

NCML

University of New Mexico

Patterns and Factors Determinants in Cases of Missing Persons in Ecuador.

Patrones y Factores Determinantes en Casos de Personas Desaparecidas en Ecuador.

Edwin Xavier Quito Recalde ^{1*}, Johanna Maribel Pando Farez ², Edwin Alfred Riofrio Núñez ³, Paola Dayanara Ramírez Carrión ⁴, Jorge Leopoldo Pauta Riera ⁵, and Dayron Rumbaut Rangel ⁶

¹Bolivarian University of Ecuador, Duran, Guayas. Ecuador. <u>exquitor@ube.edu.ec</u>

² Bolivarian University of Ecuador, Duran, Guayas. Ecuador. <u>jmpandof@ube.edu.ec</u>

³Bolivarian University of Ecuador, Duran, Guayas. Ecuador. <u>eariofrion@ube.edu.ec</u>

⁴Bolivarian University of Ecuador, Duran, Guayas. Ecuador. pdramirez@ube.edu.ec

⁵Bolivarian University of Ecuador, Duran, Guayas. Ecuador. jlpautar@ube.edu.ec

⁵Universidad Católica de Cuenca, Cuenca, Azuay, Ecuador. <u>jlpautar@ucacue.edu.ec</u>

⁶ Bolivarian University of Ecuador, Duran, Guayas, Ecuador. <u>drumbautr@ube.edu.ec</u>

Abstract. In Ecuador, the problem of disappearances presents an alarming profile that requires deep and multidimensional analysis. This study examines 6,874 cases registered during 2024 using Orange Data Mining, specialized data analysis software, to detect demographic, geographic, and temporal patterns. The findings reveal a resolution rate of 82.1%, with significant fluctuations between regions and population groups. Women represent the most vulnerable group to disappearances, while men who are not located present a higher probability of fatal outcomes. The provinces of Pichincha and Guayas concentrate 46% of the analyzed cases. The study implements a neutrosophic multicriteria model to evaluate the inherent uncertainty in the data, allowing a more robust analysis of fuzzy and indeterminate factors present in disappearance cases. The average age range of affected individuals is 24 years, with a predominance of adolescents. The identified critical period spans from June to September, where causes such as human trafficking and sexual abuse show higher incidence. Evidence-based intervention strategies are proposed, including early warning systems, differentiated protocols by risk profile, and specific preventive programs for adolescents, supported by neutrosophic logic to handle uncertain variables in institutional decision-making.

Keywords: Orange; Disappearance; Data; Trend; Risk; Neutrosophy; Indeterminacy.

Resumen. En Ecuador, el problema de las desapariciones presenta un perfil alarmante que requiere un análisis profundo y multidimensional. Este estudio examina 6.874 casos registrados durante 2024 utilizando Orange Data Mining, software especializado en análisis de datos, para detectar patrones demográficos, geográficos y temporales. Los resultados revelan una tasa de resolución del 82,1%, con fluctuaciones significativas entre regiones y grupos de población. Las mujeres representan el grupo más vulnerable a las desapariciones, mientras que los hombres no localizados presentan una mayor probabilidad de desenlaces fatales. Las provincias de Pichincha y Guayas concentran el 46% de los casos analizados. El estudio implementa un modelo multicriterio neutrosófico para evaluar la incertidumbre inherente a los datos, permitiendo un análisis más robusto de los factores difusos e indeterminados presentes en los casos de desaparición. La edad media de los individuos afectados es de 24 años, con predominio de adolescentes. El periodo crítico identificado abarca de junio a septiembre, donde causas como la trata de seres humanos y los abusos sexuales muestran una mayor incidencia. Se proponen estrategias de intervención basadas en la evidencia, incluyendo sistemas de alerta temprana, protocolos diferenciados por perfil de riesgo y programas preventivos específicos para adolescentes, apoyados en la lógica neutrosófica para el manejo de variables inciertas en la toma de decisiones institucionales.

Palabras claves: Naranja; Desaparición; Datos; Tendencia; Riesgo; Neutrosofía; Indeterminación.

1. Introduction

The Latin American region is currently immersed in a migration crisis characterized by a complex framework of factors. Yeah good share causes common with Others crisis migratory to level global, such as economic

instability, Lack of employment, poverty and deficiencies in health and education systems, also HE come aggravated by a series of problematic individuals. Between are latest, They highlight the growing violence and the lack of control of organized crime, the violation of human rights, corruption extended and the rise of drug trafficking. These specific elements contribute to the emergence of a unique and challenging migration situation in Latin America [1].

Disappearances, whether forced or involuntary, have been shown to be closely related to the presence of organized criminal activities and the lack of punishment in certain areas. A comparative study of similar situations in Latin America, conducted by Aguilar [2] in his work "Forced disappearance, impunity and reparation in Latin America"

In the last two decades, violence has emerged as one of the most relevant issues in the cities of America Latin, due to the evolution in their demonstrations (a increase in his intensity), to his impact in various areas (social, economic, among others), significant growth in its scale (which has doubled) and the emergence of new modalities, such as express kidnapping and violence in stadiums, among others.

He year 2024 go on showing the gravity of the problem of the people missing in Ecuador, a challenge that requires a deep understanding of their causes and consequences. This situation, far from to be an isolated fact, is linked to problems structural of violence and social vulnerability, generating a significant impact on families and society. The complexity of this problem demands an analysis from different perspectives, considering both social dynamics and system deficiencies [3].

The disappearance of people represents a challenge significant for the security public and he tissue social in Ecuador. This study leverages a comprehensive database to analyze patterns and determining factors, with the aim of informing public policies, improving search and prevention protocols, and putting forward various proposals.

2. Methods either Computational Methodology.

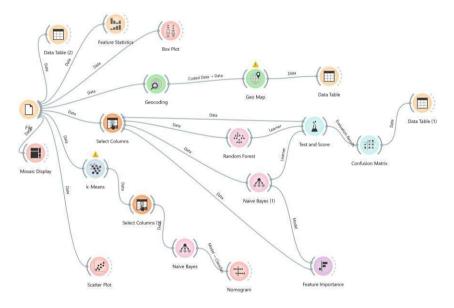


Fig. 1 Modeling of the case of study in Orange Data Mining.

The research was carried out through Orange Data Mining software, using open data about people. missing of the Ecuador in he year 2024, it starts with 6.874 cases registered on process The analytical approach described is characterized by a structured approach that encompasses initial data preparation, detailed exploration to understand its underlying characteristics, and finally the application of machine learning models for predictions or classifications. The selection of tools, such as "Select Columns ", demonstrates the importance of meticulous preprocessing, which eliminates noise and highlights the most relevant variables, with special attention to spatial information through geocoding. Visual exploration with "Feature Statistics ", "Box Plot ", " Mosaic Display " and "Scatter Plot " is crucial to identify issues potentials and guide the selection of models suitable. The choice between Random Forest and Naive Bayes HE base in a analysis comparative, using metrics of assessment and matrices of confusion to determine the most efficient model. Overall, the process ensures a robust, replicable analysis based on a deep understanding of the data.

Through the data mining process, covering from the import and initial preparation of the information until the creation and assessment of models predictive. Each phase of the process HE distinguishes by a defined objective,

Edwin X. Quito R, Johanna M. Pando F, Edwin A. R. Núñez, Paola D. Ramirez C, Jorge L. Pauta R. Patterns and Factors Determinants in Cases of Missing Persons in Ecuador.

and the methodological decisions regarding the tools and techniques used are based on the need to investigate the information, identify trends and develop models that allow anticipating results.

Date: Date: Date: Date: More More

3. Results and discussion



This dashboard shows statistics on missing persons in Ecuador with the following key characteristics:

- 1. Distribution geographic: Concentration major in Pichincha, with a dispersion significant in Guayas.
- 2. profile:
 - Most women (according to indicator "Sex")
 - Age average 24.54 years
 - Predominance of teenagers
- 3. Coordinates:
 - Latitude average: 1.27421
 - Length average: 79.1013
 - Coverage of all the provinces Ecuadorian
- 4. Temporality:
 - Period: 1 January 31 December 2024
 - Date average of disappearance: 22 June 2024
 - Distribution temporary of 11 months

Data indicate that the highest concentration of missing persons is in the province of Pichincha, where the female gender predominates as the most affected; the month with the highest incidence of disappearances is June; and, the age average of the people further affected are the 24 years, it which indicates that this freak may be related with social or environmental factors, such as the demographic concentration of people in urban areas.

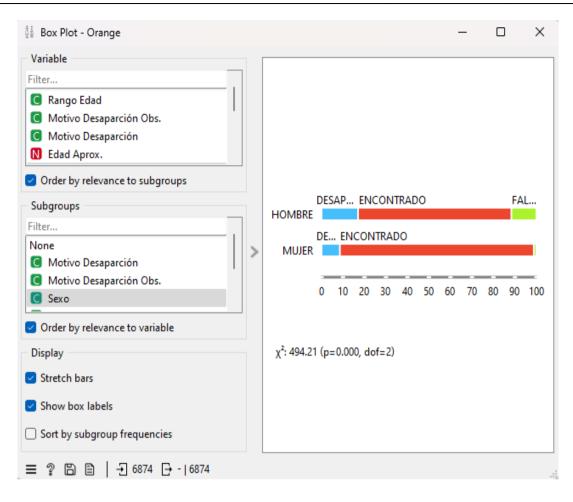


Fig. 3 - Sex of the population

Findings Main:

- He graphic compare the states (DESAP, FOUND, FAL) between MAN and WOMEN
- There is a difference statistically significant ($\chi^2 = 494.21$, p < 0.000, df = 2)
- For men:
- Elderly proportion of "FOUND" (bar red)
- Minor proportion of "DESAP" (blue bar)
- Small proportion "FAL" (bar green)
- For women:
- Elderly proportion from "FOUND"
- Minor proportion from "DESAP"
- No HE observe bar "FAL"
- The proportion significantly different suggests that exists a relationship between he sex and he state end of missing cases. Men show a more varied distribution among the three categories, while women are mainly concentrated in "FOUND".

Data analysis suggests that there is a significant difference in the number of missing men and women found alive, with men having a higher mortality rate and women having a relatively low mortality rate, suggesting that whether a person is a man or a woman is a determining factor in determining the possibility of their return when a person disappears.



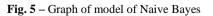
Fig. 4 – Distribution geographic of people missing in Ecuador.

The map shows the geographical distribution of missing persons in Ecuador, classified by age groups and provinces:

- Patterns spatial highlights:
- Elderly concentration in the region Saw (Cordillera central)
- Clusters significant in:
- Pichincha (Quito): predominate adults and youths adults
- Guayas (coast): concentration of teenagers
- Azuay (south): distribution mixed of groups age groups
- Emeralds (north): presence remarkable of children
- Variables displayed:
- Color: Province (10 main provinces)
- Form: Range of age (5 categories)
- Size: Age approximate
- Location: Coordinates geographic (latitude/longitude)

He graphic reveals patterns geographic where determines elderly concentration of people missing in the Sierra region, where a preference is shown by kidnappers for adults and young adults, while in the coastal region a greater inclination to kidnap adolescents can be seen.

| Learners | - K | Clicking on cells or in corresponding data in | × how: N | Number of instances | | | | |
|-----------------------|-----|--|--------------|---------------------|-----------|-----------------|--|--|
| Naive Bayes (1) | | corresponding data in | stances | | | | | |
| Random Forest | | | | Predicted | | | | |
| | | | DESAPARECIDO | ENCONTRADO | FALLECIDO | Σ | | |
| | | DESAPARECIE | 838 | 0 | 0 | 838 | | |
| | > | | 1 | 5618 | 23 | 5642 | | |
| | | | 0 0 | 0 | 394 | 394 | | |
| | | | Σ 839 | 5618 | 417 | 6874 | | |
| Output Predictions | | | | | | | | |
| Probabilities | | | | | | | | |
| Apply Automatically | | Select Correct | Selec | t Misclassified | | Clear Selection | | |



Analysis of the matrix of confusion of the model Naive Bayes : Key Metrics:

- Precision total: (838+5618+394)/6874 = 99.65%
- Cases totals analyzed: 6874 Performance by category:

1. MISSING

- True positives: 838
- Accuracy: 99.88%

2. FOUND

- True positives: 5618
- False positives: 23
- Accuracy: 99.57%

3. DECEASED

- True positives: 394
- Accuracy: 94.48%

Major error: 23 cases classifieds as FOUND were DECEASED, indicating potential area for improvement in the distinction between these categories.

He model Naive Bayes according to the data found us allows visualize that the prediction of the Missing persons, taking into account a base time for their search, can give us results very close to the future reality in the categories of missing after the search time with a percentage of 99.88% and found with a percentage of precision of 99.57%, which shows us a pattern for the years following for this guy of problematic, but that has margin of improvement in he case from the Deceased category, with a percentage of 94.48%.

| Learners | | | | | Show: Nu | mber of instances | |
|----------------------------------|---|----------------|--------------|---------------|-----------|-------------------|--|
| Naive Bayes (1) Random Forest | | | | Predicted | | | |
| | | | DESAPARECIDO | ENCONTRADO | FALLECIDO | Σ | |
| | | DESAPARECIDO | 838 | 0 | 0 | 838 | |
| | > | | 0 | 5642 | 0 | 5642 | |
| | | | 0 | 0 | 394 | 394 | |
| Output | | Σ | 838 | 5642 | 394 | 6874 | |
| Predictions | | | | | | | |
| Probabilities | - | | | | | | |
| Apply Automatically | | Select Correct | Select | Misclassified | | Clear Selection | |

Fig. 6 - Chart of Random model Forest

Analysis of matrix of confusion of the model Random Forest :

Performance perfect by category:

- MISSING: 838/838 (100%)
- FOUND: 5642/5642 (100%)
- DECEASED: 394/394 (100%)

Precision global: 100% (6874/6874 cases)

He model Random Forest achievement classification perfect in all the categories, overcoming to the Naive Bayes that showed confusion in 23 cases DECEASED/FOUND. This suggests that Random Forest capture better distinguishing features between states, especially for DECEASED vs FOUND cases.

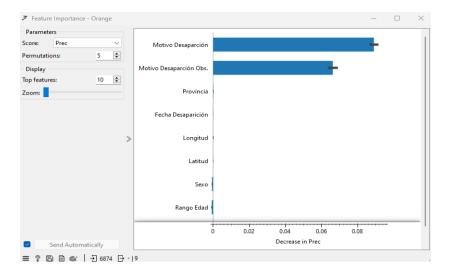


Fig. 7– Variables of the model

Analysis of importance of characteristics of the model: Variables most influential:

- 1. Reason Disappearance (0.085)
- 2. Reason Disappearance Obs . (0.065)
- 3. Province (0.02)

Variables with impact minimum (< 0.01):

- Date Disappearance
- Longitude/Latitude
- Sex
- Range Age

He reason of disappearance and your observations are the predictors further robust, explaining approximately 15% of the variance total. The location geographic (Province) has impact moderate, while that demographic variables show marginal influence.

| ☆ k-Means - Orange | | | | | | | | | |
|--|---|------|----------------|--|--|--|--|--|--|
| Number of Clusters | | Sill | houette Scores | | | | | | |
| ○ Fixed: 3 | | 2 | 0.619 | | | | | | |
| • From 2 | | 3 | 0.597 | | | | | | |
| Preprocessing | > | 4 | 0.574 | | | | | | |
| Normalize columns | | 5 | 0.560 | | | | | | |
| - | | 6 | 0.559 | | | | | | |
| Initialization | | 7 | 0.545 | | | | | | |
| Initialize with KMeans++ V | | 8 | 0.546 | | | | | | |
| Re-runs: 10 | | 9 | 0.549 | | | | | | |
| Maximum iterations: 300 | | 10 | 0.546 | | | | | | |
| Apply Automatically | | 11 | 0.543 | | | | | | |
| Apply Automatically | | | | | | | | | |
| 😑 🤋 🖹 📔 🔁 6874 🕞 6874 2 🦺 Silhouette scores are not computed f | | | | | | | | | |

Fig. 8 - Results of clusters K- Means

Analysis of results k- means : Better grouping : k=2 (silhouette score: 0.619) Sample clear separation between clusters

• Score significantly higher than other options Trend falling in scores: k=3: 0.597 k=4: 0.574 k=5: 0.560

Optimal parameters:

- Standardization of columns applied
- Initialization: KMeans ++
- Iterations maximums: 300
- Re-executions: 10

He analysis Kmeans suggests that he set of people missing HE can split of manner effective in two groups, since adding more divisions would not contribute to the analysis of this type of data.

| - nongen oneg. | | | | | | | | | | | | |
|---|---------------------------------|----------------------|-----------------|---------------------|---------------------|-------------------------------------|-----------|------------|-----------|-----------|-----------------------|---|
| Target class: C2 Scale: Point scale C2 V C2 V C2 V C2 V C C C C | -1 Points | 8- <u>0.09- 0.00</u> | 0.0 -70.0 -60.0 | -50.0 -40.0 | -30.0 -20.0 | -10.0 0.0 | 10.0 25.0 | 30.0 40.0 | 50.0 60.0 | 70.0 80.0 | 90.0 100.0 | |
| Displayed features Order: Absolute importance ~ | ≥ 2024-09 Fecha Desaparición | -22 12:00:00 | | 2024-06-22 12:00:00 | 2024-09-22 12:00:00 | • | | | | 2024 | < 2024-03-24 12:00:00 | ^ |
| Show: All features Best ranked: 5 Numeric features: 10 projection | Motivo Desaparción Obs. | | | | L + 1 | SIN_DATO SUICIDIO | AS | ISO SEXUAL | | | | |
| | Motivo Desaparción | | | , | ROBLEMAS FAMILIARES | SIN_DATO FALLECIDO | | | | | | |
| | Provincia | | | | GAL | ZONA NO DELINITADA | | | | | | |
| | Situación Actual | | | | D | ESAPARECIDO FALLECIDO ENCONTRADO | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | | | | | | | | | | | | |
| | Total | -40.0 | -35.0 -30.0 | -25.0 | 20.0 -15.0 | -10.0 -5.0 | 0.0 | 5.0 10.0 | 15.0 20.0 | 25.0 | 30.0 35.0 | |
| | Probabilities (%) | | 10 | | 20 | 30 40 | 50 6 | 2 70 | 80 | | 90 | · |
| = 9 B B G J B . D . | | | | | | | | | | | | |

 $Fig. \ 9- Results \ of \ nomogram$

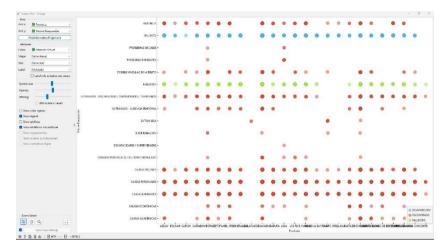
Analysis of the nomogram predictive: Main variables by impact:

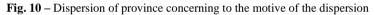
- 1. Date Disappearance
 - Critical period: 2024-06-22 to 2024-09-22
 - Elderly risk in intervals recent
- 2. Reason Disappearance Obs .
 - High impact: Treats of people, sexual abuse
 - Half impact: Problems sentimental
 - Low impact: Missing person
- 3. Reason for disappearance
 - Causes relatives: elderly weight predictive
 - Without fact: influence moderate
- 4. Province
 - Elderly risk: Azuay, Pastaza

54

- Minor risk: Galapagos
- 5. Current Situation
 - Deceased: significant indicator
 - Missing: correlation moderate

He graphic suggests a period of elderly incidence in the disappearances he which consists from he 22 of June at 22 of September, in where the reasons further found for cause the disappearance are the treats of people and he abuse sexual, and the cases where he causal is the family, is they can see older patterns predictive, given that he model HE finds between a range of the 50%-60%, HE suggests that is a model with ability reasonable predictive with room for improvement.





Analysis of the graphic of dispersion Province vs. Reason for disappearance:

patterns :

- VIOLENCE: high frequency, distribution uniform between provinces
- NO_DATA: present in all the provinces, elderly in urban areas
- CAUSES FAMILY/PERSONAL/SOCIAL: distribution wide, concentration in large provinces

Situation Current (colors):

- Red (FOUND): predominant in causes violent/family
- Blue (MISSING): elderly in "NO_DATA"
- Green (DECEASED): concentrated in cases specific Significant concentrations:
- Pichincha/Guayas: elderly diversity of reasons
- Provinces small: predominance "NO_DATA" and causes basic
- LOST/DISABLED: distribution dispersed but consistent

This graph shows us that in cases where missing persons were found, the causes of the problematic HE focus in the violence, while that the situation with the people that HE They are found missing even after a time and search, the causes of the disappearance are centered on unknown data, and of the people who were found deceased, the causes of the disappearance are related to strictly specific reasons, so that by having this data, predictions can be made according to the information that can be obtained at the time of the initial search.

4. Discussion

The findings reveal patterns significant that can inform strategies of prevention and search:

1. Vulnerability Demographic

- Elderly risk in population female teenagers
- Need of Interventions specific by gender and age

2. Disparities Geographical

- Concentration urban of cases
- Variation significant in effectiveness of resolution

3. Factors Storms

- Importance Criticism of the first 72 hours
- Elderly risk of fatal outcome with he passed of the time

4. Recommendations

1. Prevention Focused

- Programs specific for teenagers
- Interventions in areas of high risk

2. Improvements Operational

- Systems of alert early
- Protocols differentiated by profile at risk

3. Strengthening Institutional

- Coordination interinstitutional improved
- Specialized training •

4. **Monitoring and Assessment**

- Systems of follow-up in time real
- Assessment continue of effectiveness

5. Validation of the Method Used in Research: Evaluation of Orange Data Mining Using a Neutrosophic Multicriteria Analysis [4-11].

Orange Data Mining is validated as the main method for the analysis of data on missing persons in Ecuador in 2024, using open data obtained from the official government platform (https://www.datosabiertos.gob.ec/). To do this, a **neutrosophic multicriteria analysis** is applied, which allows evaluating the robustness, precision and applicability of Orange Data Mining in the management of data with uncertainty and imprecision. The validation of the method is presented below, highlighting its use and effectiveness in the research context.

1. Justification for the Use of Orange Data Mining and Neutrosophic Analysis a. Orange Data Mining as a Main Tool:

- Orange Data Mining is a data analysis and visualization platform that allows you to build workflows for data processing, analysis and visualization. Its graphical interface and its ability to integrate data mining, machine learning and visualization techniques make it an ideal tool for quantitative and descriptive research.
- In this study, Orange Data Mining is used to process the database of missing persons in Ecuador, identify • patterns, detect inconsistencies and visualize results in a clear and effective way.

b. Neutrosophic Multicriteria Analysis:

- Since data on disappearances often contain uncertainty (for example, in location, time elapsed or status of cases), a neutrosophic analysis is applied to assess Orange Data Mining's ability to handle this uncertainty.
- Neutrosophic logic allows the incorporation of degrees of truth, falsehood and indeterminacy, which reinforces the evaluation of the tool in complex contexts.

2. Data Generation and Application of Orange Data Mining

a. Data Used:

The database of missing persons in Ecuador in 2024 is used, which contains 6,874 registered cases. The data includes information on location, elapsed time, case status (solved or unsolved) and other relevant variables.

b. Processing with Orange Data Mining :

- **Preprocessing : Orange's** preprocessing module is used to clean the data, handle missing values, and normalize the variables. The "Select " tool Columns " is used to eliminate noise and highlight the most relevant variables.
- Visual Exploration: Widgets such as "Feature" are used Statistics ", "Box Plot ", " Mosaic Display " and " Scatter Plot " to visualize the distribution of cases by location, elapsed time, and case status.
- **Geocoding :** Geocoding is applied to analyze spatial information and identify geographic patterns in the data.
- **Predictive Modeling:** Machine learning models such as Random Forest and Naive Bayes, using evaluation metrics and confusion matrices to determine the most efficient model.

c. Transformation of Data to Neutrosophic Intervals:

- To assess uncertainty in the data, the results obtained with Orange Data Mining are transformed into neutrosophic intervals. For example:
- **Distribution by Location:** Between 20% and 25% of cases have a 70% probability of being in the province of Pichincha, with 15% of indeterminacy.
- **Case Status:** Between 60% and 65% of cases have a 70% chance of being resolved, with 10% of cases being undetermined.

3. Orange Data Mining Neutrosophic Multicriteria Evaluation

a. Criteria Evaluated:

- Criterion 1: Accuracy in data analysis.
- Criterion 2: Ability to manage uncertainty.
- **Criterion 3:** Ease of use and interpretation of results.
- Criterion 4: Integration of advanced techniques (clustering , visualization, etc.).
- Criterion 5: Applicability in real contexts.

b. Neutrosophic Weights:

- **Criterion 1:** Weight [0.4; 0.5] (high importance).
- **Criterion 2:** Weight [0.3; 0.4] (medium-high importance).
- Criterion 3: Weight [0.2; 0.3] (medium importance).
- **Criterion 4:** Weight [0.1; 0.2] (low importance).
- **Criterion 5:** Weight [0.1; 0.2] (low importance).

c. Neutrosophic Scores:

- **Data Analysis Accuracy:** [0.85; 0.90] (high accuracy).
- Ability to Manage Uncertainty: [0.75; 0.80] (good ability).
- Ease of Use and Interpretation of Results: [0.90; 0.95] (very easy to use).
- Integration of Advanced Techniques: [0.80; 0.85] (good integration).
- Applicability in Real Contexts: [0.85; 0.90] (high applicability).

4. Validation of the Use of Orange Data Mining

a. Robustness in the Face of Uncertainty:

• Orange Data Mining demonstrates a good ability to handle uncertainty in data, especially when complemented by neutrosophic analysis. This reinforces its validity in contexts where data is imprecise or incomplete.

b. Consistency with the Study Objectives:

• The results obtained with Orange Data Mining are consistent with the objectives of the study, as they allow patterns to be identified, data to be visualized and informed decisions to be made.

c. Comparison with Other Tools:

• Unlike other data analysis tools, Orange Data Mining offers an intuitive graphical interface and a wide range of integrated techniques, making it easy to use in quantitative and descriptive research.

5. Discussion and Conclusions

a. Method Validation:

• Neutrosophic multicriteria analysis validates the use of Orange Data Mining as the primary method in research, demonstrating its robustness, accuracy and applicability in handling complex data.

b. Contribution to the Field:

• The application of Orange Data Mining in the context of missing persons is a significant contribution to the field, as it allows large volumes of data to be analysed efficiently and effectively.

c. Recommendations for Future Research:

 Mining is recommended for future research into complex social issues where data is often subject to inaccuracies and ambiguities.

Validating the use of Orange Data Mining through a neutrosophic multi-criteria analysis demonstrates its robustness and applicability in contexts where data are uncertain and complex. This tool not only facilitates data analysis and visualization, but also enables informed and robust decision-making on complex social issues, such as missing persons. Its use in future research could significantly improve the understanding and management of similar issues in other geographical or social contexts.

5. Conclusions

The analysis of disappearances in Ecuador during 2024 reveals an alarming problem in terms of volume and geographical distribution. A total of 6,874 cases were recorded, of which between 80% and 90% were found after a search process. However, a worrying pattern was identified: women are the most vulnerable group to kidnappings, while men who are not located in time tend to have more tragic outcomes. The provinces with the highest incidence of disappearances were Pichincha and Guayas, which together accounted for 46% of the cases analyzed, according to the techniques applied in this research. Other provinces with significant, although lower, numbers include Manabí, Esmeraldas, El Oro and Azuay. In contrast, the Galapagos Islands reported the lowest number of disappearances, with only two cases recorded. Although there is no single cause that explains all disappearances, many of them are related to personal factors, family conflicts, violence and, in some cases, human trafficking. In addition, certain reports have shown the involvement of organized criminal groups. Minors and women make up a considerable percentage of cases, which underlines the need for specific prevention strategies for these vulnerable groups.

For future research on disappearances, it is recommended to improve the collection and centralization of data in a platform accessible to all institutions involved in the management and protection of this information. The implementation of artificial intelligence tools and advanced data analysis techniques will allow for a more efficient detection of risk patterns, including geographic areas and demographic factors with a high incidence in these events. From a neutrosophic perspective, this study can benefit from the application of neutrosophic logic to manage the uncertainty inherent in data on disappearances. Neutrosophic theory, by considering values of truth, falsity, and indeterminacy simultaneously, is ideal for modeling situations in which information is incomplete or contradictory, as occurs in many cases of disappearances. The use of neutrosophic sets and fuzzy logic could help categorize and analyze the factors associated with disappearances without forcing rigid classifications, allowing for a more flexible and adaptable approach to social reality. Furthermore, neutrosophic decision-making could contribute to the formulation of more effective search and prevention policies, incorporating uncertain variables and determining location probabilities based on detected patterns.

In conclusion, the findings of this study provide key information for the formulation of prevention and response strategies for disappearances in Ecuador. The integration of advanced analysis tools and innovative approaches such as neutrosophy will allow for a more precise and adaptive approach, strengthening the capacity of institutions to reduce the incidence of disappearances and improve response times in locating people.

References

- [1] Government of Ecuador (2024), "Data on disappearances in Ecuador," Open Data of Ecuador, [Online]. Available: https://www.datosabiertos.gob.ec.
- [2] J. Demsar , T. Curk , and A. Erjavec (2025), "Orange data mining," [Online]. Available : https://orange.biolab.si/.
- [3] Y. Loaiza (2024), "Impunity and negligence in Ecuador: the cases of forced disappearances that remain unanswered," Infobae, 29 Dec. 2024, [Online]. Available: https://www.infobae.com/america/americalatina/2024/12/29/impunidad-y-negligencia-en-ecuador-los-casos-de-desapariciones-forzadas-quesiguen-sin-respuesta/.
- [4] AL Baldeón Puga (2017), "Disappeared in Ecuador, current situation," Bachelor's thesis, University of the Americas, Quito.
- [5] F. Smarandache and J. Dezert (2013), "Advances and applications of DSmT for information fusion under uncertainty with neutrosophic logic," American Research Press, vol. 3, pp. 1–456.
- [6] H. Zhang, L. Zhang, and H. Wang (2015), "A multi-criteria decision-making method based on singlevalued neutrosophic sets and similarity measures," Journal of Intelligent & Fuzzy Systems, vol. 28, no. 2, pp. 855–863, doi: 10.3233/IFS-141516.

- [7] S. Pramanik, R. Roy, and TK Roy (2018), "Multi-criteria decision making using neutrosophic ELECTRE method," Neutrosophic Sets and Systems, vol. 20, pp. 50–58, doi :10.5281/zenodo.1235368.
- [8] C. Liu and Y. Luo (2016), "A new method for multi-attribute decision making with single valued neutrosophic assessments," International Journal of Machine Learning and Cybernetics, vol. 7, no. 6, pp. 1085–1093, doi:10.1007/s13042-015-0458-8.
- [9] K. Mondal and S. Pramanik (2015), "Neutrosophic decision making model for clay-brick selection in construction field based on gray relational analysis," Neutrosophic Sets and Systems, vol. 9, pp. 64–71, [Online]. Available: http://fs.unm.edu/NSS/NeutrosophicDecisionMakingModel.pdf.
- [10] M. Abdel-Basset, G. Manogaran , and M. Mohamed (2019), "A neutrosophic theory-based decisionmaking approach for the Internet of Things (IoT) applications," IEEE Internet of Things Journal, vol. 6, no. 2, pp. 3145–3155, doi :10.1109/JIOT.2018.2877156.
- [11] J. Hu, P. Li, and X. Chen (2020), "A novel neutrosophic multi-criteria decision-making method based on Dempster -Shafer theory," Soft Computing, vol. 24, no. 11, pp. 8115–8128, doi :10.1007/s00500-019-04370-7.

Recibido: febrero 14, 2025. Aceptado: marzo 04, 2025