

Red Alert! Unveiling Insights in Violence Against Women through Interactive Data Visualization

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Abstract: Governments nowadays make several open data sets available, including data on reports of violence against women. Such a type of violence is considered a public health and safety problem and requires approaches that help identify behavioral patterns, trends, and profiles of victims and perpetrators. The analysis of this type of data can be facilitated with the use of interactive visualization. Visual representation techniques enable the identification of patterns and trends, providing insights that aid decision-making. Given this context, this paper proposes using interactive visualization techniques to explore government data on violence against women, aiming at a better understanding and preventive actions. Data obtained from the Women's Service Center (Call 180) can be explored through a set of dashboards called MARIA (Mapping and Analysis of Risks and Insights on Abuse Against Women), which reveal hidden insights and patterns, helping to identify vulnerabilities. The purpose is to foster more knowledge about this data to develop strategies to prevent and combat violence against women. Interviews with domain experts have shown that MARIA is easy to use, contributes to data knowledge, and provides insights consistent with reality.

Keywords: Government Data, Violence Against Women, Open Data, Interactive Data Visualization.

1 Introduction

We live in the information age, with a society increasingly driven by data [Pentland, 2013]. Alongside the growth in the volume of data collected, generated, and stored, there has also been a rising need to structure this data for analysis to extract knowledge and relevant information [Keim *et al.*, 2010]. In this context, according to Liu *et al.* [2017], visualization plays a key role in data analysis, as it aids in understanding the information contained within datasets. The use of effective visual representation facilitates the identification of trends, correlations, patterns, and discrepancies [Tufte, 2001], thus assisting in gaining insights and making decisions [Kirk, 2016].

Currently, governments have made efforts to promote transparency by providing a wide range of open data that can be analyzed. However, analyzing this data often proves challenging for a significant portion of the population, whether due to its sheer volume, the format in which it is made available, or the lack of standardization in the files. For instance, data updated annually often features a different structure each year, with different columns, complicating the analysis process.

Government open data comes from various areas and sectors, including reports related to violence against women. In this case, the data provides information about the records made and includes the type of violence, the location where it

occurred, the profiles of both the victim and the perpetrator, and relevant demographic data. Violence against women is a public health and safety problem that affects society as a whole [de Almeida Teles and de Melo, 2017]. It represents a form of inequality between men and women and a violation of human rights, capable of causing physical, psychological, and social harm. It is very important to address this issue comprehensively, to understand its origins and consequences, and to promote cultural and structural change that eliminates tolerance of violence against women, in addition to protecting victims.

The analysis of data related to violence against women has been explored in the literature. For instance, Kasiselvanathan *et al.* [2023] applied data mining and machine learning techniques to predict and analyze patterns of violence against women, identifying high-risk areas and conditions for femicides. Montenegro [2021] employed techniques for collecting, analyzing, and visualizing government open data to investigate indicators of violence against women before and during the COVID-19 pandemic. Rios *et al.* [2023] integrated several datasets to examine sociodemographic and criminal information about the homicide of girls and women in the city of Porto Alegre.

Although there are initiatives for the collection, availability, and analysis of government open data related to violence against women, there is still room for research in this area, aiming to facilitate data exploration and accessibility for re-

searchers, professionals, public policymakers, and the general population. In this context, visual exploratory data analysis can play a significant role by enabling the extraction of insights through the identification of patterns, trends, and hidden correlations.

This work aims to demonstrate how using interactive visualization techniques and data exploration methods helps understand and gain relevant insights from government open data on violence against women. To achieve this, we developed a set of dashboards called MARIA (Mapping and Analysis of Risks and Insights on Abuse Against Women), which foster a better understanding of this data and assist in identifying the most relevant variables, aiming to support the design of preventive actions and promote the dissemination of this information. The data was collected from the “Women’s Service Center”¹, an open data portal of the Ministry of Human Rights and Citizenship containing reports on violence against women recorded by the Call 180 service.

Our research stands out for the interactivity of the created visualizations and the ease with which users can utilize and recreate them. We provide a step-by-step guide on our *GitHub*² that explains how to collect and process the data for subsequent visualization, enabling other researchers to reproduce and adapt our analyses in a transparent and accessible manner. Additionally, MARIA is available online³, and through exploratory visual analysis, it allows the identification of various patterns and vulnerability situations, aiding in the development of strategies for the prevention and combat of violence against women. Its main contribution is enabling a detailed analysis of the data to support the protection of rights and the safety of victims. Furthermore, we conducted an initial survey with domain experts, who provided positive feedback on the dashboards, highlighting their ease of use, relevance, and the utility of the presented information.

The remainder of this article is organized as follows: Section 2 explores some related works. Next, we detail the tool developed for visual analysis. In Section 4, we present the discussions, describing the impressions of domain specialists, potential users, limitations, and future work. In the final section, we describe our conclusions.

2 Related Work

Vasconcelos *et al.* [2022] used data from the 2017 VIVA Inquiry⁴ to analyze physical violence perpetrated by intimate partners against women who sought care in public emergency services in Brazil. The study examined the sociodemographic characteristics of the victims and aggressors, as well as aspects of the nature of the violence. The results revealed patterns associated with variables such as race, age, educational level of the victims, type of aggression, and other relevant aspects.

In the same context, an evaluation of the impact of the M Health Community Network project on the use of healthcare services by victims of intimate partner violence in an outpa-

tient system was conducted by Clark *et al.* [2019]. Using electronic medical records from 756 patients who screened positive for intimate partner violence, the study analyzed documents containing support information and contacts for specialized services, as well as direct referrals, versus the refusal of both. The objective was to verify whether offering support increases the use of healthcare services. The results indicate that patients who accepted some form of support had higher rates of using these services, suggesting that the protocol may enhance access to necessary support for victims of intimate partner violence.

Additionally, Sardinha *et al.* [2022] aimed to estimate the prevalence of intimate partner violence, both physical and sexual, at global, regional, and national levels, using data collected from 366 studies representing 161 countries and covering 90% of the world’s female population. Using a Bayesian model, the authors estimated that 27% of women aged 15 to 49 had experienced intimate partner violence at some point in their lives. The prevalence is higher in low-income countries, particularly among adolescents and young women. The research underscores the need for investments in multisectoral interventions and public policies to combat this violence and achieve the United Nations’ gender equality goals.

A literature study on machine learning to facilitate the analysis of domestic violence data sought to highlight the most relevant factors for predictive analysis [Júnior and Ribeiro, 2019]. Among these, age, alcohol use, local culture, economic issues, and educational level were identified as significant factors. Montenegro [2021] employed data collection, analysis, and visual representation techniques to examine indicators of violence against women in Brazil before and during the social distancing period of the COVID-19 pandemic, aiming to understand the pandemic’s impact on these cases of violence. The results showed a reduction in reported cases of violence, which may have been influenced by an increase in underreporting.

Rios *et al.* [2023] analyzed sociodemographic, criminal, and forensic data related to cases of homicides of girls and women in the city of Porto Alegre, RS. The study reveals an increase in overall rates of female homicides, particularly due to urban violence, such as involvement with drug trafficking, crimes, and robberies. Non-white women aged 15 to 29 were the most affected, and the authors emphasize that obtaining detailed data on the victims and the characteristics of the violence is essential to addressing the issue and guiding public policies.

Similarly, Moroskoski *et al.* [2022] analyzed fatalities among women aged 15 to 59 in cities of Paraná, aiming to estimate the risk of lethal violence and identify correlated factors. They found a relationship between lethal violence and the proportion of mothers who are heads of households. Additionally, they observed an association between non-lethal violence rates and the presence of female mayors and councilors in the studied cities. The analyses revealed that violence is associated with low educational levels, structural violence, and women’s political participation. Leite *et al.* [2023] used data on reported cases of violence against women in the state of Espírito Santo to analyze the recurrence of violence at different stages of women’s lives and investigate the associated factors. Statistical analyses revealed a significant in-

¹<https://tinyurl.com/ye29refu>

²<https://github.com/DAVINTLAB/MARIA.git>

³<https://tinyurl.com/4vshvkyu>

⁴<https://tinyurl.com/ey2tjrx>

cidence of repetitive violence against women, with notable cases involving older women with disabilities or disorders. The perpetrators, mostly around 25 years old, were primarily family members of the victims.

Medeiros *et al.* [2024] applied the ELECTRE Tri-B multicriteria decision model to classify municipalities in Paraíba based on their propensity for domestic and family violence against women. The authors used data from the 2019 Municipal Basic Information Survey and the Women's Service Center (Call 180), analyzing socioeconomic criteria to categorize municipalities into low, medium, high, and very high propensity classes. The results indicate that 83.85% of the municipalities exhibit a high propensity for violence, reflecting a lack of support services for victims. The study highlights the need for resource allocation and public policies targeted at vulnerable areas.

The analytical model proposed by Kasiselvanathan *et al.* [2023] employs data mining and machine learning techniques to predict and analyze crime patterns, focusing on violence against women, using historical crime data. Based on government records from India, which include occurrences such as rape, dowry-related deaths, and assaults on women's dignity, the system identifies high-risk areas and conditions for femicide crimes. The visualizations derived from crime patterns aim to support prevention policies and social awareness initiatives, providing insights for more effective interventions.

Méndez *et al.* [2023] presented the results of a qualitative analysis based on the interaction of 34 users with an interactive visualization tool developed to explore data on violence against women aged 15 to 49 in Ecuador. The tool utilizes maps, bar charts, and word clouds to present information on the prevalence, types, context, and frequency of different forms of violence occurring in public and private settings. These visualizations facilitated an understanding of the magnitude and characteristics of violence against women in the country, revealing patterns and details overlooked by traditional media coverage. The tool also demonstrated the potential to support public policy formulation and raise social awareness about domestic violence.

The priority of addressing violence against women in health policies was analyzed by Burke *et al.* [2024] using data from the World Health Organization (WHO). They evaluated the inclusion of healthcare services for victims of violence against women in national policies across 194 countries, focusing on 15 indicators aligned with WHO recommendations, such as post-violence care services and mental health assessments. The results indicate that 80% of countries have multisectoral policies addressing violence against women, but only 34% prioritize the response to this violence in national health policies. The study highlights the need to raise government awareness about the impact of violence against women on public health and to strengthen the alignment of policies with international guidelines.

These studies, summarized in Table 1, highlight the diversity of approaches used in exploring data related to domestic violence against women and show the importance of analyzing this data to raise awareness about the problem and to formulate public policies. However, it is also possible to observe a limitation concerning the geographical scope of

the analyzed data in some works, which pertains only to a municipality [Montenegro, 2021; Rios *et al.*, 2023], a state [Moroskoski *et al.*, 2022; Leite *et al.*, 2023; Medeiros *et al.*, 2024], or a country [Méndez *et al.*, 2023; Kasiselvanathan *et al.*, 2023]. Vasconcelos *et al.* [2022] used data from SUS emergency and urgent care services in 23 state capitals and some municipalities, so the sample reflects only the population served by these specific services. The study by Kasiselvanathan *et al.* [2023] was conducted in a specific and isolated context without considering the use of the tool in conjunction with other interventions, such as educational programs or public policies.

Furthermore, data incompleteness is a limitation in the studies by Burke *et al.* [2024] and Clark *et al.* [2019], exacerbated by the use of secondary data, which may underreport cases of violence, as highlighted by Leite *et al.* [2023] and Moroskoski *et al.* [2022]. Another limitation is the restricted presentation of data on victims' profiles due to the small number of studies involving public safety variables and the challenge of reconciling data from different databases [Rios *et al.*, 2023]. An additional constraint is the small sample size analyzed [Clark *et al.*, 2019; Vasconcelos *et al.*, 2022; Méndez *et al.*, 2023], while Sardinha *et al.* [2022] mention challenges related to data availability and quality.

There is a growing interest in analyzing these data, given their importance in guiding preventive actions and public policy formulation. However, not all studies utilize public data, hindering the research's reproduction or extension, and none of them made a dashboard available for analysis and presentation of results online. Only two studies shared information about their research and analyses on *GitHub*: Sardinha *et al.* [2022] made the source code of their developed statistical model accessible, and Medeiros *et al.* [2024] presented an interactive map that allows dynamic exploration of geographic information for visualizing the results. Méndez *et al.* [2023] created an interactive website for analyzing data on violence against women, and the website developed by Kasiselvanathan *et al.* [2023] analyzes user-provided data and predicts the occurrence of crimes based on this information. However, these websites are not available for analysis. MARIA utilizes public data, its code is available on *GitHub*, and the dashboards are available online, enabling the analysis of data on violence against women and facilitating the reproducibility of the research.

3 MARIA Description

In this section, we describe MARIA and its interactive visualizations that allow for the analysis and obtaining of insights from open government data on violence against women. Initially, data collection and preprocessing were carried out. After that, dashboards were created⁵.

To prepare the data, we used *Python* programming language, which has several libraries, such as *Pandas* and *NumPy*, that allowed data manipulation and statistical methods to be applied. The dashboards were created using *Tableau Desktop*⁵, a tool that enables you to quickly and interactively generate visualizations and organize them into dash-

⁵<https://www.tableau.com/pt-br/products/desktop>

Table 1. Summary of related works involving violence against women.

Reference	Objectives	Data used	Data presentation
Júnior and Ribeiro [2019]	Highlight relevant data for predictive analysis of domestic violence.	Data extracted from the literature review (1993 to 2019).	Tables and charts
Clark <i>et al.</i> [2019]	Evaluate whether the M Health Community Network project increases the use of health-care services by victims of intimate partner violence.	Electronic Health Records (2016 to 2019).	Tables and charts
Montenegro [2021]	Understand the consequences of the pandemic on cases of violence against women in Brazil.	Government open data (2019 to 2020).	Charts
Vasconcelos <i>et al.</i> [2022]	Investigate physical violence by intimate partners against women, recorded in emergency and urgent care services in Brazil.	VIVA Inquiry (2017).	Tables and charts
Sardinha <i>et al.</i> [2022]	Provide regional, national, and global estimates of the prevalence of intimate partner violence against women, aiming to monitor progress toward the goal of eliminating such violence.	WHO (2000 to 2018).	Tables and charts
Moroskoski <i>et al.</i> [2022]	Estimate the risk associated with lethal violence against women and identify correlated factors in cities of Paraná.	Data on fatalities among women aged 15 to 59 (2014 to 2018).	Tables and maps
Rios <i>et al.</i> [2023]	Analyze sociodemographic and criminal information on female homicides in Porto Alegre.	Private data (2010 to 2016).	Tables and charts
Leite <i>et al.</i> [2023]	Analyze the recurrence of violence across different stages of women's lives in Espírito Santo.	Data on reported cases of violence against women (2011 to 2018).	Tables
Kasiselvanathan <i>et al.</i> [2023]	Predict incidents of violence against women in India, providing data for intervention programs and preventive public policies.	National Crime Records Bureau and government open data.	Charts
Méndez <i>et al.</i> [2023]	Evaluate the effectiveness of the interactive visualization tool and enhance public awareness and understanding of gender-based violence in Ecuador.	Data from the National Institute of Statistics and Censuses of Ecuador (2019).	Charts, maps, and word clouds
Burke <i>et al.</i> [2024]	Evaluate how countries are prioritizing violence against women in health and multisectoral policies.	The Violence Against Women database of the WHO (2018 to 2021).	Tables and charts
Medeiros <i>et al.</i> [2024]	Classify the municipalities of the state of Paraíba according to their propensity for domestic and family violence against women.	Data from the Municipal Basic Information Survey and the Women's Service Center (2019).	Tables and maps

boards. In addition, all developed dashboards can be shared on *Tableau Public*⁶, a free platform to share interactive data visualizations.

Since we had a large amount of data and many charts to include, we decided to develop a multipage dashboard [Sarikaya et al., 2019]. Thus, we divided the data into a set of dashboards that considered each specific topic to facilitate analysis and organization. This approach aligns with the Human-Computer Interaction (HCI) design pattern known as “Module Tabs”⁷, in which related content is grouped into modular sections. This HCI pattern is used when there is no space for all the content, which is then divided into coherent groups [Tidwell, 2011]. However, our implementation uses buttons to navigate between dashboards instead of traditional tabs, maintaining usability while adapting the concept to the *Tableau* environment.

All dashboards were created using the Coordinated Multiple Views (CMV) interaction technique [North and Shneiderman, 2000], in which selections made in one visual representation directly impact the others. We chose to use traditional charts, such as heatmaps, choropleth maps, word clouds, pizza, and bar charts, as they are more appropriate considering the different experiences, expectations, and visualization literacy [D’Ignazio, 2017] of the possible users (see Section 4.1).

3.1 Data Collection and Preparation

First, data from the Women’s Service Center (Call 180)⁸ were collected from the open data portal of the Ministry of Human Rights and Citizenship. The portal provides several .csv files, organized by year or semester since 2014. Considering the files from 2014 to 2024, only the “2019 balance sheet” was excluded from the analysis, as it contained only a summary of the year 2019, already consolidated into a single table. The data contained in the files include information such as city, state, time of the complaint, the identity of the complainant, whether the victim’s life was at risk, location of the violence, as well as demographic data such as age range, education, income range, and profession of the victim and suspect, among others. The preprocessing of this data was initially divided into 3 stages, described below.

- **1° Stage:** column names are standardized (based on the file “Comparação dos campos de cada tabela.xlsx” made available together with the other files on *GitHub*), filtering for domestic violence cases (as more recent data also include reports of elder abuse and environmental crimes), the removal of duplicate records (necessary for data files from 2020 onward), and standardization to ensure that all values across all tables are in uppercase and without accents.
- **2° Stage:** tables with the same format resulting from the previous step are joined, generating four distinct datasets covering the periods from 2014 to November 2018; December 2018 to the end of 2019; first half of

2020; second half of 2020 to the end of 2023. Subsequently, specific cleaning processes are applied to each generated dataset, such as standardizing country and city names and classifying professions (open fields) based on the ENEM data dictionary⁹, as described in Table 2. It was necessary to divide the data into four different datasets due to four changes in the way the complaint data was recorded over the years. For instance, the period from 2014 to November 2018 includes data on whether the suspect was a drug or alcohol user and whether there was financial dependency between the victim and the suspect. However, this information stopped being collected in the following years.

- **3° Stage:** all tables are combined into a single dataset and standardized to ensure uniformity in columns that are common to more than one dataset. This operation is performed to generate a dataset encompassing the entire period, enabling temporal and geographical analyses of variations in the number of victims and reports.

After all the data was updated, standardized, and organized into a single dataset, the data was enriched. The column “*Categorias*” was added to the data, with the aim of classifying the violations that occurred with the victims, according to the categorization provided by the *Maria da Penha Law*¹⁰. The values in this column follow five categories: “*Physical Violence*”, “*Psychological Violence*”, “*Sexual Violence*”, “*Moral Violence*”, and “*Patrimonial Violence*”, as described in the article available on the *Maria da Penha* Institute website. The categorization was performed using Python scripts that analyzed the words in the column “*Violações*”, which contains textual data. For each record, this field was analyzed, and the categories were identified considering the presence of specific terms. For instance, if the term “*Minor Bodily Injury*” appeared, the violation was classified as “*Physical Violence*”, and so on for the other categories.

Finally, to enable continuous updates, a script for inserting new data was also created, incorporating all the operations performed in the data processing and enrichment stages. Thus, whenever new data is made available on the portal, as long as it does not present changes in the number or name of the columns, it can be quickly processed and inserted into the dataset for analysis over a longer period. Thus, through this script, we update the data until the first half of 2024.

In addition to the portal data, for analyses related to population size (by state, municipality, race, and level of education), data from the 2022 Census¹¹ were also used. This data was collected and included in *Tableau* to create the dashboards.

3.2 Demographic Profiles

To analyze and identify the demographic profiles of victims and suspects, two dashboards were developed to explore data such as race/color, level of education, age group, and profession, as illustrated in Figures 1 and 2. The victim profile dashboard also includes analyses of the victim’s relationship

⁶<https://public.tableau.com/>

⁷<https://ui-patterns.com/patterns/ModuleTabs>

⁸<https://tinyurl.com/ye29refu>

⁹<https://enem.inep.gov.br/>

¹⁰<https://tinyurl.com/2sz9cfsa>

¹¹<https://tinyurl.com/y32c879j>

Table 2. Description of professions belonging to each group according to the classification adopted in ENEM.

Group	Professions
Group 1	Farmer, agricultural worker without employees, seasonal worker, animal breeder (cattle, pigs, chickens, sheep, horses, etc.), beekeeper, fisherman, lumberjack, rubber tapper, extractor.
Group 2	Day laborer, domestic worker, elderly caregiver, nanny, cook (in private homes), private driver, gardener, office cleaner, security guard, doorman, mail carrier, office assistant, salesperson, cashier, store clerk, administrative assistant, receptionist, construction helper, stock replenisher.
Group 3	Baker, industrial or restaurant cook, shoemaker, tailor, jeweler, lathe operator, machine operator, welder, factory worker, miner, bricklayer, painter, electrician, plumber, driver, truck driver, and taxi driver.
Group 4	Teacher (elementary or high school, language, music, arts, etc.), technician (nursing, accounting, electronics, etc.), police officer, low-ranking military personnel (private, corporal, sergeant), real estate agent, supervisor, manager, construction foreman, pastor, small business owner (company with fewer than 10 employees), small trader, small landowner, self-employed worker.
Group 5	Doctor, engineer, dentist, psychologist, economist, lawyer, judge, prosecutor, public defender, police chief, lieutenant, captain, colonel, university professor, executive in public or private companies, politician, owner of companies with more than 10 employees.

with the suspect and the distribution of the number of victims by state.

These two dashboards allow the application of filters by state, time period, and type of domestic violence (Figures 1A and 2A). The filter by state, which is also available in the dashboards described in Sections 3.3, 3.5, 3.6, and 3.7, supports multiple selections, enabling the visualization of data from one or more states.

The time filter, also available in the dashboards described in Sections 3.3, 3.4, 3.6, and 3.7, enables the analysis of data for a selected period. The domestic violence type filter allows the selection of property, moral, sexual, psychological, or physical violence. This filter is also available in the dashboards described in Sections 3.3 and 3.7.

In the “*Suspect Profile*” dashboard presented in Figure 1, a significant gender disparity is observed, with a predominance of males compared to females. The ethnic distribution of suspects is similar to that of the victims, with whites (42.1%) and browns (40.69%) being the most recurrent in absolute numbers. Regarding age groups, the highest concentration of suspects is between 40 and 44 years old, followed by the 35–39 and 30–34 age groups, suggesting a prevalence of adults aged 30 to 44 years. Concerning educational attainment, it can be seen that most suspects have low levels of schooling, with the incomplete primary and complete secondary education groups standing out. This pattern suggests that individuals with a lower level of education are more frequently present in suspect records. In the analysis of suspects’ occupations, the “*Other*” group is the most representative. Group 3, which includes occupations such as truck drivers, machine operators, and bricklayers, is predominant among the classified professions. Based on this information, we can deduce that suspects have an income similar to or slightly higher than that of victims, considering the relationship outlined in Table 2.

Analyzing the “*Victim Profile*” dashboard (Figure 2) considering all Brazil states, there is an ethnic diversity, with a predominance of individuals identified as brown (45.2%)

and white (39.8%). It should be noted that although the Asian race represents a smaller number of victims in absolute numbers (0.7%), it has the highest proportion concerning the size of its population (850,130 people), according to the 2022 Demographic Census¹¹, corresponding to 0.14%.

The categorization of victims’ professions, excluding “*Other not listed*”, is dominated by Group 2, which includes occupations such as day laborers and domestic workers. In terms of educational attainment, there is a concentration of victims with a complete high school and incomplete elementary school education. However, as a proportion of the population, the majority of brown victims have an incomplete high school or higher education. Furthermore, when analyzing the relationship between victim and suspect, it can be seen that most victims have their current or ex-partner as their main suspect, followed by other categories such as others, neighbors, and close family members, including children, fathers, and mothers. These findings reveal a profile very similar to that identified by Montenegro [2021], further reinforcing the fragility of implementing public policies in areas of social vulnerability.

When applying the filter for the state of Rio Grande do Sul (RS), shown in Figure 2, and comparing it with the filtering for the state of São Paulo (SP), presented in Figure 3, it is observed that RS has a higher number of Indigenous victims, while SP has more victims of the Asian race. However, when analyzing the proportion relative to the total Indigenous population of each state, SP has a higher rate, with 0.42% of victims among its 50,528 Indigenous people. Regarding the age groups of victims, in RS, the majority fall within the 40–44 age group, followed by 30–34 years. In SP, the highest concentration is among those aged 35–39 years, with similar values for the 40–44 and 30–34 age groups. This indicates that in SP there is a higher prevalence of victims aged 30 to 44 years, whereas in RS, most victims are in the 40–44 age group. Furthermore, in SP, there is a higher concentration of victims who have completed high school education, while in RS, most victims have either incomplete elementary school

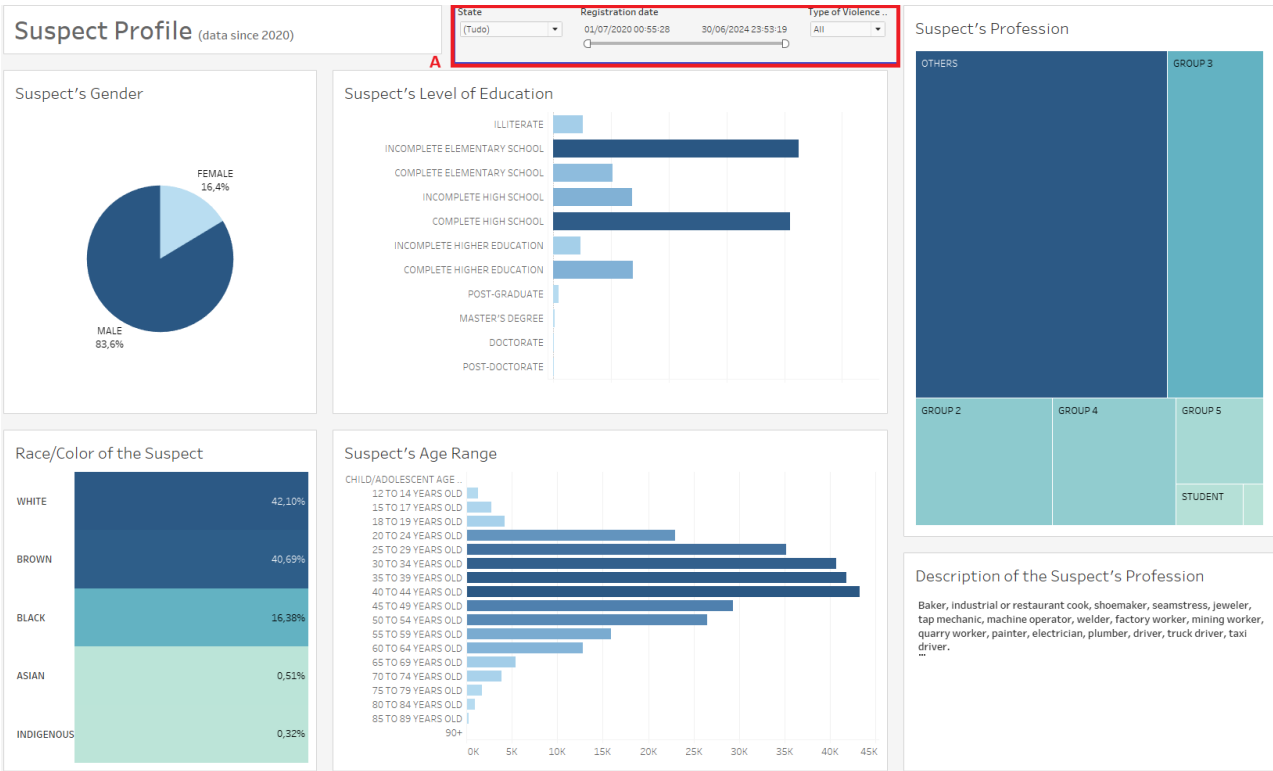


Figure 1. Dashboard for analyzing the suspect's demographic profile.

education or completed high school.

3.3 Relationships between Victims and Suspects

The “*Relationships between Victims and Suspects*” dashboard details the relationship between the victim and the suspect, aiming to clarify the violations’ context, frequency, and onset. Among the various aspects analyzed, the period marking the beginning of violations reveals important information about when victims choose to report abuse. Examining this period on the dashboard, the tendency for cases to be concentrated in the “More than a year ago” category stands out. This suggests that victims may be more likely to report abuse after a longer period of relationship, given the lower numbers in the “a week ago” and “one month ago” categories.

Another detail, which can be analyzed in Figure 4, is that when “Not applicable” is selected in the *Start of Violations* chart, the variable “Single occurrence” is the most predominant in the *Violation Frequency* chart, indicating that when a woman suffers her first aggression, she tends to report it immediately. Another relevant aspect is the variation in the frequency of violations, with an increase in the “Occasionally” category when moving from the group of partners to the group of ex-partners.

3.4 Distribution Throughout the Country

The dashboard illustrated in Figure 5, which offers a detailed mapping by states and municipalities, was created to examine the geographic distribution of complaints and victims. It provides a visualization of the location of occurrences and ar-

eas with the highest case incidences, providing insights into regions with a higher risk for potential victims. To calculate the incidence of reports and victims in each state or municipality, we divided the number of victims by the total population of the respective area, and the result was multiplied by one hundred thousand. This practice allows for a standardized comparison between different regions, accounting for population variations. This dashboard also offers a filter by year.

When analyzing the distribution of victims across the country, based on data collected from 2020, SP and Rio de Janeiro stand out for the highest absolute number of registered cases. However, when considering the total number of victims relative to the population, the highest rates are observed in Rio de Janeiro (45%) and the Federal District (34%). Regarding reports, both the absolute and relative numbers follow the same distribution pattern.

3.5 Frequency of Reports

To evaluate the temporal pattern of reports, we developed a dashboard to display the variation in the total number of reports over the years. It allows for comparisons of report frequencies between months of the year and days of the week and includes a heatmap correlating these two variables. This makes it possible to determine patterns in occurrences over time. Analyzing Figure 6, it can be seen that the visualizations help to understand the temporal dynamics of denunciations and identify trends.

When analyzing the temporal distributions of reports presented in the “*Frequency of Reports*” dashboard, an oscillating pattern is observed over the years, with notable peaks

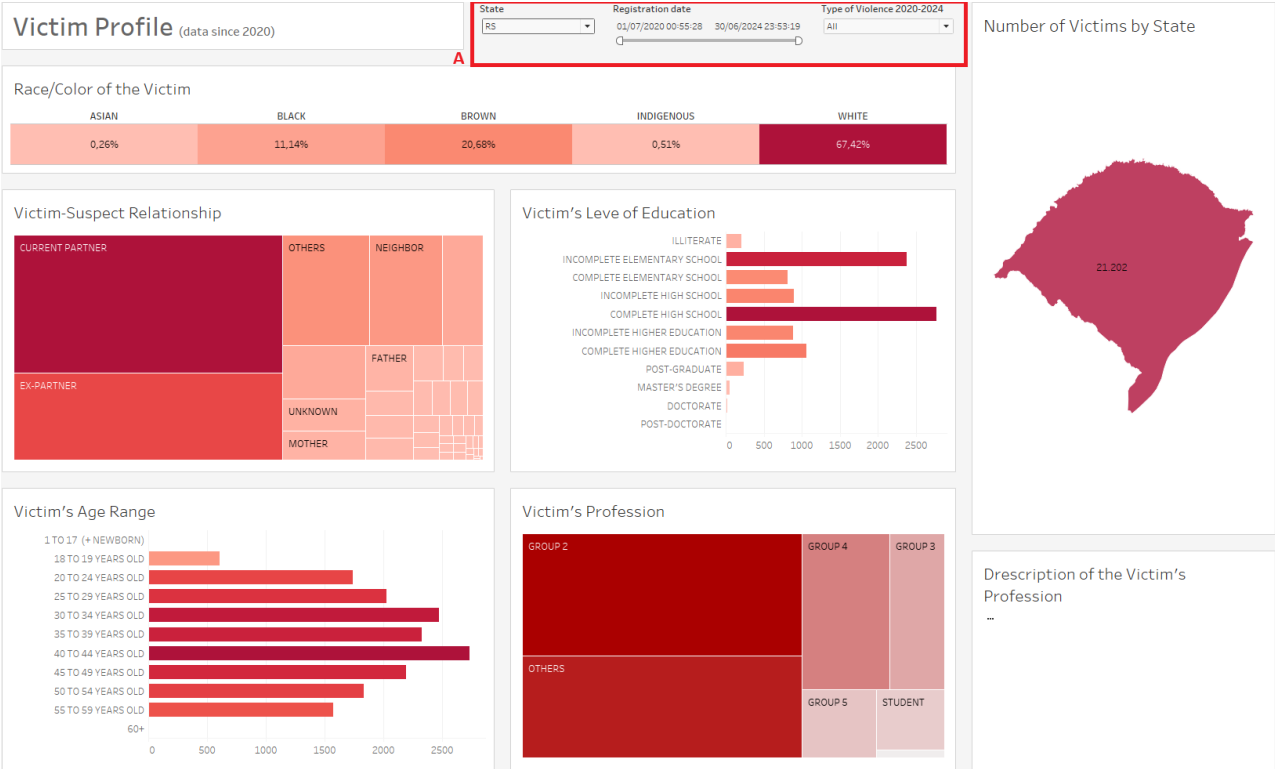


Figure 2. Victim profile dashboard with the state of Rio Grande do Sul filter applied.

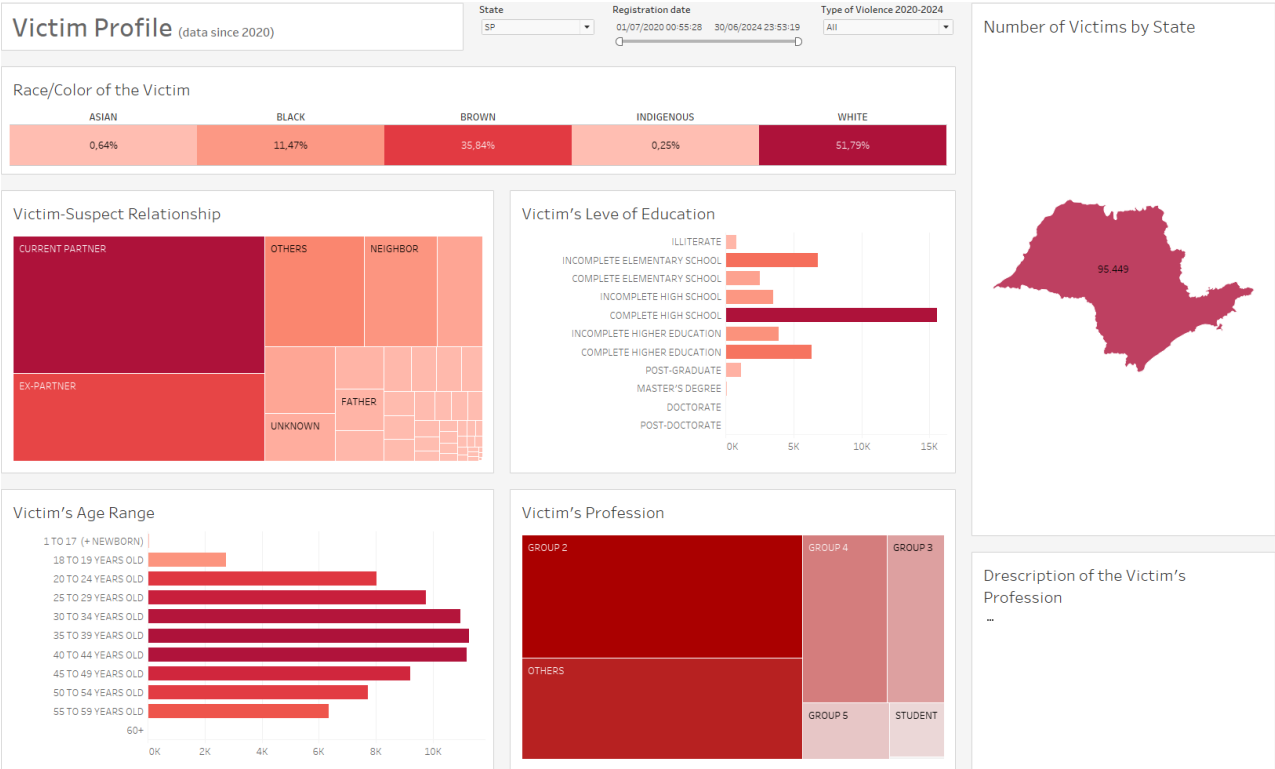


Figure 3. Victim profile dashboard with the state of São Paulo filter applied.



Figure 4. Dashboard of relationships between victims and suspects with the frequency of violation equal to “only occurrence” selected.

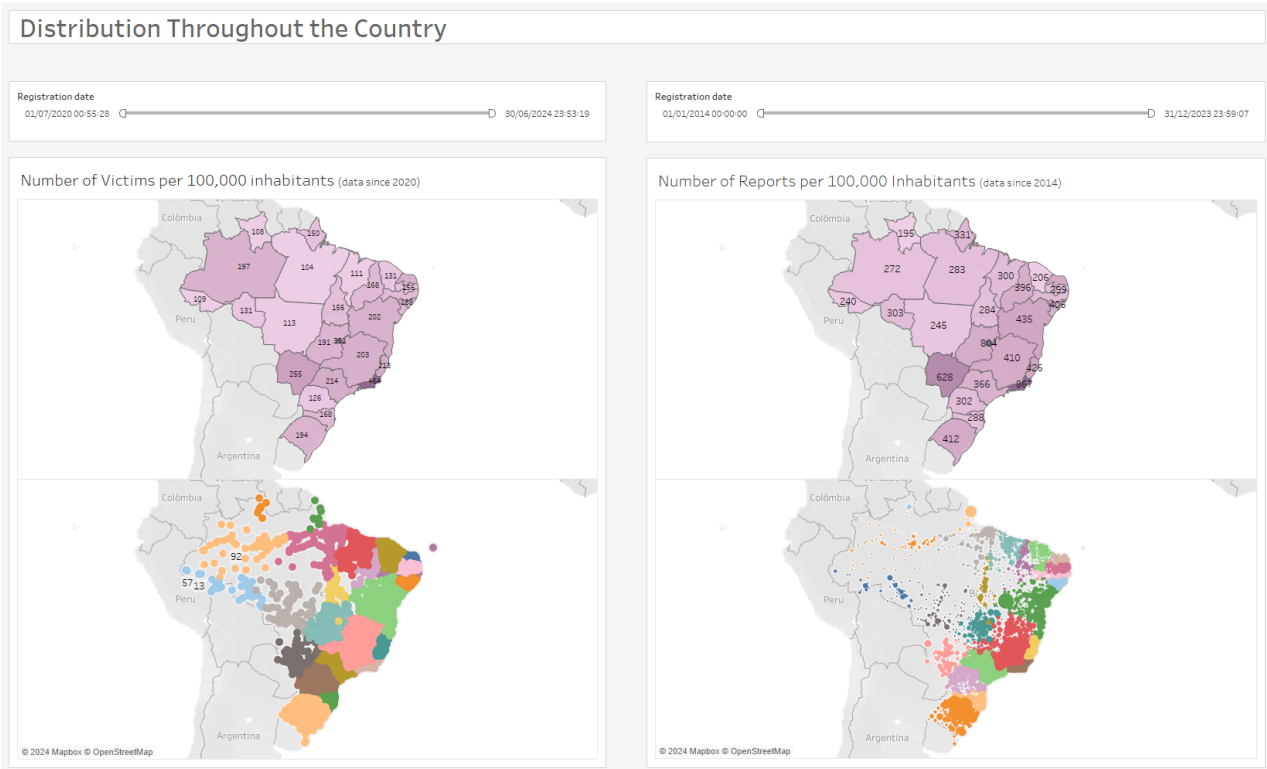


Figure 5. Dashboard of the distribution of reports and victims across the country.

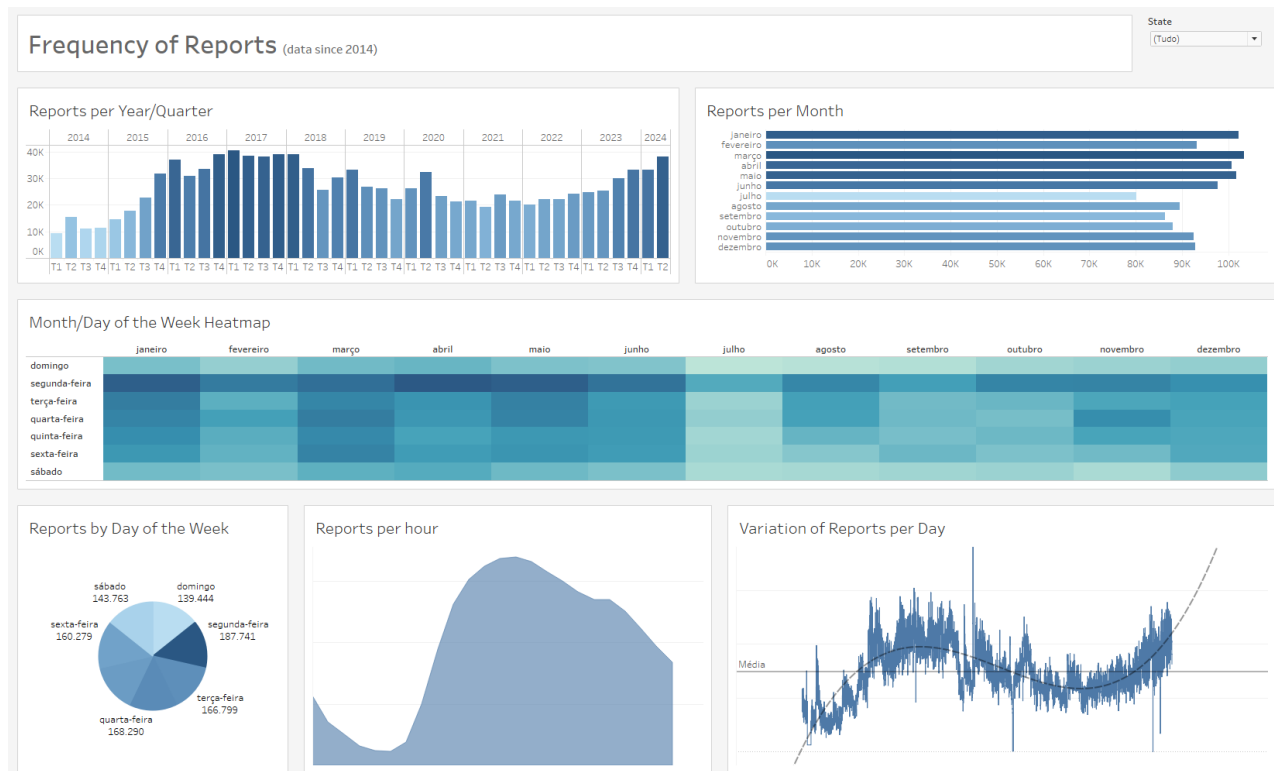


Figure 6. Dashboard for temporal analysis of reports.

between the fourth quarter of 2015 and the second quarter of 2018 and a significant increase in the second quarter of 2020. In addition, there is a gradual increasing trend in the volume of reports in 2022 and 2023, possibly indicating a recovery after a period of decline. This decline may be related to the impacts of the COVID-19 pandemic, which initially resulted in a peak followed by a substantial reduction.

Montenegro [2021] demonstrates that during the pandemic, at times of higher social isolation rates, cases of domestic violence fell slightly. He highlights a peak in social isolation in March 2020, which also corresponds to the increase in reports in the second quarter of the same year, as shown in our chart. Following this period, there is a gradual reduction in reports and a decrease in the social isolation rate.

Regarding weekly frequency, Mondays record the highest number of reports, followed by Wednesdays and Tuesdays, suggesting a tendency for cases to accumulate over the weekend and be reported at the start of the workweek. The heatmap correlating month and day of the week reveals certain combinations of months and days with higher report densities.

Examining the reports by month reveals a relatively uniform distribution throughout the year, with variations that may be related to seasonal factors or specific events, such as holidays or vacation periods. Finally, the analysis by hour shows a significant increase in reports during the early morning hours, which may reflect a tendency to report incidents at the start of the workday.

3.6 Context

To understand the context of violence and analyze the characteristics of the suspect, the “Context” dashboard (Figure 7) was developed, providing detailed visualizations of various aspects. Among them is a cohabitation chart, which reveals that more than half of the victims live with the suspect, and another chart on family violence, indicating that over 70% of suspects have familial or close ties with the victim. Additionally, it also includes an analysis of the area of residence, showing that most occurrences happen in urban areas.

This urban predominance, however, reflects a specific cut-off point, as reports made through Call 180 often come from regions with greater access to telephones and the Internet. As a result, the scenario in rural areas, where access is more restricted, may be less represented.

The dashboard also explores the use of drugs by the suspect, with 46% of them reported as alcohol consumers, and presents an analysis of the types of violence, where physical violence predominates, followed by psychological violence. Another chart addresses the duration of the violence, complementing the relationship between victim and suspect (Section 3.3), while visualizations on marital status reveal that most victims and suspects identify themselves as single. Finally, there is a visualization of the risk perceived by the victim, highlighting homicide as the most frequently reported risk. These visualizations, as presented in Figure 7, provide a deeper understanding of the temporal dynamics of reports and assist in identifying relevant trends.

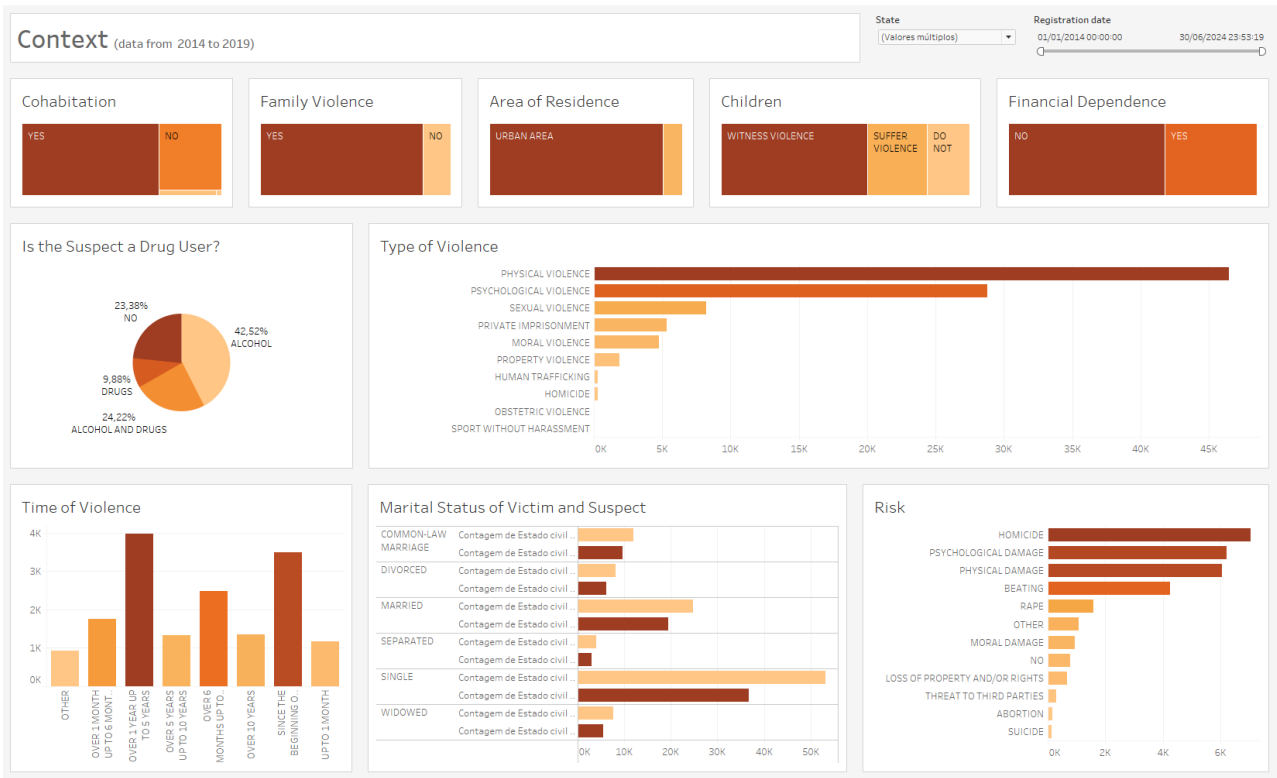


Figure 7. Dashboard for analyzing the context of the relationship between victim and suspect.

3.7 Prisoner Profile

Finally, a dashboard was developed to analyze the profile of incarcerated suspects (Figure 8), including data on the distribution of prisoners by state, age group, type of sentence by educational level, type of report, and the relationship between the prisoner and the victim. This data allows for the identification of regional patterns, an understanding of the age and educational profile of prisoners, an understanding of the context of complaints, and assess the proximity between the suspect and the victim, providing a perspective on the social and relational factors involved in the crimes.

When examining the “Prisoner Profile” dashboard without filtering by violation, it can be seen that the predominant age group among prisoners is 40 to 44 years, followed by 35 to 39 years and 30 to 34 years, indicating that the incarcerated population in cases of violence against women is mainly made up of adults in the 30 to 44 age group. Additionally, most prisoners with elementary and high school education levels were detained in flagrante delicto, and the chart of emergency reports reveals that these arrests are mainly associated with situations of imminent risk of death for the victim or the act of domestic violence. This highlights the importance of protective measures that can intervene before reaching this level of urgency.

When analyzing the relationship between the suspect and the victim, it can be seen that many suspects have close ties to the victims, such as current partners, ex-partners, friends, or acquaintances. This finding highlights that violence against women occurs mainly in intimate relationships, evidencing the need for public policies aimed at protecting women in vulnerable situations within their homes.

Regarding the geographical distribution of prisoners, states like SP, Rio de Janeiro, and Minas Gerais have a higher concentration, possibly due to these regions’ population size and urbanization. In addition, the majority of suspects arrested are brown, with 43.52% in absolute numbers, followed by white, with 37.22%. This scenario differs from the dashboard presented in Section 3.2 regarding the suspect’s profile, where the predominant race/color is white, followed by brown. This indicates that more brown suspects end up being arrested, even though the total number of white suspects is higher than the number of brown suspects.

With the violations filter set to sexual violence, as shown in Figure 8, it is observed that most suspects are identified as White, with a predominant age group of 40 to 44 years. The most frequent relationship between suspect and victim includes categories such as stranger, current partner, or friend. These data suggest the need to deepen the analysis of the contexts in which these crimes occur, especially considering that the *unknown* category may indicate attacks in public situations or unfamiliar environments for the victim, while *current partner* points to a significant risk of violence within intimate relationships. The inclusion of *friend* as a frequent relationship raises questions about vulnerability in environments considered trustworthy by the victim.

4 Discussion

The related work presented in Section 2 demonstrates the importance of providing tools to analyze data on violence against women. Several solutions have been proposed using different data and with distinct objectives. However, to the

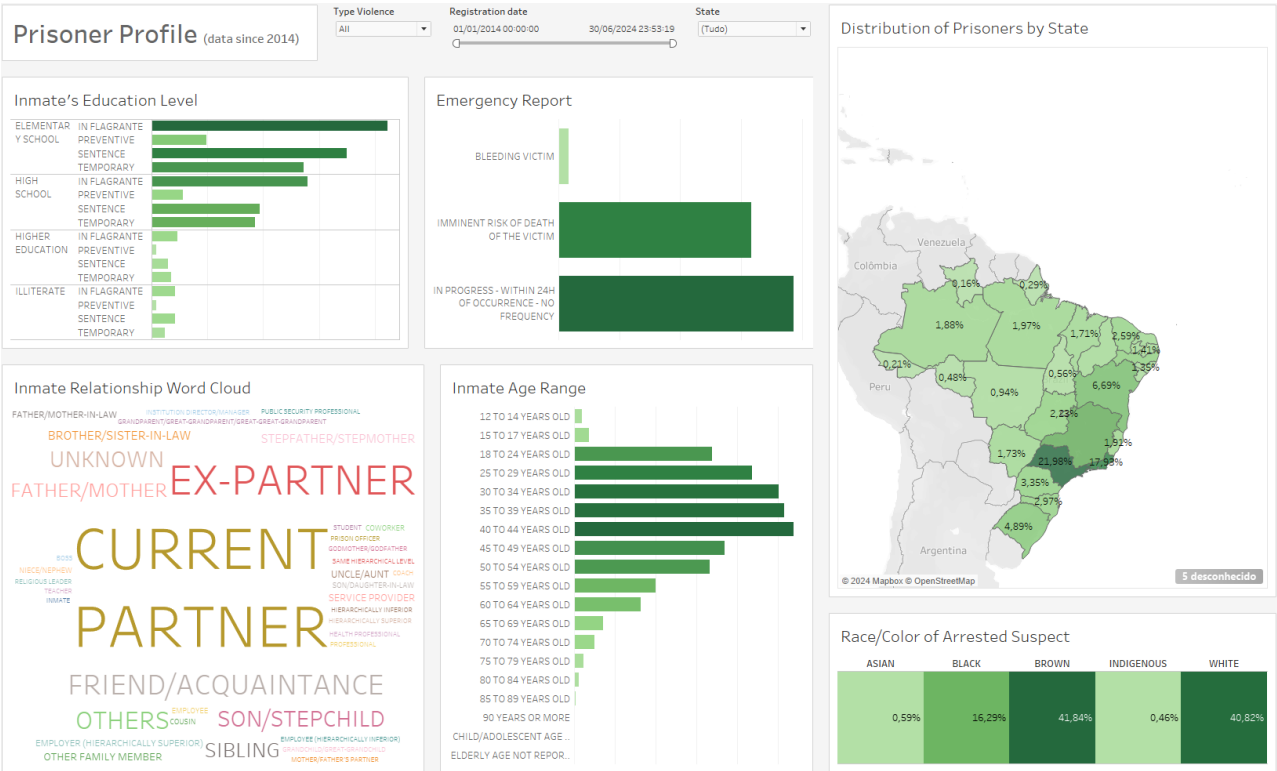


Figure 8. Dashboard for analyzing the profile of the suspect who was arrested.

best of our knowledge, none of them makes an interactive dashboard with almost 10 years of data available for public consultation.

All dashboards developed described in Section 3 are available for access in *Tableau Public*³, and it is possible to interact directly with them and analyze the data from the visualizations provided. Moreover, we provide the tools that allow you to do all the data preprocessing required before including them in *Tableau*. Thus, whenever new data becomes available, it can be included in the analysis, allowing the continuity and improvement of the time series.

In the following sections, we detail the potential users of MARIA and describe the results of an evaluation carried out with some of these users. In addition, we discuss some limitations of the work and possible future work for its improvement.

4.1 Identifying Potential Users

Considering MARIA’s functionalities, it is possible to identify potential users who can benefit from this tool. First, we can consider professors and researchers who may be from different fields, such as psychology, social work, and law. Despite the importance of understanding their interests and the data they usually work with, they could use the dashboards to gain insights and compare them with their research results.

Another group of users that may be interested includes public health authorities, policymakers, and police officers focused on gender-based violence. Access to dashboards for these users could help, for example, identify regions with the highest incidence of violence, allowing for a quick and efficient response and assisting in developing prevention

strategies. In this case, after understanding their needs, the data used, and specific workflows, the dashboards could be adapted to support other data and decision-making.

Officials who record data on violence against women could also use the tool to identify patterns, improving the registration and service offered by Call 180. This would promote more humane and efficient service to victims, benefiting the security and public health sectors.

Finally, society as a whole would benefit from data availability with visual analysis, making information more accessible. Currently, access to this type of government data is not very intuitive, requiring the download of several spreadsheets with many columns, making it difficult for the general population to analyze and use it.

4.2 First impressions

Once completed, we initially sought to publicize MARIA to potentially interested experts, such as researchers and professionals from government agencies who respond to incidents of violence against women, as described in Section 4.1. Through meetings to understand their work and demonstrate the use of MARIA, we observed that several of our insights were corroborated and that the data aligned with reality. Additionally, it came to our attention that similar work had been done at an institution. However, the data was collected manually, and all visualizations were static and presented in a PDF file.

Thus, we decided to evaluate MARIA through interviews with researchers and domain experts to understand whether the developed dashboards are easy to use and useful for data analysis. We initially identified individuals with experience

in analyzing data on violence against women or working directly with victims. We contacted them via phone calls, emails, and WhatsApp¹² messages to invite them to collaborate. Then, semi-structured interviews were conducted with open-ended questions about the use of MARIA with the three domain experts who agreed to participate. Although it may seem like a small number of participants, in qualitative research, the objective is to explore the opinion of the interviewees in greater depth [Maxwell, 2009]. Moreover, Lazar et al. [2017] (page 187) claim that “direct conversations with fewer participants can provide perspectives and useful data”.

The interviews followed the protocol of the Ethics and Research Committee¹³. Our questionnaire had some initial questions to know the specialist’s profile, such as their familiarity with the analysis of visual representations and whether issues related to gender violence are analyzed in their professional activities. Afterward, questions were asked regarding the insights gained with MARIA, how it could be improved, whether it was easy to use, and which graphs were most relevant.

The three domain experts were women, and their profiles are presented in Table 3. All of them have experience with data and chart analysis. Moreover, issues related to gender violence are part of their work-related tasks.

Table 3. Participant demographics and background.

ID	Age	Education	Profession
P1	31	Bachelor’s and Master’s in Psychology	Clinical Psychologist
P2	36	Bachelor’s in Law and Specialization in Combating Violence Against Women	Civil Police Officer in the Women’s Protection Division
P3	27	Bachelor’s and Master’s in Psychology	Clinical Psychologist and PhD Candidate in Psychology

First, it is interesting to notice that each participant analyzed MARIA from a different perspective. P1 focused mainly on the interface and usability of the dashboards, providing contributions for their improvement. P2 focused on the relationship between the data and her work, comparing the insights obtained through the dashboards with the information they have related to the analysis of femicide data. P3 highlighted some insights that caught her attention, raised questions based on the data analysis, and suggested improvements for the dashboards.

Participant P1 found MARIA easy to use and appreciated the separations made and the icons used. She focused on the tools and said she needed more time to explore and analyze the insights they could generate. She said that we were able to simplify and present the data in a visual and easy-to-access way. In addition to saying, “I thought the number of filters and the interaction that each one had was really cool”, highlighting the possibility of interaction between the charts

(CMV), P1 commented that MARIA allows selecting data for a specific audience, which can be very educational and justify the importance of interventions. However, P1 also suggested some improvements, such as changes that could be made to the initial text to make it clear which data were used. Furthermore, she said that she wished there was some type of information already ready, such as a sentence, that would provoke an analysis. Another comment was about the lack of information about the profile of the person who filed the complaint and about the issue of unemployment. However, information about unemployment was not available in the data. Other suggestions for improvements are listed at the end of this section.

Participant P2 started by highlighting that there is a serious problem with data on violence against women due to underreporting. That is why it is important to see where there are more and fewer reports, as shown in the dashboard *Distribution Throughout the Country*. For example, a city with few reports may be a city that has a lot of violence against women, which is so normalized that women do not report it. So, when talking about violence against women, it is important to think of data on femicide, “because it is violence against women that cannot be hidden”. In her work, P2 creates a “map of femicides” based on the occurrences, analyzing the profile of the victim, the aggressor, and other data about the crime, such as, e.g., the day of the week. Compared to MARIA, which she found intuitive and easy to use, she said: “My dream is for the map of femicides to be like this, dynamic.”. She liked to compare between states and noted that the age range of victims is similar to that of femicides. However, she drew attention to the level of education since most victims of femicide have completed elementary school, and in MARIA, high school is quite common. So, perhaps a higher level of education leads to more people filing a complaint. Another finding was that most complaints are made on Mondays, which reflects the reality of the police station. P2 also said that the 180 data is unreliable enough to think about public security policy within the civil police. Still, it can be helpful for the Ministry of Human Rights and Citizenship to analyze. However, considering the data provided, P2 stated that we made a correct analysis, including the time of violence, which is data that the civil police does not have.

For participant P3, what caught her attention the most was that the majority of suspects were white, followed by brown, but this proportion changed among the arrested suspects, apparently showing an issue related to racism. She found the dashboards very organized and easy to interact with and stated that they will help her with her research. She said there was a lot of information, but she liked the organization on several pages accessed through the icons. Regarding professions, she commented that it would be interesting to identify who has a formal or informal job, as this impacts violence. However, this information is not available in the data. Other information that P3 suggested including in the dashboards is the income of the victim and the suspect. Nevertheless, many records with this information are missing, sometimes missing this data for an entire year. P3 also suggested changing the image on the home page, which shows a woman with a bruise on her mouth, as other types of violence should be re-

¹²<https://www.whatsapp.com/>
¹³Access <https://plataformabrasil.saude.gov.br/login.jsf> and use the CAAE number 83879324.0.0000.5336 to confirm approval.

ported besides physical violence. Concerning the most relevant visualizations, P3 listed the victim-suspect relationship, those related to race, and types of violence.

Some other improvements suggested by participants are listed below.

- Improve the contrast to enable reading text on the home page since the image with a dark background makes it difficult to read (P1).
- Standardize all the text on the interface in Portuguese, since days of the week, months, and other expressions such as “heatmap” are in English (P1, P3).
- Include an indication that the user can scroll to the right to view other graphs (P1).
- Change the vertical legends on the bar graphs because they make them difficult to read (P1).
- Include a zoom toolbox for each map on the *Distribution Throughout the Country* dashboard (P1).
- Explain where the information about risks came from and if it was what was perceived by the person who made the complaint (P1, P2).
- Improve the part about professions since it is unclear how they work (P2, P3).
- Place in chronological order the bars that identify the time of violence in the dashboard *Context* (P3).
- Change the home page image (P3).

4.3 Limitations and Future Work

One limitation we faced was related to the data. Some of the problems we encountered were the amount of null data, the variation in the file format provided, the open text fields, the lack of an identifier for victims and suspects, and the fact that victims under the age of 18 and over the age of 60 were not included as victims of violence against women.

An initial analysis of the data revealed a large number of null values, which made the interpretation of some results challenging. For example, about 90% of the records for the suspect’s income range were null, making it impossible to analyze and compare them with the victim’s income range.

The variation in the file format provided was another problem faced with the data. The format of the data file provided by the government has varied over the years, with the inclusion and exclusion of columns. These changes undermine the creation of a standardized dataset essential for consistent and comprehensive analysis. As described in Section 3.1, we perform preprocessing steps to standardize the data, enabling analysis across the entire period in the dashboards.

Another difficulty was the existence of open text fields. For example, because it was an open text field, it was difficult to group the professions of victims and suspects since there were thousands of unique fields with the same profession written in many different ways. In addition, the lack of an identifier for victims and suspects made it impossible to identify repeat violations since each report consists of a new record in the file.

The last difficulty related to the data is that we applied the filter of violence against women to the data gathered. Then, victims under the age of 18 are classified in the category of violence against children and adolescents, and over the age

of 60 are classified in the category of violence against older people. This limited our analysis to victims between the ages of 18 and 60.

In the works of Soares and de Medeiros Filho [2020] and Mendoza *et al.* [2023], reviews and analyses of the literature on Smart Government and Data Governance were carried out, respectively. Both also point out the lack of data standardization as one of the main problems found today, and Mendoza *et al.* [2023] highlights the main problems found in data from government portals, such as incomplete and missing data and incorrect filling. Therefore, the issues that occurred with the data used in this work are consistent with the observations made by these studies, evidencing the need for more rigorous standardization and validation practices in government portals.

Another limitation of this work was the small number of domain experts participating in the MARIA evaluation. The difficulty in obtaining a more significant number of participants was mainly due to the availability of these professionals, which restricted the scope of the usability and functionality analysis presented.

In future work, we intend to continue evaluating the dashboard with more domain experts, aiming to obtain a more comprehensive and representative analysis. In addition, we are initiating contacts with researchers in Law and Psychology to establish strategic partnerships. Our goal is to identify new data sets that can be analyzed and contribute to obtaining relevant insights, helping identify patterns, and proposing preventive actions. For instance, it would be interesting to collect data from the “map of femicides” that participant P2 commented on (see Section 4.2) to compare with data from complaints.

During the dissemination of MARIA, we observed that professionals from some government agencies demonstrated interest in its features. Therefore, we intend to pursue these partnerships as well. However, there is an obstacle: the obligation to establish a cooperation agreement between institutions, to anonymize and make the data available afterward, and to go through the Research Ethics Committee. Despite the difficulties, we will try to make this partnership viable so that we can help formulate future public policies.

Considering the currently available data, we also aim to apply more advanced statistical techniques to identify patterns and correlations more precisely. Additionally, we plan to incorporate machine learning methods to estimate trends and further enhance the data analysis.

Finally, we will make the dashboard improvements raised by the domain experts, presented at the end of Section 4.2. For example, we need to enhance the way we present the professions of victims and suspects. Since the grouping of occupations according to the classification adopted in ENEM was not clear, it may be necessary to apply Natural Language Processing (NLP) techniques to identify and group the various forms of writing the same profession.

5 Final Remarks

In this study, we sought to present a diagnosis of violence against women in Brazil by analyzing data from Call 180.

We developed an open-source methodology for processing and visually analyzing the data that can be applied in the future as more data is released. In addition, we identified the need for government standardization in the collection and organization of data to enable long-term analysis.

MARIA is available online and can be used by researchers, government officials, and the general public. Some improvements identified in the expert interviews have already been implemented in this online version (e.g., the text and image on the home page were changed to contemplate the suggestions from participants P1 and P3). In addition, with the scripts available on *GitHub*, whenever Call 180 new data becomes available, it can be preprocessed and incorporated into the dashboards.

The main contributions of this work include the development of a set of interactive dashboards, MARIA, which allows a detailed analysis of the data; the online availability of MARIA, making it accessible to the general public; the provision of a script that incorporates all the necessary preprocessing, facilitating the continuous updating of the data for analysis; the obtaining of relevant insights, detailed in Section 3, through the interaction with the dashboards; and an initial evaluation with domain experts, whose feedback was positive, evidencing the relevance and usefulness of the developed tools.

The proposed solution can provide a solid basis for future research and decision-making, as monitoring data released every six months can be done more quickly, and the interactive dashboards allow for more agile analysis. Furthermore, by presenting our findings clearly and objectively, we hope to have contributed to a better understanding of the topic and advancing knowledge in this area.

Declarations

Acknowledgements

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While preparing and revising this manuscript, we used ChatGPT, Grammarly, and Google Translate to enhance clarity and grammatical precision, as English is not our first language. The authors take full responsibility for the content and its technical accuracy.

Authors' Contributions

- **Gabriel Zurawski:** Conceptualization, Data curation, Formal analysis, Software, Visualization, Writing – original draft and Writing – review & editing.

- **Vinicius Pedroso:** Data curation, Formal analysis, Software, Visualization, Writing – original draft and Writing – review & editing.
- **Eduarda Patricio:** Conceptualization, Visualization, Writing – original draft and Writing – review & editing.
- **Giovanna Castro:** Visualization, Writing – original draft and Writing – review & editing.
- **André F. Rollwagen:** Writing – original draft and Writing – review & editing.
- **Isabel H. Manssour:** Conceptualization, Funding acquisition, Project administration, Supervision, Writing – original draft and Writing – review & editing.

Competing interests

The authors of this study declare that there are no conflicts of interest of any kind, including financial, personal, institutional, or academic.

Availability of data and materials

The datasets, source code, and a step-by-step guide to collect and process the data for subsequent visualization are available at our *GitHub* repository: <https://github.com/DAVINTLAB/MARIA.git>. Additionally, the set of dashboards called MARIA is available for anyone who wants to make an exploratory visual analysis at <https://tinyurl.com/4vshvkyu>. Access on 12 July 2025.

References

- Burke, E., Watson, K., Eva, G., Gold, J., Garcia-Moreno, C., and Amin, A. (2024). Is addressing violence against women prioritised in health policies? findings from a WHO policies database. *PLOS Global Public Health*, 4(2):1–13. DOI: <https://doi.org/10.1371/journal.pgph.0002504>.
- Clark, C. J., Wetzel, M., Renner, L. M., *et al.* (2019). Linking partner violence survivors to supportive services: impact of the m health community network project on healthcare utilization. *BMC Health Services Research*, 19(1):479. DOI: <https://doi.org/10.1186/s12913-019-4313-9>.
- de Almeida Teles, M. A. and de Melo, M. (2017). *O que é violência contra a mulher*. Primeiros Passos. Brasiliense.
- D'Ignazio, C. (2017). Creative data literacy: Bridging the gap between the data-haves and data-have nots. *Information Design Journal*, 23(1):6–18. DOI: <https://doi.org/10.1075/idj.23.1.03dig>.
- Júnior, A. P. and Ribeiro, F. (2019). Análises de dados de violência doméstica com o uso de aprendizagem de máquina: um mapeamento sistemático. In *Anais da VII Escola Regional de Computação do Ceará, Maranhão e Piauí*, pages 143–150, Porto Alegre, RS, Brasil. SBC.
- Kasiselvanathan, M., Sundari, S., Ramalakshmi, R., and Tarunika, R. S. (2023). Foretelling femicides using data mining and machine learning. In *2023 Second International Conference on Augmented Intelligence and Sustainable Systems (ICAISS)*, pages 559–564. DOI: <https://doi.org/10.1109/ICAISS58487.2023.10250716>.

- Keim, D., Kohlhammer, J., Ellis, G., and Mansmann, F. (2010). *Mastering the information age solving problems with visual analytics*. Eurographics Association.
- Kirk, A. (2016). *Data Visualization: A Handbook for Data-Driven Design*. SAGE Publications, 1st edition.
- Lazar, J., Feng, J., and Hochheiser, H. (2017). *Research Methods in Human-Computer Interaction*. Elsevier Science.
- Leite, F., Garcia, M. T. P., Cavalcante, G., Venturin, B., Pedroso, M., Gomes, E., and Tavares, F. L. (2023). Violência recorrente contra mulheres: análise dos casos notificados. *Acta Paulista de Enfermagem*, 36:eAPE009232. DOI: <https://doi.org/10.37689/acta-ape/2023AO009232>.
- Liu, S., Maljovec, D., Wang, B., Bremer, P.-T., and Pascucci, V. (2017). Visualizing high-dimensional data: Advances in the past decade. *IEEE Transactions on Visualization and Computer Graphics*, 23(3):1249–1268. DOI: <https://doi.org/10.1109/TVCG.2016.2640960>.
- Maxwell, J. A. (2009). Designing a qualitative study. *The SAGE handbook of applied social research methods*, 2:214–253. DOI: <https://doi.org/10.4135/9781483348858.n7>.
- Medeiros, A. M., Júnior, J. L. d. S., Andrade, M. C. M. A. d., Costa, S. W. d., Costa, F. A. R., Neto, N. C. S., and Seruffo, M. C. d. R. (2024). Application of a multicriteria decision model for the classification of paraíba's municipalities as to the occurrence of domestic and family violence against women. *Journal on Interactive Systems*, 15(1):323–332. DOI: <https://doi.org/10.5753/jis.2024.3740>.
- Mendoza, I., Corrêa, R., and Bernardini, F. (2023). Como a governança de dados pode auxiliar na mitigação de barreiras de uso de portais de dados governamentais abertos? uma análise da literatura. In *Anais do XI Workshop de Computação Aplicada em Governo Eletrônico*, pages 212–223, Porto Alegre, RS, Brasil. SBC. DOI: <https://doi.org/10.5753/wcge.2023.229862>.
- Montenegro, T. C. (2021). Violência contra a mulher: Análise comparativa de dados públicos antes e durante a pandemia de covid-19. Monografia (Trabalho de Conclusão de Curso). <http://dspace.sti.ufcg.edu.br:8080/jspui/handle/riufcg/19900>, Access on 12 July 2025.
- Moroskoski, M., Neto, F. C., Machado de Brito, F. A., Ferracioli, G. V., de Oliveira, N. N., de Carvalho Dutra, A., Baldissera, V. D. A., and de Oliveira, R. R. (2022). Lethal violence against women in southern brazil: Spatial analysis and associated factors. *Spatial and Spatio-temporal Epidemiology*, 43:100542. DOI: <https://doi.org/10.1016/j.sste.2022.100542>.
- Méndez, G. G., Calle, A., Rizzo, H., and Chonillo, G. (2023). Data tool for exploring gender violence in ecuador: Insights from a qualitative observation. In *2023 18th Iberian Conference on Information Systems and Technologies (CISTI)*, pages 1–7. DOI: <https://doi.org/10.23919/CISTI58278.2023.10211396>.
- North, C. and Shneiderman, B. (2000). Snap-together visualization: a user interface for coordinating visualizations via relational schemata. In *Proceedings of the Working Conference on Advanced Visual Interfaces*, page 128–135, New York, NY, USA. Association for Computing Machinery. DOI: <https://doi.org/10.1145/345513.345282>.
- Patricio, E., Zurawski, G., Rollwagen, A., and Manssour, I. (2024). Explorando dados governamentais para prevenção da violência de gênero: Uma abordagem visual. In *Anais do XII Workshop de Computação Aplicada em Governo Eletrônico*, pages 145–156, Porto Alegre, RS, Brasil. SBC. DOI: <https://doi.org/10.5753/wcge.2024.2966>.
- Pentland, A. (2013). The data-driven society. *Scientific American*, 309(4):78–83. DOI: <https://doi.org/10.1038/scientificamerican1013-78>.
- Rios, A. M. F. M., Crespo, K. C., Martini, M., Telles, L. E. D. B., and Magalhães, P. V. S. (2023). Gender-related and non-gender-related female homicide in porto alegre, brazil, from 2010 to 2016. *PLOS ONE*, 18(3):1–12. DOI: <https://doi.org/10.1371/journal.pone.0281924>.
- Sardinha, L., Maheu-Giroux, M., Stöckl, H., Meyer, S. R., and García-Moreno, C. (2022). Global, regional, and national prevalence estimates of physical or sexual, or both, intimate partner violence against women in 2018. *The Lancet*, 399(10327):803–813. DOI: [https://doi.org/10.1016/S0140-6736\(21\)02664-7](https://doi.org/10.1016/S0140-6736(21)02664-7).
- Sarikaya, A., Correll, M., Bartram, L., Tory, M., and Fisher, D. (2019). What do we talk about when we talk about dashboards? *IEEE transactions on visualization and computer graphics*, 25(1):682–692. DOI: <https://doi.org/10.1109/TVCG.2018.2864903>.
- Soares, G. and de Medeiros Filho, F. (2020). Governança inteligente com análise e integração de dados: Uma revisão sistemática de literatura. In *Anais do VIII Workshop de Computação Aplicada em Governo Eletrônico*, pages 132–139, Porto Alegre, RS, Brasil. SBC. DOI: <https://doi.org/10.5753/wcge.2020.11264>.
- Tidwell, J. (2011). *Designing Interfaces: Patterns for Effective Interaction Design*. O'Reilly Media, Inc.
- Tufte, E. R. (2001). *The Visual Display of Quantitative Information*. Graphics Press, 2nd edition.
- Vasconcelos, N. M. d., Andrade, F. M. D. d., Gomes, C. S., Bernal, R. T. I., and Malta, D. C. (2022). Violência física contra mulheres perpetrada por parceiro íntimo: análise do viva inquérito 2017. *TEMAS LIVRES • Ciência e saúde coletiva*, 27(10):3993–4002. DOI: <https://doi.org/10.1590/1413-81232022710.08162022>.