Pedestrian Safety and Walkability in Urban Space: case study of schools neighborhood in Lisbon

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Extended Abstract

Thesis to obtain the Master of Science Degree in

Civil Engineering

INTRODUCTION

Walking is the simplest way man can use to transport himself, and it is an important part of the human nature allowing the him to explore, understand and interact with the world.

In our days 54% of the world population lives in cities and this percentage can grow to 66% in 2050 (United Nations, 2014). The contemporary society lives surrounded by wishes of economic, demographic and environment sustainability, that compel to find new ways of live a modern, efficient and safe live in the urban context. To ensure our survival as society urges to increase transportation modes with low carbon emissions and greenhouse emissions, as walking.

To implement this new transportation paradigm in cities is crucial establish a comfort environment and safeguard the streets adequacy, is mandatory to evaluate and measure the walkability perspective in this human habitat.

LITERATURE REVIEW

Safety is the property defined by the number of accidents by type and severity expected to occur in a segment during a certain period (Hauer, 1997).

Multiple transportation experts reflected about pedestrian problems using mathematical models to isolate variables and understand their influence on pedestrian safety. The first difficulty in road transportation and crashes study is obtain data, this point constrains serious delays and bring inertia to this area, as described by Lord and Mannering (2010) the essential factories conditioning the pedestrian safety are still unknown.

An important compilation about the work performed on pedestrian safety is the literature review by Retting et al. (2003). This paper presents the microscale interventions have relevant impact in pedestrian crash frequency. The work appoints speed control, separate areas for vehicles and pedestrians and more pedestrian visibility as ways of increase the pedestrian safety. Urban measures with these focus to are identify as ways of decrease vehicle-pedestrian crashes.

The pedestrian crashes were subject of multiple modulation methods. Clifton and Fults (2007) evaluate the risk and injury severity of trampling near public school in Baltimore, USA, using gravity models to measure exposer and risk. The presence of leisure equipment is related with pedestrian crash and with its severity. The increase of demand can explain the verified increase of occurrences but the severity is surprising in a low speed environment.

These conclusions are similar in the work of Loukaitou-Sideris et al (2007) whose work connects educational areas with high commercial land use and pedestrian safety.

The logistic regression model is used by Sze et Wong (2007) to isolate the factors responsible for high ratios of pedestrian crashes in the urban area of Hong-Kong. In this metropole the trampling represent half of road related fatalities in the years between 1991 and 2004. A relevant set of variables were used combine classic traffic variables as speed level, injurie severity or congestion level with social variables as day of the week or period of the day. Demographic and infrastructure characteristics as age, gender or congested sidewalks are isolated as keys factors to explain this problem.

Another approached are probit models use by Clifton et al (2009) to analyze and model the pedestrian crashes in Baltimore, USA since 2000 to 2004. Interesting conclusions show that a bigger pedestrian connectivity is negatively associated with the injurie severity in the victims. In this context men the paper present more probability of suffer a hit. By another hand child are the age range with high probability of being a victim although elderly people are the group that suffers more fatal crashes. Is referred the importance about study what means exposure risk in a pedestrian point of view what is the relevance of this risk in terms of injuries severity.

The generalized linear models methodology with negative binomial distribution is applied by Pulugurtha and Sambhara (2010) to study intersection pedestrian crashes in Charlotte, USA. The conclusions identify more accuracy of the models in intersections with bigger pedestrian activity and identify the need of building specific models in function of intersection attractiveness, dividing intersection with low and high activity.

THEORETICAL FRAMEWORK

In this work were used generalized linear models (GML), applied by McCullogh (1989), Karlaftis et Mannering (2003) e Moura, Ribeiro e Martinez (2015) in to transportation studies, this methodology allows to model rare, discrete, non negative events as crash frequencies.

The models are a multiple linear regressions extension and a mathematical answer available for realities with particular considerations:

- Non continuous dependente variable
- Nonlinear effects on independents variables.

There are three components in a generalized linear model:

- Random Component

The random component considers an exponential distribution of probability for the dependent variable, represent by the formula:

$$(1+x)^n = 1 + \frac{nx}{1!} + \frac{n(n-1)x^2}{2!} + \cdots$$

- Systematic Component

This component is composed by the linear predictor which brings the independent variables information to the model formulation, it is represent by an equation:

$$\eta_i = \sum_{j=1}^{p} x_{ij}\beta_j$$

Where η_i represent the observations of p independent variables.

- Link Function

The link function stablishes the relation between the linear predictor and the random distribution function, connecting random and systematic components. This is monotonous and differential function. Choose the correct link function depends on the dependent variable characteristics. In this work were used Log link function as:

$$F(x) = \log\frac{x}{(1-x)}$$

Poisson Model

This type of generalized linear model use Poisson as link function allowing to model count data models with non-negative integer dependent variables.

This distribution is used to model rare events, as crashes in general and pedestrian crashes in particular. This model is suitable for events where the probability of a non-occurrence is impossible to obtain.

The model link function obeys to a formulation:

$$f(k;\lambda) = \frac{\lambda^k e^{-\lambda}}{k!}$$

Where $f(k;\lambda)$ is the probability of occurrence for k crashes and λ is the expected value.

Negative Binomial Model

The negative binomial model is a Poisson models modification in order to consider the possible over dispersion of the data sets, this model presents good fit for count data sets with smaller sizes. To the Poisson parameter an error component is added and the new model obeys the formulation:

$$f(k) = \binom{k+r-1}{k}(1-p)^r p^k \quad , k = r, r+1, r+2, \ldots$$

Where $f(k)$ is the probability of occurrence for k crashes.

Model Calibration

Lagrange Multiplier Test

Lagrange multiplier test is a hypothesis statically test which allows to conclude about the over dispersion in a data set, and consequentially about the appropriateness of using the negative binomial model.

Log-likelihood Comparison

The log-likelihood comparison for different models provides leads about the suitability of a negative binomial model formulation, when Poisson models present low values of log-likelihood the negative binomial models does not bring considerable advantage to the model.

Wald Test

This hypothesis test permits to measure the statistical significance for each one of the model independent variables, it validates the variable influence in the model rejecting a pure random behavior in the results.

Omnibus Test

The Omnibus test is a statistic test which validates the predictive capacity of a generalized linear model as a whole. It compares the model explain variance with the model unexplained variance, permitting considerations about the model power to explain the reality.

Predictive Capacity ρ2

The determination of ρ2 establishes a measure of the model total prediction capacity, by identify a value between 0 and 1, where 0 represents a null capacity of predict the results and 1 represent the ideal model. This indicator allows to identify the value of r2, multiple linear regression determination coeficiente as suggested by McFadden.

Akaike Information Criterion

The Akaike Information Criterion gives a practical way to compare the quality of multiple different models. This parameter is as lower as the loss of information in the models caused by the adjustment process.

By being a non-statistical calibration method, the criterion is only a comparison criterion to evaluate multiple models without power to evaluate a model per se.

CASE STUDY

This work starts from two different data sources: pedestrian crash data provided by the municipality of Lisbon and Lisbon area walkability sources from IAAPE Project.

Pedestrian Crashes Data

The pedestrian data set includes all the register pedestrian crashes occurred in Lisbon municipality from 2010 to 2013, information from each accident BEAV formulary and the respective geo-refereciation. The information was collected by the policy at the time of the crash in a form of official register.

Assuming that this type of events has consequences for the involved pedestrians, even if it is minor injury, we consider the reporting ration near 100%.

Walkability Data

The walkability data and variables were provided by IAAPE project (Moura et al, 2015). The project analyzed the build environment and the urban design scoring street segments according the propensity to be used by people walking. This study used techniques as street auditing technical, mathematical modelling and geographical information systems to provide walkability classifications.

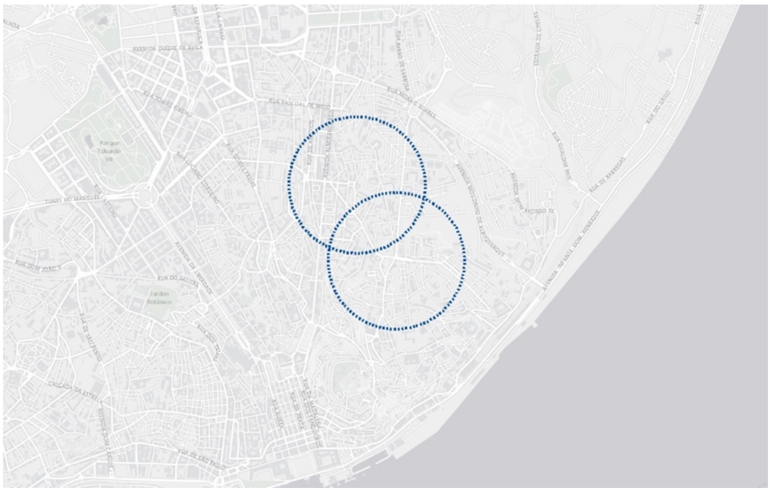

Image 1 – Study areas with walkabity score in Lisbon municipality

The walkability variables are available only in a confined area, Image 1, in consequence both data sets were combined to make possible having all the needed information. The sample are 110 pedestrian crashes in 62 street segments.

The dependent variable considered is the total number of pedestrian crashes between 2010 and 2013 by segment, considering all the street segments with walkability evaluation were at least a road accident involving a pedestrian occurred.

THE MODEL

Exploratory Analysis

To begging the analyses and understand the relation between the number of pedestrian crashes by segment and the multiple available variables were calculated Spearman and Pearson coefficients.

Spearman coefficient gives a quantification of relations between two variables without specifying the type of correlation between them.

On other hand Pearson coefficient give a measure of the linear relation between to variables and can only be calculated to continues variables.

The objective of this analyses was to validate the statistic relation between the multiple independent variables and the dependent variable, number of crash by segment. The obtained result for the variables with statistical significance in at least one coefficient can be consulted in table 1.

Variable	Description	Spearman Coefficient	Sig	Pearson Coefficient	Sig
ChildL	Walkability index for child leisure purpose	0,326	0,009	0,391	0,001
FluxoRodo	Traffic Flow	0,202	0,109	0,374	0,002
ChildT	Walkability index for child transportation purpose	0,314	0,011	0,362	0,003
C21	Land use Variety	0,345	0,005	n.a.	n.a.
AdultL	Walkability index for adults leisure purpose	0,225	0,740	0,324	0,009
AdultT	Walkability index for adults purpose	0,151	0,233	0,243	0,053
C62	Location of crosswalks on the main line of desire	0,415	0,001	n.a.	n.a.
C42	Existence of anchor places with attractiveness effect	0,131	0,304	n.a.	n.a.
C41	Existence of Public Meeting Points	-0,240	0,056	n.a.	n.a.
C31	Vigilance Effect	0,216	0,087	n.a.	n.a.

Table 1 - Independent Variables with higher correlation with the number of pedestrian crashes by segmen- statiscaly significant values

From the analyzes is possible to validate the idea that more pedestrians are probably related to more pedestrian crashes. Almost all the variables represent characteristics that make a segment appealing to walk, for example C21 land use variety or C31 vigilance effect, or are the walkability index itself, for instance AdultL or ChildL, and present positive values of correlation with the number of pedestrian crashes.

Only the variable C41 existence of public meeting points is an exception to this behavior, which can be consequence of more areas and a protection effect in public meeting places.

Factor Analysis

The factor analysis was performed with the goal of finding communalities between in the independent variables set. As advised by Hair et al. (2006) the sample presents more than 50 observations, the Kaiser.Meyer-Olkilin presents a value of 0,515 higher that 0,5 and Bartelett Test of Spherecity is statically significant. Applying Kaiser criteria six factors were obtained with a cumulative explain variance of 70,90%, table 2.

Factor	Total	% of Explained Variance	% of Cumulative Explianed Variance
1	3,679	21,644	21,644
2	2,240	13,179	34,823
3	2,008	11,813	46,636
4	1,766	10,390	57,026
5	1,243	7,313	64,338
6	1,114	6,555	70,893

Table 2 - Explained Variance

The correlation between factor and independent variables was calculated revealing the more important variables for each factor, table 3.

The last step of the facto analysis consisted in attributing a representative word to describe the six factors based on the highest variables correlations and the unifying logic between variables, table 4.

Factors					
1	**2**	**3**	**4**	**5**	**6**
C21 – Land Use Mix	C12 – Continuity of Path	C14 – Existence of Infrastrutures	C32 – Pavement Quality	C71 – Enforcement of Legislation	C51 – Sense of Place and Reference Elements
C43 – Land Use Mix and Service	C13 – Condition to Take the Most Direct Path	C75 – Standardization of Interventions and Solutions	C41 – Existence of Public Meeting Places	C61 – Safety on Road Crossing	C42 – Existence of Attractor Destinations
C24 – Everyday Use Commercial Activities	-	C22 – Footway Width	-	-	-
C31 – Vigilance Effect	-	-	-	-	-
Convenience	**Connectivity**	**Commitment**	**Comfort**	**Safety**	**Legibility**

Table 3 - Factors Description

Models

Three main models were presented in this work using the generalized linear model methodology refereed before. From one models to another the removal of variables were performed trying to isolate a set of variables able to describe the complex phenomena of pedestrian crash in urban street segments using as criteria the adjustment, parsimony and interpretations

As described in theoretical framework section for each model three sub-models were analyzed with different link functions: Poisson, Poisson with Dispersion and Negative Binomial.

In all the present models construction, the variable number of lane per segments was considered as offset of the model, as tentative of include the pedestrian risk. This decision was made on week flow traffic estimates for the segments included in the study.

In the first model considerer all the 24 available independent variables and tries to understand which are the most relevant. This model had an initiation objective allowing the construction of another models, this model served as first analysis.

Model 1

In Table 4 is possible to observe model 1, in this model were considered all the factors from the factor analyses previously obtained:

Factor 1 – Convenience
Factor 2 – Connectivity
Factor 3 – Commitment
Factor 4 – Comfort
Factor 5 – Safety
Factor 6 – Legibility

	Factor	**β**	**Confidence Interval Wald 95%**		**Hypothesis Test**	
			Inferior	**Superior**	**Chi-Square Wald**	**p-value**
Model Poisson	*Intercept****	-1,462	-1,664	-1,261	202,036	0,000
	Factor 1**	0,249	0,031	0,467	5,032	0,025
	Factor 2*	0,139	-0,096	0,375	1,349	0,245
	Factor 3	-0,094	-0,314	0,126	0,698	0,404
	Factor 4*	-0,152	-0,345	0,041	2,395	0,122
	Factor 5***	0,396	0,201	0,591	15,782	0,000
	Factor 6	-0,029	-0,235	0,177	0,076	0,783
Model Poisson with Dipersion	*Intercept****	-1,462	-1,664	-1,261	202,036	0,000
	Factor 1**	0,249	0,031	0,467	5,032	0,025
	Factor 2*	0,139	-0,096	0,375	1,349	0,245
	Factor 3	-0,094	-0,314	0,126	0,698	0,404
	Factor 4*	-0,152	-0,345	0,041	2,395	0,122
	Factor 5***	0,396	0,201	0,591	15,782	0,000
	Factor 6	-0,029	-0,235	0,177	0,076	0,783
Model Negative Binomial	*Intercept****	-1,418	-1,658	-1,177	133,399	0,000
	Factor 1**	0,253	0,024	0,481	4,682	0,030
	Factor 2*	0,146	-0,101	0,394	1,343	0,246
	Factor 3	-0,095	-0,329	0,138	0,641	0,423
	Factor 4*	-0,154	-0,361	0,054	2,110	0,146
	Factor 5***	0,386	0,172	0,599	12,515	0,000
	Factor 6	-0,023	-0,240	0,195	0,041	0,839

Table 4 - Calibration Results Model 1[1]

[1] *** - Factor statiscally significante por a confidence interval > 99%
** - Factor statiscally significante por a confidence interval superior > 95%
* - Factor statiscally significante por a confidence interval superior > 80%

Model 2

The model 2 includes four factors from the initial set and tries to obtain a smaller but consist model based on model 1:

Factor 1 – Convenience

Factor 2 – Connectivity

Factor 4 – Comfort

Factor 5 – Safety

This model calibration results are compiled in Table 5.

	Factor	β	Confidence Interval Wald 95%		Hypothesis Test	
			Inferior	Superior	Chi-Square Wald	p-value
Model Poisson	*Intercept****	-1,474	-1,675	-1,273	207,216	0,000
	Factor 1**	0,229	0,015	0,443	4,393	0,036
	Factor 2*	0,141	-0,089	0,371	1,444	0,230
	Factor 4*	-0,153	-0,347	0,040	2,404	0,121
	Factor 5***	0,402	0,209	0,596	16,621	0,000
Model Poisson with Dispersion	*Intercept****	-1,474	-1,697	-1,251	167,388	0,000
	Factor 1**	0,229	-0,009	0,467	3,548	0,060
	Factor 2*	0,141	-0,115	0,397	1,166	0,280
	Factor 4*	-0,153	-0,369	0,062	1,942	0,163
	Factor 5***	0,402	0,187	0,617	13,426	0,000
Model Negative Binomial	*Intercept****	-1,426	-1,667	-1,185	134,628	0,000
	Factor 1**	0,234	0,008	0,461	4,100	0,043
	Factor 2*	0,147	-0,096	0,391	1,404	0,236
	Factor 4*	-0,156	-0,365	0,053	2,143	0,143
	Factor 5***	0,394	0,182	0,606	13,242	0,000

Table 5 - Calibration Results Model 2[1]

Model 3

The model 3 includes four factors from model 2 set and three calculated variables that describe victim characteristics:

Factor 1 – Convenience

Factor 2 – Connectivity

Factor 4 – Comfort

Factor 5 – Safety

% Sex Fem – Percentage of female victims in a segment pedestrian crashes

% Senior* – Percentage of senior victims in a segment pedestrian crashes

% Night** – Percentage of pedestrian crashes occured by night in a segment

This model calibration results are compiled in Table 6.

	Factor	β	Confidence Interval Wald 95%		Hypothesis Test	
			Inferior	Superior	Chi-Square Wald	p-value
Model Poisson	*Intercept****	-0,810	-1,235	-0,385	13,948	0,000
	Factor 1**	0,204	-0,002	0,409	3,772	0,052
	Factor 2*	0,179	-0,070	0,427	1,981	0,159
	Factor 4*	-0,181	-0,380	0,017	3,203	0,073
	Factor 5***	0,389	0,195	0,584	15,356	0,000
	% Sex Fem.**	-0,587	-1,092	-0,081	5,171	0,023
	% Senior*	-0,405	-0,903	0,093	2,546	0,111
	% Night**	-0,714	-1,273	-0,156	6,281	0,012
Model Poisson with Dispersion	*Intercept****	-0,810	-1,239	-0,381	13,681	0,000
	Factor 1**	0,204	-0,004	0,411	3,700	0,054
	Factor 2*	0,179	-0,073	0,430	1,943	0,163
	Factor 4*	-0,181	-0,382	0,019	3,142	0,076
	Factor 5***	0,389	0,193	0,586	15,063	0,000
	% Sex Fem.**	-0,587	-1,097	-0,076	5,072	0,024
	% Senior*	-0,405	-0,908	0,097	2,498	0,114
	% Night**	-0,714	-1,278	-0,150	6,161	0,013
Model Negative Binomial	*Intercept****	-0,810	-1,235	-0,385	13,947	0,000
	Factor 1**	0,204	-0,002	0,409	3,772	0,052
	Factor 2*	0,179	-0,070	0,427	1,981	0,159
	Factor 4*	-0,181	-0,380	0,017	3,203	0,073
	Factor 5***	0,389	0,195	0,584	15,356	0,000
	% Sex Fem.**	-0,587	-1,092	-0,081	5,171	0,023
	% Senior*	-0,405	-0,903	0,093	2,546	0,111
	% Night**	-0,714	-1,273	-0,156	6,281	0,012

Table 6 - Calibration Results Model 3[1]

COMPARISOM BETWIN MODELS

Dispersion Analyses

The models analysis and comparison starts with dispersion analyzes. In first place was validated the use of Poisson link function with dispersion, using the Lagrange test. By literature, Cameron et Triverdi (2013), values in this test higher that 1 indicates severe over dispersion in the data set and validate the use of models prepared for this cases, as showed in table 7.

	Chi-Square	p-value
Model 1	16,901	0,000
Model 2	16,717	0,000
Model 3	20,04	0,000

Table 7 - Lagrange Multiplier Test

As referred in the theoretical description the log-likelihood values evaluation permits compare Poisson and Binomial model formulations. In table 8, Poisson models present lower value of log-likelihood for Model 2 and equal value for Model 3what can indicate that the use of Negative Binomial models does not contribute to the increase of predictive capacity of the model.

	Poisson/Poisson with Dispersion	Negative Binomial
Model 1	-101,760	-101,452
Model 2	-102,113	-101,773
Model 3	-96,745	-96,745

Table 8 - Log-Likelihood Values

Adjustment and Validation

This section compares the previously described models using the criteria exposed in the theoretical section.

	Poisson		Poisson with Dispersion		Negative Binomial	
	Chi-Square	p-value	Chi-Square	p-value	Chi-Square	p-value
Model 1	26,519	0,000	20,129	0,003	19,148	0,004
Model 2	24,813	0,000	20,044	0,000	18,505	0,001
Model 3	35,549	0,000	34,870	0,000	28,563	0,000

Table 9 - Omnibus Test

The Omnibus test allows to exclude the hypotheses that the explained variance in a set of data is significantly greater than the unexplained variance, overall. As visible in the table 9, all models are statically significant with a 95% confidence interval.

	Poisson/Poisson with Dispersion		Negative Binomial	
	ρ^2	r^2	ρ^2	r^2
Model 1	0,111	≅0,310	0,086	≅0,275
Model 2	0,108	≅0,300	0,083	≅0,210
Model 3	0,155	≅0,410	0,129	≅0,375

Table 10 - ρ^2 e r^2 Parameters

The ρ^2 is calculated based on log-likelihood values and r^2 is obtain by the Domenincich and Macfaden relation. This parameter provides a suitable measure comparable to the determination coefficient in linear models.

Table 10 observation indicates relevant better values of r^2 for Poisson models and interesting values of predictive capacity for models constituted by real data sets. A peculiarity is the very similar value of r^2 model 1 and model 2**.**

	Poisson/Poisson with Dispersion	Negative Binomial
Model 1	217,519	218,904
Model 2	214,225	215,547
Model 3	209,489	211,489

Table 11 - AIC Comparison Parameter

The information in table 11 shows the values of AIC parameter for the multiple models, this parameter allows to compare the amount of information lost in the model adjustment. The lower the parameter value the better are the adjustment. Model 3 is the model with low AIC values, being the Poisson formulations the ones with minor loss of detail in modelling process. This result is expected being this the only presented model using variables and no factors and having less loss of information.

Based in this chapter is possible classify model 3 as the more suitable model to describe the pedestrian crashes problem in Arroios neighborhood in Lisbon, in this Poisson formulation this models shows better values in all the previous criteria.

	Poisson/Poisson with Dispersion LL ratio test	Negative Binomial LL ratio test	LL ration Chi-Square Distribution
Model 1	25,518	19,148	12,592
Model 2	24,812	18,506	9,488
Model 3	35,548	28,562	14,067

Table 12 - Log Likelihood ratio between null model and the models

CONCLUSIONS

The previous presented Table 4, Table 5 and Table 6 indicates than all three models are consistent and appoint to the same directions, the signal of β for a factor included in more than one model is the same in all models. Analyzing this tables, p-values higher than the acceptable 0,005 indicated that some variables cannot have the influence suggested by the model and can even have no influence in pedestrian crash phenomena.

By other hand the small data set can explain this p-values and as suggested by the models have more predictive capacity than the null model Table 12.

Entering dipper in the model evaluation interesting inputs for urban planning and city governance can be extracted.

The comfort factor and related variables show a protective influence in the number of pedestrian crashes. Validating the idea that better pavement and urban shared areas as gardens contribute to increase the protection of the populations from this type of accidents, and enforcing the importance of maintenance works in the urban spaces.

Also the Commitment and Legibility appear as negatively connect with crashes and consequently as measures of populations protection. Environments more easy to understand and use turn to be more save to pedestrian and this can be explained by the increase of knowing feel and the correct understand of what to do and where to be in the street. In this point is relevant to understand the correlation between the increase of sidewalk width and the interventions standardization as ways to assure less pedestrian accidents and fatalities, being these variables a part of the commitment factor.

By other hand surprising correlations are revealed by the models the factors convenience, connectivity and safety present positive relation with the number of crashes. For these conclusions some explanations can be contemplated. The more sense of safety can induce in pedestrians and vehicles the sense of confidence and this can conduct to a higher number of pedestrian crashes. Additionally, better values of convenience bring more people to walk one streets wishing to enjoy open services and daily business, more pedestrians will conduct, unfortunate, to a more crashes.

The relation between connectivity and pedestrian crashes can indicate the need to review urban planning rules and parameters, although the pedestrians appreciate more direct paths and crosswalks in interception points this can be an increase of the risk of being a crash victim.

Finally, the inputs given by the factors directly related with the fatality: % Sex Fem – Percentage of female victims in a segment pedestrian crashes, % Senior – Percentage of senior victims in a segment pedestrian crashes and % Night – Percentage of pedestrian crashes occurred by night in a segment. The first factor % Sex Fem negative coefficient is aligned with Díaz 2002 that men are exposed to risk in pedestrian crashes, this do not permit conclude much about urban environment but indicate the need to sensitize this part of the population about the traffic exposer risks mostly pedestrian crash risk. Also % Senior negative coefficient not permit big urban conclusions but appoint to a surprising smaller risk of pedestrian crash for elder people, it can be motivated by a reinforced caution and precaution in street walking and crossing. The last factor is % Night which have a negative β value, based on this value is valid consider that low luminosity and visibility are a motivation for having more precaution and alertness for both pedestrian and drivers.

In conclusion this work shows that exists a correlation between the number of pedestrian cashes and the road characteristics, in the study area. Also the more walkability a segment is the higher is the pedestrian accident frequency, the variability explain by this model is 70% related with walkability factors and only 30% related with the victims and the occasion.

REFERENCES

1. Blazquez, C. & Celis, M. (2013). A spatial and temporal analysis of child pedestrian crashes in Santiago, Chile – Accident Analysis & Prevention
2. Chiou, Y. & Chiang, F. (2013) Modeling crash frequency and severity using multinomial-generalized Poisson model with error components, Accident Analysis & Prevention
3. Clifton, K. & Kreamer- Fults, K. (2006). An examination of the environmental atribute associeted with pedestrian-vehicular crashes near public schools
4. Clifton, K., Burnier, C. & Akar, G. (2009) Severity of injury resulting from pedestrian-vehicle crashes: What can we learn from examining the built environment. Transportation Research Part D
5. Cottrill, C. & Thakuriah, P. (2010) Evaluating pedestrian crashes in areas with low-income or minority populations. Accident Analysis & Prevention
6. Elias, W. & Shiftan Y. (2014). Analyzing and modelin risk exposure of pedestrian chindren to the involment in car crashes – Accident Analysis & Prevention
7. Garder, P. (2004) The impact of speed and other variables on pedestrian safety in Maine. Accident Analysis & Prevention
8. Griswold, J., Fishbain, B., Washington, S. & Ragland, D. (2011) Visual assessment of pedestrian crashes. Accident Analysis & Prevention
9. Hauer, E. (1997) Observational before-after studies in road safety. Pergamon, Oxford
10. Hilbe, J., Negative Binomial Regression, Cambridge, UK: Cambridge University Press (2007) Negative Binomial Regression - Cambridge University Press
11. IMT, 2012. CiclAndo - Plano de Promoção da Bicicleta e Outros Modos Suaves 2013>2020, 92
12. IMTT, 2011. Acalmia de Tráfego. In Colecção de Brochuras Técnicas/Temáticas - Pacote da Mobilidade
13. IMTT, 2011. Rede Pedonal – Princípios de planeamento e Desenho. In Colecção de Brochuras Técnicas/Temáticas - Pacote da Mobilidade
14. Leden, L. (2002) Pedestrian risk with pedestrian flow. A case study based on data from signalizes intersection in Hamilton, Ontario. Accident Analysis & Prevention
15. Lee, C. & Abdel-Aty, M. (2005) Comprehensive analysis of vehicle crashes at intersections in Florida. Accident Analysis & Prevention
16. Lord, D., & Mannering, F. (2010). The statistical analysis of crash-frequency data: a review and assessment of methodological alternatives. Transportation Research Part A: Policy and Practice, 44(5)
17. McCullagh, P. & Nelder, J. (1989). Generalized Linear Models, Second Edition. Boca Raton: Chapman and Hall/CRC. ISBN 0-412-31760-5
18. Ministério da Economia, 2014. Plano Estratégico dos Transportes e Infraestruturas - Horizonte 2014- 2020
19. Ministério da Economia e do Emprego, 2011. Plano Estratégico dos Transportes para o Horizonte 2011-2015 - Mobilidade Sustentável
20. Moura, F., Cambra, P.; Gonçalves, A. (2014): "IAAPE - Pedestrian accessibility and attractiveness assessment tool when planning for walkability", CITTA 7th annual conference
21. Moura, F., Cambra, P., & Gonçalves, A. B. (2017). Measuring walkability for distinct pedestrian groups with a participatory assessment method: A case study in Lisbon. Landscape and Urban Planning
22. Moura, F. (2015). Transport Demand Modeling – Generalized Linerar Models, Lessons Material
23. Pordata, 2015. População residente segundo os Censos: total e por dimensão dos lugares
24. Pulugrutha, S. & Sambhara, V. (2011) Pedestrian crash estimation for signalizes intersections. Accident Analysis & Prevention
25. Shankar, V., Ulfarsson, G., Pendyala & Nebergall, M. (2003) Modeling crashes involving pedestrians and motorized traffic. Safety Science
26. Sze, N. & Wong, S. (2007) Diagnostic analysis of the logistic model for pedestrian injury severity in traffic crashes. Accident Analysis & Prevention
27. Washington, S., Karlaftis, M. e Mannering (2003) Statistical and Econometric Methods for Transportation Data Analysis, CRC
28. Wier, M., Weintraub, J. Weintraub, Humphreys, E., Seto, E. & Bhatia, R. (2009) An area-level model of vechicle-pedestrian injury collisions with implications for land use and transportation planning. Accident Analysis & Prevention