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# A MULTICRITERIA PRIORITIZATION MODEL TO SUPPORT PUBLIC SAFETY PLANNING

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**ABSTRACT.** Setting out to solve operational problems is a frequent part of decision making on public safety. However, the pillars of tactics and strategy are normally disregarded. Thus, this paper focuses on a strategic issue, namely that of a city prioritizing areasin which there is a degree of occurrences for criminality to increase. A multiple criteria approach is taken. The reason for this is that such a situation is normally analyzed from the perspective of the degree of police occurrences. The proposed model is based on a SMARTS multicriteria method and was applied in a Brazilian City. It combines a multicriteria method and a Monte Carlo Simulation to support an analysis of robustness. As a result, we highlight some differences between the model developed and police occurrences model. It might support differentiated policies for zones, by indicating where there should be strong actions, infrastructure investments, monitoring procedures and others public safety policies.

**Keywords**: public safety, prioritization, SMARTS.

## 1 INTRODUCTION

The World Health Organization defines violence as the intentional use of physical force against oneself, a person or a community. As a result, Krug *et al.* (2002) divided it into three sets which they called: collective, self-directed or interpersonal violence which is characterized mainly as urban violence.

Therefore, the strong combat of crime and public policies such as bringing about long-term improvements in income and in education and reducing unemployment are requirements if urban violence is to be reduced. However, there is a resources shortage that prevents the simultaneous application of such actions in the same proportions in all areas in a city.

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Consequently, several studies tackled police operational problems as scheduling problems (Taylor & Huxley, 1989; Zeng *et al.*, 2006), as facility location problems (D'Amico, 2002; Curtin *et al.*, 2007) and as econometric models (Correa, 2005; Wang *et al.*, 2005; Yusuf *et al.*, 2011).

These models could contribute towards reducing operational costs, although it is also important that public safety decision makers receive support with regard to strategic and tactical issues that would allow effective public policies to develop.

As a result, a strategic model was drawn up to support the decision maker in evaluating the differences between zones in a city from a multicriteria perspective, whereas hit her to the perspective of the degree of police occurrences has normally been used to analyze these differences.

This paper sets out a multicriteria model that seeks to prioritize areas based on spatial criminology using social and demographic criteria. It will allow points of danger to be visualized that need different actions such as investment in the infrastructure. In addition, it permits different policies for safe places, such as monitoring policies being more necessary than other policies.

This paper is structured into six sections: Section 1 contextualizes the problem of violence and defines the problem; Section 2 gives an overview of spatial criminology; Section 3 reviews SMARTS and SMARTER methods; Section 4 gives a detailed presentation of the problem; in Section 5 there is a numerical application and Section 6 draws some conclusions and gives some final remarks.

## 2 SPATIAL CRIMINOLOGY

According to Townsley (2009), criminology is the study of criminals, their actions (crimes), and society's response to these actions (the criminal justice system). Thus, Andresen (2011) defines spatial criminology as a sub-field that seeks to understand the variation of criminal activity across the urban landscape. The use that some published papers have made of these concepts is given below.

Andresen (2011) developed a statistical model to identify local crime clusters. A tool that he used for his problem was a sub-field within geographic information science called local indicators of spatial association (LISA) and he defined social indices as explanatory variables. Therefore, his model was able to identify some patterns for specific crime types in Vancouver City.

Yang (2009) designed an experiment to disprove the broken windows thesis that neighborhood disorder is the root of violent crime. He uses spatial analysis to correlate hot spots of violent crime and disorder. Thus, he showed that places that are free of disorder are guaranteed to have low rates of violence. However, high levels of disorder were not predictors of problems of violence.

Andresen & Malleson (2010) developed a test to identify different pattern points in a space. According to the authors, spatial criminology needs to study units that are smaller than zones or regions. So, they investigate similarities in street segments and concluded that general crime patterns are similar at all spatial scales, but more refined scales than these showed significant variations.

Stucky & Ottensmann (2009) proposed a statistical model to identify some crime patterns on land use in a region. Thus, they divided land use into categories such as business premises, hospitals, schools and churches. Moreover, they included socio-economic characteristics and correlated these to crime rates. They looked for a pattern to the structure of land use that would indicate the prevalence of certain types of crime. Their findings were that some forms of commercial activity and high-density residential lands were associated with high criminality.

In addition, there are theoretical approaches such as that taken by Townsley (2009) which studies the importance of geography for criminology studies and focuses on new advances. He draws attention to spatial autocorrelation. Furthermore, Tita & Radil (2010) discuss new challenges on spatial analysis focusing mainly on the concept of "place".

## 3 SMARTS

A multicriteria decision refers to situations in which there areat least two alternative actions to choose from. Thus, Roy (1996) defines decision support as an activity that enables the problem to be clarified by supporting a decision maker to find a solution that is compatible with his/her preference structure.

Given that that there is a large number of contexts, a multicriteria model has often been applied to situations, such as: portfolio problems (Almeida & Duarte, 2011; Ballestero *et al.*, 2012; Ehrgott *et al.*, 2012), water supply (Morais *et al.*, 2010; Abu-Taleb & Mareschal, 1995), selecting members of a project team (Alencar & Almeida, 2010), building inventory (Szajubok *et al.*, 2006), preventive maintenance (Chareonsuk *et al.*, 1997; Cavalcante *et al.*, 2010), information systems planning (Almeida Filho & Cabral, 2010) and so forth.

According to Edwards & Barron (1994), SMARTS is a modification of the SMART method which used an additive model, given that the latter considered the importance of criteria. This correction was necessary, since additive methods use an interval scale. Moreover, SMARTS is an additive single criterion synthesis method. Hence, it aggregates all criteria on a single criterion synthesis using a compensatory logic as shown in Equation 1.

$$V_h = \sum_{n=1}^{N} k_n \cdot v_h(x_{hn}) \tag{1}$$

where:
$K_n$: criterion scale constant $n$;
$v_h(x_{hn})$: function value to criterion $n$ for each alternative $h$;
$N$: number of criteria.

Besides this, SMARTS method has some peculiarities, such as the criteria value functions being simplified into four shapes, as shown in Figure 1 and a scale constant being elicited by a procedure called "swing weights". Consequently, SMARTS makes it easier for the decision maker to understand the decision process.

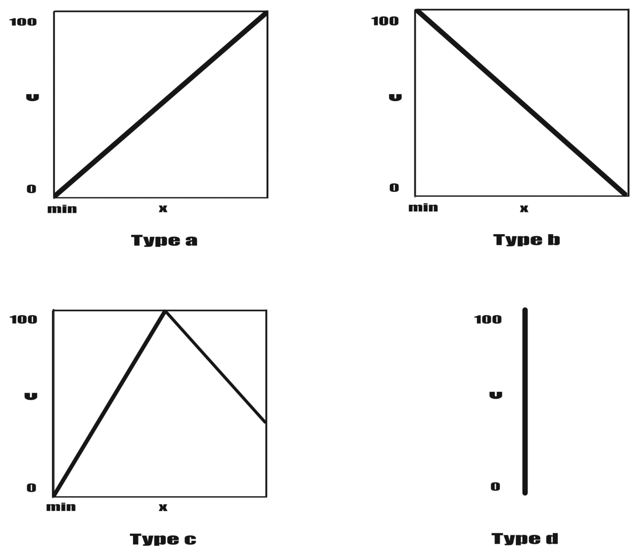


**Figure 1** – One-dimensional utility functions applied to SMARTS.
Source: Edwards & Barron (1994).

Moreover, Edwards & Barron (1994) developed another method named SMARTER that is characterized by its use of preference ranking to obtain Rank Order Centroid (ROC) weight criteria without applying a second phase from swing weights. Thus, it is important to analyze the problem and the decision maker's characteristics so as to choose the best method for each model.

Choosing a proper multicriteria method is an important aspect of the decision process. The model should provide a ranking of actions, more precisely, the prioritization of zones of a city in order to support public safety policies. Thus, we selected the SMARTS method, since that it is easy to use, if correctly applied, and enables the decision maker to solve a ranking problem. As the method is classified as an additive method, it reflects a compensatory effect which must be accepted by the decision maker.

Besides the simplicity of SMARTS, it requires a careful elicitation process of the constants of scales in order to reflect the trade-off amongst the criteria (Keeney & Raiffa, 1976; Daher & Almeida, 2012). Hence, we propose to reduce this effort by a swing weights elicitation procedure combined with a Monte Carlo Simulation that analyze the results of the model. Using this approach, the preferences of the decision maker is still taken into account.

## 4 MULTICRITERIA MODEL FOR PRIORITIZING URBAN AREAS FOCUSING ON FACTORS THAT CAN AFFECT URBAN CRIMINALITY

As mentioned in Section 1, it is important to develop a strategic model to support the planning of public safety to prioritize zones based in factors that influence criminality to support the decision maker to target his/her budget on infrastructure investments, strong actions and other differentiated public policies in these areas.

Thus, the multi-criteria model, which was structured on factors that influence criminality, involves mainly socioeconomic and demographic issues as indicated by Coulton & Pandey (1992) and Andresen (2011). From this reasoning, a criteria hierarchy emerges as demonstrated in Figure 2.

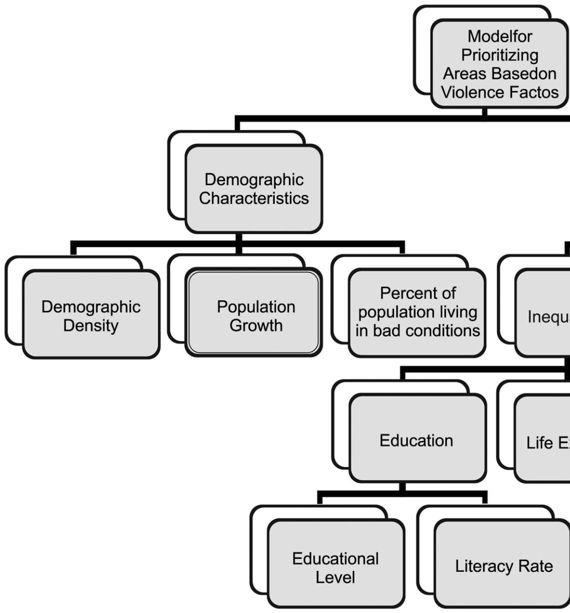


**Figure 2** – Model for prioritizing regions based on factors of violence.

These criteria were collected in various ways, as detailed in the list:

- Population density: defined as people/km$^2$. It is a representative criterion as shown in Stucky & Ostelman (2009);
- Population growth: the percentage growth in population between one census and another. Andresen (2011) showed the importance of this criterion in his paper;
- Percentage of population living in bad conditions: percentage of people living in unfit housing or sites with deficient infrastructure;
- HDI: measures the degree of inequality. It is used in a qualitative scale defined by the Human Development Report in 2010 which divides the regions into four distinct classes;
- Income concentration: this uses the GINI index to measure the income concentration on a scale of 0 to 1, where 1 means maximum inequality;
- Degree of police occurrences: a qualitative criterion that varies between 1 and 5 and measures the level of events occurring in each zone.

As mentioned above, demographic density, population growth and percent of population in bad conditions enable the demographic characteristics of each region to be better seen. Thus, they have a maximization functional form, since if the rate of growth of one of these criteria rises, there is a strong probability of a growth in crime.

According to Klugman *et al.* (2011), HDI is a composite index aggregating three basic dimensions into a summary measurement using country level information. It is noteworthy that the HDI is formed from statistics on health, education and living standards dimensions that are aggregated according to the Human Development Report (HDR), using an additive value function that varies between 0 and 1 as shown in Eq. 2:

$$
\begin{aligned}
HDI &= \frac{H_h + H_e + H_{ls}}{3} \\
H_h &= \frac{le - le_{\min}}{le_{\max} - le_{\min}} \\
H_e &= \frac{1}{3} \cdot \left( \frac{ger - ger_{\min}}{ger_{\max} - ger_{\min}} \right) + 2/3 \cdot \left( \frac{lit - lit_{\min}}{lit_{\max} - lit_{\min}} \right) \\
H_{ls} &= \frac{\ln(gdp) - \ln(gdp_{\min}))}{\ln(gdp_{\max}) - \ln(gdp_{\min})}
\end{aligned}
\tag{2}
$$

where:
$H_h$: health;
$H_e$: education;
$H_{ls}$: dimensions of living standards;
$le$: life expectancy;
$ger$: gross enrolment ratio;
$lit$: literacy;
$gdp$: GDP per capita.

According to Klugman *et al.* (2011), this indicator received some critiques such as the choice of variables excludes some dimensions, such as equity, sustainability and happiness. Moreover, it has a functional form that causes some concern, such as its normalization of indicators.

Thus, the HDI was reformulated in 2010 and incorporated improvements such as a geometric mean and new sub criteria as shown in Eq. 3.

$$
\begin{aligned}
HDI &= (H_h \cdot H_e \cdot H_{ls})^{1/3} \\
H_h &= \frac{le - le_{\min}}{le_{\max} - le_{\min}} \\
H_e &= \left[ \left( \frac{mys - mys_{\min}}{mys_{\max} - mys_{\min}} \right) \cdot \left( \frac{eys - eys_{\min}}{eys_{\max} - eys_{\min}} \right) \right]^{1/2} \\
H_{ls} &= \frac{\ln(gni) - \ln(gni_{\min})}{\ln(gni_{\max}) - \ln(gni_{\min})}
\end{aligned}
\tag{3}
$$

where:
$H_h$: health;
$H_e$: education;
$H_{ls}$: dimensions of living standards;

$le$: life expectancy;
$mys$: mean years of schooling;
$eys$: expected years of schooling;
$gni$: gross national income.

These modifications ended some HDI problems, mainly on the method of aggregation. Thus, it is a useful estimate for measuring the inequality difference across countries.

Income concentration is a dimension characterized as being calculated by an index, viz. the Gini coefficient. According to Jedrzejczak (2008), the Gini index can be used to measure the spread of a distribution of income, consumption, or wealth and can be expressed as a ratio of two regions defined by a line of equal shares and a Lorenz curve in a unit box, such as Lorenz (1905) developed in his paper.

Therefore, by using these concepts, it is possible to compare different areas and determine a measurement scale of between 0 and 1, 0 being an equality region and 1 an income zone of complete inequality. Thus, in this case a maximization functional form was established, given that higher indices generate a greater degree of occurrences to a growth in violence.

Finally, degrees of police occurrences are measured on a qualitative scale. Thus, the decision maker defines a degree of criminality based on his/her knowledge of the violence in each area.

Subsequently, it is possible to formulate a final aggregation function for this model and a brief summary of the criteria structure from the model, as shown in Table 1 and Eq. 4.

**Table 1** – Summary of criteria structure.

| Criterion | Scale | Function shape |
|---|---|---|
| Demographic density | Quantitative criterion | Maximization |
| Population growth | Quantitative criterion | Maximization |
| Percent of population living in bad conditions | Interval scale 0-100% | Maximization |
| Inequality | Ordinal scale 1;2;3;4 | Minimization |
| Income concentration | Interval scale 0-1 | Maximization |
| Degree of police occurrences | Ordinal scale 1;2;3;4;5 | Maximization |

$$V_h = \sum_{n=1}^{6} k_n \cdot v_h(x_{hn}) \tag{4}$$

where:
$h$: alternative $h$;
$n$: criteria set {1: demographic density, 2: population growth, 3: percent of population in bad conditions, 4: HDI, 5: income concentration, 6: police occurrences degree};

$k_n$: $n$ criterion scale constant;
$v_h(x_{hn})$: $n$ criterion function value to alternative $h$.

Therefore, a framework was formulated so as to apply the model in a consistent manner, as shown in Figure 3.

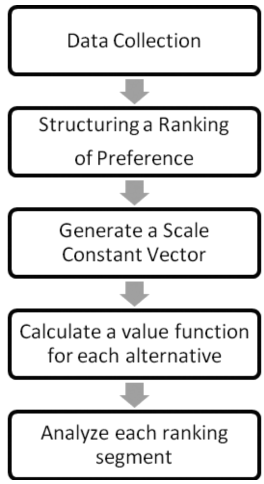


**Figure 3** – Model framework.

## 5 NUMERICAL APPLICATION

Usually in criminality analysis, the number or the degree of occurrences in each region/zone is noted. However, it is important to aggregate other factors to increase the accuracy of the analysis of violence, as shown in Section 4.

The model was applied in the City of Recife. The city was divided into 62 human development units, as per the 2000 UDR, as shown in Appendix. The data were collected from the 2006 Human Development Atlas of Recife. However, the degree of occurrences data was aggregated based in the number of occurrences. Thus, we used the decision maker's knowledge and these events to create a scale going from a very low to a very high degree of occurrences for the growth in criminality.

Based on this degree of occurrences, it was divided the zones into five subsets, as enumerated below.

Very low degree of occurrences:
{A2, A3, A7, A16, A17, A26, A29, A36, A40, A51, A61}

Low degree of occurrences:
{A6, A9, A14, A15, A25, A27, A35, A47, A48, A49, A50}

Medium degree of occurrences:
{A1, A20, A22, A23, A28, A32, A33, A37, A39, A42, A43, A45, A55, A60}

High degree of occurrences:
{A8, A12, A13, A21, A24, A30, A31, A34, A44, A46, A56, A57, A58, A59}

Very high degree of occurrences:
{A4, A5, A10, A11, A18, A19, A38, A41, A52, A53, A54, A62}

In addition, a first phase of "swing weights" procedure was applied to define a ranking of preferences for the set of criteria, as shown in Table 2. However, it is difficult for the decision maker in this model to define a unique scale constant vector. Moreover, it is necessary to generate constant scale vectors using this ranking preference as a guideline. Hence, considering the preferences of the decision maker, a SMARTER method was applied so that a scale constant vector was generated, as shown in Table 3.

**Table 2** – Decision maker's preference structure.

| Ranking | Criterion |
|---|---|
| $1^{st}$ | Demographic Density |
| $2^{nd}$ | Percent of Population Living in Bad Conditions |
| $3^{rd}$ | Degree of Police Occurrences |
| $4^{th}$ | Inequality – Human Development Index (HDI) |
| $5^{th}$ | Percent of Growth in Population |
| $6^{th}$ | Income Concentration (GINI Index) |

**Table 3** – Scale constants criteria based on smarter method.

| Criterion | Scale constant |
|---|---|
| Demographic density | $\dfrac{(1 + 1/2 + 1/3 + 1/4 + 1/5 + 1/6)}{6} = 0.40833$ |
| Percent of population living in bad conditions | $\dfrac{(0 + 1/2 + 1/3 + 1/4 + 1/5 + 1/6)}{6} = 0.24167$ |
| Degree of police occurrences | $\dfrac{(0 + 0 + 1/3 + 1/4 + 1/5 + 1/6)}{6} = 0.15833$ |
| Inequality – Human Development Index (HDI) | $\dfrac{(0 + 0 + 0 + 1/4 + 1/5 + 1/6)}{6} = 0.10278$ |
| Percent of population growth | $\dfrac{(0 + 0 + 0 + 0 + 1/5 + 1/6)}{6} = 0.06111$ |
| Income concentration (GINI Index) | $\dfrac{(0 + 0 + 0 + 0 + 0 + 1/6)}{6} = 0.02778$ |

Therefore, the model shows a difference between police degree occurrences analysis in all five segments. As observed in Figure 4 and Figure 5, there are key changes that demonstrate model applicability.

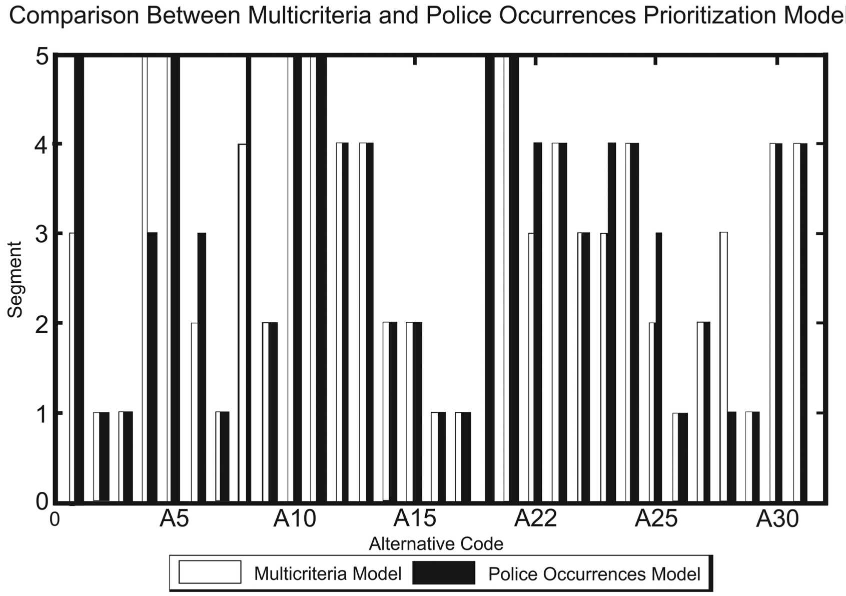


**Figure 4** – Comparison between the model of the degree of police occurrences and multicriteria prioritization from zone A1 to A31.

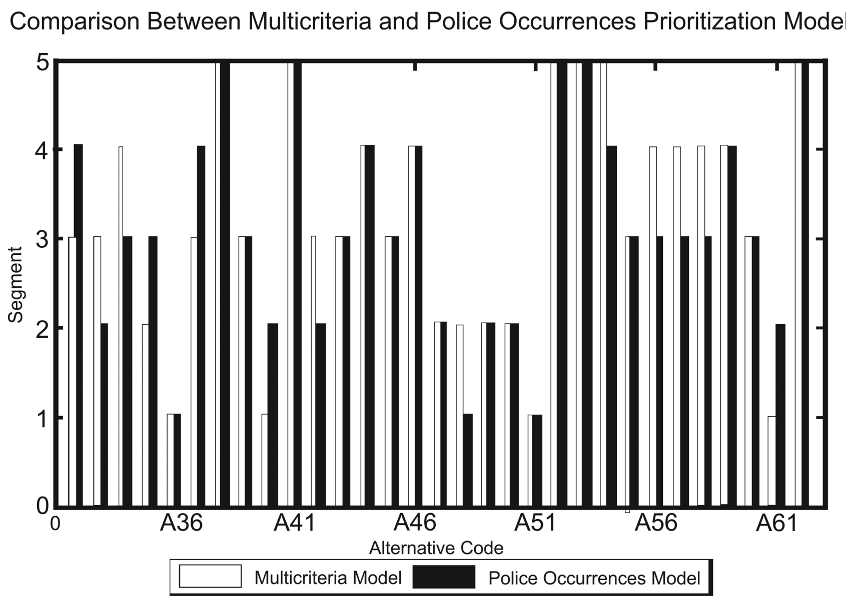


**Figure 5** – Comparison between the model of the degree of police occurrences and multicriteria prioritization from zone A32 to A62.

For example, Alternative A1 it was allocated on medium degree of occurrences to criminality growth, but it on multicriteria model this alternative was positioned on first place in the SMARTER ranking.

In addition, a sensitivity analysis tests the robustness of the model by using a Monte Carlo Simulation. This generates ten thousand constant scale vectors uniformly distributed and an SMAA first phase procedure developed by Tervonen & Lahdelma (2007) was applied, thus creating the sets of weight criteria, as shown on Algorithm 1.

**Algorithm 1** – Scale constant vector generation procedure. Source: Tervonen & Lahdelma (2007).

```
Output: k vector
1: for j ← 1 to 5 do
2:     q_j ← RANDOM_U[0,1]
3: end for
4: SORT_asc(q)
5: q_0 ← 0
6: q_6 ← 1
7: for j ← 1 to 6 do
8:     k_j ← q_j − q_{j−1}
9: end for
```

Thereafter, it is possible to calculate a global function value for each alternative using all the vectors generated by the Algorithm 1 procedure. However, it is necessary to do some robustness analyses. For this, some indicators were developed, such as those given in Eqs. 5, 6, 7 and 8.

$$I_1 = \frac{n_1}{N} \tag{5}$$

where:
$n_1$: number of alternatives in the same position as in the SMARTER ranking;
$N$: number of alternatives in set.

$$I_2 = \frac{n_2}{N} \tag{6}$$

where:
$n_2$: number of alternatives between one position above or below the SMARTER ranking;
$N$: number of alternatives in set.

$$I_3 = \frac{n_3}{N} \tag{7}$$

where:
$n_3$: number of alternatives between two positions above or below the SMARTER ranking;
$N$: number of alternatives on set.

$$I_4 = \frac{n_4}{N}$$

where:
$n_4$: number of alternatives among three positions above or below the SMARTER ranking;
$N$: number of alternatives in set.

In Table 4, the I1 indicator has a low correlation as between the SMARTER ranking and the sensitivity analysis ranking. However, this happens since the variation in the scale constants is very large.

**Table 4** – Sensitivity analysis indicators.

| Indicator | Mean value | Minimum | Maximum |
|---|---|---|---|
| I1 | 30.86% | 3.23% | 93.54% |
| I2 | 60.14% | 20.97% | 96.77% |
| I3 | 73.07% | 37.10% | 96.77% |
| I4 | 80.24% | 45.16% | 96.77% |

However, at I2, I3 and I4 a high correlation is observed between the SMARTER and analysis rankings. Therefore, these indicators show the model is robust, given that a large variation in scale constants does not cause a great change in ranking. In addition, when a segment analysis is conducted, there are not large changes in the subsets.

## 6 CONCLUDING REMARKS

Public safety planning involves three action plans, namely operational, strategic and tactical ones. Many papers have contributed to operational models, but they have not dealt with strategic problems. Thus, it is noted that strategic planningfor a region is important so as to allocate differentiated public policies that support combating and reducing violence and criminality.

Hence, a multicriteria model combined with a Monte Carlo Simulation was developed to allow zone ranking based on demographic and socioeconomic issues that may have an impact on violence. Moreover, this model was applied in the City of Recife to examine its soundness and this led to a robust result which allows the decision maker to transform the alternatives into subsets and for different public policies to be created for each one.

It was concluded that the model developed is applicable and can be expanded to other regions where it may help to improve the management of public safety and to reduce violence. However, it is important to note that this model is applicable to situations where the decision maker has a compensatory preference structure and is unable to elicit a single constant scale vector.

Finally, it is important that future papers tackle questions about public policies that can be applied in each region, new models that could be developed for decision makers with a non-compensatory preference structure and other important criteria that incorporate new characteristics to improve this model, such as geographic conditions and the absolute number of occurrences.

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## APPENDIX

**Table A** – Function values for each criterion in very low degree of occurrences subset.

| Alternative Code | Demographic density | Population in bad conditions | Population growth | Income concentration | HDI |
|---|---|---|---|---|---|
| A2 | 0,07855 | 0 | 0,00663 | 0,50834 | 0,33 |
| A3 | 0,13155 | 0 | 0,04578 | 0,50809 | 0 |
| A7 | 0,17594 | 0 | 0,26184 | 0,50294 | 0 |
| A16 | 0,13553 | 0,10023 | 0,37509 | 0,50566 | 0 |
| A17 | 0,22567 | 0,05708 | 0,36095 | 0,40321 | 0 |
| A26 | 0,2112 | 0 | 0,39904 | 0,53913 | 0,33 |
| A29 | 0,24946 | 0 | 0,25057 | 0,51946 | 0 |
| A36 | 0,1722 | 0 | 0,22372 | 0,54087 | 0,33 |
| A40 | 0,26489 | 0,13517 | 0,19586 | 0,46748 | 0,33 |
| A51 | 0,28233 | 0 | 0,16053 | 0,4506 | 0,33 |
| A61 | 0,33042 | 0 | 0,31377 | 0,46383 | 0,33 |

**Table B** – Function values for each criterion in low degree of occurrences subset.

| Alternative Code | Demographic density | Population in bad conditions | Population growth | Income concentration | HDI |
|---|---|---|---|---|---|
| A6 | 0,27989 | 0,5149 | 0,30452 | 0,62656 | 0,33 |
| A9 | 0,23916 | 0,14078 | 0,27465 | 0,5262 | 0,33 |
| A14 | 0,0071 | 0,28799 | 0,66008 | 0,63958 | 0,66 |
| A15 | 0,21777 | 0,04915 | 0,39254 | 0,52771 | 0 |
| A25 | 0,25475 | 0,56626 | 0,33384 | 0,56575 | 0,33 |
| A27 | 0,21289 | 0,14422 | 0,31537 | 0,54749 | 0,33 |
| A35 | 0,03247 | 0,48567 | 0,71066 | 0,55226 | 0,66 |
| A47 | 0,24481 | 0 | 0,30455 | 0,55155 | 0 |
| A48 | 0,19775 | 0 | 0,28746 | 0,6117 | 0 |
| A49 | 0,30641 | 0 | 0,57639 | 0,41755 | 0 |
| A50 | 0,14074 | 0,09779 | 0,39467 | 0,47875 | 0,33 |

**Table C** – Function values for each criterion in medium degree of occurrences subset.

| Alternative Code | Demographic density | Population in bad conditions | Population growth | Income concentration | HDI |
|---|---|---|---|---|---|
| A1 | 0,85712 | 1 | 0,40232 | 0,54919 | 0,66 |
| A20 | 0,5644 | 0,92275 | 0,2951 | 0,47556 | 0,66 |
| A22 | 0,14463 | 0,83703 | 0,62983 | 0,45453 | 0,66 |
| A23 | 0,32359 | 0,86393 | 0,68321 | 0,55608 | 0,66 |
| A28 | 0,13231 | 0 | 0,2339 | 0,46887 | 0 |
| A32 | 0,37108 | 0,96397 | 0,38216 | 0,52836 | 0,66 |
| A33 | 0,11804 | 0 | 0,30384 | 0,5713 | 0,33 |
| A37 | 0,32184 | 0,95557 | 0,27977 | 0,56276 | 0,66 |
| A39 | 0,16207 | 0,6259 | 0,23979 | 0,55708 | 0,33 |
| A42 | 0,18285 | 0,15516 | 0,3635 | 0,53141 | 0,33 |
| A43 | 0,26388 | 0,63065 | 0,27095 | 0,51234 | 0,33 |
| A45 | 0,05013 | 0,8941 | 0,38825 | 0,50248 | 0,66 |
| A55 | 0,22199 | 0,90228 | 0,5466 | 0,5888 | 0,66 |
| A60 | 0,32827 | 0,67942 | 0,30354 | 0,47651 | 0,66 |

**Table D** – Function values for each criterion in high degree of occurrences subset.

| Alternative Code | Demographic density | Population in bad conditions | Population growth | Income concentration | HDI |
|---|---|---|---|---|---|
| A8 | 0,45316 | 1 | 0,47059 | 0,58093 | 0,66 |
| A12 | 0,33949 | 1 | 0,33016 | 0,56924 | 0,66 |
| A13 | 0,20532 | 1 | 0,39414 | 0,48184 | 0,66 |
| A21 | 0,37014 | 1 | 0,23281 | 0,45865 | 0,66 |
| A24 | 0,37897 | 1 | 0,20069 | 0,44882 | 0,66 |
| A30 | 0,34458 | 1 | 0,36981 | 0,64849 | 0,66 |
| A31 | 0,30742 | 1 | 0,98604 | 0,53809 | 0,66 |
| A34 | 0,14799 | 1 | 0,4135 | 0,59582 | 0,66 |
| A44 | 0,36464 | 1 | 0,17015 | 0,54449 | 0,66 |
| A46 | 0,12776 | 1 | 0,95907 | 0,45922 | 0,66 |
| A56 | 0,0956 | 0,02748 | 0,40737 | 0,55209 | 0,66 |
| A57 | 0,17382 | 0,58609 | 0,66989 | 0,53492 | 0,66 |
| A58 | 0,10166 | 1 | 0,51971 | 0,46965 | 0,66 |
| A59 | 0,30343 | 1 | 0,51838 | 0,51114 | 0,66 |

**Table E** – Function values for each criterion in very high degree of occurrences subset.

| Alternative Code | Demographic density | Population in bad conditions | Population growth | Income concentration | HDI |
|---|---|---|---|---|---|
| A4 | 0,05659 | 0,88536 | 0,14423 | 0,60575 | 0,66 |
| A5 | 0,53731 | 1 | 0,43475 | 0,53316 | 1 |
| A10 | 0,47927 | 1 | 0,23898 | 0,46308 | 0,66 |
| A11 | 0,43339 | 1 | 0,27347 | 0,44447 | 0,66 |
| A18 | 0,4197 | 1 | 0,20759 | 0,49544 | 0,33 |
| A19 | 0,47913 | 1 | 0,20626 | 0,47421 | 0,66 |
| A38 | 0,52252 | 1 | 0,27237 | 0,54115 | 0,66 |
| A41 | 0,46286 | 1 | 0,63923 | 0,56185 | 0,66 |
| A52 | 0,4095 | 0,97192 | 0,5756 | 0,71644 | 0,66 |
| A53 | 0,56844 | 1 | 0,37621 | 0,50021 | 0,66 |
| A54 | 0,09011 | 0,97521 | 0,32521 | 0,60455 | 0,66 |
| A62 | 0,42756 | 1 | 0,35649 | 0,45624 | 0,66 |