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# SPATIAL DECISION MODEL FOR URBAN PLANNING

RECIFE

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Thesis submitted to the Graduate Program in Management Engineering at the Federal University of Pernambuco, as a partial requirement for obtaining the title of Doctor of Philosophy (PhD) in Management Engineering.

Concentration Area: Production Management

Supervisor: Profa. Dra. Caroline Maria de Miranda Mota

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**ABSTRACT**

The decision-making process is an innate task for human beings, and since all choices and actions are based on preferences, decisions are naturally made. However, there are more complex decisions that require the use of Multiple Criteria Decision Making/ Analysis (MCDM/A). This thesis presents a collection of articles based on the use of statistical, optimization, and multi-criteria methods for urban planning regarding spatial decision-making. Particularly, we propose the assessment of attractiveness, connectivity, vulnerability to crime and exploration of the role of attractiveness and connectivity in crime event. For this, we used multiple data sources (Brazilian Institute of Geography and Statistics (IBGE), Brazilian National Civil Aviation Agency (ANAC), Brazilian National Telecommunications Agency (ANATEL), Brazilian Central Banking (BCB), OpenStreetMaps (OSM), Google Maps and crime data) which were cleaned and preprocessed to select criteria to achieve these objectives. *Utilités Additives Discriminantes* (UTADIS) and Dominance-based Rough Set Approach (DRSA) are MCDM/A methods. Through UTADIS, we found that almost 86% of municipalities in Pernambuco are classified as very low attractive, which can alert policymakers to meet population demands. In order to reveal the vulnerability of an area in a city in the state of Pernambuco, Brazil, we used DRSA and found that the presence of at least 15 restaurants can lead to a Census tract (CT) being classified as very highly vulnerable. The results also demonstrated pessimism in relation to vulnerability by indicating the evaluation of areas as more vulnerable than they really are. Regarding the connectivity, we proposed the elucidation of logistics terminals in individual perception, once the connectivity can be measured through the data of connectivity, the information concerning the coverage area and the flows between logistics terminal were considered as factor of contribution in preference analysis, Goal Programming (GP) and Linear Programming (LP) were considered for this objective. Lastly, the exploration of crime events based on attractiveness and connectivity outputs analysis revealed that even during the COVID-19 pandemic, the concentration of robberies remained in the same area, and both attractiveness and connectivity are significant in crime patterns. Thus, this thesis presents different approaches to support urban planning and regional development.

**Keywords:** decision model; urban planning; spatial decision-making

**RESUMO**

O processo de tomada de decisão é uma tarefa inerente ao ser humano, e como todas as escolhas e ações são baseadas em preferências, decisões são tomadas naturalmente. No entanto, existem decisões mais complexas que requerem o uso da abordagem multicritério para suporte à decisão (MCDM/A). Esta tese apresenta a construção de um processo multimetodológico para suporte a problemas de planejamento urbano. Em particular, propõe-se a análise de atratividade, conectividade e vulnerabilidade ao crime. Para isso, múltiplas fontes de dados foram utilizadas para seleção de critérios. A análise de atratividade considerou seis indicadores administrativos de um conjunto de 127 variáveis e a disponibilidade de serviços em uma dada região, que em conjunto evidenciaram a necessidade de 86% dos municípios pernambucanos em atender as demandas populacionais e organizacionais. Na análise de vulnerabilidade ao crime, a identificação dos critérios baseou-se no processo de exploração de fatores por meio de técnicas de análise espacial e estatística. A caracterização de vulnerabilidade de uma região se deu por meio da geração de regras de decisão no método DRSA, tornando mais intuitivo os fatores que levam uma região a ser mais vulnerável que outra. Em relação à conectividade, propôs-se a elucidação dos terminais logísticos, suas respectivas áreas de cobertura, e fluxos entre eles como fator de contribuição à conectividade resultante dos aspectos locais. Por fim, as exploração de eventos criminais com base nas saídas das análises de atratividade e conectividade revelou que ambas são significativas nos padrões de criminalidade. Assim, esta tese apresenta diferentes abordagens para apoiar o planejamento urbano e o desenvolvimento regional.

**Palavras-chave:** modelo de decisão; planejamento urbano; tomada de decisão espacial

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## LIST OF ABBREVIATIONS AND ACRONYMS

| | |
|---|---|
| ACI | Attitudinal Choquet Integral |
| ADMM | Alternating Direction Method of Multipliers |
| AE-MCCF | Autoenconder-based Multi-Criteria Collaborative Filtering |
| AFB | Artifitial Feeding Birds |
| AHP | Analytic Hierarchy Process |
| AMNL | Attitudinal Multinomial Logit |
| ANAC | Brazilian National Civil Aviation Agency |
| ANATEL | Brazilian National Telecommunications Agency |
| ANFIS | Adaptative Neuro-fuzzy Inference Systems |
| ANP | Analytical Network Process |
| BCB | Brazilian Central Banking |
| CA | Cojoint Analysis |
| CAWS | Capability Wise Walkability Score |
| CBR | Case-Based Reasoning |
| CDC | Coherency Driven Choice |
| CF | Colaborative Filtering |
| CI | Choquet Integral |
| CIEMO/D | Co-Evolutionary Algorithm for Interactive Multiple Objective Optimization |
| CIMO | Context, Interventions, Mechanisms and Observed results |
| CPT | Conditional Preference Table |
| CRS | Common Rating Weight Similarity |
| CT | Census tract |
| DC | Difference of Convex functions |
| DeFIMKL | Fuzzy Integral Multiple KernelLearning |
| DEMATEL | Decision Making Trial and Evaluation Laboratory |
| DISWOTH | Distance-based Sorting Method |
| DM | Decision-Maker |
| DRSA | Dominance-based Rough Set Approach |
| DRSA-PL | Dominance-based Rough Set Approach and Preference Learning |
| ELECTRE | Elimination and Choice Expressing the Reality |
| EM | Expectation-Maximization |

| | |
|---|---|
| EMOA | Evolutionary Multiobjective Algorithm |
| EMOSOR | Evolutionary Multiple Objective Optimization Guided by Interactive Stochastic Ordinal Regression |
| EPA | Evolutive Preference Analysis |
| ER | Evidential Reasoning |
| FA | Factor Analysis |
| GasPK | Gaussian Process Scalable Preference Model via Kronecker Factorization |
| GCE | Grey Comprehensive Evaluation |
| GIS | Geographyc Information Systems |
| GIS-MCDM/A | Geographich Information Systems and Multiple Criteria Decision Making/ Analysis |
| GLTF | Global and Local Tensor Factorization |
| GP | Goal Programming |
| GS-IVIULCA | Generalized Shapley Interval-Value Intuitionistic Uncertain Linguist Choquet Averaging |
| GWR | Geographically Weighted Regression |
| HOSVD | Higher Order Singular Value Decomposition |
| IBGE | Brazilian Institute of Geography and Statistics |
| IODS | Incomplete Decision System |
| KDE | Kernel Density Estimation |
| kNN | k-Nearest Neighbor |
| LDA | Latent Dirichlet Allocation |
| LP | Linear Programming |
| LPAA | Linear in Parameter and Additive in Attributes |
| LRAR | Label Ranking Association Rules |
| MACBETH | Measuring Attractiveness by a Categorical Based Evaluation Technique |
| MAGRM | Multiattention-based Group Recommendation Model |
| MAUT | Multiattribute Utility Theory |
| MAVT | Multi-Attribute Value Theory |
| MCDA | Multi-Criteria Decision Analysis |
| MCDM/A | Multiple Criteria Decision Making/ Analysis |
| MCGDM | Multiple Criteria Group Decision Making |

| | |
|---|---|
| MCPPI | Multicriteria Correlation Preference Information |
| MCS | Multiple Criteria Sorting |
| MGLP | Multiple Goal Linear Programming |
| MILP | Mixed-Integer Linear Programming |
| MIP | Mixed Integer programming |
| ML | Machine Learning |
| MNL | Multinomial Logit |
| MOP | Multiobjective Optimization Problem |
| MR-Sort | Majority Rule Sorting |
| MSVD | Multi-linear Singular Decomposition |
| NAROR | Non-Additive Robust Ordinal Regression |
| NAROR-HC | Non-Additive Robust Ordinal Regression for Hierarchical Criteria |
| NB | Negative Binomial |
| NM-MCDA | Neural Network-based Multiple Criteria Decision Analysis |
| NPR | Numerical Preference Relations |
| OLS | Ordinary Least Square |
| OSM | OpenStreetMaps |
| OWA | Ordered Weighted Average |
| PAR | Pairwise Association Rules |
| PAVA | Pool-Adjacent-Violators Algorithm |
| PCA | Principal Component Analysis |
| PDA | Preference Disaggregation Analysis |
| PDTOPSIS-Sort | Preference Disaggregation on Technique for Order of Preference by Similarity to Ideal Solution - Sort |
| PL | Preferennce Learning |
| PL-NSGA2 | PL-based NSGA-2 |
| PLEMOA | PL-based EMOA |
| PRBPL | Pair-wise Ranking-based Preference Learning |
| Pric-DEA | Preference Information Incorporation Using the Choquet Integral in DEA method |
| PROMETHEE | Preference Ranking Organization Method for Enrichment Evaluation |
| PSO | Particle Swarm Optimization |
| RMR | Metropolitan Region of Recife |

| | |
|---|---|
| ROR | Robust Ordinal Regression |
| RSA | Ruleset Aggregation Algorithm |
| RST | Rough Set Theory |
| S-RMP | Simple Ranking with Multiple Points |
| SAT | Boolean Satisfiability Problem |
| SD | Segment Description |
| SMAA | Stochastic Multicriteria Acceptability Analysis |
| SOM | Self-organizing Map |
| SOR | Stochastic Ordinal Regression |
| SPA | Stochastic Preference Analysis |
| SRF | Simos-Roy-Figueira method |
| SVM | Support Vector Machine |
| TDR | Tolerance Dominance Relation |
| TOPSIS | Technique for Order of Preference by Similarity to Ideal Solution |
| U-NCS | Non-Compensatory Sorting Models With Unique Set of Sufficient Coallitions |
| UTA | Additive Utility Functions |
| UTA GMS | UTA Group Decision Making System |
| UTADIS | *Utilités Additives Discriminantes* |
| WIN | Weight Induced Norm |
| WOD | Weighted Overlap Dominance |
| WSM | Weighted Sum |

**CONTENTS**

# 1 INTRODUCTION

The human being is conditioned by their environment and the opportunities presented by it. Therefore, urban planning is fundamental to improve living conditions, including health, education, security, food, and employment. To provide effective actions to support people's lives, decisions need to be made in public planning.

In this sense, understanding the space and the interactions that take place within it is important for the creation of solid policies and effective measures. Spatial relations have a direct or indirect impact on regional development. Historically, urban growth was fueled by the manufacturing industry and the related commercial activities. However, today's urban growth is shaped by factors such as the distribution of flows, changes in consumption, and mobility. Increased mobility has given rise to new patterns of urban and regional development, which enable access to new markets beyond the scope of traditional manufactured exports (CREVOISIER; RIME, 2020).

Besides providing positive gains for social and organizational demands, urban growth has also created various problems such as traffic jams, pollution, congestion, infrastructure shortfalls, service inconveniences (LI; LAN, 2022; BROERE, 2016), violence (PEREIRA *et al.*, 2017b; PEREIRA *et al.*, 2017a), environmental problems (OH *et al.*, 2005), urban sprawl (ŹRÓBEK-RÓŻAŃSKA; ZADWORNY, 2016a) and agglomeration (FANG *et al.*, 2020). Unplanned urban agglomeration can lead to negative consequences such as increasing social and economic inequalities and marginalizing certain areas (KOYLU; GUO, 2013; CILLIERS *et al.*, 2021). According to Broere (2016), dense urban environments also face problems due to the lack of infrastructure for transit, distribution of resources, goods, and services.

In light of the aforementioned issues in urban planning, this thesis proposes a methodology to evaluate the spatial attractiveness of a region to identify the criteria and demands that contribute to its potential for agglomeration and potential problems that may arise. Given that spatial relationships tend to focus on attractive regions (YAN *et al.*, 2017), this methodology may assist public planning efforts in mitigating the negative effects of unplanned urban development. Additionally, a methodology for analyzing spatial connectivity is presented, which considers the interactions between logistics terminals, their coverage areas, and the flows between them. This analysis can support public planning efforts related to the logistical potential of regions for transporting goods, people, and services, as well as stimulate the competitiveness of regions by overcoming distance barriers (LYONS, 2018) and forming networks between regions

(RODRIGUE, 2020).

A further context explored in this thesis is the problem of violence in urban planning. To handle this, a multi-methodology is proposed to reveal the vulnerability of areas based on criteria related to socio-demographic and socio-interaction features, and mobility. The goal is to support the identification of vulnerable regions to crime and aid public security in creating effective actions in space by providing a set of criteria composed of multi-datasets that engage people in active decision-making in the environment (ROSA *et al.*, 2023).

All the methodologies proposed to support urban planning are multi-methodologies that combine the use of different datasets and methods (statistical, spatial, and MCDM/A). By combining these tools, the results obtained can characterize the local aspects of regions and enable spatial visualization for better decision-making. This makes it possible to design strategies to support actions for capable, sustainable, resilient, and even intelligent regions/cities based on their specific characteristics.

## 1.1 RELEVANCE AND CONTRIBUTION OF THE STUDY

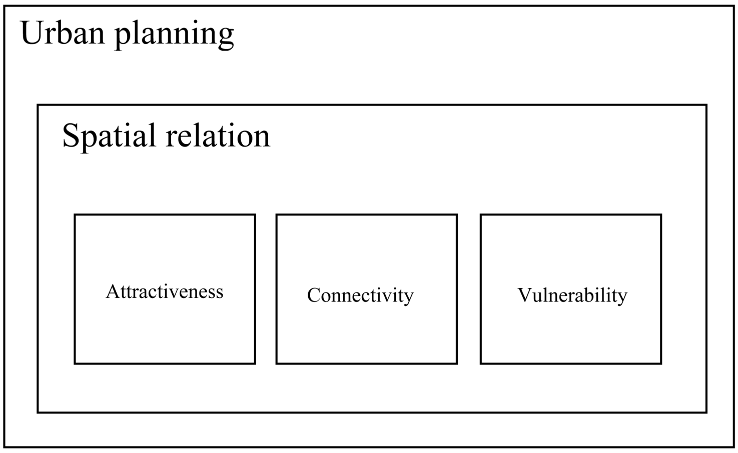
This thesis proposes a set of Geographich Information Systems and Multiple Criteria Decision Making/ Analysis (GIS-MCDM/A) methodologies for urban planning to consider spatial attractiveness, connectivity, and vulnerability to crime. The novelty of these approaches is that they aim to understand human actions in space and the implications of spatial aspects on people's perceptions to support policies that can benefit individuals and organizations. This can contribute to create safer and more livable urban environments, which are crucial for promoting the well-being and security of the population.

In spatial attractiveness, the analysis takes into account not only the physical characteristics of a location, but also the availability and quality of services, as well as administrative policies that may affect the attractiveness of the location. This approach allows for a more comprehensive understanding of what people are looking for in a place, which can then support urban planning and policy decisions to better respond to the needs and desires of individuals and communities.

The analysis of connectivity enables the understanding of factors that contribute to inter-regional linkages and how people perceive them in terms of access to and movement of information, money, goods, and people. This analysis also contributes to regional competitiveness by evaluating interconnections and flows and indicating their potential for logistics chains.

Lastly, the preference analysis of vulnerability enables an overview of people's apprehensions when visiting certain places due to the perceived vulnerability of becoming a victim of crime. This leads to the formulation of security policies in urban spaces, and once they are perceived as safe, they become frequented and are integrated into people's activities, which contributes to the development of the region. Figure 1 presents the concepts to support urban planning.

Figure 1 – Concepts to support urban planning




Source: The Author (2023)

Hence, this thesis proposes the aforementioned concepts as pillars for the construction of spatial decision analysis to support urban planning from different perspectives. These perspectives can be viewed separately, but together they can enhance regional development by supporting decision-making in dealing with different paradigms, allowing for a more accurate modeling approximation to the real world.

## 1.2 OBJECTIVES OF THE RESEARCH

### 1.2.1 General objective

The general objective is to propose a methodology for structuring a GIS-MCDM/A approach focused on the assessment and learning of attractiveness, connectivity, and vulnerability to crime for urban and regional planning. To this end, a methodology for preference learning is considered that takes into account the relationships arising from human-space.

### 1.2.2 Specific objectives

**SO 1.** To identify possible gaps in preference learning in MCDM/A field through the systematic review of literature;

**SO 2.** To reveal regional attractiveness classification based on administrative competences and location of facilities/amenities for learning and assess indicators for urban planning;

**SO 3.** To reveal the ranking of connectivity of regions given the inherent local aspects as well as individuals' perception in terms of coverage and logistics terminal flows to support urban planning;

**SO 4.** To develop a multi-methodology framework for learning in urban planning preferences to reveal the vulnerability of the area to street robberies;

**SO 5.** To explore the role of attractiveness and connectivity in robbery event patterns.

## 1.3 THESIS METHODOLOGY

This thesis is designed as a multi-paper approach, which focuses on MCDM/A preference learning to support decision-making in spatial context regarding urban planning and regional development. To identify possible gaps of research studies in MCDM/A preference learning, a systematic review was fulfilled (**SO 1**) in the basis of Context, Interventions, Mechanisms and Observed results (CIMO) logic (FINK, 2014). The databases used were Scopus and Web of Science and an analysis was done for relevant papers.

The regional attractiveness classification (**SO 2**) is explored through the use of administrative and geographic data of Brazilian municipalities via Factor Analysis (FA) and UTADIS methods. The study assesses data related to housing, transport, agriculture, environment, risk and disaster management policies, as well as previous classifications of municipalities' hierarchies from the IBGE (2022). Additionally, spatial data on facilities and amenities were extracted from OSM (2022). The final result of the study includes spatial visualizations of the classification of attractiveness.

The ranking spatial connectivity (**SO 3**) is explored from two perspectives. First, an index of connectivity was proposed based on inherent aspects of information flow, money circulation, people and goods movements, betweenness centrality of municipalities, and road network structure of a region. Second, the previous index was used to construct a relation with different types of logistics hubs in connectivity preference. The method is based on GP, and spatial visualization is provided to support results. The databases used were open data from ANAC (2022), BCB (2022), ANATEL (2022), and IBGE (2022).

In view of vulnerability analysis, Kernel Density Estimation (KDE), Negative Binomial (NB) regression, Ordinary Least Square (OLS) regression, Geographically Weighted Regression (GWR), DRSA were used to reveal the vulnerability of regions (**SO 4**) and to explore the preferences implications in crime incidences (**SO 5**). The previous data were used as well as the results of spatial attractiveness and connectivity. Table 1 presents the methods used to fulfill each specific objective in urban planning.

Table 1 – Methods used for specific objectives in urban planning analysis

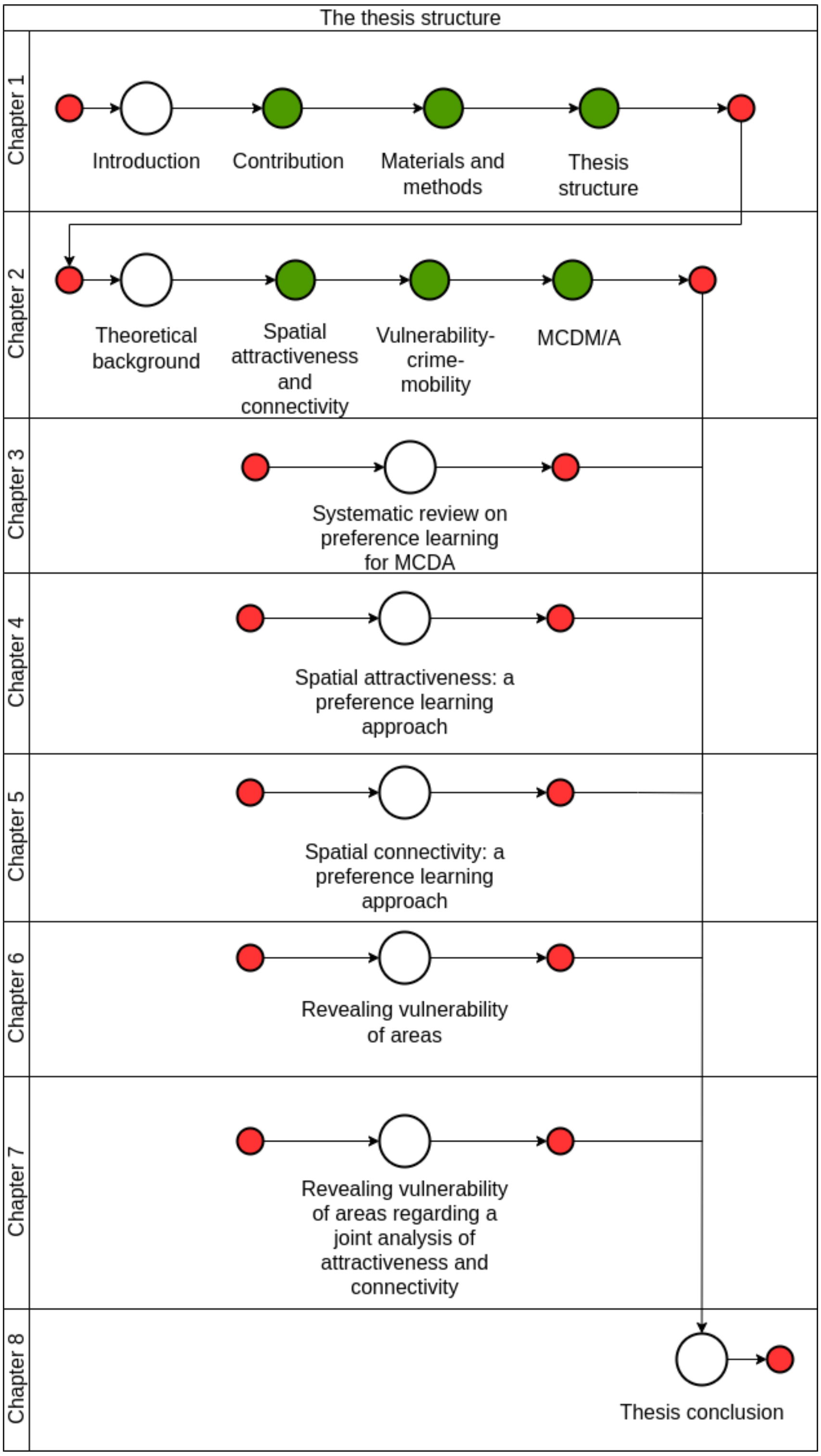
| | | Urban Planning | | | |
|---|---|---|---|---|---|
| | | Attractiveness SO 2 | Connectivity SO 3 | Vulnerability analysis SO 4 | Pattern of crime SO 5 |
| Regression | NB | | | x | |
| | OLS | | | | x |
| Regression/Saptial analysis | GWR | | | x | x |
| Spatial analysis | KDE | | | x | x |
| | Local Moran | | | x | |
| Optimization methods Decision methods | GP DRSA | | x | x | |
| | UTA-methods | x | | | |
| Multivariate analysis | FA | x | | | |

Source: The Author (2023)

## 1.4 THESIS STRUCTURE

This thesis is structured as follows. Chapter 2 presents basic concepts of spatial attractiveness, spatial connectivity, and vulnerability to crime regarding urban planning and regional development, as well as a brief introduction to the methods presented in Table 1. Chapter 3 provides a systematic literature review of MCDM/A preference learning. Chapter 4 presents a methodology to understand preferences in spatial attractiveness, while Chapter 5 proposes a methodology to assess preferences on spatial connectivity. Chapter 6 presents a multi-methodology approach in urban planning, while Chapter 7 proposes a methodology that integrates spatial attractiveness and connectivity into urban planning, with a focus on crime. Figure 2 illustrates the thesis organization.

Figure 2 – Thesis structure




Source: The author (2023)

# 2 THEORETICAL BACKGROUND

This section introduces the concepts and theoretical background of three branches: (i) spatial attractiveness and connectivity, (ii) vulnerability to crime and public security, and (iii) quantitative methods (Table 1).

## 2.1 SPATIAL ATTRACTIVENESS AND CONNECTIVITY

Spatial attractiveness and connectivity are concepts in spatial analysis. The former arouses the interest of people or organizations in regional attributes, the latter comes with the need to achieve places. Whatever it is the geographical scale, humans are interacting in spaces and promote changes in them. The issue is to make these changes benefits to the population and empower regional competitiveness in local and global markets. That so, spatial interactions are pretty close to urban planning, regional development, and economic geography (LI *et al.*, 2017).

Concerning spatial attractiveness, Mueller *et al.* (2018) propose a method of simulation based on self-perceived well-being into a given space to identify a suitable site for event location. However, it is empirically known that people are also spatially attracted to places that they have never been before.

Stouffer (1940) stated the hypothesis that the number of people going to a given distance is proportional to opportunities. It means people have their preferences regarding their objectives and space characteristics. Therefore, considering the surrounding attributes of a region is a prerequisite of spatial attractiveness analysis. Such attributes could be generally described through physical, demographic, service, and labor market factors (LI *et al.*, 2008).

In this manner, it is posted that spatial attractiveness can be measured in many forms. Zhu *et al.* (2021) argue in favor of rich-clubs approach to explore regional economy as a factor of attractiveness in view of internal migration. The memory effect and local population are brought up for attractiveness discussion, as good impression of places increases the probability of future visits (YAN *et al.*, 2017).

Models of differential equations (ZHANG, 2007), mobility (WALTERT *et al.*, 2011), and Poisson quasi maximum-likelihood (WU *et al.*, 2022) show that services and leisure places contribute to the quality of life, and attract tourists and industries. Once a region becomes industrialized, young adults are attracted by job opportunities, however, they also look for schools, businesses, marketplaces, and housing incentives (TAIMA; ASAMI, 2020; HANANEL *et al.*, 2021). Smart cities have their parcel of contribution to spatial attractiveness due to potential research and development, cultural interactions, accessibility, and environment (ROMÃO *et al.*, 2018).

Besides spatial attractiveness, connectivity fulfills an important role in spatial interaction. It is impossible to talk about globalization without flows of people, goods, services, energy, information, intellectual and financial capital (LEI *et al.*, 2021; WANG, 2017; JING *et al.*, 2022; FANG *et al.*, 2020).

Although most of models does not represent spatial connectivity (WANG *et al.*, 2022) it can be measured through the financial outputs (LEI *et al.*, 2021), region centrality (KOYLU; GUO, 2013), people movement (GALPERN *et al.*, 2018), information flow data (FANG *et al.*, 2020), and networks (FANG *et al.*, 2020; HU *et al.*, 2018). In addition, transportation systems are inevitably considered in the connectivity context (KALUZA *et al.*, 2010).

By analyzing connectivity and attractiveness, urban planners can have insights into how people interact with the urban environment and how they move around the city. This information can be used to develop a more informed and robust decision-making model for urban planning. By identifying the factors that attract people to certain areas and understanding how they move through the city, planners can develop more effective strategies for managing urban growth and improving the quality of life for residents.

## 2.2 VULNERABILITY TO CRIME AND PUBLIC SECURITY

Vulnerability refers to the degree to which a system, community, or individual is susceptible to harm from an external stressor or hazard (O'BRIEN *et al.*, 2004). In the case of crime, vulnerability can be seen as the likelihood of being victimized or exposed to criminal activities. Policies in public security aim to reduce vulnerability to crime by implementing measures that enhance security, prevent crime, and respond effectively to criminal incidents.

Public security is a branch of urban planning, and as a result of human interactions in a space, criminality relates to the concepts of spatial attractiveness and connectivity, guided by two main theories: Opportunity Theory (GROFF; LOCKWOOD, 2014) and Social Disorganization Theory (SHAW; MCKAY, 1942). According to Dugato (2022), the use of factors from these theories favors a more complete analysis of criminogenic mechanisms and leads to more effective actions.

Such theories suggest that factors of the flow of people, circulation of money and goods, location of facilities, social interactions, and demographic characteristics contribute to the vulnerability of regions to crime (YU; MAXFIELD, 2013; NEWTON *et al.*, 2014; BERNASCO; BLOCK, 2011; WARD *et al.*, 2014; CAPLAN *et al.*, 2011), as they reveal regional inequalities and potential targets for offenders. Additionally, Patten *et al.* (2009) suggest that robberies are likely the result of intentional behavior of motivated offenders, which highlights the role of the environment in creating opportunities for crime (DUGATO, 2022).

Therefore, the proposed crime analysis approach aims to obtain a deeper understanding of people's preferences from different perspectives, including environmental, socio-demographic, and spatial connectivity and attractiveness, to support decision-making in public planning. This approach can help to better comprehend the context and circumstances surrounding robberies. For this, the tools presented in Table 1 are used, as learning the vulnerability perception and developing action plans based on data and preferences are fundamental to effective social and spatial interventions, beyond just discovering the patterns of crimes.

## 2.3 METHODS

To achieve the general purpose of understanding and learning preferences, and identifying patterns to generate insights for supporting decisions in public planning, this section presents the methods used in this thesis. These methods are organized into five categories: regression (OLS, NB, and GWR), spatial analysis (KDE and Local Moran), optimization methods (GP), decision methods (DRSA and UTADIS), and multivariate analysis (FA), as presented in Table 1. These methods were used to conduct analyses on attractiveness, connectivity, vulnerability to crime, and identification of crime patterns.

### 2.3.1 Regression methods

Regression methods are statistical techniques used to examine the relationship between a dependent variable and one or more independent variables (HAIR *et al.*, 2009). In the context of urban planning, regression methods can be used to understand how different factors may influence spatial events of a region. Following there are presented the OLS, NB, and GWR methods.

#### *2.3.1.1 OLS regression*

The OLS regression is the simplest and the best-known regression method (DUDLEY *et al.*, 1993). Its advantage being that its coefficient is easy to interpret (GRUBESIC *et al.*, 2012), and it is calculated by:

$$y_i \approx \alpha + \sum(\beta_i(x_i)) + \varepsilon \tag{2.1}$$

where $\alpha$ is the intersection point on the regression line, $\beta_i$ is the regression coefficient, $x_i$ are the independent variables and $\varepsilon$ is the error.

OLS assumes a continuous dependent variable. However, when dealing with count data or binary outcomes, the assumption of normality and homoscedasticity may not hold, and linear regression may not be suitable. In such cases, NB regression is often recommended as it models count data and accounts for overdispersion.

#### *2.3.1.2 NB regression*

The NB regression estimates the relationship between independent variables and a count-dependent variable by modeling the expected count as a function of the independent variables. The model includes a dispersion parameter that accounts for overdispersion (MELO *et al.*, 2017), which occurs when the variance of the data is larger than the mean. The equation for NB regression is:

$$y_i \approx NB[t_j exp(\sum_k \beta_k x_{jk}), \alpha] \tag{2.2}$$

where $t_j$ is a variable, $\alpha$ is the overdispersion parameter, $\beta_k$ is the parameter of independent variables $x_k$, $y_j$ is the independent variable, and NB is the negative binomial that is result of a combining Poisson and Gamma distributions.

As OLS, the NB regression is a global regression model. This means that both models are used for general analysis. However, there are regression models that consider the local variations as the case of GWR (MALCZEWSKI; POETZ, 2005).

#### *2.3.1.3 GWR*

The GWR is a local model developed by Fotheringham *et al.* (1998) and is also considered a spatial analysis technique (PÁEZ; WHEELER, 2009). It is an expansion of the OLS that considers the variability through the observed space, and thus better describes the non stationary relations in space (BRUNSDON *et al.*, 1996). The regression equation is:

$$y_i = a_{i0} + \sum_{k=1}^{m} a_{ik} x_{ik} + \varepsilon_i \tag{2.3}$$

where $a_{ik}$ is the $k^{th}$ parameter at location $i$, $a_{i0}$ is the intercept, $x_{ik}$ is the value of $k^{th}$ independent variables, $y_i$ is the $i^{th}$ observation of the dependent variable, and $\varepsilon_i$ is the random error at location $i$ (SOUZA *et al.*, 2022).

To identify the location and pattern of crime occurrences, visual analysis is also used to support some inferences. Kernel density estimation (KDE) and Local Moran are two methods used in this thesis for this purpose.

### 2.3.2 Spatial analysis

In spatial analysis, it is possible to visualize the relationships between events and spatial factors, and identify them using tools. Local Moran and KDE are used for this purpose.

#### *2.3.2.1 Local Moran and KDE*

Local Moran is a statistical method used in spatial data analysis to identify spatial autocorrelation or clustering of a variable of interest. It calculates the correlation between the values of a variable at a specific location and the values of its neighboring locations. In other words, it assesses whether similar values of a variable are clustered together in space. It can be calculated as Anselin (1995):

$$I_i = z_i \sum_j w_{ij} z_j \tag{2.4}$$

where $z_i$ are the observations, $z_j$ are the standard deviations, and $w_{ij}$ are the weights.The result of the function ranges from -1 to +1, and the data is grouped into four clusters: high-high (HH), low-high (LH), high-low (HL), and low-low (LL). The HH cluster represents areas with high numbers of occurrences and their neighbors, while the LH cluster represents areas with low occurrences and their neighbors with high occurrences. The HL cluster represents areas with high occurrences and their neighbors with low occurrences, and the LL cluster represents areas with low occurrences and their neighbors with low occurrences (ANDRESEN, 2015).

As Local Moran, KDE returns a visual result. KDE works by creating a smooth surface over the data points, where areas with a high concentration of incidents are more visible (AN-

DRESEN, 2015) and as the distance between the data point increases, the influence decreases (DUGATO, 2022). The result is a visual representation that helps to identify hotspots or areas with high crime density, which can be used to guide interventions or target resources to reduce crime in those areas. KDE is calculated as follows:

$$density = \frac{1}{(radius)^2} \sum_{i=1}^{n} [\frac{3}{\pi} pop_i (1 - (\frac{dist_i}{radius})^2)^2] \tag{2.5}$$

where:

- $i$: input points
- $pop_i$: parameter
- $dist_i$: distance between a point $i$ and $(x, y)$

Given the data and information, mathematical modeling is applied to reduce data dimension in view of preference analysis.

### 2.3.3 Multivariate analysis

Multivariate analysis is a set of statistical methods that allow for the analysis of multiple variables simultaneously. It is useful when analyzing large datasets and helps to identify relationships between variables and to understand the underlying structure of the data (HAIR *et al.*, 2009). In this thesis, multivariate analysis is utilized to reduce data dimensions and to identify factors that contribute to the understanding of the attractiveness of regions.

#### *2.3.3.1 Factor analysis*

The FA aims to group a set of variables into a smaller arrangement capable of synthesizing the information from the original data (SCHILDERINCK, 1970). The smaller set, named latent variables, allows for the analysis of the data in a smaller dimension that flexibly explores the different contexts of high dimensions (COSTELLO; OSBORNE, 2005; LIU *et al.*, 2019).

Mathematically, FA is based on the correlation of variables (SHARMA, 1996). The most correlated variables are combined in the same factor (JUNIOR *et al.*, 2021), and is calculated as follows (PREACHER *et al.*, 2013):

$$\mathbf{x} = \Lambda \varepsilon + \delta \tag{2.6}$$

Where,

- $\mathbf{x}$: vector of data

- $\Lambda$: matrix of factor loadings
- $\varepsilon$: vector of latent variables
- $\delta$: specific score on unique factor

The interpretability of the method resides in maximize the explanation of variance given the minimum subset of latent variables as follows (JUNIOR *et al.*, 2021; JOHNSON; WICHERN, 2007):

$$\begin{aligned} & \min Tr \quad (\Psi) \\ & \text{s.t.} \\ & \qquad \Psi = \Sigma - \Lambda|\Lambda^{'} \end{aligned} \tag{2.7}$$

Where,

- $\Psi$: unique factor matrix
- $\Sigma$: covariance matrix
- $\Lambda^{'}$: $\Lambda^{t}$

Additional mathematical information can be found in Johnson and Wichern (2007). Also, optimization techniques are used to find criteria weights.

### 2.3.4 Optimization methods

Optimization techniques aims to maximize the benefits and minimize costs, its use is determined by the the objectives (ARENALES *et al.*, 2011). In this thesis, it was explored the goal programming (GP).

#### *2.3.4.1 Goal programming*

GP is an optimization technique that involves optimizing multiple conflicting objectives simultaneously by minimizing the deviations from predefined goals or targets (ARENALES *et al.*, 2011; HILLIER; LIEBERMAN, 2013).

In GP, the objective function can be represented as a vector of goals, where each goal represent different objective that the DM wants to optimize. Let us consider a GP problem with 3 objectives:

$$
\begin{aligned}
&\text{Maximize } f_1(\mathbf{x}) = c^\top x \\
&\text{Minimize } f_2(\mathbf{x}) = d^\top x \\
&\text{Minimize } f_3(\mathbf{x}) = e^\top x \\
&\qquad s.t \\
&\qquad\quad Ax \geq b \\
&\qquad\quad x \geq 0
\end{aligned}
\tag{2.8}
$$

where $c$ is a vector of coefficients for the objective function, $x$ is a vector of decision variables, $A$ is a matrix of coefficients for the constraints, $b$ is a vector of values for the constraints, and $x \geq 0$ is a non-negativity constraint on the decision variables. The objective is to find the values of the decision variables that minimize/maximize the objective function subject to the constraints.

There are possibilities for DM to designate goals for each objective and solve it using two methods: weights or hierarchical structure.

Finally, to achieve the specific objectives of understanding and learning spatial preferences in urban planning, MCDM/A methods are used to support decision-making.

### 2.3.5 MCDM/A methods

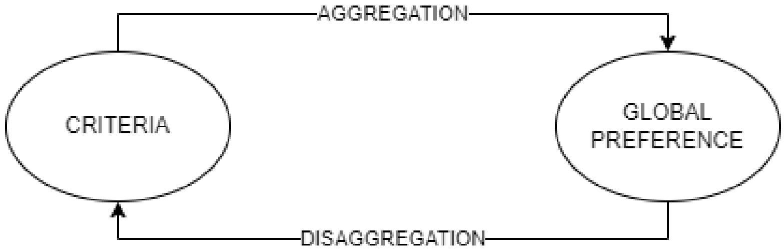
The MCDM/A methods aim to support decision problems with multiple conflicting attributes and objectives. Its main idea is to provide a satisfying preference model through preference elicitation (DOUMPOS; ZOPOUNIDIS, 2011).

According to (ROY, 1996a), there are three primary operational approaches: (i) single criteria synthesis of information, which involves types of aggregation functions such as weighted sum, additive, multiplicative, and lexicographic; (ii) outranking methods, which are based on making explicit the conditions that characterize the outrankings relations, such as ELECTRE and PROMETHEE methods; and (iii) interactive methods, which involve a protocol in which the analyst engages in successive interactions with the Decision-Maker (DM).

Another approach can be added, the disaggregation preference modeling. According to this paradigm, the aim is to discover the preference model from a global preference (JACQUET-LAGRÈZE; SISKOS, 2001), Figure 3.

As Figure 3, it is possible to note the learning process in disaggregation paradigm intends to translate the natural preferences of a DM into a model, and from that, it is possible to evaluate new instances (alternatives). The paradigm is stated at the prior knowledge about the sorting or

Figure 3 – Aggregation and disaggregation paradigm in MCDA




Source: Jacquet-Lagrèze and Siskos (2001)

ranking of alternatives.

In Preference Disaggregation Analysis (PDA), the DM provides a holistic assessment of alternatives. Its main objective is to identify a model consistent with DM's preferences. Also, it can infer models in form of value functions and outranking relations in form of an optimization problem. Disaggregation methodologies are also applied to other modeling approaches. One of them is the use of Choquet integral. In general, the advantage of use new types of decision modeling is to take in consideration a more general preference structures (DOUMPOS; ZOPOUNIDIS, 2019).

Due to its capacity to handle holistic assessment, PDA can work with large data (DOUMPOS; ZOPOUNIDIS, 2019), and to create sophisticated models (JACQUET-LAGRÈZE; SISKOS, 2001). As the PDA "consider the problem of learning a (decision/ prediction) model from data" (DOUMPOS; ZOPOUNIDIS, 2011), the next chapter brings a literature review on preference learning in MCDM/A field. In this thesis there are used UTA-methods and DRSA.

#### *2.3.5.1 UTA-methods*

UTADIS method is applied in sorting problems (ZOPOUNIDIS; DOUMPOS, 1999). Let $g = (g_1, g_2, ..., g_m)$ be a family of criteria, $A = \{a1, a2, ...a_n\}$ be the set of alternatives to be classified into $Q$ ordered classes $C_1, C_2, ..., C_q$, we have that $C_1\mathbf{P}C_2, ..., C_{Q-1}\mathbf{P}C_Q$, where $P$ represents the strict preference relation between the classes defined *a priori*.

Each criterion $g_i$ is evaluated by a piecewise function with $\alpha - 1$ intervals, the break points of which are calculated according to Equation 2.9:

$$g_i^j = g_{i*} + \frac{j-1}{\alpha_i - 1} * (g_i^* - g_{i*}) \tag{2.9}$$

Where $g_{i*}$ and $g_i^*$ represent the minimum and maximum values of criterion i. Thus, supposing the interval $[g_i^j, g_i^{j+1}]$ of the criterion $g_i$ the utility of the criterion for the subinterval is also given by linear interpolation obtained by 2.10:

$$u_i[g_i(a)] = u_i(g_{g_i^j}) + \frac{g_i(a) - g_i^j}{g_i^{j+1} - g_i^j} * (u_i(g^{j+1}) - u_i(g_i^j)) \tag{2.10}$$

Under the restrictions:

$$\begin{cases} w_{ij} = u_i(g_i^{j+1}) - u_i(g_i^j) \geq 0, \forall i \\ u_i(g_{i*}) = 0 \\ u_i(g_i^j) = \sum_{k=1}^{j-i} w_{ik} \end{cases} \tag{2.11}$$

Thus, the global utility of alternative $a$ be given by Equation 2.12.

$$u[g(a)] = \sum_{i=1}^{m} u_i[g_i(a)] \tag{2.12}$$

The classification errors related to global utility are $\sigma(a)^+$ and $\sigma(a)^-$, which represent overestimation and underestimation errors, respectively. They refer to the error of classifying an alternative to a higher or lower class than it really belongs to, respectively (ZOPOUNIDIS; DOUMPOS, 1999). Thus, the model consists of Equation 2.13.

$$\min F \quad \sum_{\alpha \in C_1} \sigma^+(\alpha) + ... + \sum_{\alpha \in C_k} [\sigma^+(\alpha) - \sigma^-(\alpha)] + ... + \sum_{\alpha \in C_Q} \sigma^-(\alpha)$$

s.t.

$$\begin{aligned} & \sum u_i[g_i(\alpha)] - u_1 + \sigma^+(a) \geq 0, \forall a \in C_1 \\ & \sum u_i[g_i(\alpha)] - u_{k-1} + \sigma^-(\alpha) \leq -\delta, \forall a \in C_k \\ & \sum u_i[g_i(\alpha)] - u_k + \sigma^+(a) \geq 0, \forall a \in C_k \\ & \sum u_i[g_i(\alpha)] - u_{Q-1} + \sigma^-(a) \leq -\delta, \forall a \in C_Q \\ & \sum_{i=1}^{m} \sum_{j=1}^{\alpha_i - 1} w_{ij} = 1 \\ & u_{k-1} - u_k >= s, k = 2, 3, ..., Q-1 \\ & w_{ij}, \sigma^+(a), \sigma^-(a) >= 0 \end{aligned} \tag{2.13}$$

The continuity of the method consists in optimizing the solution F when possible, with the error objective transformed into a new constraint and the new objective is to maximize and minimize the criteria weights $u_i[g_i(\alpha)]$ and the utility thresholds $u_k$.

UTA-methods may also be applied for ranking problems. The difference is that the analysis is focused on ordering the alternatives instead of ordered classes of alternatives. In UTASTAR method (SISKOS; YANNACOPOULOS, 1985), the minimization of errors is calculated as follows:

$$\min F \quad \sum_{i}[\varepsilon^{+}(\alpha)+\varepsilon^{-}(\alpha)]$$

s.t.

$$\begin{aligned} &\sum u_i[g_i(\alpha)] - \sum u_{i+1}[g_{i+1}(\alpha)] - \varepsilon^{+}(a_i) + \varepsilon^{-}(a_i) + \varepsilon^{+}(a_{i+1}) - \varepsilon^{-}(a_{i+1}) \geq \delta \\ &\sum w_{ij} = 1 \\ &w_{ij}, \varepsilon^{+}(a), \varepsilon^{-}(a) >= 0 \end{aligned} \tag{2.14}$$

In Equation 2.14, $\varepsilon^{+}(a), \varepsilon^{-}(a)$ represent the over and under estimation in alternatives ranking. The post-optimization proposed by Siskos and Yannacopoulos (1985) is based on the objective of maximizing and minimizing the weights for each criterion.

#### *2.3.5.2 DRSA*

Established the variables that make part of preference analysis to the classification of the vulnerability of areas to street robberies, DRSA is used to discovery preference rules in the classification of areas. The content of this section is part of Rosa *et al.* (2023). For further details of DRSA see Szeląg *et al.* (2014), Kadziński *et al.* (2014), Greco *et al.* (2013).

DRSA is a method based on a data table represented by a four-tuple information system, $S = \{A, Q, V, f\}$, where $A$ is a finite set of objects, $Q$ is a finite set of criteria that can be divided into the subsets $C$ (condition criteria) and $D$ (decision attributes), $V_q$ is the domain of criterion $q$, and $V = \bigcup_{q \in Q} V_q$, and $f : A \times Q \rightarrow V$ is a total function such that $f(a,q) \in V_q$ for each $q \in Q$ and $a \in A$.

Given a set of classes $Cl = \{Cl_t, t \in T\}$, $T = \{1, ..., n\}$ is the set classes where $a^* \in A$ belongs to one and only one class $Cl_t \in Cl$ for all $r, s \in T \times T$, such that $r > s$, the objects from $Cl_r$ are more preferred than the objects from $Cl_s$, which means the approximated sets are an upward and downward union of classes as presented in Equations 2.15 and 2.16:

$$Cl_t^{\geq} = \bigcup_{s \geq t} Cl_s \tag{2.15}$$

$$Cl_t^{\leq} = \bigcup_{s \leq t} Cl_s; t = 1, \ldots, j \tag{2.16}$$

In DRSA, the dominance principle is expressed as: Let $P \subseteq C$ be a subset of condition criteria, assuming that $a_1^*$ dominates $a_2^*$ in the space of condition criteria (denoted by $a_1^* D_p a_2^*$)

if $a_1^* \gtrsim a_2^*$ $\forall c \in P$. The domains of the criteria are numerical and they are ordered so that the preference increases with the value, so $a_1^* D_p a_2^*$ $\forall c \in P$, $P \subseteq C$. An analogous definition holds for the decision class space.

Using the dominance relation, the approximations are the dominance cones defined as following in the objects that are dominating and dominated, respectively, with respect to $P$ (Equations 2.17 and 2.18):

$$D_p^+ a_1^* = \{a_2^* \in A^* : a_2^* D_p a_1^*\} \tag{2.17}$$

$$D_p^- a_1^* = \{a_2^* \in A^* : a_1^* D_p a_2^*\} \tag{2.18}$$

The upper and lower approximations of unions of decision classes with respect to $P$ are calculated as follows:

- The $P$-upper approximation of $Cl_t^{\geq} : \bar{P}(Cl_t^{\geq}) = \{a_1^* \in A^* : D_p^-(a_1^*) \cap Cl_t^{\geq} \neq \emptyset\}$
- The $P$-lower approximation of $Cl_t^{\geq} : \underline{P}(Cl_t^{\geq}) = \{a_1^* \in A^* : D_p^+(a_1^*) \subseteq Cl_t^{\geq}\}$
- The $P$-upper approximation of $Cl_t^{\leq} : \bar{P}(Cl_t^{\leq}) = \{a_1^* \in A^* : D_p^+(a_1^*) \cap Cl_t^{\leq} \neq \emptyset\}$
- The $P$-lower approximation of $Cl_t^{\leq} : \underline{P}(Cl_t^{\leq}) = \{a_1^* \in A^* : D_p^-(a_1^*) \subseteq Cl_t^{\leq}\}$

The $P$-boundaries (doubtful regions) of the unions $Cl_t^{\geq}$ and $Cl_t^{\leq}$ are defined, respectively, as (Equation 2.19 and Equation 2.20):

$$Bn_p(Cl_t^{\geq}) = \bar{P}(Cl_t^{\geq}) - \underline{P}(Cl_t^{\geq}) \tag{2.19}$$

$$Bn_p(Cl_t^{\leq}) = \bar{P}(Cl_t^{\leq}) - \underline{P}(Cl_t^{\leq}) \tag{2.20}$$

Given that, decision rules are obtained to a subset of alternatives and then applied to all others to classify them into levels of vulnerability.

UTADIS and DRSA are well-known MCDM/A methods, but their application in this thesis offers a new perspective for evaluating regions based on a meaningful set of criteria to support spatial decision-making in urban planning. Furthermore, their integration with other methods presented in this section results in a gain of information and knowledge for taking actions to improve societal and organizational demands in the areas of attractiveness, connectivity, and vulnerability to crime.

## 2.4 FINAL CONSIDERATIONS

All the presented methods are useful for several issues, whether spatial, numerical, or decision analysis. The goal is to use these methods to construct a methodology that enables the understanding and learning process to generate knowledge for spatial decision-making. To achieve this, it is crucial to know each of them in order to construct and propose something that makes sense and has value for policymakers.

The next chapter presents a systematic review of the literature on MCDM/A preference learning, where points for improvement were identified and can be applied in urban planning.

# 3 SYSTEMATIC REVIEW: MCDM/A AND PREFERENCE LEARNING

This chapter addresses a systematic review regarding **SO 1** through the use Context, Interventions, Mechanisms, and Observed results (CIMO) framework (DENYER *et al.*, 2008). The central idea is to identify recent studies in preference modeling concerning learning structures. Hence, it is possible to find out the evolution in preference learning and fields to explore. For this, a search was performed in Web of Science and Scopus databases.

## 3.1 CONTEXTUALIZATION

Learning is part of the decision-making process. According to Belton and Stewart (2002), the advantage of using MCDM/A methodologies is to facilitate the understanding of a problem regarding DMs' and other parties' preferences.

However, the traditional MCDM/A methodologies consider the use of all alternatives and parameters assessment, demanding a cognitive effort from DM. On the other hand, PDA can work with a set of alternatives, and if the model obtained follows DMs' preferences, it can be applied to new system entries. On the contrary, at least it is possible to use the result as a basis to calibrate a model until it is consistent. In that view, MCDM/A methods approximate to statistical and machine learning (DOUMPOS; ZOPOUNIDIS, 2011). Although advances and applications of MCDM/A in the learning field have been developed, it is still a fertile area of exploration and experiments. That is, through the systematic review it is expected to find out opportunities in face of real problems.

## 3.2 METHODS

The systematic review of the literature consists of carrying out clear, objective, and replicable operations to set out the research scope from the identification of the objectives (FINK, 2014). In this sense, the present systematic review accounts for the CIMO framework (DENYER *et al.*, 2008) to identify studies of MCDM/A that fall into learning problems, with effective communication between objectives and results. For this, it was used the Web of Science and Scopus databases.

It was selected articles published between January 2018 and December 2021. The idea is to cover recent final articles published in journals and in the English language. Book chapters, conference proceedings, reports, interviews, and abstracts were excluded from analysis,

Table 2. For literature review it was used the search string **((("preference learning")) AND ("multi$criteria" OR " decision analysis" OR "decision theory" OR "decision model*" OR "decision making" OR "multiple criteria"))**.

Table 2 – Selection criteria for systematic review

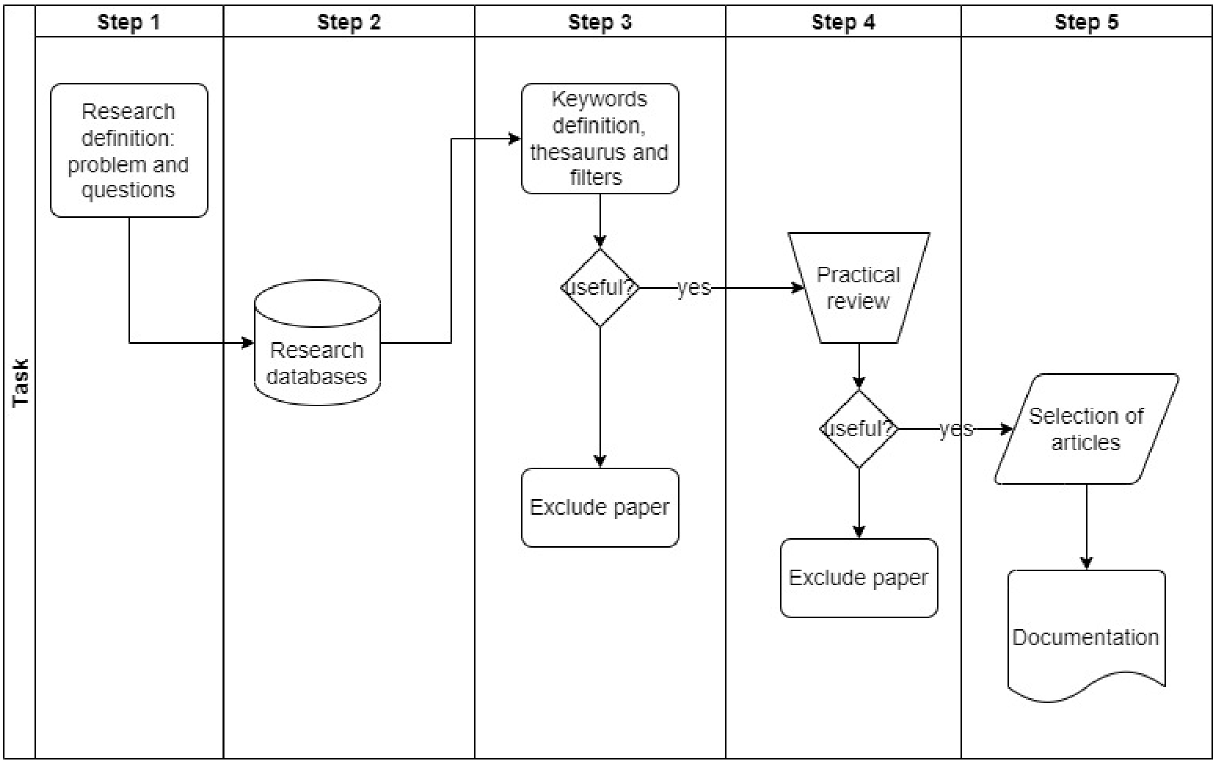
| **Inclusion criteria** | **Type** |
|---|---|
| *journal* Article | Publication |
| Published | Status |
| English | Language |
| Jan/2018 - Dec/2021 | Publication period |
| Title and *abstract* | Content |
| **Exclusion criteria** | **Type** |
| Conference proceedings, reports, interviews, book chapters, abstracts | Publication |
| Non-English | Language |

Source: The Author (2023)

The process of the systematic review can be summarized in 5 steps (Figure 4). According to this,

- Step 1: definition of preference learning in MCDM/A field and how it has been explored in different contexts;
- Step 2: definition of the research base to find relevant papers. The databases chosen were Web of Science and Scopus due to their popularity and the variety of journals available on there;
- Step 3: definition the filters to select relevant papers to review, and to do a preliminary screening based on keywords, titles, and abstracts. If the paper is useful to review than the next step, otherwise the paper is excluded from the analysis;
- Step 4: after a preliminary screening, practical review is carried out, i.e. the potential papers are read. Again, if the papers is useful to review than next step, otherwise the paper is excluded from the analysis;
- Step 5: at this step, there is a collection of articles that meet the definitions established in the first step. Here, it is important to document the articles to identify points of improvements, gaps, and applications.

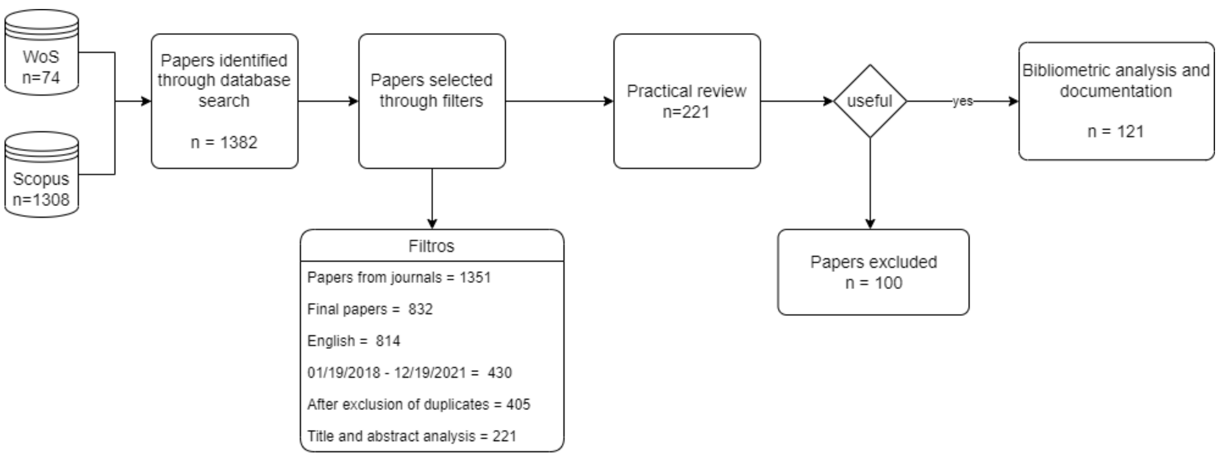
Figure 4 – Literature review: steps




Source: The Author (2023)

According to the steps shown in Figure 4, initially 1328 articles were identified. Out of this total, 1308 were collected in Scopus and 74 in Web of Science. To practical review, there were 221 papers to be read. At the end, 121 papers were included to qualitative synthesis. Figure 5 summarizes the number of papers by screening step.

Figure 5 – Number of publications




Source: The Author (2023)

The organization of surveyed articles and its analysis were supported by JabRef 5.6 and

VosViewer 1.6.19 applications. The results are presented in next section.

## 3.3 RESULTS AND DISCUSSION

Through the CIMO framework, there were selected articles with practical objectives, whether to present a review, a new methodology with applications, or a pure methodology with the purpose of application. The importance given to a paper was defined by its potential to achieve an objective or goal.

As result of analysis of papers, it was found that the articles published between 2018 and 2021 are, in majority, from China ( 32.23%), France ( 13.22%), Poland and United Kingdom ( 11.57%, each), United States ( 10.74%), and Australia ( 7.44%). And together, according to the subject areas established by Scopus, the fields of computer science and decision sciences are responsible to cover 51,5% of the total number of papers, Table 3.

Table 3 – Top 5 subject area of publication

| Subject area | % of total |
|---|---|
| Computer science | 33.5 |
| Decision science | 18.0 |
| Mathematics | 16.2 |
| Engineering | 13.2 |
| Business, management and accounting | 7.4 |

Source: The Author (2023)

Another issue is that the five sources that most published articles with the search keys (European Journal of Operational Research, Expert Systems With Applications, Knowledge Based Systems, Information Sciences, and Omega) are all classified as the first quantile at both Web of Science and Scopus. Moreover, the metrics used in Brazilian research institutes, Qualis CAPES, indicate these same five sources as A1, the highest evaluation of journals. This demonstrates the importance and relevance of the theme over time, since in 2018, 2019, 2020, and 2021 were published 22, 32, 32, and 35 papers, in addition to publications in journals of trust.

Though MCDM/A and machine (and statistical) learning are different fields, it is possible to see hybrid use between them for application or simply to bench-marking results. Such example, Aggarwal (2019a) use the Attitudinal Choquet Integral (ACI) to learn about consumer decision-making, from that perspective, the model is powered by the preferences of a decision-maker

(DM), hence it is possible to learn and easy to predict preferences than to consider the evaluation of all alternatives by a DM. Table 4 presents the articles which make use of ML methods.

Table 4 – ML methods used in decision making

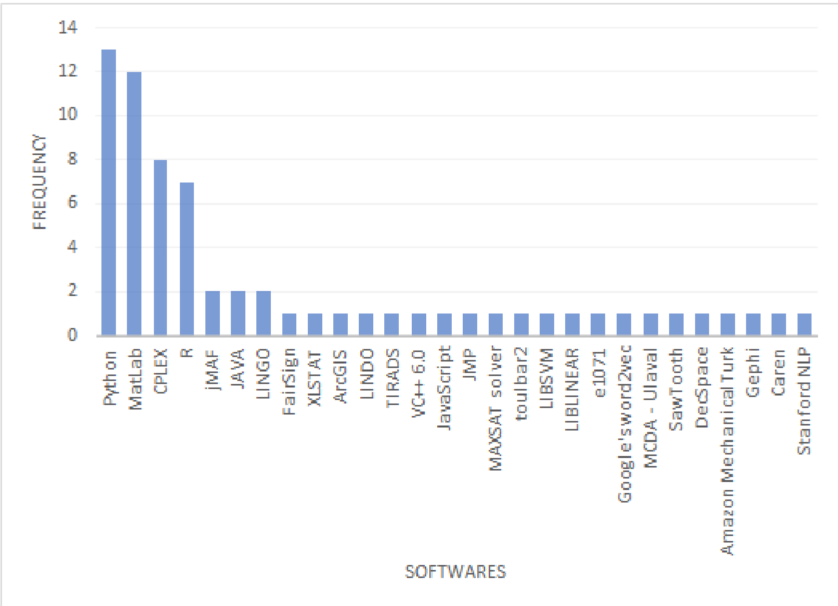
| **Authors** | **Methods** |
|---|---|
| Aggarwal (2018), Aggarwal (2019a), Aggarwal (2019d) | Attitudinal Multinomial Logit (AMNL) and Multinomial Logit (MNL) |
| Aggarwal (2019c) | PL-based EMOA (PLEMOA), Evolutionary Multiobjective Algorithm (EMOA), and PL-based NSGA-2 (PL-NSGA2) |
| Ahn and Lin (2020) | Machine Learning (ML) work flow implemented in a system |
| Balugani *et al.* (2021) | Principal Component Analysis (PCA) |
| Batmaz and Kaleli (2019) | Autoencoders |
| Ding *et al.* (2019) | Factorization machine |
| Fei and Feng (2020) | Case-Based Reasoning (CBR) |
| Fancello and Tsoukiàs (2021), Houari and Taghezout (2021), Nguyen *et al.* (2020), Fei and Feng (2020) | Cluster analysis, k-means, c-means |
| Forouzandeh *et al.* (2021) | Artificial bee colony |
| Guo *et al.* (2021), Hamada and Hassan (2018), Liu *et al.* (2021b) | Neural network |
| Hamada and Hassan (2018), Wasid and Ali (2021) | Particle Swarm Optimization (PSO) |
| Hong and Jung (2021b) | Tensor factorization |
| Lang *et al.* (2018), Li and Wang (2019), Liu and Truszczynski (2019), Nilashi *et al.* (2019a) | Decision tree |
| Liu *et al.* (2019) | Support Vector Machine (SVM) |
| Liu *et al.* (2020) | Regularization techniques |
| Nilashi *et al.* (2019a), Nilashi *et al.* (2019b) | Self-organizing Map (SOM) |
| Nilashi *et al.* (2021), Nilashi *et al.* (2019b) | Expectation-Maximization (EM) |

| | |
|---|---|
| Nilashi *et al.* (2019b), Nilashi *et al.* (2021), Nilashi *et al.* (2019a) | Adaptative Neuro-fuzzy Inference Systems (ANFIS) |
| Wasid and Ali (2021) | Colaborative Filtering (CF) |
| Nilashi *et al.* (2019b) | Latent Dirichlet Allocation (LDA) |
| Peters *et al.* (2018) | Bayesian model |
| Jung *et al.* (2019) | Binomial regression |

Source: The Author (2023)

Table 4 shows that the majority of articles in the MCDM/A field that use ML methods employ cluster analysis and decision tree with 4 articles each. Besides that, the surveyed articles use software to support their analysis, Figure 6.

Figure 6 – Software used by surveyed articles




Source: The Author (2023)

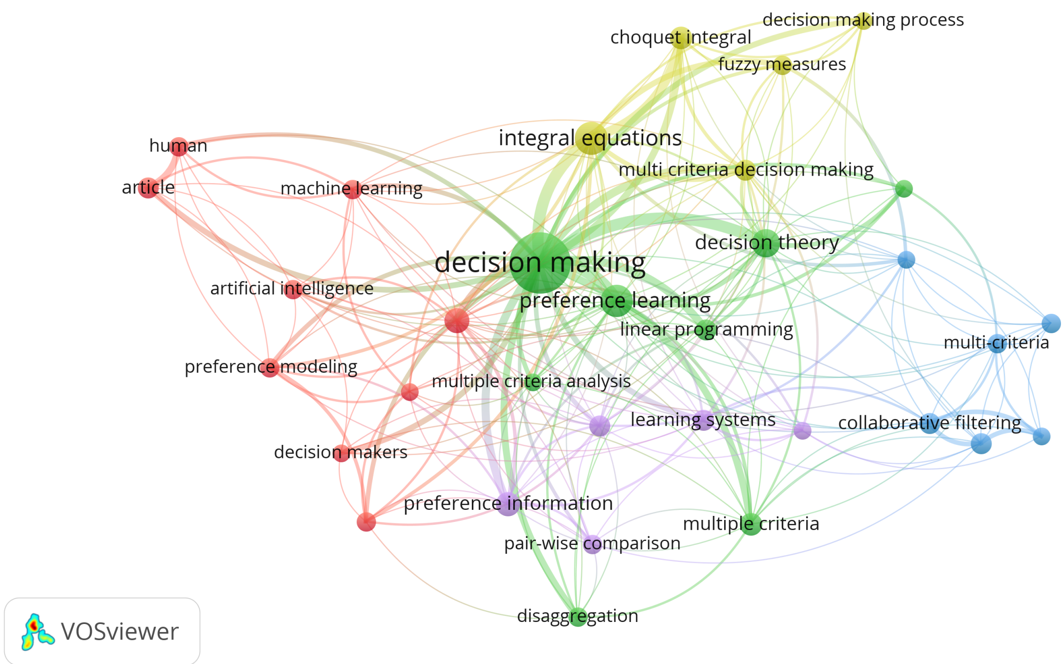
As shown in Figure 6, the four most commonly used tools are not specific to MCDM/A methods, but are general modeling tools. Among these, Python and R are free software, while MATLAB and CPLEX are commercial tools. This suggests that researchers may value flexibility in the choice of tools, in addition to using dedicated software for specific purposes.

Although there is a promotion of holistic/disaggregation methods for preference learning, the decision methods in the surveyed articles are generally not restricted to disaggregation methods. Such example, it is possible to note Stochastic Multicriteria Acceptability Analysis

(SMAA) (ANGILELLA *et al.*, 2018; ARCIDIACONO *et al.*, 2021; COSTA *et al.*, 2020), Linear in Parameter and Additive in Attributes (LPAA) (BALBONTIN *et al.*, 2019), Elimination and Choice Expressing the Reality (ELECTRE) (CHAUVY *et al.*, 2020), Analytic Hierarchy Process (AHP) (CHAUVY *et al.*, 2020; DESTERCKE, 2018), linear programming (DIAS *et al.*, 2021), Dempster-Shafer Theory (FEI *et al.*, 2021), Multi-Attribute Value Theory (MAVT) (HAAG *et al.*, 2019), additive weighted sum (KUPPELWIESER *et al.*, 2020). And traditional disaggregation methods are also found such as Additive Utility Functions (UTA) (FANCELLO *et al.*, 2020; FANCELLO; TSOUKIàS, 2021), UTADIS (BABASHOV *et al.*, 2020) and DRSA (LUO *et al.*, 2018; EGAJI *et al.*, 2019; DU; HU, 2018).

The analysis of the co-occurrence of keywords in accepted papers reveals that the most discussed topics are divided into 5 clusters. There are those concerning to (i) fuzzy measures, Choquet, and integral equations; (ii) disaggregation, preference learning and decision making; (iii) collaborative filtering, and recommender systems; (iv) preference information, regression analysis, and predictive models; and (v) artificial intelligence, and machine learning (Figure 7).

Figure 7 – Keywords co-occurrence




Source: The Author (2023)

In Figure 7, the biggest circles indicates the keywords with greatest occurrences, the same is for the edges which establishes links between keywords. Thus, it is possible to infer the *decision making* and *integral equations* are the most used keywords and comparatively they are associated with a large number of keywords, as they occur 56 and 17 times, and their total link strength are 140 and 51, respectively.

Regarding the use of datasets, only 17 articles does not present the used datasets. For details see Appendix A.

## 3.4 FINAL CONSIDERATIONS

It is undeniable that there are limitations in the systematic review, whether due to the theme being a branch of MCDM/A methods, period, type of publication, language, or even due to the databases. Despite its limitations, the review serves an important purpose in organizing the papers related to the use of preference learning in the MCDM/A field and identifying areas for further exploration.

The present review is the first concerning the general preference learning and MCDM/A methods between 2018 and 2021. Since during this period Dimuro *et al.* (2020) presents a review of the generalization of Choquet Integral.

As it is known by the author, the previous paper of Doumpos and Zopounidis (2011) is the closest to this literature review. However, the authors present the difference between preference learning in MCDM/A and machine (and statistical) learning. On the other hand, this chapter presents a range of papers with different applications and methodologies which that may use hybrid approach of MCDM/A and ML.

Although there are MCDM/A methods that consider the interactions between criteria, one noteworthy aspect is the lack of clear considerations of spatial interaction relationships in GIS-MCDM/A. Another issue is that according to the surveyed articles in Appendix A, studies such as Gao *et al.* (2021), Tehrani (2021), Fancello *et al.* (2020), Fancello and Tsoukiàs (2021), Figueiredo and Mota (2019) make use of Geographyc Information Systems (GIS) without fully considering spatial interaction. Instead, they assess spatial preference with regards to social-demographic factors or the urban structure of services.

Therefore, the review contributes in identifying opportunities of explore the spatial decision through the perspective of spatial interactions. This process is constructed in the next chapters.

# 4 SPATIAL ATTRACTIVENESS: A PREFERENCE LEARNING APPROACH

This chapter addresses the specific objective **SO 2**, which is to investigate spatial attractiveness preferences in urban planning. It presents a model for learning municipal attractiveness to support decision-making.

## 4.1 CONTEXTUALIZATION

From the spatial perspective, there is a dynamic relationship that can reach different geographic scales, generally restricted to attractive locations (YAN *et al.*, 2017), due to the food-energy-climate security nexus, access to education, medical care, tourism, and transport, as well as commercial, professional, and business relationships (SHEN, 2016; GREENWOOD, 1985; WU *et al.*, 2022; WALTERT *et al.*, 2011).

Understanding and identifying factors that are involved in the determination of greater attractiveness becomes important in planning and executing actions that have an impact on public policies to avoid overloading services and the environment, and also to reduce the risks of social inequality and the economic marginalization of certain regions (KOYLU; GUO, 2013; ŹRÓBEK-RÓŻAŃSKA; ZADWORNY, 2016b; KüHN, 2014; CILLIERS *et al.*, 2021; ZHU *et al.*, 2021; BASILE *et al.*, 2021).

On the other hand, public policies have their mechanisms to influence people and business (OECD, 2017) and, as a consequence, influence spatial attractiveness. In that manner, it is a "two-way street" that demands cooperation regarding people's and organization's desires, and the public sector to coordinate investment actions (COUSSI *et al.*, 2018) which affect the preferences of different sectors.

The analysis of spatial attractiveness provides a space for in-depth discussions of factors that both influence and are influenced by human action, according to the different objectives that interfere in the development of a region, the maintenance of services, and sustainable growth in the medium and long term. As such, the literature presents studies that explore spatial attractiveness analysis in different ways. For example, the rich-clubs, which refer to the tendency of prominent elements to participate in stronger interactions among themselves than expected, have been used to explore regional economic inequalities as an impact factor of attractiveness on internal migration (ZHU *et al.*, 2021). Attractiveness is also a result of the memory effect and the local population. According to this idea, a good impression of a place increases the probability of future visits (YAN *et al.*, 2017). This effect could be related to traditional or online word-of-mouth and partially justify the interest in tourist attractions and the tendency for people to gather in large numbers in certain places. Another factor that may improve spatial attractiveness is the presence of landscape amenities (WALTERT *et al.*, 2011). Furthermore, reducing noise pollution and traffic intensity can also enhance spatial attractiveness (MUELLER *et al.*, 2018). In addition, different types of amenities may attract different sectors; for instance, industries are attracted by the presence of government departments and public services, while the creative industries prioritizes life services and shopping centers (WU *et al.*, 2022). Finally, according to the Theory of Central Places, places are attractive due to economic conditions regarding the goods and services offered in a region (CHRISTALLER, 1966).

The difference of the proposed approach is to take into account the administrative factors and geographic data of location of services as a way to elucidate the aspects that make a region attractive for people. The administrative factors include things like the availability of public services, and actions of local government to support public demands. By considering both administrative and geographic data, the proposed approach may provide a more comprehensive understanding of what makes a region attractive to people. This is useful for urban planning for economic development, or marketing and tourism initiatives.

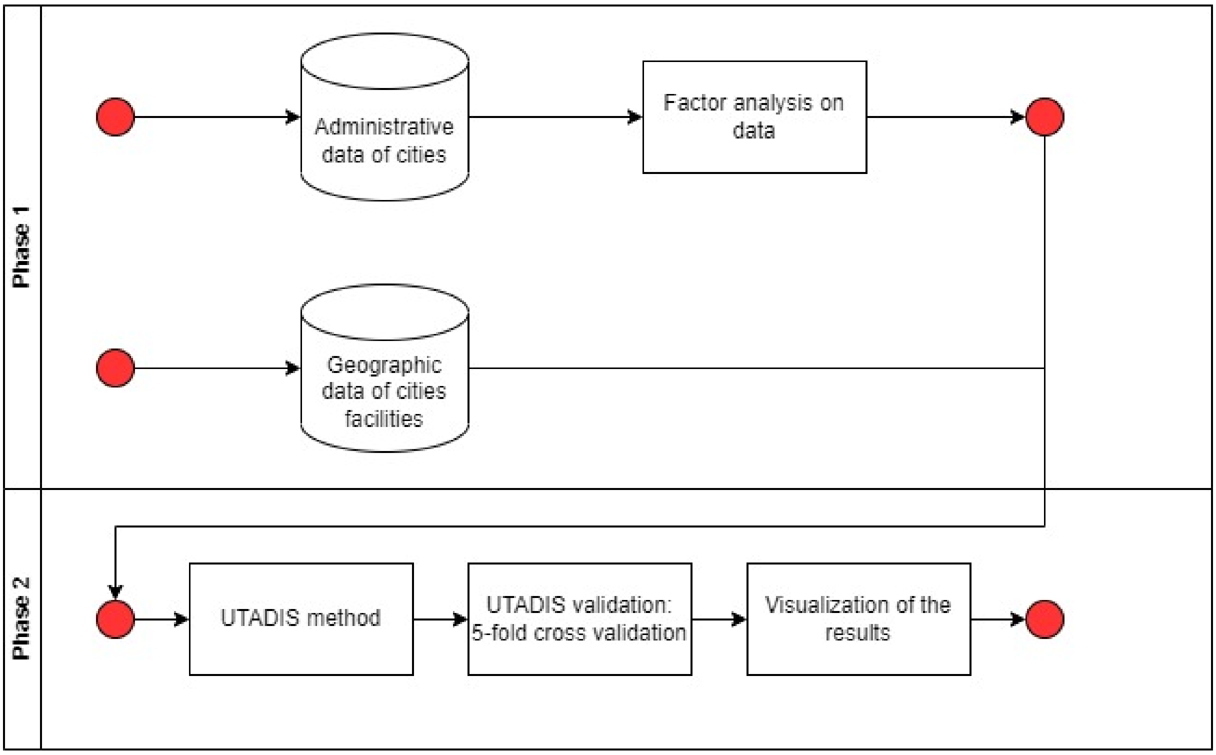
As the objective is to investigate and learn the spatial attractiveness regarding preferences, it is proposed the use of GIS-MCDM/A method to evaluate the spatial attractiveness of municipalities of the state of Pernambuco - Brazil. The analysis considered 184 municipalities, and as a result, attractiveness classes were found regarding the spatial distribution of places of services and public policies perceived by people who live and work in those municipalities.

## 4.2 DATA AND METHODS

The attractiveness analysis was developed for classification of municipalities of Pernambuco, which is located in Northeast region of Brazil. This state has an estimated population of 9,674,793 inhabitants and an area of approximate 98,067.88 $km^2$. In terms of geopolitical regions, the state stands out with the third HDI, behind the states of Rio Grande do Norte and Ceará. For the analysis of state of Pernambuco, it was developed a 2-phase methodology, as presented in Figure 8.

In phase 1, the study does a survey of open data from IBGE and OSM. From the IBGE, the population density and 127 administrative categorical variables about municipal halls actions in

Figure 8 – Flow process of spatial attractiveness analysis




Source: The Author (2023)

housing, transport, agriculture, environment, and risk an disaster management policies (Appendix B) were extract. These administrative variables were pre-processed and transformed in small subset of latent variables through FA. Therefore, the use of latent variables is proposed as the basis of MCDM/A modeling to represent important dimensions of attractiveness.

The hierarchy of municipalities is also collected from IBGE (2022). According to IBGE's methodology, the hierarchy, or degree of importance, of a municipality can be classified by a group of three volunteers into five groups: metropolis, regional capital, sub-regional center, zone center, and local center (IBGE, 2020). For these classes, the municipalities are classified from the greatest power of regional influence to the least power of regional influence. For the sake of simplicity, this study adopted *cl1* as very attractive, *cl2* as attractive, *cl3* as moderate attractive, *cl4* as low attractive, and *cl5* as very low attractive.

The geographic data of cities facilities were obtained from OSM (OSM, 2022). In our MCDM/A analysis, we considered the spatial distribution of hospitals, clinics, retail businesses, marketplaces, industries, universities, colleges, schools, kindergartens, and hotels and hostels (accommodation). As in Figure 8, these data do not participate in the factor analysis, the reason is to investigate and learn the contribution of each kind of facility/amenity to the spatial attractiveness preference perception, thus placing them as a single factor would mean loss of information.

The data selection was based on the literature (ZHU *et al.*, 2021; ZHANG, 2007; WALTERT *et al.*, 2011; WU *et al.*, 2022; TAIMA; ASAMI, 2020; HANANEL *et al.*, 2021; ROMÃO *et al.*, 2018; MUELLER *et al.*, 2018) which indicates that the environmental, local management, job and education opportunities are factors of spatial attraction. However, unlike other studies, we aimed to consider all possible aspects through latent variables. To do so, as the objective was to indicate a value function to classify the municipalities of Pernambuco, the preference of attractiveness was analyzed in phase 2 of the methodology through the UTADIS method.

To implement the UTADIS method, the data was divided in 5-fold cross validation to find a model with the greatest number of criteria to revealing the attractiveness of municipalities and better accuracy. The model was implemented using R MCDA[1] (BIGARET *et al.*, 2017).

## 4.3 RESULTS AND DISCUSSION

This section presents the results of factor analysis and UTADIS methods, respectively, for dimensional reduction and to preference learning regarding factors that interfere in spatial attractiveness.

### 4.3.1 Phase 1: Data survey and factor analysis

Spatial attractiveness refers to a subjective arrangement of preferences regarding access to education, job, health care, facilities/amenities (SHEN, 2016; WU *et al.*, 2022; TAIMA; ASAMI, 2020; MUELLER *et al.*, 2018), and incentives of public policies (OECD, 2017; COUSSI *et al.*, 2018). Among these factors, there are the physical and visible factors, such as clinics, colleges, retail businesses, kindergarten, schools, hospitals, industries, marketplaces, universities, accommodation facilities and the population concentration (population density), which are used in this study and denominated as geographic data of facilities in the cities.

There are also factors of incentive administrative policies perceived by inhabitants, tourists, businesses, companies, and rural producers. To cover these factors, the application of factor analysis competes with the 127 administrative variables, which concern to the municipal sphere in terms of housing, transport, agriculture, environment, and risk and disaster management. In general, these variables reflect the actions of the city halls of those municipalities aiming at supporting local inhabitants regarding land use, accessibility, development of the local economy,

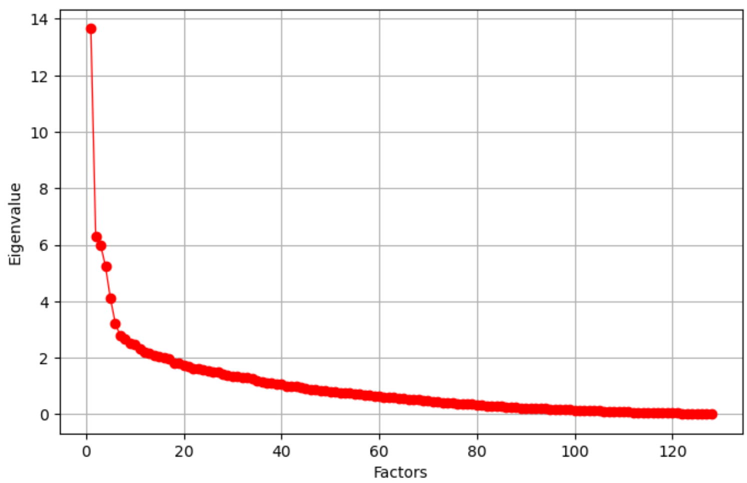
[1] Available at: https://cran.r-project.org/web/packages/MCDA/index.html

and environmental disasters, in a grained view that is considered too much information for the decision model construction.

Hence, to reproduce the most prominent elements in the decision model we adopted the factor analysis due to its capacity to reduce data dimension, favoring the interpretability of latent variables. Given that factor analysis is a numerical process and all administrative 127 variables described in Appendix B are categorical, they were pre-processing to dummy variables. As a result, the process gave us a data table with more columns that represented each variable in its respective category. All variables were represented by more than one category with opposite meanings. In this case, we excluded the negative categories, except for the variable MTRA21 (municipal buses adapted for people with disabilities or reduced mobility), which was classified as adapted partially, adapted totally, without adaptation, and no information. For MTRA21, we only considered the positive evaluations of buses that were partially or totally adapted. Also, we excluded categories without information.

Factor analysis was performed with varimax rotation (DILBECK, 2017), and the number of latent variables was determined by analyzing where the difference of eigenvalue of factors started to diminish at the scree-plot graph (Figure 9).

Figure 9 – Scree plot - eigenvalue




Source: The Author (2023)

The dots in Figure 9 represent the eigenvalue for each factor. As a result, a total of 6 factors were selected. To name these factors, we considered the loadings of the first ten variables of each factor, which represent the importance of each variable to the factor, as shown in Table 5. Thus, the latent variables were named *policies for environmental disasters* (factor

1), *sustainability policies* (factor 2), *policies of access to water* (factor 3), *policies of structure of transport* (factor 4), *policies of agricultural incentives* (factor 5), *policies of urban mobility* (factor 6), with a greater loading of policies regarding mapping of flood risk (0.74), protection of biodiversity (0.82), monitoring of occurrence of drought (0.76), structure to passenger support system (0.92), incentive to production of community garden (0.53), and existence of bicycle racks (0.56), respectively. For detailed description of variables presented in Table 5 see Appendix B.

Table 5 – Loadings of 10 first variables of factors

| Factor 1 | | Factor 2 | | Factor 3 | | Factor 4 | | Factor 5 | | Factor 6 | |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Variable | Loading | Variable | Loading | Variable | Loading | Variable | Loading | Variable | Loading | Variable | Loading |
| Mgrd181 | 0.74 | Mmam2010 | 0.82 | Mgrd01 | 0.76 | Mtra082 | 0.92 | Magr155 | 0.53 | Mtra25 | 0.56 |
| Mgrd201 | 0.71 | Mmam208 | 0.81 | Mgrd047 | 0.7 | Mtra084 | 0.88 | Magr154 | 0.53 | Mtra187 | 0.56 |
| Mgrd11 | 0.68 | Mmam209 | 0.8 | Mgrd044 | 0.68 | Mtra086 | 0.81 | Magr151 | 0.52 | Mtra24 | 0.55 |
| Mgrd14 | 0.67 | Mmam206 | 0.74 | Mgrd041 | 0.59 | Mtra081 | 0.79 | Magr152 | 0.52 | Mtra182 | 0.47 |
| Mgrd06 | 0.66 | Mmam207 | 0.71 | Mgrd042 | 0.55 | Mtra085 | 0.77 | Magr222 | 0.45 | Mgrd211 | 0.42 |
| Mgrd184 | 0.65 | Mmam203 | 0.71 | Mgrd043 | 0.54 | Mtra083 | 0.73 | Magr16 | 0.42 | Mtra188 | 0.38 |
| Mgrd08 | 0.64 | Mmam204 | 0.68 | Mgrd046 | 0.49 | Mmam262 | 0.26 | Magr191 | 0.42 | Mhab201 | 0.36 |
| Mgrd207 | 0.63 | Mmam205 | 0.67 | Mmam261 | 0.46 | Mtra25 | 0.24 | Magr22111 | 0.41 | Mtra21* | 0.36 |
| Mgrd187 | 0.62 | Mmam202 | 0.62 | Mgrd05 | 0.42 | Mtra19 | 0.23 | Magr153 | 0.41 | Mtra19 | 0.35 |
| Mgrd186 | 0.6 | Mmam2011 | 0.59 | Magr18 | 0.4 | Mtra24 | 0.22 | Magr22113 | 0.4 | Mgrd213 | 0.3 |

* For factor 6, the variable Mtra21 concerns municipal buses adapted totally for people with disabilities or reduced mobility.

Source: The Author (2023)

The six factors that indicate political actions to maintain and support residents were used as criteria in the MCDM/A model, along with geographic data of the cities' facilities.

### 4.3.2 Phase 2: Learning attractiveness model and mapping spatial preferences

Considering that attractiveness is a concept based on individual or organizational preferences, the hierarchical classification of municipalities given by the methodology of the Brazilian Institute of Geography and Statistics (IBGE) is used for the evaluation (IBGE, 2022). Thus, applying UTADIS focuses on the preferences of the participants of the IBGE survey through a preference learning approach, within the scope of geospatial relations. The factors from FA and the geographic data of clinics, colleges, commerce, schools, hospitals, industry, marketplaces, universities, accommodation, and population density in those cities were used as criteria.

Having determined the decision and preference criteria, we divided the data into 5-fold cross validation. The UTADIS model was run with $\alpha = 3$ for each criterion $g_i$, and the difference threshold classes equals to 0.05. Each run gave us a value function for municipalities classification, Table 6 presents the accuracy of each k-fold.

As shown in Table 6, not all 17 initial criteria were considered by the decision model.

Table 6 – Accuracy of 5-fold cross validation

| | Accuracy | | |
|---|---|---|---|
| k-fold | Train | Test | Number of criteria |
| 1 | 0.8095 | 0.8108 | 11 |
| 2 | 0.8027 | 0.8378 | 11 |
| 3 | 0.8095 | 0.8108 | 10 |
| 4 | 0.8707 | 0.7837 | 10 |
| 5 | 0.7905 | 0.8055 | 11 |
| Mean | 0.8166 | 0.8097 | |

Source: The Author (2023)

This is because some criteria were deemed irrelevant in the preference analysis, indicating that certain criteria were more important to the surveyed population than others. Also, it is possible to note that the mean accuracy of training and test samples were close (0.8166 and 0.8097, respectively). However, as each k-fold generated a different utility function, by the reason of understanding the maximum number of criteria which influenced the preference of attractiveness, the model generated by the first k-fold was determined as the utility function to the fulfillment of the preference evaluation of attractiveness in the municipalities of the state of Pernambuco. Figure 10 presents the value function of each criterion.

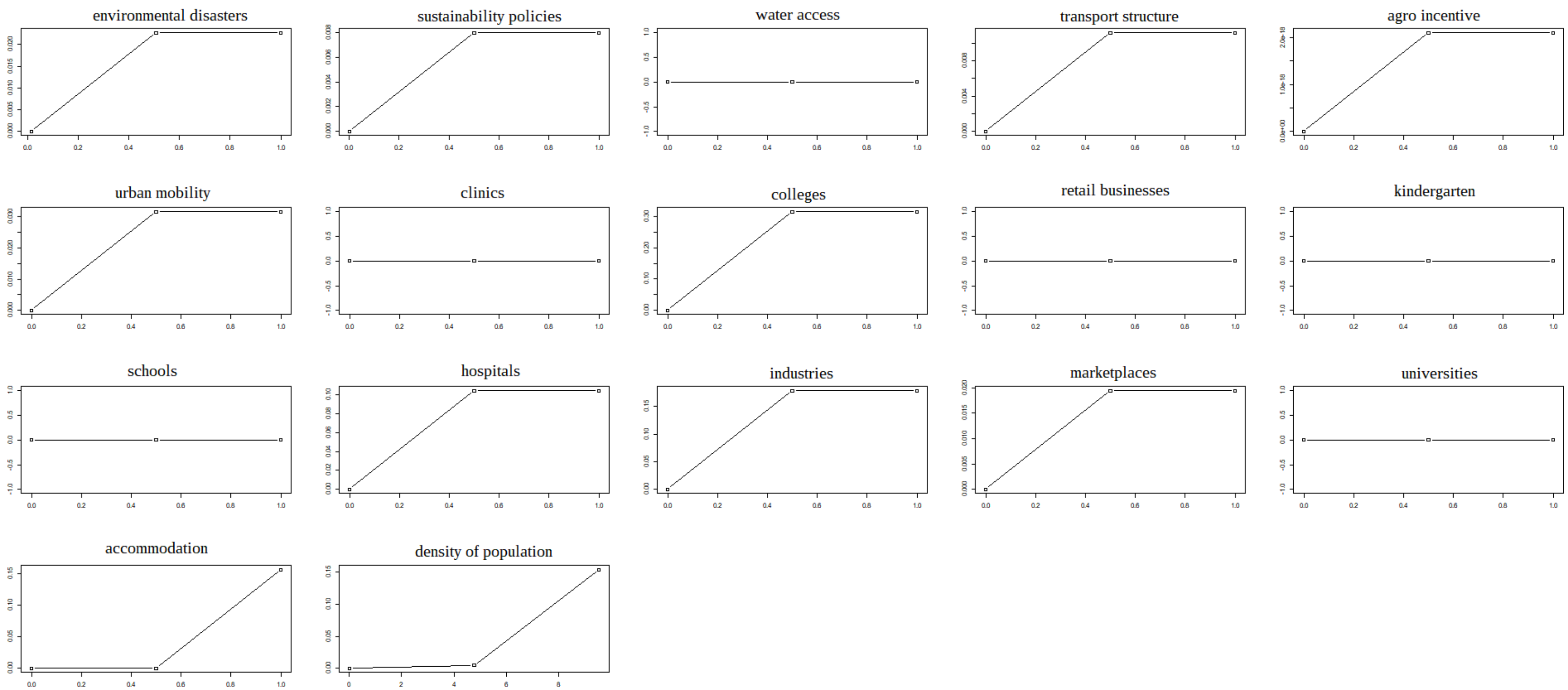
Therefore, Equation 4.1 represents the global utility function generated by the UTADIS method.

$$\begin{aligned} U(a) =& 0.022718153u_1(g_1) + 0.007996821u_2(g_2) + 0u_3(g_3) + 0.011192508u_4(g_4) + \\ & 2.11E-18u_5(g_5) + 0.031524989u_6(g_6) + 0u_7(g_7) + 0.314557083u_8(g_8) + \\ & 0u_9(g_9) + 0u_{10}(g_{10}) + 0u_{11}(g_{11}) + 0.10418738u_{12}(g_{12}) + 0.178634717u_{13}(g_{13}) + \\ & 0.019396489u_{14}(g_{14}) + 0u_{15}(g_{15}) + 0.156227934u_{16}(g_{16}) + 0.153563925u_{17}(g_{17}) \end{aligned} \tag{4.1}$$

Where,

- $u_1(g_1)$: policies for environmental disasters
- $u_2(g_2)$: sustainability policies
- $u_3(g_3)$: policies of access to water
- $u_4(g_4)$: policies of transport structure
- $u_5(g_5)$: policies of agricultural incentives
- $u_6(g_6)$: policies of urban mobility
- $u_7(g_7)$: clinics
- $u_8(g_8)$: colleges

Figure 10 – Plot of the value functions of the criteria




Source: The Author (2023)

- $u_9(g_9)$: retail businesses
- $u_{10}(g_{10})$: kindergarten
- $u_{11}(g_{11})$: school
- $u_{12}(g_{12})$: hospital
- $u_{13}(g_{13})$: industry
- $u_{14}(g_{14})$: marketplace
- $u_{15}(g_{15})$: universities
- $u_{16}(g_{16})$: accommodation
- $u_{17}(g_{17})$: density of population

From Equation 4.1, we can learn that the presence of colleges, hospitals, industries, accommodation facilities, and population density influence the preferences of people in terms of the attractiveness of cities in the state of Pernambuco. On the other hand, policies related to water access, agriculture incentives, clinics, retail businesses, kindergarten, school, and universities are not considered relevant for attractiveness decision, as their coefficients are zero. Assuming the Central Places Theory of Christaller (1966), which states that people tend to find places attractive when they seek different services than those offered in their regions, it is also possible to infer that the criteria with a coefficient of zero are those that municipalities already act upon to support their internal demands, except in the case of universities where further investigation is needed, as this facility is not equally distributed among all municipalities analyzed.

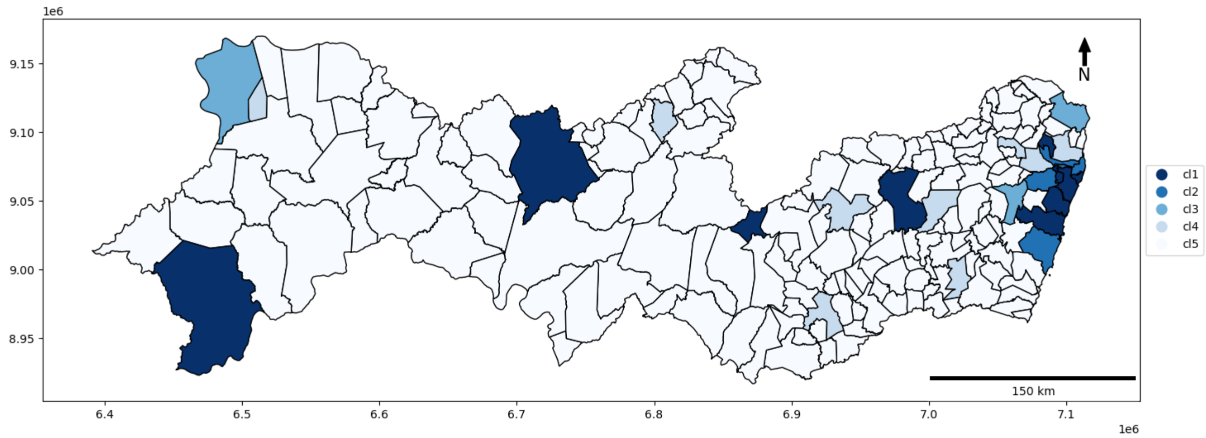
Thus, for the attractiveness of municipalities in Pernambuco, the preference relates to elements that represent facilities in a city. From that view, we could infer that people focus on professional education and job opportunities, and they tend to search for places with support of health systems. Also, people tend to go to populated places with availability of accommodation, which is usually connected with tourism-related activities.

To frame an alternative to an attractiveness class, the model provided us with the following thresholds:

- $a \in cl_1 \iff U(a) > 0.240930644151494$
- $a \in cl_2 \iff 0.190930644151494 < U(a) < 0.240930644151494$
- $a \in cl_3 \iff 0.140930644151494 < U(a) < 0.190930644151494$
- $a \in cl_4 \iff 0.0909306441514939 < U(a) < 0.140930644151494$
- $a \in cl_5 \iff U(a) < 0.0909306441514939$

The classification given by the model is represented in Figure 11. Where a better classification is observed for the municipalities in the extreme east, the metropolitan region of Pernambuco, where Recife, the capital of the state, is located. Moving from east to west, the next city to stand out is the town of Caruaru, which is prominent as a textile industrial center. Throughout the middle region of the state of Pernambuco, from east to west, the cities of Arcoverde and Serra Talhada are observed as most prominent, and to the south of the extreme west of the state, the town of Petrolina stands out.

Figure 11 – Classification of attractiveness




Source: The Author (2023)

Another learning comes from the attractiveness mapping interpretation (Figure 11), which shows that preference of high attractiveness relates a region of the state to one municipality, except for the case of the metropolitan region of Recife, which leads us to reflect upon the importance of the neighborhood to improve the attractiveness perception. As regards Pernambuco, for instance, the capital Recife seems to improve the perception of its vicinity.

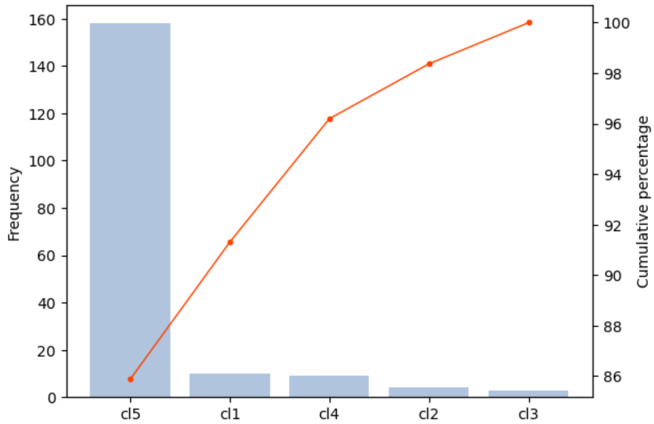
### 4.3.3 Discussion

This section discusses the results obtained and possible applications in the field of urban planning, since attractiveness enables urban sprawl and favors the emergence of marginalized areas (KOYLU; GUO, 2013; ŹRÓBEK-RÓŻAŃSKA; ZADWORNY, 2016a; KüHN, 2014; CILLIERS *et al.*, 2021) that are poorly monitored by municipal administrative agencies, resulting in major problems arising from social disorganization.

From this perspective, one can mention problems of public safety, of access to sanitation and hospital health facilities, of environmental disasters and related fatalities, and of water supply, to mention some of the possible consequences arising from the pressure both on the public service system and on the local environment.

Learning the criteria that influence the decision of attractiveness is a valuable tool for managers in the decision-making process and to improve the maintenance of services in their municipalities and cater for their inhabitants', visitors', and businesses' needs. Taking into account the near places are more related than distant places (TOBLER, 1970), namely, knowing people's preferences could be a valuable tool to turn cities competitive and to think about collaborative gains. Figure 12 represents a Pareto curve related to attractiveness to compare the frequency and cumulative percentage of municipalities in each class.

Figure 12 – Pareto curve of attractiveness of municipalities




Source: The Author (2023)

When analyzing Figure 12, we observed the need of nearly 86% of municipalities in Pernambuco to invest in attracting people. By making their cities attractive, the managers also call cash flow and revenue generation to reinject on urban planning, as a cyclical exercise to improve the inhabitants' well-being.

Although we presented holistic evaluation of municipalities in Pernambuco, the same process could be replicated with a different region or spatial scale. Possibly a new utility function could be appreciated because of the change in detail of spatial information and knowledge.

The model developed can be applied both in the context of public policies and in the private sector when selecting alternative locations for plant installation, for example. It has proved to be flexible to the use of the criteria proposed.

## 4.4 FINAL CONSIDERATIONS

The presented methodology makes a contribution by considering the utility of attractiveness, thereby showing that attractive municipalities meet the individuals' demands in distinguishing and refining criteria. In our analysis, we worked with 17 criteria to learn what motivates people to seek certain municipalities, and 6 of them were derived from factor analysis of a wide range of administrative actions and policies found in the municipalities to support people. Besides that, our analysis of holistic evaluation showed that people tend to look for places with education (colleges), health care (hospitals), job opportunities (industries), tourism (accommodation), and because they are known places (density). Even if regarding preference people seek specific services, cities are integrated and at this point managers should work to ensure that they run smoothly. In this sense, the analysis proposes a model that can give insights to local managers to improve their respective management areas to promote urban and regional development actions. In the case of the state of Pernambuco, our results indicated that approximately 86% of the municipalities have little visibility, at the same time indicating the criteria that can open up opportunities for growth. The study developed can be applied on a different geographic scale, and can contribute to the analysis of a town or neighborhoods.

The primary constraint of the framework lies in the data used for factor analysis. While it is feasible for DMs to handle a smaller number of criteria, selecting them from hundreds of variables is challenging. The selection of pertinent variables and their relevance to decision-making plays a crucial role in preference assessment. In this regard, factor analysis not only aids in dimension reduction but also returns variables with preference meaning to decision-making. Failure to consider this aspect would render the latent variables irrelevant to the preference model.

Next chapter will discuss different ways to handle spatial connectivity in decision making and how the logistic terminals influence the regions given a distance.

# 5 SPATIAL CONNECTIVITY: A PREFERENCE LEARNING APPROACH

This chapter addresses the specific objective **SO 3**, which is to investigate spatial connectivity in urban planning through modeling preferences on interactions between logistics terminals.

## 5.1 CONTEXTUALIZATION

Spatial interactions are due to the ability of places to connect with each other. In general, connectivity establishes links between elements which can be represented by an arrangement of networks (RODRIGUE, 2020). Spatially, these networks relate to physical and/or virtual connections between locations (IAMMARINO, 2018; NUFFEL *et al.*, 2010; WALTERT *et al.*, 2011).

In the globalization context where regions are interconnected, the spatial connection between them is responsible for the flows of people, goods, services, energy, information, as well as intellectual and financial capital (LEI *et al.*, 2021; WANG, 2017; JING *et al.*, 2022; FANG *et al.*, 2020). This naturally implies on the demand for capable, sustainable, resilient, and even intelligent services and structures, and certainly fulfill an important role in urban planning and regional development.

In this sense, it is argued that volumes of exports, gross domestic product, and retail sales are indices that, in addition to conferring an advantage and economic potential, are related to the intensity of interurban relations, i.e., financial outputs can be used to measure the connectivity of a location (LEI *et al.*, 2021). Furthermore, the calculation of centrality can be used as a metric for connectivity (KOYLU; GUO, 2013; LEI *et al.*, 2021), and for a larger geographic scale, connectivity can be measured by the movement of people on the streets in different modalities (on foot or in vehicles) (GALPERN *et al.*, 2018), besides the perspective of networks (FANG *et al.*, 2020; HU *et al.*, 2020).

Furthermore, logistics terminals play a relevant role in the connectivity of regions, especially due to their contribution to supply chain management (DIAS *et al.*, 2010), besides the fact that they are the means by which goods and people move between regions. According to Dong *et al.* (2022), connectivity benefits intercity relations. However, this could also impact local relations. Under this premise, this study proposes a spatial connectivity analysis by considering the logistics terminals coverage area to evaluate the influence of regions on each other given flow interactions to assess the individual connectivity of each location in an integrated context. In this analysis, in addition to the infrastructure of logistics terminals of a region, spatial connectivity is expressed as factors that indicate money circulation, centrality of regions, and centrality of road networks, access to global internet network, and airport operations.

Therefore, in an attempt to discover and learn about spatial connectivity and the influence of regions on each other, we have developed a methodology that is divided into two phases. Initially, we propose an assessment based on the data on inherent connectivity attributes of each location, and after that, we implement preferences regarding the contribution of logistics terminals to the perception of connectivity. Although social activities are usually ignored in connectivity analysis (RONALD *et al.*, 2012), the main objective is to present a multi-criteria method to rank regions based on their potential for spatial connectivity to support managers' decisions on urban planning and regional development.

The first issue is the fact that although connectivity plays an important role in urban planning, most models do not represent the spatial connectivity (WANG *et al.*, 2022). However, it is possible to find studies that consider connectivity for fuel station location (ZHAO *et al.*, 2019), cost of travel (MUELLER; ARAVAZHI, 2020), multinational enterprise location (CASTELLANI *et al.*, 2021), transport operations (ALAMÁ-SABATER *et al.*, 2013), human migration (DAVIS *et al.*, 2013), and money movement regarding mobile connectivity (ASONGU *et al.*, 2021). All these cases impact environment and human relations.

Spatial connectivity impacts both the inner space of a region and its neighboring areas. Boudet *et al.* (2020) examined rural-urban connectivity and found that urban areas can influence the rural area, and that regions with very high market access and rural migration are those with concentration of building areas, high population density, and the greatest yields. Esch *et al.* (2014) argued that the regions are not relevant by themselves, but by their relationship due to connectivity.

In health, connectivity is a key factor for disease spread analysis, for example. According to Jing *et al.* (2022), greater connectivity means greater human mobility between areas, and greater exposure to diseases. Also, the web connection has improved the analysis of links between regions through the use of information flow data (mail flows, internet traffic, and data from social networks) (FANG *et al.*, 2020).

Regarding security, connectivity has been considered in the context of water security in urban areas (GU *et al.*, 2022), and in public security through the use of bus stops as a proxy of connectivity (ROSA *et al.*, 2023).

Another issue is the importance of transportation, which plays a fundamental role in human and cargo movements, in spatial connectivity (KALUZA *et al.*, 2010). The examples of its importance are the studies of multimodal transportation (ZHOU *et al.*, 2021), and resilience (JANIĆ, 2019).

Spatial connectivity is influenced by a region's intrinsic characteristics, which impact the perception of its connectivity. However, the interactions between regions, facilitated by logistics terminals of different types, can also play a significant role in shaping their importance to people, organizations and decision-makers. Therefore, a multi-criteria methodology was developed to take into account for decision-makers' preferences regarding terminals and the interactions between those belonging to the same type of terminal.

MCDA methods have been used to solve decision problems with multiple conflicting attributes, extending this to spatial decision problems (MOTA *et al.*, 2021). The aim of MCDM/A is efficient preference modeling, and to achieve this, decision-makers emerge in the process through the preference elicitation (DOUMPOS; ZOPOUNIDIS, 2011; ERIŞKIN, 2021).

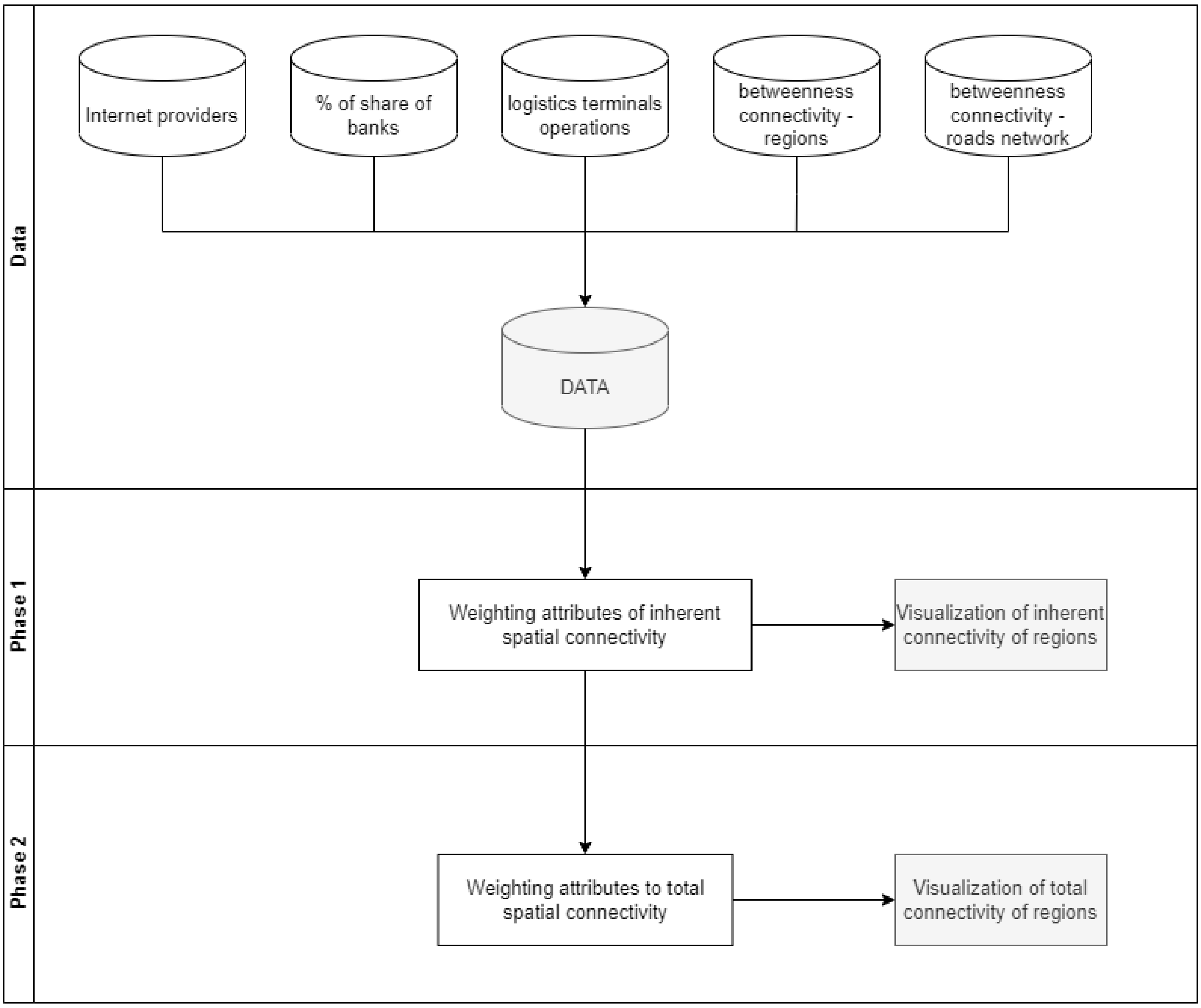
The application of MCDM/A considers spatial connectivity as an attribute or a means to reach an objective. Rahman *et al.* (2022), for example, developed a method based on Simple Additive Weighting (SAW) to construct an index of compactness of city based on indicators of density, evenness of development, clustering of development, diversity, floor use mix and connectivity. The Analytic Hierarchy Process (AHP) approach was used to plan and implement cycle lanes to improve the connectivity and integration of bicycles in the city traffic (ZUO; WEI, 2019). Zhang *et al.* (2021) carried out an assessment of locations based on 5 indices of connectivity constructed through the GARA-TOPSIS and AHP joint analysis. Regarding road networks, connectivity of rural areas is measured with fuzzy-TOPSIS (SINGH *et al.*, 2021). Meanwhile, railway networks are assessed with SIMUS method with connectivity as one of criteria (STOILOVA *et al.*, 2020).

None of the papers presented in this section considers the evaluation of connectivity per se, even less the fact that regions spatially influence each other. Therefore, our contribution is on the construction of a multi-methodology to address this issue, presenting the connectivity as a result of an assessment of indicators instead of using this concept as a tool to support other situations, providing a general view to support urban planning. Moreover, we present the importance of connectivity in spatial interactions and its influence on neighboring regions.

## 5.2 DATA AND METHODS

To conduct the spatial connectivity analysis, a two-phase framework was proposed. The first concerns the inherent connectivity by considering the local aspects of a city. The second one regards total connectivity, which considers the local connectivity and spatial influence between regions by taking into account the presence of logistics hubs. Figure 13 presents the spatial connectivity analysis framework.

Figure 13 – Framework of spatial connectivity analysis




Source: The Author (2023)

According to Figure 13, each phase of the framework produces a different result. The first phase involves a numerical analysis of the data, while the second phase considers the preferences of logistics terminals and their contributions to connectivity perception. These methodologies will be presented in detail in the following sections. The data used included the number of internet providers (ANATEL, 2022) as a proxy of information flow, percentage of share of the banking agencies per region (BCB, 2022) to consider the money circulation, logistics terminals operations (ANAC, 2022), betweenness centrality from the perspective of proximity between regions and betweenness centrality from the perspective of the road network.

The main objective was to explore and provide a decision method focused on spatial connectivity to urban and regional planning, due to its capacity to influence growth and improve the economic potential of a region. Our main concern was to represent the spatial connectivity in the perspective of influx of people, goods and information, and money circulation. To provide an illustrative example, we applied the framework to the state of Pernambuco - Brazil.

### 5.2.1 Proposed method for inherent connectivity

In this phase, connectivity is derived from the attributes of a region and was formulated based on UTASTAR method (SISKOS; YANNACOPOULOS, 1985) to determine the competitive levels between municipalities. Once the method provides the global utility, the assessment of local characteristics is proposed, which may be considered as the inherent connectivity index. This will be adjusted to account for interactions with logistics terminals.

The adaptation from UTASTAR takes advantage of the method's consideration of holistic preferences to search for possible models. Thus, any inconsistencies may be considered part of the learning process to reveal the ranking of municipalities' connectivity, rather than errors. For the present adaptation, the DM's ability to holistically distinguish the relative importance of criteria and to provide a rank of a small set of alternatives (in this case, municipalities) is considered.

Under these conditions, the challenge in this proposal is to consider the knowledge of the problem context in terms of criteria, alternatives, and learning. Once the ranking of inherent connectivity is calculated, a map is generated to visualize the results, without considering the interactions of regions towards the presence and flows of logistics terminals.

### 5.2.2 Proposed approach for spatial influence of neighbors

This second phase of the framework is an extension of the first phase. The idea is to explore the influence of interactions between logistics terminals in spatial connectivity such as a contribution to inherent spatial connectivity to create a total index of spatial connectivity. At this latter point, holistic preferences on logistics terminals are considered. For this purpose, we created what we call *absolute imposing value* (AIV) to evaluate the flows between the same type of logistic terminal. After that, we carried out analysis of interactions given the coverage area of the logistics terminals.

#### *5.2.2.1 Absolute imposing value*

The AIV proposal concerns the absolute value of the influence of flows of terminals over others of the same type. To calculate AIV, let $T$ be a matrix from/to describe the flows $t_{i,j}$ between terminal $i$ and terminal $j$ such that $t_{i,i}$ is equal to 1 (Equation 5.1).

$$T = \begin{bmatrix} 1 & t_{1,2} & \dots & t_{1,n} \\ t_{2,1} & 1 & \dots & t_{2,n} \\ \vdots & \vdots & \ddots & \vdots \\ t_{n,1} & t_{n,2} & \dots & 1 \end{bmatrix} \tag{5.1}$$

For each $\mathbf{v}_{l_i}$ line vector in matrix $T$ representing the outflows of terminal $i$, and $\mathbf{v}_{c_i}$ column vector in matrix $T$ representing the inflows in terminal $i$, let $\mathbf{v}_i$ be the sum of $\mathbf{v}_{l_i}$ and $\mathbf{v}_{c_i}^T$. The AIV of each terminal is the $\mathbf{v}_i$ norm, where the greater the influence of a terminal is, the greater its value is (Equation 5.2).

$$\begin{aligned} &\mathbf{v}_i = \mathbf{v}_{l_i} + \mathbf{v}_{c_i}^T \\ &AIV = \|\mathbf{v}_i\| \\ &AIV = \sqrt{\mathbf{v}_i \cdot \mathbf{v}_i} \end{aligned} \tag{5.2}$$

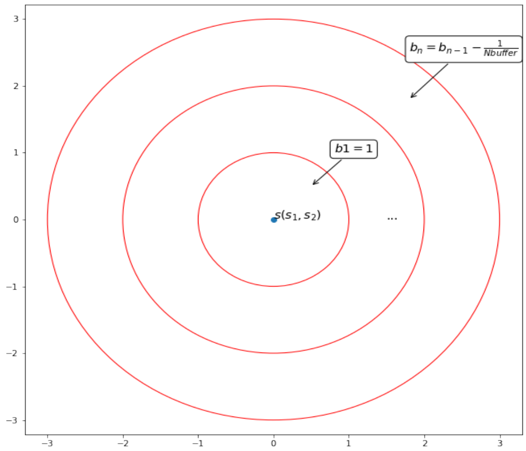
The AIV value is used to calculate the total spatial connectivity, as presented in the next section.

#### *5.2.2.2 Total spatial connectivity index*

Let $s(s_1, s_2)$ be the spatial coordinate of $s_1$ longitude and $s_2$ latitude of a logistic terminal. Suppose an $r$ is the coverage radius of logistic terminal divided into $\eta$ number of ranges of distance, both given by the decision-maker. For each $n = \{1, \dots, n\}$ range of distance, a $b_n$ scalar value calculated through a decay arithmetic sequence is assigned (Equação 5.3) as $\eta$ moves away from $s(s_1, s_2)$ spatial coordinate of logistic terminal, such as presented in Figure 14.

$$\begin{aligned} &b_1 = 1 \\ &\vdots \\ &b_n = b_{n-1} - \frac{1}{\eta} \end{aligned} \tag{5.3}$$

Figure 14 – Buffers' values




Source: The Author (2023)

To provide an example, let's imagine that we have a logistic terminal such that a decision-maker defines the $r$ coverage radius of 30 km and he wants to assess $\eta$ ranges of distance equal to 3. In this case, the $b_n$ assigned to each $\eta$ range of distance are:

$$\begin{cases} b_1 = 1 & , 0 < r \leq 10 \\ b_2 = 2/3 & , 10 < r \leq 20 \\ b_3 = 1/3 & , 20 < r \leq 30 \end{cases} \tag{5.4}$$

Retaking the logistics terminals evaluation, it is possible to find $Z_i = [\mathbf{z_1}, \ldots, \mathbf{z_i}]$ regions covered by multiple ranges of distance of multiple logistic terminals. In this case, let $z_i(t)$ be the influence of the logistics terminal $t$ in region $\mathbf{z_i}$, if a region $\mathbf{z_i}$ is covered by a terminal $t$, $z_i(t) = 1$, otherwise, $z_i(t) = 0$. See Table 7 for spatial data table representation.

Table 7 – Spatial data table for geo-referenced points

| terminal | s(i) | | variables | | |
|---|---|---|---|---|---|
| (t) | $s_1(i)$ | $s_2(i)$ | $\mathbf{z_1}$ | $\cdots$ | $\mathbf{z}_i$ |
| 1 | $s_1(1)$ | $s_2(1)$ | $z_1(1)$ | $\cdots$ | $z_i(1)$ |
| $\vdots$ | $\vdots$ | $\vdots$ | $\cdots$ | $\ddots$ | $\cdots$ |
| t | $s_1(t)$ | $s_2(t)$ | $z_1(t)$ | $\cdots$ | $z_i(t)$ |

Source: Adapted from (HAINING, 2003)

Table 7 can be generalized to a matrix $M_n$ of spatial data for each $n$ range of distance, Equation 5.5.

$$
M_n = \begin{array}{c} terminal \\ 1 \\ 2 \\ \vdots \\ t \end{array}
\begin{array}{c} \begin{array}{cccc} \mathbf{z_1} & \mathbf{z_2} & \dots & \mathbf{z_i} \end{array} \\
\begin{bmatrix} z_1(1) & z_2(1) & \dots & z_n(1) \\ z_1(2) & z_2(2) & \dots & z_n(2) \\ \vdots & \vdots & \ddots & \vdots \\ z_1(t) & z_2(t) & \dots & z_i(t) \end{bmatrix} \end{array} \quad (5.5)
$$

To get $M_{total}$ total valuation matrix per region per logistics terminal, let's consider the matrix multiplication between the $diag[AIV_1, \dots, AIV_t]$ diagonal matrix of AIV values for each terminal $t$ and the sum of matrix scalar multiplication of $b_n$ and $M_n$, Equation 5.6

$$
\begin{aligned}
M_{total} &= \left[ \left( \sum_n b_n \cdot M_n^T \right) \cdot diag[AIV_1, \dots, AIV_t] \right]^T \\
&= \begin{bmatrix} z'_1(1) & z'_2(1) & \dots & z'_n(1) \\ z'_1(2) & z'_2(2) & \dots & z'_n(2) \\ \vdots & \vdots & \dots & \vdots \\ z'_1(t) & z'_2(t) & \dots & z'_n(t) \end{bmatrix}
\end{aligned} \quad (5.6)
$$

The $z'_i$ total score per region $\mathbf{z_i}$ is calculated from the sum of elements of each column vector of $M_{total}$.

$$
z'_i = z'_i(1) + z'_i(2) + \dots + z'_i(n) \quad (5.7)
$$

The values $z'_i$ are linearly interpolated to the interval $[0, max(z'_i)]$ to indicate the contribution $\phi_i$ of the logistic terminal coverage to the spatial connectivity of a region $z_i$ in the interval $[0, 1]$. Where 0 is the contribution to the areas not covered by terminals and 1 is the maximum contribution received by the region with the largest coverage.

To calculate the $C(a)$ index of total connectivity, let's consider that $\rho \in [0, 1]$ is the preference weight of total connectivity, taking into account both inherent connectivity and the contribution of logistics terminals, as shown in Equation 5.8.

$$
C(a) = \rho W[g(a)] + (1 - \rho)\phi_i W[g(a)] \quad (5.8)
$$

Equation 5.8 concerns the analysis of one type of logistics terminal. To consider more types of terminals, the term $(1 - \rho)\phi_i W[g(a)]$ can be seen in two parts: (i.) $(1 - \rho) = \sum \omega_i$ to indicate the preferences over different types of terminals, and (ii.) $\phi_i W[g(a)]$ which is resulted from the process of Equation 5.3, Equation 5.5, Equation 5.6 and Equation 5.7 for each $k$ type of logistics terminal considered in the analysis. Thus, Equation 5.8 becomes Equation 5.9.

$$C(a) = \rho W[g(a)] + \omega_1 \phi_i W[g(a)] + \ldots + \omega_k \phi_i W[g(a)] \tag{5.9}$$

The values of $\rho$ and $\omega_i$ are calculated as an analogy between the holistic preferences expressions with goal programming, in a similar way to Frikha and Charfi (2018) who made an analogy between the outranking relations and the goal programming.

To provide an example, let's consider a decision-maker who is dealing with three types of logistics terminals: airports, seaports, and rail terminals. In addition to the inherent connectivity, the decision-maker assigns weights $\omega_1$, $\omega_2$, and $\omega_3$ to the three types of terminals, respectively, and assigns a weight of $\rho$ to the preference for total connectivity. The decision-maker's statements of preferences are as follows. For references on goal programming, see Choo and Wedley (1985) and Tamiz *et al.* (1998).

- $\omega_2$ weight of seaport and $\omega_3$ weight of rail terminals are equally preferred;
- $\rho$ weight of inherent connectivity is at least preferred as the sum of the weights of logistics terminals;
- $\omega_1$ weight of airports is at least preferred as the sum of $\omega_2$ weight of seaports and $\omega_3$ weight of rail terminals.

Based on these statements, the DMs preferences can be modeled according to the goal programming presented in Equation 5.10, whose optimal value of the minimization function was equal to 0 and the weights $\rho$ of inherent connectivity, $\omega_1$ of airports, $\omega_2$ of seaports, and $\omega_3$ of rail terminals were respectively 0.5, 0.25, 0.125, and 0.125.

$$\begin{aligned}
\min \text{F} = \quad & d_1^- + d_2^- + d_3^+ + d_3^- + d_4^+ + d_4^- \\
\text{s.t.} \quad & \\
& \rho - \omega_1 - \omega_2 - \omega_3 - d_1^+ + d_1^- = 0 \quad (1) \\
& \omega_1 - \omega_2 - \omega_3 - d_2^+ + d_2^- = 0 \quad (2) \\
& \omega_2 - \omega_3 - d_3^+ + d_3^- = 0 \quad (3) \\
& \rho + \omega_1 + \omega_2 + \omega_3 - d_4^+ + d_4^- = 1 \quad (4) \\
& \rho, \omega_i, d_i^-, d_i^+ \geq 0 \quad (5)
\end{aligned} \tag{5.10}$$

The constraints in $(1), (2)$, and $(3)$ of Equação 5.10 represent preference goals, while constraint $(4)$ ensures that the sum of $\rho, \omega_1, \omega_2$, and $\omega_3$ is equal to 1, as they represent preference weights. The $d_i^+$ and $d_i^-$ values represent the errors associated with the constraints. Therefore, the outputs can vary in the interval $[0, 1]$. Additionally, assuming that the decision-maker has more knowledge, they can provide more specific values regarding their preferences. For example, in the hypothetical case presented in Equação 5.10, suppose the decision-maker evaluates inherent connectivity $\rho$ to be at least 0.6. In that case, a new goal would be added to the model, and so on.

The proposal reaches the following objectives:

1. assesses the contribution of logistics terminals to the index of total connectivity through its coverage area;
2. represents the gains of distance intervals in which a region is covered by the nearest terminal, given the radius $r$;
3. evaluates the influence of multiple terminals of the same type or different types over a region.

According to the proposal above, our framework is in accordance with the first law of geography (TOBLER, 1970), which claims that the near regions are more related than the distant regions. An application was done to the state of Pernambuco - Brazil.

## 5.3 RESULTS AND DISCUSSION

### 5.3.1 Inherent connectivity

For the analysis of the state of Pernambuco, the study uses open data from government agencies. From the IBGE (2022), data on the structure of the state's highways (shapefile file) and geo-referenced points of airports were considered. Data on the inbound and outbound aircraft flows of airport operations were extracted from the database provided by ANAC (2022). ANATEL (2022) informed the number of internet providers as a proxy measure of connectivity with the total internet network by municipality and the data on financial transactions by municipality were expressed in terms of the equity of their respective financial organizations BCB (2022). The aforementioned data used in connectivity analysis are presented in Table 8.

The betweenness centralities of the municipalities, as presented in Table 8, were calculated based on the queen contiguity weight, which considers neighboring units that share a common vertex or edge, similar to the movement of a queen in a game of chess. This was applied to the centroid referring to each municipality using Equation 5.11 (BRANDES, 2008). The betweenness centralities were calculated by summing the $\sigma(s,t|m)$ number of shortest paths that pass through the municipality $m$, divided by the $\sigma(s,t)$ number of shortest paths existing between any pair of municipalities. Figure 15 presents a visualization betweenness centrality of municipalities.

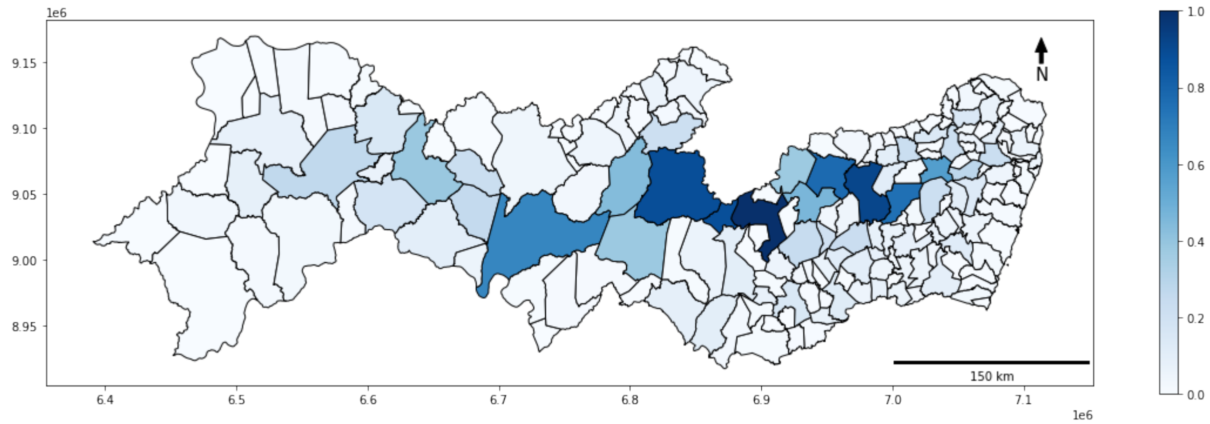
Table 8 – Criteria performed

| **Criteria of connectivity** | **Preference meaning** |
|---|---|
| Number of internet providers | Proxy of information flow |
| Percentage of share of the banking agencies of the municipalities in the net worth of the state | Proxy of money circulation |
| Airport operations of arrivals and departures | Proxy of people and goods movements |
| Betweenness centrality from the perspective of proximity between municipalities | Importance of municipality in inter-urban network |
| Betweenness centrality from the perspective of the road network | Ease of connectivity of municipalities by land |

Source: The Author (2023)

$$c_B(m) = \sum \frac{\sigma(s,t|m)}{\sigma(s,t)} \tag{5.11}$$

Figure 15 – Betweenness centrality by municipality

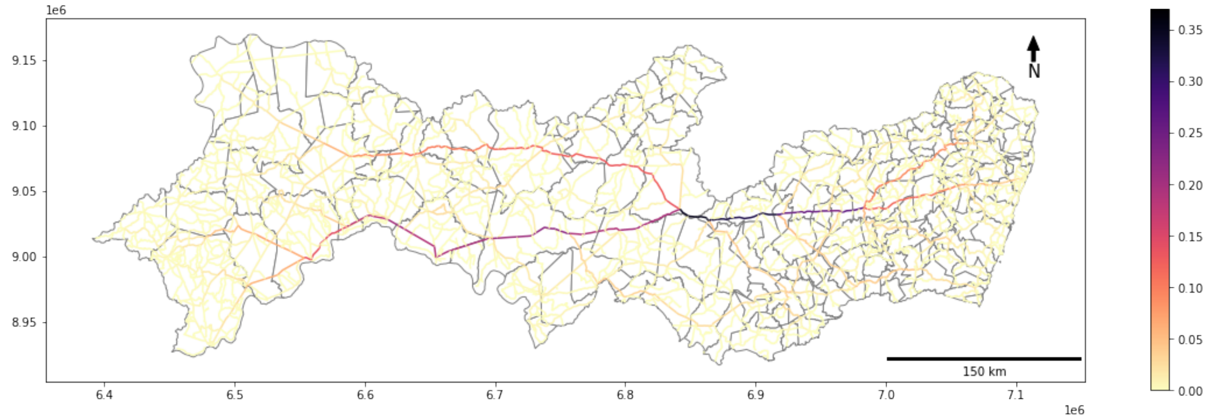



Source: The Author (2023)

The betweenness centrality of the highways, presented in Table 11, was calculated using the queen weight applied to the network, as shown in Figure 16. The betweenness centrality was then aggregated by municipality using the average of the centrality of the sections that passed through them, as shown in Figure 17. The calculation was performed using Equation 5.12, which considers the sum of $\sigma(s,t|h)$ number of shortest paths that pass through the highway $h$ divided by the total $\sigma(s,t)$ number of shortest paths existing between any pair of highways (BRANDES, 2008).

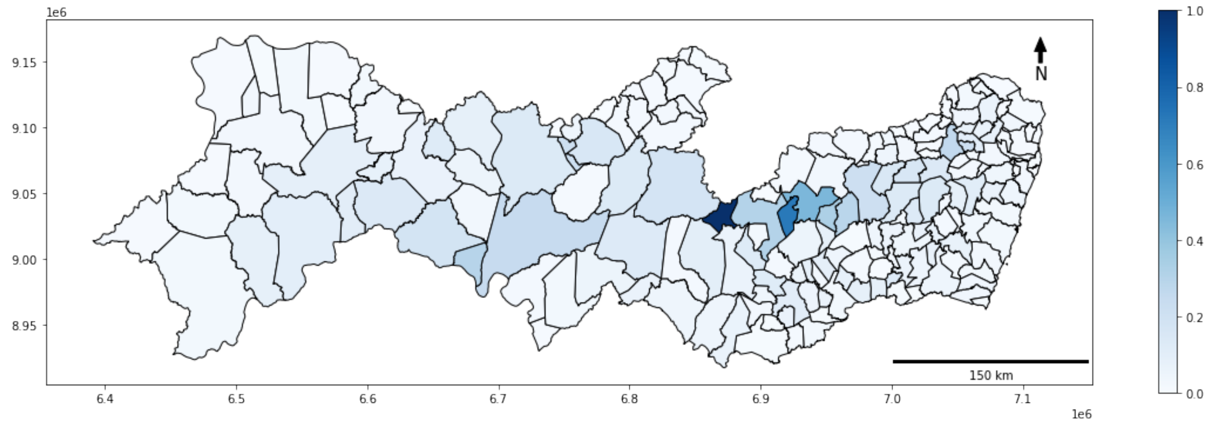
$$c_B(h) = \sum \frac{\sigma(s,t|h)}{\sigma(s,t)} \tag{5.12}$$

Figure 16 – Betweenness centrality applied to the highway network




Source: The Author (2023)

Figure 17 – Betweenness centrality of the highway network aggregated by municipality




Source: The author (2023)

In Figure 16, a convergence of flow can be seen in the network of the east and west ends to the center of the state, pointing to the possibility of a logistical bottleneck in the terrestrial modal in case of interruption of the highways in the confluence zone. As the criteria are in different scales, they were normalized. In Figure 15 and Figure 17 betweenness centrality is already normalized.

In the case study, $\alpha$ number of break points to piecewise analysis is equal to 3 for all criteria. Given that, we calculated the index of inherent. As a result, we found the Equation 5.13 which describes the inherent connectivity $W[g(a)]$ of alternatives.

$$W[g(a)] = 0.499w_1(g_1) + 0.02w_2(g_2) + 0.176w_3(g_3) + 0.204w_4(g_4) + 0.099w_5(g_5) \tag{5.13}$$

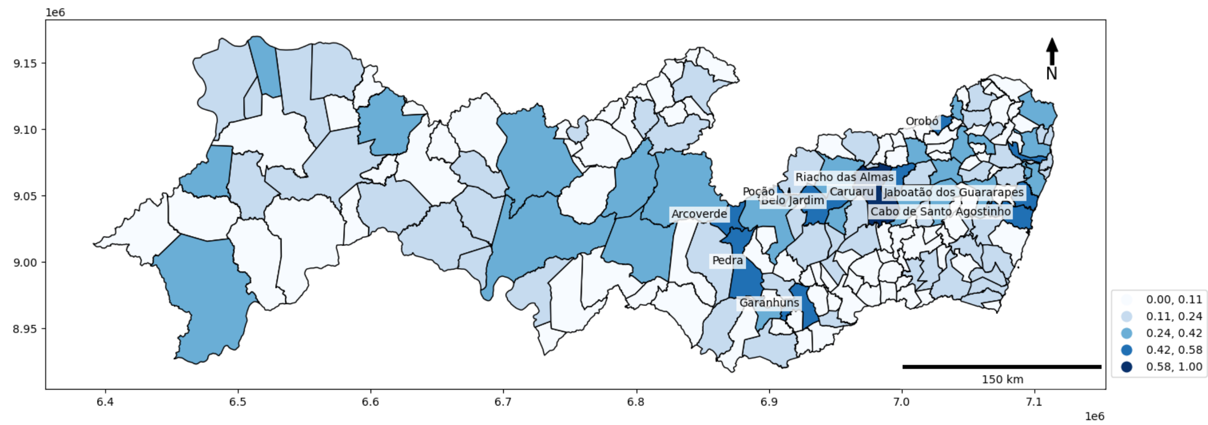
Where,

- $w_1(g_1)$: internet providers;

- $w_2(g_2)$: financial movements (representative rate of the net profit of the banking entities per municipality);
- $w_3(g_3)$: airport operations;
- $w_4(g_4)$: betweenness centrality per municipality;
- $w_5(g_5)$: betweenness centrality per stretch of highway in municipal territory.

Equation 5.13 provides a way to model the behavior of criteria over inherent connectivity, highlighting the importance of information flows, the centrality of municipalities and airport operations. The resulting index can then be mapped out to visually represent the inherent connectivity of each municipality. Figure 18 displays the results of this mapping, with municipalities grouped according to natural breaks in the index values.

Figure 18 – Index of inherent connectivity



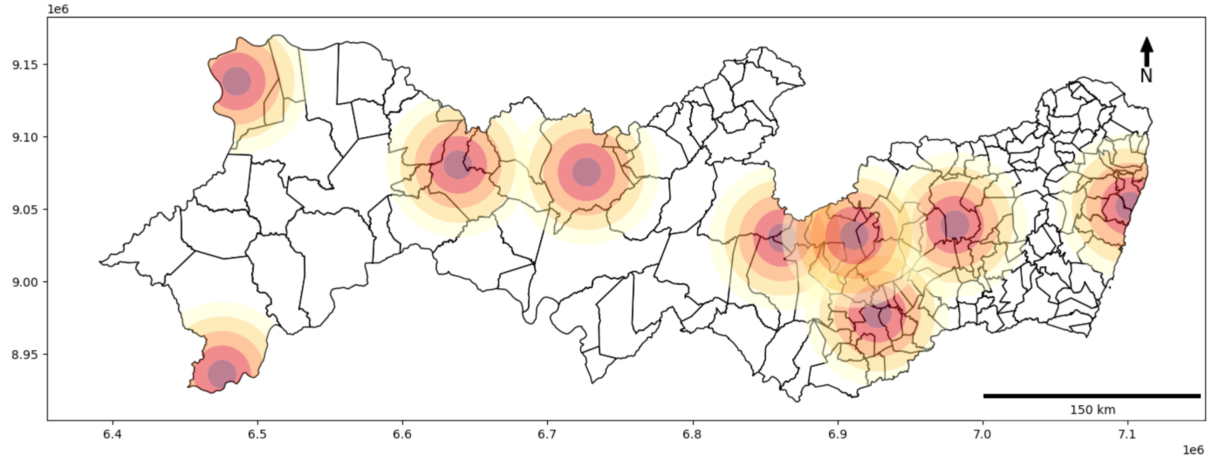

Source: The Author (2023)

In Figure 18, the ten municipalities with the highest inherent connectivity index are labeled. They are Caruaru, Arcoverde, Riacho das Almas, Belo Jardim, Jaboatão dos Guararapes, Pedra, Cabo de Santo Agostinho, Orobó, Poção, and Garanhuns. However, it is important to note that this ranking cannot be associated with spatial relations since the interactions of flows and logistics terminals' coverage areas were not considered. Nevertheless, this ranking serves as a starting point for further explorations and model correction, such as the total connectivity presented in the next section.

### 5.3.2 Total connectivity

To consider the influence of logistics terminals in the neighborhood, a type of logistics terminal (airports) was considered, and 5-layer buffers were created with a growth radius of 10 km per layer (Figure 19), so that from the center to the edges the layers are evaluated at 1, 0.8, 0.6, 0.4, 0.2, and as it is possible to have transportation flow between terminals we calculated the $AIV_i$ for each terminal.

Figure 19 – Multi-layers for analysis of proximity to airports

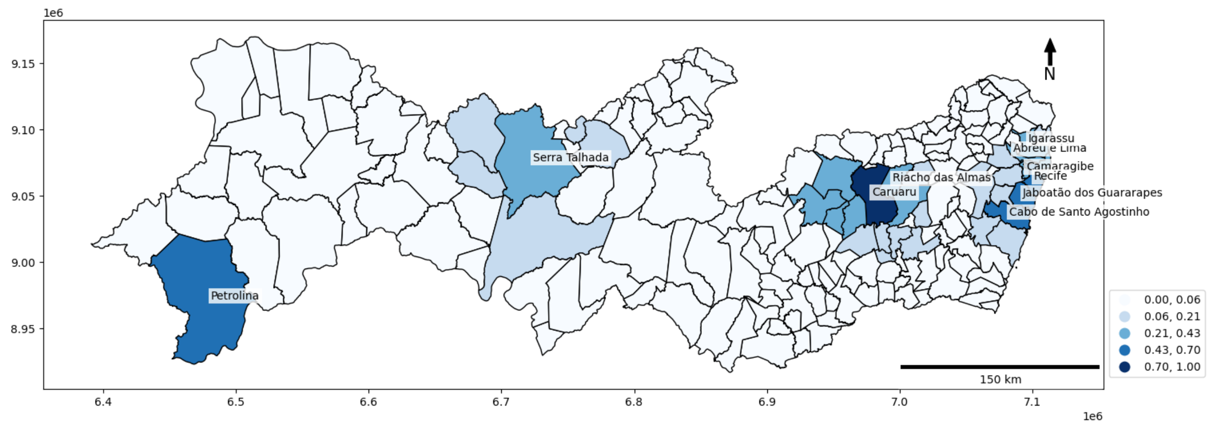



Source: The Author (2023)

Since some municipalities are overlapped by more than one layer (Figure 19), their contribution is determined by $\phi_i$. Then, the index of total connectivity $C(a)$ can be calculated through Equation 5.8. For the sake of simplicity, $\rho = 0.5$ (Equation 5.14). Thus, it is possible to obtain the aggregated assessment of connectivity, as shown in Figure 20.

$$C(a_i) = 0.5W(a) + 0.5\phi_i W(a) \tag{5.14}$$

Figure 20 – Index of total connectivity of the municipalities of Pernambuco




Source: The Author (2023)

Figure 20 shows the municipalities that fall into the group with the ten best indexes:

Caruaru, Cabo de Santo Agostinho, Jaboatão dos Guararapes, Recife, Petrolina, Riacho das Almas, Camaragibe, Abreu e Lima, Serra Talhada, and Igarassu. When comparing Figure 18 and Figure 20, we observe the impact of logistics terminals on connectivity perception. The first observation is that spatial connectivity is centered in some municipalities that seems to influence their neighboring. The second is the decay of influence of logistics terminals with distance, as stated in the first law of geography (TOBLER, 1970). We could also identify four poles of connectivity in Pernambuco state. In the extreme east, there are the metropolitan region and the capital of the state, Recife. Going westwards, the next stop is the Caruaru influence zone, which has economic importance due to the farming and textile industry. Further northwards, there is the influence zone of Serra Talhada. Finally, in the extreme west, there is Petrolina which borders another Brazilian state in a conurbation and has been improved due to the positive influence of airports.

Comparing the inherent and the total connectivity, the former was seen to be related to intrinsic aspects of a region. However, considering the influence of terminals in municipalities and their vicinity as well as the directions of their flows, an additive analysis can be considered between inherent connectivity and logistics terminals. In this sense, it is up to the DMs to express their preferences. At this point, the advantage of the proposal is to approximate the decision modeling to real-world spatial interaction and to allow the DM to learn and contribute to different fronts of urban planning in the sense of promoting win-win relationships between neighbors. Table 9 presents the top 10 municipalities according to inherent connectivity ($W[g(a)]$) and total connectivity ($C(a)$). The complete ranking is presented in Appendix C.

Table 9 – Top 10 ranking of index of connectivity

| | Index of connectivity | |
|---|---|---|
| # Ranking | # $W[g(a)]$ | # $C(a)$ |
| 1 | Caruaru | Caruaru |
| 2 | Arcoverde | Cabo de Santo Agostinho |
| 3 | Riacho das Almas | Jaboatão dos Guararapes |
| 4 | Belo Jardim | Recife |
| 5 | Jaboatão dos Guararapes | Petrolina |
| 6 | Pedra | Riacho das Almas |
| 7 | Cabo de Santo Agostinho | Camaragibe |
| 8 | Orobó | Abreu e Lima |
| 9 | Poção | Serra Talhada |
| 10 | Garanhuns | Igarassu |

Source: The Author (2023)

Table 9 shows how the ranking of municipalities changes as different criteria and preferences are added to the decision analysis. This may be attributed to the fact that these municipalities are interacting due logistic terminals, which significantly contribute to the perception of connectivity. This is supported by the analysis of airport locations in Figure 18 and the top connected municipalities in Figure 20. It can be concluded that the total connectivity index is higher in regions closer to logistics terminals, and this would probably be even greater if other types of terminals were analyzed as well.

### 5.3.3 Discussion

In this section, the results and possible applications in the field of urban planning are discussed. Connectivity can be represented both physically by the flows of operations, loads and people, and municipality centrality; as well as virtually with the flow and transfer of data on the internet network and flows of financial operations that do not necessarily demand a displacement in the literal sense.

Moreover, we are also aware of the need for connectivity in the logistical sense. A poorly connected location has less flexibility in terms of flow, which makes it dependent on neighboring locations, especially from a physical point of view when it comes to the supply of inputs and human mobility, for example. In decision-making, these are sensitive to DMs' preferences.

According to what is observed when comparing Figure 18 and Figure 20, the influence of logistics terminals in spatial interactions created a new ranking of connectivity and promoted greater understanding of spatial connectivity scores, i.e., total connectivity succeed in indicating the strategic municipalities in the state of Pernambuco, while the inherent index did not clearly indicate the influence of one region in another. An implicit aspect of the proposed model is that there is a dependence on the size of the buffer and the number of layers, this aspect should be determined by the DM.

According to Appendix C, the inherent connectivity does not always determine the level of competition of a municipality or area on a global scale where interactions are fundamental to advertise and negotiate services/products in the market, boosting the local economy and moving up the value chain. Also, it draws attention to urban planning in a holistic perspective, in which where the whole is the result of a joint analysis of parts.

The model developed can be applied both in the context of public policies and in the private sector when selecting alternative locations for plant installation, for example. It has proved to be flexible to the use of the criteria proposed.

## 5.4 FINAL CONSIDERATIONS

This thesis makes a contribution by considering the total connectivity as an analysis of the proximity of a logistics terminal, thereby showing that neighboring locations benefit from structures that are not necessarily part of their territory. This could be adapted for a study of the phenomenon of pendulum migration on a different geographical scale. In the same way, we also presented a total perspective of spatial dynamics when comparing and contrasting connectivity in the context of planning the maintenance of services. This can be applied on a different geographic scale, and can contribute to the analysis of a town or neighborhoods, thus providing greater details of the dynamics of the place. These include being able to cooperate in strategies to identify places, positioning, and communication of police patrols, in terms of connectivity; in the event of street stoppages and closures, to identify alternative connections to attractive locations; with regard to supply, and to identify risk. Thus, it seems that the study can be extended to different sectors of the economy.

This chapter presents different perspectives of spatial connectivity, inherent and total, where the former do not relates to preference, however it is capable to supply an initial insight about connectivity. The later take the preferences and interactions into account to promote a participatory process of identify, understand and promote strategic actions for regional development.

Improvements could be done regarding considering the flows between different types of terminals. In counterpart, the potential results should give a complete logistic analysis given inter-modal connections and their influence on total connectivity and regional insertion in global markets, opening spaces to create policies and subsidies to structure competitive regions.

Next chapter presents a vulnerability analysis to crime for urban planning.

# 6 REVEALING VULNERABILITY OF AREAS: AN ANALYSIS IN THE CONTEXT OF CRIME

This chapter is addressed to achieve the specific objective **SO 4**, develop a multi-methodology framework of preference learning in urban planning to reveal the vulnerability of areas to street robberies. This chapter is based on the published article of Rosa *et al.* (2023).

## 6.1 CONTEXTUALIZATION

Criminality can affect how people behave in an environment. However, people are also responsible for shaping what is around them (BRANTINGHAM; BRANTINGHAM, 1993). In the context of crime, some authors present and discuss different theories about crime involving offenders' cognitive features such as their response to opportunities for anti-social actions (COHEN; FELSON, 1979), their exercise of self-control (LONGSHORE; TURNER, 1998), and the influence of friends (YARBROUGH *et al.*, 2012).

On the other hand, studies concerning Opportunity Theory are interested in analyzing the factors that can determine the pattern of occurrences of crime by using variables such as mass transit, flow of people and accessibility (PIZA, 2003; NEWTON *et al.*, 2014), social interactions and the presence of stores, restaurants and public services such as education services and health services (YU; MAXFIELD, 2013; HE *et al.*, 2020), parks (NAZMFAR *et al.*, 2020), pubs and clubs (CECCATO; OBERWITTLER, 2008), i.e., places characterized by a large flow of people and the circulation of goods and money (BERNASCO; BLOCK, 2011; JEAN, 2007).

Besides the variables of social interactions, factors concerning Disorganization Theory such as characteristics of the population and demographic variables (people's age, amount of income, and level of education) are also considered elements associated with the incidence of crime (WARD *et al.*, 2014; PERES; NIVETTE, 2017; PEREIRA *et al.*, 2017b; ANDRESEN, 2006).

Based on the pattern of occurrences, preventative policies have been supported by modeling statistical data on crime. For example, regression models have been used to analyze day-time and night-time robberies (CECCATO; OBERWITTLER, 2008), homicides (PEREIRA *et al.*, 2017a), and to measure fear of crime (ALKIMIM *et al.*, 2013). The negative binomial (NB) regression showed the propensity of females to be victims of violence in mass transit (MOREIRA; CECCATO, 2021), and a statistical test based on multilevel Poisson regression revealed that more attention needs to be given to preventative actions in places where there is an intense flow of people and traffic (DERYOL *et al.*, 2016).

Spatial crime analysis is interesting when evaluating the spatial dynamic in occurrences of crime. From that perspective, (NAZMFAR *et al.*, 2020) use Moran's index to analyze the spatial correlation between areas, (HU *et al.*, 2018) use kernel density in order to visualize places with high occurrences of crime so as to aid patrolling strategies, while by using spatial and temporal analysis, (VALENTE, 2019) found that homicides are less sensitive to the seasons of the year than street robberies. Moreover, studies are found on computational skills, such as use being made of neural networks to predict crime (WANG *et al.*, 2020) and machine learning being used to classify crimes by categories (NIU *et al.*, 2019).

More than analyzing spatial patterns of crime, this study is concerned with constructing a multi-methodology framework in order to reveal vulnerabilities of areas to incidences of street robberies. To do so, social-demographic data, the distribution of places and the location of bus stops are used to explore their association with the occurrences of crime in public spaces. This is because understanding the variables forms part of the process of understanding a locality. To achieve this, a GIS-based analysis is integrated with a holistic MCDA model with a view to contributing to supporting decision-making on crime prevention priorities.

The main objective of MCDA methods is to assist at least one of the decision processes for choosing, ordering and classifying (GRECO *et al.*, 2002). This means that the decision model supplies a final recommendation including (i) the best alternative, (ii) the definition of alternatives in different presorted classes, and (iii) the set of alternatives ranked from worst to best or vice-versa (ROY, 1996b). Unlike statistical learning which focuses on massive data exploration, MCDA enables decision-makers (DMs) to participate actively in the decision process, assumes small reference alternatives and the inconsistencies are of value to supporting DMs' decisions (DOUMPOS; ZOPOUNIDIS, 2011).

A few studies have applied MCDA to crime issues. (OLIVEIRA *et al.*, 2018) applied the Analytic Hierarchy Process (AHP) and cognitive maps to group decision and found the safety levels of residential zones. (MANNING *et al.*, 2013) used AHP to provide a structured method to consider the most meaningful actions to prevent juvenile delinquency. To evaluate ambiguity in decision-making, (ISHIZAKA *et al.*, 2019) integrate the AHP and fuzzy sorting to classify the districts of London according to their level of security. ELECTRE has been used to aid a portfolio of policy strategies in the metropolitan region of Rio de Janeiro. The main idea was to identify the subset of alternatives that dominates others based on the evaluation of 20 kinds of crimes (BASILIO *et al.*, 2020). Using the knowledge of experts on types of arrests performed, (NAZMFAR *et al.*, 2020) built a framework based on integrating the Analytical Network Process (ANP) and Preference Ranking Organization Method for Enrichment Evaluation (PROMETHEE) II to create a ranking of security for parks.

GIS-MCDM/A models are widely applied to problem-solving (BILLAUD *et al.*, 2020; SONG *et al.*, 2021; SHEN *et al.*, 2021; SCHITO *et al.*, 2021). This approach has been applied in crime analysis to aid the development of public security policies. (FIGUEIREDO; MOTA, 2019) developed a model named DRSA-PL for group decision-making that was based on decision rules to access the holistic preferences of multiple DMs to create what they call a learning map and to present the final result of aggregating DMs' preferences to construct a collective map of vulnerability to violence in an interactive way. (MOTA *et al.*, 2021) present a methodology using DRSA to reveal the areas most vulnerable to homicides by examining social-demographic data and by analyzing spatial clusters of the most vulnerable areas, thus offering an integration of GIS and MCDA to represent the classification of vulnerability.

This analysis uses the DRSA method, and our contribution is with regard to exploring the combination of factors from Opportunity Theory, Disorganization Theory and mobility, represented by the social interaction features, socio-demographic features, and the number and location of bus stops. Even though these theories are known in crime studies, the MCDA literature fails to bring them together. Therefore, by making use of GIS and statistical tools, we hope to indicate, based on the context of real crimes, preferences which analyze issues that may or may not be considered as criteria in decision analysis. As to the authors cited in this section, Table 10 summarizes those working on classifying areas according to security levels and shows the contributions.

Table 10 – MCDA papers on the vulnerability of areas to crime incidences

| **Authors** | **MCDA methods** | **Criteria group** | **GIS** | **Spatial techniques** | **Summary** | **Other techniques** |
|---|---|---|---|---|---|---|
| Ishizaka *et al.* (2019) | AHPSort | Types of crime | Yes | - | AHPSort to sort London's neighborhoods according to security levels | Fuzzy |

| | | | | | | |
|---|---|---|---|---|---|---|
| Nazmfar *et al.* (2020) | PROMETHEE II and ANP | Types of arrests performed | Yes | kriging and Global Moran Index | ANP to build weights for PROMETHEE II for ranking security levels in parks | - |
| Figueiredo and Mota (2019) | DRSA for group decision-making | Socio-economic indicators | Yes | - | Preference learning from a group of DMs regarding homicide crime and aggregation using the learning map of each DM | - |
| Mota *et al.* (2021) | DRSA | Socio-demographic indicators | Yes | Local Moran and hot spots analysis | Identification of vulnerable areas to help allocate resources to combat and prevent homicide | Cluster technique |
| Contributions | DRSA | Socio-demographic indicators, social interaction indicators and movement indicators | Yes | Local Moran and kernel density | Identification of vulnerable areas to support decision-making on preventing street robberies by a constructed framework based on data exploration for local dynamic comprehension and subsequent DRSA modeling | Regression models (GWR and NB) |

Source: The Author (2023)

This chapter undertakes an analysis of vulnerability to street robbery. Here, a street robbery is a crime that may involve any of the following: a thief snatching a bag or similar in the street; or one or more thieves stopping a pedestrian, showing a weapon and asking the pedestrian to hand over their bag, wallet and other valuables.

The vulnerability may be understood as being a function derived from several factors that expose individuals at risk, such as climate change (O'BRIEN *et al.*, 2004), social and economic circumstances (MORROW, 1999) and natural disasters (OUMA; TATEISHI, 2014). The concept of vulnerability addressed in this chapter concerns the exposure of society to potential losses resulting from being the victim of a crime, which enables us to identify, control and monitor the areas most at risk (KENNEDY *et al.*, 2016).

## 6.2 DATA AND METHODS

The methodology considers the combination of factors derived from Disorganization Theory, Opportunity Theory and mobility to support the decision-making process in the spatial context of crime. Thereby, spatial and statistical analysis are used to explore the factors that influence crime occurrences in an area. In this way, it is developed a decision model that gives the user potential to actively intervene in the societal and environmental dimensions while at the same time he/she is learning about the local dynamic and its effects on crime distribution.

Hence, the methods used in Rosa *et al.* (2023) were Local Moran, NB regression, GWR, KDE, and DRSA. These methods were used for different purposes: study area selection, selection of socio-demographic features as criteria, identification of spatial aspects that influence the occurrence of crime, identification of the distribution of crimes, socio-interaction features, and bus stops, and finally, to reveal the classes of vulnerability based on preferences of criteria, respectively.

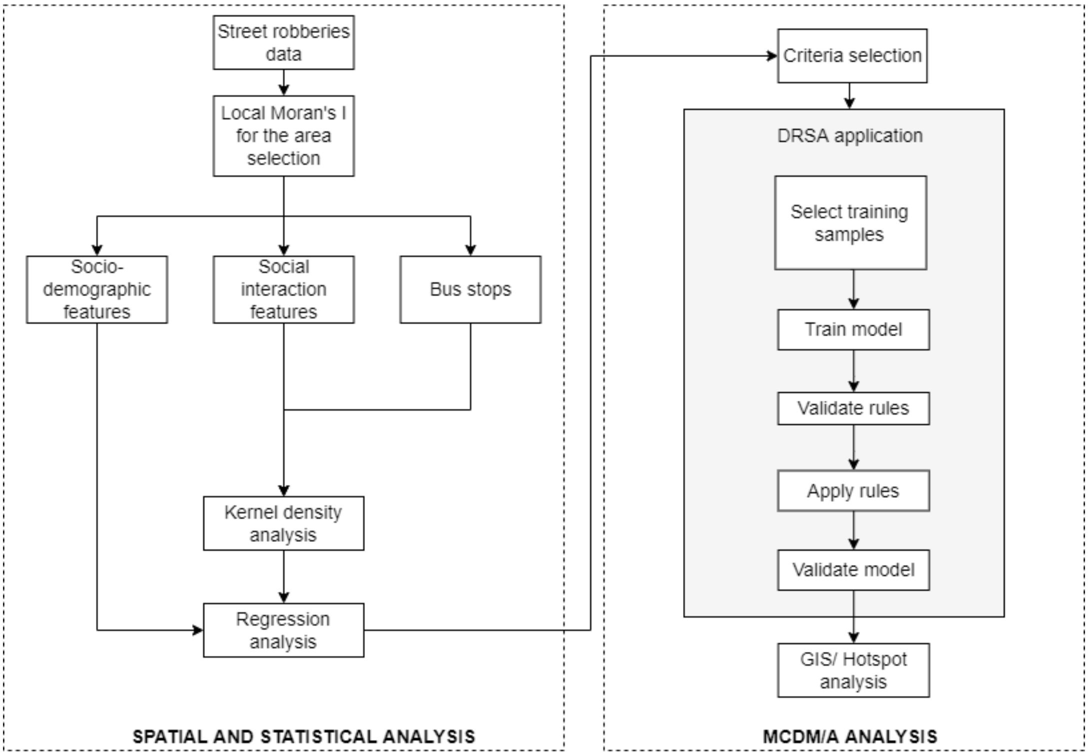
The developed GIS-MCDA framework was construct to include the expected gain of information and knowledge from data visualization and from mathematical approximation tools in the decision process. The framework procedures are divided into spatial and statistical analysis, including data visualization and statistical associations, and MCDA analysis, Figure 21.

Due to spatial heterogeneity, the first step of the framework is to analyze the distribution of crime occurrences in a city and the demographic characteristics of that city. Thus, we apply local Moran to crime distribution to find the spatial characteristics of the incidences of street robberies. Based on what areas are selected, additional data collection and posterior analysis could be undertaken.

Since the primary objective of our study is to explore as extensively as possible the group of factors which influence street robberies, in this paper we have emphasized the importance of identifying, in the context of crime, multiple perspectives with a view to understanding this phenomenon. Thus, we focus our analysis on three perspectives which justify the analysis of three kinds of data to confirm and to aggregate knowledge to support the selection of criteria for the decision model, Figure 22.

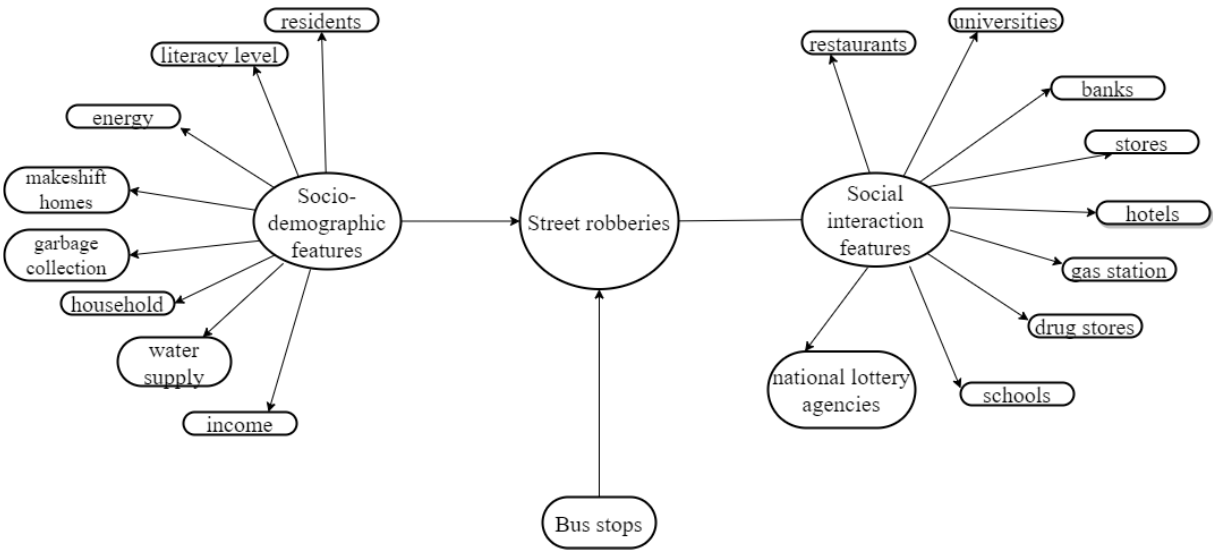
The reason for choosing these perspectives shown in Figure 22 is because they contextu-

Figure 21 – Proposed framework to build model




Source: Rosa *et al.* (2023)

Figure 22 – Perspectives evaluated on the framework




Source: Rosa *et al.* (2023)

alize the incidence of crimes in terms of social vulnerabilities (socio-demographic features) and of general shops where day-to-day social or economic activities take place (social interaction features). Bus stops were chosen with a view to considering the movement of people.

To analyze Disorganization Theory in crime street robberies, we explored the association of crime events to socio-demographic, economic and urbanization fields (ANDRESEN, 2006).

Like (PEREIRA *et al.*, 2017b) who set out to capture the vulnerability of households and neighborhoods, we analyzed, by using data from the CTs, the households with electricity, garbage collection, water supply, and the presence of makeshift homes on CTS. Note that variables also capture the level of urbanization of an area. According to (ANDRESEN, 2006; PEREIRA *et al.*, 2017b; PERES; NIVETTE, 2017; ADLER; OSTROVE, 1999), education and income are metrics for socio-economic status inequalities. Therefore, we analyzed the level of income and number of people who can read and write to determine socio-economic deprivation.

Given social interaction features, we consider Opportunity Theory. In this sense, schools can be viewed as a criminogenic factor due to attracting students and employees (GROFF; LOCKWOOD, 2014; HE *et al.*, 2020; CECCATO; MOREIRA, 2021), and for similar reasons, we evaluate universities. Bus stops (NEWTON *et al.*, 2014; STUCKY; SMITH, 2017; HART; MIETHE, 2014), restaurants, fast-food locations (YU; MAXFIELD, 2013; JEAN, 2007; HART; MIETHE, 2014), drug stores, stores (HE *et al.*, 2020; JEAN, 2007), gas stations (HART; MIETHE, 2014; BERNASCO; BLOCK, 2011), as well as places where cash and cheque transactions are high such as national lottery agencies and banks (JEAN, 2007), and hotels (YANG; HUA, 2020) attract the presence of offenders. Therefore, we also considered these factors in our analysis.

Bus stops and variables of social interaction features are public services. However, they contrast with each other. Bus stops, as a proxy, can be viewed as connectivity spots that take people between places. On the other hand, social interaction features attract people to places without the capacity to connect them.

Based on these perspectives, the proposed framework is used to make a preliminary analysis for spatial association by GIS, thereby providing a visual analysis of the occurrences of street robberies while kernel density is used to make a comparison between the distribution of crimes, spatial features and the distribution of bus stops so as to better understand the spatial dynamic of crime. Thereafter, we analyze GWR and NB regressions.

The NB and GWR regressions are conducted separately for socio-demographic features and social interaction features for the sake of avoiding complexities in analysis. According to (WAAL *et al.*, 2020), integrating data sources raises 8 problems: complementary variables, complementary metrics, estimating overlapping, estimating the value of conflicting variables, estimating the population size, making estimates in a way that is consistent with making previous estimations, achieving numerical consistency in equations and dealing with unbalanced data that can have different time, scales and dimensions.

Thus, NB regression was used for socio-demographic features analysis due to the over-dispersion of data and GWR was applied for social interaction features due to the movement and circulation of people and money which contribute to inherent non-stationary characteristics in the social interaction features. The AIC is applied in NB regression to indicate the socio-demographic features that can best describe the street robberies. It is important to mention that bus stops were analyzed in these two regression models since bus stops represent the movement of people, i.e., potential victims. The data were visualized and explored in ArcGis 10.4 and RStudio.

The use of DRSA (GRECO *et al.*, 2013) allowed for the development of a framework for modeling holistic preferences by training samples, which are then used to construct a learning table for creating decision rules that can be replicated for other alternatives. This is possible because a partial preference profile that requires less cognitive effort from the DM can be used.

In the DRSA application, the process of generating decision rules starts with a specialist selecting a training sample. We used GIS for the visual exploration to support the training set by choosing alternatives that represent 5 vulnerability levels established in the study. Three of these five vulnerability levels are defined as the main levels (no vulnerability, medium vulnerability and very high vulnerability) for a comfortable decision process since we offer an intermediate (low vulnerability and high vulnerability) evaluation between the extreme cases. For this, we use the DOMLEM algorithm and the jMAF[2] application.

The analysis deals with 155 census tracts (CTs). As it is difficult for a specialist to make a holistic evaluation of all CTs, 50 reference alternatives (approximately 32.3% of the total) were selected to induce decision rules. These rules were validated by 5-fold cross-validation and used to assess the 105 other alternatives.

Besides the cross-validation, in our framework we consider making a comparison between the DRSA recommendation for the classification and the real data of crime distribution. Beyond guaranteeing the quality of the rules, we believe the model needs to be near as possible to reality. This is done by drawing a parallel between the preference model and real data. This is different from doing validations based on a data table that only contains data on conditional criteria and decision criteria. For this we make use of GIS.

Seeking to aggregate the clusters of vulnerability, when the rules and model are validated,

[2] http://www.cs.put.poznan.pl/jblaszczynski/Site/jRS.html

a hot-spots map is generated by applying the local Moran to help in taking actions per zones instead of per separate CTs.

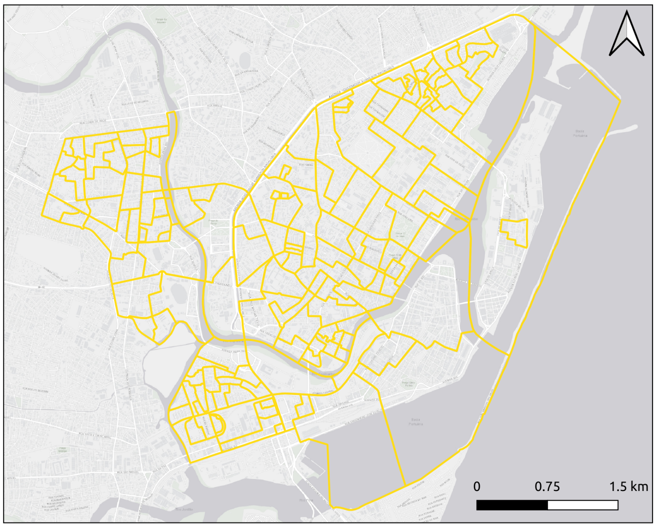
## 6.3 RESULTS

The analysis was developed in a city, located in the Northeast of Brazil. The city has more than 1.5 million inhabitants (IBGE, 2016) and has the highest number of violent crimes in the state of Pernambuco (SDS, 2018) which is ranked as the fourth most violent state in Brazil, behind Rio Grande do Norte, Acre, and Ceará, respectively (FBSP, 2018).

### 6.3.1 Spatial and statistical analysis

The area of the city was selected via the hot-spots analysis by local Moran which used data on street robberies. Having noted there were clusters of occurrences, the area selected for study was the one seen to be the zone with an HH cluster, i.e. the CTs and their neighbors have a high incidence of crime. Hence, in a set of 1,854 CTs our analysis is restricted to 155 CTs (Figure 23) corresponding to an area of a commercial zone with an intense flow of goods and people and significant amounts of cash in circulation due to high concentrations of retail stores and other kinds of local services and the holding of events such as Carnival and fairs.

Figure 23 – Study area



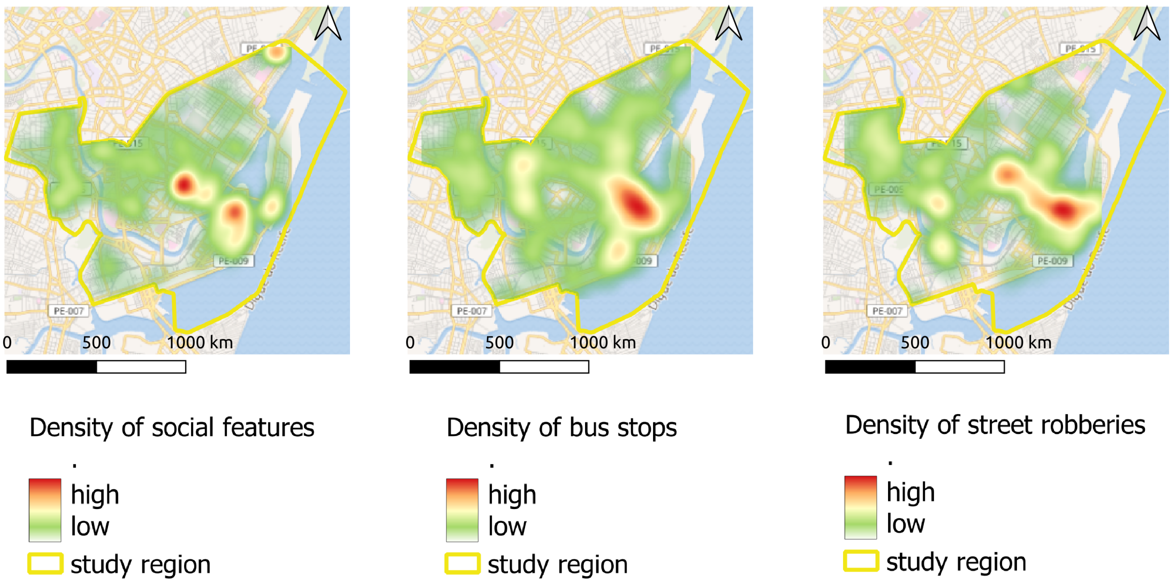

Source: Rosa *et al.* (2023)

The exploration of the study area is based on the data on the distribution of street robberies, socio-demographic data (or socio-demographic features), spatial data (or social interaction features) and the distribution of bus stops, respectively obtained from a collaborative project for victims themselves who reported the crime during the period from 2012 to 2016 (ONDEFUIROUBADO, 2016); the 2010 national census (a census is held every 10 years, and therefore the study uses the 2010 Census) (IBGE, 2016); Google Maps and Open Street Maps (OSM).

i Kernel density analysis

After the area has been selected, the distribution of social interaction features, bus stops and street robberies are analyzed from the kernel density point of view, as presented in Figure 24. The main objective of kernel density is to establish connections between the concentrations of data by making a comparative analysis of social interaction, the movement of people and the occurrence of crime.

Figure 24 – Density




Source: Rosa *et al.* (2023)

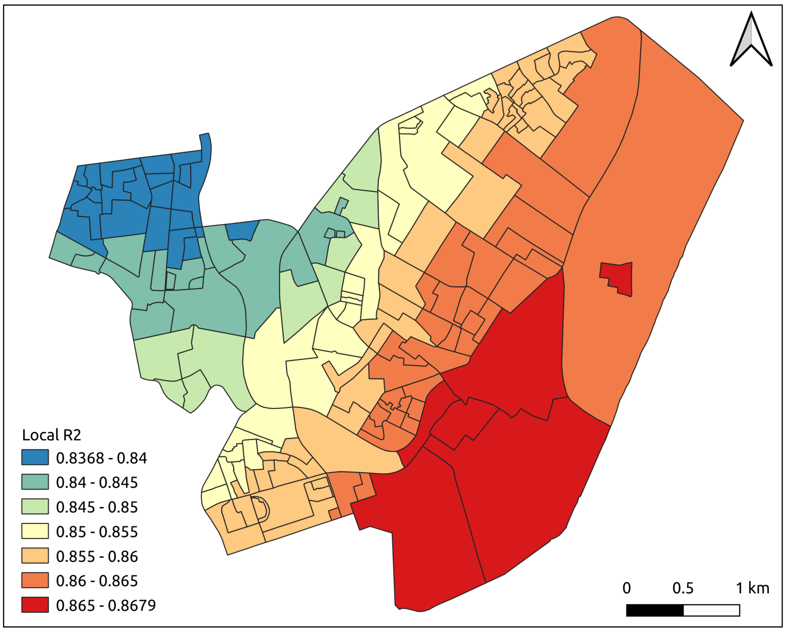
According to Figure 24, it is possible to note similarities in concentrations of social features, bus stops and of street robberies, thus a possible relation between the spatial dynamic and its influence in crime as presented in the findings of (PIZA, 2003; NEWTON *et al.*, 2014; YU; MAXFIELD, 2013; HE *et al.*, 2020; CECCATO; OBERWITTLER, 2008).

ii Regression analysis

For data exploration, we considered the variables presented in Figure 22 to represent the factors of Opportunity Theory, Disorganization Theory, and mobility. Due to the places accounting for opportunities to commit crime (CAPLAN *et al.*, 2011) even when social demographic factors are controlled (GROFF; LOCKWOOD, 2014), social interaction features and the bus stops are analyzed by the GWR model in order to evaluate their relation with street robberies because of their non-static nature.

GWR regression confirms (numerically) that the social interaction features and location of bus stops have an impact on street robberies since the regression model gives a Quasi-Global $R^2$ of approximately 85.64%, thus indicating the extent to which these influence the study of crime, thereby solidifying the argument that social interaction features have an impact on this. Although the difference between the local $R^2$ of each CT is not so significant (lower and upper value of $R^2$ are 0.8368 and 0.8679, respectively, Figure 25), it can be seen that the variability of social interaction features of east zones have more power in explaining street robberies and this decreases as we move in a westerly direction.

Figure 25 – Local GWR




Source: Rosa *et al.* (2023)

The NB regression (Table 11) is used to explore social and economic deprivation from Disorganization Theory . For this, socio-demographic features are used to seek to express the link with poverty (income), social inequality (literate people), housing condition (water supply, garbage collection, energy supply, makeshift homes), agglomeration of buildings (households) and people (residents) (PEREIRA *et al.*, 2017b; PERES; NIVETTE, 2017), and place accessibility (bus stops) (WARD *et al.*, 2014), through total household income, number of people who can read and write, number of households with a water supply, number of households with garbage collection, number of households with an energy supply, number of makeshift homes, number of households, total number of inhabitants, and number of bus stops, for each CT.

Table 11 – Negative binomial regression to explain the occurrences of robberies

| **Independent variables** | **P-value** |
|---|---|
| Number of households | 0.7594 |
| Number of households with water supply | 0.61402 |
| Number of households with garbage collection | 0.53574 |
| Number of households with energy supply | 0.33705 |
| Number of makeshift homes | 0.17743 |
| Total household income | 0.58766 |
| Number of people who can read and write | 0.13625 |
| Total number of inhabitants | $0.00949^{**}$ |
| Number of bus stops | $(2e^{-16})^{**}$ |
| $\theta = 1.097$ | |
| Standard error = 0.246 | |

Source: Rosa *et al.* (2023)

In order to reduce this data set and to compile a smaller subset with greater significance in such a way that its elements can fully describe the occurrences of thefts in the public space, we apply AIC. As a result, AIC highlights four elements, namely, the number of makeshift houses, the number of people who can read and write, the total number of inhabitants and the number of bus stops.

After confirming the impact of social interaction features on street robberies, the statistical support in discovering the socio-demographic features leads us to conclude that the variables most associated to crime are, besides bus stops which are visually associated to crime, the number of people who can read and write and the number of makeshift houses. So far, so good. But by combining these two analyses, we have a complementary interpretation.

Spatial and statistics exploration are fundamental for constructing knowledge and for reinforcing previous knowledge because the interpretation of features can aggregate value, at some level, with respect to the real situation and can aid the selection of criteria for DRSA modeling.

### 6.3.2 MCDA analysis

Based on the first step of our framework and previous knowledge, the criteria used in the decision model were: the number of makeshift homes, the number of people who can read and write (literate people), the total number of inhabitants, bus stops, universities, banks, national lottery agencies, restaurants, schools, stores, gas stations, drug stores and hotels. These variables, besides being associated with social inequality, also provide evidence of there being spatial elements that have a propensity for being where robberies occur (WEISBURD *et al.*, 2014).

The choice of makeshift homes and the number of people who can read and write as criteria is associated to the social inequalities since type of housing and access to education are important metrics to measure poverty and the lack of job opportunities (KELLY, 2000). The number of residents and bus stops are related to mobility and consequently to social disorder (COHEN; FELSON, 1979).

Spatial criteria such as banks, universities, schools, hotels, restaurants, drug stores, retail stores, national lottery agencies (called 'casas lotéricas' in Portuguese which also act as sub-agencies of a Brazilian Government bank - the 'Caixa Econômica Federal' - and thus they are also where account holders can receive financial aid from the government or deposit or withdraw cash) and gas stations are linked to the economy and consequently to the circulation of money; and from the point of view of decision-making, bus stops are not only associated with the flow of people but are also the points from which criminals may go in order to commit a crime and which they may use to escape from the scene of a crime. In brief, the summary of criteria is presented in Table 12, where gain type indicates the positive monotonic relation between the street robberies and preference criteria.

Table 12 – Descriptive statistics of criteria

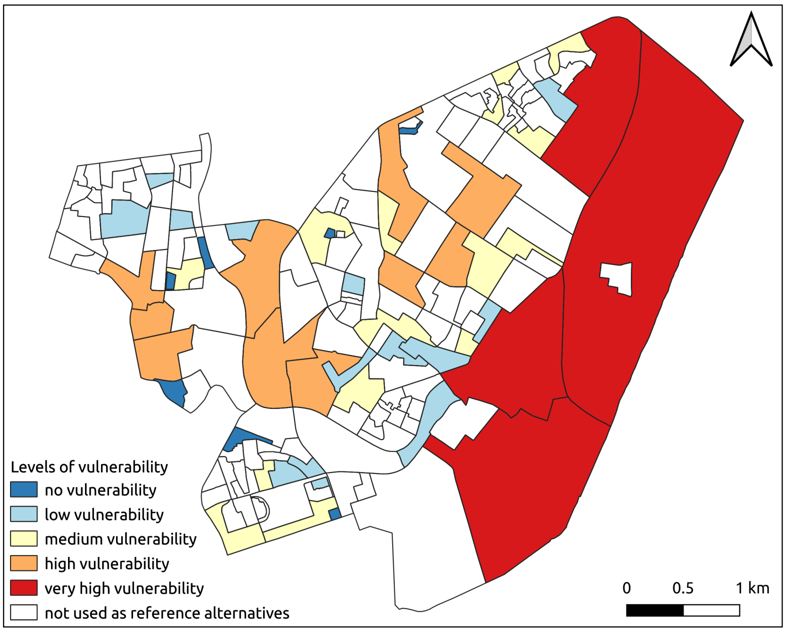
| **Criteria** | **Max** | **Min** | **Mean** | **Standard Deviation** | **Type** |
|---|---|---|---|---|---|
| Universities | 6 | 0 | 0.48 | 1.44 | Gain |
| Banks | 29 | 0 | 0.8 | 1.2 | Gain |
| National lottery agencies | 11 | 0 | 0.32 | 1.15 | Gain |
| Restaurants | 31 | 0 | 1.86 | 3.97 | Gain |
| Schools | 10 | 0 | 0.26 | 0.97 | Gain |
| Stores | 38 | 0 | 1.78 | 4.61 | Gain |
| Gas stations | 6 | 0 | 0.4 | 0.93 | Gain |
| Drug stores | 25 | 0 | 0.95 | 2.5 | Gain |
| Hotels | 5 | 0 | 0.27 | 0.66 | Gain |

| | | | | | |
|---|---|---|---|---|---|
| Bus stops | 81 | 0 | 2.5 | 7.12 | Gain |
| Makeshift houses | 40 | 0 | 0.522 | 3.28 | Gain |
| People who can read and write | 1222 | 0 | 576.48 | 224.87 | Gain |
| Total number of inhabitants | 1345 | 0 | 680.36 | 268.04 | Gain |

Source: The Author (2023)

After defining the decision criteria, the sample of 50 alternatives for holistic assessment in the DRSA approach are chosen and evaluated by a specialist with know-how in crime analysis based on visual analysis of the kernel density so that at least one representative alternative of each category will be used. The sample is distributed in the study area as shown Figure 26.

Figure 26 – Training sample




Source: Rosa *et al.* (2023)

Although we sought to include at least one representative of each vulnerability class as presented in Figure 26,we also understand that point as an opportunity for improvement, but, since we are doing an experimental analysis, what we propose in this initial study seems satisfactory and so the DRSA was run.

Thus, as we are seeking to develop a holistic model that can give a plausible and coherent solution in support of allocating resources, the defined criteria were used in the decision-making and the table of decision rules was generated as presented in Table 13.

Table 13 – Training sample for decision modeling

| **# Certain at least rules** | |
|---|---|
| 1 | restaurants >= 15.0 =>preference >= very high vulnerability |
| 2 | stores >= 6.0 =>preference >= high vulnerability |
| 3 | restaurants >= 1.0 & bus stops >= 6.0 =>preference >= high vulnerability |
| 4 | restaurants >= 4.0 =>preference >= medium vulnerability |
| 5 | bus stops >= 7.0 =>preference >= medium vulnerability |
| 6 | gas stations >= 2.0 =>preference >= medium vulnerability |
| 7 | restaurants >= 1.0 & bus stops >= 3.0 =>preference >= medium vulnerability |
| 8 | banks >= 1.0 & restaurants >= 1.0 =>preference >= medium vulnerability |
| 9 | restaurants >= 1.0 =>preference >= low vulnerability |
| 10 | bus stops >= 2.0 =>preference >= low vulnerability |
| 11 | gas stations >= 1.0 =>preference >= low vulnerability |
| 12 | hab_improp >= 2.0 =>preference >= low vulnerability |
| **# Certain at most rules** | |
| 13 | bus stops <= 0.0 & people who can read and write <= 191.0 =>preference <= no vulnerability |
| 14 | banks <= 1.0 & restaurants <= 0.0 & gas stations <= 0.0 =>preference <= low vulnerability |
| 15 | restaurants <= 1.0 & stores <= 0.0 & bus stops <= 0.0 =>preference <= low vulnerability |
| 16 | restaurants <= 3.0 & stores <= 1.0 & gas stations <= 0.0 & bus stops <= 0.0 =>preference <= low vulnerability |
| 17 | banks <= 0.0 & restaurants <= 1.0 & gas stations <= 0.0 & bus stops <= 2.0 =>preference <= low vulnerability |
| 18 | bus stops <= 1.0 =>preference <= medium vulnerability |
| 19 | restaurants <= 0.0 =>preference <= medium vulnerability |
| 20 | stores <= 3.0 & bus stops <= 4.0 =>preference <= medium vulnerability |
| 21 | stores <= 7.0 =>preference <= high vulnerability |

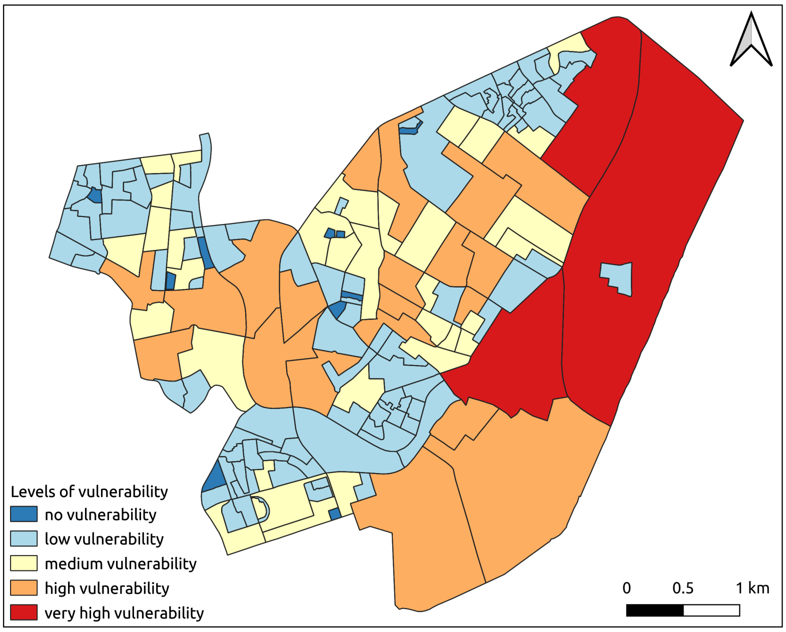
Source: Rosa *et al.* (2023)

On returning to Table 13, note that there are two decision rules to classify an alternative directly on the extremes of vulnerability levels. First, we have the condition of at least 15 restaurants which immediately classifies the CT as being of very high vulnerability. Other criteria contribute to classifying a CT as being in at least in high vulnerability, but they are not enough to guarantee that the CT will remain classified as being very highly vulnerable. Secondly, we have the conditions of no bus stops and at most 191 people who can read and write to directly classify an alternative as not vulnerable, but note that unlike the first case, no vulnerability can result from other decision rules.

For these decision rules, the model presented a quality of 88% for the sample of 50 alternatives, which means that the percentage of alternatives was classified correctly by the specialist. That result was considered good given the considerable number of alternatives for preference elicitation and then they were used to classify all other 105 alternatives, Figure 27.

In Figure 27 the areas with cold colors (shades of blue) tend to be less vulnerable to robberies, compared to the areas in hot colors (red and orange) which are the places characterized

Figure 27 – Rules of aggregated criteria applied to the 155 census tracts

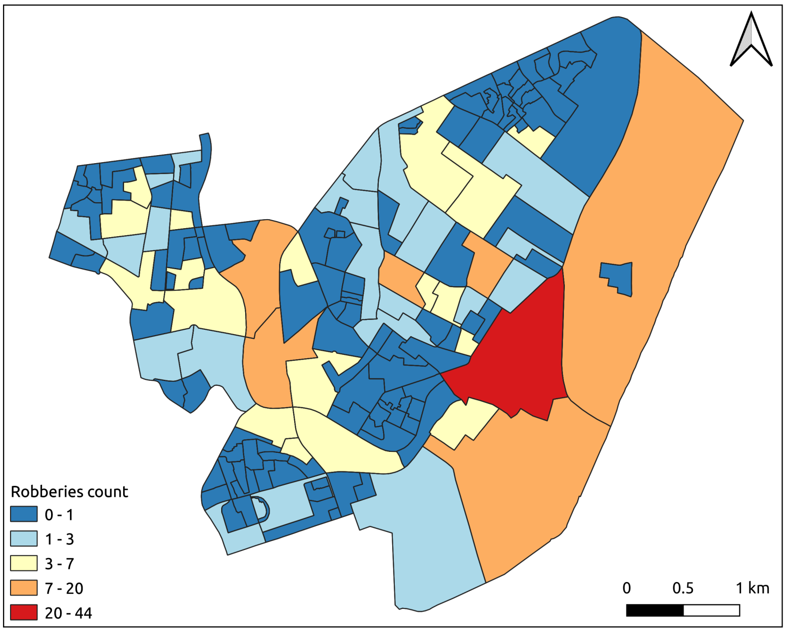



Source: Rosa *et al.* (2023)

by the presence of commercial activities that need most attention.

The results from the decision model were compared with the real distribution of street robberies (Figure 28), where the number of crimes per CT was stratified in 5 groups as a way to facilitate the comparative analysis since the number of vulnerability classes is the same.

Figure 28 – Map of the occurrences of street robberies

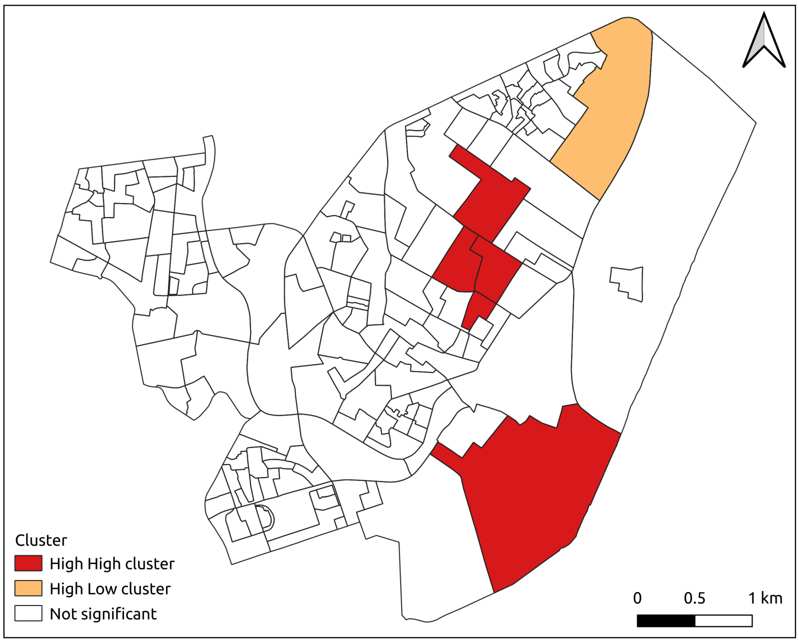



Source: Rosa *et al.* (2023)

From our analysis, what can be seen is that the model developed presents a more pessimistic evaluation of alternatives if compared to the real data on the distribution of street crime. Moreover, we consider that the pessimism arising from comparing Figures 27 and 28 is justifiable because dealing with public security implies minimizing errors. Thus, extra efforts made to guarantee hoped-for results, in the sense of protecting citizens, could be acceptable.

According to the first law of geography (Tobler's First Law), "everything is related to everything else, but near things are more related than distant things" (TOBLER, 1970). Hence, it is reasonable to suppose that there are interactions between adjacent CTs in our analysis. To evaluate the interactions resulting from applying the framework application, we used local Moran I to discover clusters of vulnerability (Figure 29).

Figure 29 – Local Moran of the aggregated criteria of the decision model




Source: Rosa *et al.* (2023)

According to Figure 29, the vulnerability evaluation of the DRSA model using aggregated criteria has 2 clusters of vulnerability: HH, HL, to be considered in setting strategies to mitigate robberies in the area under study. The HH area on the southeast of the map in Figure 29 is near CTs with a very high vulnerability classification, and the HH areas in the middle of the map share the same high vulnerability classification. The HL area belongs to the class of very high vulnerability, and their neighbors are less vulnerable.

The model is subject to improvements as the study conducts a preliminary learning analysis, suggesting that, over time, more knowledge and data about street robberies can be integrated with the aim of creating a responsive model in the sense of implementing robust solutions.

### 6.3.3 Discussion

As a seed idea, the proposed framework seeks to blossom into the posture of adopting real holistic decision-making in the crime context, for which we make use of visual and statistical analysis as support.

With a view to comparing different groups of criteria in decision analysis, we undertook the 5-fold cross-validation approach for the cases of considering socio-demographic criteria separately from social interaction criteria, and we also proposed combining the perspectives to promote learning regarding different factors in decision making in the context of analyzing the occurrence of crime, Table 14.

Table 14 – Validation of the model

| **Model** | **Cross-validation (5-fold)** | | | |
|---|---|---|---|---|
| *Group of information criteria* | *Average accuracy (%)* | *Average precision (%)* | *RMSE* | *MAE* |
| socio-demographic | 19.167 | 10.0 | 0.948 | 0.66 |
| social interaction | 47.919 | 59.134 | 0.721 | 0.48 |
| proposed model | 56.4 | 53.025 | 0.583 | 0.34 |

Source: Rosa *et al.* (2023)

As expected, Table 14 gives us different results. Even though these models aim to support how resources are allocated in public security to combat robberies in public spaces, the isolated proposals give us a reduced view of reality compared with the proposed model that contemplates a greater variety of environmental perspectives. As can be noted, although the average precision of the decision model which contemplates only the social interactions as criteria is better when compared with other models, when we analyze other metrics such as accuracy and the Root Mean Squared Error (RMSE) and the Mean Absolute Error (MAE) the results suggest that the proposed model is a better fit, demonstrating that exploiting spatial data is a useful way to reach a better understanding of spatial characteristics in order to design better solutions which will also result in a better decision-making experience. The contribution of our framework proposal to the GIS-MCDA field concerns the use of statistical and spatial learning to construct a holistic decision model that requires previous knowledge supplemented by recognition of patterns of crime occurrence and the factors associated with crime. As DRSA is a holistic method, these tools are valuable to classify areas into levels of vulnerability.

From the perspective of technique, the framework is suited to exploring criteria of a different nature, but it still has critical points that need to be improved. In this case, it is recommended returning to the beginning of the framework in order to plan strategies and to have the actors of the decision process refine the model.

Statistical studies on crime, which handle crime patterns through the analysis of (i) restaurants and gas stations (BERNASCO; BLOCK, 2011), (ii) transit elements (bus stops) (DERYOL *et al.*, 2016; NEWTON *et al.*, 2014; CECCATO; MOREIRA, 2021; JEAN, 2007), (iii) schools (GROFF; LOCKWOOD, 2014; HE *et al.*, 2020), (iv) commercial places like stores and drug stores (HE *et al.*, 2020; JEAN, 2007),(v) social and economic deprivation (PEREIRA *et al.*, 2017b; ANDRESEN, 2006; PERES; NIVETTE, 2017) given housing conditions, sanitation, poverty, and population, (vi) and finally but not least the occurrence of different crimes (ALKIMIM *et al.*, 2013; VALENTE, 2019), demonstrate that the places where the flow of cash and people has a substantial impact on the incidence of street crime. Our analysis also demonstrates this.

Moreover, due to the first law of geography, we cannot forget the possible spatial interrelationship resulting from our framework. Thus, the use of Local Moran I helps identify clusters of vulnerability. We obtain two types of cluster according to the results of applying the framework, namely HH located at the southeast and center of our area indicating that places have the same characteristics (highly vulnerable zones with their neighbors in the same situation), and HL located in the north of study area which call our attention to a particular case of where we have a danger zone surrounded by a less vulnerable zone.

By combining these statistical results with MCDA, our proposal has the potential to engage people in understanding social, spatial and mobility factors for conscious and active decision-making in the environment, and it contributes to constructing learning starting with a holistic methodology where previous knowledge is imperative in order to take decisions. This is one of the advantages of our framework over the other MCDA studies on vulnerability to crime, see Table 8. Another positive aspect of our framework is that it considers a holistic MCDA methodology and thus there is no need to define parameters. So, it is possible to learn and generalize the decision rules from reference alternatives for new preference instances to find and reveal the characteristics of an area, thereby enabling the DMs to act on categories of vulnerability.

## 6.4 FINAL CONSIDERATIONS

While the MCDA literature on crime studies usually opts for considering the socio-demographic elements or types of crimes, our framework succeeds in supporting a decision model based on Disorganization Theory, Opportunity Theory and mobility, and gives people the ability to understand the social and environmental relations and to act on them. The main statistical and spatial findings are as follows: (i) social interaction features, bus stops, and street robberies are spatial related and GWR numerically confirms the relation between them with an explanation of $83.68\% - 86.79\%$ of street robberies variability; (ii) NB regression highlights the importance of makeshift houses, the number of people who can read and write, the total number of inhabitants, and the bus stops; (iii) the bus stops, as a proxy of connectivity and place of people attraction, analyzed by GWR and NB regressions contributes to mass transportation analysis on crime studies in different fronts; (iv) the use of Local Moran I supports the spatial interrelationship resulting from our framework, where its use helps identify the clusters HH and HL of study area. Regarding the DRSA results, the preferences tend to be pessimistic. What is admissible in the risk context is to adopt a strict behavior. For the study area, findings indicates that the presence of at least 15 restaurants is enough to classify a CT as being of very high vulnerability in addition to which no bus stops and at most 191 people who can read and write is enough to classify a CT as being not vulnerable.

Although the present paper presents an application in Brazilian public safety, we encourage using the framework in other contexts related to land use since we consider there is a real possibility that the use of another group of features can be adapted to support other kinds of problem.

This methodology can be used to support how best to allocate resources in public security. This is done in accordance with how the model classifies the level of vulnerability of an area and is supported by environmental knowledge refined by traditional and spatial statistics. The study was presented to managers who showed interest in a future partnership and in refining the model.

# 7 REVEALING VULNERABILITY OF AREAS REGARDING A JOINT ANALYSIS OF ATTRACTIVENESS AND CONNECTIVITY

This chapter concerns the specific objective **SO 5**, the discovery of the implications of spatial preferences in event patterns for urban planning. According to Brantingham and Brantingham (1993), both the environment and humans influence each other. In violence studies, as far as we know, multi-criteria analysis has been contributing to revealing the vulnerability of regions according to DMs preferences (MOTA *et al.*, 2021; ROSA *et al.*, 2023; FIGUEIREDO; MOTA, 2019) . However, DMs preferences' are not used to discover patterns of violence. In this sense, through the previous results of spatial preferences of attractiveness and connectivity, it is proposed an exploratory analysis in view of the occurrence of robberies in the state of Pernambuco - Brazil regarding the effects of spatial interaction preferences.

## 7.1 CONTEXTUALIZATION

Preference learning has been considered in MCDM/A to support preferences and predict them (DOUMPOS; ZOPOUNIDIS, 2011). In urban planning, it is useful to support public policies and to take effective actions in space. However, it is not clear how these preferences affect the events in space. Hence, this chapter discusses how preferences may affect the urban planning issue.

The discussion is centered on public security in light of the robberies in Metropolitan Region of Recife (RMR). Instead of using attributes from the Opportunity Theory, Disorganization Theory, and mobility as proposed by Rosa *et al.* (2023), the main objective is to discover and explore the pattern of crime based on the preferences of attractiveness and connectivity of regions, since they contribute to the flow of people, goods, services, and money, which according to the theory of crimes, appeal to human interactions regarding individuals objectives in space.

This proposal is based on the results of Chapter 4 and Chapter 5, taking a pro-active approach to understanding human preferences in spaces. This approach provides policymakers with a response from society to public actions in space. In other words, instead of developing public policies based solely on societal demands, we argue that it is important to consider the response of society to existing policies. This can help create more effective planning by providing important information for decision-making.

## 7.2 DATA AND METHODS

As the present analysis was executed at RMR, there were used the results of the methods proposed in Chapter 4 and Chapter 5 for preference learning regarding the attractiveness and connectivity. Thus, both the attractiveness score and the index of total connectivity of the cities of Abreu e Lima, Araçoiaba, Camaragibe, Igarassu, Ilha de Itamaracá, Itapissuma, Paulista, Recife, São Lourenço da Mata, Cabo de Santo Agostinho, Ipojuca, Jaboatão dos Guararapes, Moreno and Olinda were used.

The data of occurrences were provided by the Secretary of Social Defense of Pernambuco. The robbery data used are from January 1, 2019, to December 31, 2021. It was possible to capture the pattern of crime before (2019), during (2020), and in the final (2021) of the pandemic of COVID-19 in Brazil. The analysis per year was executed in a four-month period. Due to the available data in this analysis, the preferences of attractiveness and connectivity were considered the same during the time.

A visual analysis regarding robbery occurrences was made with Kernel Density Estimation (KDE), and the Ordinary Least Square (OLS) (or linear) regression, and Geographically Weighted Regression (GWR) were used. The OLS allows the understanding of global relationship of variables, and the GWR take an advantage in considering the preferences results to explore the local variability of robberies occurrences (FOTHERINGHAM *et al.*, 1998). For methods details see Chapter 2, section 2.3.1, section 2.3.3, and section 2.3.4.

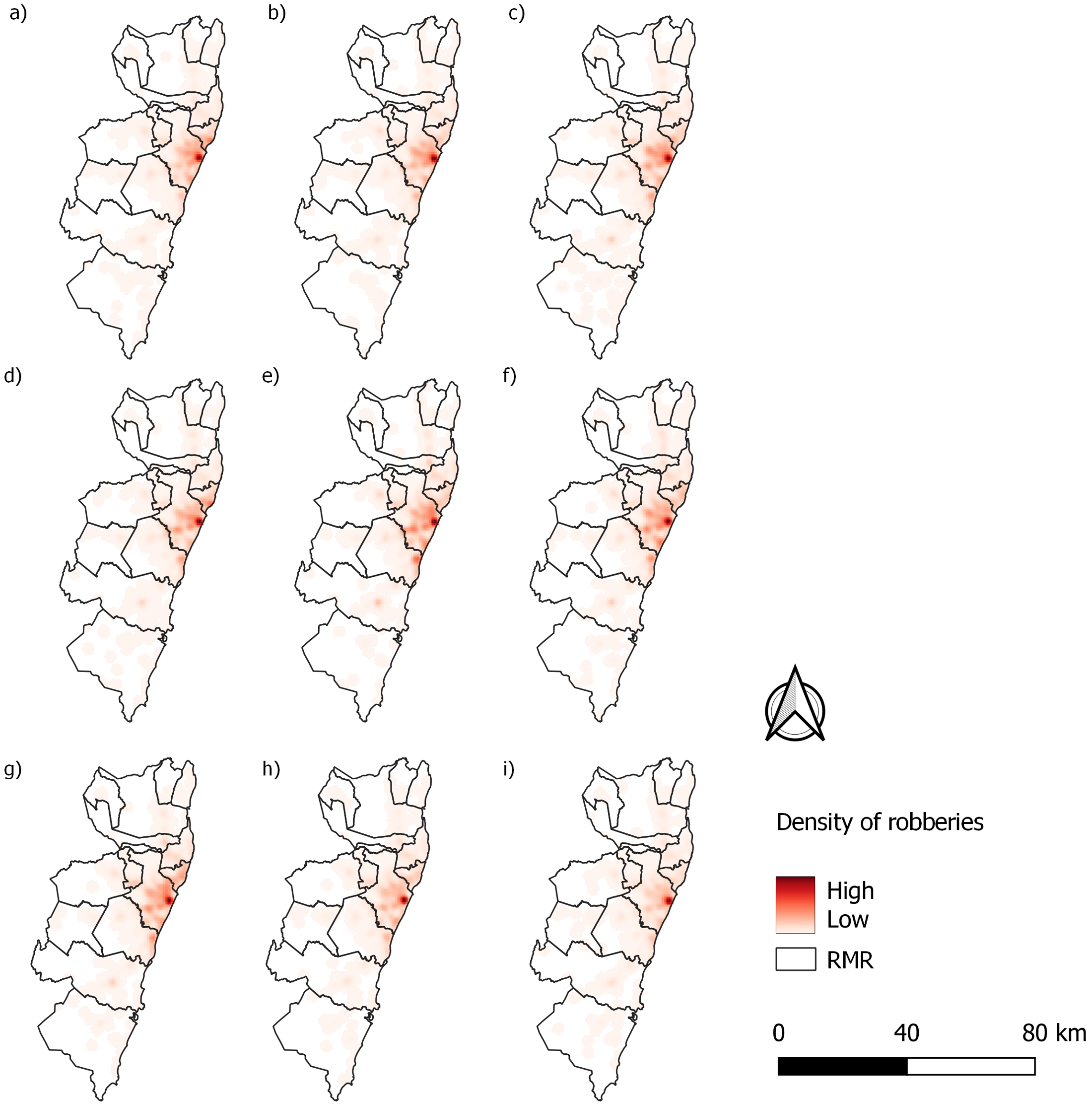
## 7.3 RESULTS AND DISCUSSION

Initially, a Kernel Density Estimation (KDE) was used to evaluate the distribution of robberies over time. Despite the period of the pandemic, it did not significantly affect the concentration of robbery occurrences, as present in Figure 30.

In Figure 30, the vibrant color indicates the high density of crime events. As possible to note, very few changes occurred over 3 years, although the number of cases get a reduction (Table 15) the target areas remains the same. One possible reason is that the preferences of attractiveness and connectivity did not change even during the pandemic period.

To understand the spatial preferences in crime occurrences in different time interval it was executed OLS and GWR regression for period. The OLS presents and $R^2$ of approximately of 0.751, 0.741, 0.747, 0.745, 0.760, 0.773, 0.761, 0.747, and 0.757, in this order. And all

Figure 30 – Density of robbery in RMR (2019-2021)




*Note:*a) 2019-01-01 to 2019-04-30, b) 2019-05-01 to 2019-08-31, c) 2019-09-01 to 2019-12-31, d) 2020-01-01 to 2020-04-30, e) 2020-05-01 to 2020-08-31, f) 2020-09-01 to 2020-12-31, g) 2021-01-01 to 2021-04-30, h) 2021-05-01 to 2021-08-31, i) 2021-09-01 to 2021-12-31

Source: Adapted from SDS (2018)

Table 15 – Crime occurrence per period

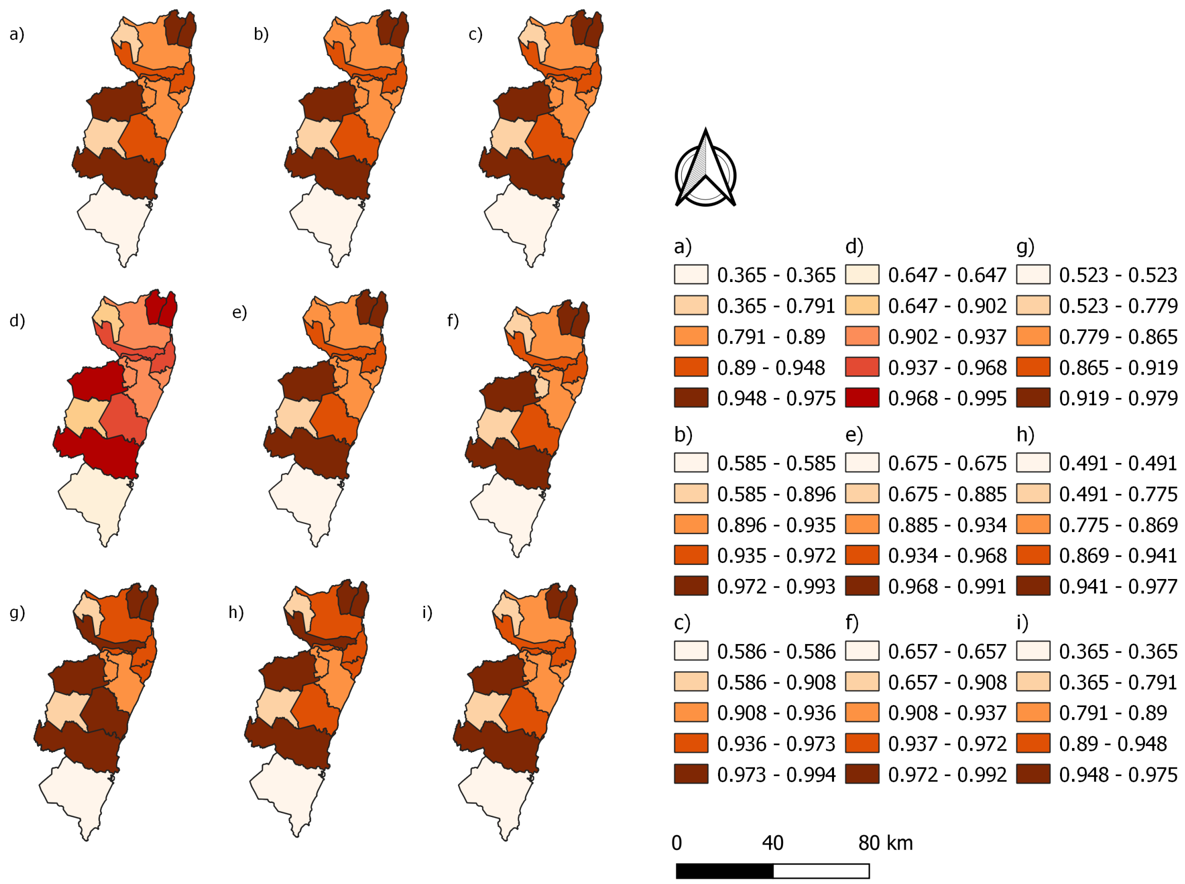
| Municipality | 2019-01 to 2019-04 | 2019-05 to 2019-08 | 2019-09 to 2019-12 | 2020-01 to 2020-04 | 2020-05 to 2020-08 | 2020-09 to 2020-12 | 2021-01 to 2021-04 | 2021-05 to 2021-08 | 2021-09 to 2021-12 |
|---|---|---|---|---|---|---|---|---|---|
| Abreu e Lima | 255 | 239 | 191 | 157 | 167 | 146 | 196 | 194 | 170 |
| Araçoiaba | 16 | 5 | 4 | 6 | 4 | 7 | 11 | 16 | 4 |
| Camaragibe | 469 | 434 | 426 | 300 | 250 | 239 | 410 | 357 | 341 |
| Igarassu | 221 | 211 | 221 | 226 | 155 | 257 | 164 | 144 | 245 |
| Ilha de Itamaracá | 50 | 32 | 49 | 42 | 15 | 57 | 33 | 21 | 37 |
| Itapissuma | 42 | 51 | 36 | 24 | 26 | 22 | 9 | 24 | 19 |
| Paulista | 974 | 892 | 678 | 683 | 547 | 596 | 762 | 703 | 609 |
| Recife | 9248 | 8824 | 6557 | 5874 | 4085 | 4649 | 5139 | 5530 | 5393 |
| São Lourenço da Mata | 334 | 383 | 262 | 183 | 159 | 178 | 181 | 197 | 187 |
| Cabo de Santo Agostinho | 511 | 511 | 524 | 424 | 308 | 334 | 363 | 359 | 418 |
| Ipojuca | 127 | 57 | 93 | 75 | 42 | 68 | 69 | 55 | 61 |
| Jaboatão dos Guararapes | 1944 | 2259 | 1870 | 1846 | 1350 | 1266 | 1304 | 1388 | 1363 |
| Moreno | 103 | 111 | 112 | 107 | 46 | 43 | 57 | 79 | 62 |
| Olinda | 2252 | 1565 | 1303 | 1524 | 746 | 965 | 1306 | 1176 | 985 |

Source: SDS (2018)

of them with the attractiveness preference with most significance than the total connectivity preference. To avoid multicollinearity, the Variation Inflation Factor (VIF) was calculated. The results showed a VIF value of 1.655126 for both attractiveness and connectivity, indicating that the model is stable.

To discover the spatial variability of attractiveness and connectivity in impacting robberies, GWR model was executed to each period of time. As result, few differences could be observed (Figure 31).

Figure 31 – GWR results




*Note:*a) 2019-01-01 to 2019-04-30, b) 2019-05-01 to 2019-08-31, c) 2019-09-01 to 2019-12-31, d) 2020-01-01 to 2020-04-30, e) 2020-05-01 to 2020-08-31, f) 2020-09-01 to 2020-12-31, g) 2021-01-01 to 2021-04-30, h) 2021-05-01 to 2021-08-31, i) 2021-09-01 to 2021-12-31

Source: The Author (2023)

According to Figure 31, there is evidence that the preferences for attractiveness and connectivity have an impact on the variability of robberies in a region, specifically in the period between May and August where the local $R^2$ increase for each stratified group.

According to Figure 31, there is evidence that the preferences for attractiveness and connectivity have an impact on the variability of robberies in a region. Specifically, there is an increasing movement of the local $R^2$ for each stratified group by color from the beginning to the middle of the year, followed by a decreasing movement from the middle to the end of the year. This suggests that the preferences for attractiveness and connectivity have a seasonal influence on robbery variability, independently of pandemics.

It is also possible to consider that these preferences may relate to few changes in the density of crime. Despite the pandemic changing people's routines during the quarantine period, it may not have significantly altered the spatial preferences for committing crimes.

## 7.4 FINAL CONSIDERATIONS

The proposal innovates in considering the preferences as variables to discover the pattern of crimes, as an attempt to find out the human influence in urban events, as well as provide insights for policy managers in monitoring the people response to urban planning policies. Jointly with the analysis of Rosa *et al.* (2023), it is possible to create a proactive analysis of what are the policies to reduce robberies and how people behave to these policies.

The methodology developed in this thesis focuses on the preference for attractiveness and connectivity, as calculated in Chapter 4 and Chapter 5, respectively, concerning the occurrence of robberies. However, this methodology could also be applied to other spatial events, such as real estate prices and tourism, to establish the relationship between attractiveness, connectivity, and urban planning, for example.

The analysis demonstrates that the attractiveness and connectivity preferences can feedback the environment events as result of preferences in space and such as consequence of human spatial interactions. Furthermore, the proposed methodology can be applied to different geographical scales, as the measures of attractiveness and connectivity are defined at the same geographic level.

# 8 CONCLUSION

This chapter presents the conclusion of the thesis by presenting the main contributions, limitations and future work.

## 8.1 CONCLUDING REMARKS

This thesis focuses on the development of MCDM/A model to solve problems. The analysis highlights the importance of incorporating prior knowledge and understanding to support decision-making, by proposing a multi-methodology framework for identifying relevant indicators to deal with spatial relations. Given the potentially complex and time-consuming nature of this process, the objective was to develop a methodology that can be easily applied across different geographic scales and utilizing commonly available analytical tools, such as those presented in Chapter 2.

From this perspective, a systematic literature review was conducted to identify possible gaps in MCDM/A preference learning. In addition to the limited number of analyses conducted with multiple data sources, we found a lack of decision-making in spatial interaction due to the presence of logistics terminals, their coverage area, and their flows. Therefore, we proposed a methodology to address these issues.

Thus, it was used multiple data sources to provide a comprehensive analysis of preferences, including socio-demographic data, facility locations, coverage areas and flows of logistics terminal, financial data, information data, centrality of municipalities within a Brazilian state, and road networks. These analyses are intended to support urban planning regarding attractiveness, connectivity, and vulnerability to crime, as well as exploring the role of attractiveness and connectivity preferences in crime occurrences.

However, the use of multiple data sources increases the number of criteria, which adds complexity to the decision-making process. Hence, we proposed the hybrid use of MCDM/A with statistical analysis and FA for criteria selection. This allows us to analyze the relevance of variables to compose and to reduce the dimension of criteria, respectively. It is important to emphasize that this process is based on elements that have preference meaning; otherwise, the analysis is not useful. Additionally, other techniques are encouraged to support the criteria choice.

The flexibility in geographic scale is given by the DMs needs. In this thesis, the analysis of attractiveness and connectivity was conducted for the 184 municipalities of the state of Pernambuco, Brazil. Meanwhile, the vulnerability analysis was conducted for a region of a city in Pernambuco, and the exploration of preferences in crime events was carried out for the RMR.

The attractiveness analysis was conducted in two phases. In the first phase, six administrative indicators were identified and used along with geographic data of city facilities as criteria for UTADIS. The second phase revealed that out of the 17 criteria, six were deemed unimportant (policies for access to water, clinics, retail businesses, kindergartens, schools, and universities), while one had very low importance (policies for agricultural incentives). This suggests that municipalities already have access to these services and that people consider other factors as more attractive. The results showed that people tend to value criteria related to professional education and job opportunities (colleges and industries), tourism (accommodation), and well-known places (population density), and around 86% of municipalities were classified as having very low levels of attractiveness and should prioritize investment in these areas. Additionally, Figure 11 indicates isolated poles of attractiveness, except for the case of RMR, where Recife, the capital of the state of Pernambuco, appears to be supporting its neighboring municipalities.

In the connectivity analysis, this thesis explores two perspectives: inherent connectivity and total connectivity. For inherent connectivity, we considered local aspects of connectivity based on information flow, money circulation, people and goods movements, the importance of municipalities in the inter-urban network, and ease of connectivity by land. Based on this data, we were able to rank the municipalities of Pernambuco. However, to consider the contribution of logistics terminals in people's preference regarding connectivity, we developed a total connectivity index that takes into account the coverage area and interaction between logistics terminals. As a result, a new ranking of connectivity was found (Appendix C). Equation 5.8 shows that inherent connectivity is mainly influenced by Internet and land connection, but this changes when considering the contribution of logistics terminals. It is worth noting that the analysis of municipalities of Pernambuco considered only one type of logistics terminal, and the addition of new logistics terminals or the addition of different types of logistic terminals may change the perception of connectivity and create a new rank. Furthermore, the index of total connectivity presented in the map in Figure 20 is in accordance with the first law of geography (TOBLER, 1970), unlike the index of inherent connectivity presented in the map in Figure 18.

Regarding urban planning for public security, the vulnerability analysis of an area in the state of Pernambuco revealed its susceptibility to crime. The use of spatial, statistical, and

MCDM/A analysis has made it possible to develop a multi-methodology to identify the perceived vulnerability and support policymakers in making informed decisions and taking action to provide a safe environment for citizens. Moreover, the use of GIS enables effective strategies in space. As a result, it was found that the location of facilities, bus stops, and street robberies are nearly the same, and there is a tendency to be pessimistic in evaluating the vulnerability of an area. Additionally, it was found that the presence of 15 restaurants is enough to classify a CT as having very high vulnerability and at most 191 people who can read and write to classify a CT as not vulnerable.

After considering a set of criteria to reveal vulnerability, we used the outputs from attractiveness and connectivity preferences to explore their impact on the pattern of crime events. This analysis was applied to the RMR during the years 2019, 2020, and 2021. As a result, we found that even during the COVID-19 pandemic, the concentration of robberies remained consistent over the years. In terms of global analysis, it was found that over a four-month period, the average $R^2$ was approximately 0.753, and only a few changes were noted.

## 8.2 MAIN CONTRIBUTIONS OF THIS THESIS

The main contribution of this thesis is to assist urban planning, by providing support in spatial attractiveness and connectivity, joint analysis of both to discover the pattern of crime due to human preferences, and to reveal vulnerability levels due by analyzing preferences regarding criteria from traditional theories of crime. Thus, by exploring these paradigms of urban planning, it is possible to provide results that can support policy-making and help prioritize areas for development and improvement.

The systematic literature review conducted in this thesis is a novelty in compiling papers on preference learning in MCDM/A, as it is the first to consider the proposed search string. Through this review, it was possible to identify gaps in the literature, which led to the proposition of a general attractiveness analysis based on multiple data sources and provided directions to policymakers in meeting the needs of the population.

Furthermore, this thesis presents the first attempt to integrate logistics terminals and their spatial interactions with the coverage area in connectivity analysis. Additionally, a multi-methodology framework was developed to identify the vulnerability of areas to crime (ROSA *et al.*, 2023). This approach provides valuable feedback for urban planners and policymakers to identify specific areas that are more vulnerable to crime due to their spatial characteristics and the preferences of individuals who interact in those areas. Additionally, it was explored the relationship between the pattern of robberies and a joint analysis of attractiveness and connectivity.

In summary, this thesis introduces several contributions. The results obtained from these chapters validate the proposed models and demonstrate their effectiveness in addressing urban planning challenges in different geographic scales. Also, the methodologies may be generalized to other decision-maker contexts.

In view of socio-economic impacts, the proposal may support resource allocation by providing actions for improvement in infrastructures, security, and transportation services. Such consequences contribute to the creation of employment and economic growth, as safer and more connected cities. From an environmental perspective, urban planning promotes sustainable, cleaner, and healthier cities.

## 8.3 LIMITATIONS AND FUTURE WORK

This thesis has limitations. One issue is the use of official and non-official records, which may not accurately reflect the actual situation in the region. Additionally, crime data may be underreporting. Another issue comes with the need to represent the temporal dynamics, besides the presence of an analyst to guide the process.

The thesis acknowledges a further limitation of the MCDM/A techniques used, which is that they are highly dependent on the subjective preferences of decision-makers. Although the validity and reliability of the preferences were ensured, there is still a possibility that they may not accurately reflect the broader population's preferences, leading to biased or incomplete assessments. To address this limitation, future research could consider using a diverse sample of decision-makers. Additionally, future research could consider exploring the interactions between criteria to improve group decision-making.

Other improvements could be made. For example, the zeros coefficients in UTADIS application could be well explored to explain the predilection for certain criteria. In connectivity, instead of using fixed values for the rings in the buffers of the coverage area of logistics terminals, it would be beneficial to consider irregular or dynamic values to capture geographic barriers. For the future, it is hoped to find a solution to aggregate different modules into one tool.

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# APPENDIX A – ARTICLES OF SYSTEMATIC LITERATURE REVIEW

| Author | Year | Journal | Type of article | Sector of application | Method used | Software/ algorithm | Method output | Data |
|---|---|---|---|---|---|---|---|---|
| Aggarwal (2018) | 2018 | Kybernetes | method and application | research | AMNL and MNL | Algorithm available in article | new methodology to econometric models which considers the attitudes to predict DM's choice | SCJ, CPU, ESL, MMG, LEV, CAR, DBD, BCD, ERA, MPG, SWD and CCS from WEKA and UCI |
| Aggarwal and Tehrani (2019) | 2019 | INFORMS JOURNAL ON COMPUTING | method and application | research | ACI, ML and Preferennce Learning (PL) | - | methodology to handle cases of redundance in criteria with the objective to automate and scale the acquisition of preferences | ESL, ERA, LEV, MMG, CPU, CEV, BCC, DBS, MPG, CYD from WEKA, UCI, Daniels and Kamp (1999) and Nasiri and Berlik (2009). |
| Aggarwal (2019b) | 2019 | Information Sciences | method | research | entropy | - | the model propose a model to represent individualistic evaluation models, then the DM can choose the alternative with greatest utility | car selection problem |
| Aggarwal (2019a) | 2019 | International Journal of Intelligent Systems | method and application | research | AMNL | - | there is a proposal of choice in context of big datasets with a large number of attributes | car selection problem |

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|---|---|---|---|---|---|---|---|---|
| Aggarwal (2019d) | 2019 | Knowledge and Information Systems | method and application | research | MNL and PL | MATLAB | the authors propose a methodology to predict the DM's choise based on his/her behavior | SCJ, CPU, ESL, MMG, LEV, CAR, DBD, BCD, ERA, MPG, SWD and CCS from WEKA and UCI |
| Aggarwal (2019c) | 2019 | IEEE Transactions on Neural Networks and Learning Systems | method | research | PLEMOA, EMOA, PL-NSGA2 | MATLAB | the method proposed aid DM to find the preferred alternative without explore the whole set of Pareto-optimal solutions | Zitzler et al. (2001) |
| Ahn and Lin (2020) | 2020 | IEEE Transactions on Visualization and Computer Graphics | method | research | ML | FairSign | the method is an way to reduce the bias in data-driven decision-making | German Credit Dataset from UCI |
| Angilella *et al.* (2018) | 2018 | Knowledge-Based Systems | method and application | research | Choquet Integral (CI), Non-Additive Robust Ordinal Regression (NAROR), SMAA | - | the authors find the composite index to sustainable development | Data of municipalities in ISTAT (Italian Institute of Statistics) |

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|---|---|---|---|---|---|---|---|---|
| Arcidiacono *et al.* (2021) | 2021 | European Journal of Operational Research | method and application | research | CI, Multiple Criteria Hierarchy Process, Robust Ordinal Regression (ROR), SMAA and Non-Additive Robust Ordinal Regression for Hierarchical Criteria (NAROR-HC) | - | the model is an attempt to fill a gap regarding the use of NAROR in sorting problems | Standard & Poor's Market Intelligence |
| Babashov *et al.* (2020) | 2020 | Medical Decision Making | method and application | public | UTADIS | - | the method allows the use of data rather than the direct elicitation of parameters, and provide robust results by removal of inconsistent decisions regarding oncology drugs | Skedgel et al. (2018) |

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|---|---|---|---|---|---|---|---|---|
| Balbontin *et al.* (2019) | 2019 | Transportation Research Part B: Methodological | method and application | research | LPAA | pythonBiogeme | through the developed model, the authors shows the synergy among experience, multiple decision process strategies and behaviooral refinements | Northwest and Metro Rail datasets |
| Balugani *et al.* (2021) | 2021 | Expert Systems with Applications | method and application | research | UTA Group Decision Making System (UTA GMS) and PCA | MATLAB | the proposed model achieves the the objective to manage noise data, and works with dimensional reduction with PCA technique | Lahdelma et al. (1998) |
| Batmaz and Kaleli (2019) | 2019 | Arabian Journal for Science and Engineering | method and application | research | Autoenconder-based Multi-Criteria Collaborative Filtering (AE-MCCF) | Keras and TensorFlow | the authors present a model capable to handle the aggregation of users through a non-linear relations | Yahoo!Movies |

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|---|---|---|---|---|---|---|---|---|
| Belahcène *et al.* (2018) | 2018 | Computers and Operations Research | method | research | Non-Compensatory Sorting Models With Unique Set of Sufficient Coallitions (U-NCS), Mixed Integer programming (MIP) and Boolean Satisfiability Problem (SAT) | - | the proposed model regards the non-compesatory sorting model with the computational advantage of handle large datasets and outperforms MIP approachs in computation time | random dataset |

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|---|---|---|---|---|---|---|---|---|
| Beliakov and Divakov (2019) | 2019 | International Journal of Intelligent Systems | method | research | Sugeno and Pool-Adjacent-Violators Algorithm (PAVA) | R | there is a method to solve problem of fuzzy learning. The authors propose a method with computational cost of quantifying inconsistencies with linear complexity showing its superiority over other methods with quadratic complexity | artificial data-set |
| Beliakov *et al.* (2019) | 2019 | Information Sciences | method and application | research | Sugeno, NAROR and fuzzy | R | the method allows the use of piece-wise linear objective function which facilitates the use of difference convex and opens space to the use of Sugeno integral which is flexible to modeling redundant and complementary attributes | artificial data-set |

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|---|---|---|---|---|---|---|---|---|
| Beliakov *et al.* (2020b) | 2020 | Knowledge-Based Systems | method | research | fuzzy, NAROR and entropy | R | the method takes the advantage of entropy to maximize the learning from DM's preferences by the linear programming problem | - |
| Beliakov *et al.* (2020a) | 2020 | Optimization | method | research | Difference of Convex functions (DC) decomposition | R | the method considers the fuzzy measures in context of ordinal regression by aggregating data through Sugeno integral. The advantage of this is the reduction in the number of constraints | artificial dataset |
| Brabant and Couceiro (2018) | 2018 | Fuzzy Sets and Systems | method | research | Sugeno integral | - | the method improves the k-additivity to the k-maxitivity, as result the authors find the optimum value for k equals to 4 as the greater values over-fitting model | TripAdvisor |

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|---|---|---|---|---|---|---|---|---|
| Chai (2021) | 2021 | Soft Computing | method | research | DRSA | - | the proposal address a new strategy for knowledge reduction based on classes rather than conventional class unions | - |
| Chakhar *et al.* (2020) | 2020 | European Journal of Operational Research | method and application | research | DRSA | jMAF | the proposal uses DRSA methodology but it innovates in use measures to aggregate into a comprehensive measure the overall importance of each condition attribute | data from crowdfunding platform LWC |
| Chauvy *et al.* (2020) | 2020 | Sustainable Production and Consumption | method and application | research | LexiMin/LexiMax, Weighted Sum (WSM), AHP, ELECTRE | - | the authors use different MCDA methods to select carbon dioxide, and found that the outranking methods are more robust | - |
| Chen *et al.* (2020) | 2020 | Expert Systems with Applications | method | research | Choquet, fuzzy, interval-valued Sugeno probability space | - | the method based on Choquet integral and interval-valued Sugeno probability space supplies an interval value more elastic and easier to be accept and understood | Chung, Okudan, and Wysk (2011) and Ma et al. (2018) . |

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|---|---|---|---|---|---|---|---|---|
| Chi *et al.* (2021) | 2021 | Mathematical Problems in Engineering | method and application | research | Generalized Shapley Interval-Value Intuitionistic Uncertain Linguist Choquet Averaging (GS-IVIULCA) | MATLAB | the method uses the interval uncertainty language for evaluation reflects people's hesitation meanwhile avoids the lack of information | survey |
| Chiu *et al.* (2020) | 2020 | IEEE Systems Journal | method and application | research | Multiobjective Optimization Problem (MOP) and Weight Induced Norm (WIN) (weight induced norm) | - | the proposal of MOPs in group decision can be interpreted using geometrical or algebraic arguments, which facilitates the understanding of decision process | - |

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|---|---|---|---|---|---|---|---|---|
| Costa *et al.* (2020) | 2020 | European Journal of Operational Research | method | research | and Simos-Roy-Figueira method (SRF) | - | there is proposed a method to consider the probability relation in categorization by similarity-dissimilarity. Although it is applied with SMAA, it also can be used with ELECTRE | - |
| Couceiro *et al.* (2019) | 2019 | International Journal of Foundations of Computer Science | method | research | Sugeno integral | - | there is present a method that presents necessary and sufficient consitions for the existence of quasi- and pseudo-polinomial functions in a context of finite set of example. With this, the authors presents explicit descriptions of solutions when it exist | - |
| Csiszár *et al.* (2020) | 2020 | Knowledge-Based Systems | method | research | fuzzy operators and Multi-Criteria Decision Analysis (MCDA) operators | TensorFlow | the new is this method is to implement deep networks by combining building blocks of disjunctions and negation operator in aggregation preference | - |

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|---|---|---|---|---|---|---|---|---|
| Demirkiran *et al.* (2021) | 2021 | Journal of Intelligent and Fuzzy Systems | method | research | Rough Set and regression function | - | the method is an aggregation-function based on multi-criteria collaborative filtering. As a result it is produced a single aggregation-function for each item | data table from Dms |
| Destercke (2018) | 2018 | International Journal of Approximate Reasoning | method | research | AHP | - | there is described a generic way to handle imprecise preference information within believe function. This can be jointly use with different methods | - |
| Dias *et al.* (2021) | 2021 | Central European Journal of Operations Research | method and application | research | linear programming | XLSTAT | although the study is limited by its scope the authors presented a found that the even the Dms were inconsistent there is smalll internal error | survey |

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|---|---|---|---|---|---|---|---|---|
| Dimuro *et al.* (2020) | 2020 | Information Fusion | review | research | CI | - | There is a paper regarding to present and discuss the generalizations of Choquet Integral in decision-making. Its main contribution is implicit in view of provide material for the improvement of existing methods | - |
| Ding *et al.* (2019) | 2019 | Cluster Computing | method | research | factorization machine for multi-criteria | - | the proposal concerns a method of collaborative filtering by considering the individuals preferences of different criteria of items. The authors shown that method overcome the tradicional | TripAdvisor |

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|---|---|---|---|---|---|---|---|---|
| Du and Hu (2018) | 2018 | European Journal of Operational Research | method | research | Rough Set Theory (RST) and DRSA | - | to find reducts of DRSA there are high computational complexities for large scale systems. The method proposed of accelerator helps in computational time | Australian Credit Approval, cardiotocography, pasture production, squash harvest stored, SWD, teaching assistant evaluation, Wisconsin diagnostic and prognostic breast cancer, from UCI and WEKA |
| Egaji *et al.* (2019) | 2019 | EXPERT SYSTEMS WITH APPLICATIONS | application | private | DRSA | - | DRSA method is used to support decisions in tyre monitoring system, its use has substantial reduction in false alarms | tyre pressure |
| fallah2021 | 2021 | Expert Systems | method | research | CI | - | the study presents a technique to reduce the optimization complexity of predictive models underlying Choquet integral | ESL, ERA, LEV, MMG, CPU, CEV, BCC, car MPG, from UCI and WEKA |

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|---|---|---|---|---|---|---|---|---|
| Fancello *et al.* (2020) | 2020 | Socio-Economic Planning Sciences | method and application | research | MAVT, UTA and Capability Wise Walkability Score (CAWS) | R | the author use decision model to walkability policy concerning the citizens' preferences to aid policy maker to take better actions | individual data collected with an ad-hoc survey, and data of street network |
| Fancello and Tsoukiàs (2021) | 2021 | Socio-Economic Planning Sciences | method and application | research | GIS-MCDA, UTA+ and cluster analysis | - | there is a proposal that considers the inhabitants preferences to evaluate territorial oppportunities to designing legitimate public policies | survey study |
| Fei and Feng (2020) | 2020 | Engineering Applications of Artificial Intelligence | method and application | research | CBR, ACI, k-Nearest Neighbor (kNN) and Ordered Weighted Average (OWA) | - | the proposal is based on the DM attitudes and introduces the recent aggregation researchs into a retrieval problems in CBR such as the presented method seems superior than others | banknote, wine, iris, seeds, customers, bood, knowledge, immunotherapy, ecoli, breast cancer from UCI |

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|---|---|---|---|---|---|---|---|---|
| Fei *et al.* (2021) | 2021 | Computers and Industrial Engineering | method and application | research | Dempster-Shafer Theory | - | the method is centered in human perceptions, the authors argue the importance of the participation of DM in decision process under uncertain information | empirical data |
| Feng *et al.* (2019) | 2019 | Applied Sciences (Switzerland) | method and application | research | fuzzy and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) | - | the method fill the gap of MCDM methods which does not considers the interaction of criteria by combining Grey Comprehensive Evaluation (GCE), TOPSIS and fuzzy integral | artificial data |
| Ferretti *et al.* (2018) | 2018 | Environmental Modeling and Software | method and application | research | Simple Ranking with Multiple Points (S-RMP) | - | the use of S-RMP is tested in toy example of landfill site. The innovation is the fact of it is the first application of this method on real setting, and an advantage os the use of qualitative assessment protocols | <http://www.atorifiutitorinese.it/cms/ente/atti-e-documenti/documentitc/discarica-per-rifiuti-non-pericolosi-del-pinerolese> |

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| Figueiredo and Mota (2019) | 2019 | International Journal of Information Technology and Decision Making | method and application | research | Dominance-based Rough Set Approach and Preference Learning (DRSA-PL) | jMAF, MATLAB and ArcGIS | the proposal regards the use of preference learning of multiple DMs to direct resources to combat crime, also the method allows the update of preferences | public security data |
| Forouzandeh *et al.* (2021) | 2021 | International Journal of Information Technology and Decision Making | method and application | research | fuzzy TOPSIS and artificial bee colony algorithm | - | the method propose a recommendation of hotels to tourists based on criteria intended by users, however it innovates in prioritize the criteria selected with the use of fuzzy TOPSIS | TripAdvisor |
| Franco *et al.* (2018) | 2018 | Applied Soft Computing Journal | method | research | Weighted Overlap Dominance (WOD) operators and fuzzy intervals | algorithm LPA | the model propose the learning from imprecise data through the use of fuzzy that can be extended to fuzzy linguist structures | artificial dataset |

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|---|---|---|---|---|---|---|---|---|
| Frikha and Charfi (2018) | 2018 | International Journal of Multicriteria Decision Making | method | research | ELECTRE I and goal programming | LINDO | the authors use goal programming to determine the criteria weights that are used in ELECTRE, the advantage is to consider is to reduce the subjective of direct elicitation without eliminating the imprecision in decision process | - |
| Fu *et al.* (2021) | 2021 | Applied Soft Computing | method and application | research | Evidential Reasoning (ER) | TIRADS | the apporach is applied to diagnosis of thyreoid nodules based on considering the evidential reasoning in decision making context, and considering the MCDM for comparing and diciding what will be done when historical data is available, the result is that the approach allows a comprehensive about the problem | historical diagnosis of thyreoid nodules |

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|---|---|---|---|---|---|---|---|---|
| Gao *et al.* (2021) | 2021 | Journal of Cleaner Production | method and application | research | SMAA, ROR and CI | - | by composite index it is possible to aggregate urban bubble indices inetarctions as well as deal robust weights of urbanisation bubble indicators | Statistical Yearbook of every province in China from 2000 to 2017 |
| Guan (2019) | 2019 | Journal of Intelligent and Fuzzy Systems | method | research | DRSA, Incomplete Decision System (IODS) and Tolerance Dominance Relation (TDR) | VC++ 6.0 | the papers pesents a joint analysis of incomplete ordered decision systems with tolerance dominance relation, the result is the reduction of attributes and reduction of computational burden | Wisconsin prognostic and diagnostic breast cancer (WPBC and WDBC), wine quality-red and car evaluation from UCI |

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| Guo *et al.* (2020) | 2020 | Omega (United Kingdom) | method and application | research | text mining, data driven, LDA and CI | Python (Jieba and nltk packages) and CPLEX | the method is design to extract online information to recommender systems, the method improves the product manager in determine the relative importance criterion and criteria values by the exploration of clicked products which are preferable to non-observed ones | online review, Twitter, blogs, social network platforms |
| Guo *et al.* (2021) | 2021 | Omega (United Kingdom) | method and application | research | Neural Network-based Multiple Criteria Decision Analysis (NM-MCDA) | - | the method is novel hybrid machine learning model which combines MCDA with neural networks, as result the model presents a good balance betweeninterpretability and predictability | <https://www.topuniversities.com>, Health & Retirement Study (HRS), <https://archive.ics.uci.edu/ml/datasets/Bank+Marketing> |

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| Haag *et al.* (2019) | 2019 | Omega (United Kingdom) | method and application | public | statistical learning and MAVT | R (Rsolnp package) | the model suggest to test different models regarding indifference statements in assessing ecological state of rivers. The result is choice of a model that better represents the preferences | artificial dataset |
| Hamada and Hassan (2018) | 2018 | Informatics | method | research | neural network and PSO | - | the model shows for the first time the uso of PSO to improve the accuracy of decision, meanwhile supports the relevance of artificial neural networks for modeling preferences in MCDM problems | Yahoo!Movies |

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|---|---|---|---|---|---|---|---|---|
| Hong and Jung (2021b) | 2021 | Expert Systems with Applications | method and application | research | Multi-linear Singular Decomposition (MSVD), tensor factorization, C#R, HOSVD | Python and CARSKit | the paper is the first to use multi-criteria ratings and a cultural factor into a single model for tourism recommendation. The proposed model take into account the inter-relations of factors and can predict missing values | TripAdvisor |
| Hong and Jung (2021a) | 2021 | Journal of Ambient Intelligence and Smart Environments | method and application | research | Higher Order Singular Value Decomposition (HOSVD) | Python | the model considers the latent interrelations between multi-criteria and spatial and temporal information, and the results shows that model outperforming other techniques, and regarding the tourism recommendation the analysis shon a positive ralation of restaurants and places | TripAdvisor |

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|---|---|---|---|---|---|---|---|---|
| Hornsby and Love (2020) | 2020 | COGNITION | method and application | research | Coherency Driven Choice (CDC) | JavaScript | the method is based on the coherency maximization, where the idea is to assure the previous choices even with an update of preferences | <https://osf.io/5bvmp/> |
| Houari and Taghezout (2021) | 2021 | International Journal of Interactive Multimedia and Artificial Intelligence | method and application | private | K-mans and c-means algorithms, and PROMETHEE II | - | the method introduces the classification of similar competent experts in the same cluster k-means to apply PROMETHEE II in order to negotiating and evaluate the problem solution. The method brings improvements in terms of recall, precision, response time, and memory space compared with previous approach | empirical data |

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|---|---|---|---|---|---|---|---|---|
| Huang *et al.* (2020) | 2020 | IEEE TRANSACTIONS ON NEURAL NETWORKS AND LEARNING SYSTEMS | method and application | research | Multiattention-based Group Recommendation Model (MAGRM) | TensorFlow | the model achieves appropriate recommendations for groups take into account two steps. The first introduces the learning of semantic features, and the second uses the semantic learning to predict group decision | <https://grouplens.org/datasets/movielens/> |
| Huang *et al.* (2020a) | 2020 | Journal of Intelligent and Fuzzy Systems | method and application | research | Multicriteria Correlation Preference Information (MCPPI) | - | the method is based on non-additivity index, and its main advantage is from the easy understanding of index | - |
| Huang *et al.* (2020b) | 2020 | Mathematics | method and application | research | CI and non-additivity index | - | the method can dealing with large scale decision making problem with deeply correlative criteria | empirical data |

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|---|---|---|---|---|---|---|---|---|
| Jung *et al.* (2019) | 2019 | IEEE Transactions on Intelligent Transportation Systems | method and application | research | nbinomial regression, Spearman correlation and Wald test | - | the method uses historical decision data to learn the preferences in arriving flights sequences,the authors argue that model contributes to increasing the learning of humans strategies on aircraft sequencing problems | historical traffic data |
| Kadziński *et al.* (2018) | 2018 | European Journal of Operational Research | method and application | research | ROR, Stochastic Ordinal Regression (SOR), Monte Carlo simulation, Mixed-Integer Linear Programming (MILP) and threshold-based value-driven sorting procedure | - | the model is used to green nanosynthesis protocols. The process is based on expert preferences, then the inconsistencies are solved, and the final result is a classification of preferential constructs. The analysis present that 8 criteria were meaningful to comprehensive evaluation of the green chemistry. Also, the authors argue about the applicability for other contexts | protocols |

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|---|---|---|---|---|---|---|---|---|
| Kadziński *et al.* (2020) | 2020 | Expert Systems with Applications | method and application | research | Segment Description (SD) and UTA | - | the method is a multiple criteria ranking method which does not make use of optimization technique but the segmenting description, the authors demonstrates the use of inconsistency to generate arguments to validity of results | - |
| Kadziński *et al.* (2020a) | 2020 | European Journal of Operational Research | method and application | research | Contingent preference disaggregation model and MILP | - | the authors introduce a new approach to learning a set of contingent preference by using mathematical programming, however it is argued the mathematical programming are not suitable for big datasets | Koksalam et al. (2009) and Fontana and Cavalcante (2013) |

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|---|---|---|---|---|---|---|---|---|
| Kadziński *et al.* (2020b) | 2020 | International Journal of Approximate Reasoning | method and application | research | MILP, threshold-based value-driven sorting procedure | - | the authors propose an novel approach for multiple criteria sorting incorporating threshold-based value-driven procedure, which considers a pre-defined exact shapes of a=marginal value function and tolerate partial information | <http://trace.tennessee.edu/cgi/viewcontent.cgi?article=2413&context=utk_graddiss>. |
| Kadziński and Martyn (2021) | 2021 | Annals of Operations Research | method and application | research | ELECTRE Tri-B, Monte Carlo simulation and MILP | - | the paper presents a novelty in integrating a framework for preference and robust analysis with ELECTRE Tri-B, the model considers the mathematical programming for incorporationg indirect and imprecise preferences, and algorithm for multiple robust results | Finantial Times – 30 MBA courses |

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|---|---|---|---|---|---|---|---|---|
| Kadziński and Ciomek (2021) | 2021 | European Journal of Operational Research | method and application | research | ROR, Monte Carlo simulation, and Min-Max regret | - | the method argues to use the progressive preference elicitation for active learning and its advantage is indicated in results which presents best performing strategies questions at the current stage interaction | PMSHE (2014) |
| Kadziński *et al.* (2021) | 2021 | Knowledge-Based Systems | method and application | research | Threshold-based value-driven sorting method | JMP | the method propose the classification of an alternative in which it is not classified in more than one class, since the idea is to construct interrelated prence models | <https://doi.org/10.1016/j.knosys.2021.106879> |
| Kakula *et al.* (2021) | 2021 | IEEE Transactions on Fuzzy Systems | method | research | Fuzzy Integral Multiple KernelLearning (DeFIMKL) | MATLAB | the authors aim to specify a fuzzy measure to understand the unlearned parts in the training dataset through an extension of the DeFIMKL algorithm | in supplemental materials |

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|---|---|---|---|---|---|---|---|---|
| Karasakal and Civelek (2021) | 2021 | Journal of Multi-Criteria Decision Analysis | method and application | research | Distance-based Sorting Method (DISWOTH) | - | the authors propose a new classification method based on distances and uses cluster principles as a reference | Lens, R&D projects, Teaching Assistant, Credit and Car datasets from UCI and Fernandez et al. (2009) |
| Kaynar2018 | 2018 | Omega (United Kingdom) | method and application | research | UTA, convex cone method and OWA | MATLAB and CPLEX | the authors use an approach that leads to the selection of an alternative through the value function | - |
| Ke *et al.* (2021) | 2021 | Applied Soft Computing | method and application | research | DirectRec | - | given the limitations of collaboration systems, the authors present a methodology focused on the use of social networks, behavior of individuals and networks of friends in social media. Authors capture preferences and use reinforcement learning | Sina Weibo and taobao |

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|---|---|---|---|---|---|---|---|---|
| Kuppelwieser *et al.* (2020) | 2020 | Annals of Operations Research | method and application | research | additive weighted sum and CI | - | In the context of the market, using traditional methods is not feasible in the sense that the selection criteria are generally interrelated, in this sense the authors apply 3 models, a simple additive model, a stable fuzzy model and an unstable one, in this way the authors show better adequacy of the latter that was developed by them | <http://usnews.rankingsandreviews.com/cars-trucks/rankings/Affordable-Midsize-Cars>/ |
| Lang *et al.* (2018) | 2018 | Artificial Intelligence | method and application | research | decision tree | MAXSAT solver | the authors use the lexicographical method to find individual preferences | - |

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|---|---|---|---|---|---|---|---|---|
| Li and Wang (2019) | 2019 | International Journal of Innovative Computing, Information and Control | method and application | research | decision tree and CP-nets | - | the authors create a method for "mining" preference rules to find conditional dependencies between attributes based on CP-nets and decision trees, which is called PRT. Where each node in the tree is associated with a Conditional Preference Table (CPT) (conditional preference table) | artificial dataset and SUSHI dataset |
| Li *et al.* (2020) | 2020 | Information Sciences | method and application | research | Evolutive Preference Analysis (EPA), Numerical Preference Relations (NPR) and Stochastic Preference Analysis (SPA) | - | the authors develop an EPA considering the evaluation over time so that it is possible to delineate a trend evolution according to the evaluations of product preferences | Data from Zol (recommendation platforms for digital products in China) |

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|---|---|---|---|---|---|---|---|---|
| Li *et al.* (2021) | 2021 | IEEE Transactions on Signal Processing | method and application | research | , Prima++ and kNN | Python (scikit-learn package) | the authors propose a probabilistic model of preference learning, in order to learn the individual preferences of the decision maker. | eBay and survey |
| Liao *et al.* (2020) | 2020 | Information Fusion | method and application | research | CI and Multiple Criteria Group Decision Making (MCGDM) | - | the authors propose the use of a tool that considers the decision-maker's attitudes in group decision-making in such a way that the gains and losses resulting from the decision-making process are evaluated, considering the flow of dominance over the experts' hesitations | Wang and Xu (2016) |

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|---|---|---|---|---|---|---|---|---|
| Silva *et al.* (2020) | 2020 | Expert Systems with Applications | method and application | research | Preference Disaggregation on Technique for Order of Preference by Similarity to Ideal Solution - Sort (PDTOPSIS-Sort) | - | the authors suggest an adaptation of the TOPSIS model for ordering debentures from the perspective of holistic assessment of preferences | Bovespa |
| Liu *et al.* (2018) | 2018 | European Journal of Operational Research | method and application | research | Multiple Criteria Sorting (MCS) and PL | CPLEX and JAVA | the authors present a preference disaggregation methodology that considers the analysis of an unbalanced set of reference alternatives | DBS, CPU, BCC, MPG, ESL, MMG, ERA, LEV and CEV, from UCI and WEKA |

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|---|---|---|---|---|---|---|---|---|
| Liu and Truszczynski (2019) | 2019 | Annals of Mathematics and Artificial Intelligence | method and application | research | CI, CP-trees and PLP-trees | toulbar2 | the authors propose an extension to the PMR method for obtaining preferences that comes up against two problems: 1. the model does not provide an order and; 2. Complexity in doing dominance tests, to work around the problem the authors use voting rules to aggregate PLP-trees forests | BCW, CE, CA, GC, IN, MM, MS, NS, SH, TTT, VH, WN, from UCI |
| Liu *et al.* (2019) | 2019 | European Journal of Operational Research | method and application | public | SVM | LIBSVM, LIBLINEAR, Python (scikit-learn package) and e1071 | the authors seek to develop a preference disaggregation method that presents a good fit for predictions of alternatives that are not references, in such a way that overfitting is avoided through regularization techniques | BCUR 2018 |

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|---|---|---|---|---|---|---|---|---|
| Liu *et al.* (2020) | 2020 | European Journal of Operational Research | method and application | research | Alternating Direction Method of Multipliers (ADMM) | Python (CVXPY package) | the authors seek, through the model, to work with an approach that considers the classification of an alternative in more than one class, for this they use different types of value function and regularization method, using ML concepts for large-scale problems | QS World Universities Rankins |
| Liu *et al.* (2021b) | 2021 | Knowledge-Based Systems | method and application | research | Neural networks, Pair-wise Ranking-based Preference Learning (PRBPL), Gradient Descent | Google's word2vec | the authors seek to learn from the preferences of users of local sharing networks through POI in the perspective of similarity and distance between them. The authors use semantic evaluation, which according to them ends up being neglected in this type of analysis. | Foursquare and Weeplaces |

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|---|---|---|---|---|---|---|---|---|
| Liu *et al.* (2021a) | 2021 | Informs Journal on Computing | method and application | research | additive piecewise-value function | Lingo, CPLEX and MATLAB | the authors present the literature to differ preference learning between the areas of ML and MCDA, and develop a new methodology for learning preferences based on the history of preferences through an additive model, so that the created model not only has a good predictive capability as well as being interpretable. The model considers the possibility of interaction between the criteria. The model also does not account for direct DM interaction. | DBS, CPU, BCC, MPG, ESL, MMG, ERA, LEV, CEV, from UCI and WEKA |

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|---|---|---|---|---|---|---|---|---|
| Luo *et al.* (2018) | 2018 | Information Sciences | method | research | DRSA | JAVA – Eclipse Kepler | the authors are concerned with developing a decision model based on rules, paying attention to the hierarchical evaluation in the sense of updating the rough approximations through algorithms | User knowledge modeling, car evaluation and turkiye student evaluation, from UCI |
| Madhooshiarzanagh and Abi-Zeid (2021) | 2021 | Journal of Multi-Criteria Decision Analysis | method and application | research | ELECTRE Tri-nC | CPLEX, MCDA-Ulaval | The authors develop a preference disaggregation method for learning the criteria weights and credibility of the Electre TRI-nC thresholds without considering the vetoes for the climate assessment of potential tourism sites | CRU CL 1.0 climate database, from New et al. (1999) |

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|---|---|---|---|---|---|---|---|---|
| Meyer and Olteanu (2019) | 2019 | Computers and Operations Research | method | research | ELECTRE Tri - Majority Rule Sorting (MR-Sort) | - | the authors propose an extension of MR-Sort to consider inaccuracies within the model based on the proposition of evaluating the alternatives in two versions: optimistic evaluation of the minimum and maximum criteria. The model also uses meta heuristics with an adaptation of the annealing algorithm | artificial dataset |
| Montazery and Wilson (2021) | 2021 | International Journal of Approximate Reasoning | method and application | research | maximum margin preference relation | CPLEX | the authors seek to adapt SVM to perform an analysis with maximum preference margins in order to propose a robust modeling for the assessment of preferences | ridesharing and car preference databases |

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|---|---|---|---|---|---|---|---|---|
| Nguyen *et al.* (2020) | 2020 | Knowledge-Based Systems | method and application | research | OWA and clusters | - | the authors use the clustering technique to group consumers with similar profiles to propose a ranking relationship between restaurants | Yelp and AirBnb |

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|---|---|---|---|---|---|---|---|---|
| Nilashi *et al.* (2021) | 2021 | Expert Systems with Applications | method and application | research | EM, HOSVDHigh-Order Singular-Value Decomposition, ANFIS, and entropy-weight | - | the authors seek to use supervised and unsupervised learning the objective to verify whether the learning of forecasting strategies are useful in assessing user preferences and the priorities pursued in eco-hotels. In summary, clusters are used to aggregate users with similar profiles, the multi-criteria approach is used for the selection of important criteria, while the prediction of decision makers' preferences is obtained through the adaptive neuro-fuzzy inference system | TripAdvisor |

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|---|---|---|---|---|---|---|---|---|
| Nilashi *et al.* (2019) | 2019 | Computers and Industrial Engineering | method and application | research | Decision Making Trial and Evaluation Laboratory (DEMATEL) and fuzzy-TOPSIS | - | through the combined use of DEMATEL and fuzzy TOPSIS, the authors seek to find criteria that determine success in hospital tourism, focusing on hotels | hotels' managers |
| Nilashi *et al.* (2019b) | 2019 | Sustainability (Switzerland) | method and application | research | SOM, LDA, TOPSIS and neuro-fuzzy | - | the authors combine machine learning techniques with a mcda model for word mining and subsequent construction of ranking criteria for green hotel evaluation and predictions | TripAdvisor |
| Nilashi *et al.* (2019a) | 2019 | Journal of Cleaner Production | method and application | research | SOM, ANFIS, HOSVD and decision trees | - | the authors seek to identify the evaluations of green hotels for the construction of a forecasting model, through the analysis of big data using machine learning techniques | TripAdvisor |

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|---|---|---|---|---|---|---|---|---|
| Olgun *et al.* (2021) | 2021 | Neutrosophic Sets and Systems | method and application | research | 2-additive Choquet | - | the authors seek to use the method to identify the illness of patients based on the symptoms presented and based on historical data | - |
| Oliveira and Dias (2020) | 2020 | Annals of Operations Research | method and application | research | Cojoint Analysis (CA) and Multiattribute Utility Theory (MAUT) | SawTooth | the authors analyze the gains of the elicitation process through CA and MCDA in relation to the stated preference elicitation methods that use only one methodology, usually the one of choice | Survey |
| Pelegrina *et al.* (2020) | 2020 | European Journal of Operational Research | method and application | research | 2-additive capacity (Choquet) | - | the authors seek to formulate a decision model based on the multilinear 2-additive capacity, according to the authors little explored in the context of the interrelationships between the criteria | Raufaste et al. 2001 |

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|---|---|---|---|---|---|---|---|---|
| Pereira *et al.* (2020) | 2020 | European Journal of Operational Research | method and application | research | Preference Information Incorporation Using the Choquet Integral in DEA method (Pric-DEA) and Choquet | MATLAB, CPLEX and DecSpace | the authors use the DEA and Choquet to incorporate preferences in the decision model, considering the interaction between the criteria | <http://benchmarking.acss.min-saude.pt>/ |
| Peters *et al.* (2018) | 2018 | Machine Learning | method | research | Baysian model and Gaussian Process Scalable Preference Model via Kronecker Factorization (GasPK) | Amazon Mechanical Turk | authors develop a gaussine-based model for learning user preferences for autonomous decision making – fully computational, uses preference inputs from human decision makers to automate preferences | Abbasnejad et al. (2013) and Houlsby et al. (2012) |

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|---|---|---|---|---|---|---|---|---|
| Petrović *et al.* (2018) | 2018 | Omega (United Kingdom) | method and application | research | ElECTRE MLO | - | through preference modeling, the author intends, through indirect elicitation of preferences, to evaluate benchmarking perceptions using Electre for this, since, unlike the usual application of DEA, the model does not have data and indicator restrictions | DESI |
| Prathama *et al.* (2021) | 2021 | Computers and Industrial Engineering | method and application | research | MCF | - | the authors, through implicit user feedback, transform the data into explicit data, since such an action contributes to the improvement of the model. | Wu et al. (2016) and Birlutiu et al. (2010) |

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|---|---|---|---|---|---|---|---|---|
| Ren *et al.* (2021) | 2021 | Information Sciences | method and application | research | robust optimization and NPR | GEPHI | the authors present an approach for social network users to understand consumption preferences efficiently. The authors use consumer evaluation data and network connection information to work with group decision making. | FilmTrust |
| Sá *et al.* (2018) | 2018 | Information Fusion | method and application | research | Pairwise Association Rules (PAR) and Label Ranking Association Rules (LRAR) | CAREN | the authors explore the use of LRAR and present a new model of rules called PAR, treating them as complementary in the analysis of real data | Bodyfat, calhousing, Cpu-small, elevators, fried, glass, housing, isis, segment, stock, vehicle, vowel,wine, Winconsis, algae and sushi |

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|---|---|---|---|---|---|---|---|---|
| Salehi-Abari *et al.* (2019) | 2019 | Artificial Intelligence | method and application | research | weighted preference aggregation, empathetic social choice framework | algorithms ICE and WICE | the authors insert the concept of empathy in social networks to evaluate group decisions, in general lines the authors create a framework entitled empathetic social choice framework where agents derive their utilities based on their personal preferences and preferences for which they have empathy | 2002 Irish General Election |
| Sheeba and Krishnan (2019) | 2019 | International Journal of Innovative Technology and Exploring Engineering | method and application | research | fuzzy | - | the authors develop a model to evaluate the profile of students on online teaching platforms in order to help their teaching, since the systems do not differentiate between users. The model performs is based on semantics and uses fuzzy concepts | Moodle Learning Management System |

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|---|---|---|---|---|---|---|---|---|
| Sobrie *et al.* (2018) | 2018 | European Journal of Operational Research | method and application | research | UTA-poly and UTA-splines | MATLAB | the authors propose an approximation of the marginal function by polynomial function and splines instead of the piecewise function | artificial dataset |
| Sobrie *et al.* (2019) | 2019 | International Transactions in Operational Research | method and application | research | MR-Sort | CPLEX | the authors propose the use of MR-SORT to deal with a large number of attributes, for that the authors create an algorithm to learn all the parameters of the model | <http://www.github.com/oso/pymcda> |
| Tan *et al.* (2020) | 2020 | Expert Systems with Applications | method and application | research | Ruleset Aggregation Algorithm (RSA) | algorithm RSA | the authors propose a recommendation system based on the user's context | MovieLens |

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|---|---|---|---|---|---|---|---|---|
| Tian *et al.* (2021) | 2021 | IEEE Transactions on Systems, Man, and Cybernetics: Systems | method and application | research | FGCI and ITLBO | - | the authors develop a new approach to support decision-making that considers the use of the gray and Choquet integral techniques to deal with the relationships between criteria as well as deal with any uncertainties | models of air conditioning |
| Tomczyk and Kadziński (2019) | 2019 | Computers and Operations Research | method and application | research | Evolutionary Multiple Objective Optimization Guided by Interactive Stochastic Ordinal Regression (EMOSOR) and Monte Carlo simulation | algorithm EMOSOR | the authors use evolutionary algorithm together with ordinal regression in order to obtain the classification of criteria evaluated by the decision maker | - |

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|---|---|---|---|---|---|---|---|---|
| Tomczyk and Kadziński (2021) | 2021 | Information Sciences | method and application | research | Co-Evolutionary Algorithm for Interactive Multiple Objective Optimization (CIEMO/D) | - | The authors, through CIEMO/D, seek to use more than one preference model in the optimization process | <https://doi.org/10.1016/j.ins.2020.11.030.> |
| Tsopra *et al.* (2018) | 2018 | Artificial Intelligence in Medicine | method and application | research | Artifitial Feeding Birds (AFB) and metaheuristics | Python and PyPy | the authors use the AFB for learning in the medication recommendation process. According to the authors, the manual construction of the learning process is a complex task, while data learning is faster and more targeted considering the availability of data, which does not exactly apply to the elicitation methods that can result in different conclusions. | <https://doi.org/10.1016/j.artmed.2018.04.013> |

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| Tsopra *et al.* (2019) | 2019 | Journal of the American Medical Informatics Association | application | research | AntibioHelp | - | the authors used the 2018 study that was also part of the systematic analysis and created a software, which showed better performance than the non-use of the created system | - |
| Wang *et al.* (2020) | 2021 | Patterns | method and application | research | Global and Local Tensor Factorization (GLTF) | - | the authors present a new approach of recommender systems based on the three-dimensional factorization matrix to deal with specific evaluations | TripAdvisor, Yahoo!Movies, RateBeer |

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|---|---|---|---|---|---|---|---|---|
| Wasid and Ali (2021) | 2021 | Applied Soft Computing | method and application | research | CF, Common Rating Weight Similarity (CRS),PSO | - | the authors develop a multi-criteria recommendation system using similarity rates to group similar users and use the PSO to learn the real preferences of decision makers, for that purpose it calculates the appropriate weights for the criteria in such a way that recommendations can be made and appropriate predictions. | Yahoo!Movies |

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|---|---|---|---|---|---|---|---|---|
| Wu *et al.* (2019a) | 2019 | Information (Switzerland) | method and application | research | Multiple Goal Linear Programming (MGLP)-based inconsistency recognition, orness of capacity, Shapley interaction index, Choquet integral | R (LpSolve package) | the authors, through the MGLP, seek to create a method capable of considering a model adjusted to inaccuracies, so that the proposed GLP can help the decision maker to recognize inconsistent and redundant restrictions and to later suggest adjustment strategies | empirical data |

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|---|---|---|---|---|---|---|---|---|
| Wu and Beliakov (2019) | 2019 | International Journal of Intelligent Systems | method and application | research | NAROR and multiple goal linear programming | - | the authors develop a methodology that consists of applying the calculation of capabilities in NAROR and dealing with inconsistencies of preferences through MGLP to minimize deviation variables. Unlike the additive approach, the authors use the non-additivity index defined by them in another work | cars example |
| Wu *et al.* (2019b) | 2019 | Mathematics | method and application | research | MCCPI and CI | - | the authors seek to develop a model whose idea is to evaluate the interaction between more than 2 criteria | car example |

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|---|---|---|---|---|---|---|---|---|
| Wu and Liao (2021) | 2021 | Or Spectrum | method and application | research | mathematical programming | Stanford NLP and Python | the authors develop a group decision method considering the evaluation of feelings through a preference learning approach, as well as the analysis of the ranking of alternatives. The authors found that the ratings given by people who use a service may indicate that their maximum star rating does not mean they are really satisfied with the products or services purchased. | TripAdvisor |

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|---|---|---|---|---|---|---|---|---|
| Xia *et al.* (2018) | 2018 | International Journal of Information Technology and Decision Making | method | research | CI and regret theory | Lingo and MATLAB | unlike the use of the Choquet integral for the analysis of interactions between criteria, the authors seek to understand the interactions of uncertainty in the weights and evaluation of the criteria. In addition, the authors seek to unravel the worst alternatives | empirical data |
| Yao *et al.* (2018) | 2018 | Knowledge-Based Systems | method and application | research | Measuring Attractiveness by a Categorical Based Evaluation Technique (MACBETH) and CI | MATLAB | the authors aim to reduce the gap between theory and practice in the use of tolerance constraints, through application in a financial context and a classic student assessment problem | WIND database |

# APPENDIX B – VARIABLES USED IN FACTOR ANALYSIS

| Areas | Code | Data description |
|---|---|---|
| Housing | MHAB18 | Registration or survey of families interested in housing programs - existence |
| | MHAB191 | Favelas, shacks, stilt houses or similar |
| | MHAB192 | Tenements, rooming houses or pig-heads |
| | MHAB193 | Irregular and/or clandestine subdivisions |
| | MHAB194 | Occupations of land or buildings by housing movements |
| | MHAB201 | Construction of housing units |
| | MHAB202 | Acquisition of housing units |
| | MHAB203 | Improvement of housing units |
| | MHAB204 | Supply of construction material |
| | MHAB205 | Lots offer |
| | MHAB206 | Land regularization |
| | MHAB207 | Urbanization of settlements |
| | MHAB21 | Does the city hall have a program that grants the benefit of social rent |
| Transport | MTRA081 | The city's road circulation and transport policy |
| | MTRA082 | The structure and form of organization of the passenger transport system, as well as its basic operating rules |
| | MTRA083 | The tariff policy |
| | MTRA084 | The structure, form of organization and rules for using public road space |
| | MTRA085 | Pedestrian and cyclist use of public road space |
| | MTRA086 | The inclusion of people with disabilities in the road network and transport system |
| | MTRA181 | Transport service: Boat |
| | MTRA182 | Transport service: Subway |
| | MTRA183 | Transport service: Bike taxi |
| | MTRA184 | Transport service: Taxi |
| | MTRA185 | Transport service: Train |
| | MTRA186 | Transport service: Van |
| | MTRA187 | Transport service: Plane |

| | | |
|---|---|---|
| | MTRA188 | Service by application (Uber, Cabify, and others) |
| | MTRA19 | Collective transport by intracity bus |
| | MTRA21 | Fleet of municipal buses adapted for people with disabilities or reduced mobility |
| | MTRA23 | Public transport by intercity bus |
| | MTRA24 | Bike path in the municipality |
| | MTRA25 | Bicycle rack in the municipality |
| Agriculture | MAGR131 | Facilitated access to seeds |
| | MAGR132 | Facilitated access to seedlings |
| | MAGR133 | Facilitated access to fertilizers |
| | MAGR134 | Facilitated access to feed or fodder |
| | MAGR135 | Facilitated access to fingerlings |
| | MAGR136 | Facilitated access other inputs |
| | MAGR141 | Machinery available: free temporary assignment |
| | MAGR142 | Machinery available:rent |
| | MAGR143 | Machinery available:other |
| | MAGR151 | Program of organic agriculture |
| | MAGR152 | Program of family farming |
| | MAGR153 | Program of aquaculture |
| | MAGR154 | Program of fishing |
| | MAGR155 | Production of community gardens |
| | MAGR16 | The city hall develops a program or action to stimulate the agroindustry |
| | MAGR18 | The city hall develops a program or action to prevent climate problems for the agricultural sector |
| | MAGR191 | Municipal technical assistance |
| | MAGR192 | State technical assistance |
| | MAGR193 | Federal technical assistance |
| | MAGR211 | Private company technical assistance |
| | MAGR22111 | City hall develops a program of education |
| | MAGR22112 | City hall develops a program of health or hygiene |
| | MAGR22113 | City hall develops a program of food distribution |
| | MAGR22114 | City hall develops other programs |

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|---|---|---|
| | MAGR222 | City hall develops a program to promote crafts in rural communities |
| | MAGR261 | Program for acquisition of agricultural products from producers |
| | MAGR262 | Program for acquisition of agricultural products through associations |
| | MAGR263 | Family farming food acquisition program |
| | MAGR264 | Other program for acquisition of agricultural products |
| | MAGR271 | Program of access free vaccination of herds |
| | MAGR272 | Program of access to cheaper or funded vaccines for herd |
| | MAGR273 | Other program for herd vaccination |
| Environment | MMAM201 | Legislation on selective collection of domestic wast |
| | MMAM202 | Legislation about basic sanitation |
| | MMAM203 | Legislation about watershed management |
| | MMAM204 | Legislation about environmental protection |
| | MMAM205 | Legislation on the destination of pesticide products |
| | MMAM206 | Legislation about air pollution |
| | MMAM207 | Legislation about mineral extractive activities |
| | MMAM208 | Legislation about wildlife |
| | MMAM209 | Legislation about forests |
| | MMAM2010 | Legislation on protecting biodiversity |
| | MMAM2011 | Legislation on climate change adaptation and mitigation |
| | MMAM21 | Municipality has an integrated solid wast management plan |
| | MMAM229 | Environmental programs in partnership with Federal Government |
| | MMAM261 | Extreme weather conditions |
| | MMAM262 | Air pollution |
| | MMAM263 | Pollution of a body of water |
| | MMAM264 | Siltation of a body of water |
| | MMAM265 | Decreased flow of some body of water |
| | MMAM266 | Deforestation |
| | MMAM267 | Fires |
| | MMAM268 | Soil contamination (by pesticides, fertilizers) |
| | MMAM269 | Loss of soil due to erosion and/or desertification (gullies, sanding) |
| | MMAM2610 | Degradation of legally protected areas |
| | MMAM2611 | Decreased biodiversity (fauna and flora) |

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| | MMAM2612 | Existence of housing in a situation of environmental risk |
| | MMAM2613 | Lack of sanitation (inadequate disposal of domestic sewage) |
| | MMAM2614 | Others environmental impact |
| Risk and disasters management | MGRD01 | The municipality has been suffered by drought for the last 4 years |
| | MGRD041 | Action to reduce damage caused by drought: construction of cisterns |
| | MGRD042 | Action to reduce damage caused by drought: construction of weir |
| | MGRD043 | Action to reduce damage caused by drought: construction of dams |
| | MGRD044 | Action to reduce damage caused by drought: construction of water wells |
| | MGRD045 | Action to reduce damage caused by drought: re-vegetation |
| | MGRD046 | Action to reduce damage caused by drought: public incentives for agriculture adapted to the region's climate and soil |
| | MGRD047 | Action to reduce damage caused by drought: regular distribution of water through tank trucks in times of drought (emergency situations) |
| | MGRD048 | Action to reduce damage caused by drought: sustainable use of natural resources (wind or solar energy sources, basin plans, and awareness programs, etc.) |
| | MGRD049 | Action to reduce damage caused by drought: others |
| | MGRD05 | Actions for the sustainable use of natural resources (wind or solar energy sources, basin plans, awareness and awareness programs, etc.) |
| | MGRD06 | The municipality has been hit by floods in the last 4 years |
| | MGRD07 | The municipality has been affected by an accelerated erosion process in the last 4 years |
| | MGRD08 | The municipality has been affected by flooding or gradual flooding in the last 4 years |
| | MGRD10511 | Actions to avoid or mitigate damages caused by floods |
| | MGRD11 | The municipality has been hit by flash floods or flash floods in the last 4 years |
| | MGRD14 | The municipality has been affected by landslides or landslides in the last 4 years |
| | MGRD181 | Regarding to floods: mapping of flood risk areas |

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| | MGRD182 | Regrading to floods: housing program for relocating the low-income population in a risk area (resettlement in a social housing project, payment of social rent or similar, compensation for improvements, purchase of a new home, aid |
| | MGRD183 | Regrading to floods: control and inspection mechanisms to avoid occupation in areas susceptible to disasters |
| | MGRD184 | Regrading to floods: contingency plan |
| | MGRD185 | Regrading to floods: engineering projects related to the event |
| | MGRD186 | Regrading to floods: disaster early warning system |
| | MGRD187 | Regrading to floods: risk register |
| | MGRD19 | Regarding the risk management of disasters arising from floods or gradual flooding, or flash floods or flash floods, the municipality carries out periodic cleaning of the city's culverts, especially before the rainy season |
| | MGRD201 | Regarding to landslide: mapping of flood risk areas |
| | MGRD202 | Regarding to landslide: housing program for relocating the low-income population in a risk area (resettlement in a social housing project, payment of social rent or similar, compensation for improvements, purchase of a new home, aid |
| | MGRD203 | Regarding to landslide: control and inspection mechanisms to avoid occupation in areas susceptible to disasters |
| | MGRD204 | Regarding to landslide: contingency plan |
| | MGRD205 | Regarding to landslide: engineering projects related to the event |
| | MGRD206 | Regarding to landslide: disaster early warning system |
| | MGRD207 | Regarding to landslide: risk register |
| | MGRD211 | Fire Brigade Unit |
| | MGRD212 | Municipal Coordination of Protection and Civil Defense (COMPDEC) or similar body |
| | MGRD213 | Civil Defense Nucleus (NUDECs) |
| | MGRD214 | Municipal guard |

## APPENDIX C – RANKING OF SPATIAL CONNECTIVITY

| | Index of connectivity | |
|---|---|---|
| # Ranking | # W[g(a)] | # C(a) |
| 1 | Caruaru | Caruaru |
| 2 | Arcoverde | Cabo de Santo Agostinho |
| 3 | Riacho das Almas | Jaboatão dos Guararapes |
| 4 | Belo Jardim | Recife |
| 5 | Jaboatão dos Guararapes | Petrolina |
| 6 | Pedra | Riacho das Almas |
| 7 | Cabo de Santo Agostinho | Camaragibe |
| 8 | Orobó | Abreu e Lima |
| 9 | Poção | Serra Talhada |
| 10 | Garanhuns | Igarassu |
| 11 | Abreu e Lima | Bezerros |
| 12 | Floresta | Tacaimbó |
| 13 | Bezerros | Paulista |
| 14 | Igarassu | Brejo da Madre de Deus |
| 15 | Camaragibe | Belo Jardim |
| 16 | Petrolina | São Caitano |
| 17 | Ipubi | Olinda |
| 18 | Pesqueira | Floresta |
| 19 | Tacaimbó | Altinho |
| 20 | Surubim | São Lourenço da Mata |
| 21 | Sertânia | Paudalho |
| 22 | Vitória de Santo Antão | Vitória de Santo Antão |
| 23 | Gravatá | Moreno |
| 24 | Carpina | Agrestina |
| 25 | Custódia | Triunfo |
| 26 | Goiana | São Joaquim do Monte |
| 27 | Serrita | Escada |
| 28 | Brejo da Madre de Deus | Mirandiba |
| 29 | Santa Filomena | Sairé |
| 30 | Recife | Cumaru |

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|---|---|---|
| 31 | São Vicente Férrer | Glória do Goitá |
| 32 | Serra Talhada | Ipojuca |
| 33 | Limoeiro | São José do Belmonte |
| 34 | Saloá | Flores |
| 35 | Passira | Itapissuma |
| 36 | Ibimirim | Ilha de Itamaracá |
| 37 | Nazaré da Mata | Cupira |
| 38 | Palmeirina | Bonito |
| 39 | Buíque | Panelas |
| 40 | Olinda | Cachoeirinha |
| 41 | São Caitano | Carpina |
| 42 | Timbaúba | Goiana |
| 43 | Tamandaré | Calumbi |
| 44 | Cachoeirinha | Taquaritinga do Norte |
| 45 | Palmares | Araçoiaba |
| 46 | Escada | Carnaubeira da Penha |
| 47 | Paulista | Camocim de São Félix |
| 48 | Araripina | Betânia |
| 49 | Triunfo | Santa Cruz da Baixa Verde |
| 50 | Caetés | Barra de Guabiraba |
| 51 | Belém do São Francisco | Sirinhaém |
| 52 | Sirinhaém | Surubim |
| 53 | Taquaritinga do Norte | Gravatá |
| 54 | Cabrobó | Vertentes |
| 55 | Jataúba | Ibirajuba |
| 56 | Sanharó | Lagoa dos Gatos |
| 57 | Petrolândia | Frei Miguelinho |
| 58 | Afogados da Ingazeira | Toritama |
| 59 | Bom Conselho | Passira |
| 60 | Itacuruba | Belém de Maria |
| 61 | São José do Egito | Chã de Alegria |
| 62 | Barreiros | Tracunhaém |
| 63 | Parnamirim | Arcoverde |
| 64 | Paudalho | Pesqueira |

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|---|---|---|
| 65 | Ribeirão | Pedra |
| 66 | Rio Formoso | São Bento do Una |
| 67 | Sairé | Lagoa de Itaenga |
| 68 | Glória do Goitá | Pombos |
| 69 | Águas Belas | Palmares |
| 70 | Mirandiba | Lagoa do Carro |
| 71 | Carnaubeira da Penha | Lajedo |
| 72 | Cumaru | Catende |
| 73 | Vicência | Feira Nova |
| 74 | Altinho | Itaquitinga |
| 75 | Catende | Garanhuns |
| 76 | Água Preta | Sertânia |
| 77 | Iguaracy | Santa Maria do Cambucá |
| 78 | Primavera | Poção |
| 79 | Toritama | Amaraji |
| 80 | Santa Cruz | Jurema |
| 81 | Trindade | Cortês |
| 82 | Bodocó | Buíque |
| 83 | São Bento do Una | Serrita |
| 84 | Itapissuma | Araripina |
| 85 | São Lourenço da Mata | Caetés |
| 86 | Lajedo | Santa Cruz do Capibaribe |
| 87 | Exu | Sanharó |
| 88 | Ilha de Itamaracá | Ipubi |
| 89 | Aliança | Capoeiras |
| 90 | Canhotinho | Venturosa |
| 91 | Tracunhaém | Jataúba |
| 92 | Venturosa | Saloá |
| 93 | Flores | Alagoinha |
| 94 | Tacaratu | Palmeirina |
| 95 | São José do Belmonte | São João |
| 96 | Chã Grande | Salgueiro |
| 97 | São Joaquim do Monte | Canhotinho |
| 98 | Inajá | Jupi |

| | | |
|---|---|---|
| 99 | Jatobá | Cabrobó |
| 100 | São João | Jucati |
| 101 | Angelim | Parnamirim |
| 102 | Santa Maria do Cambucá | Paranatama |
| 103 | Barra de Guabiraba | Ibimirim |
| 104 | Cupira | Terra Nova |
| 105 | Capoeiras | Trindade |
| 106 | Bonito | Angelim |
| 107 | Carnaíba | Verdejante |
| 108 | Lagoa Grande | Orobó |
| 109 | Moreilândia | Belém do São Francisco |
| 110 | Santa Maria da Boa Vista | Brejão |
| 111 | Itaíba | Calçado |
| 112 | João Alfredo | Bom Conselho |
| 113 | Tabira | Tupanatinga |
| 114 | Amaraji | Correntes |
| 115 | Bom Jardim | Lagoa do Ouro |
| 116 | Gameleira | Custódia |
| 117 | Quipapá | Santa Filomena |
| 118 | Paranatama | São Vicente Férrer |
| 119 | Macaparana | Limoeiro |
| 120 | Lagoa de Itaenga | Quipapá |
| 121 | Iati | Nazaré da Mata |
| 122 | Pombos | Águas Belas |
| 123 | Orocó | Terezinha |
| 124 | Vertentes | Timbaúba |
| 125 | Correntes | Tamandaré |
| 126 | São Benedito do Sul | Ouricuri |
| 127 | Moreno | Bodocó |
| 128 | Cortês | Cedro |
| 129 | Salgadinho | Petrolândia |
| 130 | Itambé | Afogados da Ingazeira |
| 131 | Joaquim Nabuco | Itacuruba |
| 132 | Panelas | São José do Egito |

| | | |
|---|---|---|
| 133 | Buenos Aires | Barreiros |
| 134 | Ibirajuba | Itaíba |
| 135 | Agrestina | Ribeirão |
| 136 | Lagoa dos Gatos | Rio Formoso |
| 137 | Frei Miguelinho | Vicência |
| 138 | Lagoa do Carro | Iati |
| 139 | Terra Nova | Água Preta |
| 140 | Camocim de São Félix | Iguaracy |
| 141 | Ingazeira | Primavera |
| 142 | Jurema | Santa Cruz |
| 143 | Salgueiro | Exu |
| 144 | Lagoa do Ouro | Aliança |
| 145 | Itapetim | Tacaratu |
| 146 | Araçoiaba | Chã Grande |
| 147 | Calçado | Inajá |
| 148 | Jupi | Jatobá |
| 149 | Maraial | Carnaíba |
| 150 | Condado | Lagoa Grande |
| 151 | Calumbi | Moreilândia |
| 152 | Ferreiros | Santa Maria da Boa Vista |
| 153 | Alagoinha | João Alfredo |
| 154 | Jaqueira | Tabira |
| 155 | Camutanga | Bom Jardim |
| 156 | Ouricuri | Gameleira |
| 157 | Belém de Maria | Macaparana |
| 158 | Brejão | Orocó |
| 159 | Xexéu | São Benedito do Sul |
| 160 | Santa Cruz da Baixa Verde | Salgadinho |
| 161 | Cedro | Itambé |
| 162 | Jucati | Joaquim Nabuco |
| 163 | Feira Nova | Buenos Aires |
| 164 | Manari | Ingazeira |
| 165 | Verdejante | Itapetim |
| 166 | Dormentes | Maraial |

| | | |
|---|---|---|
| 167 | Itaquitinga | Condado |
| 168 | Quixaba | Ferreiros |
| 169 | Vertente do Lério | Jaqueira |
| 170 | Granito | Camutanga |
| 171 | Ipojuca | Xexéu |
| 172 | Afrânio | Manari |
| 173 | Tupanatinga | Dormentes |
| 174 | Betânia | Quixaba |
| 175 | São José da Coroa Grande | Vertente do Lério |
| 176 | Santa Cruz do Capibaribe | Granito |
| 177 | Casinhas | Afrânio |
| 178 | Chã de Alegria | São José da Coroa Grande |
| 179 | Santa Terezinha | Casinhas |
| 180 | Solidão | Santa Terezinha |
| 181 | Tuparetama | Solidão |
| 182 | Terezinha | Tuparetama |
| 183 | Machados | Machados |
| 184 | Brejinho | Brejinho |