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The role of accessibility and connectivity in mode choice. A structural equation modeling approach.

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Abstract

This study addresses the effect that characteristics of the Public Transport (PT) network layout and service provision have on mode choice, mainly focusing on accessibility and connectivity. Using data from a mobility survey conducted in Lisbon, Portugal we model the binary choice between PT and private car through a structural equation model. The results indicate a duality in the choice process; good accessibility of the system as a whole encourages PT use but poor connectivity on a particular trip might deter it. A convergence of good performance both in overall accessibility and trip specific connectivity seems necessary for an individual to choose PT over private car.

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Keywords: public transport; mode choice; structural equation modelling

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1. Introduction

The expansion of urban areas around the world constantly creates new mobility challenges to transportation planners. Public transport – transit (PT) is perhaps the easiest and most efficient way to solve many of these issues, especially in dense urban areas. An efficient PT system can lead the way to a greener and more sustainable city, serving the peoples' mobility needs (Haghshenas & Vaziri, 2012). This however, clashes with the current social norm favorable to private vehicles; as well as the feeling of freedom and ease that they give to their users.

We come across mode choice decisions several times in our everyday life. Many of us are captives to a specific mode (Beimborn, et al., 2003), but this can change depending on the regularity and type of the trip. In order for PT to be a competitive alternative with private car, its overall quality of service needs to be improved. Quality of service is usually addressed as the overall performance of a given PT system. Operators and authorities frequently focus on improving service reliability, introduce new information services and provide better riding experience (i.e. safer and cleaner vehicles and infrastructure). The literature has explored these possibilities in depth, but it is the authors' belief that regular satisfaction assessment techniques are unable to find ways for PT to attract new users; a change in the structure of the network is required instead.

In this paper we examine mainly two aspects of PT operation and design: accessibility and connectivity. In the literature these elements are very closely related and often confused or mentioned as one. In this work we address accessibility at the strategic tactical level, and we define it as the ease of access to the PT system and the diversity of land use, both combining into the possibilities of a user to perform his desired activities. Connectivity on the other hand is the performance of the PT system in terms of time, speed, directness of travel and number of transfers for a specific origin-destination connection. We use travel data from a small mobility survey conducted in Lisbon in 2011 and examine whether these system's design concepts have an effect on the final mode choice.

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This paper is divided in four main sections; after this brief introduction, a literature review about mode choice, captive and non-captive users, PT accessibility and connectivity is provided, followed by the description of our methodological approach and the calibration of the model as well as the discussion of the obtained results; finally the paper ends with some conclusions and thoughts for further research.

2. Literature

The modes that we use to cover our mobility needs can be categorized in several ways. Motorized vs. non-motorized; private vs. public; fixed route vs. variable route are just a few. For most trips or trip chains that we do, there are a number of possible alternative modes or combination of modes to pick from. Every time we have to choose how to make a trip there are several factors that influence our decision. Some of them are easier to spot and understand and others require a more in-depth analysis.

A commonly used term in mode choice research is captivity/captive to a specific mode (Beimborn, et al., 2003; Habib & Weiss, 2014). This expression refers to an individual that does not consider other transport alternatives for his mobility needs. There are two types of captivity, captivity by force or by choice (Jacques, et al., 2013). Captivity by force is the situation where there are no other viable transport alternatives. Usually a person is a car captive when PT stops are too far away from his origin and/or destination. A PT captive is usually an individual that doesn't have a private car or motorcycle and his travel needs can't be done by walking. The phenomenon of a user having the ability to use more than one transport mode, but completely disregarding all the options but one is called captivity by choice. This usually happens because of some personal attitude towards a specific mode, positive or negative (sensation of freedom when driving, ability to engage in other activities when using PT, etc.). Sometimes bad experiences on a random trip (accident, theft) can cause major dissatisfaction for that mode and the user doesn't consider it as a feasible alternative.

From a Travel Demand Management (TDM) perspective, captive by choice users are more difficult to influence than the others. In regards with sustainable transport in urban environments, the limited options of forced captives make them a factor to be considered in any case, while captives by choice are an ambiguous issue. Car captives can often cause problems to the application of sustainable policies, while captives to PT or non-motorized modes may be considered a positive influence. Understanding the dynamics behind choice captivity is one of the keys towards more effective and sustainable transport planning (Beimborn, et al., 2003).

Therefore, captivity plays a dominant role on the decisions regarding the transport mode of our trips. However not everyone is a captive user, and even those that are, are usually driven by different attributes of a mode. Understanding mode choice has been a research focus for many years and socio-demographic characteristics are used to understand the behavioral drives behind it (Klöckner & Friedrichsmeier, 2011). But as Goodwin (1995) noted almost 20 years ago, the most important thing that we need to understand when talking about travel behavior is that every person is different. Many researchers have tried to segment the market into groups and distinguish the differences between them (Beirao & Cabral, 2007). Some of the methods used to do this task include: behavior change based on family, social status or location (Anable & Gatersleben, 2005); clustering of travel attitudes, preferences or motivations (Vredin Johansson, et al., 2006); and travel habits and behavior homogeneity (Gärling, et al., 1998). They all have their own explanation of how and why people in each group behave like they do. The psychological aspects in the behavior behind mode choice decisions have also been examined (Bronner, 1982; Donald, et al., 2014). From the available literature we may conclude the existence of a link between attitudes and socio-demographics. However the difficulty in identifying the composition of different user groups in the society and the variation between urban contexts makes this link harder to recognize and confirm.

The attributes of the trip itself play if not the most, one of the most important roles in our decision process; and trips can vary. Differences in distance (Scheiner, 2010) and travel agenda complexity (Bhat, 1997; Ye, et al., 2007) may change our mode choice, but trip purpose and timing are two of the most important variables. There are many factors that are interrelated with them, but perhaps the biggest difference is our attitude and behavior towards them (Azari, et al., 2013). There is an extensive body of literature on the mode choice differences between work and non-work trips, commuting and non-commuting trips (Whalen, et al., 2013), shopping (Bhat & Steed, 2002), leisure and other trip purposes, during peak hours or not. Characteristics like repetitiveness, lack of time flexibility (Nurul Habib, et al., 2009), are evident in commuting work or study trips and often cause a form of captivity for these specific trips.

Another interesting aspect of mode choice is the difference between objective and subjective choice sets (Van Exel & Rietveld, 2009). The objective choice set of a person is the total of transport alternatives that are available to him, while the subjective choice set is the subset of the alternatives that the individual knows off or considers plausible and desirable. Our modal decisions are done with the subjective choice set, and may sometime exclude us from an alternate option that may serve us better; for example a captive by choice may consider his mode as his only alternative, therefore making this his subjective choice set, ignoring the objective choice set that may include other possibilities (Srinivasan, et al., 2007).

In most urban areas in developed countries modal share is heavily favoring private modes, mostly private car. When trying to develop TDM measure to influence mode choice towards PT, two approaches can be taken. The first includes implementing policies and rules that restrict or reduce car use in the CBD, while the second aims to improve the quality of service of PT, thus making it a more attractive alternative. There is extensive literature on this topic, trying to point out potential improvements and innovations that can make that happen.

One of the key issues to be addressed is accessibility, which represents the potential of the user to perform his activities, closely related with land use location. We may distinguish two different perspectives to this concept. The first one is the proximity relative to the points of access to the PT system, both at origin and destination, which has been proven a very deciding factor on the modal choice process (Givoni & Rietveld, 2007; Moniruzzaman & Páez, 2012). The second perspective is the easiness of displacement considered to "cost" (in time or tariff) to reach the desired activities. This is associated with the build environment, namely its density, diversity and design, usually called the 3D's (R. Cervero & Kockelman, 1997), both at trip origin and destination. Modal share tends to shift in favor of PT or non-motorized modes at high densities of 3D's (Taylor, et al., 2003), high diversity of land use (Robert Cervero, et al., 2009) and the number of jobs accessible (Thakuriah & Metaxatos, 2000). Some authors analyze the activity space diagram of users in order to identify their space of activity. The easiness of displacement in this area may play a vital role in their mode choice (Miller, 1991). In general several studies (Alshalalfah & Shalaby, 2007; Robert Cervero, et al., 2009; Taylor, et al., 2003) have shown that increased accessibility is correlated with increased PT share.

Another area that has a big influence on the share of PT is connectivity. We define connectivity as the ease of accessing a specific location in the urban area using PT. Factors like travel time and number of transfers are related with the design of the network and sometimes them having high values plays a deterrent role in the choice of PT as a transport mode (Guo & Wilson, 2011). Other aspects, like the route of the PT service, change travelled distance vs. actual distance between origin and destination affect the speed of PT (Raveau, et al., 2012). These come in direct contrast with the ability of private vehicles to choose direct routes to the destinations and achieve higher speeds; and hence are restricting parameter for choosing PT (Beimborn, et al., 2003).

Data gathering for mode choice preferences is done through revealed and stated preference surveys and interviews (Azari, et al., 2013; Hensher & Rose, 2007). These surveys are often used to identify various levels of attractiveness to different available alternative modes (Abou-Zeid & Ben-Akiva, 2011; Páez & Whalen, 2010). Some issues related with stated preference surveys are non-trading and lexicographical choice (Hess, et al., 2010). Non-trading is something that often occurs with respondents that are choice captives, always picking the same mode no matter the attributes related with it and the other alternatives. Lexicographic responses arise when someone will always prefer the cheapest or fastest alternative, regardless of the mode. Lexicographical responders are evident in simple tradeoffs between time and cost; and are harder to spot in more complex experiments when more alternatives, besides time or cost, can influence their decision.

For the development of mode choice models, the most widely used tool is discrete choice modeling, under its diverse forms. Multinomial logit (MNL) allows the modeling of multiple options, making it the most used method in mode choice modeling (Azari, et al., 2013; Bhat, 1997; Nurul Habib, et al., 2009). Binary logit is a particular case of MNL that examines the choice between two alternatives and thus is used only in simple "do or don't" scenarios (Correia & Viegas, 2011). In the case that two or more transport alternatives share common characteristics and therefore are correlated with each other nested logit is used (Hensher & Rose, 2007). Mixed logit models are used when instead of a single response on mode choice preference, a distribution is given (Crabbe, et al., 2014). In this case the coefficients of the model don't correspond do a single value but are represented by statistic distribution. Other techniques for predicting travel behavior include Bayesian and neural networks (Omrani, et al., 2013; Wu & Yang, 2013).

Structural equation modeling (SEM) is another modeling tool that is used in transportation research to evaluate complex relations such as travel behavior (Donald, et al., 2014; Klöckner & Friedrichsmeier, 2011; Van Acker, et al., 2007). In this paper, we use this latter method to try to assess how PT planning, measured through accessibility and connectivity, may influence mode choice. This knowledge may allow induce more PT use against private motorized transport (PrT).

3. Data

For this research we used data from a mobility survey for Lisbon conducted in 2011 (Santos, et al., 2011) that collected information about users' revealed mobility and their preferences. The data covers the entire Lisbon Metropolitan Area (LMA); the LMA is separated in 281 zones and 35,487 census blocks, from which 118 zones and 3,623 census blocks respectively are inside the city of Lisbon. The survey consisted of three main parts: socio-demographic information, revealed mobility and stated preference. In the revealed mobility sections respondents recorded their mobility for their previous weekday. Ten different transport alternatives were used to cover all possible mode combinations: bus, car, car and public transport (e.g. car plus bus), combination of light and heavy public transport (e.g. bus plus subway), heavy transport (e.g. subway or commuter rail), motorcycle, taxi, cycling and walking. The survey had 1993 responses and the total number of recorded trips was 3911. However we took into account only survey respondents that live within the city of Lisbon (382 cases) and trips with origin and destination in the city limits (892 trips). The trips origins and destinations can be seen in Figure 1a and Figure 1b. We can see that there is a higher concentration of observations in areas with higher net human density as expected. The most used mode is private car, with a total of 330 trips, while bus and heavy PT are the most appealing PT options, with 174 and 195 trips respectively. Walking is also a very popular choice, with 136 trips, mainly for people whose mobility is characterized as local.

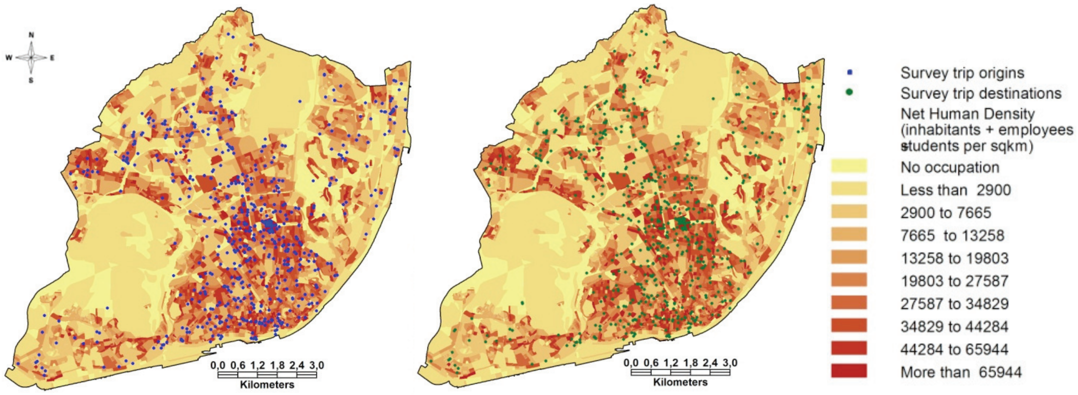

Figure 1 a) Trip origins b) Trip destinations

In the revealed mobility section of the survey, respondents were asked on every trip to state which of the other transport modes they considered as a feasible alternative for their trip. Using this we were able to separate the users in PT captives (those that did not consider any of the private motorized modes), car captives (those that did not consider any of the PT alternatives) and non-captives. For our analysis we used only trips whose respondents were classified as car captives and non-captives, having a total of 530 trips. Out of these 530 trips, 316 were done by private car (288) or motorcycle (28). Bus and heavy PT remain the most used PT options, with 56 and 79 trips correspondingly; 45 trips were done on foot, while the rest are a combination of PT modes and taxi (14). This data segregation was done because as identified in the literature, PT captives will use PT modes regardless of the service attributes or their characteristics. Thus we considered more important to examine the rest of the trips to understand if some socio-demographic or PT elements play a role in the mode choice decision.

4. Measurements

In order to assess the impact of the PT network design on mode choice, a set of measurements that characterize the accessibility and connectivity of each location as source of mobility was developed.

The accessibility measurements developed for this study were based on a gravity based model that presents a distance-decay function calibrated for Lisbon and PT travelling based on Martinez and Viegas (2013). In that paper the authors present a new accessibility modeling procedure calibrated from individual stated preferences data on how they access different types of land uses using different transport modes. This division by transport mode and land use type allowed the computation for each census block of an equivalent interaction mass with opportunities. The developed procedure requires a detailed land use database for each census block with the specification of the size of the activities, the number of employees or the number of students, as well as calibrated networks for the different modes (i.e. public transport, private car). For the current study the different land uses or activities tested were: employment, private services, public services, retail, leisure, health or medical care and schools (elementary and high schools). The developed GIS procedure computes the required time to reach by PT each activity/service for each census block within 60 minutes threshold. This time period was set due to the low distance decay value obtained for land uses located farther than 60 minutes away. Proximity to PT stops was also used as an accessibility indicator at the census block level. PT stop location influence mode choice greatly and land use patterns change around PT infrastructure, especially in heavy transit systems (Luis M. Martínez & Viegas, 2012).

As identified in the literature, quality of connectivity is a function of the spatial performance of the connections between the different zones. The measurements that were developed for connectivity are focusing on how an area is linked by PT with the rest of the city. Using a calibrated PT network, and having as spatial unit the aforementioned 118 zones, we used a fastest path algorithm to compute the best PT alternative between all zones. The obtained path is then decomposed in: access walking time to boarding stop/station, waiting time, on-board time, transfer time and access time from stop/station to final destination. Using this database for each zone, several measurements can be calculated: number of transfers, linear speed, directness, access time, on-board time, on-board speed and the characterization of the multimodal trip (i.e. bus+subway). Having created this matrix for all destinations from every origin we calculated the average value of each measurement for all origin zones. But each zone generates a different number of trips depending on its size, activities, etc. Therefore the measurements needed to be weighted to have a comparable value. This was achieved by estimated the percentage of trips that each zone contributes to the total. The following equation shows how the new weighted measurements were calculated.

$$M_0 = \frac{\sum_{d}^{119}\left(w_d \times m_d\right)}{\sum_{d}^{119} w_d}$$

Where: M_0 = Average weighted value of a measurement for an origin zone
w_d = Weight for each destination zone
m_d = Measurement value for each destination zone

To incorporate additional exogenous variables, other land use and aggregate socio-demographic data was also collected. From the land use side, a land use mixture indicator for each zone was computed using the entropy index defined by Cervero (1997). Regarding demographic information, the percentage of age groups and the number of residents, students or employees in each zone was also computed.

Since the accessibility measurements that were computed at the census block level while the connectivity measurements on the zone level, we tried to match the aggregation of both measures. To overcome this, the measurements of each zone were assigned to all the census blocks of that zone. Using the measurements that were previously computed for all census blocks each trip was assigned a set of variables depending on its OD pair. The accessibility indicators had separate values for origin and destination, while connectivity indicators were specific for the OD pair. Since accessibility and connectivity have many factors and measurements that are interrelated with each other we performed two factor analyses with principal components extraction method and orthogonal rotated correlation matrix (Varimax) in order to create independent variables that can be used in our model. The first factor analysis included the accessibility and land use measurements while the second one the connectivity measurements. Some of the resulting factors were used in the model. The resulting factors and loadings can be found in Table 1.

Table 1: Factor Analysis

	1st Factor Analysis (Accessibility and Land Use)			
Characterization of factors	Accessibility D	Accessibility O	Accessibility 3	
Variables & loadings	Entropy D - 0.612	Entropy O - 0.580	PPresure D - -0.156	
	PPresure D - 0.619	Zemployment D - 0.983	Dest - 0.774	
	Zemployement O - 0.962		Origin - 0.806	
	2nd Factor Analysis (Connectivity)			
Characterization of factors	Connectivity 1	Connectivity 2	Connectivity 3	Connectivity 4
Variables & loadings	OB time - -0.213	Tran - 0.869	Subway Share - -0.960	Ratio Dist LinD - -0.881
	OB speed - -0.214	TranTime - 0.772	TranTime - 0.456	Speed - 0.844
	Rail share - 0.978	OB speed - 0.852	Speed - -0.337	OB speed - 0.340
	TranTime - 0.186			Tran - -0.272

5. Model

In order to assess the link between the accessibility and connectivity measurements and mode choice, a Structural Equation Model (SEM) formulation was used. Since SEMs can handle indirect and multiple relationships and also study reverse relationships, we consider it a particularly adequate as a tool to model the complex relationships such as the ones pursued in this study.

The use of SEMs is becoming more common in the last decade in the field of Transportation. The use of specific packages such as LISREL (Linear Structural Relations) (Jöreskog, et al., 1988) and AMOS (Asset Management Operating System) (Arbuckle & SPSS Inc., 1997) have greatly enabled the use and application of SEM techniques. SEM represents an evolution and a combination of two types of statistical methods: factor analysis and simultaneous equations models (Kaplan, 2009) and variables can be either exogenous or endogenous (Golob, 2003).

SEM tools are constituted of two main parts. (i)A latent variable model which describes the relationship between the endogenous and the exogenous latent variables and allows the direct assessment of both the path and the strength of the underlying impacts among these variables. (ii)A measurement model which depicts the correlation between latent and observed variables (Bollen, 1989). The most common application of SEM is confirmatory analysis, where the objective is to test whether a set of data fits an a priori hypothesized measurement model. Another application of SEM is path analysis where it is used to measure the direct dependencies among a set of variables.

We used a path analysis with a forward procedure that enables the estimation of mode choice given a set of observed measurable variables. Given our objectives, the use of latent endogenous variables was avoided in order to ensure the use of the resulting model for forecasting. In our estimation process, as binary variables are present in the model structure, it was computed through Bayesian Estimation (BE), including the estimation of means and intercepts.

Most of the research using SEM on understanding travel behavior focuses on the outputs of mobility instead of the choice decision of the user. In our approach we want to explain the choice between PT and PrT based on the accessibility and connectivity of the trips origin and destination. For this purpose we treated all PT alternatives plus walking as PT.

As mentioned in the methodology for our modeling procedure we used SEM with no latent endogenous variables. Instead we used the factors that were computed with the factorial analyses as unobserved exogenous variables, explained by some of the observed exogenous variables. Those factors, together with the socio-demographic characteristics and the activity data collected from the survey were used to model the choice between PT and PrT.

There were several model formulations; the one yielding the best results is presented in Figure 2. The measurements, factors, and socio-demographic variables that were used in this model can be seen in Table 2.

Table 2: Model Variables

	Variable Name	Variable Type	Variable explanation
	Accessibility D	factor	deals with trip destination characteristics
Factors	Accessibility O	factor	deals with trip origin characteristics
	Connectivity 1	factor	deals with directness of the trip
	NoCar	binary	value of 1 if no car
Socio-demographic variables	PTpass	binary	value of 1 if PT pass
	Worker	binary	value of 1 if employed
Activity variables	Night	binary	value of 1 if trip during night
	ZEmployment O	standardized	jobs accessible from origin within 60 minutes
Accessibility variables	ZEmployment D	standardized	jobs accessible from destination within 60 minutes
	Dest	measured	walking time required at trip destination
	Entropy O	continuous	value ranges from 0 to 1 (1 represents a heterogeneous area where all land-uses are equally distributed at origin)
Land use variables	Entropy D	continuous	value ranges from 0 to 1 (1 represents a heterogeneous area where all land-uses are equally distributed at destination)
	PPressure D	estimated	ratio of parking demand vs. parking availability
	Ratio Dist LinD	estimated	ratio of actual travelled distance and Euclidean distance
	Speed	estimated	door-to-door travel time by Euclidean distance
	Tran	measured	number of transfers
Connectivity variables	TranTime	measured	total waiting time at PT stops
	OBTime	measured	total in vehicle time
	OBSpeed	estimated	commercial speed
	Subway Share	estimated	percentage of distance in OD pair performed by subway

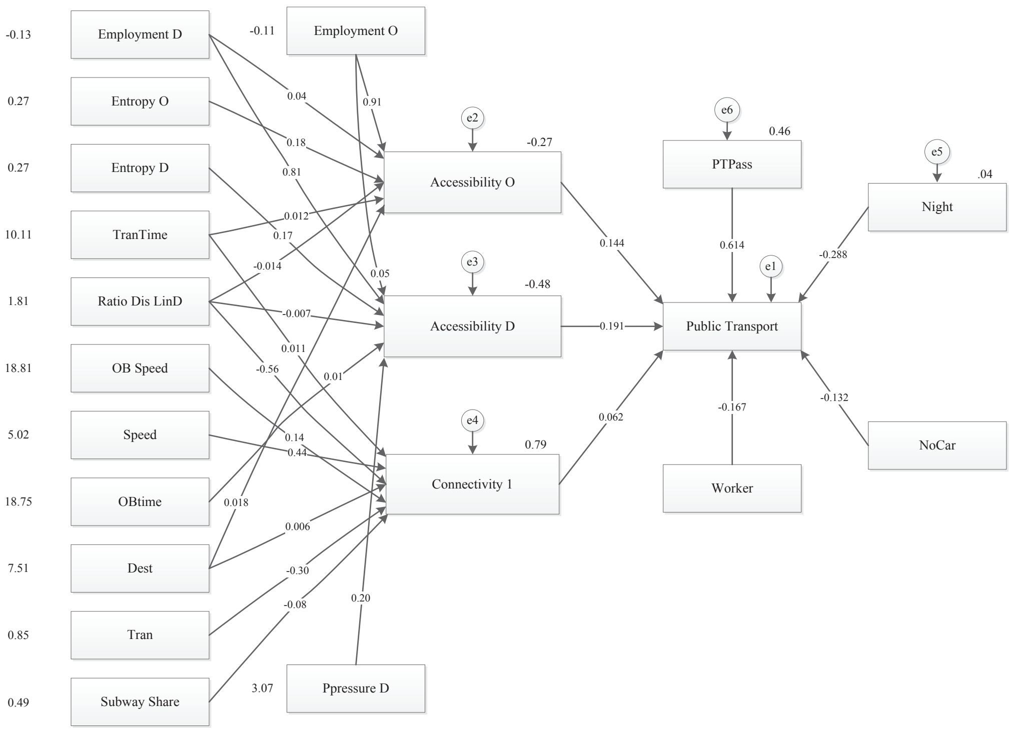

Figure 2: Model formulation, standardized regression weights, means and intercepts

6. Results

In this section, we will discuss the model's results. Three types of effects are taken into consideration when analyzing SEM results, namely: direct effects, indirect effects and total effects. Direct effects are the coefficients of the model obtained from the relation between a dependent and independent variables in each equation of the model, while indirect effects represent the influence of a variable through the mediation of at least a third variable. Finally total effects are the sum of the direct and indirect effects and represent the actual effect off each variable on the dependent variable (Kaplan, 2009).

There were several model formulations; the one yielding the best results is presented in **Error! Reference source not found.**. Since the dependent variable was binary, the mode choice model was calculated using Bayesian estimation on AMOS. For the validation of Bayesian SEMs, the literature has been mainly about the posterior variance (optimum value 0.5) the convergence of the process and according to some authors (Gelman, et al., 1996) the variances of the error terms can be used as a measure of model fit. In our case our model had a posterior variance of 0.367, showing an acceptable fit and the convergence statistic is 1.0007. The pseudo-R^2 estimated from the error terms is 0.607. All of our intercepts and variables are significant at the 95% confidence interval, except the factor "Connectivity 1" which is significant at the 80% interval. In the validation of the results our model was able to predict 66% of the actual choices the users made.

In general the effects obtained in the model, are consistent with what one would expect from the literature review. For the factors and the other variables that affect the dependent variable directly, the direct and the total effects are the same, while for the rest of the independent variables, the indirect and the total effects are the same. For this reason, in regard with the dependent variable, we will only comment the total standardized effects, which can be seen at Table 3. Before that we will briefly discuss about the direct effects of the measurements on the factors.

For Accessibility D, employment opportunities and parking pressure at trip destination play the most important role. As expected, the employment opportunities at trip origin play most dominant part in Accessibility O, which is also influenced to a lesser degree by transfer time and the Ratio Dist LinD. In regards with the Connectivity 1 factor, the directness of the trip (described by Speed and Ratio Dist LinD) has twice as much importance than the number of transfers and five times the importance of on board speed (OB speed).

Proceeding now to the total effects, it's easy to perceive that having PT pass influences the mode choice towards PT when compared with other factors, while trips performed during night times push mode choice towards PrT. The rest of socio-demographic characteristics that we used, namely Worker and NoCar, seem also important, yet less significant. From the accessibility measurements, employment opportunities at origin and destination have around one fourth of the importance of owning a PT pass. From connectivity, the ratio of traveled distance vs. Euclidian distance (Ratio Dist LinD) plays the most important role, followed by Speed and number of transfers. These variables however, are almost insignificant for the choice of PT or PrT compared with the ownership of PT pass or night travel. On Table 3 bellow you can see the variables that have the highest impact on the dependent variable in bold.

Table 3: Total standardized effects

	Variables	Effect		Variables	Effect
Aggregated accessibility	**Zemployment D**	**0.159**	Connectivity	Ratio Dist LinD	-0.038
	Zemployment O	**0.141**		Tran	-0.019
	Dest	0.003		Subway Share	-0.005
Land use	Entropy O	0.026		Speed	0.028
	Entropy D	0.032		OBTime	0.002
	Ppressure D	0.038		OBSpeed	0.008
Socio-demographic	**Worker**	**-0.167**		TranTime	0.003
	Ptpass	**0.614**	Factors	**Accessibility D**	**0.190**
	NoCar	**-0.132**		**Accessibility O**	**0.145**
Activity	**Night**	**-0.288**		Connectivity 1	0.062

7. Conclusions

The paper has examined the elements of accessibility and connectivity in PT and their connection with mode choice. We make use of a revealed mobility survey data to calibrate a SEM.

The model uses the choice of PT or not as a binary dependent variable and inspects how accessibility and connectivity, along with socio-demographic and trip characteristics drive mode choice.

The results suggest that for individual choices trip accessibility plays an important role, while connectivity elements such as transfer time are less significant. This can be explained by the fact that when talking about individual trips, the user usually has a notion of the system performance in that specific OD pair in advance, but that does not reflect his perception of the system as a whole. It seems that accessibility, which considers all your potential mobility has a bigger impact in your decision than connectivity, which is related more with a specific trip. This indicates a duality in the choice process; at the first stage people decide to use PT generically if they have good PT accessibility and secondary for a specific trip, they use PT if they have good connectivity. But even if the connectivity of a specific trip is good, an overall bad accessibility would prevent them from using PT.

We can observe from the analysis that owning a PT pass plays a very important role in the mode choice process. The results suggest that connectivity and accessibility measures may also affect PT pass ownership and therefore we can claim that accessibility and connectivity have an even greater indirect effect towards PT choice. Possibly an increase in PT use might be better stimulated by measures aimed at an increase of PT pass ownership.

We should highlight that we focused our analysis on non PT captives, excluding people who can't use private motorized vehicles for their mobility. We focused on this area specifically because it's expected that improving network configuration and PT provision could impact mode choice in this group greatly. Yet we should acknowledge that the 59% of the respondents maybe driven by other types of incentives which in the case of PT captives may focus on price.

Our research was limited by data and focused only in the city of Lisbon, which is a dense urban area, part of a greater metropolis. It is possible that expanding the scope of research to a larger area might reveal other factors playing a more decisive role. Further research in this area is recommended, both on captive and non-captive user groups, in order to identify the effect that different elements have on mode choice for each group.

References

Abou-Zeid, M., & Ben-Akiva, M. (2011). The effect of social comparisons on commute well-being. *Transportation Research Part A: Policy and Practice, 45*, 345-361.

Alshalalfah, B., & Shalaby, A. (2007). Case Study: Relationship of Walk Access Distance to Transit with Service, Travel, and Personal Characteristics. *Journal of Urban Planning and Development, 133*, 114-118.

Anable, J., & Gatersleben, B. (2005). All work and no play? The role of instrumental and affective factors in work and leisure journeys by different travel modes. *Transportation Research Part A: Policy and Practice, 39*, 163-181.

Arbuckle, J., & SPSS Inc. (1997). *Amos user's guide, version 3.6*. Chicago, Ill.: Marketing Division SmallWaters Corporation.

Azari, K. A., Arintono, S., Hamid, H., & Davoodi, S. R. (2013). Evaluation of demand for different trip purposes under various congestion pricing scenarios. *Journal of Transport Geography, 29*, 43-51.

Beimborn, E. A., Greenwald, M. J., & Jin, X. (2003). Accessibility, connectivity, and captivity - Impacts on transit choice. *Transit: Planning and Development, Management and Performance, Marketing and Fare Policy, and Intermodal Transfer Facilities*, 1-9.

Beirao, G., & Cabral, J. A. S. (2007). Understanding attitudes towards public transport and private car: A qualitative study. *Transport Policy, 14*, 478-489.

Bhat, C. R. (1997). Work travel mode choice and number of non-work commute stops. *Transportation Research Part B: Methodological, 31*, 41-54.

Bhat, C. R., & Steed, J. L. (2002). A continuous-time model of departure time choice for urban shopping trips. *Transportation Research Part B: Methodological, 36*, 207-224.

Bollen, K. A. (1989). *Structural equations with latent variables*. New York: Wiley.

Bronner, A. E. (1982). Decision styles in transport mode choice. *Journal of Economic Psychology, 2*, 81-101.

Cervero, R., & Kockelman, K. (1997). Travel demand and the 3Ds: Density, diversity, and design. *Transportation Research Part D-Transport and Environment, 2*, 199-219.

Cervero, R., Sarmiento, O. L., Jacoby, E., Gomez, L. F., & Neiman, A. (2009). Influences of Built Environments on Walking and Cycling: Lessons from Bogotá. *International Journal of Sustainable Transportation, 3*, 203-226.

Correia, G., & Viegas, J. M. (2011). Carpooling and carpool clubs: Clarifying concepts and assessing value enhancement possibilities through a Stated Preference web survey in Lisbon, Portugal. *Transportation Research Part A: Policy and Practice, 45*, 81-90.

Crabbe, M., Akinc, D., & Vandebroek, M. (2014). Fast algorithms to generate individualized designs for the mixed logit choice model. *Transportation Research Part B: Methodological, 60*, 1-15.

Donald, I. J., Cooper, S. R., & Conchie, S. M. (2014). An extended theory of planned behaviour model of the psychological factors affecting commuters' transport mode use. *Journal of Environmental Psychology, 40*, 39-48.

Gärling, T., Gillholm, R., & Gärling, A. (1998). Reintroducing attitude theory in travel behavior research: The validity of an interactive interview procedure to predict car use. *Transportation, 25*, 129-146.

Gelman, A., Meng, X.-l., & Stern, H. (1996). Posterior Predictive Assessment of Model Fitness Via Realized Discrepancies. *Statistica Sinica*, 733-807.

Givoni, M., & Rietveld, P. (2007). The access journey to the railway station and its role in passengers' satisfaction with rail travel. *Transport Policy, 14*, 357-365.

Golob, T. F. (2003). Structural equation modeling for travel behavior research. *Transportation Research Part B-Methodological, 37*, 1-25.

Goodwin, P. (1995). Car Dependence. *Transport Policy, 2*, 151-152.

Guo, Z., & Wilson, N. H. M. (2011). Assessing the cost of transfer inconvenience in public transport systems: A case study of the London Underground. *Transportation Research Part a-Policy and Practice, 45*, 91-104.

Habib, K. N., & Weiss, A. (2014). Evolution of latent modal captivity and mode choice patterns for commuting trips: A longitudinal analysis using repeated cross-sectional datasets. *Transportation Research Part A: Policy and Practice, 66*, 39-51.

Haghshenas, H., & Vaziri, M. (2012). Urban sustainable transportation indicators for global comparison. *Ecological Indicators, 15*, 115-121.

Hensher, D. A., & Rose, J. M. (2007). Development of commuter and non-commuter mode choice models for the assessment of new public transport infrastructure projects: A case study. *Transportation Research Part A: Policy and Practice, 41*, 428-443.

Hess, S., Rose, J. M., & Polak, J. (2010). Non-trading, lexicographic and inconsistent behaviour in stated choice data. *Transportation Research Part D: Transport and Environment, 15*, 405-417.

Jacques, C., Manaugh, K., & El-Geneidy, A. (2013). Rescuing the captive [mode] user: an alternative approach to transport market segmentation. *Transportation, 40*, 625-645.

Jöreskog, K. G., Sörbom, D., & SPSS Inc. (1988). *LISREL 7 : a guide to the program and applications*. Chicago, Ill.: SPSS.

Kaplan, D. (2009). *Structural equation modeling : foundations and extensions* (2nd ed.). Los Angeles: SAGE.

Klöckner, C. A., & Friedrichsmeier, T. (2011). A multi-level approach to travel mode choice – How person characteristics and situation specific aspects determine car use in a student sample. *Transportation Research Part F: Traffic Psychology and Behaviour, 14*, 261-277.

Martínez, L. M., & Viegas, J. M. (2012). The value capture potential of the Lisbon Subway. *Journal of Transport and Land Use, 5*.

Martínez, L. M., & Viegas, J. M. (2013). A new approach to modelling distance-decay functions for accessibility assessment in transport studies. *Journal of Transport Geography, 26*, 87-96.

Miller, H. J. (1991). Modeling Accessibility Using Space-Time Prism Concepts within Geographical Information-Systems. *International Journal of Geographical Information Systems, 5*, 287-301.

Moniruzzaman, M., & Páez, A. (2012). Accessibility to transit, by transit, and mode share: application of a logistic model with spatial filters. *Journal of Transport Geography, 24*, 198-205.

Nurul Habib, K. M., Day, N., & Miller, E. J. (2009). An investigation of commuting trip timing and mode choice in the Greater Toronto Area: Application of a joint discrete-continuous model. *Transportation Research Part A: Policy and Practice, 43*, 639-653.

Omrani, H., Charif, O., Gerber, P., Awasthi, A., & Trigano, P. (2013). Prediction of Individual Travel Mode with Evidential Neural Network Model. *Transportation Research Record*, 1-8.

Páez, A., & Whalen, K. (2010). Enjoyment of commute: A comparison of different transportation modes. *Transportation Research Part A: Policy and Practice, 44*, 537-549.

Raveau, S., Guo, Z., Munoz, J. C., & Wilson, N. H. M. (2012). Route choice analysis for metro networks: a comparison between Santiago and London. In *EWGT 2012*. Paris, France.

Santos, G. D., Martínez, L. M., Viegas, J. M., & Alves, D. (2011). Design and deployment of an innovative mobility survey for the lisbon metropolitan area oriented to assess the market potential and obtain the best configuration of new alternative transport modes. In *European Transport Conference*. Glasgow.

Scheiner, J. (2010). Interrelations between travel mode choice and trip distance: trends in Germany 1976–2002. *Journal of Transport Geography, 18*, 75-84.

Srinivasan, K., Pradhan, G., & Naidu, G. (2007). Commute Mode Choice in a Developing Country: Role of Subjective Factors and Variations in Responsiveness Across Captive, Semicaptive, and Choice Segments. *Transportation Research Record: Journal of the Transportation Research Board, 2038*, 53-61.

Taylor, B., Miller, D., Iseki, H., & Fink, C. (2003). Analyzing the Determinants of Transit Ridership Using a Two-Stage Least Squares Regression on a National Sample of Urbanized Areas. *Annual Meeting of the Transportation Research Board*.

Thakuriah, P., & Metaxatos, P. (2000). Effect of Residential Location and Access to Transportation on Employment Opportunities. *Transportation Research Record: Journal of the Transportation Research Board, 1726*, 24-32.

Van Acker, V., Witlox, F., & Van Wee, B. (2007). The effects of the land use system on travel behavior: A structural equation modeling approach. *Transportation Planning and Technology, 30*, 331-353.

Van Exel, N. J. A., & Rietveld, P. (2009). Could you also have made this trip by another mode? An investigation of perceived travel possibilities of car and train travellers on the main travel corridors to the city of Amsterdam, The Netherlands. *Transportation Research Part A: Policy and Practice, 43*, 374-385.

Vredin Johansson, M., Heldt, T., & Johansson, P. (2006). The effects of attitudes and personality traits on mode choice. *Transportation Research Part A: Policy and Practice, 40*, 507-525.

Whalen, K. E., Páez, A., & Carrasco, J. A. (2013). Mode choice of university students commuting to school and the role of active travel. *Journal of Transport Geography, 31*, 132-142.

Wu, J., & Yang, M. (2013). Modeling Commuters' Travel Behavior by Bayesian Networks. *Procedia - Social and Behavioral Sciences, 96*, 512-521.

Ye, X., Pendyala, R. M., & Gottardi, G. (2007). An exploration of the relationship between mode choice and complexity of trip chaining patterns. *Transportation Research Part B: Methodological, 41*, 96-113.