THE INFLUENCE OF THE BUILT ENVIRONMENT ON THE TRIP CHAINING BEHAVIOR OF A LATIN AMERICAN CITY

BRUNO GONZALEZ NÓBREGA

MASTER'S THESIS IN TRANSPORTATION

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“Cars, in theory, give you a terrifically fast method of traveling from place to place. Traffic jams, on the other hand, give you a terrific opportunity to stay still. In the rain, and the gloom, while around you the cacophonous symphony of horns grew ever louder and more exasperated.”

-Terry Pratchett

DEDICATÓRIA

A Deus primeiramente;
Aos meus pais, Elizabeth e Júlio, pelo apoio na minha trajetória acadêmica e professional;
Ao meu irmão pelo apoio em todas minhas iniciativas.

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ABSTRACT

People seldom travel only for moving around, they travel to attend their needs. In this sense single trips models, used on transportation planning, cannot fully represent reality. Models that use chains of trips, also known as tours, may help to solve this problem and better understand mode choice, since literature shows that tours that start by car usually do not use other modes. There is an interest in determining what variables are significant for modeling trip chaining and therefore mode choice. However, despite the efforts, researchers still have to come to an agreement of the effects of land use on trip chaining. This study aims to further understand the influence of the built environment on two aspects of travel behavior: trip chaining complexity and mode choice across different populations. Using the data from the Federal District Urban Mobility Survey, six groups were formed, three income classes divided between workers and non-workers resulting in a total of 30,871 tours. Due to the different nature of data, the trip chaining behavior were modeled through a ordered logit model and mode choice modeled through a multinomial logit model. Results showed that the built environment had an effect on trip chaining, but that different classes are affected by different variables. Difference on the average income of the destination of a person and his home is significant across the studied populations, indicating that the trip chaining process might be sensible to how much one can afford in a region. The mode choice results showed that tours with more stops had a greater probability of using the car over transit, but it had no significant effects on choosing an active mode over car. By analyzing both results the research concludes that large trip chains may not be only in the realm of motorized travel.

RESUMO

As pessoas raramente viajam apenas para se locomover, mas para atender às suas necessidades. Nesse sentido, os modelos de viagens simples, amplamente utilizados em planos de transporte, não representam totalmente a realidade. Uma alternativa para melhorar o entendimento desse problema é o uso de modelos de encadeamentos de viagens. Existe um interesse em determinar quais variáveis são significativas para modelar o encadeamento de viagens e, portanto, a escolha do modo. No entanto, apesar dos esforços, os pesquisadores ainda têm que chegar a um acordo sobre os efeitos do uso do solo na cadeia de viagens. Assim, esse estudo tem como objetivo compreender a influência do ambiente construído em dois aspectos do comportamento de viagem: complexidade de encadeamento de viagens e escolha de modo em diferentes segmentos da população. Com os dados da Pesquisa de Mobilidade Urbana do Distrito Federal, foram formados seis grupos, três classes de renda divididas entre trabalhadores e não trabalhadores, resultando em um total de 30.871 viagens. Devido à natureza diferente dos dados, o comportamento de encadeamento de viagens foi modelado através de um modelo de logit ordenado e escolha de modo modelado através de um modelo de logit multinomial. Os resultados mostraram que o ambiente construído teve um efeito sobre o encadeamento de viagens, mas que diferentes classes são afetadas por diferentes variáveis. A diferença na renda média do destino de uma pessoa e sua casa é significativa entre as populações estudadas, indicando que o processo de encadeamento de viagens pode ser sensato para o quanto se pode pagar em uma região. Os resultados da escolha do modo mostraram que passeios com mais paradas tinham maior probabilidade de usar o carro em excesso de trânsito, mas não teve efeitos significativos na escolha de um modo ativo em vez de carro. Analisando ambos os resultados, a pesquisa conclui que grandes cadeias de viagens podem não estar apenas no domínio das viagens motorizadas.

INDEX

LIST OF TABLES

LIST OF FIGURES

LIST OF SYMBOLS, NAMES AND ABREVIATIONS

API – Application Programming Interface
AR – Administrative Region
BE – Built Environment
CBD – Central Business District
FDUMS – Federal District Urban Mobility Survey
GDF – Government of the Federal District (*Governo do Distrito Federal*)
IPEA – Institute for Applied Economic Research (*Instituto de Pesquisa Econômica Aplicada*)
UNESCO – United Nations Educational, Scientific and Cultural Organization
HHI – Herfindahl–Hirschman Index
MAUP – Modifiable Area Unit Problem
MNL – Multinomial Logit model(s)
OD – Origin/Destination
PDTT – Plano Diretor de Transporte sobre Trilhos
RTDP/FD – Federal District Rail Transit Development Plan
RUM – Random Utility Maximization theory
SE – Structural Equations
SEM – Structural Equations Model
SRID – Spatial Reference Identifier
SIRGAS – Geocentrical Reference System for the Americas (*Sistema de Referência Geocêntrico para as Americas*)
TAZ – Traffic Analysis Zones
USA – United States of America
VIF – Variance inflation factor

1 INTRODUCTION

Cars have made it easier for populations to live further from city centers, as they allow users to reach higher speeds. Since regions outside of traditional cities' limits have more available space, they are associated with large houses with ample gardens, and their urban form has fewer retail and office area and more dead ends, also known as cul-de-sacs, than urban centers. This phenomenon is known as urban sprawl and is related to the suburbanization of the population. The mentioned characteristics result in calmer, safer and greener streets, which in turn translate into more quality of life (NEUMAN, 2005).

However, in urban planning, urban sprawl is more often related to the problems it creates than to its benefits. Their issues have been especially discussed in the field of transportation studies Since road transport is generally preferred by governments, there has been a surge of issues, such as congestion in the streets, use of public space for parking, transit deaths and problems with air, soil and noise pollution (NAESS, 2006).

While some countries from the developed world are in the late state of this urban growth, most developing countries are still facing the problems related to the lack of proper city planning (BAUTISTA-HERNÁNDEZ, 2020). These problems are intensified by the lack of adequate infrastructure and by the rapid motorizations rates resulting in the decline of travel speed in all modes (KANDT, 2018).

One of the most used methods in the planning of transport solutions is the "4 steps model", in which a survey is performed to collect data about the transportation patterns; after those patterns are identified, the planner must conduct several simulations to evaluate which scenario has the better potential results. Over the years, there have been some critics of the traditional model, since it takes into account neither the activities that motivate people to travel nor the built environment in the city (SILVA, 2018).

One of the main criticisms is that the model does not evaluate the influence of the previous trip on the next one. As a solution many transport planners are migrating to activity-based models. In these, the traditional steps are substituted by an equivalent but more specific step. Rather than generating trips from a simple OD matrix, the activities must be generated and scheduled throughout the day (HASNINE & HABIB, 2021).

As out-of-home activities are usually scheduled, more than one is done per travel, as a manner of optimizing time. An example of this phenomenon is the manner in which a mother plans her day: she will take her children to school before going to work, or she will shop for groceries after work. Also, it is expected that, if she uses an automobile in her first trip-segment, she will use it in following trip-segments (CHOWDHURY & SCOTT, 2020A; HE *et al.*, 2020; LI *et al.*, 2020).

Other commonly studied aspect of travel behavior is its relationship with built environment. The influence of the latter on trips share and travel distance has been established in past works (MANOJ & VERMA, 2016; ZHU *et al.*, 2020). The most accepted understanding is that the denser the region is and more mixed land use it has, the less inclined to use cars the population will be. The opposite is also true: a land with a less mixed use and fewer people in it, such as American suburbs, influence people to take the car more often and make longer trips (CHOWDHURY & SCOTT, 2020b; DE VOS & WITLOX, 2016; DING *et al.*, 2014; MANOJ & VERMA, 2016).

The influence of built environment on trip chaining is not so clear. Some studies have found that denser neighborhoods induce simpler trips, with less stops. Other studies, however, have found that, with a higher density and a more mixed land use, people tend to carry out more complex trips, as they can optimize their travel by making more stops (ANTIPOVA & WANG, 2010; LEE, 2016).

Moreover, most of these studies are done in Europe or in the USA (DE VOS *et al.*, 2012), where cities have a CBD (CENTRAL BUSINESS DISTRICT) that most people don’t live in; those who do usually have a lower household income. Conversely, the suburbs away from the center are occupied by people with a higher household income. Research has shown that the contrary may be true in parts of the developing world, such as in Mexico (BAUTISTA-HERNÁNDEZ, 2020), where the poor live away from the CBD and, thus, make longer trips for their daily commute.

Brasília is no exception to the exposed state of affairs. According to Metro-DF (2018), there is a concentration of jobs on the center of the city, while most of its population lives far away from this center. Moreover, there is still a sizeable influx of migrants to the city, since it is relativity new and has many job opportunities. The capital of Brazil is thus a good example of a developing city and has much to contribute, regarding the effect of built environment on travel behavior.

1.1 PROBLEM DEFINITION

As cities grow both in population and in sprawl, more problems appear, such as crime, air pollution, traffic accidents, and congestion. Cervero & Kockelman (1997) indicate that some of these problems may occur because cities have become car oriented. Since cars permit greater travel distances, populations have migrated to less dense regions, such as suburbs, in a phenomenon known as urban sprawl. A urbanism philosophy, known as “new urbanism” proposes that an alternative for the mentioned issue is to alter the urban form to promote more sustainable travel behaviors. Lee *et al.* (2017), for example, indicate that, in the region of Los Angeles, short trips are seldom made by active modes or transit. They theorize that, since the built environment appeared as a significant factor in this decision, retail area and street design could help promote a more sustainable behavior.

The logic behind this relation may be explained by the conceptual land use transportation cycle proposed by Wegener and Fuerst (2000). In this framework, land use determines the location of activities. Since people must travel to get home or to participate in desired activities, they must use the transportation system, which can be measured in terms of accessibility, which is determined by the land use. As the population must allocate more time to mandatory activities, it may be implied, by an econometric view, that they will try to minimize travel time to allocate it in more non-work activities. One manner of doing that is by chaining these activities together in destinations close to each other, taking less time to go between them (CONCAS & DESALVO, 2014; HENSHER & REYES, 2000; HO & MULLEY, 2013).

The number of out of home activities a person partakes in before returning to his house is commonly defined as trip chain or tour. The more stops he makes, the more complex the trip chain or tour is. These activities can be made repeatedly throughout the week, such as commutes, or be more flexible, such as a visit to a park in the middle of a working day. It is theorized that people usually schedule their day before choosing how they will travel between their activities (SCHNEIDER *et al.*, 2021b). Planners, therefore, must be aware of these patterns to act accordingly. The more complex schedules get, the more inclined one is to choose a more flexible mode, such as an individual automobile (YE *et al.*, 2007).

One may infer that a dense location, which has a large variety of uses to be chained and great accessibility could minimize the costs of engaging in more activities. Although, in recent years, there has been a surge in the research investigating the influence of land use on various trip chaining aspects, such as trip chain complexity and mode choice, results have so far been contradictory (DAISY *et al.*, 2020; GRUE *et al.*, 2020).

Chowdhury and Scott (2020b) found that people living in high mixed-use neighborhoods trip-chain less, since they can coordinate trips where they live. Bautista-Hernández (2020) found that Mexico City residents tend to make less trips per tour when living in high density areas, while distance to center has no effect on any travel behavior variable. Ding *et al.* (2014) found that only diversity variables have some influence on travel choices.(MANOJ & VERMA, 2016) Manoj and Verma (2016) found that areas with higher density, diversity and distance accessibility have a negative influence on trip chaining. Ma *et al.* (2014), found that, in Beijing, people working in a denser area usually trip chain more, since there is a great availability of shops around work areas. Silva (2018), on the contrary, has found that, for some municipalities in Portugal, working in a denser area led to fewer stops in the tour. He also found that, after accounting for self-selection, land use variables have a negligible influence on travel behavior.

Additionally, Silva and Melo (2018) indicate that such variability in results may occur due to heterogeneity in studies or to regional differences. Urban disposition in American cities is quite different from that of European ones. The former are more auto-oriented, while the latter have a better disposition to transit and active modes (GUAN *et al.*, 2019). Also, developing countries conduct fewer research, making this relation even less clear (BAUTISTA-HERNÁNDEZ, 2020; ELIAS *et al.*, 2015; ETMINANI-GHASRODASHTI & ARDESHIRI, 2015).

In opposition to Western results, the population of Osaka, Japan, took more transit than private automobiles to trip chain. Therefore, regions that had a greater transit accessibility promoted a more sustainable and efficient way of engaging in commute and non-work activities throughout the day (SUSILO & KITAMURA, 2008). Although other places are yet to show similar results, this discovery implies that the built environment could possibly help solve the urban sprawl problems. Ho and Mulley (2013) mentioned that, although cars do more complex tours, a place with good transit accessibility and mixed land use could promote more bus and bicycle tours, with shorter distance. Finally, it is possible to foresee a hypothesis in which the built environment cannot change behavior, since it is incapable of satisfying the need for a flexible mode. Consequently, it is preferable for a planner to think of a different strategy , such as a Mobility as a Service (MAAS) solution, in which there is a greater flexibility of the transport supply (COHEN & JONES, 2020), combined with some built environment changes to help the transition (SCHNEIDER *et al.*, 2021).

Income is also commonly an important variable in determining travel behavior. People with higher income can afford to buy and maintain a car, which gives them more flexibility for longer and more complex tours (BOUKARTA & BEREZOWSKA-AZZAG, 2020; SADHU & TIWARI, 2016). Other demographic factors affect tour complexity and travel behavior. Traditional household roles play a part in determining mode choice and trip chaining complexity. The head of the family, the “moneymaker”, usually gets to use the car, leaving nonworking members fewer options to choose from. Also, as they are workers, they have more time constrains, leaving little time for groceries or taking the children to school, for example. Instead, such activities are carried out by nonworking members of the household, typically women, who end up trip chaining more (ELIAS *et al.*, 2015; SCHEINER, 2014; SUSILO *et al.*, 2019).

As exposed in this chapter, the effects of both variables on travel behavior are still unclear. In most regions, city planners, engineers, and architects struggle with proposing effective policies to promote a sustainable travel behavior, diverting from a car-oriented situation to a more transit-oriented and active one. The problem this study aims to solve is thus “**How the built environment affects tour complexity and mode choice in a city in a developing country?**”

1.2 RESEARCH GOALS

The objective of this study is to contribute to the understanding of the influence of built environment on travel behavior, focusing on trip chains and mode choice, since there are few studies on this topic, as of 2022. Also, it sought to deepen the understanding of this relation in a growing city of a developing country, to help propose more effective urban planning policies.

1.2.1 Main Objective

The main objective of this research is to develop models that determine the influence of built environment, and socioeconomic variables on mode choice and tour complexity of workers and non-workers, from multiple income classes.

1.2.2 Specific Objectives

- Understand the effects of built environment on both tour complexity and mode choice.
- Understand the effects of built environment, tour complexity and socioeconomic variables on mode choice.

1.3 MOTIVE

As in other cities, Brasilia faces problems of poor integration between transport and land use planning, even though the literature indicates that they both influence each other to some degree. Consequently, new residential and employment areas are created without a proper transport infrastructure to meet the demand, leading to further problems.

Not only that, but the agency responsible for the mobility plan seemly discontinued the original plan, since the last update on it was on 2014 (GDF, 2014; SEMOB, 2010). This initiative tried to work with the local zoning plan to create an integrated land use and transportation mobility plan for Brasília. However, this approach was not well developed since it did not account explicitly for land use variables. Finally, although there are more advanced models available for forecasting demand and planning, the agency keeps working with the "4 steps model", not accounting for the activities that motivate the trips.

As previously explained, to propose better policies, it is important to understand how the planned action will affect travel behavior. Even though there is a good number of research on the topic, it is early to affirm that the subject has been exhausted. Mixed results show that the relation between land use, trip chaining and travel behavior is a complex one, with great geographical variability. Consequently, solutions that may work well in some places, such as

MaaS, bike sharing services or the densification of a zone, may end up performing poorly in other. Such failures lead to arguments that the chosen solutions do not work well, but their shortcomings might be due to poor implementation strategies.

To aid the city government, local transport researchers have organized other models, in order to render proposed policies more precise. Recently, developed an activity-base mode choice model with a random forest algorithm, with the benefit of creating a cheap but precise method to forecast mode choice. Vanderley (2016) proposed a land use and transportation integrated model for the city based on the TRANUS and could simulate a scenario similar to the official plan. Even though both studies helped to better understand Brazilian travel behavior, they lack the understanding of the relation between built environment, trip chains and travel behavior. This research pretends to fill this gap, thus complementing both works and promoting more effective policies, considering both workers and non-workers from all income groups.

Also, even though Vanderley (2016) tried to model an integrated land use information with transportation, the lack of a structured and extensive land use database prevented him from making great advances. A similar approach was done by Nóbrega *et al.* (2019), in a smaller scale, but ended up facing similar problems. This indicates that, more research is needed to create a land use database for transport studies. Further research should not only construct such a dataset, but also determine the most relevant built environment variables for each income group.

Furthermore, this research helps to remedy the lack of academic works on the subject in the global south. As the countries on the global north gain a better understanding of this relation, they can develop more complex theories and technologies from big data technology. By understanding tour formation and built environment influence on it, it is possible to use smart card data to create an OD matrix, for example (CUI *et al.*, 2021). Most developing countries are yet to achieve the same level of knowledge on the basis interaction to develop a large-scale project as such.

1.4 DISSERTATION STRUCTURE

The methodological structure of this study is presented on Figure 1.1. This research is composed of 5 chapters: a brief introduction of the study and its objectives, a literature review of the effects of the built environment and trip chaining on mode choice, a description of the data and methods used, the results and its analysis and, finally the conclusions of the authors and recommendations for future research.

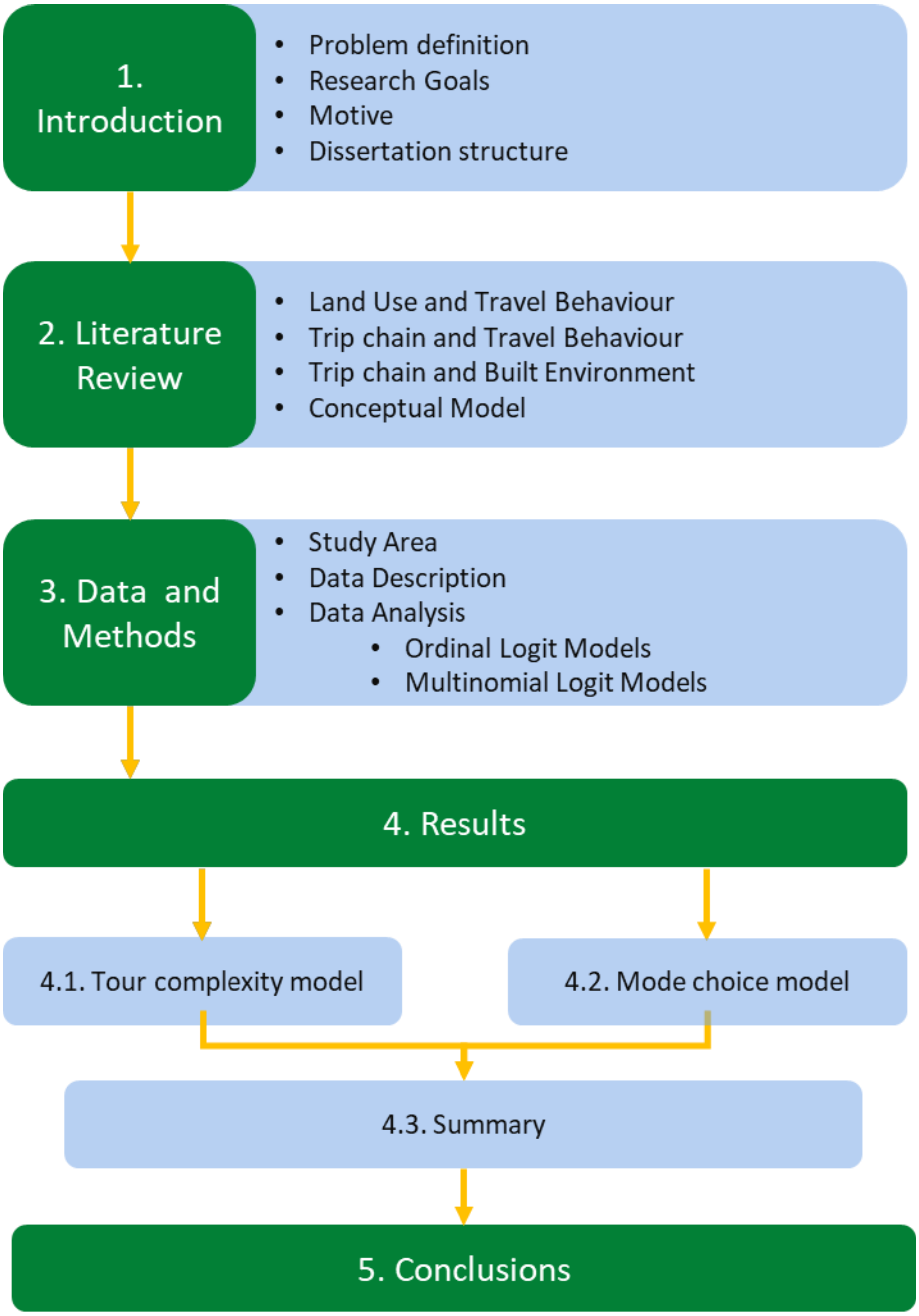

Figure 1.1 – Methodological design of this research

2 LAND USE AND TRIP CHAIN

2.1 LAND USE AND TRAVEL BEHAVIOUR

The influence of travel behavior and built environment has been studied for a long time. The idea that city planners could alter land use to induce a desirable travel behavior is attributed to the neo-urbanism movement. This movement argues that, by creating a pedestrian oriented design, cities could mitigate common congestion problems (CRANE, 1995).

The main idea is that the land use of a city and its transportation infrastructure are not individual systems; rather, they are integrated and dependent. The urban form determines the location of activities and, as most of them must be done out of home, people must travel, using the transportation system. Thus, regions with more accessibility, with a more robust transport infrastructure, are prone to have a more diverse use with more activities. This simplified model of this interaction is called “land-use transport feedback cycle” was proposed by Wegener and Fuerst (2000).

However, Crane (1995) argues that these effects may not be in the magnitude stated by the movement. By analyzing travel demand functions, he concludes that, while this “neo urbanism” may have had a positive impact on cities there was no good groundings for affirming that the built environment alone could mitigate transportation problems since its influence seemed minimal at the time.

Later, Ewing & Cervero (2010), evolved on this issue, carrying out a meta-analysis of the scientific findings regarding the influence of built environment on travel behavior. They found that such relation exists, but, as foresaw by Crane (1995), the individual strength of each variable is weak. This indicates that policies need to account for actions in various fronts to obtain the expected results.

Aston *et al.* (2020, 2021) updated those reviews confirming that the impact of the urban form on travel behavior exists to an extent. They argue that not only the impact of the variables is greater when grouped, but also the setting and context may influence this relation. Finally, all the reviews alert that, as this relation is not precise or even consistent, studies must be specific on what they cover and have a solid design, with both validations and bias control.

Studies usually group the built environment variables into clusters to better represent the influence of related variables in travel behavior. One of the most common type of clusters is the “3Ds”, coined by Cervero and Kockelman (1997). Such authors believed that most built environment attributes could be grouped as a Density, Diversity or Design variable, hence the abbreviation “3Ds”. After the evolution of studies, researchers felt the need to aggregate two more “Ds”: Destination accessibility and Distance to transit (EWING & CERVERO, 2010), reaching “5Ds”. In the same study, they propose two more “Ds”, Demand management, such as parking and tolls, and Demographics, which the authors understand that is not a part of built environment per se, but it influences its effect on travel behavior.

Density as a variable of built environment is self-explanatory. It measures how much of a variable there is in a certain unit of area. Examples include population density, residential density or employment density (Ewing and Cervero, 2010). In theory, a denser region would be more attractive for walking (ETMINANI-GHASRODASHTI & ARDESHIRI, 2015). Both Chen *et al.* (2008); Chen and McKnight, (2007) found that people in a very dense environment, such as Manhattan, used active transportation more often than people in the suburbs or less dense neighborhoods.

Density has also been hypothesized to influence travel distance and time. Zhang *et al.* (2012) found that, for American cities, both residential and employment densities have a negative impact on distance traveled by each vehicle, as did Pang and Zhang (2019), although they found that this effect is reduced when accounting for car ownership. Zhu *et al.* (2020), conversely, evaluated this hypothesis in the Hong Kong region, and, although population and job denser areas did reduce time and travel distance, regions that are already dense seemed to suffer from longer commutes. While density is a common variable in land use research, it seems to have by itself small impact on mode choice (CHEN *et al.*, 2008; CONCAS & DESALVO, 2014).

Diversity measures how diverse the built environment is, by analyzing how many different uses or how much of each type of occupation there is in a parcel of land. A planner might not induce the desired behavior in a city only by densifying it. If a region only has residences, its inhabitants will have to go elsewhere to conduct their activities. Thus, an area must not only have a degree of density but also several different options of activities to engage in. Moreover, as the distance between the activities gets shorter, diversity may promote more active travel, such as walking or bicycle (EWING AND CERVERO, 2010). Song *et al.* (2013) reviewed the different measures of land use mix in a city. They indicate that choosing a specific measure depends on the number of uses studied and the scale on which the analysis made. If more than two types are analyzed, it is recommended to use an Entropy Index or a Herfindahl–Hirschman Index (HHI).

The Entropy Index varies between 0, when there is only one type, to 1, when there is an equal area to each type of variable. By using the Entropy Index, Zhang *et al.*(2012) analyzed four American cities and came to the conclusion that people in a more diverse environment tend to use less car, since the average distance is smaller. Other studies have found similar results using this index, like Etminani-Ghasrodashti and Ardeshiri (2016) and van Acker and Witlox (2011). Similarly, the HHI is also calculated by the percentage of each type, however it has a greater interval, from 0 to 1. Although common in market concentration research in economics (SONG *et al.*, 2013), few transport studies calculate this measure. Eom and Cho (2015) used the HHI to discover that diversity promoted walking until a certain level, which after people start using motorized modes, consonant with Chowdhury and Scott (2020a) results.

Design variables are more related to characteristics of transport networks, such as street density, highway density, amount of cul-de-sacs, or the existence of pedestrian or cyclist dedicated infrastructure, like sidewalks, cycleways or crosswalks (EWING & CERVERO, 2010). As expected, regions with more walking facilities promote, to a certain level, a more active way of traveling (EOM & CHO, 2015) and possibly a lower auto ownership ratio at the region (SHAY & KHATTAK, 2012). Street connectivity, usually measured in intersection density, dead ends, and street density, has shown mixed results. While Frank *et al.* (2008) have found that more intersections and streets increased the likelihood of walking, Etminani-Ghasrodashti and Ardeshiri (2016) have found that a better connectivity leads to a more auto oriented design.

Destination accessibility is, as the name suggests, the measure of how easy it is to get to one's destination. As destination is a very broad term, this land use variable is usually related to commute or to shopping trips; as such, it is measured as the distance to the CBD (MANOJ & VERMA, 2015b), to one's job (HO AND MULLEY, 2015) or to the closest retail area or grocery store. Lee (2016) has found that the distance to the nearest store has a negative impact on the number of nonwork trips made by car, while the distance to the CBD has a small but significant impact on the distance traveled by car. Similarly, Neves *et al.* (2021) have found for the city of São Paulo that people who live farther from the city center prefer a motorized mode to travel, while those who work near the center usually walk more, since the other possible activities are closer to the workplace.

Finally, distance to transit is a self-explanatory term since this variable measures how far a person must travel to access the local public transport system. Apart from obvious measures, such as distance to the nearest bus or rail stop, the transit accessibility can be measured by the existence of rail, density of stops or even density of transit lines. Again, the logic behind this measure is that, if a person does not have to travel long distances to get to the stop, he may be more inclined to use this service instead of cars. This idea is easy to grasp and has been proved by some research over the years (LEE, 2016; VAN DE COEVERING *et al.*, 2021).

As can be interpreted from the descriptions and examples above, the borders between each "D" are slim and, more often than not, those groups intersect. So, it may be inferred from this that using the 3, 5 or even 7Ds may be too limited, even for making comparisons. In this article, employment density was used as a density variable, but it could be as easily interpreted as a Diversity one. Also, density is used sometimes as a proxy for accessibility measures (NOLAND & THOMAS, 2007).

Some authors used aggregated variables to account for built environment. Chen and McKnight, (2007) and Wallace *et al.*, (2000) did not study the effects of individual variables on travel behavior, as they preferred to classify the built environment in urban center or in suburban, urban and a heavily dense and mixed urban space. Another example is De Vos *et al.* (2021), where the researchers understood that the "Ds" exist, but are often corelated. Instead of analyzing each variable, they classified their built environment in suburban and urban ones. With this distinction, they used a structural equation model to evaluate the direct and indirect effects of this relationship and were able to determine that, although the built environment played a part in changing behavior, it was much more significant for leisure trips than for commutes. Although they were unable to explain how each variable influences the trip chaining behavior, they could get an ampler understanding of the urban form on travel behavior.

As mentioned before, other authors, such as Crane (1995) and, more recently, Stevens (2017), indicate that the mixed results combined with the small magnitude seen in research is enough proof that the new urbanism approach is not adequate for decision making. In response to Stevens (2017), Ewing and Cervero (2017) compared their previous work to the new one and suggested that Stevens' work, by mixing data from different countries, may have lost some of its explanatory power, incorporating data that would have been outliers in an American context. In fact, Neves *et al.* (2021), in his research in São Paulo, indicates that a mixed development might work better only in regions with greater social equality, since the poorer portion of the population cannot participate in activities in medium and high-income neighborhoods.

So, are cultural and geographical differences the only explanation to the aforementioned results? Many of the presented documents so far indicate that some biases may play a role in explaining build environment influence in travel behavior, especially residential self-selection and the Modifiable Areal Unit Problem (MAUP) (HONG *et al.*, 2014). Residential self-selection bias occurs when the people chose a place to live that is consonant with their lifestyle and preferences, meaning that the build environment has little to do on promoting any travel behavior. MAUP, in turn , occurs when a spatial analysis unit may be defined in various ways, leading to different results, and is a well-known issue on geographic analysis (OPENSHAW, 1983). Both problems are usually a problem of data collection, and, as noted by Gim (2012), studies often select variables that are available from previous collections instead of its value to the research

2.2 TRIP CHAIN AND TRAVEL BEHAVIOR

Traditional transport modelling uses the four-step model where the planner works on traffic analysis zones (TAZ) to understand the movements of the population by analyzing each trip as an isolated element. As this approach is fairly limited, it is very hard to use it to understand more profoundly the dynamics of transport demand (SADHU & TIWARI, 2016). Models have advanced in the last decades, and more disaggregated alternatives have been developed, such as tour based models, which try to understand whether a trip influences the next one (LEE *et al.*, 2017), and activity based models (SIVAKUMAR, 2007).

The focus of activity based models is to understand the motive behind each trip (SUSILO & AXHAUSEN, 2014) while tour-based models. Activity based models commonly use a trip chain representation of travel, as this allows it to get a better understanding of situation (ACHEAMPONG & SILVA, 2015).

Primerano *et al*. (2008) did a review on the most common definitions and found that most were based on the concept of number of stops done between two anchors, with an anchor being the place where the primary activity is done or where the day ends, like being home to home or home to work or to school. Limanond *et al.* (2005) uses a home-to-home definition to evaluate the trip chaining shopping behavior. For this, they further filtered the tours by analyzing those that had a shopping stop and found that the people from the Puget Sound region make more and more chained shopping trips on weekends, when there are less time constraints. Olojede and Samuel (2018) studied the trip chaining behavior of the evening commute in Ibadan, Nigeria, based on the hypothesis that this kind of trip is longer and more complex than its morning counterpart, since there are less time constrains.

Other works use a time restraint, such as an anchor, that is the place where an activity is done for more than a certain period of time (MCGUCKIN *et al.*, 2005). After this amount of time, they consider that subsequent trips are not influenced by previous ones. Other research has slightly altered this concept. Portoghese *et al.* (2011), for example, use the limit of 10 minutes to separate a stop from an anchor. With this definition, they concluded that households with small children trip chained more. Since the drop off of a young child is a relatively shorter activity than, say, shopping such a trip is better analyzed by a stricter definition. Wallace *et al.* (2000) went on a different direction and considered as an anchor any stay longer than 90 minutes, confirming the relation between trip chains and workdays found by Limanond *et al.* (2005). To standardize this definition to better compare results, the FHWA (2001) proposed a 30 minutes limit, as mentioned in Schmöcker *et al.* (2010).

It can be concluded that both definitions can efficiently capture the trip chaining effect, the home to home analyzing a broader aspect of daily trips, and the timed definition capturing a more focused evaluation, permitting to the researcher to understand, for example, the effect in different periods of the day. However, since the first definition is more comprehensive, it enables a greater analysis of the activities throughout the day and was found to be more common (thus permitting comparisons between an ampler number of results), this text will consider a tour being the number of trips a person engages between stops at home, unless explicitly stated otherwise.

Stopher *et al.* (1996) classified activities in three main groups, discretionary, flexible, and mandatory activities. Discretionary activities are those optional activities that have close to no time constraints such as leisure trips or visits to family and friends. On the other hand, mandatory, or subsistence, activities are those that are needed to be done at a certain time with a determined frequency, such as work or school (CHEN AND AKAR, 2017). Flexible trips, also known as maintenance trips, refer to the trips to activities that individuals must attend to, but does not have time constraints, such as shopping trips or health trips (MAAT & TIMMERMANS, 2006). Also, according to Lee *et al.* (2009) they are associated with a period of the day, mandatory activities are made usually during the morning and the afternoon, while discretionary ones tend to start at night.

Using this classification helps to understand how trip chains can be formed, by establishing a hierarchy between trip motives. As mandatory trips have the least flexible time schedule, they are often the main destination of a travel, and other activities must be planned according to the time windows left on the day. Maintenance trips are below mandatory trips, as they can be conducted at almost any time, but one cannot abstain from them. Finally, discretionary trips are in the bottom of this hierarchy, as people must allocate them in their remaining time. Lee *et al.* (2009) corroborate this understanding, as they found that there is a tradeoff between those categories. To better accommodate all these activities, an individual usually schedules a daily trip chain, optimizing his time.

Thus, a person first plans his day in the necessary degree of tour complexity, to attend the desired number of activities. For such a plan to work, the person needs to choose how to travel between places. More complex trips would demand more flexible transportation, such as cars. This line of thought is supported by Huang *et al*. (2021), who has found that, in Shanghai, China, travelers first design how their day will go before they choose the most appropriate mode. As they tend to allocate trips before work or in the lunchbreak, they need a reliable transportation, which is not found in transit, increasing the share of car trips.

Their research is not alone in concluding that, if the traveler knows beforehand that transit will not attend to his needs throughout a complex trip chain, there is a greater chance that he will abandon transit altogether. Vande Walle and Steenberghen (2006) studied travel patterns in Belgium and concluded that tours containing “missing links”, stops that were insufficiently by transit system, were more likely to be conducted by cars, since the total distance traveled was greater than 5 km, a distance too large to be covered by active modes.

Travel modes, however, are not always available to everyone. If a household only has one car, its members will have to plan jointly how it will be used, and whoever gets the car will be able to attend more complex trips. Seo *et al.* (2013) indicate that, as the most frequent maintenance activities, such as shopping for groceries and picking up/dropping off children at school, do not need to be done by all members, the household organizes itself to optimize the trips. After the household defines who will conduct the most complex tour and, therefore, use the car, the other members will schedule their activities in a way that could be done either by transit or by active modes.

Additionally, Hadiuzzaman *et al.* (2019) have found that, in Bangladesh, where the majority of the population cannot afford cars, there was an insignificant influence of trip chains on mode choice. An individual would need to have prior access to more modes to account for trip when scheduling his day. In a situation of social inequality, one cannot choose a transportation mode according to a schedule, as options may be limited to the available modes.

Other individual and socioeconomical variables can be expected to interfere in the process of trip chaining. Gender, for example, is widely used as a control variable in trip chaining, since it plays a determining role to separate the chores that need to be done by household members. Antipova and Wang (2010) found that women tend to trip chain more around work than men, possibly because they perform the maintenance trips of the family. In fact, trip chaining is mentioned by McGuckin *et al.* (2005) as the domain of women, especially those who have just entered the workforce, but still accumulate their other family duties (SUSILO *et al.*, 2019). It is a common conclusion that households with children, especially at small ages, trip chain more, since the adults must find a time slot to attend to toddlers' needs (KHAN AND HABIB, 2020; LEE *et al.*, 2009).

Even though this conclusion is frequent in developed countries, such as the USA and Sweden, some works in developing countries have reached an opposite conclusion. Although Bautista-Hernández (2020) has found that, in Mexico City, females trip chain more, Olivieri and Fageda (2021), in Uruguay, Pitombo *et al.* (2011), in São Paulo, and Elias *et al.* (2015), in Israel, have found that women, especially if married , trip chain less than men. A possible reason is the fact that such countries are still transitioning to more equal gender roles, where there are households with dual earners. Most research, however, agree that women are less inclined to use the car and more prone to use transit, probably because the vehicle stays with their spouse (CHENG *et al.*, 2019).

Age is also commonly identified as an influence factor on trip chaining. Studying the travel patterns of older Londoners, Schmöcker *et al.* (2010) concluded that older people combine more trips into one tour to optimize their time. Habib and Hui (2017) reached a similar conclusion by studying Canadian travelers, not only did they take more complex trips, but they also finished their tours earlier than younger people. Their pattern, however, seemed to be influenced by their income level. The highest and lowest income level tend to choose the same options in a consistent manner, while the middle-income level showed a more random behavior.

Finally, education level also seems to play a role on trip chaining and travel behavior. Cheng *et al.* (2019), using a SEM approach to analyze travel behavior in Nanjing, China, found that a higher education level not only has a positive influence on tour complexity, but also on car choice to attend to all daily activities. This relation is also found by Silva (2018) and Rashidi *et al.* (2010). One possible reason for this is the fact that educated people have fewer demanding jobs and value more their time, so they chain trips to better optimize their travel.

A closer look on all mentioned factors reveals two recurring variables: income and employment status. Yang *et al.* (2019) has found that higher income individuals tend to make more complex maintenance and discretionary tours. Also, as higher income people can afford one or more cars, they generally have more flexible schedules. Kuppam and Pendyala (2001), Lee *et al.* (2009) and Soo *et al.* (2008) hypothesize that wealthier groups have a greater “disposable income”, that allows them to pursue in more out-of-home discretionary activities, even though they spend more time at work. Also, wealthier households are able to own more private vehicles, which has been consistently related to more complex tours, even in developing countries (GUZMAN *et al.*, 2017). Hence, it is important to analyze income groups separately, as low and high income households might have different behaviors regarding tour formation, thus needing different policies to achieve an adequate mobility level (CHENG *et al.*, 2019; SALON & GULYANI, 2010).

The relation of employment situation with trip chaining is also clear. Since workers have more time constraints, they may have less time to engage in other activities. In a household with workers and nonworkers, the latter are more likely to be responsible for the maintenance activities (SCHMÖCKER *et al.*, 2010). Also, since workers have a routine to follow and a place to go, they are less prone to change their behavior (SUSILO & AXHAUSEN, 2014). Nonworkers, on the other hand, may conduct shorter trips with various modes, for they may have a more flexible routine. This could also explain the fact that nonworkers are more likely to engage in discretionary activities than workers (HINE *et al*, 2012).

Taking all mentioned factors into account, this research will investigate the trip chaining complexity of workers and nonworkers of different income groups, while controlling for other socioeconomic variables. Tour complexity will account for number of trips per tour and number of trip types (subsistence, maintenance and discretionary) per tour.

2.3 TRIP CHAIN AND BUILT ENVIRONMENT

As activities must occur somewhere in each time it is logical to infer that the daily schedule of an individual is affect by the regional organization of sites. This relation is known as the time-space prism, and was first proposed by Hägerstrand (1970). Timmermans *et al.* (2002) point out that one of the trade-offs people must do when scheduling their trips is travel time versus activity time, since a greater time destinated to travel would mean less time for activities and vice versa, a result also supported by Lee *et al.* (2009). Even though the concept that built environment can influence activity engagement, and thus trip chaining behavior, is not new, Acheampong and Silva (2015) indicates that most transportation models are still not able to properly represent it.

Complex trip chains, as previously mentioned, are usually made by car. If more complex tours imply a less sustainable transport system, such behavior should not be promoted. In fact, Chowdhury and Scott (2020b) advocate that people who are used to trip chaining frequently are less responsive to transit-oriented policies. Even so, McGuckin *et al.* (2005) indicates that some USA agencies endorsed trip chains as a way of promoting a sustainable travel behavior, since the total distance traveled would be smaller. Lee *et al.* (2017) indicate that trip chaining shorter distances could increase walking trips, depending on the diversity of land use.

Several planners and researchers have focused on controlling the built environment, as it seems like a path to maximize the potential sustainability of trip chains, by combining the optimization of travels and transit and active modes-oriented design. Over the last 20 years, there has been an increasing literature focused on determining the nuances of this relation over the globe, to determine whether this behavior could be endorsed, or whether, even after controlling for land use variables, trip chaining resulted in more car use congestion problems. Table 2.1 presents a list of recent articles on that subject.

A great part of research has been conducted in the USA, China, Europe, and Canada, which is expected, since these locations have an academic tradition in the transportation field. In the developing world, there are articles from Asian countries, such as, Bangladesh, India, and the Philippines. In Latin America, there are only articles from Mexico. Hence, there seems to be a research gap in poorer regions of the world. As stated by Guan *et al.* (2019), developed countries have a different self-selection problem, more focused on auto ownership and land price.

Three methods seem to be more popular when studying built environment variables on trip chaining complexity: Ordered Probit Models, Ordered Logit Models and Structural Equation Systems (SEM). Ordered Statistical Models are used in the case of count variables, and they have an order that must be analyzed, such as activities done in a day (DAISY *et al.*, 2018; LIU *et al.*, 2016). Since the location of each trip may affect how the next trip is made, this approach may help to identify more accuratelly travel patterns. SEM, in turn, are used to evaluate complex relationships between variables, helping to determine endogenous and exogenous influences (SILVA, 2018; VAN ACKER & WITLOX, 2011). Structural equations are especialy useful for determining causal relations between variables, so they can evaluate the direction of each relation – for example, whether choosing a car as the main mode implies that a person may engage in more complex tours.

According to the results of the multiple studies in the Table 2.1, the influence of land use variables on trip chaining behavior is not clear, similarly to the realtion with other aspects of travel behavior. Density variables, for example, have shown the most mixed results in all cases. One possibility for this finding is that density variables do not have a very specific definition and are heavily influenced by others. American suburbs, for example, not only have low density, but they also have low diversity and accessibility. Some researchers use density as the sole built environment variable, when the results could be better explained by other BE variables (CHENG *et al.*, 2016; MA *et al.*, 2014; PETTERSSON & SCHMÖCKER, 2010; SCHMÖCKER *et al.*, 2010).

Table 2.1 – Research that evaluated built environment influence on trip chain

Author	Country	Objective	Method of analysis	Results
(ANTIPOVA & WANG, 2010)	USA	To understand if land use variables, especially diversity ones, influence the travel behavior of male and female workers and nonworkers in a different manner.	Ordered Logit Model	Non workers of non-urban areas trip chain more than those from urban areas, since the time optimized by trip chaining at the destination was greater. Also, a more mixed residential location affects female workers and non-workers differently. Female workers tripped chain more around work while non-workers took advantage of the facilities near home.
(BAUTISTA-HERNÁNDEZ, 2020)	Mexico	To understand if there is a relation between urban structure and tour complexity of commuters	Zero-Inflated Negative Binomial	Greater job accessibility and population density increased transit trip chain by one stop, and had no effect on car or mixed transportation travels
(CHEN AND MCKNIGHT, 2007)	USA	To understand if the built environment affects the travel behavior of homemakers and to identify the different patterns	SEM	Denser regions made fewer trip chains, but very dense regions, such as Manhattan, resulted in more chains, which may imply that diversity may play a part on tour complexity behavior
(CHEN AND AKAR, 2017)	USA	To investigate how joint travel, trip chain and travel distances influence each other and how socio-demographics and urban form explain travel patterns	SEM	Retail density at destination affects tour complexity negatively, by doing so, it also has negative indirect effects on travel distance. Other variables, such as Residential density and non-retail density, have shown positive influence on trip chaining.
(CHENG *et al.*, 2016)	China	To find if people from different income levels have different trip chain patterns as well as to identify explanatory variables to trip chain complexity and mode choice	Stereotype Logit Model	Density has a positive influence on trip chain complexity, especially on non-work trips, even more if the person is from a lower income group.
(CHENG *et al.*, 2019)	China	To develop a model that can explain the relation between activity participation, trip generation and mode choice	SEM	Population density positively affect tour complexity; however, employment density has not shown any influence.
(CHOWDHURY & SCOTt, 2020b)	Canada	To examine the relation of built environment and trip chaining, focusing on its effect on trips that are more susceptible to its influence	OLS	Living in greater accessibility and diversity areas lead to less complex non works tours, however working on such areas lead to more complex tours.
(CONCAS & DESALVO, 2014)	USA	To develop models to evaluate how residential location, area of non-work activities and sociodemographic affect the tradeoff of commuting and no work travel	Three-stage least squares	Even though proximity to transit promotes its usage, houses farther from the center, thus with longer commutes, resulted in more complex tours and less transit use.
(DAISY *et al.*, 2020)	Canada	To identify different trip chaining behavior and mode choice clustered by worker groups	Ordered Tobit model	Greater land use mix and accessibility were found to increase tour complexity, as population density, even if with little significance. Trips chained in dense, mixed areas tend to be short and made by walk instead of car.
(DAISY *et al.*, 2018)	Canada	To identify tour characteristics of non-worker clusters	Ordered Probit model	Living close to the core of the city resulted in less complex tours and leaving home more often. Denser, more mixed regions with more intersections are related to more stops made by walking.

Author	Country	Objective	Method of analysis	Results
(SILVA, 2018)	Portugal	To develop a framework that exposes the relations between trip chaining, built environment auto ownership and travel distance	SEM	Both living or working in denser areas are related to less complex tours while reducing total travel distances.
(SILVA *et al.*, 2014)	Portugal	To explore the role of land use on tour type choice	SEM	Variables measured at home have a greater influence on tour complexity. Greater transit accessibility increases the amount of stops in tours, while reducing non-work tours. Suburban regions reduced the probability of trip chaining more.
(DHARMOWIJOYO *et al.*, 2016)	Indonesia	To examine the interactions between activity travel pattern, given sociodemographic and land use constraints	SEM	Built environment variables influenced the trip chaining behavior of workers and students but the relation was not significant for non-workers. Living in denser areas reduced the need to trip chain, while people in suburbs tended to trip chain more.
(FRANK *et al.*, 2008)	USA	To investigate the relations between travel time, cost, and land use variables in mode choice and trip chain patterns	Ordered Logit Model	Land use variables at home and work were found to be significant to tour behavior. More mixed and more walkable areas were found to decrease the number of stops on each tour, as the cost of doing a simple tour was low.
(GEHRKE & WELCH, 2017)	USA	To understand if land use can encourage more trip chains on foot, and if the land use can promote more discretionary trips	bivariate selection model	An increase of blocks per TAZ, more roads, more mixed design, and less cul-de-sacs are related to more trip chain, implying that greater car accessibility is related to trip chains patterns
(GRUE *et al.*, 2020)	Norway	To explore the relationship between land use, tour complexity and mode choice controlled by tour type (mandatory and non-mandatory)	Ordered Logit Model	Denser, more mixed destination areas, as well as with more transit stops are related to less complex trips and lower chance of choosing auto.
(HABIB & HUI, 2017)	Canada	To understand the activity scheduling of the elderly, according to activity duration, location and start and end time.	Random Utility Maximization	Older people trip chained more in less dense regions, which could imply that creating a more mixed land use could result in less auto trips
(HADIUZZAMAN *et al.*, 2019)	Bangladesh	To investigate the relations of trip chains and mode choice, evaluating whether there is a mutual causality between them	SEM	A greater distance to destination resulted in more chains, since they could optimize their travel costs
(HUANG,& LEVINSON, 2017)	USA	To create a framework that considers more than one destination in non-commute chains, identifies travel patterns from GPS data and tests hypothesis about land use on trip chains structures	Multinomial Logit	Greater accessibility and more diversity in the first destination resulted in one more stop, but only accessibility on the second destination was found to result in more complex tours
(KRIZEK, 2003)	USA	To investigate the influence of neighborhood accessibility on trip purpose and trip chaining	Poisson regression model	A longer commute was not significant to explain trip chains however greater accessibility resulted in more stops
(LEE., 2016)	USA	To investigate whether residential locations influence tour complexity and mode choice	Poisson regression model	A greater walkability resulted in shorter trips but had different results for work tours and non-work tours. For work tours it had a positive influence on complexity; for non-work tours, it had a negative one

Author	Country	Objective	Method of analysis	Results
(LEE *et al.*, 2017)	USA	To understand whether land use can affect tour complexity and distance to promote the substitution of car trips to other modes	Multinomial Logit	Denser regions were related to more low complexity tours, especially if the motive for the travel is shopping
(LI *et al.*, 2021)	China	To identify the relationship between the spatial distribution of activities and land use characteristics	Multiple Linear Regression	Higher density, diversity and transit accessibility were related to more stops on tours
(LI *et al.*, 2020)	China	To identify the influencing factors of multi-purpose trip chain complexity	Markov chain	Proximity to shopping or dinner, both at home and work, had a positive impact on two-stops tours.
(LIMANOND & NIEMEIER, 2004)	USA	To understand whether a greater accessibility implies a greater shopping tour complexity	Stockholm Model System	Living in neighborhoods with poorer accessibility is related to more complex non-work tours
(LIMANOND *et al.*, 2005)	USA	To understand the factors related to shopping travel decision-making and propose a model to better forecast travel demand	Stockholm Model System	Better accessibility at home increased the number of stops by one but had no significance in creating more stops.
(LIU *et al.*, 2016)	Sweden	To explore the influence of sociodemographic, household, weather, and land use characteristics on trip chaining behavior	Ordered Probit Model	Living in denser regions resulted in more work trip chains and less discretionary trip chains
(MA *et al.*, 2014)	China	To investigate the associations between urban form and tours in Beijing, China	Ordered Logit Model	Higher population density was related to simpler tour while more diversity was related to more stops
(MAAT & TIMMERMANS, 2006)	Netherlands	To understand the relationship between trip chain and land use	OLS	Density at home location was found to be significant to increase maintenance and discretionary stops on tours, but only when measured at a 2.5 km radius. Density, mixed land use at workplaces and accessibility showed no significant effect on tour complexity
(MAAT & TIMMERMANS, 2009)	Netherlands	To evaluate whether the land use in both residential and work locations affects the daily schedule of the population	SEM	Density at home meant slightly less stops per tour and density at work meant a slightly more complex tour.
(MANOJ & VERMA, 2015b)	India	To compare, in an exploratory manner, the behavior of non-workers in India with other developing countries and develop a model that use land use and sociodemographic variables to forecast activity travel	Linear Regression	More diverse land use increase tour complexity, except for low-income households, while distance to the CBD showed a positive effect on trip chain, except for high income households
(MANOJ & VERMA, 2015a)	India	To develop a model to each income level of travel activity, using land use and sociodemographic variables as inputs	Multinomial Logit model	Density and mixed land use showed a negative effect on trip chain complexity and distance to the CBD showed a positive one.
(MCGUCKIN *et al.*, 2005)	USA	To compare the tour behavior of workers who trip chain and those who do not	Exploratory analysis	Workers who had longer commutes trip chained more

Author	Country	Objective	Method of analysis	Results
(NOLAND & THOMAS, 2007)	USA	To understand whether density affects tour complexity and density	Ordered probit model	Density has not shown a linear relation to trip chain, while greater density was related to fewer stops per tour, a medium density showed a peak of tour complexity
(OLOJEDE & SAMUEL, 2018)	Nigeria	To examine the travel behavior at trips returning to home in an African country	Anova test	Lower density zones showed greater tour complexity
(PETTERSSON & SCHMÖCKER, 2010)	Philippines	To understand whether commonalities and accessibility of older population affect their travel behavior	Ordered probit model	Lower density zones showed lesser tour complexity
(SCHEINER, 2014)	Germany	To understand how change due to key life events affect the complexity of tours	Cluster-robust regression	Only two built environment variables have shown a significant effect on trip chaining, the connection of a workplace location to transit and the availability of parking. Less connection to transit and more parking were related to less stops per tour
(SCHMÖCKER *et al.*, 2010)	UK	To understand the impact of sociodemographic and land use on older Londoners' trip chains	Ordered Probit Model	Density has not shown any effect on the population younger than 65, as less dense regions on London are much less dense than suburban and rural areas in the US
(SEO *et al.*, 2013)	South Korea	To examine the effect of accessibility on maintenance and discretionary tours among different age clusters	Ordered Probit Model	Density had no effect on tour complexity. however, denser regions with more diversity lead to fewer maintenance tours and more discretionary ones.
(SRINIVASAN, 2002A)	USA	To assess what differences in various travel behavior characteristics are due to land use patterns	Binary Logit Estimation	Highway proximity and nonwork destination proximity were related to less complex car chains, while higher diversity reduced the active mode chains and increase car ones
(VAN ACKER & WITLOX, 2011)	Belgium	To evaluate how land use affect car trips through different tour types	SEM	Proximity to rail stations at work, combined with poor car accessibility, resulted in less car use even in complex trips
(WALLACE *et al.*, 2000)	USA	To determine which factors, increase the tendency to trip chain	Poisson Regression Model	Distance to work seems to increase chains while reducing the average total tour distance
(WANG, 2015)	USA	To investigate how land use variables aggregated at different scales can influence travel behavior	Negative Binomial Model	Density shows a slight negative influence on the number of stops per tour, while denser rail areas showed a small positive effect on trip chains
(YANG *et al.*, 2019)	USA	To investigate how built environment affect trip chaining in Beijing China	Ordered Logit Model	Land use variables had more relation with work tours and less relation with discretionary ones. For subsistence tours, density and diversity resulted in more complex tours; for maintenance tours, these variables showed a negative relation
(ZHANG *et al.*, 2019)	USA	To increase the sensitivity of activity-demand model to land use characteristics of the Portland population	Negative Binomial Model	Less dense neighborhoods generated more trips per tour, while diversity showed no significant impact on it.

The negative influence of Accessibility at home location on tour complexity is reported to be related with people optimizing their travel since making more single stops would take more time (LIMANOND & NIEMEIER, 2004). When this relation is found to be positive, the authors conclude that the cost of linking activities is reduced (DAISY *et al.*, 2018). In this case, the altered variable seems to be distance traveled. When the influence is negative, the papers reported a long-distance trip followed by a series of short trips; when it is positive, the tours are a series of just short trips.

When researching accessibility at work, the influence reported is shifted, and papers often have found that greater accessibility at work is related to more chains. One possible reason is the fact that people tend to compensate for poor diversity at home by trip chaining before or after work, using the infrastructure present at work. When land use mix has a positive influence on trip chain complexity, accessibility at work also have a positive relation on it, implying that these variables may influence each other.

This apparent inconsistency may indicate that there are other factors influencing this relation. A factor which comes up repeatedly in research is is employment status, mentioned in section 2.2. As workers and non-workers have different schedules, they may also have different trip chain patterns. Yang *et al.* (2019) has found that density and diversity have a positive effect on tour complexity when the motive of travel is work, otherwise they had a negative effect. In Indonesia, Dharmowijoyo *et al.* (2016) have found that built enviroment in general had no influence on the trip chaining complexity of non-workers, probably because their more flexible schedule made it possible to make more simple tours.

The effect of built environment on trip chaining was shown to be heavily influenced by the location of the study, which is in line with the research presented in section 2.1. Manoj and Verma (2015b) have found that spatial inequallity affects the influence of land use on trip chaining. For their study area, it did not matered how much diverse the region was since poorer family households could not afford to engage in more trips on them it had no significant effect on trip chaining behaviour. This behavior was also reported by Neves *et al.* (2021), in the previous section. If planners use land use zoning policies to promote certain travel behaviors effitiently, they should be aware of how different income groups will react to it.

2.4 CONCEPTUAL MODEL

The analysis of previous research shows that the built environment is slightly related to trip chaining complexity. Thus, it is important to evaluate the direct and indirect effects of built environment on tour complexity and mode choice. The researched literature sugests that distinct built environment variables have different effects on both trip chaining complexity and travel mode choice, although such effects are limited compared to sociodemographic variables. Regarding mode choice, trip chaining complexity has also shown to positively influence automobile use. Such an effect could be mitigated with a more mixed and transit accessible land use. The relations observed in the literature can be demonstrated by the conceptual model in Figure 2.1.

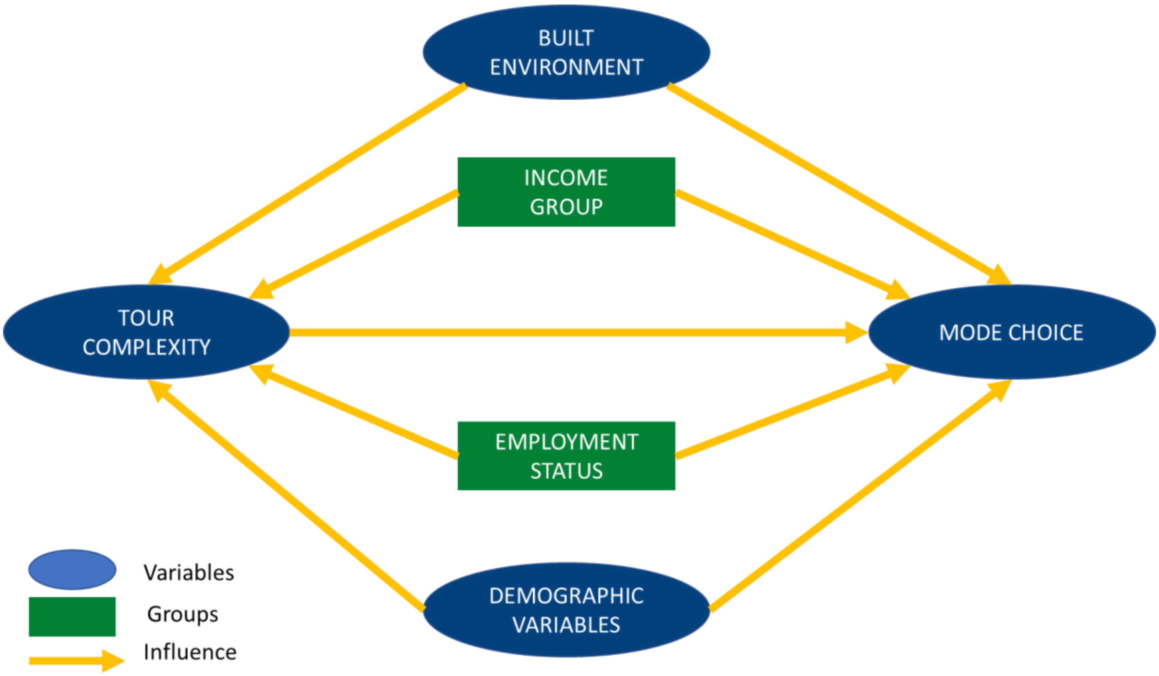

Figure 2.1 – Conceptual model

The model indicates that built environment and sociodemographic variables can affect mode choice both directly and indirectly, having their effect mitigatated by planned schedules. Such effects might be controlled by variables such as the traveler's employment status and his income level.

Literature reviews such as Ewing and Cervero, (2010) and Aston *et al.*, (2021) state that land use has an impact on mode choice. The increase the alternatives of activities, such as work, shopping, and diner, is expected to increase the chance of choosing a more active mode. Also, as reported by van de Coevering *et al.* (2021), the closer one is to transit, greater the possibility of choosing it as the main transport mode. Denser regions, measured either by employment or population densitycould embody all such characteristics, since there must be a large group of facilities to support the needs of a large population (CHENG *et al.*, 2016; MA *et al.*, 2014; PETTERSSON & SCHMÖCKER, 2010; SCHMÖCKER *et al.*, 2010). Finally,in situations of greater inequality, lower income class citizens will likely have different responses to built environment, since they may not afford to attend activities at all locations (MANOJ & VERMA, 2015b; NEVES *et al.*, 2021).

The expected impact of built environment variables on tour complexity was extensively addressed on section 2.3. Since the decision to trip chain is theorized to be made to optimize time and cost, a greater number of activity possibilities in one place could result in a greater number of shorter trips (MANOJ & VERMA, 2015a; OLOJEDE & SAMUEL, 2018; WANG, 2015; ZHANG *et al.*, 2019). Another possibility is that, by reducing costs to engage in activities near home or work, people would carry out simpler tours, taking advantage of more stops at either location (LI *et al.*, 2021; MAAT & TIMMERMANS, 2009; PETTERSSON & SCHMÖCKER, 2010). Also, some authors indicate that reducing transit costs, with locations with better transit accessibility, for example, could lead to a greater tour complexity (SILVA *et al.*, 2014).

Trip chain complexity is expected to have an influence in individuals mode choice. The literature indicates that, if a person has to make more stops in tours, he is more likely to choose a car as his mode of transportation. The reason for this could be the fact that a more complex tour likely needs a flexible mode (HUANG *et al.*, 2021). Cars allow passengers to fastly travel between points at any time, without the need to follow a prefixed schedule (SEO *et al.*, 2013; VANDE WALLE & STEENBERGHEN, 2006). The literature also presents evidence that simpler tours are related to trips made by transit or active modes (GUZMAN *et al.*, 2017; YANG *et al.*, 2019), as each adtional trip adds a greater generalized cost, compared to taking a car .

Although authors have presented evidence that greater tour complexity results in a greater chance to choose a car as the main transportation mode, some research indicates that this relation could be mediated by local land use. A greater land use mix, especially at work location, and a design that prioritize active modes lessen the need for car, diminishing the cost of each additional trip carried out on foot (DAISY *et al.*, 2020, 2018). In a similar sense, regions with a greater transit accessibility diminish the costs of travel by public transportation (VAN ACKER & WITLOX, 2011). By reducing the costs of other transportations modes, built environment variables could increase tour complexity and, at the same time, reduce car use. Srinivasan (2002b), however, found that a greater land use increased the total number of tours but reduced the trip complexity.

Besides the relations between land use variables, trip chaining and mode choice, the literature suggests that sociodemografic variables have a greater impact on both trip chaining and mode choice. Sociodemographic variables, such as age (GOLOB & HENSHER, 2007; PETTERSSON & SCHMÖCKER, 2010; SCHMÖCKER *et al.*, 2010), gender (ANTIPOVA *et al.*, 2011; CHEN AND MCKNIGHT, 2007; SCHEINER, 2014), household size (KITAMURA & SUSILO, 2005; SUSILO *et al.*, 2019), and car ownership have shown to have a significant influence on tour complexity and mode choice. Also, as exposed by Manoj and Verma (2015b) and Neves *et al.* (2021) land use variables had different effects, depending on which social class the traveler comes from. Lower income people are less sucetible to changes in the built environment , since they might not afford extra trips.

2.4.1 Required dataset

To evaluate the conceptual model proposed in section 2.4, each latent variable presented must be defined. Latent variables, or constructs, are variables that are indirectly measured, such as built environment or tour complexity. Manifest variables, in turn, can be directly observed and measured. Therefore, to measure each latent variable there must be a set of manifest variables related to one another.

Table 2.2 shows the built environment variables that the literature has shown to have a significant influence on either tour complexity or mode choice. Variables, such as population density, employment density, and entropy, are usually obtained through a census. Other built environment variables, such as cul-de-sac density, street density, transit density and transit stop, can be obtained by either government inventories or opensource databases, such as OpenStreetMap and Google Maps. Finally, the presented distance variables are usually calculated either as a direct line between points or as the distance in a network. The variety of manners in which the built environment can be measured make this concept an abstract one.

Though each of these variables can be directly measured, the concept of built environment cannot.

Table 2.2 – Built Environment variables

Latent variable	Manifest Variable	Authors
Built environment	Population density	Chen & McKnight, (2007); Noland & Thomas, (2007); Pettersson & Schmöcker, (2010); Rashidi *et al.*, (2010); Schmöcker *et al.*, (2010); Ma *et al.*, (2014); Concas & DeSalvo, (2014); Silva *et al.*, (2014); Wang, (2015);Cheng *et al.*, (2016, 2019); Dharmowijoyo *et al.*, (2016); Gehrke & Welch, (2017); Habib & Hui, (2017); Manoj & Verma, (2015a); Silva, (2018); Yang *et al.*, (2019); Daisy *et al.*, (2020, 2018);. Bautista-Hernández, (2020)
	Enployment density	Srinivasan, (2002a); Limanond & Niemeier, (2004); Limanond *et al.*, (2005); C. Chen & McKnight, (2007); Maat & Timmermans, (2006, 2009); Rashidi *et al.*, (2010); van Acker & Witlox, (2011); Seo *et al.*, (2013); Silva *et al.*, (2014); Wang, (2015); Liu *et al.*, (2016); Chen & Akar, (2017); Cheng *et al.*, (2016, 2019); Chowdhury & Scott, (2020a); Daisy *et al.*, (2020, 2018); Gehrke & Welch, (2017); Grue *et al.*, (2020); Habib & Hui, (2017); Lee *et al.*, (2017); Yang *et al.*, (2019)
	Entropy	Srinivasan, (2002a); Krizek, (2003); Maat & Timmermans, (2009); Antipova & Wang, (2010); van Acker & Witlox, (2011); Silva *et al.*, (2014); Manoj & Verma, (2015b); Lee, (2016); Gehrke & Welch, (2017); Huang & Levinson, (2017); Lee *et al.*, (2017); Silva, (2018); Yang *et al.*, (2019); Bautista-Hernández, (2020); Daisy *et al.*, (2020, 2018)
	Cul de sac density	Krizek (2003); Srinivasan (2002)
	Intersection density	Srinivasan, (2002b); Frank *et al.*, (2008); Chen & Akar, (2017); Gehrke & Welch, (2017); Lee *et al.*, (2017); Chowdhury & Scott, (2020b)
	Road density	Srinivasan, (2002a); Rashidi *et al.*, (2010); Silva *et al.*, (2014); Gehrke & Welch, (2017); Silva, (2018)
	Sidewalk density	Srinivasan, (2002a); Chowdhury & Scott, (2020b); Daisy *et al.*, (2020, 2018)
	Distance to stop	Srinivasan, (2002a); van Acker & Witlox, (2011); Concas & DeSalvo, (2014); Seo *et al.*, (2013); Silva *et al.*, (2014); Grue *et al.*, (2020)
	Stop density	Frank *et al.*, (2008); Seo *et al.*, (2013); Dharmowijoyo *et al.*, (2016); Chen & Akar, (2017); Grue *et al.*, (2020);
	Transit density	Frank *et al.*, (2008); Rashidi *et al.*, (2010); Seo *et al.*, (2013); Lee *et al.*, (2017); Yang *et al.*, (2019)
	Distance to CBD	Krizek, (2003); van Acker & Witlox, (2011); Silva *et al.*, (2014); Concas & DeSalvo, (2014); Silva *et al.*, (2014); Wang, (2015); Manoj & Verma, (2015a); Lee, (2016); Dharmowijoyo *et al.*, (2016); Habib & Hui, (2017); Huang & Levinson, (2017); Daisy *et al.*, (2020, 2018); Grue *et al.*, (2020); Bautista-Hernández, (2020)
	Distance traveled	Krizek, (2003); van Acker & Witlox, (2011); Silva *et al.*, (2014); Concas & DeSalvo, (2014); Silva *et al.*, (2014); Wang, (2015); Manoj & Verma, (2015a); Lee, (2016); Dharmowijoyo *et al.*, (2016); Habib & Hui, (2017); Huang & Levinson, (2017); Daisy *et al.*, (2020, 2018); Grue *et al.*, (2020); Bautista-Hernández, (2020)

Socioeconomic variables have been found to influence travel behavior in multiple instances, as exposed in section 2. Age, number of residents in the household, education level, number of children in the household, driver license ownership, vehicle ownership and housing type are variables commonly used in both trip chaining and land use research. Income and employment status have consistently shown to have a great influence on both topics. To better account for the influence of other variables, income and employment status will be treated as classes. Table 2.3 shows all authors who researched each cited socioeconomic variable.

Table 2.3 – Socioeconomic variables

Latent variable	Manifest Variable	Authors
Socioeconomic variables	Age	Wallace *et al.* (2000); Srinivasan (2002a)); Limanond & Niemeier (2004); Limanond *et al.* (2005); Maat & Timmermans (2006); Chen & McKnight (2007); Noland & Thomas (2007); Frank *et al.* (2008); Maat & Timmermans (2009); Antipova & Wang (2010); Rashidi *et al.* (2010); Schmöcker *et al.* (2010); Pettersson & Schmöcker (2010); van Acker & Witlox (2011); Seo *et al.* (2013); Ma *et al.* (2014); Silva *et al.* (2014); Scheiner (2014); Concas & DeSalvo (2014); R. Wang (2015); Manoj & Verma (2015a); Cheng *et al.* (2016); Dharmowijoyo *et al.* (2016); Liu *et al.* (2016); Lee (2016); Lee *et al.* (2017); Gehrke & Welch (2017); Habib & Hui (2017); Y. Chen & Akar (2017); Daisy *et al.* (2018); Olojede & Samuel (2018); Silva (2018); Yang *et al.* (2019); Y. Chen & Akar (2019);Daisy *et al.* (2020); Grue *et al.* (2020); Li *et al.* (2020); Bautista-Hernández (2020); Chowdhury & Scott (2020b)
	Household size	Wallace *et al.* (2000); Srinivasan (2002a); Antipova & Wang (2010); Pettersson & Schmöcker (2010); Schmöcker *et al.* (2010); Scheiner (2014); Dharmowijoyo *et al.* (2016); Habib & Hui (2017); Cheng *et al.* (2019)
	Gender	Wallace *et al.* (2000); Srinivasan (2002a); Limanond & Niemeier (2004); Limanond *et al.* (2005); Chen & McKnight (2007); Noland & Thomas (2007); Frank *et al* (2008); Maat & Timmermans (2009); Antipova & Wang (2010); Pettersson & Schmöcker (2010); Schmöcker *et al.* (2010); van Acker & Witlox (2011); Seo *et al.* (2013); Ma *et al.* (2014); Scheiner (2014); Silva *et al.* (2014); Manoj & Verma (2015a); Wang (2015); Dharmowijoyo *et al.* (2016); Liu *et al.* (2016); Lee (2016); Gehrke & Welch (2017); Habib & Hui (2017); Chen & Akar (2017); Lee *et al.* (2017); Daisy *et al.* (2018);Silva (2018); Olojede & Samuel (2018); Cheng *et al.* (2019); Yang *et al.*, (2019); Bautista-Hernández (2020); Chowdhury & Scott (2020b);Daisy *et al.* (2020); Grue *et al.* (2020); Li *et al.* (2020)
	Education Level	Antipova & Wang (2010); Manoj & Verma (2015a); Cheng *et al.* (2016); Daisy *et al.* (2018); Silva (2018); Gehrke *et al.* (2019); Yang *et al.* (2019); Bautista-Hernández (2020); Cheng *et al.* (2020); Chowdhury & Scott (2020b); Daisy *et al.* (2020); Li *et al.* (2020)
	Number of children	Wallace *et al.* (2000) Srinivasan (2002a); Maat & Timmermans (2006); Chen & McKnight (2007); Noland & Thomas (2007); Maat & Timmermans (2009); Antipova & Wang (2010); Pettersson & Schmöcker (2010); van Acker & Witlox (2011); Concas & DeSalvo (2014); Ma *et al.* (2014); Scheiner (2014); Manoj & Verma (2015a); Wang (2015); Dharmowijoyo *et al.* (2016); Lee (2016); Chen & Akar (2017); Gehrke & Welch (2017); Lee *et al.* (2017); Olojede & Samuel (2018); Silva (2018); Yang *et al.* (2019); Chowdhury & Scott (2020b); Grue *et al.* (2020)

Latent variable	Manifest Variable	Authors
	Housing type	Wallace *et al.* (2000) Srinivasan (2002a); Antipova & Wang (2010); Pettersson & Schmöcker (2010); Schmöcker *et al.* (2010); Scheiner (2014); Manoj & Verma (2015a); Habib & Hui (2017); Dharmowijoyo *et al.* (2016); Cheng *et al.* (2019)
	Driver license	Antipova & Wang (2010); Pettersson & Schmöcker (2010); Rashidi *et al.* (2010); Manoj & Verma (2015a); Wang (2015); Cheng *et al.* (2016); Lee (2016); Chen & Akar (2017); Habib & Hui (2017); Cheng *et al.* (2019); Daisy *et al.* (2020); Li *et al.* (2020)
	Vehicle ownership	Wallace *et al.* (2000); Krizek (2003); Limanond & Niemeier (2004); Maat & Timmermans (2006); Chen & McKnight (2007); Frank *et al.* (2008); Maat & Timmermans (2009); Antipova & Wang (2010); Pettersson & Schmöcker (2010); Rashidi *et al.* (2010); van Acker & Witlox (2011); Seo *et al.* (2013); Concas & DeSalvo (2014); Scheiner (2014); Manoj & Verma (2015a); Wang (2015); Dharmowijoyo *et al.* (2016); Lee (2016); Chen & Akar (2017); Gehrke & Welch (2017); Lee *et al.* (2017); Daisy *et al.* (2018); Olojede & Samuel (2018); Silva (2018); Chowdhury & Scott (2020b); Daisy *et al.* (2020); Grue *et al.* (2020); Li *et al.* (2020)
	Income	Wallace *et al.* (2000); Srinivasan (2002a); Krizek (2003); Limanond & Niemeier (2004); Limanond *et al.* (2005); Chen & McKnight (2007); Noland & Thomas (2007); Frank *et al.* (2008); Maat & Timmermans (2009); Antipova & Wang (2010); van Acker & Witlox (2011); Seo *et al.* (2013); Silva *et al.*, (2014); Manoj & Verma (2015a); Concas & DeSalvo (2014); Wang (2015); Lee (2016); Chen & Akar (2017); Gehrke & Welch (2017); Lee *et al.* (2017); Olojede & Samuel (2018); Silva (2018); Cheng *et al.* (2019); Chowdhury & Scott (2020b); Grue *et al.* (2020); Li *et al.* (2020)
	Employment status	Wallace *et al.* (2000); Noland & Thomas (2007); Antipova & Wang (2010); Schmöcker *et al.*, (2010); van Acker & Witlox (2011); Ma *et al.* (2014); Scheiner (2014); Wang (2015); Cheng *et al.* (2016); Dharmowijoyo *et al.* (2016); Chen & Akar (2017); Gehrke & Welch (2017); Habib & Hui (2017); Daisy *et al.* (2020)

As explained in section 2.2, tour complexity can be measured by several variables, such as the number of stops between two anchors. There are numerous factors hypothesized to influence it. The number of tours made each day can negatively influence tour complexity, as well as the activity time at one location. Other variables were reported to be related to tour complexity, such as number of each type of activity, total distance traveled, total travel time, and distance to main objective. Apart from the authors which studied number of stops as a variable, which have been explored in detail in Table 2.1, Table 2.4 presents the other variables that influence tour complexity.

Table 2.4 – Tour complexity variables

Latent variable	Manifest Variable	Authors
Tour complexity	Number of stops	See Table 2.1
	Number of tours	Krizek (2003); Limanond & Niemeier (2004); Maat & Timmermans (2006); Rashidi *et al.* (2010) ; Schmöcker *et al.* (2010); Dharmowijoyo *et al.* (2016); Lee (2016); Daisy *et al.* (2018); Cheng *et al.* (2019); Daisy *et al.* (2020); Grue *et al.* (2020)
	Total distance	Limanond *et al.* (2005); Maat & Timmermans (2006); Antipova & Wang (2010); Rashidi *et al.* (2010); van Acker & Witlox (2011); Ma *et al.* (2014); Scheiner (2014); Bautista-Hernández (2020); Chowdhury & Scott (2020b); Daisy *et al.* (2020); Grue *et al.* (2020); Li *et al.* (2020)
	Total activity time	Srinivasan (2002a); Chen & McKnight (2007); Maat & Timmermans (2009); Concas & DeSalvo (2014); Dharmowijoyo *et al.* (2016); Huang & Levinson (2017); Chowdhury & Scott (2020b)
	Total travel time	Wallace *et al.* (2000); Limanond *et al.* (2005); Chen & McKnight (2007); Maat & Timmermans (2009); Antipova & Wang (2010); Rashidi *et al.* (2010); van Acker & Witlox (2011); Concas & DeSalvo (2014); Ma *et al.* (2014); Dharmowijoyo *et al.* (2016); Huang & Levinson (2017); Olojede & Samuel (2018); Chowdhury & Scott (2020b); Daisy *et al.* (2020)
	Main motive	Limanond & Niemeier (2004); Limanond *et al.* (2005); Maat & Timmermans (2006); Frank *et al.* (2008); Lee *et al.* (2009) Manoj & Verma (2015a); Liu *et al.* (2016); Habib & Hui (2017); Lee *et al.* (2017); Daisy *et al.* (2018); Daisy *et al.* (2020)
	Mandatory trips	Krizek (2003); Maat & Timmermans (2006); Maat & Timmermans (2009);Pettersson & Schmöcker, (2010); Rashidi *et al.* (2010); Manoj & Verma (2015b) Gehrke & Welch (2017); Daisy *et al.* (2018); Cheng *et al.* (2019); ; Yang *et al.* (2019); Daisy *et al.* (2020); Li *et al.* (2020)
	Maintanence trips	Krizek (2003); Maat & Timmermans (2006); Chen & McKnight (2007); Maat & Timmermans (2009);Pettersson & Schmöcker, (2010); Rashidi *et al.* (2010); Manoj & Verma (2015b) Gehrke & Welch (2017); Daisy *et al.* (2018); Cheng *et al.* (2019); ; Yang *et al.* (2019); Daisy *et al.* (2020); Li *et al.* (2020)
	Discretionary trips	Krizek (2003); Maat & Timmermans (2006); Chen & McKnight (2007); Maat & Timmermans (2009);Pettersson & Schmöcker, (2010); Rashidi *et al.* (2010); Manoj & Verma (2015b) Gehrke & Welch (2017); Daisy *et al.* (2018); Cheng *et al.* (2019); ; Yang *et al.* (2019); Daisy *et al.* (2020); Li *et al.* (2020)
	Period of the day	Lee *et al.*, (2009)

3 DATA AND METHODS

3.1 DATA COLLECTION AND PREPARATION

It was necessary to collect data on both built environment and trips to test the proposed model. The primary source of data was the survey carried by the Brasília Metro in 2016, the Federal District Urban Mobility Survey – FDUMS (Pesquisa de Mobilidade Urbana do DF – PMU, in Portuguese). This survey was part of the Federal District Rail Transit Development Plan – RTDP/FD (Plano de Desenvolvimento do Transporte Público sobre Trilhos do DF – PDTT/DF). The objective of this data was to evaluate the demand of rail transit in the Federal District.

The survey interviewed 61,359 citizens in 19,253 different households, distributed in 983 Traffic Analysis Zones (TAZ). The total analysis area used in the plan encompassed a total of 1053 TAZ. The survey considered the cities in the influence area of the capital, but, since there were no detailed built environment data in such zones, they were removed from analysis in this study.

All tables were imported into a local PostgreSQL server for data treatment. The FDUMS questionnaire was imported as three different tables, “hhld_household”, “hhld_person”, hhld_trips”, where the first two hold the socioeconomic data, shown on Table 3.1, and the last hold the data about trips made by each person in the household, shown in Table 3.2.

Table 3.1 – Socioeconomic variables

Attribute	Type	Description
age	String (dummy)	Age group of residents
gender	String (dummy)	Gender
education_level	String (dummy)	Class of education level of resident
occupation	String (dummy)	Main occupation of resident
driver_license	Boolean	Indicates ownership of driver license
number_of_residents	Integer	Number of people in the household
number_of_children	Integer	Number of children in the household
number_of_cars	Integer	Number of cars in the household
household_income	String (dummy)	Income class of the household

Table 3.2 – Trip characteristics

Attribute	Type	Description
trip_id	Integer	Identification of trip
household_id	Integer	Identification of household
resident_id	Integer	Identification of resident
resident_tour_id	integer	Identification of each tour of each resident
ztorigin	Integer	Origin TAZ zone
ztdestination	Integer	Destination TAZ zone
motive_origin	String (dummy)	Motive of trip at origin
motive_destination	String (dummy)	Motive of trip at destination
motive_trip	String (dummy)	Motive of trip, considering the motive of accompanying person, if the declared motive was “accompanying another person”
start_time	Time	Departure time
endtime	Time	Arrival time
trip_closer_than_500m	Integer	1 if the trip was less than 500m long, 0 otherwise
travel_time	Time	Travel time
activity_time	Time	Time spent at activity
pedestrian	Integer	1, if the resident walked on the trip, 0 otherwise
bike	Integer	1, if the resident used a bike on the trip, 0 otherwise
transit	Integer	1, if the resident used transit on the trip, 0 otherwise
privatemode	Integer	1, if the resident used a private vehicle on the trip, 0 otherwise
taxi	Integer	1, if the resident used a taxi on the trip, 0 otherwise

The column “number_of_children” was calculated by aggregating the number of residents with school age, equal or less than 18 years old, in each household. The column “activity_time” was calculated by subtracting the departure time from the arrival time. Those two columns were calculated in the pgadmin4 interface, and the query used is available in the Appendix I. The column “resident_tour_id” was calculated in Microsoft Excel before its importing into the Postgres server. This column is created by a concatenation of the “resident_id”, tour number (a counter that increases at each stop at one’s residence), and number of stops (a counter that increases by each trip and resets at each stop at one residence). The “resident_tour_id” was used in a further processing stage, where each trip had to be grouped in a tour, using the definition established in section 2.1.

With both tables, the next step was to aggregate the characteristics of each tour. In the column “resident_tour_id” can be used for this purpose, as it had the resident index, the tour index, and the trip index. Table 3.3 presents the variables explored from this query.

Table 3.3. – Tour characteristics

Attribute	Type	Description
person_id	Integer	Identification of tour and person
main_destination_zone	Integer	Identification of main destination zone
main_motive	String (dummy)	Identification of main motive
Start_time	String (dummy)	Period of the day in which the tour started
activity_time	Time	Time spent at main activity
total_activity_time	Time	Total time spent at activities
total_trip_time	Time	Total time spent travelling
total_distance	Float	Total distance traveled
num_stops	Integer	Number of stops on tour
n_mandatory	Integer	Number of stops on tour with a mandatory motive
n_discretionary	Integer	Number of stops on tour with a discretionary motive
n_maintenance	Integer	Number of stops on tour with a maintenance motive
Active_mode	Integer	Number of times in which an active mode was the chosen mode on tour
transit	Integer	Number of times in which transit was the chosen mode on tour
private_transit	Integer	Number of times in which private transit was the chosen mode on tour
taxi	Integer	Number of times in which taxi was the chosen mode on tour
car	Integer	Number of times in which car was the chosen mode on tour

The columns “total_activity_time”, “total_trip_time”, “total_distance”, “num_stops”, “pedestrian”, bike”, “transit”, “private_transit”, “taxi” and “car” were calculated as the sum of the corresponding attribute for the tour. The day was separated in three periods in the variable “start_time”, “morning”, from 5:00 to 11:59, “afternoon”, from 12:00 to 17:59 and “night”, from 18:00 to 4:59. The main destination was the location where the resident spent most time at a singular activity. To filter the data related to the main destination, first the activity with most time spent on tour was found; then, the zone and motive corresponding to this activity were selected. To count the number of tours having each motivation, this research used the classification shown in Table 3.4. Finally, the total distance traveled was calculated by the shortest route between two zones. The full query can be consulted in the Appendix I.

Table 3.4 – Cluster used for activity type

Type of activity	Activity
Mandatory	Primary workplace
	Secondary workplace
	Primary study place
	Secondary study place
	Business
Maintenance	Shopping
	Health
Discretionary	Dining
	Personal affairs
	Leisure
	Other
	Did not respond

The data from the built environment in turn, comes from different sources since each data has an official government provider. Table 3.5 presents the description of the sources for the built environment data and date. While the data on TAZ, density, streets and income was readily available online, the information on transit stops, transit routes and jobs had to be formally requested from the government sector responsible for it. It is also important to take notice that the data on employment is classified and the authors had to aggregate the data before the publication of this work.

Table 3.5 – Built environment characteristics

Data	Description	Source
Traffic Analysis Zones	Delimitation of each traffic analysis zone	(Metro-DF, 2018)
Population	Total population by census zone	(IBGE & SEGETH, 2010)
Transit Stops	Location of each bus stop	(DFTRANS and SEMOB – Secretaria de Estado de Mobilidade do Distrito Federal, 2016)
Transit Routes	All transit routes available in the Federal District	(DFTRANS and SEMOB – Secretaria de Estado de Mobilidade do Distrito Federal, 2016)
Streets	All streets in the Federal District	(GEOFABRIK GmbH & Openstreetmaps, 2021)
Land use type	Land use type for each floor in each building	(Infraestrutura de Dados Espaciais – IDE/DF, 2020)
Cicleways	Location of each cycleway	(SEMOB – Secretaria de Estado de Mobilidade do Distrito Federal, 2021)
Jobs	Number of jobs by zip code	(Observatório do Trabalho & Ministério da Economia, 2021)
Average income in region	Average income in region	(CODEPLAN, 2018)

Each kind of data was imported into QGIS for both visualization and processing. Most were imported directly since they already were georeferenced. “Jobs” and “Average income in region” demanded preprocessing. The average income in each administrative region was included by joining tables by the AR name as index. The information on jobs was comprised by the number of jobs by zip code and address. Since there is not an official zip code database allocating each code to a corresponding area, two processes had to be conducted. The first was a geocoding algorithm in Python, presented in the Appendix II, which verified each zip code in the Application Programming Interface (API) available in Projeto CEP Aberto (2021). The second was geocoding it through the app “GEOCODE”, made available by CODEPLAN (2021). Both results were then compared on QGIS, and inconsistencies were treated one by one.

All layers were then imported to the Postgres server, so that all data could be in the same platform. As all of the georeferenced data needs to be at the same DATUM for calculations that use their position, they were reprojected to the SRID 37983, corresponding to the SIRGAS 2000 23S DATUM, where Brasília is located. This conversion was conducted using the

ST_TRANSFORM function in PostgreSQL, which reprojects the layer in the desired Spatial Reference Identifier (SRID).

Finally, with all the necessary data in hands, the processing stage started. The first data aggregated into the TAZ was the population census. When the TAZ and the census zones were compared, one could notice that their limits were not equal, which leads to an incorrect assessment of the population. To correct the limits, it was necessary to first conduct an operation of symmetric difference, in which the overlapping area between two layers are removed. Then, the aggregate function in QGIS was used to sum the population data in the census zone into the traffic analysis zone.

After population, the next data aggregated into the TAZ was the number of jobs per zone. Since this data was already at a disaggregated level, it did not need additional processing. So, the number of jobs was aggregated into the zones with the aggregate function in QGIS. Similarly, the number of stops was already in a disaggregated level. To import the number into the TAZ, the function aggregate was used, counting the number of stops. The land use data also did not need further processing, so the areas inside the zone were grouped by use and summed using the function aggregate.

The data represented by lines, such as streets, transit routes and cycleways, needed to be cut in a way no line was in two zones at the same time. The operation of intersection was used for this purpose, since the result of this operation is the line that is inside the zone. After this step, the length of each line was summed and aggregated into each zone.

The data on cul-de-sacs was generated by creating points at the start and at the end of each line, with the function "extract specific vertices". The two-point layers were then subtracted from each other, only remaining the points at the dry ends. The data from cul-de-sacs was aggregated by counting the number of points in each zone, similarly as the data on stops.

Since most data had to be aggregated into TAZ zones, the MAUP effect could not be effectively addressed. Still, the literature has showed that the distance from stop can be used as a proxy for transit accessibility, which would minimize the scaling effect, as in the average minimal distance to stop in any zone is not directly correlated to its size. For this, a layer of buildings was imported from the OpenStreetMap database, and the centroid of each building was generated using the centroid function. Then, the distance of each building to each stop to was calculated using the ST_DISTANCE function in PostgreSQL, and the minimal value was attributed as the minimal distance. Finally, the data was aggregated into zones by calculating the average minimum distance with the aggregate function in QGIS.

With all land use data grouped by zone, the proxies proposed by the literature, shown in Table 3.6 were calculated. Table 3.6 shows how each proxy was calculated for each TAZ. The dummy variable comparing the income at the origin of the tour with the at the destination is proposed by the author to try to capture the relation found in Neves *et al.* (2021), that reported that people had different behavior in neighborhoods richer than their own.

Table 3.6 – Equation for each proxy

Observable variable	Equation
Population Density	$\frac{\sum Population}{TAZ\ area}$
Enployment Density	$\frac{\sum Employment}{TAZ\ area}$
Entropy	$\frac{\sum_i^n P_i \times LN(P_i)}{LN(n)}$
Cul de sac density	$\frac{Number\ of\ Cul\ de\ sac}{TAZ\ area}$
Road density	$\frac{\sum Extension\ of\ roads}{TAZ\ area}$
Sidewalk density	$\frac{\sum Extension\ of\ sidewalk}{TAZ\ area}$
Distance to Stop	$\frac{\sum^{number\ of\ builbings} MIN(Distance\ to\ stop)}{number\ of\ buildings}$
Stop Density	$\frac{\sum Number\ of\ stops}{TAZ\ area}$
Transit densit	$\frac{\sum Extension\ of\ transit}{TAZ\ area}$
Distance between zones	Distance in network between two zones
Distance to CBD	Distance in network between a zone and the CBD
Is average income in destiny greater than in origin	1, if yes 0, if no

P_i in the entropy formula means the proportion of a land use type in the traffic analysis zone, and “n” means the number of types of land uses. In the database, land use has 5 classes:

“Residential”, “Commercial”, “Industrial”, “Leisure/Institutional” and “Mixed use”. Since “Mixed use” is, as the name suggests, a mix of the other uses, it is not considered a class in the entropy calculation. Thus, the number of classes used in the calculation of entropy was 4.

Finally, the tables were joined into a single one, in order for each line to represent a tour made by a person, containing the data about the resident, his household, his tour, the built environment at home location, and main destination, which, as explained before, is the destination where most time was spent at single on an activity The query used for this join is available in the Appendix I.

3.2 STUDY AREA

The Federal District was officially created in 1960, in an attempt to populate the countryside of Brazil. Its construction started in the 1950s, according to a plan made by urbanist Lucio Costa. The capital of Brazil is worldly famous for being the youngest city to have its urban patrimony considered a World Heritage Site (UNESCO, 2021).

However, as appointed by the Institute for Applied Economic Research (IPEA) (2010), its occupation was anything but planned. Brasília has an estimated population of 3 million (IBGE, 2020). The Federal District is divided into 32 neighborhoods, or Administrative Regions (AR) as they are locally called, shown in Figure 3.1. The name Brasília may refer both to the city as a whole or to one of its AR. For clarity, this text will use Brasília to refer to the Administrative Region, and Federal District as the area which contains all the AR.

Since Brasília hosts the political center of the country, it has the greatest number of jobs and services in the city. Despite containing the CBD, Brasília has a suburban disposition, with residential areas with a low population density, low connectivity between streets and a high accessibility to arterial roads. 89.3% of its population does not live in Brasília, but in the other AR, which are often called “satellite cities”. Although they have a local center, a high population density and a variety of services, most of its population work in Brasília.

Thus, most commuting traffic will go towards the center of the region in the morning and away from it in the afternoon. Since most of the day is spent at the CBD, one might expect that the population also do activities there. However, the Federal District suffers from social inequality, making it a good candidate to test the hypothesis, proposed by Neves *et al.* (2021), that, in face of social inequality, most land use characteristics have little influence on mode choice, which would make poor people carry our more trips close to home.

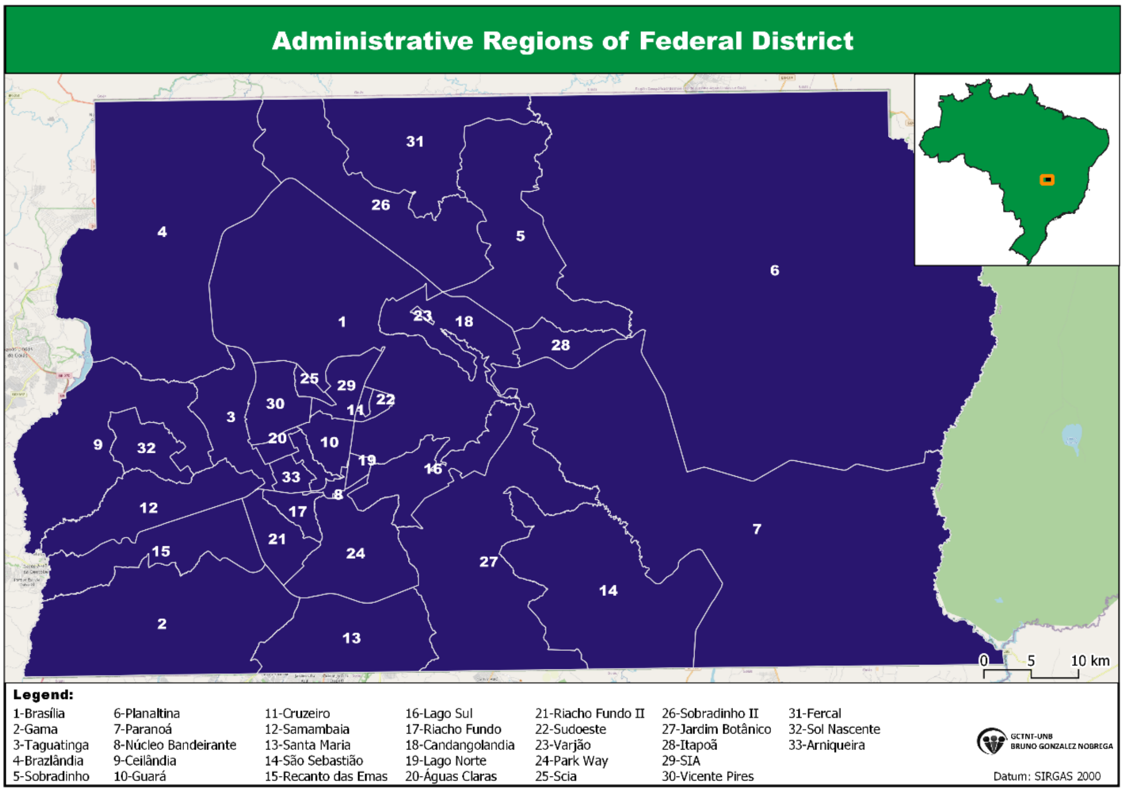

Figure 3.1. – Map of the Federal District

3.3 DATA ANALYSIS

3.3.1 Exploratory Analysis

As explained before, the data will be analyzed in groups of occupation and income class. The summary of the worker and non-worker data can be seen in Table 3.7.

People belonging to a higher income class have not only a greater chance of having greater education but also of having a driver license, which is in line with CODEPLAN (2018). Lower income is related with younger respondents, bigger households with more children and less cars. The gender of the worker population is evenly distributed. The distribution of the non-worker population, however, shows that there are more women than men in this category. The distribution is even more unequal for lower income classes in the non-worker group.

In respect of the activity patterns, higher income workers spend less time at their main activity, leaving more time for other activities, which explains both the greater average of stops per tour and the average number of tours. Even though people with a greater income make more activities, they also spend less time traveling and travel shorter distances. In average, people with a higher income live closer to the CBD, which could mean that they travel less because they are closer to their workplace. Non workers trip chain less than workers, which contrasts Schmöcker *et al.* (2010).

The wealthier inhabitants of Federal District live near the center. The summary also shows that, even though the higher income population lives in regions closer to the CDB and with greater work concentration, such regions still share characteristics with the American suburbs, such as lower street connectivity and density, lower population density and lower transit accessibility. When comparing the density of jobs, the worker population lives in places with higher job density, indicating that workers prefer to live closer to work.

Menezes (2008) explains that Brasília has three types of pedestrians, those who use the urban space near home for physical activities and other discretionary and maintenance activities, those who walk to use the transit service and conduct their activities somewhere else, and those from other regions who may attend activities there.

Table 3.7 – Summary of data

Variables	Non worker			Worker		
	Low income	Medium income	High income	Low income	Medium income	High income
age_avg	46,54	55,34	60,71	37,76	40,72	43,21
gender						
Masculine	29,07%	35,74%	41,12%	55,24%	54,57%	53,54%
Feminine	70,93%	64,26%	58,88%	44,76%	45,43%	46,46%
education_level						
K12	45,73%	12,40%	4,08%	26,40%	3,96%	0,88%
High school	41,96%	38,26%	15,88%	48,01%	22,66%	7,30%
Undergraduate	12,30%	49,33%	80,04%	25,59%	73,38%	91,82%
driver_license						
Y	32,92%	76,76%	89,31%	56,90%	88,83%	96,33%
N	67,08%	23,24%	10,69%	43,10%	11,17%	3,67%
n_residents	3,62	3,47	3,34	3,71	3,56	3,65
n_car	0,65	1,63	2,15	0,78	1,62	2,27
children	1,04	0,63	0,38	1,01	0,70	0,70
activity_time_min	1,77	1,77	1,78	6,55	5,78	5,33
total_time_activity_min	1,83	1,89	1,95	6,74	6,11	5,76
total_trip_time_min	0,76	0,69	0,70	1,38	1,09	0,95
num_stops	1,10	1,21	1,29	1,14	1,28	1,40
number_of_tour	1,52	1,67	1,64	1,75	1,76	1,82
total_distance_km	10,33	13,29	15,97	24,96	22,69	21,40
density_main_destination	89,40	73,57	56,17	68,43	55,03	40,54
job_density_main_destination	47,10	72,64	112,72	116,43	166,98	182,95
entropy_destination	0,49	0,46	0,40	0,45	0,40	0,35
density_residence	102,10	92,67	81,94	100,38	95,17	81,15
job_density_main_residence	9,52	22,30	99,68	11,32	26,35	54,84
entropy_origin	0,48	0,46	0,41	0,48	0,48	0,45
stops_main_residence	0,12	0,10	0,08	0,11	0,10	0,08

Variables	Non worker			Worker		
	Low income	Medium income	High income	Low income	Medium income	High income
culdesacdensity_residence	0,13	0,24	0,28	0,12	0,22	0,27
dist_cbd_origin	26,92	17,76	11,74	26,33	18,69	11,99
dist_stop_origin	0,22	0,23	0,26	0,22	0,23	0,27
ciclewaydensity_residence	0,02	0,24	0,90	0,01	0,16	1,00
streetdensity_residence	0,33	0,29	0,28	0,32	0,30	0,29
transit_density_residence	0,16	0,19	0,21	0,15	0,20	0,18
origin_income	4,65	8,87	12,43	4,77	8,49	12,50
stops_main_destination	0,12	0,10	0,09	0,11	0,11	0,09
culdesacdensity_dest	0,09	0,16	0,18	0,10	0,10	0,10
dist_cbd_dest	24,87	15,96	10,07	18,82	13,70	8,34
dist_stop_dest	0,21	0,21	0,23	0,22	0,22	0,22
cicleway_density_dest	0,04	0,40	0,87	0,29	0,26	0,45
street_density_dest	0,32	0,30	0,30	0,31	0,30	0,30
transit_density_dest	0,20	0,25	0,26	0,27	0,28	0,28
dest_income	5,73	8,13	9,32	7,91	9,46	11,51
Mode						
combined	4,01%	3,15%	2,10%	4,93%	5,37%	3,21%
transit	18,33%	5,58%	1,88%	34,47%	13,48%	3,74%
walk	50,88%	22,93%	15,93%	24,22%	10,70%	7,03%
car	26,41%	68,06%	79,76%	35,42%	69,40%	85,73%
Combination						
Car & active	29%	41%	58%	22%	34%	63%
Car & Transit	35%	38%	37%	50%	50%	31%
Active & Transit	36%	21%	5%	28%	16%	7%

It is also interesting to observe a cross tabulation of the data. Table 3.8 shows that, on average, complex tours are chains of shorter activities for all income classes and both groups. If an activity takes too long, it may be more difficult to schedule other ones in the tour.

Table 3.8 – Average time spend at activities by tour complexity

Tour complexity	Worker			Non worker		
	Low income	Medium income	High income	Low income	Medium income	High income
1	6,65	5,87	5,41	1,76	1,72	1,77
2	2,93	2,77	2,59	0,90	1,02	0,81
>=3	1,72	1,55	1,51	0,78	0,69	0,79

Also, gender has an influence on mode choice, as shown in Table 3.9. Excluding high income female workers, in all other groups the parcel of car use is greater for men than for women. Also, medium income non workers have shown the greatest share of active travel, and the medium income group have the smallest car use percentage, showing a more balanced mode use.

Table 3.9 – Mode choice for tour for each gender on the interest groups

Income class	Gender	Worker				Non worker			
		Combined	Transit	Active	Car	Combined	Transit	Active	Car
High income	**Feminine**	2,81%	3,42%	6,30%	87,47%	3,20%	2,26%	17,51%	77,02%
	Masculine	4,10%	4,03%	7,66%	84,21%	1,34%	1,34%	13,67%	83,65%
Medium income	**Feminine**	7,41%	41,91%	26,25%	24,42%	4,55%	18,06%	53,60%	23,78%
	Masculine	4,66%	28,40%	22,56%	44,38%	3,96%	18,98%	44,24%	32,83%
Low income	**Feminine**	7,09%	15,58%	11,35%	65,98%	4,22%	5,62%	25,52%	64,64%
	Masculine	5,88%	11,72%	10,15%	72,25%	2,01%	5,50%	18,23%	74,26%

The spatial data is shown on Figure 3.2 and Figure 3.3. As it can be seen, the central region of the city has the residents with the highest mean income, and it is home to the greatest concentration of jobs. Despite having the greatest concentration of jobs, it does not have a good mix of land uses, as can be seen by the yellow color in the entropy map.

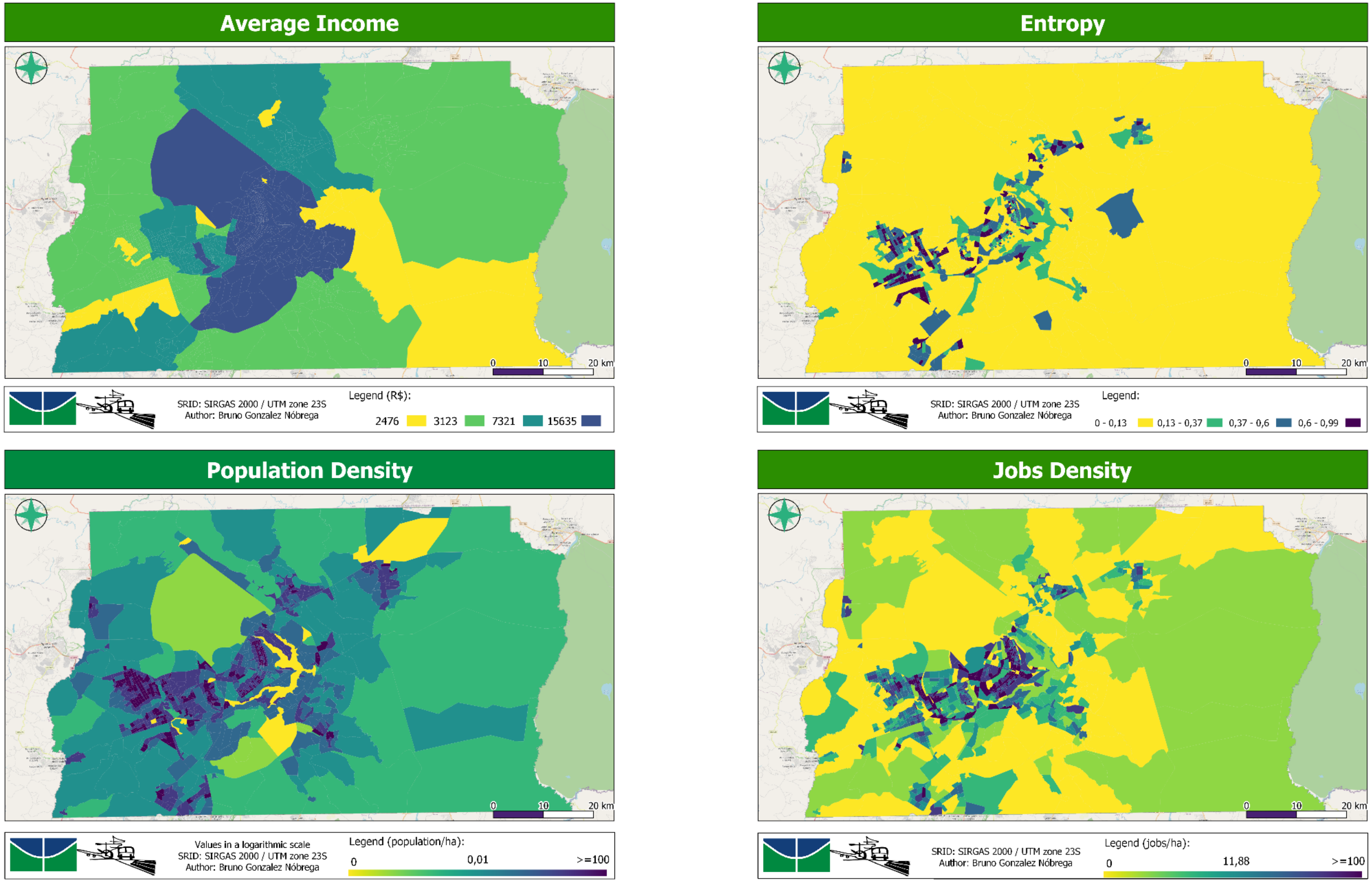

Figure 3.2. – (top left) Mean income in each, (top right) Entropy per zone, (bottom left) population density per zone, (bottom right) job density per zone

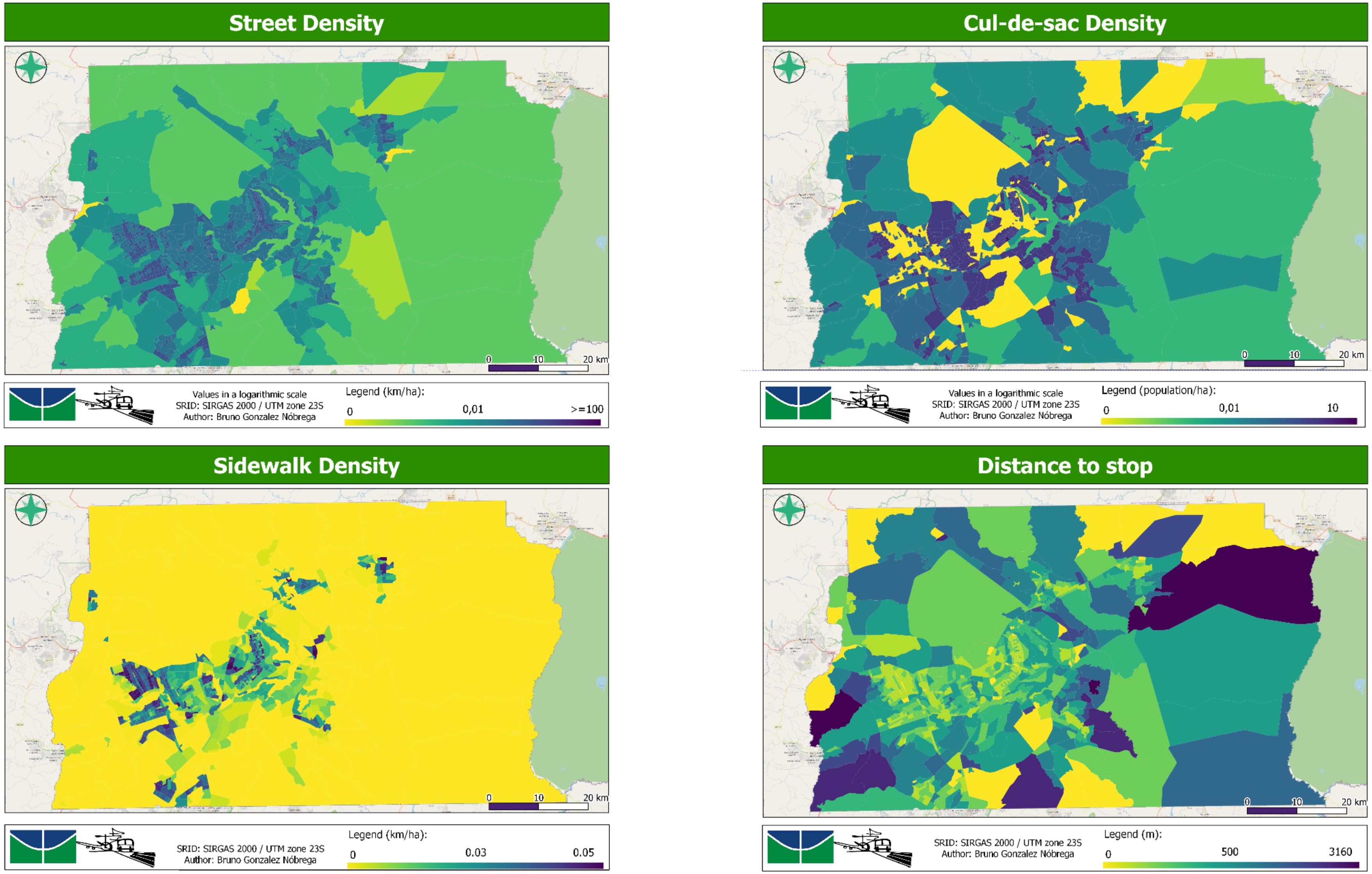

Figure 3.3. – (top left) Street density per zone, (top right) Cul-de-sac density per zone, (bottom left) Sidewalk density per zone, (bottom right) Average distance to stop in each zone

Brasília was planned to be divided into zones with a very restricted use, residential with a local commerce, or commercial areas with little residential use. At the same time, its center is home to the federal government, concentrating the most jobs in the region. As the zones move away from the city center, their mean income decreases. Also, by combining the maps from Figure 3.2, one can identify other centralities in those regions, places with a great population or job density, and an even greater entropy than the CBD.

While its core was planned to allow for its residents to be able to conduct shorter trips, the Federal District has very few zones with a low street density. Most neighborhoods have large roads that may encourage more people to take the car. At the same time, most medium and high-income zones have a fair share of dead-ends. Though common, its existence must be understood differently than other cul-de-sacs. They can be understood are an obstacle only for motorized modes, allowing pedestrians and cyclists to pass through, which may actually promote this active behavior.

The urban centers, in average, have plenty of sidewalks, with the western subcenter having a higher sidewalk density than the CBD. This can help understand the behavior shown in Figure 3.4, which shows that pedestrians are more prone to walking in regions with a greater sidewalk density are more prone to pedestrian tours. However, it is important to take notice of the sidewalk quality. Menezes (2008) explains that this system suffers from troubles with connectivity, and its structure is often broken, which may be an obstacle for some users.

Finally, the bottom right map from Figure 3.3 shows measures of transit accessibility. It shows that, apart from rural areas, the city has a good transit accessibility. This corroborates the data in Table 3.7, which shows that, on average, both origin and destination zones have transit stops within walkable distances (HONG *et al.*, 2014). It is important to consider, however, that the metro area does not have a good public transport system. As da Silva *et al.* (2021) explains, its users are most prone group to complain, but the least probable to opt out, which could be interpreted as not having an option to use another mode.

This behavior can be observed both by the Table 3.7 and by the maps on Figure 3.4. For most zones, the most common travel mode is the car, with active modes been used to leave home, and conduct a closer discretionary trip. Transit is the second most common mode to go to the CDB.

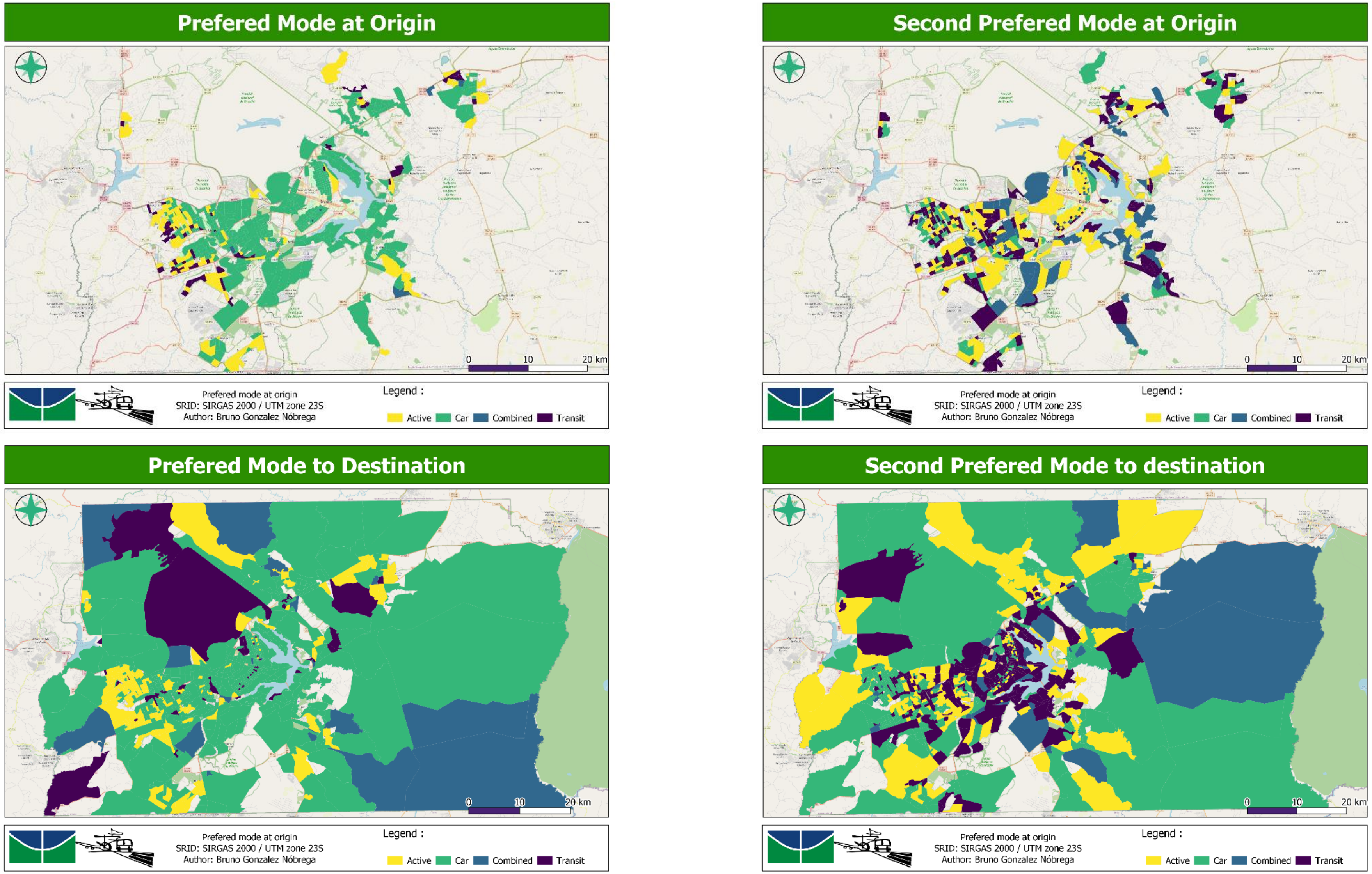

Figure 3.4. – (top left) Most used mode to leave the zone, (top right) second most used mode to leave the zone, (bottom left) most used mode to go to zone (bottom right) Second most used mode to go to zone

3.3.2 Tour complexity Ordered Logit Model

As explained in section 2.2, in this study, tour complexity is measured through the number of stops a person makes between two stops at home. Its nature is both one of a count and an ordinal variable, and it should be modeled as such. In this study, this variable will be modeled through an ordered logit model.

Ordered, or sequential models, are more appropriated to model number of stops than the traditional Multinomial Logit (MNL) models, because the latter consider that the independent variable has an "independence of irrelevant alternatives". In other words, MNL models consider that each alternative is independent of every other, without a rank between them (CHU, 2002). Since a person must first choose to make a stop, then to make another, or to go home, this variable is best represented by a series of binary options.

Since ordinal logit models are merely a sequence of logit models, basic assumptions of such models must be met for the analysis to be valid: all independent variables must be mutually exclusive; all observations must be independent; there should be an adequate number of events for each covariable; and there must be absence of multicollinearity (STOLTZFUS, 2011). The first two assumptions are related to the nature of the dependent variable and have been met in the present case. To evaluate for multicollinearity in the data for tour complexity, a variance inflation factor (VIF) model package in SPSS is used. The results after all variables with multicollinearity are removed can be seen in Table 3.10

Table 3.10 – VIF multicollinearity test for the ordinal logit model

Variables	**Worker**			**Non Worker**		
	Low income	**Medium income**	**High income**	**Low income**	**Medium income**	**High income**
gender	**1,228**	**1,091**	**1,031**	**1,163**	**1,135**	**1,087**
only_worker	**1,254**	**1,267**	**1,172**			
education_level	1,414	1,292	1,106	1,092	1,387	1,386
driver_license	1,555	1,278	1,068	1,402	1,366	1,387
motive	1,390	1,392	1,651	1,250	1,198	1,216
age_avg	1,162	1,112	1,055	1,350	1,404	1,483
n_residents	2,541	2,192	2,544	2,647	2,282	2,872
n_car	1,388	1,291	1,834	1,340	1,273	2,031
Start_time	1,211	1,112	1,360	1,057	1,052	1,131
children	2,313	1,725	1,866	2,824	2,104	1,930

Variables	Worker			Non Worker		
	Low income	Medium income	High income	Low income	Medium income	High income
activity_time_hrs	1,696	1,627	1,854			
total_time_activity_hrs				1,269	1,289	1,290
total_trip_time_hrs	2,278	2,663	1,667	2,454	2,432	2,515
number_of_tour	1,520	1,522	1,618	1,290	1,340	1,327
total_distance_km	3,811	3,042	2,098	3,061	2,974	2,955
density_main_destination	2,289	2,249	2,405	2,768	2,280	2,484
job_density_main_destination	1,684	2,030	1,962	1,410	1,413	1,574
entropy_destination	1,229	1,330	1,340	1,373	1,360	1,329
stops_main_destination	1,928	2,290	2,451	1,815	1,853	1,990
culdesacdensity_dest	1,280	1,417	1,703	1,504	1,601	1,919
dist_cbd_dest	4,307	3,813	2,643	5,231	5,487	3,543
dist_stop_dest_KM	1,503	1,569	1,774	1,538	1,563	1,764
walkway_density_dest	1,844	1,612	1,419	2,922	1,962	1,775
cicleway_density_dest	1,070	1,079	1,131	1,040	1,243	1,223
street_density_dest_km	1,508	1,459	1,541	1,717	1,556	1,704
transit_density_dest_KM	1,194	1,123	1,100	1,258	1,175	1,176
Dest_income_greater_Origin_income	2,181	2,201	2,055	1,992	1,795	1,842
density_residence	2,324	1,876	2,136	2,496	2,094	2,314
job_density_main_residence	1,029	1,033	1,063	1,152	1,063	1,158
entropy_origin	1,167	1,123	1,162	1,361	1,270	1,388
stops_main_residence	1,695	1,480	1,489	1,910	1,550	1,544
culdesacdensity_residence	1,295	1,465	1,448	1,607	1,549	1,634
dist_cbd_origin	2,481	3,398	3,013	3,961	5,156	4,023
dist_stop_origin_KM	1,639	1,679	2,086	1,816	1,749	2,500
ciclewaydensity_residence	1,020	1,096	1,224	1,039	1,205	1,257
walkway_density_residence	2,574	1,666	1,619	2,899	1,830	1,824
transit_density_residence_KM	1,102	1,084	1,139	1,222	1,206	1,214
streetdensity_residence_KM	1,518	1,558	1,751	1,743	1,687	1,965

The time spend at the main activity and the total time spend at activities suffer from multicollinearity (VIF>10). The researchers evaluated the worker and non-worker models with both models. The results showed better model adjustment with the main activity time for worker models and with total time spend at activities for non-worker models.

Finally, as previously mentioned, an ordered logit model predicts a ranked discrete outcome Y (1, 2, 3…,k), in this case, the number of stops made in a tour, through a regression of the latent continuous variable Y^* and a number N of explanatory variables (socioeconomic, activity related and land use), shown in equation 3.1.

$$\boldsymbol{Y^* = \alpha X_n + \varepsilon_n;\ n = 1, 2, 3, \ldots . N} \qquad \text{Equation 3.1}$$

The relation between Y and Y^* is done by estimating k-1 threshold values θ_n, where the threshold values are sorted in ascending order (θ_n>θ_{n-1}) and comparing the expected value of Y to each θ_n, as shown in equation 3.2.

$$Y = \begin{cases} 0\ if\ Y^* \leq \theta_0 \\ 1\ if \theta_0 \leq\leq \theta_1 \\ . \\ . \\ . \\ k-1\ if\ \theta_{K-2} \leq\ Y^* \leq \theta_{K-1} \\ k\ if\ Y^* > \theta_{K-1} \end{cases} \qquad \text{Equation 3.2}$$

To analyze the probability of an individual of choosing between the options, it is possible to use the probability functions written in equation 3.3.

$$P(Y_i = 1) = \frac{e^{(X_i\alpha - \theta_1)}}{1 + e^{(X_i\alpha - \theta_1)}}$$

$$P(Y_i = k) = \frac{e^{(X_i\alpha - \theta_{k-1})}}{1 + e^{(X_i\alpha - \theta_{k-1})}} - \frac{e^{(X_i\alpha - \theta_k)}}{1 + e^{(X_i\alpha - \theta_k)}} \qquad \text{Equation 3.3}$$

$$P(Y_i = K) = \frac{e^{(X_i\alpha - \theta_{K-1})}}{1 + e^{(X_i\alpha - \theta_{K-1})}}$$

3.3.3 Mode choice Multinomial Logit model

In contrast to the ordinal logit model previously explained, in which the object of interest is modeled by a series of binary choices, the MNL simulate a simultaneous choice between three or more options. Since mode choice is a choice between categorical variables MNL models can be used.

As both the ordinal logit model and the MNL are variations of the logit model, both have a similar set of assumptions. As explained in the previous section, an independent variable cannot be in more than one category at once; all observations must be independent; there should be an adequate number of observations for each covariable; and there must be absence of multicollinearity. Since all combinations of mode were grouped in one class, more than one transportation mode cannot be chosen for the tour, meeting the first assumption. The second assumption is met by the data distribution shown in 3.3.1. Finally, as in the ordinal logit model, this study uses the test for multicollinearity in the data in the VIF model package in SPSS. The results, after the removal of all variables with multicollinearity, can be seen in Table 3.11.

Table 3.11 – VIF multicollinearity test for the multinomial model

Variables	Worker			Non Worker		
	Low income	Medium income	High income	Low income	Medium income	High income
gender	1,223	1,090	1,022	1,170	1,129	1,083
driver_license	1,553	1,275	1,069	1,509	1,364	1,383
n_car	1,375	1,284	1,829	1,344	1,271	2,015
n_residents	2,549	2,195	2,593	2,644	2,290	2,857
children	2,313	1,744	1,916	2,763	2,060	1,839
total_trip_time_hrs	2,916	2,755	2,202	2,542	2,525	2,457
total_distance_km	4,673	3,129	2,455	3,441	2,903	2,953
num_stops	1,098	1,159	1,315	1,076	1,202	1,363
number_of_tour	1,502	1,508	1,621	1,223	1,289	1,289
density_main_destination	2,507	2,348	2,472	2,769	2,240	2,445
culdesacdensity_dest	1,282	1,410	1,668	1,499	1,607	1,885
dist_cbd_dest	4,231	3,218	2,200	4,957	4,824	3,015
walkwaydensity_dest	2,181	1,850	1,633	2,901	1,956	1,764
street_density_dest_km	1,496	1,468	1,532	1,674	1,515	1,641
density_residence	2,309	1,854	2,095	2,477	2,065	2,265
culdesacdensity_residence	1,293	1,464	1,442	1,601	1,554	1,576
dist_cbd_origin	2,561	3,045	2,381	3,825	4,701	3,296
dist_stop_origin_km	1,638	1,678	2,037	1,803	1,746	2,461
walkwaydensity_residence	2,567	1,637	1,560	2,831	1,818	1,754
Dest_income_greater_origin_income	1,060	1,091	1,096	1,072	1,070	1,088
education_level	1,271	1,214	1,098	1,251	1,389	1,379
Start_time	1,329	1,390	1,381	1,057	1,044	1,077
only_worker	1,243	1,247	1,162			

Variables	Worker			Non Worker		
	Low income	Medium income	High income	Low income	Medium income	High income
job_density_main_destination	1,697	2,038	1,965	1,406	1,430	1,566
stops_main_destination	1,927	2,282	2,440	1,805	1,857	1,984
transit_density_dest_km	1,190	1,124	1,099	1,258	1,167	1,181
job_density_main_residence	1,028	1,033	1,064	1,152	1,060	1,156
entropy_origin	1,160	1,109	1,155	1,344	1,260	1,362
stops_main_residence	1,696	1,479	1,478	1,905	1,548	1,529
streetdensity_residence_km	1,517	1,543	1,720	1,713	1,677	1,939
transit_density_residence_km	1,101	1,086	1,134	1,226	1,202	1,202
activity_time_hrs	1,858	1,894	1,925	1,261	1,238	1,201
dist_stop_dest_km	1,492	1,552	1,784	1,526	1,571	1,765
entropy_destination	1,228	1,334	1,345	1,369	1,357	1,331

As briefly explained before, a multinomial logit model evaluates a choice between N options. It utilizes the Random Utility Maximization theory (RUM) described by McFadden (1982), which theorizes that each choice has an utility associated with it, as shown in equation 3.4, where U_{Ni} is the utility of the choice N for individual I; X is the vector of observed variables; β_{Ni} is the vector of parameters; and α_{Ni} is the random error representing all the unobserved determinants of the utility.

$$\boldsymbol{U_{Ni} = \beta_{Ni} X_{Ni} + \alpha_{Ni}} \qquad \text{Equation 3.4}$$

In this hypothesis, the probability that an individual i will choose option N instead of choosing the reference choice M is calculated by the logit probabilities shown by equation 3.5.

$$\begin{gathered} \boldsymbol{ln\left(\frac{P_N}{P_M}\right) = U_{Ni}} \\ \boldsymbol{\left(\frac{P_N}{P_M}\right) = e^{U_{Ni}}} \\ \boldsymbol{P_N = (P_M) \times e^{U_{Ni}}} \end{gathered} \qquad \text{Equation 3.5}$$

Also, the summatory of the probability of choosing any of the classes must be equal to one, as presented in equation 3.6.

$$\sum_{n=1}^{m} \boldsymbol{P}_{\boldsymbol{N}} = \mathbf{1}$$

Equation 3.6

$$\boldsymbol{P}_{\boldsymbol{M}} + \sum_{n=1}^{m-1} (\boldsymbol{P}_{\boldsymbol{M}}) \times \boldsymbol{e}^{\boldsymbol{U}_{\boldsymbol{N}i}} = \mathbf{1}$$

Substituting equation 3.5. into equation 3.6., it is possible to calculate the probability of each individual making each choice, as shown in equation 3.7.

$$\boldsymbol{P}_{\boldsymbol{M}} \times \left(\mathbf{1} + \sum_{n=1}^{m-1} \boldsymbol{e}^{\boldsymbol{U}_{\boldsymbol{N}i}}\right) = \mathbf{1}$$

$$\boldsymbol{P}_{\boldsymbol{M}} = \frac{\mathbf{1}}{\mathbf{1} + \sum_{n=1}^{m-1} \boldsymbol{e}^{\boldsymbol{U}_{\boldsymbol{N}i}}}$$

Equation 3.7

$$\boldsymbol{P}_{\boldsymbol{N}} = \frac{\boldsymbol{e}^{\boldsymbol{U}_{\boldsymbol{N}i}}}{\mathbf{1} + \sum_{n=1}^{m-1} \boldsymbol{e}^{\boldsymbol{U}_{\boldsymbol{N}i}}}$$

4 RESULTS

The trips from the data set were grouped into tours, totalizing 21,955 worker tours (13,039 from low-income, 6,085 from medium-income and 2,831 from high-income workers) and 8,916 non-workers tours (5,914 from low-income, 2,098 from medium-income and 904 from high-income individuals). The sample size consisted of 24,453 individuals from all groups. After the treatment of the data, 12 models were constructed, six for tour complexity and six for mode choice.

4.1 TOUR COMPLEXITY MODEL

The model adjustment for all classes is shown in Table 4.1. According to McFadden (1977) a value for this index between 0.2 and 0.4 indicates a good fit. Although the data may seem poorly adjusted, this behavior is in line with the research of Pettersson and Schmöcker (2010), Schmöcker *et al*. (2010), Ma *et al.* (2014). This may indicate that this phenomenon is complex, and more study is needed to develop a better model, especially for lower income classes.

Table 4.1 – McFadden Pseudo R results

	Low-income	Medium-income	High-income
Worker	.109	.118	.190
Non-worker	.099	.154	.209

The results for the model are available in Table 4.2, for workers, and Table 4.3 for non-workers. All three worker models, and the model of medium-income non-workers, reported that households with children trip chain more, which is in line with the research done by Portoghese *et al*. (2011), Khan & Habib, (2020) and Lee *et al*., (2009). Since children are not allowed to travel alone, the adults in the household must adjust their schedule to attend to such needs.

While children tend to increase tour complexity in the household, a larger number of residents has consistently shown to lower the complexity of the trip chain in all worker models, and in the medium-income non-worker one as well. As Seo *et al*. (2013) explains, more people in the household means that they can organize themselves to optimize non-discretionary activities. Similarly, contexts in which a worker from low- and high-income classes is the sole employed member of a household mean that they will trip chain less, leaving the flexible trips to the other members.

Even though gender was not significant in most models, non-worker women from lower income classes tend to trip chain more. Such a result was expected, since women, especially non-employed ones, are usually responsible for the maintenance trips of the household, as well as for taking the children to their mandatory trips, such as schools (ANTIPOVA & WANG, 2010; MCGUCKIN *et al*. 2005; SUSILO *et al*., 2019).

Education was a significant predictor for lower income worker classes. Less education meant less complex trip chains. As hypothesized by Cheng *et al*. (2019), Silva (2018) and Rashidi *et al*. (2010), higher education often means less physically demanding jobs, which in turn leave more time and energy for more activities.

The access to a car, measured by both the ownership of a driver license and the number of cars in the household, has a positive correlation with tour complexity. The flexibility provided by cars to one's schedule, specially by reducing travel times, opens the possibility of doing more activities for lower income classes, who must travel longer distances.

All models show that tours that start earlier have a greater chance of being more complex, as Lee *et al*. (2009) observed for the Atlanta region. Since all activities must be completed in a single day, it is expected that the more time one has, the more activities one is able to conduct. Also, worker models show that people who have longer worker hours trip chain less, which is in line with what Chowdhury and Scott (2020b) found for the Halifax region and Maat and Timmermans (2009) found for the Netherlands. This relation can be explained by a similar argument of the period of the day. The more time and energy someone spends at work, the less of both they will have for other activities.

As explained in chapter 3.3.2, the non-workers models used the total time spent at activities as time spent at work substitute. However, in contrast to the relation of the working time variable to workers' trip chains, the more time spent at activities, the more activities are conducted. This was expected by the behavior observed on Table 3.8, and in line with the findings of Lee *et al*. (2009). As hypothesized before, long activities may create restraints to more stops on a tour.

Table 4.2 – Worker tour complexity model

	Low Income		Medium income		High Income	
	Estimate	**Sig.**	**Estimate**	**Sig.**	**Estimate**	**Sig.**
[Tour_complexity = 1]	.549	**	.214	.332	1.461	*
[Tour_complexity = 2]	2.012	*	1.511	*	2.766	*
n_residents	-.185	*	-.214	*	-.340	*
n_car	.145	*				
children	.311	*	.371	*	.639	*
[education_level=K12]	-.744	*	-.451	**		
[education_level=High school]	-.614	*	-.375	*		
[education_level=Undergraduate or higher]	0[a]	.	0[a]			
[driver_license=No]	-.413	*	-.274	**		
[driver_license=Yes	0a	.	0[a]			
[only_worker=No]	.154	**			.295	**
[only_worker=Yes]	0[a]	.			0[a]	
activity_time_min	-.171	*	-.178	*	-.200	*
total_trip_time_min	.446	*	.669	*	.844	*
number_of_tour	-.247	*	-.231	*	-.286	*
total_distance_km	.023	*	.023	*	.048	*
[Start_time=Night]	-.614	*	-1.026	*	-1.889	*
[Start_time=Afternoon]	-.254	*	-.377	*	-1.288	*
[Start_time=Morning]	0[a]	.	0[a]		0a	
[mandatory=No]	-.681	*	-.746	*		
[mandatory=Yes]	0[a]	.	0[a]			

	Low Income		Medium income		High Income	
	Estimate	**Sig.**	**Estimate**	**Sig.**	**Estimate**	**Sig.**
stops_main_destination	1.084	*				
walkway_density_dest	1.321	*			1.944	*
dist_cbd_dest	.038	*	.017	**	-.035	*
dist_stop_dest_KM			-.678	**		*
density_residence	-.003	*			.003	*
dist_cbd_origin	-.057	*	-.047	*	-.036	*
dist_stop_origin_KM	-.535	**	.525	**		
[Dest_income_greater_Origin_income=No]	.312	*	.346	*	.905	*
[Dest_income_greater_Origin_income=Yes	0[a]	.	0[a]		0a	

* significance<0.01

** significance<0.05

Table 4.3 – Non Worker tour complexity model

	Low Income		Medium income		High Income	
	Estimate	Sig.	Estimate	Sig.	Estimate	Sig.
[Tour_complexity = 1.00]	3.972	*	3.015	*	4.568	*
[Tour_complexity = 2.00]	6.060	*	4.492	*	6.857	*
n_car	.167	.*				
n_residents			-.264	*		
children			.460	*		
gender=Feminine	.269	**				
gender=Masculine	0[a]					
driver_license=N	-.651	*				
driver_license=Y	0[a]					
total_trip_time_hrs	.722	*	.926	*	1.335	*
total_distance_km			.020	*	0.045	*
number_of_tour	.284	*				
total_time_activity_hrs	.110	*	.147	*	0.116	*
Motive=Discretionary	-.869	*	-1.365	*	-1.430	*
Motive=Maintenance	0[a]		0[a]		0[a]	
Day_or_night=day	-.967	*				
Day_or_night=night	0[a]					
density_main_destination	-.004	**				
entropy_destination					-0.869	*
walkwaydensity_dest	2.155	*			1.931	**
stops_main_destination			3.055	*		

	Low Income		Medium income		High Income	
	Estimate	Sig.	Estimate	Sig.	Estimate	Sig.
density_residence	.004	*				
stops_main_residence	-2.247	*	-2.339	**	0.007	*
walkwaydensity_residence	-1.659	*				
Dest_income_greater_Origin_income=N	.780	*	.799	*	1.067	*
Dest_income_greater_Origin_income=Y	0[a]		0[a]		0[a]	

* significance<0.01

** significance<0.05

Regarding the impact of main motive of tour, workers and non-workers have similar behaviors. Workers prefer to chain stops on their commuting trips, while non-workers have shown a similar behavior in their trips accompanying spouses and children on their mandatory trips. This behavior could be explained by the possibility of accommodating other activities that need to be done early, such as taking children to school, or at the end of their day. This relation is similar to what Antipova and Wang (2010) found for women in their study; further research would be needed to verify whether this relation is stronger for women in Brasília.

All six models showed a positive correlation between total time spent traveling and tour complexity. Also, aside from the non-worker low-income group, all other models have showed the same relation between total distance traveled and tour complexity. Both relations were also found by Maat and Timmermans (2006).

The number of daily tours is a significant variable in explaining tour complexity for all three worker classes. To optimize their time, these groups tend to trip chain on their work trips, which is the same behavior found by Daisy *et al*. (2018) in Halifax region. Workers that stop at home before initiating a new activity have a greater chance of making simple tours. In contrast, this same variable has the opposite effect on low-income non-workers. Without the time constraints of an occupation, this group tends to optimize its time outside by conducting as much activities as possible each tour.

Sidewalks density at destination was a significant variable for low- and high-income models, with a positive correlation with tour complexity for workers. This would mean that, while the trip chaining phenomenon has been linked with car use, more walkable neighborhoods with a greater concentration of employment can promote a more sustainable trip chain behavior in those groups. This results are in line with the findings of Chowdhury and Scott (2020b). In contrast, greater sidewalk density at home implied less complex trip chains for low-income non-workers.

Greater sidewalk density at home implied less complex trip chains for low-income non-workers, which implies that walking may decrease the chance of trip chaining for this population. One possible reason for such a result is the fact that this research did not account for sidewalk quality. As Menezes (2008) points out, many of Brasilia’s sidewalks are in poor quality, which may increase the difficulty of each new trip, effectively reducing tour complexity.

Distance to the CBD from workplace is positively correlated with trip chain complexity for low- and medium-income worker groups, and negatively correlated for high-income worker groups while distance to the CBD from home resulted in a negative relation with tour complexity for all worker clusters. This means that living far from it decreases chances of greater tour complexity for all worker classes, which is in agreement with the results found by Daisy *et al*. (2020). Alternatively, the farther lower income classes work from the center of the city, the higher the chance of trip chaining, which is similar to Manoj and Verma (2015a).

One explanation for this behavior could be that, even though Federal District center has options of activities to engage in, it is also one of the most expensive areas in the city. The models show that all groups tend to trip chain more in regions where the average income is lower than that of their residence. This finding helps to understand the trip chaining behavior in developing countries, as it corroborates the hypothesis of Neves *et al*. (2021). The affordability of an area influences the decision to do activities there; people will not spend more time in a region if they cannot afford the prices offered there. Still, more study is necessary to find whether this result implies more trip chains near home.

Transit accessibility at home and at destination increased the chance of greater tour complexity for low-income workers and low- and middle-income non-workers, as reported by van Acker and Witlox (2011), Chen and Akar (2017); Concas and DeSalvo (2014) and Silva *et al.* (2014). Since lower income classes have less access to cars and, thus, are dependent on the transit system, one can expect that, as the difficulty of accessing the system decreases, such individuals are more prone to use it. The model for workers in the medium income class showed that the decrease of transit accessibility at home would increase the chance of trip chaining, which could mean that, as this class chooses the car more often, their schedule became more flexible, and they could trip chain more.

Density was a significant factor for the lower income class, while showing a divergent behavior for workers and non-workers. While denser locations at home implied less trip chains for workers, the reverse was true for non-workers. A greater density means that this population incurs lower costs of doing activities near home. For a person with little free time, such as a worker, each activity done near home has a greater chance of being the sole one. Conversely, for a non-worker, the greater proximity between activities means that they can better optimize their time, an explanation that can also be applied for higher income workers. Finally, denser destinations have a negative relation to trip chaining complexity for low-income non-workers, which was also reported by Grue *et al*. (2020).

4.2 MODE CHOICE MODEL

The Table 4.4 shows the Pseudo-R results for all 6 models. In contrast to the tour complexity model, the mode choice modeled through the logit multinomial has achieved a good adjustment. The McFadden Pseudo-R ranged between 0,400 and 0,482. According to McFadden (1977) a value for this index between 0.2 and 0.4 indicates a good fit.

Table 4.4 – McFadden Pseudo-R results for the multinomial mode choice model

	Low income	Medium income	High income
Worker	.482	.424	.400
Non-worker	.447	.415	.458

As expected, the access to a car reduces the chance of an individual to choose other travel modes. Both the number of cars at the residence and the possession of a driver license increased the chance of choosing a car to travel, for all income classes, workers and non-workers. In a similar perspective, tours that went through greater distances also had a greater chance of being made by cars. As Yang *et al.*, (2019) explains, people will not walk or cycle great distances. Moreover, greater distances may involve more planning, moving people away from transit.

While a greater traveled distance increased the chance of choosing the car as the sole mode for the tour, longer travel times increased the chance of choosing transit or a combined mode for the tour. This may reflect that transit, walking, or a combined mode that uses either, operates at lower speeds than private vehicles, thus taking longer to cover the same distance.

Also, individuals in households with children have a greater chance of using car for their tours. As theorized in the tour formation model, the planning of activities with children is often complex and, thus, more easily done by cars. In contrast, the number of residents in a household negatively impacted car use, possibly because the access of additional members to cars is more restricted.

Table 4.5 – Worker mode choice model

	Combined						Transit						Active					
	Low income		Medium income		High income		Low income		Medium income		High income		Low income		Medium income		High income	
	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.
Intercept	-3.872	*	-4.002	*	-4.561	*	-.698	*	-.843	*	-3.383	*	1.277	*	1.114	*	1.703	*
n_car	-.815	*	-.814	*	-.480	**	-1.138	*	-1.137	*	-.997	*	-1.024	*	-1.028	*	-.420	*
n_residents	.150	*	.150	*	.329	**	.253	*	.252	*	.528	*	.147	*	.144	*	.340	*
children	-.200	*	-.200	*	-.378	*	-.288	*	-.287	*	-.425	*	-.182	*	-.182	*	-.479	*
gender=Female	.773	*	.770	*	-.586	*	.650	*	.650	*	-.524	**	-.002	.977	-.026	.716	-.595	*
gender=Male	0^b		0^b		0^b		0^b		0^b		0^b		0^b		0^b		0^b	
driver_license=N	1.495	*	1.493	*	1.255	*	1.788	*	1.785	*	2.629	*	2.121	*	2.116	*	1.636	*
driver_license=Y	0^b		0^b		0^b		0^b		0^b		0^b		0^b		0^b		0^b	
total_trip_time_hrs	1.440	*	1.440	*	.472	**	2.013	*	2.011	*	.990	*	-.076	.477	-.079	.460	.559	.227
total_distance_km	-.032	*	-.032	*	-.042	*	-.037	*	-.037	*	.016	.124	-.239	*	-.239	*	-.449	*
num_stops	.624	*	.618	*	.853	*	-1.465	*	-1.465	*	-1.291	*	-.043	.643	-.066	.474	-.102	.771
number_of_tour	-.179	**	-.184	**	-.709	*	-.430	*	-.436	*	-.940	*	-.130	*	-.131	*	-.176	.156
density_main_destination	-.004	*	-.003	*	.002	.536	-.002	**	-.001	.144	.002	.439	.005	*	.002	.*	.006	*
density_residence	.002	.163	.002	.192	.003	.190	.005	*	.005	*	.011	*	.002	.071	.003	*	.004	**
culdesacdensity_dest	.426	.146	.358	.216			-.174	.412	-.269	.198			.639	**	.512	**		
culdesacdensity_residence	-.429	.123			1.315	**	-.531	*			-.071	.912	-.546	**			-.954	.087
dist_cbd_dest	.012	.051	.012	.061	-.071	.*	-.027	*	-.028	*	-.035	**	.084	*	.093	*	-.046	.551
dist_cbd_origin	-.006	.427	-.002	.762	.088	*	.019	.*	.024	*	-.001	.981	-.088	*	-.094	*	-.005	.949
walkwaydensity_dest	.194	.700			1.021	.358	.469	.182			1.109	.354	-2.218	*			-2.269	**
walkwaydensity_residence	-.556	.329	-.407	.463			-1.133	.*	-.936	**			.026	.957	-.639	.137		
street_density_dest_km	1.111	*	1.181	*	.396	.663	1.250	*	1.390	*	2.211	*	.711	.060	.266	.468	-.550	.471
dist_stop_origin_km	-.759	.051	-.792	**			-1.392	*	-1.422	*			-.078	.803	-.171	.581		

* significance<0.01

** significance<0.05

Table 4.6 – Non worker mode choice model

	Combined						Transit						Active					
	Low income		Medium income		High income		Low income		Medium income		High income		Low income		Medium income		High income	
	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.	B	Sig.
Intercept	-4.410	*	-3.915	*	-4.376	*	-.412	.394	-1.951	*	-4.322	*	-.150	.843	2.272	*	.282	.636
n_car	-.892	*	-.444	*	-.046	.869	-1.169	*	-.735	*	-.823	.106	-1.072	*	-.457	*	-.880	*
n_residents	.182	**	.148	.248	.291	.221	.242	*	.474	*	.250	.491	.168	*	.086	.228	.463	*
children	-.260	**	-.138	.503	-.501	.237	-.280	*	-.606	*	-1.576	**	-.036	.554	-.064	.552	-.608	**
driver_license=N	1.278	*	1.168	*	1.317	*	1.428	*	.687	*	4.142	*	1.744	*	1.348	*	1.138	*
driver_license=Y	0^b		0^b		0^b		0^b		0^b		0^b		0^b		0^b		0^b	
Activity_time_min	.064	**	.109	.054			-.012	.592	.141	*			-.128	*	-.089	.087		
total_trip_time_hrs	2.010	*	1.543	*	1.807	*	2.615	*	2.599	*	3.230	*	.568	*	.985	*	1.035	**
total_distance_km	-.065	*	-.072	*	-.073	**	-.051	*	-.051	*	-.103	*	-.264	*	-.529	*	-.448	*
num_stops	.610	*	.472	*			-1.983	*	-2.481	*			-.025	.856	-.253	.286		
number_of_tour	-.063	.623	-.220	.245			-.240	*	-.249	.207			.075	.211	-.319	*		
density_main_destination	.001	.702			-.005	.536	.000	.980			.011	.122	.007	*			.007	**
culdesacdensity_dest	.942	.082			-1.509	.440	.398	.326			-8.496	*	1.095	*			.975	.144
dist_cbd_dest	-.025	.102			-.112	**	-.026	*			.090	.202	.096	*			.323	*
dist_cbd_origin	.025	.134			.098	.074	.014	.196			-.167	**	-.113	*			-.371	*
walkwaydensity_dest	.630	.520	-.521	.674	-2.502	.311	.978	.153	-1.542	.166	-4.007	.209	-2.702	*	-1.583	.**	-2.864	**
walkwaydensity_residence	-.999	.129			2.121	.280	-.215	.659			2.327	.380	.569	.198			3.188	**
job_density_main_destination	.000	.919	.000	.755			.000	.159	.001	**			-.010	*	-.001	.497		
stops_main_destination	-.824	.450	1.716	.270			2.238	*	3.683	*			.656	.345	-.205	.863		
Dest_incom_greater_Orig_incom =N	.540	.187					-.152	.543					1.534	.**				
Dest_incom_greater_Orig_incom =y	0^b						0^b						0^b					

* significance<0.01

** significance<0.05

Gender was shown to be significant for workers, with a different influence according to one's income class. Female workers from low- and middle-income households are negatively correlated with car use, preferring other modes for their tours. High-income female workers, conversely, are more prone to car use. As presented before, lower income women have a lower average number of cars in the household than men. Such a tendency, combined with the findings of Cheng *et al.* (2019), which indicates that men usually take precedence over women on the use of a single car, may explain this phenomenon. In higher income worker classes, the shift in the preferences may reflect that, if choices are not restricted by the number of cars, women will choose the car more often than men, since they often have more complex routines that could need the car.

Regarding tour complexity, workers from all income classes and non-workers from the lower classes have a greater chance of using a combined mode when they trip chain more. This result was expected, since, to choose more than one mode, one must make more than one travel. Also, more complex chains reduced the chance of taking the transit on their travel. This result is in line with the findings of both Huang *et al.* (2021) and Vande Walle and Steenberghen (2006), which hypothesized that complex tours involve more planning, and that transit systems might not comply with its planned schedule, making it more difficult to use.

The number of daily tours is negatively related to choosing modes other than cars for all income classes of workers. For low-income non-workers, this variable was negatively related to choosing the bus over cars, and, for medium-income non-workers, it negatively influenced the choice of active modes. While not significant for all groups and modes, the negative relation between choosing non-car modes and the number of tours may indicate that people that stop more at home throughout the day are more prone to use car as their main mode.

Time spent at one activity was shown to be significant for low- and medium-income non-workers. While it increases the chance of using a combined mode for low-income individuals, and of taking the bus for medium-income ones, it decreased the chance of using an active mode for low-income non-workers.

Accounting for BE variables, population density at destination was shown to be positively related to active modes for both workers and non-workers groups from all income groups (the group of medium-income non-workers being the exception). This result was also reported extensively in the literature, such as in the works of Etminani-Ghasrodashti & Ardeshiri (2015). Chen *et al.* (2008) and Chen & McKnight, (2007). As regions get denser, their walkability increases by the fact that activities get closer to each other. At the same time, density decreased the for low-income workers to take transit, and the chances for the two lower income worker classes of taking a combined mode. Population density near home also was positively influenced the choice for active modes over cars for high- and medium-income workers and for transit over cars for workers from all income classes.

Greater distance to the CBD at destination also increased the chance for low- and medium-income workers, and all non-workers, of walking instead of taking the car. This relation could be similar to what Neves *et al.* (2021) reported. While the center has a more mixed land use, it is also more expensive, which may be a barrier to some people. In contrast, the farther the destination is from the CBD, the greater the possibility of choosing the car over transit for the worker models. This can be explained by the decrease of transit accessibility, as the destination moves away from the city center.

Conversely, the distance to the CBD from home had the opposite effect of that between the destination and the city center. For this variable, greater distances decrease the chance of walking for the same groups, while increasing the chance of taking transit over cars. The latter can be explained by understanding that people who live farther from the center have less access to cars; hence, they are more prone to choosing transit for their commute.

Likewise, cul-de-sac density at destination was also shown to be positively correlated to active modes for low- and medium-income workers, presumably because, by decreasing car access to a region, the city can improve its walkability. It is important to take notice that, in contrast to other cities, some cul-de-sacs in Brasília, especially those near the CBD, can be transposed by foot, being only an obstacle for motor vehicles.

Also, this variable is negatively correlated to transit use for high-income non-workers. This income class has the lowest percentage of transit usage. As previously explained, cul-de-sacs are an obstacle for motorized vehicles, making it harder to create a good transit system for this population. More dead ends near home, conversely, negatively influenced low-income workers to take the bus or walk on their tour. This contrast could be an effect of the nature of dead ends at poorer neighborhoods. Not only do they tend to be closed for pedestrians, but they also have more safety issues.

Transit accessibility, measured by the distance to a transit stop for workers, and by the density of transit stops for non-workers, was shown to be a significant variable for choosing transit. In both cases, for low- and medium-income groups, a better transit accessibility predictably resulted in a greater chance of taking the bus rather than the car. Both Lee, (2016) and van de Coevering *et al.* (2021) have reached a similar conclusion regarding this variable, arguing that ease of access may foster transit usage.

Street density was shown to be significant for the worker population to choose more than one mode or transit over cars. This could have happened because zones with a greater street density had a better transit connectivity. and allowed for a better transition from car to transit, a combination that accounted for 50% of the combined option for those groups.

Sidewalk density at destination reduced the chances of using an active mode for all groups but middle-class workers. This unexpected behavior may be explained by the quality of the sidewalks in the city. Higher concentrations of sidewalks also may contain more problems, such as poor connectivity or infrastructure. In this sense, even if a region has a fair extension of sidewalks, it may be even harder to walk on them, compared to regions with less sidewalk concentration but with better quality.

Finally, tours whose main destination was a zone with an average income higher than that of the traveler’s origin had less chance of using active modes on their tour. This behavior corroborates what has been hypothesized by Neves *et al.* (2021) and Manoj and Verma (2015a). They stated that the built environment could be dense, diverse, walkable, and with a great transit accessibility, but, if its activities were more expensive than one could afford, an individual would not conduct activities there, preferring to travel greater distances by transit or car to spend his money more efficiently.

4.3 SUMMARY

While the groups had a different behavior in both models, its differences were in the significant variables, and not so much in their effect. As Table 4.7 shows, only the number of tours and population density near home had an opposing effect in low-income workers and non-workers. On the one hand, more tours and denser regions reduced the number of stops for workers; the other, such variables increased stops for non-workers.

Table 4.7 – Summary of tour complexity model results

Variable	Worker			Non worker		
	Low Income	Medium income	High Income	Low Income	Medium income	High Income
n_residents	-	-	-		-	
n_car	+			+		
children	+	+	+		+	
activity_time_min	-	-	-			
total_time_activity_hrs				+	+	+
total_trip_time_min	+	+	+	+	+	+
number_of_tour	-	-	-	+		
total_distance_km	+	+	+		+	+
density_main_destination				-		
density_residence	-		+	+		
entropy_destination						-
walkway_density_dest	+		+	+		+
walkwaydensity_residence				-		
stops_main_destination	+				+	
stops_main_residence				-	-	+
dist_stop_dest_KM		-				
dist_stop_origin_KM	-	+				
dist_cbd_dest	+	+	-			
dist_cbd_origin	-	-	-			
education_level=K12	-	-				
education_level=High school	-	-				
education_level=Undergraduate or higher	0^a	0^a				
gender=Feminine				+		
gender=Masculine				0^a		
driver_license=No	-	-		-		

Variable	Worker			Non worker		
	Low Income	Medium income	High Income	Low Income	Medium income	High Income
driver_license=Yes	0^a	0^a		0^a		
Dest_income > Origin_income=No	+	+	+	+	+	+
Dest_income > Origin_income=Yes	0^a	0^a	0^a	0^a	0^a	0^a
Start_time=Night	-	-	-	-		
Start_time=Afternoon	-	-	-	0^a		
Start_time=Morning	0^a	0^a	0^a	0^a		
only_worker=No	+		+			
only_worker=Yes	0^a		0^a			
mandatory=No	-	-				
mandatory=Yes	0^a	0^a				
Motive=Discretionary				-	-	-
Motive=Maintenance				0^a	0^a	0^a

Positive correlation	0^a reference
Negative correlation	

Both phenomena were explained in the section 2.2. Since workers have a stricter schedule, more tours may imply an extra activity in the remaining time of the day. For non-workers, an extra tour may allocate different activities. While the density relation with trip chaining is not as simple as the number of tours, the explanation may be quite similar. Workers whose homes have a greater density nearby may prefer to go on an extra tour near home rather than chaining it near their workplaces. Non-workers, however, do not travel longer distances and have more time to allocate as they wish, making it easier to chain trips near home.

Also, some characteristics of the built environment had to be measured differently for their effect to be assessed. Transit accessibility, for example, is better represented by the distance to the stop for workers, and by density of stops in a zone for non-workers. This could be an effect of the Modifiable Area Problem, described in section 2.1. While similar, they can be different – a larger zone could have few stops near buildings; thus, it will have a small density and a short distance to stops.

The only land use variable that consistently impacted tour complexity was the difference between income in one's home location and destination. In all models, people were more prone to trip chain if the destination had lower income than their origin, implying that, to conduct more activities, they must be able to afford them. While this behavior has not been extensively reported in the literature, the results found for Brasilia corroborate the hypothesis of Manoj &Verma, (2015b) and Neves *et al.* (2021) and presents more insight on the topic of how the urban form influences travel behavior.

The demographics “D”, proposed by Ewing and Cervero (2010), may not be a built environment variable in the strict meaning of the term, but it seems to impact how other variables are perceived by people. The data shows that most individuals, even those coming from higher classes, prefer to trip chain where their money gets the most return. While this result contributes to the understanding of land use and travel behavior, more study is needed to better comprehend how the average cost of an activity in a zone affects the manner in which the population chooses to engage in them.

Albeit the income difference was proven relevant to the manners in which people trip chain, it was only relevant for low-income non-worker when choosing active modes over cars, as Table 4.8 presents. With both information in hand, it is possible to speculate that the results are correlated.

Low-income non-workers are the most sensible class to spending money, and the class most prone to taking active modes and transit. This would mean that, as they may trip chain more in a region with affordable prices, they also to do it by foot instead of taking a motorized mode. Overall, non-workers were less susceptible to the influence of the built environment when combining more than one mode over car than workers. This could have happened because workers are more bound by locations, and, thus, are more prone to make cheaper trips to further explore their workplace surroundings.

Table 4.8 – Summary of mode choice model results

Employment Status	Worker			Non Worker			Worker			Non Worker			Worker			Non Worker		
Mode	**Combined**						**Transit**						**Active**					
Income Group	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**	**Low**	**Medium**	**High**
n_car	-	-	-	-	-		-	-	-	-	-		-	-	-	-	-	-
n_residents	+	+	+	+			+	+	+	+	+		+	+	+	+		+
children	-	-	-	-			-	-	-	-	-	-	-	-	-			-
Activity_time_min				+							+					-		
total_trip_time_hrs	+	+	+	+	+	+	+	+	+	+	+	+				+	+	+
total_distance_km	-	-	-	-	-	-	-	-		-	-	-	-	-	-	-	-	-
num_stops	+	+	+	+	+		-	-	-	-	-							
number_of_tour	-	-	-				-	-	-	-			-	-			-	
density_main_destin.	-	-					-						+	+	+	+		+
density_residence							+	+	+					+	+			
culdesacdensity_dest												-	+	+		+		
culdesacdensity_residence			+				-						-					
dist_cbd_dest			-			-	-	-	-	-			+	+		+		+
dist_cbd_origin			+				+	+				-	-	-		-		-
walkwaydensity_dest													-		-	-	-	-
walkwaydensity_residence							-	-										+
street_density_dest_km	+	+					+	+	+									
dist_stop_origin_km		-					-	-										
job_density_main_destin											+					+		
stops_main_destination										+	+							
gender=Female	+	+	-				+	+	-						-			
gender=Male	0^b	0^b	0^b				0^b	0^b	0^b						0^b			
driver_license=N	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+	+
driver_license=Y	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b	0^b
Dest_incom_>_Orig_incom=N																+		
Dest_incom_>_Orig_incom=y																0^b		

Positive correlation

Negative correlation

0^b reference

Even so, the number of stops did not increase the number of active tours, only that of combined ones. This shows that an increased tour complexity in a developing country may be imply a behavior closer to that of the USA than that of Japan or Australia. In the former, people tend to trip chain more by car, as Chowdhury & Scott (2020b) and McGuckin *et al.* (2005) argue. In the latter, people seem to trip chain by transit, as explained by Susilo & Kitamura (2008) and Ho & Mulley (2013). Still, more stops added to the probability of choosing a combined mode for most classes, which leaves space for debate on this influence.

The results showed that there are a few built environment variables which influenced both trip chaining and mode choice. Distance to the CBD, for example, influenced both trip chaining and the built environment and, by doing so, may have had a greater effect on the choice of taking the car over transit for workers. Working far from the CBD increased tour complexity and decreased the chance of using transit, while living far from it had the opposite effect. This result shows that bringing subcenters closer to the population could increase transit ridership by decreasing the need to trip chain, as well as by increasing the number of activities nearby.

In general, variables from the household, such as number of cars, children, and overall residents, have shown a more consistently significant impact on mode choice across groups than land use variables. This was expected, as the reviewed meta-analysis agreed that the impact of built environment is small when compared to other variables. The concept presented in section 2.1 was that the impact of built environment on mode choice could be mediated by tour complexity, inducing a more sustainable travel.

The results showed that, while this concept may be true for some aspects of the built environment, it may not be as straightforward as presented. Different measures of each “D” were significant at different levels, implying that their effect may be easier to interpret if analyzed as a latent variable which encompasses more aspects than a single variable is able to represent.

5 CONCLUSIONS

Most research on built environment and travel behavior focused on its influence on mode choice. To the best knowledge of this author, at least two meta-analyses, Ewing & Cervero, (2010) and Aston *et al.* (2020), were carried out on the subject. Both recognized the lack of study on this matter. Moreover, as Bautista-Hernández (2020) notes, there is not enough research on the subject in Latin America. Hence, the aim of this study was to better understand the effect of built environment on travel behavior of workers and non-workers from different income classes, focusing on trip chaining and mode choice.

Using the database from the FDUMS, a total of 21,955 worker tours and 8,916 non-worker tours were analyzed. Also, land use data for the origin and main destination of each tour was collected from various sources in an effort to create a complete picture of each zone in the study. This dataset was then used to build the models to accomplish the first specific goal, the understanding of the effects of BE variables on tour complexity.

First, it could be concluded that the impact of the built environment in trip chaining appears to be less consistent than the those of tour characteristics and sociodemographics. In general, the less obligatory the motive of the journey was, the more likely people were to trip chain. Also, it seemed that the more schedule constraints the diminish one's probability to trip chain.

Nonetheless, it was concluded that, even though different populations are impacted with different BE variables all the 5 "Ds" were observed to be significant to some extent. In the literature, it was found that density at home was the most used variable when analyzing trip chaining, but it was not clear whether more density near home increased or decreased tour complexity. This uncertainty was reflected on this research, as density near home had different effects for different groups. Density of sidewalks, a Design variable, and transit accessibility also had a significant effect on tour complexity.

Moreover, this research showed that the commonly used variables to represent the BE may not be enough to convey all its influences. The data shows that, if the average income of one's destination is greater than that of one's origin, people will trip chain more. One implication of this finding is that not all diversities in the built environment are equally significant. Individuals engage more in activities they can afford. City planners must be aware of this when proposing a densification of an area or a diversification of one since it may not be enough to induce more activities in the region.

Still, this research observed that the built environment had an effect on mode choice. Denser regions influence people to use less cars, while the effect is more consistent in the region where people engage in activities than near home. This could indicate a relation between the easiness of getting to one destination and using more sustainable modes. Also, the distance to the CBD also influenced the mode choice, living far from it decreased the chance of using an active mode while engaging in activities far from it increased these odds.

This study also aimed to contribute to the understanding of the effects trip chaining on mode choice. While most studies agreed that car was the preferred mode when chaining trips, the behavior in some regions, such as Osaka, implied that this could not be an universal truth (Susilo & Kitamura, 2008). The results presented here were in line with the current understanding of the phenomenon. Not only more stops were a significant predictor of more car use, but a greater car availability one had in his household was related to more complex tours.

Still, tour complexity was a significant variable in choosing more than one mode of transportation. And while the built environment had close to no influence on taking this option over a car for non-workers, it had some influence for workers, due to more location restrictions. This behavior could be explored by city planners to induce a more sustainable trip chaining, while effectively reducing the number of tours made by workers, a variable known to increase car use, by reducing the need of more tours to engage in maintenance activities, for example.

5.1 Limitations and recommendations

The literature presented two definitions of trip chaining, one that described tours by a number of stops in which none of them spent more than 30 min in one place and one that limited tours in the chains of trips between two stops at home. This study used the latter for its analysis, but there was not a comparison of the results using both definitions to better understand how the built environment impact on each one.

This comparison may also help to shine more light in the low adjustment of the models made by researchers that try to explain the trip chaining behavior. Schmöcker *et al.* (2010) presents a brief comparison for both definitions using London data. In their study the use of the timed tour may result in a better adjustment of models, which may indicate the need for further research with the Brasilia data as well.

This research was also limited by the data available, which was grouped by zones and did not have any indication of preferences. This meant that this research could not control for the MAUP, which may have affected the model adjustments as well. As Yang *et al* (2019) calculated, there seems to be a better distance to group built environments variables to emulate its influence on trip chaining. Also, it was not possible to control for the self-selection problem. When researching about land use influence on transport it is important to understand that people may choose to live in a certain neighborhood because it better suits their lifestyle.

This study also found the need to further investigate the effect of sidewalks on tours mode choice. The data used for sidewalks did not account for its quality or connectivity, which could explain the behavior observed, that more sidewalks reduced the probability of taking an active mode. It could be possible by refining the data and classifying between quality that this result could be better explained.

Also, this study used logit two models to predict trip chaining behavior and mode choice. However, the results showed that some variables are significant in both models, indicating that some indirect effects of the built environment may exist between the behaviors. Thus, it is important to use a statistical model that can demonstrate this relation. The literature reported the use of structural equations and Bayesian networks, such as Markov chains, which can explain both direct and indirect effects of variables in an outcome of a model. Future researchers must also be aware of the assumptions of any chosen model and test their validity before applying them to their research.

Finally, this study used only data from one city, Brasilia, and while the model may be valid for this location more tests must be made in order to fully understand if the relations found are valid in other places. Future research could use data from other Brazilian cities such as São Paulo and Curitiba, to further investigate those relations. Also, the research could benefit by using panel, or even pseudo panel, data to try to validate the model over time, understanding if the results were an effect of their time or if they are valid in the same city over time as well. Both are methods of external validation of models and should be done to confirm the transferability of the model.

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APPENDIX I -SQL QUERIES

Number_of_children query

--create column number of children

```
Alter table hhld_household1
ADD column number_of_children integer;

--Adding values to the new column
update hhld_household1
SET number_of_children=
        (Select number_of_children from (
        --select for each household the number of residents that are 17 years old or younger
        Select a.domicilio_id,
        count(*)
        FILTER (WHERE idade = '0 a 4 anos' or
                        idade = '5 a 9 anos' or
                        idade = '10 a 14 anos'or
                        idade = '15 a 17 anos') AS number_of_children
                from hhld_person as a
                group by a.domicilio_id) as a
--indicates the column to join the data
                where hhld_household1.domicilio_id =a.domicilio_id);
```

Activity_time query

--create column activity_time

```
Alter table hhld_trips3
ADD column activity_time time without time zone;

--Adding values to the new column
update hhld_trips3
SET activity_time =
        (Select a.activity_time from
                (Select
                b.morador_tour_id, select tour id
                Case when a.morador_id= b.morador_id then a."horaOrigem"-b."horaDestino"
else '00:00:00' end as activity_time –subtract time when the resident left the destination
from time when the resident arrived at destination
                from hhld_trips3 as a
                join hhld_trips3 as b
                on a.id=b.id+1
                order by b.id) as a where a.morador_tour_id=hhld_trips3.morador_tour_id)
```

TOUR CARACTERISTICS

```
SELECT
        --collects the person id and the tour number to create an new id for later joins
        "left"(a.morador_tour_id::text, '-2'::integer) AS person_tour,
        -- says that the zone where the person spent most time as main_destination
        a.ztorigem AS main_destination_zone,
```

```
        -- indicates the activity that the person most invested time in
        a."motivoOrigem" AS main_motive,
        -- indicates the time the person spent on main activity
        a.tempo_atividade AS activity_time,
        --indicates the total time the person spent on activities on each tour
        b.total_time_activity,
        --indicates the total time the person spent on activities on each tour
        b.total_trip_time,
        --indicates the number of stops the person made on each tour
        b.num_stops,
        --indicates the total time the person spent on activities on each tour
        a.ta_ape as walk,
        a.ta_bicicleta as bike,
        a.tc_publico as transit,
        a.tc_privado as private_transit,
        a.ti_publico as taxi,
        a.ti_privado as car
 FROM hhld_trips3 a
 RIGHT JOIN ( SELECT max(hhld_trips3.tempo_atividade::text) AS tempo_atividade,
 sum(hhld_trips3.tempo_atividade::interval) AS total_time_activity,
 sum(hhld_trips3.tempoviagem::interval) AS total_trip_time,
 count(hhld_trips3.morador_tour_id) – 1 AS num_stops,
 "left"(hhld_trips3.morador_tour_id::text, '-2'::integer) AS morador_tour,
 concat("left"(hhld_trips3.morador_tour_id::text, '-2'::integer), '-',
max(hhld_trips3.tempo_atividade::text)) AS time_id
 FROM hhld_trips3
 WHERE char_length(hhld_trips3.tempo_atividade::text) = 8
 GROUP BY ("left"(hhld_trips3.morador_tour_id::text, '-2'::integer))
 ORDER BY ("left"(hhld_trips3.morador_tour_id::text, '-2'::integer)::integer)) b ON
concat("left"(a.morador_tour_id::text, '-2'::integer), '-', a.tempo_atividade) = b.time_id
 ORDER BY ("left"(a.morador_tour_id::text, '-2'::integer)::integer);
```

APPENDIX II - GEOCODING PYTHON SCRIPT

```
import pandas as pd
import requests
import time

Lista_de_CEPs=pd.read_csv("CEP.csv")
df = pd.DataFrame (columns = 'altitude', 'cep', 'latitude', 'longitude', 'logradouro', 'bairro'])
i=1
for CEP in Lista_de_CEPs.CEP:

 url = "https://www.cepaberto.com/api/v3/cep?cep="+str(CEP)
 # O seu token está visível apenas pra você
 headers = {'Authorization': 'Token token=xxxxxxxxxxxxxxxxxxxxxx'}
 response = requests.get(url, headers=headers)
 data = pd.read_json(response.text,orient='records')
 if data is not None:
 data = pd.DataFrame (data, columns = 'altitude', 'cep', 'latitude', 'longitude', 'logradouro',
'bairro'])
 data = pd.DataFrame.drop_duplicates(data)
 data = pd.DataFrame (data, columns = 'altitude', 'cep', 'latitude', 'longitude', 'logradouro',
'bairro'])
 df = df.append(data)
 else:
 df = df.append('0',CEP,'0','0','0','0'])
 i=i+1
 print(CEP)
 print(round(i/(9150)*100,2), '%')
 time.sleep(1.01)
df.set_index('cep')

print (df)
df.to_csv('CEPlong21.csv')
```

APPENDIX III – SPSS SYNTAX WORKER ORDERED LOGIT MODEL

```
GET
  FILE='.....\work_low.sav'.
   DATASET NAME low_income .
      GET
        FILE='.....\work_medium.sav'.
      DATASET NAME medium_income.
 GET
  FILE='.....\work_high.sav'.
 DATASET NAME high_income.

     *VIF TEST*.
     DATASET ACTIVATE low_income.
     REGRESSION
       /MISSING LISTWISE
       /STATISTICS COLLIN TOL
       /CRITERIA=PIN(.05) POUT(.10)
       /NOORIGIN
       /DEPENDENT num_stops
       /METHOD=ENTER gender only_worker education_level motive
        driver_license age_avg n_residents n_car Start_time children activity_time_hrs
total_trip_time_hrs
        number_of_tour total_distance_km density_main_destination
job_density_main_destination entropy_destination
        stops_main_destination culdesacdensity_dest dist_cbd_dest dist_stop_dest_KM
walkway_density_dest
        cicleway_density_dest street_density_dest_km transit_density_dest_KM
Dest_income_greater_Origin_income density_residence job_density_main_residence
        entropy_origin stops_main_residence culdesacdensity_residence dist_cbd_origin
dist_stop_origin_KM
        ciclewaydensity_residence walkway_density_residence transit_density_residence_KM
streetdensity_residence_KM.


     *VIF TEST*.
     DATASET ACTIVATE medium_income.
     REGRESSION
       /MISSING LISTWISE
       /STATISTICS COLLIN TOL
       /CRITERIA=PIN(.05) POUT(.10)
       /NOORIGIN
       /DEPENDENT num_stops
       /METHOD=ENTER gender only_worker education_level motive
        driver_license age_avg n_residents n_car Start_time children activity_time_hrs
total_trip_time_hrs
        number_of_tour total_distance_km density_main_destination
job_density_main_destination entropy_destination
```

```
stops_main_destination culdesacdensity_dest dist_cbd_dest dist_stop_dest_KM walkway_density_dest
cicleway_density_dest street_density_dest_km transit_density_dest_KM Dest_income_greater_Origin_income density_residence job_density_main_residence
entropy_origin stops_main_residence culdesacdensity_residence dist_cbd_origin dist_stop_origin_KM
ciclewaydensity_residence walkway_density_residence transit_density_residence_KM streetdensity_residence_KM.


*VIF TEST*.
DATASET ACTIVATE high_income.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT num_stops
  /METHOD=ENTER gender only_worker education_level motive
   driver_license age_avg n_residents n_car Start_time children activity_time_hrs total_trip_time_hrs
  number_of_tour total_distance_km density_main_destination job_density_main_destination entropy_destination
  stops_main_destination culdesacdensity_dest dist_cbd_dest dist_stop_dest_KM walkway_density_dest
  cicleway_density_dest street_density_dest_km transit_density_dest_KM Dest_income_greater_Origin_income density_residence job_density_main_residence
  entropy_origin stops_main_residence culdesacdensity_residence dist_cbd_origin dist_stop_origin_KM
  ciclewaydensity_residence walkway_density_residence transit_density_residence_KM streetdensity_residence_KM.


*Full  TEST*.
DATASET ACTIVATE low_income.
PLUM Tour_complexity BY education_level driver_license Dest_income_greater_Origin_income Start_time only_worker mandatory WITH n_residents n_car
  children activity_time_hrs total_trip_time_hrs number_of_tour total_distance_km
  stops_main_destination walkway_density_dest
  dist_cbd_dest density_residence
 dist_cbd_origin dist_stop_origin_KM
  /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(100) MXSTEP(5) PCONVERGE(1.0E-6) SINGULAR(1.0E-8)
  /LINK=logit
  /PRINT=FIT PARAMETER SUMMARY.

*Full  TEST*.
DATASET ACTIVATE medium_income.
```

```
PLUM Tour_complexity BY education_level driver_license
Dest_income_greater_Origin_income Start_time mandatory WITH n_residents
  children activity_time_hrs total_trip_time_hrs number_of_tour total_distance_km
  dist_cbd_dest dist_stop_dest_KM
 dist_cbd_origin dist_stop_origin_KM
  /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(100) MXSTEP(5)
PCONVERGE(1.0E-6) SINGULAR(1.0E-8)
  /LINK=logit
  /PRINT=FIT PARAMETER SUMMARY.

  *Full  TEST*.
  DATASET ACTIVATE high_income.
PLUM Tour_complexity BY  Dest_income_greater_Origin_income Start_time only_worker
WITH n_residents
  children activity_time_hrs total_trip_time_hrs number_of_tour total_distance_km
  walkway_density_dest dist_cbd_dest
  density_residence  dist_cbd_origin
  /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(1000) MXSTEP(5)
PCONVERGE(1.0E-6) SINGULAR(1.0E-8)
  /LINK=logit
  /PRINT=FIT PARAMETER SUMMARY .
```

APPENDIX IV – SPSS SYNTAX NON-WORKER ORDERED LOGIT MODEL

```
GET
  FILE='.....\nw_low.sav'.
   DATASET NAME nw_low .
GET
        FILE='.....\nw_medium.sav'.
      DATASET NAME nw_medium.
 GET
  FILE='.....\nw_high.sav'.
 DATASET NAME nw_high.

      *VIF TEST*.
      DATASET ACTIVATE nw_low.
      REGRESSION
        /MISSING LISTWISE
        /STATISTICS COLLIN TOL
        /CRITERIA=PIN(.05) POUT(.10)
        /NOORIGIN
        /DEPENDENT num_stops
        /METHOD=ENTER gender education_level driver_license
Dest_income_greater_Origin_income
         total_trip_time_hrs total_distance_km density_main_destination
job_density_main_destination entropy_destination stops_main_destination
         culdesacdensity_dest dist_cbd_dest dist_stop_dest_km walkwaydensity_dest
cicleway_density_dest street_density_dest_km transit_density_dest_km
         density_residence job_density_main_residence entropy_origin stops_main_residence
culdesacdensity_residence
         dist_cbd_origin dist_stop_origin_km walkwaydensity_residence
ciclewaydensity_residence streetdensity_residence_km transit_density_residence_km
         n_residents n_car children number_of_tour total_time_activity_hrs .


      *VIF TEST*.
      DATASET ACTIVATE nw_medium.
      REGRESSION
        /MISSING LISTWISE
        /STATISTICS COLLIN TOL
        /CRITERIA=PIN(.05) POUT(.10)
        /NOORIGIN
        /DEPENDENT num_stops
        /METHOD=ENTER gender education_level driver_license
Dest_income_greater_Origin_income
         total_trip_time_hrs total_distance_km density_main_destination
job_density_main_destination entropy_destination stops_main_destination
         culdesacdensity_dest dist_cbd_dest dist_stop_dest_km walkwaydensity_dest
cicleway_density_dest street_density_dest_km transit_density_dest_km
```

```
density_residence job_density_main_residence entropy_origin stops_main_residence culdesacdensity_residence
	dist_cbd_origin dist_stop_origin_km walkwaydensity_residence ciclewaydensity_residence streetdensity_residence_km transit_density_residence_km
	n_residents n_car children number_of_tour total_time_activity_hrs .

*VIF TEST*.
DATASET ACTIVATE nw_high.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT num_stops
  /METHOD=ENTER gender education_level driver_license Dest_income_greater_Origin_income
	total_trip_time_hrs total_distance_km density_main_destination job_density_main_destination entropy_destination stops_main_destination
	culdesacdensity_dest dist_cbd_dest dist_stop_dest_km walkwaydensity_dest cicleway_density_dest street_density_dest_km transit_density_dest_km
	density_residence job_density_main_residence entropy_origin stops_main_residence culdesacdensity_residence
	dist_cbd_origin dist_stop_origin_km walkwaydensity_residence ciclewaydensity_residence streetdensity_residence_km transit_density_residence_km
	n_residents n_car children number_of_tour total_time_activity_hrs .



DATASET ACTIVATE nw_low.
PLUM Tour_complexity BY gender education_level driver_license Day_or_night Dest_income_greater_Origin_income WITH
 total_trip_time_hrs total_distance_km density_main_destination job_density_main_destination entropy_destination stops_main_destination
culdesacdensity_dest dist_cbd_dest dist_stop_dest_km walkwaydensity_dest cicleway_density_dest street_density_dest_km transit_density_dest_km
density_residence job_density_main_residence entropy_origin stops_main_residence culdesacdensity_residence
dist_cbd_origin dist_stop_origin_km walkwaydensity_residence ciclewaydensity_residence streetdensity_residence_km transit_density_residence_km
n_residents n_car children number_of_tour total_time_activity_hrs
  /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(100) MXSTEP(5) PCONVERGE(1.0E-6) SINGULAR(1.0E-8)
  /LINK=LOGIT
  /PRINT=FIT PARAMETER SUMMARY.

DATASET ACTIVATE nw_medium.
PLUM Tour_complexity BY gender education_level driver_license Start_time Dest_income_greater_Origin_income WITH
```

```
 total_trip_time_hrs total_distance_km density_main_destination
job_density_main_destination entropy_destination stops_main_destination
culdesacdensity_dest dist_cbd_dest dist_stop_dest_km walkwaydensity_dest
cicleway_density_dest street_density_dest_km transit_density_dest_km
density_residence job_density_main_residence entropy_origin stops_main_residence
culdesacdensity_residence
dist_cbd_origin dist_stop_origin_km walkwaydensity_residence ciclewaydensity_residence
streetdensity_residence_km transit_density_residence_km
n_residents n_car children number_of_tour total_time_activity_hrs
  /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(100) MXSTEP(5)
PCONVERGE(1.0E-6) SINGULAR(1.0E-8)
  /LINK=LOGIT
  /PRINT=FIT PARAMETER SUMMARY.

DATASET ACTIVATE nw_high.
PLUM Tour_complexity BY gender education_level driver_license Start_time
Dest_income_greater_Origin_income WITH
 total_trip_time_hrs total_distance_km density_main_destination
job_density_main_destination entropy_destination stops_main_destination
culdesacdensity_dest dist_cbd_dest dist_stop_dest_km walkwaydensity_dest
cicleway_density_dest street_density_dest_km transit_density_dest_km
density_residence job_density_main_residence entropy_origin
dist_cbd_origin dist_stop_origin_km walkwaydensity_residence ciclewaydensity_residence
streetdensity_residence_km transit_density_residence_km
n_residents n_car children number_of_tour total_time_activity_hrs
  /CRITERIA=CIN(95) DELTA(0) LCONVERGE(0) MXITER(100) MXSTEP(5)
PCONVERGE(1.0E-6) SINGULAR(1.0E-8)
  /LINK=LOGIT
  /PRINT=FIT PARAMETER SUMMARY.
*Variaveis retiradas stops_main_residence culdesacdensity_residence .
```

APPENDIX V – SPSS SYNTAX WORKER LOGIT MODEL

```
GET
  FILE='.....\mode.sav'.
    USE ALL.
    COMPUTE filter_$=((activity='Worker' ) & (IBGE='Low income')).
    VARIABLE LABELS filter_$ "(activity='Worker' ) & (IBGE='Low income') (FILTER)".
    VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
    FORMATS filter_$ (f1.0).
    FILTER BY filter_$.
    EXECUTE.
 DATASET NAME low_income_mode .

 GET
  FILE='.....\mode.sav'.
    USE ALL.
    COMPUTE filter_$=((activity='Worker' ) & (IBGE='Medium Income')).
    VARIABLE LABELS filter_$ "(activity='Worker' ) & (IBGE='Medium Income')
(FILTER)".
    VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
    FORMATS filter_$ (f1.0).
    FILTER BY filter_$.
    EXECUTE.
 DATASET NAME medium_income_mode .

 GET
  FILE='.....\mode.sav'.
    USE ALL.
    COMPUTE filter_$=((activity='Worker' ) & (IBGE='High income')).
    VARIABLE LABELS filter_$ "(activity='Worker' ) & (IBGE='High income') (FILTER)".
    VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
    FORMATS filter_$ (f1.0).
    FILTER BY filter_$.
    EXECUTE.
 DATASET NAME high_income_mode .

*Modelo 1 - socioeconomicas.
DATASET ACTIVATE  low_income_mode.
NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY gender education_level
driver_license
 WITH n_car n_residents children
   /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
```

```
DATASET ACTIVATE  low_income_mode.
NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY gender education_level driver_license
 WITH n_car n_residents children activity_time_hrs total_trip_time_hrs total_distance_km num_stops number_of_tour
   /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
* Start_time age only_worker

DATASET ACTIVATE  low_income_mode.
NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY gender driver_license
WITH n_car n_residents children  total_trip_time_hrs total_distance_km num_stops number_of_tour
 density_main_destination  culdesacdensity_dest dist_cbd_dest
walkwaydensity_dest street_density_dest_km density_residence
 culdesacdensity_residence dist_cbd_origin dist_stop_origin_km walkwaydensity_residence
   /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.

* Education_level Dest_income_greater_origin_income  Start_time age only_worker job_density_main_destination activity_time_hrs
stops_main_destination transit_density_dest_km
job_density_main_residence  entropy_origin  dist_stop_dest_km
stops_main_residence streetdensity_residence_km
transit_density_residence_km entropy_destination stops_main_destination



  DATASET ACTIVATE  medium_income_mode.
  NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY gender education_level driver_license
   WITH n_car n_residents children
   /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
```

```
* Modelo 2 - socio+tour.

  DATASET ACTIVATE  medium_income_mode.
  NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY gender education_level
driver_license
   WITH n_car n_residents children activity_time_hrs total_trip_time_hrs total_distance_km
num_stops number_of_tour
    /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.

  DATASET ACTIVATE  medium_income_mode.
  NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY gender driver_license
   WITH n_car n_residents children total_trip_time_hrs total_distance_km num_stops
number_of_tour
  density_main_destination  culdesacdensity_dest dist_cbd_dest street_density_dest_km
density_residence
 dist_cbd_origin dist_stop_origin_km walkwaydensity_residence
    /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
*Start_time age only_worker job_density_main_destination stops_main_destinatio
dist_stop_dest_km culdesacdensity_residence streetdensity_residence_km
transit_density_residence_km
walkwaydensity_dest transit_density_dest_km job_density_main_residence entropy_origin
stops_main_residence entropy_destination education_level job_density_main_destination .

  DATASET ACTIVATE  high_income_mode.
  NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY gender education_level
driver_license
  WITH n_car n_residents children
    /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.


  DATASET ACTIVATE  high_income_mode.
```

```
 NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY gender education_level driver_license
 WITH n_car n_residents children activity_time_hrs total_trip_time_hrs total_distance_km num_stops number_of_tour
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
 /MODEL
 /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR) REMOVALMETHOD(LR)
 /INTERCEPT=INCLUDE
 /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
/*Start_time age only_worker*/

*Modelo 3 - Land+socio+tour*.


 DATASET ACTIVATE  high_income_mode.
 NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY gender driver_license
 WITH n_car n_residents children total_trip_time_hrs total_distance_km num_stops number_of_tour
 density_main_destination dist_cbd_dest
walkwaydensity_dest street_density_dest_km density_residence culdesacdensity_residence dist_cbd_origin
  /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20) LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
 /MODEL
 /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE) ENTRYMETHOD(LR) REMOVALMETHOD(LR)
 /INTERCEPT=INCLUDE
 /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
* Dest_income_greater_origin_income  education_level Start_time age only_worker dist_stop_origin_km walkwaydensity_residence
job_density_main_destination stops_main_destination
 transit_density_dest_km
job_density_main_residence entropy_origin stops_main_residence
streetdensity_residence_km transit_density_residence_km activity_time_hrs culdesacdensity_dest dist_stop_dest_km  .entropy_destination


*VIF.

DATASET ACTIVATE  low_income_mode.
REGRESSION
 /MISSING LISTWISE
 /STATISTICS COLLIN TOL
 /CRITERIA=PIN(.05) POUT(.10)
 /NOORIGIN
 /DEPENDENT Mode
 /METHOD=ENTER gender driver_license n_car n_residents children  total_trip_time_hrs total_distance_km num_stops number_of_tour
```

```
 density_main_destination  culdesacdensity_dest dist_cbd_dest
walkwaydensity_dest street_density_dest_km density_residence
 culdesacdensity_residence  dist_cbd_origin  dist_stop_origin_km  walkwaydensity_residence
Dest_income_greater_origin_income  education_level
Start_time only_worker  dist_stop_origin_km walkwaydensity_residence
job_density_main_destination stops_main_destination
 transit_density_dest_km
job_density_main_residence entropy_origin stops_main_residence
streetdensity_residence_km       transit_density_residence_km                activity_time_hrs
culdesacdensity_dest dist_stop_dest_km  entropy_destination.

DATASET ACTIVATE  medium_income_mode.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Mode
  /METHOD=ENTER gender driver_license n_car n_residents children   total_trip_time_hrs
total_distance_km num_stops number_of_tour
 density_main_destination  culdesacdensity_dest dist_cbd_dest
walkwaydensity_dest street_density_dest_km density_residence
 culdesacdensity_residence  dist_cbd_origin  dist_stop_origin_km  walkwaydensity_residence
Dest_income_greater_origin_income  education_level
Start_time only_worker  dist_stop_origin_km walkwaydensity_residence
job_density_main_destination stops_main_destination
 transit_density_dest_km
job_density_main_residence entropy_origin stops_main_residence
streetdensity_residence_km       transit_density_residence_km                activity_time_hrs
culdesacdensity_dest dist_stop_dest_km  entropy_destination.

DATASET ACTIVATE  high_income_mode.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Mode
  /METHOD=ENTER gender driver_license n_car n_residents children   total_trip_time_hrs
total_distance_km num_stops number_of_tour
 density_main_destination  culdesacdensity_dest dist_cbd_dest
walkwaydensity_dest street_density_dest_km density_residence
 culdesacdensity_residence  dist_cbd_origin  dist_stop_origin_km  walkwaydensity_residence
Dest_income_greater_origin_income  education_level
Start_time only_worker  dist_stop_origin_km walkwaydensity_residence
job_density_main_destination stops_main_destination
 transit_density_dest_km
job_density_main_residence entropy_origin stops_main_residence
streetdensity_residence_km       transit_density_residence_km                activity_time_hrs
culdesacdensity_dest dist_stop_dest_km  entropy_destination.
```

```
GET
  FILE=‘.....\mode.sav'.
    USE ALL.
    COMPUTE filter_$=((activity='Non worker' ) & (IBGE='Low income')).
    VARIABLE LABELS filter_$ "(activity='Non worker' ) & (IBGE='Low income')
(FILTER)".
    VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
    FORMATS filter_$ (f1.0).
    FILTER BY filter_$.
    EXECUTE.
 DATASET NAME nwlow_income_mode .
```

APPENDIX VI – SPSS SYNTAX NON-WORKER LOGIT MODEL

```
 GET
   FILE=‘.....\mode.sav'.
     USE ALL.
     COMPUTE filter_$=((activity='Non worker' ) & (IBGE='Medium Income')).
     VARIABLE LABELS filter_$ "(activity='Non worker') & (IBGE='Medium Income')
(FILTER)".
     VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
     FORMATS filter_$ (f1.0).
     FILTER BY filter_$.
     EXECUTE.
 DATASET NAME nwmedium_income_mode .

 GET
   FILE=‘.....\mode.sav'.
     USE ALL.
     COMPUTE filter_$=((activity='Non worker') & (IBGE='High income')).
     VARIABLE LABELS filter_$ "(activity='Non worker' ) & (IBGE='High income')
(FILTER)".
     VALUE LABELS filter_$ 0 'Not Selected' 1 'Selected'.
     FORMATS filter_$ (f1.0).
     FILTER BY filter_$.
     EXECUTE.
 DATASET NAME nwhigh_income_mode .

DATASET ACTIVATE  nwlow_income_mode.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT mode
  /METHOD=ENTER  driver_license  Start_time
Dest_income_greater_origin_income    n_car    n_residents    children    activity_time_hrs
total_trip_time_hrs total_distance_km num_stops number_of_tour
 density_main_destination  culdesacdensity_dest dist_cbd_dest dist_stop_dest_km
walkwaydensity_dest    dist_cbd_origin    walkwaydensity_residence
job_density_main_destination
stops_main_destination
job_density_main_residence  entropy_origin
stops_main_residence
 entropy_destination stops_main_destination  .



*Modelo 1 - socioeconomicas.
DATASET ACTIVATE  nwlow_income_mode.
```

```
NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY  education_level driver_license
 WITH n_car n_residents children
   /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
*Gender.

   DATASET ACTIVATE  nwmedium_income_mode.
   NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY  driver_license
    WITH n_car n_residents children
   /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
*Gender education_level

   DATASET ACTIVATE  nwhigh_income_mode.
   NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY driver_license
  WITH n_car n_residents children
   /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
*gender  education_level

* Modelo 2 - socio+tour.

DATASET ACTIVATE  nwlow_income_mode.
NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY  driver_license Start_time
 WITH n_car n_residents children activity_time_hrs total_trip_time_hrs total_distance_km
num_stops number_of_tour
   /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
* Gender age only_worker education_level
```

```
   DATASET ACTIVATE  nwmedium_income_mode.
   NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY   driver_license Start_time
    WITH n_car n_residents children activity_time_hrs num_stops number_of_tour
total_trip_time_hrs total_distance_km
    /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
*Start_time age only_worker education_level

   DATASET ACTIVATE  nwhigh_income_mode.
   NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY driver_license Start_time
  WITH n_car n_residents children activity_time_hrs total_trip_time_hrs total_distance_km
num_stops number_of_tour
    /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
/*age only_worker gender education_level  */

*Modelo 3 - Land+socio+tour*.
DATASET ACTIVATE  nwlow_income_mode.
NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY  driver_license
Dest_income_greater_origin_income WITH n_car n_residents children activity_time_hrs
total_trip_time_hrs total_distance_km num_stops number_of_tour
 density_main_destination  culdesacdensity_dest dist_cbd_dest
walkwaydensity_dest dist_cbd_origin walkwaydensity_residence
job_density_main_destination
stops_main_destination
stops_main_destination
    /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.

* gender  age only_worker street_density_dest_km density_residence  Start_time
 culdesacdensity_residence dist_stop_origin_km dist_stop_dest_km
transit_density_residence_km streetdensity_residence_km transit_density_dest_km
education_level job_density_main_residence  entropy_origin
stops_main_residence  entropy_destination
```

```
   DATASET ACTIVATE  nwmedium_income_mode.
   NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY  driver_license
    WITH n_car n_residents children activity_time_hrs total_trip_time_hrs total_distance_km
num_stops number_of_tour
walkwaydensity_dest job_density_main_destination stops_main_destination
    /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
  /MODEL
  /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
  /INTERCEPT=INCLUDE
  /PRINT=CLASSTABLE FIT PARAMETER SUMMARY LRT CPS STEP MFI IC.
* Street_density_dest_km density_residence

   DATASET ACTIVATE  nwhigh_income_mode.
   NOMREG Mode (BASE=LAST ORDER=ASCENDING) BY  driver_license
     WITH n_car n_residents children total_trip_time_hrs total_distance_km
    density_main_destination  culdesacdensity_dest dist_cbd_dest
   walkwaydensity_dest dist_cbd_origin  walkwaydensity_residence
    /CRITERIA CIN(95) DELTA(0) MXITER(100) MXSTEP(5) CHKSEP(20)
LCONVERGE(0) PCONVERGE(0.000001) SINGULAR(0.00000001)
    /MODEL
    /STEPWISE=PIN(.05) POUT(0.1) MINEFFECT(0) RULE(SINGLE)
ENTRYMETHOD(LR) REMOVALMETHOD(LR)
    /INTERCEPT=INCLUDE
    /PRINT=CLASSTABLe fit PARAMETER SUMMARY LRT CPS STEP MFI IC.
*Gender age only_worker Dest_income_greater_origin_income num_stops number_of_tour
Start_time street_density_dest_km density_residence culdesacdensity_residence
dist_stop_origin_km streetdensity_residence_km transit_density_residence_km
 transit_density_dest_km job_density_main_destination job_density_main_residence
ensity_residence culdesacdensity_residence dist_stop_origin_km streetdensity_residence_km
transit_density_residence_km
 transit_density_dest_k  stops_main_destination  activity_time_hrs  dist_stop_dest_km
 entropy_origin stops_main_residence     street_density_dest_km
 entropy_destination m education_level

DATASET ACTIVATE  nwlow_income_mode.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Mode
  /METHOD=ENTER gender driver_license n_car n_residents children  total_trip_time_hrs
total_distance_km num_stops number_of_tour
 density_main_destination  culdesacdensity_dest dist_cbd_dest
walkwaydensity_dest street_density_dest_km density_residence
 culdesacdensity_residence  dist_cbd_origin  dist_stop_origin_km  walkwaydensity_residence
Dest_income_greater_origin_income  education_level
```

```
Start_time only_worker  dist_stop_origin_km walkwaydensity_residence
job_density_main_destination stops_main_destination
 transit_density_dest_km
job_density_main_residence entropy_origin stops_main_residence
streetdensity_residence_km  transit_density_residence_km  activity_time_hrs
culdesacdensity_dest dist_stop_dest_km  entropy_destination.

DATASET ACTIVATE  nwmedium_income_mode.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Mode
  /METHOD=ENTER gender driver_license n_car n_residents children  total_trip_time_hrs
total_distance_km num_stops number_of_tour
 density_main_destination  culdesacdensity_dest dist_cbd_dest
walkwaydensity_dest street_density_dest_km density_residence
 culdesacdensity_residence  dist_cbd_origin  dist_stop_origin_km  walkwaydensity_residence
Dest_income_greater_origin_income  education_level
Start_time only_worker  dist_stop_origin_km walkwaydensity_residence
job_density_main_destination stops_main_destination
 transit_density_dest_km
job_density_main_residence entropy_origin stops_main_residence
streetdensity_residence_km  transit_density_residence_km  activity_time_hrs
culdesacdensity_dest dist_stop_dest_km  entropy_destination.

DATASET ACTIVATE nwhigh_income_mode.
REGRESSION
  /MISSING LISTWISE
  /STATISTICS COLLIN TOL
  /CRITERIA=PIN(.05) POUT(.10)
  /NOORIGIN
  /DEPENDENT Mode
  /METHOD=ENTER gender driver_license n_car n_residents children  total_trip_time_hrs
total_distance_km num_stops number_of_tour
 density_main_destination  culdesacdensity_dest dist_cbd_dest
walkwaydensity_dest street_density_dest_km density_residence
 culdesacdensity_residence  dist_cbd_origin  dist_stop_origin_km  walkwaydensity_residence
Dest_income_greater_origin_income  education_level
Start_time only_worker  dist_stop_origin_km walkwaydensity_residence
job_density_main_destination stops_main_destination
 transit_density_dest_km
job_density_main_residence entropy_origin stops_main_residence
streetdensity_residence_km  transit_density_residence_km  activity_time_hrs
culdesacdensity_dest dist_stop_dest_km  entropy_destination.
```