sustainability

MDPI

Article

Predictive Model of Pedestrian Crashes Using Markov Chains in the City of Badajoz

Alejandro Moreno-Sanfélix [1,2,*], F. Consuelo Gragera-Peña [1] and Miguel A. Jaramillo-Morán [1]

[1] Escuela de Ingenierías Industriales, Universidad de Extremadura, Avenida de Elvas s/n, 06006 Badajoz, Spain; cgragera@unex.es (F.C.G.-P.); miguel@unex.es (M.A.J.-M.)
[2] Judicial Traffic Police of the Local Police of Badajoz, St. Gaspar Méndez, 2, 06011 Badajoz, Spain
* Correspondence: almorenos@alumnos.unex.es

Abstract: Driving a vehicle, whether motorized or not, is a risky activity that can lead to a traffic accident and directly or indirectly affect all road users. In particular, road crashes involving pedestrians have caused the highest number of deaths and serious injuries in recent years. In order to prevent and reduce the occurrence of these types of traffic accidents and to optimize the use of the available resources of the administrations in charge of road safety, an updatable predictive model using Markov chains is proposed in this work. Markov chains are used in fields as diverse as hospital management or electronic engineering, but their application in the field of road safety is considered innovative. They are prediction and decision techniques that allow the estimation of the state of a given system by simulating its stochastic risk level. To carry out this study, the available information on traffic accidents involving pedestrians in the database of the Local Police of Badajoz (a medium-sized city in the southwest of Spain) in the period 2016 to 2023 were analyzed. These data were used to train a predictive model that was subsequently used to estimate the probability of occurrence of a traffic crash involving pedestrians in different areas of this city, information that could be used by the authorities to focus their efforts in those areas with the highest probability of a road crash occurring. This model can improve the identification of high-risk locations, and urban planners can optimize decision making in designing appropriate preventive measures and increase efficiency to reduce pedestrian crashes.

Keywords: road crash; Markov chain; predictive model; pedestrian road traffic accident; risk scale; victims

check for updates

Citation: Moreno-Sanfélix, A.; Gragera-Peña, F.C.; Jaramillo-Morán, M.A. Predictive Model of Pedestrian Crashes Using Markov Chains in the City of Badajoz. *Sustainability* **2024**, *16*, 10115. https://doi.org/10.3390/su162210115

Received: 16 October 2024
Revised: 10 November 2024
Accepted: 18 November 2024
Published: 20 November 2024

1. Introduction

Since the first death attributed to a case of road crashes suffered by the scientist Bridget Driscoll on August 17 of 1896 [1], numerous studies have focused on the search for a responsible party, as well as on the reduction of victims.

A road crash is understood as the phenomenon that causes a harmful result in the land transport system to people or their property due to a series of defective or negative interrelationships between the elements that make up that system [2]. The World Health Organization (WHO) defined road crashes as an epidemic [3] and, a posteriori, as a pandemic [4]. Generally speaking, a road crash is an unplanned and uncontrolled event in which the action, or reaction of an object, substance, person, or radiation, resulted in injury or the probability of injury to persons [5] or a brief, sudden, and unexpected event or fact that results in an undesirable result and is due, directly or indirectly, to human activity rather than a natural event [6].

Studies such as this one, or others available in the state of the art, are necessary to prevent this type of event or, if necessary, to reduce the number of victims because road traffic injuries are estimated to be the eighth leading cause of death worldwide, with an impact similar to that caused by malaria [7]. Every year more than one million people die in the world as a result of road crashes, multiplying this value by fifty the number of people who are injured, according to the Organization for Economic Cooperation and Development (OECD). Thus, road crashes can be considered among the problems that have the greatest negative effects on society given the high incidence they have in various areas of human activity and the associated high economic costs they generate. These consequences are not only related to the injury of the victims, the material damage or the resulting economic costs, but may also give rise to civil, administrative or even criminal liabilities.

As mentioned in the European Commission's press release [8], the road safety strategies adopted in recent years are saving lives, but the pace of progress is too slow for the objectives set based on the different strategies proposed at both the national and the European levels. According to the data released by this organization, the average for the European Union (EU) in 2021 will be 44 road deaths per million inhabitants, an increase of 5% compared to 2020, but a decrease of 13% compared to 2019, before the COVID-19 pandemic. In 2023, the number of deaths on EU roads as a result of road crashes was 20,400. This is a slight decrease of 1% from last year [9].

Focusing on one specific country, Spain, the number of fatalities increased by 10% in 2021 compared to 2020, the safest year on record [10]. In 2022, 1145 people died on Spanish roads and another 4008 were seriously injured [11]. The number of pedestrian fatalities also increased, 126 in 2022 compared to 118 in 2019, which means that 1 in 10 road fatalities were pedestrians [12]. In 2023, the figures recorded were 36 road deaths per million inhabitants [9], which is significantly lower than the EU average (36 road deaths per million inhabitants).

Encompassed in the "Road Safety Strategy 2030" plan, the goal would be to reduce the number of traffic accidents and victims on public roads by promoting and coordinating the actions and results of all the actors involved in the field of safe mobility, making progress towards the ambitious goal that no one is killed or seriously injured by road crashes by 2050 [13].

Police presence and surveillance continue to be considered the main action to prevent road crashes [14,15]. The DGT also maintains that police surveillance clearly influences the reduction of the road crash rate [16]. However, it is not feasible to monitor all roads, especially with the lack of human and material resources that most of the staff of the security forces and corps in charge of traffic have [17,18], in addition to the increase in tasks they are experiencing over the years. For this reason, it is essential to model the traffic accident rate and predict the most critical points with even more precise techniques. This model could help to manage the available resources in a much more efficient and effective way, leading to the deterrence of dangerous behaviors in the specific areas derived from the study conducted [19]. The aim will not be to focus on what has happened to date to propose measures but to try to predict future road crashes to try to anticipate these events, with tragic outcomes in many cases [20].

In this sense, this paper would allow the implementation of a rigorous model that indicates where there is a probability that a pedestrian crash could happen through easily interpretable and accurate indicators, which will help to plan, guide and optimize the monitoring of those areas with the highest percentage of risk of pedestrian crash [21]. New measures could be implemented in these areas (speed controls, asymmetrical pedestrian crossings, increased police presence, etc.) to reduce pedestrian crashes.

A pedestrian crash can be defined as the more or less violent contact of a vehicle with a pedestrian [22] or as a road crash between a vehicle and a pedestrian in which one or more vehicles and pedestrians are involved, regardless of whether the pedestrian participated in the first or a later phase of the road crash [23]. In addition, a pedestrian crash is also considered to be a road crash where there is a disproportion of the masses of the vehicles involved [24].

According to the current regulations, a pedestrian is defined as "a person who, without being a driver, travels on foot on roads or land, who pushes or pulls a stroller or a pram of a person with a disability or any other small non-motorized vehicle, those who ride a two-wheeled bicycle or moped on foot, and persons with disabilities who circulate in a wheelchair, with or without a motor" [25]. The vehicles, the other party involved in a pedestrian crash, are defined as "a device suitable for travelling on roads or terrain" [25].

There are two main types of pedestrian crashes depending on the point of contact between the pedestrian and the vehicle: collision with the sides of the vehicle and collision with the frontal [23]. A third category, which is much less common, could be added: collision with the rear of the vehicle when it is reversing [2]. In addition, in terms of the trajectory after the vehicle–pedestrian impact, five typologies can be established: envelopment trajectory, flip on the fin, flip on the roof, somersault and forward projection [26,27].

In this work, the prediction of the risk of the occurrence of a pedestrian crash in a city is carried out. This prediction should be related to a city because this type of event mostly happens in areas where there is a high density of pedestrian cities. Therefore, a specific one will be selected to test the tool that will be proposed: Badajoz, a small city (150,090 inhabitants) located in the southwest of Spain. The predictions will be made using Markov chains. Markov chains were chosen to do so because, although they are widely used in other fields with very good results, their application is not widespread in the road safety sector, and there are not many known precedents that develop the model in this field.

The rest of the paper is organized as follows. A literature review of the methods used for studying pedestrian crashes is presented in Section 2. Section 3 presents the materials and methods, describing the parameters and models used in the development of the work, while in Section 4 all the results are shown. Finally, the discussions are developed in Section 5 and the conclusions obtained in this work are analyzed in Section 6.

2. Literature Review

Over the years, there has been a great deal of work in the scientific literature analyzing the causes of traffic accidents in order to understand why and how they occur [28–35]. Other works analyze the crash–injury severities and try to establish predictive models that manage to mitigate these events, trying to propose techniques and solutions to reduce the number of victims [36–40]. And others seek to predict where new traffic accidents will occur [41–44].

Standard methods such as regression or deep learning have been used to predict traffic accidents among others. However, in the scientific literature, there are not many works on traffic accident prediction using Markov chains. As discussed in the previous section, the predictive model used in this paper is Markov chains. Markov chains have been used as an engineering prediction technique, simulation and decision making in numerous fields and with very accurate results. However, its use in the field of traffic accidents is not very widespread. Therefore, the aim of this article is to reproduce in the field of traffic accidents the good results obtained in other fields with the Markov model. Some of these most notable works using the Markov model in the field of road crashes are shown below.

Lin Y., et al. (2011) used the Markov chain model, which predicts the future situation based on the characteristics of previous situations to predict the damages in a certain highway in the next several months in China [45]. Hanchu Zhou et al. (2019) used a Markov chain spatial model to incorporate spatial effects into the temporal dynamics of road traffic fatality rates [46]. Chengcheng Xu et al. (2020) proposed a Markov switching logit model with spatial dependencies for real-time crash risk assessment, with the purpose of identifying hazardous traffic-flow conditions with high crash potential [47]. Taoufik Y. and Sadok Ben Y. (2021) proposed a mathematical model to manage vehicle mobility in the road network [48]. Mohammadi, A. et al. (2023) used 5354 multi-year data of twelve socio-economic and built-in environmental factor incidents to predict pedestrian road traffic accidents with the Markov chain and cellular automata Markov chain models [49].

The present work aims to fill up this knowledge gap in the field, providing predictions of urban areas of Badajoz where pedestrian crashes are more likely to happen in order to allow traffic safety officers to develop and apply measures to try to reduce the occurrence of these events.

3. Materials and Methods

3.1. General Description

Data on traffic accidents involving pedestrians were obtained from the reports of the Judicial Traffic Police of the Local Police of Badajoz in Spain (2016–2023). The total number of pedestrian crashes analyzed was 816, with 85 in 2016, 119 in 2017, 105 in 2018, 108 in 2019, 84 in 2020, 108 in 2021, 123 in 2022, and 84 in 2023.

The crash data span from 2016 to 2023, a period during which the COVID-19 pandemic occurred, but this would not affect the results of the model because the restrictions were applied equally to all sectors. The impact of the COVID-19 pandemic affected the total number of road crashes compared to other years, as shown by the statistics of the Badajoz Local Police.

Moreover, if we examine the number of pedestrian crashes in these eight years of study, we observe an upward dynamic in the number of pedestrian crashes (except for the year 2020 due to the restrictions imposed by the COVID-19 pandemic). Due to this clear upward dynamic, the Chief Superintendent of the Local Police of Badajoz elaborated a detailed study to try to reduce this dynamic [24], and the urban planners through this study implemented generic measures throughout the city of Badajoz in early 2023, thus reducing pedestrian crashes in that year. In economic terms, these measures were very costly and inefficient because, although pedestrian crashes were reduced overall, many measures were implemented in areas that did not have a significant impact on this reduction, and these resources could have been used in areas with a greater impact. In this sense, the model developed in this paper will try to improve the decision-making of urban planners when using existing or new resources.

With this large disbursement of resources (especially economic) in the measures implemented in early 2023, the competent authority did not apply new measures at the beginning of 2024 to continue with the reduction of pedestrian crashes, observing how the dynamics of pedestrian crashes in this first six months reached the dynamics of 2022, using these 59 pedestrian crashes that occurred in the city of Badajoz during the first half of 2024 (January–June) to validate the model developed in this article. In addition, to verify the accuracy of the model, pedestrian crashes were analyzed during the months of July, August and September, after the implementation of new measures in the sector that the model predicted would be most at risk.

Badajoz is located in southwestern Spain, bordering Portugal. It is the most populous city in the autonomous community of Extremadura, with 150,090 inhabitants according to data published on 1 January 2023 [50]. However, its daily floating population increases by about 15,000 to 20,000 people due to the different activities of the city according to the latest available data [51].

For operational purposes of the city's Local Police and for the development of this work, Badajoz is divided into four sectors (Figure 1), with Sector 3 currently being the sector with the largest population [52].

3.2. Markov Model

Markov chains are used as a prediction technique, allowing simulations and accurate decisions to be made in the field of engineering [53] or in other branches such as economics or health.

These models allow the study of stochastic processes that evolve randomly and without memory over time and over a set of possible states [54,55].

Using this model, it is possible to determine the probability that a system will go from state i to state j in time t. Since in this work, these states are related to risk levels, in what follows the word level will be used instead of state for the sake of simplicity. Therefore, the system that evolves in time (t = 0, 1, . . .) is in level i_t at instant t, if at instant $t-1$ it was in level i_{t-1}:

$$\mathrm{P}(\mathrm{X_t} = \mathrm{i_t} | \mathrm{X_0} = \mathrm{i_0}, \ldots, \mathrm{X_{t-1}} = \mathrm{i_{t-1}}) = \mathrm{P}(\mathrm{X_t} = \mathrm{i_t} | \mathrm{X_{t-1}} = \mathrm{i_{t-1}}) = \mathrm{p_{i_{t-1}, i_t}} \quad (1)$$

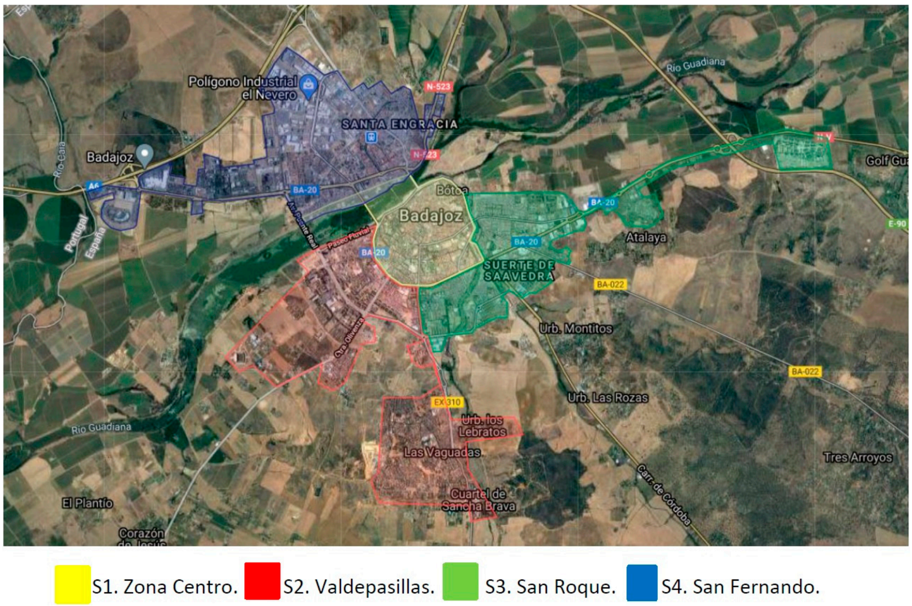


Figure 1. Sectors of the city of Badajoz for the Local Police. Source: Muñoz Garrido R., 2021 [24].

If $p_1(t), \ldots, p_n(t)$ are the probabilities of being in level n at time t and $p_{ij}(t)$ the probability of the evolution from level i to j at time t, $1 \leq i, j \leq n$, the corresponding probabilities at time $t + 1$ can be represented in its matrix form as:

$$\begin{pmatrix} p_1(t+1) \\ \vdots \\ p_n(t+1) \end{pmatrix} = \begin{pmatrix} p_{11}(t) & \cdots & p_{1n}(t) \\ \vdots & \ddots & \vdots \\ p_{n1}(t) & \ldots & p_{nn}(t) \end{pmatrix} \begin{pmatrix} p_1(t) \\ \vdots \\ p_n(t) \end{pmatrix} \quad (2)$$

For the case study, we are interested in homogeneous Markov chains, i.e., those in which no term $p_{ij}(t)$ depends on t and satisfies Equation (3):

$$p(t) = A^t p(0) \text{ where } A(t) = \begin{pmatrix} p_{11}(t) & \cdots & p_{1n}(t) \\ \vdots & \ddots & \vdots \\ p_{n1}(t) & \ldots & p_{nn}(t) \end{pmatrix}, \quad (3)$$

where $A(t)$ is the transition matrix representing the number of times the system evolves from state i to state j at time t ($1 < i, j < n$).

Thus, in the case of a homogeneous chain, the following equality is satisfied for the distribution to be stationary:

$$x = \lim_{t\to\infty} p(t) = \lim_{t\to\infty} A^t p(0) \quad (4)$$

If matrix A is irreducible, this limit will exist. Furthermore, if the transition matrix is primitive, the limit x is independent of the initial probability distribution $p(0)$ and equal to the eigenvector (EVE) of eigenvalue (EVA) 1 of the matrix according to the equation:

$$x = \frac{1}{\sum v_i} \begin{pmatrix} v_1 \\ \vdots \\ v_n \end{pmatrix} = \text{EVE of EVA 1, normalized} \quad (5)$$

The EVA is a scalar $\lambda \in \mathbb{C}$ of the square matrix A if there exists a column vector $v \in M_{n,1}(\mathbb{C})$ satisfying $Av = \lambda v$ and $v \neq 0$. The EVEs are vectors $v \in M_{n,1}(\mathbb{C})$ related to the square matrix A if $v \neq 0$ and there exists $\lambda \in \mathbb{C}$ satisfying $Av = \lambda v$. The characteristic polynomial of the matrix A is used to calculate the EVAs, which are its roots:

$$Q_A(\lambda) = \det(A - \lambda I_n), \tag{6}$$

where I is the identity matrix of order n. Once the EVAs (λ) are calculated, the corresponding EVEs can be found by solving $det(A - \lambda I) = 0$. In addition, once the EVAs and EVEs are calculated, the diagonal matrix (the values of the diagonal are the EVAs) and the stationary matrix (the values of the columns are the EVEs) can be obtained [56–58].

In order to develop the Markov model, and to allow it to estimate the risk of a crash occurring, a risk scale must be defined. In this work, five levels were defined by taking into account the number of pedestrian crashes per month, as shown in Table 1, from Level 1 (no risk with 0 victims/month) to Level 5 (extreme risk with more than 5 victims/month). These five crash risk levels and thresholds were selected based on other works that also predict road accidents in the scientific literature, mainly following the criteria of Muñoz Garrido, R. [24] and Aparicio Azcárraga, R. [21]. The corresponding values assigned to each sector were obtained from the data available from 2016 to 2023, regardless of whether the road crashes involved minor, serious, very serious or fatal victims. In this way it is possible to calculate the probability that a given sector will be in one or another risk level after a certain period of time. This makes it possible to quantify the probability of the system being at an acceptable level of risk relative to other areas of higher risk, and thus to plan the use of available resources to prevent the occurrence of future road crashes.

Table 1. Level and scale of risk established in the Markov model based on the number of pedestrian crashes with monthly victims (V) in the city of Badajoz.

Level	Victims (V)/Month	Risk Scale
1	0	No risk
2	1	Low risk
3	$1 < V \leq 3$	Moderate risk
4	$3 < V \leq 5$	High risk
5	$V > 5$	Extreme risk

4. Results

From the available historical data and taking into account the five levels defined in Table 1, the transition matrix and the probability matrix can be obtained for each one of the four sectors into which the city is divided [59]. This type of study requires that the future level is independent of the past level and depends only on the current state [60], as is the case with the problem at hand.

The results obtained are shown in Table 2. The transition matrix represents in each row the number of times a risk level is reached from the other ones. From this matrix, the probability matrix is calculated by dividing each value in a column by the sum of all values in this column. Therefore, the sum of all elements in a column is 1.

Table 2. Transition matrix and probability matrix for each sector as a function of the number of pedestrian crashes with monthly victims in the city of Badajoz.

Sector	Transition Matrix	Probability Matrix
1	$\begin{pmatrix} 1 & 10 & 5 & 1 & 0 \\ 9 & 8 & 10 & 2 & 1 \\ 5 & 11 & 20 & 2 & 2 \\ 1 & 0 & 4 & 0 & 0 \\ 0 & 1 & 2 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0.0625 & 0.3333 & 0.1220 & 0.2000 & 0 \\ 0.5625 & 0.2667 & 0.2439 & 0.4000 & 0.3333 \\ 0.3125 & 0.3667 & 0.4878 & 0.4000 & 0.6667 \\ 0.0625 & 0 & 0.0976 & 0 & 0 \\ 0 & 0.0333 & 0.0488 & 0 & 0 \end{pmatrix}$
2	$\begin{pmatrix} 0 & 2 & 3 & 0 & 0 \\ 2 & 4 & 11 & 4 & 3 \\ 4 & 14 & 14 & 6 & 5 \\ 0 & 2 & 10 & 1 & 1 \\ 0 & 2 & 5 & 2 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0.0833 & 0.0698 & 0 & 0 \\ 0.3333 & 0.1667 & 0.2558 & 0.3077 & 0.3333 \\ 0.6667 & 0.5833 & 0.3256 & 0.4615 & 0.5556 \\ 0 & 0.0833 & 0.2326 & 0.0769 & 0.1111 \\ 0 & 0.0833 & 0.1163 & 0.1538 & 0 \end{pmatrix}$

Table 2. *Cont.*

Sector	Transition Matrix	Probability Matrix
3	$\begin{pmatrix} 1 & 2 & 3 & 2 & 1 \\ 0 & 12 & 7 & 6 & 0 \\ 6 & 9 & 21 & 5 & 0 \\ 2 & 3 & 7 & 5 & 1 \\ 0 & 0 & 2 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0.1111 & 0.0769 & 0.0750 & 0.1111 & 0.5000 \\ 0 & 0.4615 & 0.1750 & 0.3333 & 0 \\ 0.6667 & 0.3462 & 0.5250 & 0.2778 & 0 \\ 0.2222 & 0.1154 & 0.1750 & 0.2778 & 0.5000 \\ 0 & 0 & 0.0500 & 0 & 0 \end{pmatrix}$
4	$\begin{pmatrix} 0 & 3 & 6 & 1 & 0 \\ 3 & 9 & 12 & 4 & 0 \\ 3 & 13 & 20 & 7 & 0 \\ 2 & 4 & 5 & 1 & 1 \\ 1 & 0 & 0 & 0 & 0 \end{pmatrix}$	$\begin{pmatrix} 0 & 0.1034 & 0.1395 & 0.0769 & 0 \\ 0.3333 & 0.3103 & 0.2791 & 0.3077 & 0 \\ 0.3333 & 0.4483 & 0.4651 & 0.5385 & 0 \\ 0.2222 & 0.1379 & 0.1163 & 0.0769 & 1.0000 \\ 0.1111 & 0 & 0 & 0 & 0 \end{pmatrix}$

As described in Section 2, after obtaining the above transition matrix and probability matrix (Table 2), the EVAs and EVEs values, the diagonal and the stationary matrices and the characteristic polynomial can be obtained for each sector. They are all shown in Figure 2. By analyzing these values, we can predict the level of risk we will face in a sector if no new measures are taken to reduce pedestrian crashes. Based on this prediction, the available resources can be allocated in the most effective and efficient way according to the needs of each sector. This will be discussed in the next section.

	Diagonal matrix	Stationary matrix	EVA	EVE	Characteristic polynomial
Sector 1	$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & -0.2870 & 0 & 0 & 0 \\ 0 & 0 & 0.1981 & 0 & 0 \\ 0 & 0 & 0 & 0.0133 & 0 \\ 0 & 0 & 0 & 0 & -0.1074 \end{pmatrix}$	$\begin{pmatrix} 0.1790 & 0.1790 & 0.1790 & 0.1790 & 0.1790 \\ 0.3191 & 0.3191 & 0.3191 & 0.3191 & 0.3191 \\ 0.4187 & 0.4187 & 0.4187 & 0.4187 & 0.4187 \\ 0.0520 & 0.0520 & 0.0520 & 0.0520 & 0.0520 \\ 0.0311 & 0.0311 & 0.0311 & 0.0311 & 0.0311 \end{pmatrix}$	$\begin{bmatrix} 1 \\ -0.2870 \\ 0.1981 \\ 0.0133 \\ -0.1074 \end{bmatrix}$	$\begin{bmatrix} 0.1790 \\ 0.3191 \\ 0.4187 \\ 0.0520 \\ 0.0311 \end{bmatrix}$	$\lambda^5 - \frac{8039}{9840}\lambda^4 - \frac{6877}{29520}\lambda^3 + \frac{729}{16400}\lambda^2 + \frac{821}{147600}\lambda - \frac{1}{12300}$
Sector 2	$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & 0.0279 & 0 & 0 & 0 \\ 0 & 0 & -0.1886 & 0 & 0 \\ 0 & 0 & 0 & -0.1351 & 0 \\ 0 & 0 & 0 & 0 & -0.1351 \end{pmatrix}$	$\begin{pmatrix} 0.0525 & 0.0525 & 0.0525 & 0.0525 & 0.0525 \\ 0.2525 & 0.2525 & 0.2525 & 0.2525 & 0.2525 \\ 0.4508 & 0.4508 & 0.4508 & 0.4508 & 0.4508 \\ 0.1480 & 0.1480 & 0.1480 & 0.14800 & 0.1480 \\ 0.0962 & 0.0962 & 0.0962 & 0.0962 & 0.0962 \end{pmatrix}$	$\begin{bmatrix} 1 \\ 0.0279 \\ -0.1886 \\ -0.1351 \\ --0.1351 \end{bmatrix}$	$\begin{bmatrix} 0.0525 \\ 0.2525 \\ 0.4508 \\ 0.1480 \\ 0.0962 \end{bmatrix}$	$\lambda^5 - \frac{1909}{3354}\lambda^4 - \frac{7523}{20124}\lambda^3 - \frac{836}{15093}\lambda^2 - \frac{103}{60372}\lambda + \frac{1}{10062}$
Sector 3	$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & -0.0077 & 0 & 0 & 0 \\ 0 & 0 & -0.0077 & 0 & 0 \\ 0 & 0 & 0 & 0.2170 & 0 \\ 0 & 0 & 0 & 0 & 0.1739 \end{pmatrix}$	$\begin{pmatrix} 0.0950 & 0.0950 & 0.0950 & 0.0950 & 0.0950 \\ 0.2590 & 0.2590 & 0.2590 & 0.2590 & 0.2590 \\ 0.4336 & 0.4336 & 0.4336 & 0.4336 & 0.4336 \\ 0.1907 & 0.1907 & 0.1907 & 0.1907 & 0.1907 \\ 0.0217 & 0.0217 & 0.0217 & 0.0217 & 0.0217 \end{pmatrix}$	$\begin{bmatrix} 1 \\ -0.0077 \\ -0.0077 \\ 0.2170 \\ 0.1739 \end{bmatrix}$	$\begin{bmatrix} 0.0950 \\ 0.2590 \\ 0.4336 \\ 0.1907 \\ 0.0217 \end{bmatrix}$	$\lambda^5 - \frac{6437}{4680}\lambda^4 + \frac{36601}{84240}\lambda^3 - \frac{5827}{84240}\lambda^2 + \frac{313}{28080}\lambda - \frac{29}{28080}$
Sector 4	$\begin{pmatrix} 1 & 0 & 0 & 0 & 0 \\ 0 & -0.1907 & 0 & 0 & 0 \\ 0 & 0 & 0.0043 & 0 & 0 \\ 0 & 0 & 0 & 0.0043 & 0 \\ 0 & 0 & 0 & 0 & 0.0344 \end{pmatrix}$	$\begin{pmatrix} 0.1041 & 0.1041 & 0.1041 & 0.1041 & 0.1041 \\ 0.2947 & 0.2947 & 0.2947 & 0.2947 & 0.2947 \\ 0.4512 & 0.4512 & 0.4512 & 0.4512 & 0.4512 \\ 0.1385 & 0.1385 & 0.1385 & 0.1385 & 0.1385 \\ 0.0116 & 0.0116 & 0.0116 & 0.0116 & 0.0116 \end{pmatrix}$	$\begin{bmatrix} 1 \\ -0.1907 \\ 0.0043 \\ 0.0043 \\ 0.0344 \end{bmatrix}$	$\begin{bmatrix} 0.1041 \\ 0.2947 \\ 0.4512 \\ 0.1385 \\ 0.0116 \end{bmatrix}$	$\lambda^5 - \frac{13818}{16211}\lambda^4 - \frac{18127}{145899}\lambda^3 - \frac{896}{48633}\lambda^2 - \frac{752}{145899}\lambda + \frac{10}{48633}$

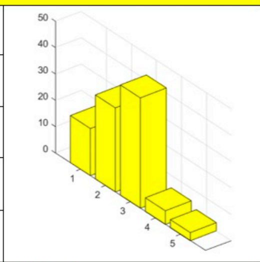
Figure 2. Results obtained of the predictive model for each sector in the city of Badajoz.

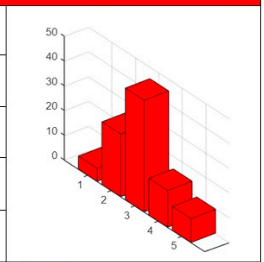
By analyzing the results obtained in Figure 2 for each one of the sectors into which the city of Badajoz has been divided, it can be seen that in all cases the values of the diagonal matrix coincide with the values of the corresponding EVA. Moreover, these values are equal to the roots of the characteristic polynomial if we solve the corresponding equation of degree five [54,55]. On the other hand, once it was possible to find the stationary distribution represented by its corresponding matrix, i.e., the distribution representing the evolution of road crashes for each sector over time, it is observed that the values of the columns of this stationary matrix are equal and coincide with the EVE values of EVA 1, which satisfies what is established in Equations (4) and (5) [61].

5. Discussion

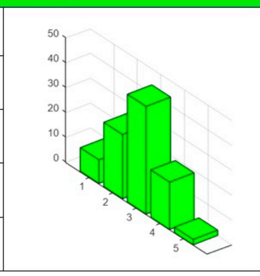
The evolution of pedestrian crashes in each sector over time is marked by the stationary distribution. This stationary distribution has all columns equal to and equivalent to the EVEs of EVA 1 (Figure 2). According to this trend predicted by the Markov chains and multiplying each of these values by one hundred, we obtain the percentages of the probability of being in one risk level or another in each sector. The results are shown in Figure 3.

Sector 1		Sector 2	
Level 1	17.9035 %	Level 1	5.2495 %
Level 2	31.9101 %	Level 2	25.2508 %
Level 3	41.8749 %	Level 3	45.0816 %
Level 4	5.2043 %	Level 4	14.7956 %
Level 5	3.1064 %	Level 5	9.6225 %





Sector 3		Sector 4	
Level 1	9.5030 %	Level 1	10.4094 %
Level 2	25.8975 %	Level 2	29.4669 %
Level 3	43.3620 %	Level 3	45.1212 %
Level 4	19.0694 %	Level 4	13.8459 %
Level 5	2.1681 %	Level 5	1.1566 %



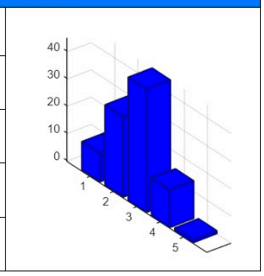


Figure 3. Results obtained from the analysis of the Markov model for each sector in the city of Badajoz in percent (%).

To begin the analysis of the results obtained, it is necessary to analyze the values of Level 5 that each sector has since it defines the highest risk that a pedestrian crash will occur. Higher values will mean that the probability of a pedestrian crash with victims will be higher in these sectors than in the sectors with lower values. The aim is to drive the analysis from the values of this level to try to find out an overall behavior that allows comparing the overall risk level of each sector. This analysis will make it possible to use the existing and new resources, both human and material, in a much more effective and efficient way, trying to achieve the final objective of reaching Level 1 (no risk) in all sectors, that is, with zero victims [62].

Analyzing the results shown in Figure 3 sector by sector, it can be concluded that in the four sectors, the most probable level to be in over time would be Level 3 (moderate risk), with a probability of more than 40% in all cases. The four sectors show the same behavior, so it must be assumed that no sector can be excluded from the policies to be implemented to reduce the number of victims of pedestrian crashes since they all must tend to reach the level of lowest risk possible. The bulk of Sector 1 is in the first three levels, so we could prioritize and use available resources and means in other sectors with higher levels of risk. In Sector 2, unlike Sector 1, the bulk is in the last three levels, which is not surprising since this is also the sector where Level 5 (extreme risk) presents a higher value. Sectors 3 and 4 show similar profiles, both being strongly influenced by Levels 3 (moderate risk) and 4 (high risk), so it would be interesting to make a detailed study of these areas as well.

As shown in Figure 3, the sectors could be ranked by the sum of their percentages in the last two levels because the last two levels are more suitable for assessing the severity of pedestrian crashes. These two levels represent the highest risk of producing a pedestrian crash with casualties, which is what is intended to be prevented. In this way, and according to the prediction of the model, from the highest to the lowest risk, we would have Sector 2 (24.4181%), followed by Sectors 3 (21.2375%) and 4 (15.0025%), and finally Sector 1 (8.3107%). Therefore, according to this prediction, the available resources, both human and material, as well as the study, search and implementation of new resources, would have to be based on the previous order (Sectors 2, 3, 4 and 1). In other words, if the resources were used more intensively in those areas with a higher incidence of high-risk crashes for pedestrians, the resulting beneficial effect would consequently be higher, since a greater overall reduction in pedestrian crashes would be achieved.

If new road crash prevention measures were to be implemented based only on the characteristics of each sector, they could be less efficient because they could be applied to sectors that actually have lower risk levels than others. For example, in Sector 1, we could expect the prediction in this sector based on its characteristics to be a risk Level 1 or 2 (zero risk or low risk) due to the low traffic density in this area, since most of the roads in the center of Badajoz are limited traffic roads and, therefore, traffic is very limited. However, the model predicts a moderate risk level (Level 3), with the highest percentage in this level. The prediction results show that despite the low traffic in this area, urban planners should not forget to implement measures in this sector to further reduce traffic accidents. Another example might be that the characteristics of Sectors 2 and 3 might also lead urban planners to use available resources less efficiently. One might expect that Sector 3 would have the highest crash risk level, rather than Sector 2 as predicted by the model, because Sector 3 is the sector with the highest number of residents who drive (unlike the other three sectors) and with the highest traffic density, according to local police statistics. However, the model results show that Sector 2 has a higher crash risk level than Sector 3 (Figure 3). New measures should preferably be applied to Sector 2 rather than to Sector 3. These facts show that the "a priori" assumptions based on the characteristics of each sector could lead to low efficiency in applying accident prevention measures. The model proposed in this work provides urban planners with a more reliable tool, based on the numerical analysis of the available data, to make more efficient choices when defining road crash prevention measures.

Model Checking

In order to validate the reliability of the prediction of the Markov model developed in this work, 59 pedestrian crashes in the city of Badajoz were analyzed during the first six months of the year 2024 (January–June). Of these 59 pedestrian crashes, regardless of whether they were road crashes with minor, serious, very serious or fatal victims, 9 occurred in Sector 1, 21 in Sector 2, 15 in Sector 3 and 14 in Sector 4. These data are shown graphically in Figure 4. This verification has taken into account that in these first months of 2024, in the city of Badajoz, no new measures were implemented in any of the sectors to reduce pedestrian crashes and, therefore, the result would not be altered compared to the prediction according to the Markov chains analyzed in this paper.

As shown in Figure 4, in the first six months of 2024, and without having implemented any measure to prevent pedestrian crashes in that year, the prediction of the Markov model is fulfilled for all sectors. Sector 2 has the highest number of pedestrian crashes (21), and Sector 1 has the lowest (9). Sector 3 ranks second with 15 pedestrian crashes and Sector 4 ranks third with 14 pedestrian crashes. Therefore, from the highest to the lowest risk, the positions of the sectors based on pedestrian crashes with victims in these first six months of 2024 are Sectors 2, 3, 4 and 1 and coincide with the order established with the predictions of the Markov model (Sector 2 with 24.4181%, followed by Sectors 3 with 21.2375% and 4 with 15.0025%, and finally Sector 1 with 8.3107%).

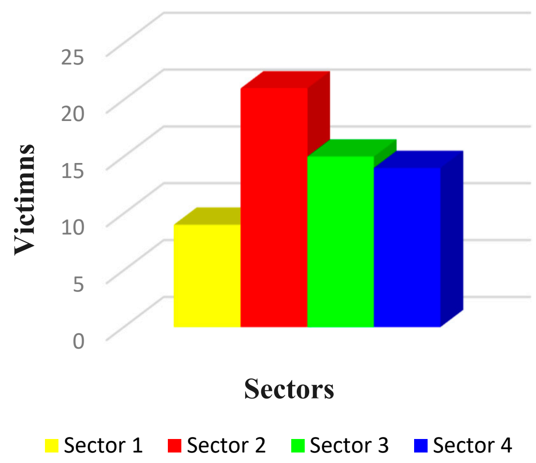


Figure 4. Victims in pedestrian crashes in each sector of the city of Badajoz in the first six months of 2024 (January–June).

This forecast was taken into account by the Local Police and new measures were implemented over the next three months (July, August and September) in Sector 2, the sector with the highest percentage of risk according to the results obtained. These new measures in this sector were as follows: increased police presence and increased enforcement by law enforcement officers at conflict points; increased speed enforcement; installation of speed bumps; removal of obstacles that reduce visibility, such as tree branches; increased vertical and horizontal signage; or installation of more lighting at pedestrian crossings.

As shown in Figure 5, in Sector 2, the number of victims was reduced as a result of these new measures implemented by the competent administration, and it was observed that the model is also relevant in this sense and valuable for the decision-making of the authorities in charge of road crashes. In this way, the available human and material resources can be used more effectively and efficiently. It will also be useful to optimize new economic expenditures in other new resources, such as video surveillance zones or intelligent pedestrian crossings.

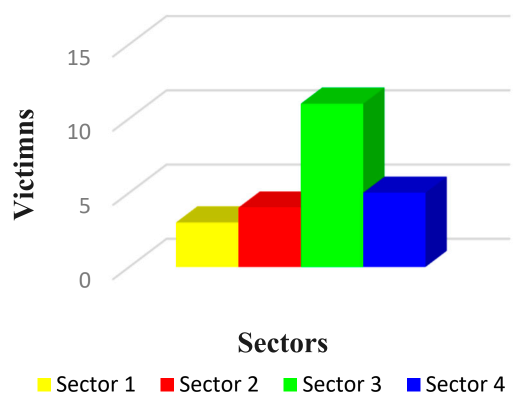


Figure 5. Victims in pedestrian crashes in each sector of the city of Badajoz in July, August and September, after preventive measures were applied in Sector 2.

6. Conclusions

This paper tries to predict the pedestrian crash rate in the city of Badajoz. The prediction model used is a Markov chain. In total, 816 pedestrian collisions were analyzed from the reports of the Judicial Traffic Police of the Local Police of Badajoz in Spain (2016–2023). To carry it out, the city was divided into four sectors. In addition, the number of pedestrian collisions per month in each sector was evaluated using a risk scale with five levels, from Level 1 (no risk and zero victims per month) to Level 5 (extreme risk and more than five victims per month).

The probability matrix of the Markov model was obtained for each one of these four sectors, taking into account the available historical data and the risk scale. After calculating the corresponding EVAs and EVEs, the diagonal and the stationary matrices and the characteristic polynomials were obtained. All these data were analyzed, and future predictions were obtained in order to allocate the available resources in the most effective and efficient way, according to the needs of each specific sector.

Analyzing the results sector by sector, the most likely risk level in which a sector can be allocated over time would be Level 3 (moderate risk) across all four sectors, with a probability greater than 40%. In addition, the sectors could be ranked by the sum of their percentages in the last two levels (those with a higher risk level). In this way, from highest to lowest risk, Sector 2 would be in first place (24.4181%), followed by Sectors 3 (21.2375%) and 4 (15.0025%), and finally Sector 1 (8.3107%). Therefore, according to this prediction, the available resources should be allocated based on this order (Sectors 2, 3, 4 and 1), so that it can be expected that the effect achieved by these measures would be more effective and efficient.

In order to validate the reliability of the prediction of the developed Markov model, the pedestrian crashes in the city of Badajoz were analyzed during the first six months of the year 2024, taking into account that during these first months, no new measures were implemented in any of the sectors to reduce pedestrian crashes. The results show that the Markov model is reliable since the model prediction is consistent with the pedestrian crashes that actually occurred during this period. In addition, the results of the Markov model were taken into account by the Local Police and new measures were implemented in July, August and September in the most critical sector according to the forecast. Pedestrian crashes in Sector 2 were reduced as a result of these new measures, thus also verifying the model and giving it value as a useful tool for decision-making by road safety authorities. The results obtained and the adjustment to reality also show that no sector could be neglected in order to avoid a higher level of risk.

This study has focused only on pedestrian crashes in the city of Badajoz in a given period. Therefore, the study could be improved by extending the period of data collection, as well as by analyzing other types of road crashes (rear-end collisions, run-offs, etc.) or by analyzing a larger population area, as is the case of the Autonomous Community of Extremadura. In this way, it would be possible to verify with greater certainty that the predictive model continues to be reliable.

In future lines of research, the development of this model could be combined with other predictive models such as regression or deep learning to compare which would be more reliable and try to optimize road safety in this way, creating, in turn, more robust, accurate and reliable models that can be implemented for any type of road crash. In this sense, predictive models based on artificial intelligence could be used.

Author Contributions: Conceptualisation, A.M.-S., F.C.G.-P. and M.A.J.-M.; methodology, A.M.-S. and M.A.J.-M.; software, A.M.-S. and M.A.J.-M.; validation, A.M.-S., F.C.G.-P. and M.A.J.-M.; formal analysis, A.M.-S.; investigation, A.M.-S.; resources, A.M.-S.; data curation, A.M.-S.; writing—original draft preparation, A.M.-S.; writing—review and editing, A.M.-S., F.C.G.-P. and M.A.J.-M.; visualisation, A.M.-S., F.C.G.-P. and M.A.J.-M.; supervision, A.M.-S., F.C.G.-P. and M.A.J.-M.; project administration, A.M.-S., F.C.G.-P. and M.A.J.-M.; funding acquisition, A.M.-S., F.C.G.-P. and M.A.J.-M. All authors have read and agreed to the published version of the manuscript.

Funding: This research did not receive any specific grant from funding agencies in the public, commercial, or not-for-profit sectors.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data associated with this study have not been deposited into a publicly available repository. The data that were used are confidential and are available on the database of the Judicial Traffic Police of the Local Police of Badajoz upon request.

Acknowledgments: The authors would like to thank the entire Local Police of Badajoz, especially the members of the Judicial Traffic Police. Without the tireless daily work of all of them, this research would not have been possible.

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

References

1. Figueras, M. La Vanguardia. Available online: https://www.lavanguardia.com/motor/actualidad/20211120/7784546/primer-peaton-muerto-accidente-trafico.html (accessed on 20 July 2024).
2. Campón Domínguez, J.A. El Diseño de Una Base de Datos de Investigaciones en Profundidad Sobre Atropellos a Peatones. Ph.D. Dissertation, Universidad Carlos III, Madrid, Spain, 2015.
3. Norman, L.G. *Road Traffic Accidents*; World Health Organization (WHO): Geneva, Switzerland, 1962.
4. Peden, M.; Scurfield, R.; Sleet, D.; Mohan, D.; Hyder Adnan, A.; Jarawan, E.; Mathers, C. *World Report on Road Traffic Injury Prevention*; World Health Organization (WHO): Geneva, Switzerland, 2004.
5. Heinrich, H.W. *Industrial Accident Prevention: A Scientific Approach*; McGraw-Hill: New York, NY, USA, 1931.
6. Hollnagel, E. *Barriers and Accident Prevention*; Routledge: Oxfordshire, UK, 2016.
7. World Health Organization (WHO). *Global Status Report on Road Safety 2013: Supporting a Decade of Action*; World Health Organization (WHO): Geneva, Switzerland, 2013.
8. European Comission. *Seguridad Vial En La UE: Las Muertes Están Por Debajo de Los Niveles Previos a La Pandemia, Pero El Progreso Sigue Siendo Demasiado Lento*; Dirección General de Movilidad y Transportes: Brussels, Belgium, 2024.
9. European Comission. Mobility and Transport. Available online: https://road-safety.transport.ec.europa.eu/european-road-safety-observatory_en (accessed on 7 November 2024).
10. European Road Safety Observatory. Facts and Figures-Urban Áreas-2022. Available online: https://road-safety.transport.ec.europa.eu/document/download/9650635a-2982-4391-9d3b-62bed93aadd0_en?filename=ff_roads_inside_urban_areas_20220707.pdf (accessed on 21 May 2024).
11. Dirección General de Tráfico (DGT). 1145 Personas Fallecieron en Siniestros de Tráfico Durante 2022. *Madrid, Spain.* Available online: https://www.dgt.es/comunicacion/notas-de-prensa/1.145-personas-fallecieron-en-siniestros-de-trafico-durante-2022/ (accessed on 16 June 2024).
12. Dirección General de Tráfico (DGT). Datos Municipales-Siniestralidad 2022. *Madrid, Spain.* Available online: https://www.dgt.es/menusecundario/dgt-en-cifras/dgt-en-cifras-resultados/ (accessed on 20 May 2024).
13. Dirección General de Tráfico (DGT). Seguridad Vial 2030. Available online: https://seguridadvial2030.dgt.es/vision-2030/mision-vision-y-principios-de-la-estrategia/ (accessed on 10 June 2024).
14. Muñoz Garrido, R. *Artículo De Investigación: Evaluación de la Efectividad De Las Actuaciones En Carreteras Sobre La Accidentalidad*; Centro Universitario de la Guardia Civil: Madrid, Spain, 2021.
15. Aparicio, F.; Arenas, B.; Bernardos, E.; Gómez, A. El modelo DRAG–España: Análisis de los principales factores de influencia en el número de accidentes en las carreteras españolas. *Secur. Vialis* **2009**, *1*, 59–64. [CrossRef]
16. Dirección General de Tráfico (DGT). *El Impacto Sobre La Seguridad Vial de la Vigilancia Y Control de la Normativa De Tráfico*; Observatorio de Seguridad Vial: Madrid, Spain, 2010.
17. Onda Cero. Policía Local. Available online: https://www.ondacero.es/emisoras/extremadura/badajoz/noticias/aspolobba-senala-que-falta-policias-badajoz-hecho-que-hay-negociacion-gobierno-local_2024012965b7e910327cdd0001937606.html (accessed on 19 January 2024).
18. El Ideal Gallego. La Plantilla de la Policía Local Sufre un Déficit de Más de Cien Agentes. Available online: https://www.elidealgallego.com/articulo/a-coruna/plantilla-policia-local-sufre-deficit-cien-agentes-4456689 (accessed on 12 January 2024).
19. Medina Sarmiento, J.E. Prevención de la Conducción Influenciada Por Medio de Los Mapas Del Crimen. Un Análisis Desde La Aplicación De Las Teorías Criminológicas. Ph.D. Dissertation, Universidad Miguel Hernández, Elche, Spain, 2013.
20. Úbeda González, D. Predicción de la Severidad De Accidentes De Tráfico En La Red De Carreteras De España Y Reino UNIDO Mediante Modelos Estadísticos Basados En Random Forest Y Regresión Logística. Ph.D. Dissertation, Universidad Miguel Hernández, Elche, Spain, 2017.
21. Aparicio Azcárraga, R. *Artículo De Investigación: Aproximación a La Construcción De Un Indicador De Riesgo Vial*; Centro Universitario de la Guardia Civil: Madrid, Spain, 2021.

22. Toledo Castillo, F.; Mera Redondo, A.; García Sánchez, J.; Hidalgo Fuentes, S. *Manual De Investigación Y Reconstrucción De Accidentes De Tráfico*; Universidad de Valencia: Valencia, Spain, 2009.
23. Campón Domínguez, J.A.; San Román García, J.L.; Rodríguez Luque, P.A.; Díaz López, V.; Cocaña Rosco, J.F.; García-Pozuelo Ramos, D.; Fuentes Ortega, P.; Santos Cuadros, S.; Vidal Barrientos, J.L. *Manual la Reconstrucción de Siniestros Viales*; Centro Universitario de la Guardia Civil: Madrid, Spain, 2020.
24. Muñoz Garrido, R. La Reducción de Los Atropellos a Peatón En La Ciudad De Badajoz Y Su Lesividad. Propuestas De Actuación. Revista de Investigación CUGC 2021, ISSN-e 2444-6556, Nª 9. Available online: https://www.cugc.es/component/abook/author/978-ruben-munoz-garrido.html?Itemid=1600 (accessed on 6 May 2024).
25. Ministerio del Interior. Real Decreto Legislativo 6/2015, de 30 de octubre, por el que se aprueba el texto refundido de la Ley sobre Tráfico, Circulación de Vehículo a Motor y Seguridad Vial. BOE núm. 261. Madrid, Spain, 2015. Available online: https://www.boe.es/buscar/act.php?id=BOE-A-2015-11722 (accessed on 6 May 2024).
26. Ravani, B.; Brougham, D.; Mason, R.T. Pedestrian post-impact kinematics and injury patterns. *Soc. Automot. Eng. (SAE)* **1981**, *90*, 811024.
27. Eubanks, J.; Haight, R. Pedestrian involved traffic collision reconstruction methodology. *Soc. Automot. Eng. (SAE)* **1992**, 921591. [CrossRef]
28. Fricke, L.B.; Baker, S. *Traffic Accident Reconstruction*; Northwestern University Traffic Institute: Evanston, IL, USA, 1990.
29. San Román García, J.L.; Campón Domínguez, J.A.; Díaz López, V.; Sanz Sánchez, S. *La Reconstrucción De Accidentes: El Atropello De Peatones (2ª Parte)*; STA: Sociedad de Técnicos de Automoción: Barcelona, Spain, 2008; Nº. 183; pp. 12–14. ISSN 1138-5006.
30. Tang, J.; Zheng, L.; Han, C.; Yin, W.; Zhang, Y.; Zou, Y.; Huang, H. Statistical and machine-learning methods for clearance time prediction of road incidents: A methodology review. *Anal. Methods Accid. Res.* **2020**, *27*, 100123. [CrossRef]
31. Zheng, L.; Sayed, T.; Mannering, F. Modeling traffic conflicts for use in road safety analysis: A review of analytic methods and future directions. *Anal. Methods Accid. Res.* **2021**, *29*, 100142. [CrossRef]
32. Arun, A.; Haque, M.; Washington, S.; Sayed, T.; Mannering, F. A systematic review of traffic conflict-based safety measures with a focus on application context. *Anal. Methods Accid. Res.* **2021**, *32*, 100185. [CrossRef]
33. Yan, X.; He, J.; Wu, G.; Zhang, C.; Wang, C.; Ye, Y. Differences of overturned and hit-fixed-object crashes on rural roads accompanied by speeding driving: Accommodating potential temporal shifts. *Anal. Methods Accid. Res.* **2022**, *35*, 100220. [CrossRef]
34. Zou, R.; Yang, H.; Yu, W.; Yu, H.; Chen, C.; Zhang, G.; Ma, D.T. Analyzing driver injury severity in two-vehicle rear-end crashes considering leading following configurations based on passenger car and light truck involvement. *Accid. Anal. Prev.* **2023**, *193*, 107298. [CrossRef] [PubMed]
35. Moreno-Sanfélix, A.; Gragera-Peña, F.C.; Jaramillo-Morán, M.A. An improvement of the conceptual system of the sequential events model of road crashes (i-MOSES). *Heliyon* **2024**, *10*, e37268. [CrossRef]
36. Abellán, J.; López, G.; De Oña, J. Analysis of traffic accident severity using Decision Rules via Decision Trees. *Exp. Syst. with Applic.* **2013**, *40*, 6047–6054. [CrossRef]
37. Zhang, J.; Li, Z.; Pu, Z.; Xu, C. Comparing Prediction Performance for Crash Injury Severity Among Various Machine Learning and Statistical Methods. *IEEE Access* **2018**, *6*, 60079–60087. [CrossRef]
38. Riccardi, M.R.; Augeri, M.G.; Galante, F.; Mauriello, F.; Nicolosi, V.; Montella, A. Safety Index for evaluation of urban roundabouts. *Accid. Anal. Prev.* **2022**, *178*, 106858. [CrossRef] [PubMed]
39. Navarro-Moreno, J.; Calvo-Poyo, F.; de Oña, J. Influence of road investment and maintenance expenses on injured traffic crashes in European roads. *Intern. J. Sustain. Transp.* **2023**, *17*, 649–659. [CrossRef]
40. Hossain, M.; Zhou, H.; Sun, X.; Hossain, A.; Das, S. Crashes involving distracted pedestrians: Identifying risk factors and their relationships to pedestrian severity levels and distraction modes. *Accid. Anal. Prev.* **2024**, *194*, 107359. [CrossRef] [PubMed]
41. Dinesh, D. A Novel Multi-Model Machine Learning Approach to Real-Time Road Accident Prediction and Driving Behavior Analysis. In Proceedings of the International Symposium on Computer Science and Intelligent Controls (ISCSIC), Rome, Italy, 14 November 2021; pp. 67–72. [CrossRef]
42. Chang, I.; Park, H.; Hong, E.; Lee, J.; Kwon, N. Predicting effects of built environment on fatal pedestrian accidents at location-specific level: Application of XGBoost and SHAP. *Accid. Anal. Prev.* **2022**, *166*, 106545. [CrossRef]
43. Wu, D.; Zhang, Y.; Xiang, Q. Geographically weighted random forests for macro-level crash frequency prediction. *Accid. Anal. Prev.* **2024**, *194*, 107370. [CrossRef]
44. Roland, J.; Way, P.D.; Firat, C.; Doan, T.-N.; Sartipi, M. Modeling and predicting vehicle accident occurrence in Chattanooga, Tennessee. *Accid. Anal. Prev.* **2021**, *149*, 105860. [CrossRef]
45. Lin, Y.; Chen, Y.; Lin, G.; Zhai, J. Forecasting for the freeway traffic accidents base on Markov model. In Proceedings of the International Conference on Business Management and Electronic Information, Guangzhou, China, 16–17 April 2011; pp. 259–261. [CrossRef]
46. Zhou, H.; Huang, H.; Xu, P.; Chang, F.; Abdel-Aty, M. Incorporating spatial effects into temporal dynamic of road traffic fatality risks: A case study on 48 lower states of the United States, 1975–2015. *Accid. Anal. Prev.* **2019**, *132*, 105283. [CrossRef]
47. Xu, C.; Li, Z.; Yang, Z. A Markov switching regression analysis of freeway crash risks considering spatial effect. *Proc. Inst. Civ. Eng. Transp.* **2020**, *173*, 159–170. [CrossRef]

48. Taoufik, Y.; Sadok Ben, Y. A Markov chain-based data dissemination protocol for vehicular ad hoc networks. *Comp. Commun.* **2021**, *180*, 303–314. [CrossRef]
49. Mohammadi, A.; Kiani, B.; Mahmoudzadeh, H.; Bergquist, R. Pedestrian Road Traffic Accidents in Metropolitan Areas: GIS-Based Prediction Modelling of Cases in Mashhad, Iran. *Sustainability* **2023**, *15*, 10576. [CrossRef]
50. Instituto Nacional de Estadística (INE). Población del Padrón Continuo por Unidad Poblacional. Available online: https://www.ine.es/nomen2/index.do?accion=busquedaDesdeHome&nombrePoblacion=badajoz (accessed on 21 July 2024).
51. La Crónica de Badajoz. Población Flotante de Badajoz Fluctúa Entre 15000 y 20000 Personas Diarias. Available online: https://www.lacronicabadajoz.com/badajoz/2014/02/02/poblacion-flotante-badajoz-fluctua-15-100183214.html (accessed on 21 September 2024).
52. La Crónica de Badajoz. La Población de Badajoz Vuelve a Crecer y Llega a 153559 Habitantes. Available online: https://www.lacronicabadajoz.com/badajoz/2023/04/02/poblacion-badajoz-vuelve-crecer-llega-100039175.html (accessed on 21 September 2024).
53. Papakonstantinou, K.G.; Shinozuka, M. Planning structural inspection and maintenance policies via dynamic programming and Markov processes. Part II: POMDP implementation. *Reliab. Eng. Syst. Saf.* **2014**, *130*, 214–224. [CrossRef]
54. Bapat, R.B.; Raghavan, T.E.S. *Nonnegative Matrices and Applications*; Encyclopedia of Mathematics and Its Applications (No. 64); Cambridge University Press: Cambridge, UK, 1997.
55. García, J.M. Matrices no negativas, paseos aleatorios y cadenas de Markov. In *Matemática Aplicada y Estadística*; Universidad del País Vasco: Lejona, España, 2002.
56. Cohen-Tannoudji, C. The mathematical tools of quantum mechanics. In *Quantum Mechanics*; Wiley: Hoboken, NJ, USA, 1977; ISBN 0-471-16432-1.
57. Horn Roger, A.; Johnson Charles, R. *Matrix Analysis*; Cambridge University Press: Cambridge, UK, 1985; ISBN 0-521-30586-1.
58. De Burgos, J. *Álgebra Lineal*; McGraw-Hill: New York, NY, USA, 1993.
59. Karunarathna, W.; Zhang, T.D.R.; El-Akruti, K. Bridge deterioration modeling by Markov Chain Monte Carlo (MCMC) simulation method. In Proceedings of the 8th World Congress on Engineering Asset Management & 3rd International Conference on Utility Management Safety, Hong Kong, China, 30 October–1 November 2013.
60. Masetti, G.; Robol, L. Computing performability measures in Markov chains by means of matrix functions. *J. Comput. Appl. Math.* **2020**, *368*, 112534. [CrossRef]
61. Gongadze Gogvadze, T. *Diseño Y Simulación De Un Modelo Predictivo Para La Velocidad Y Dirección Del Viento*; Final Degree Project; Escuela Técnica Superior de Ingeniería Industrial de Barcelona: Barcelona, Spain, 2016.
62. European Commission. *'Vision Zero': EU Road Safety Policy Framework 2021–2030*; Directorate-General for Mobility and Transport; Next Steps Towards; Publications Office of the European Union: Brussels, Belgium, 2020; Available online: https://data.europa.eu/doi/10.2832/391271 (accessed on 6 May 2024).