—A Review. *Int. J. Traffic Transp. Eng.* **2012**, *2*, 286.
10. Cao, M. Transportation Resilience: A Summative Review on Definition and Connotation. In *International Conference on Automation, Mechanical Control and Computational Engineering (AMCCE 2015)*; Atlantis Press: Paris, France, 2015; pp. 1127–1132. [CrossRef]
11. Suarez, P.; Anderson, W.; Mahal, V.; Lakshmanan, T.R. Impacts of Flooding and Climate Change on Urban Transportation: A Systemwide Performance Assessment of the Boston Metro Area. *Transp. Res. D Transp. Environ.* **2005**, *10*, 231–244. [CrossRef]
12. Pregnolato, M.; Ford, A.; Wilkinson, S.M.; Dawson, R.J. The Impact of Flooding on Road Transport: A Depth-Disruption Function. *Transp. Res. D Transp. Environ.* **2017**, *55*, 67–81. [CrossRef]
13. Koetse, M.J.; Rietveld, P. The Impact of Climate Change and Weather on Transport: An Overview of Empirical Findings. *Transp. Res. D Transp. Environ.* **2009**, *14*, 205–221. [CrossRef]
14. Bollinger, L.A.; Bogmans, C.W.J.; Chappin, E.J.L.; Dijkema, G.P.J.; Huibregtse, J.N.; Maas, N.; Schenk, T.; Snelder, M.; van Thienen, P.; de Wit, S.; et al. Climate Adaptation of Interconnected Infrastructures: A Framework for Supporting Governance. *Reg. Environ. Chang.* **2014**, *14*, 919–931. [CrossRef]
15. Gonçalves, L.A.P.J.; Ribeiro, P.J.G. Resilience of Urban Transportation Systems. Concept, Characteristics, and Methods. *J. Transp. Geogr.* **2020**, *85*, 102727. [CrossRef]
16. Moriarty, P. Reducing Levels of Urban Passenger Travel. *Int. J. Sustain. Transp.* **2016**, *10*, 712–719. [CrossRef]
17. Samimi, A.; Mohammadian, A.K. Health Impacts of Urban Development and Transportation Systems. *J. Urban Plan. Dev.* **2010**, *136*, 208–213. [CrossRef]
18. Anastasopoulos, P.C.; Islam, M.B.; Perperidou, D.; Karlaftis, M.G. Hazard-Based Analysis of Travel Distance in Urban Environments: Longitudinal Data Approach. *J. Urban Plan. Dev.* **2012**, *138*, 53–61. [CrossRef]
19. Anastasopoulos, P.C.; Haddock, J.E.; Karlaftis, M.G.; Mannering, F.L. Analysis of Urban Travel Times: Hazard-Based Approach to Random Parameters. *Transp. Res. Rec.* **2012**, *2302*, 121–129. [CrossRef]
20. Gonçalves, L.A.P.J.; Ribeiro, P. The Impact of the Ring Road Conclusion to the City of Guimarães, Portugal: Analysis of Variations of Traffic Flows and Accessibilities. *WSEAS Trans. Environ. Dev.* **2020**, *16*, 11–22. [CrossRef]

21. Hasan, S.; Mesa-Arango, R.; Ukkusuri, S. A Random-Parameter Hazard-Based Model to Understand Household Evacuation Timing Behavior. *Transp. Res. Part C Emerg. Technol.* **2013**, *27*, 108–116. [CrossRef]
22. Yang, X.; Huan, M.; Abdel-Aty, M.; Peng, Y.; Gao, Z. A Hazard-Based Duration Model for Analyzing Crossing Behavior of Cyclists and Electric Bike Riders at Signalized Intersections. *Accid. Anal. Prev.* **2015**, *74*, 33–41. [CrossRef]
23. Bella, F.; Gulisano, F. A Hazard-Based Model of the Motorcyclists' Overtaking Duration. *Accid. Anal. Prev.* **2020**, *141*, 105522. [CrossRef] [PubMed]
24. Li, M.-D.; Doong, J.-L.; Huang, W.-S.; Lai, C.-H.; Jeng, M.-C. Survival Hazards of Road Environment Factors between Motor-Vehicles and Motorcycles. *Accid. Anal. Prev.* **2009**, *41*, 938–947. [CrossRef] [PubMed]
25. Lin, L.; Wang, Q.; Sadek, A.W. A Combined M5P Tree and Hazard-Based Duration Model for Predicting Urban Freeway Traffic Accident Durations. *Accid. Anal. Prev.* **2016**, *91*, 114–126. [CrossRef] [PubMed]
26. Roque, C.; Jalayer, M. Improving Roadside Design Policies for Safety Enhancement Using Hazard-Based Duration Modeling. *Accid. Anal. Prev.* **2018**, *120*, 165–173. [CrossRef] [PubMed]
27. Haque, M.M.; Washington, S. The Impact of Mobile Phone Distraction on the Braking Behaviour of Young Drivers: A Hazard-Based Duration Model. *Transp. Res. Part C Emerg. Technol.* **2015**, *50*, 13–27. [CrossRef]
28. Nam, D.; Mannering, F. An Exploratory Hazard-Based Analysis of Highway Incident Duration. *Transp. Res. Part A Policy Pract.* **2000**, *34*, 85–102. [CrossRef]
29. Shi, Z.; Zhang, N.; Zhang, Y. Hazard-Based Model for Estimation of Congestion Duration in Urban Rail Transit Considering Loss Minimization. *Transp. Res. Rec.* **2016**, *2595*, 78–87. [CrossRef]
30. Stathopoulos, A.; Karlaftis, M.G. Modeling Duration of Urban Traffic Congestion. *J. Transp. Eng.* **2002**, *128*, 587–590. [CrossRef]
31. Rahimi, E.; Shamshiripour, A.; Shabanpour, R.; Mohammadian, A.; Auld, J. Analysis of Transit Users' Waiting Tolerance in Response to Unplanned Service Disruptions. *Transp. Res. D Transp. Environ.* **2019**, *77*, 639–653. [CrossRef]
32. Libnao, K.; Agbelie, B. Development of Hazard Based-Models for the Metrorail of the Washington Metropolitan Area Transit Authority. In Proceedings of the International Conference on Transportation and Development 2018, Pittsburgh, PA, USA, 15–18 July 2018; pp. 247–256. [CrossRef]
33. Sharman, B.W.; Roorda, M.J.; Habib, K.M.N. Comparison of Parametric and Nonparametric Hazard Models for Stop Durations on Urban Tours with Commercial Vehicles. *Transp. Res. Rec.* **2012**, *2269*, 117–126. [CrossRef]
34. Zheng, Y.; Ran, B.; He, S.; Zhang, J. Survival Analysis of Bus Running Time near Bus-Stop Areas. *J. Transp. Eng. A Syst.* **2019**, *145*, 4019010. [CrossRef]
35. Van den Berg, P.; Arentze, T.; Timmermans, H. A Latent Class Accelerated Hazard Model of Social Activity Duration. *Transp. Res. Part A Policy Pract.* **2012**, *46*, 12–21. [CrossRef]
36. Jordan, G.A.; Anastasopoulos, P.C.; Peeta, S.; Somenahalli, S.; Rogerson, P.A. Identifying Elderly Travel Time Disparities Using a Correlated Grouped Random Parameters Hazard-Based Duration Approach. *Res. Transp. Bus. Manag.* **2019**, *30*, 100369. [CrossRef]
37. Joly, I.; Vincent-Geslin, S. Intensive Travel Time: An Obligation or a Choice? *Eur. Transp. Res. Rev.* **2016**, *8*, 10. [CrossRef]
38. Moylan, E.K.M.; Rashidi, T.H. Latent-Segmentation, Hazard-Based Models of Travel Time. *IEEE Trans. Intell. Transp. Syst.* **2017**, *18*, 2174–2180. [CrossRef]
39. Ermagun, A.; Erinne, J.; Fan, Y. Travel Duration Tolerance: Examining the Sensitivity of Emotional Well-Being to Trip Duration. *Transp. Res. D Transp. Environ.* **2022**, *102*, 103137. [CrossRef]
40. He, J.; Yamamoto, T.; Miwa, T.; Morikawa, T. Hazard Duration Model with Panel Data for Daily Car Travel Distance: A Toyota City Case Study. *Sustainability* **2020**, *12*, 6331. [CrossRef]
41. Ding, C.; Mishra, S.; Lu, G.; Yang, J.; Liu, C. Influences of Built Environment Characteristics and Individual Factors on Commuting Distance: A Multilevel Mixture Hazard Modeling Approach. *Transp. Res. D Transp. Environ.* **2017**, *51*, 314–325. [CrossRef]
42. Anastasopoulos, P.C.; Fountas, G.; Sarwar, M.T.; Karlaftis, M.G.; Sadek, A.W. Transport Habits of Travelers Using New Energy Type Modes: A Random Parameters Hazard-Based Approach of Travel Distance. *Transp. Res. Part C Emerg. Technol.* **2017**, *77*, 516–528. [CrossRef]
43. Washington, S.; Karlaftis, M.G.; Mannering, F.; Anastasopoulos, P. *Statistical and Econometric Methods for Transportation Data Analysis*; CRC Press: Boca Raton, FL, USA, 2020.
44. Heckman, J.; Singer, B. A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data. *Econometrica* **1984**, *52*, 271–320. [CrossRef]
45. Gourieroux, C.; Monfort, A.; Trognon, A. Pseudo Maximum Likelihood Methods: Theory. *Econometrica* **1984**, *52*, 681–700. [CrossRef]
46. INE. *Inquérito à Mobilidade nas Áreas Metropolitanas do Porto e de Lisboa (IMob)*; INE: Lisboa, Portugal, 2017.
47. Feng, J.; Dijst, M.; Prillwitz, J.; Wissink, B. Travel Time and Distance in International Perspective: A Comparison between Nanjing (China) and the Randstad (The Netherlands). *Urban Studies* **2013**, *50*, 2993–3010. [CrossRef]
48. Departement of Statistics. *Geographical Distribution & Transport*; Departement of Statistics: Singapore, 2020.
49. Sun, H.; Zhen, F.; Jiang, Y. Study on the Characteristics of Urban Residents' Commuting Behavior and Influencing Factors from the Perspective of Resilience Theory: Theoretical Construction and Empirical Analysis from Nanjing, China. *Int. J. Environ. Res. Public Health* **2020**, *17*, 1475. [CrossRef]

50. Bauer, M.; Kisielewski, P. The Influence of the Duration of Journey Stages on Transport Mode Choice: A Case Study in the City of Tarnow. *Sustainability* **2021**, *13*, 5922. [CrossRef]
51. Wilkins, J.; Weekes, S.; Cameron, C.; Sevenel, P. *Transport Statistics Great Britain 2017. Modal Comparisons*; United Kingdom, Government Digital Service: London, UK, 2017.