Mapping and Profiling Access to Brazil's Continued Provision Benefit: A Data-Driven Analysis Using Clustering and Regional Indicators

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Abstract

We analyze 892,591 requests for the Brazilian Continued Provision Benefit (BPC), revealing a rejection rate of 63.6%. Our geospatial and statistical analysis highlights that denials related to disabilities (B87) are more frequent in the Northeast, while rejections for elderly applicants (B88) dominate in the Southeast. The leading denial cause is failure to meet disability criteria, indicating widespread misunderstanding of eligibility rules. Judicial dependence emerges as a critical access route: in several states, over 25% of benefits are granted via litigation. We also show that judicial or appeal-based approvals take 15 to 24 times longer than standard concessions.

1 Introduction and contextualization

The Continued Provision Benefit (BPC), established by Brazil's Organic Law of Social Assistance (LOAS), is a non-contributory income transfer program designed to ensure a minimum income for elderly individuals and people with disabilities living in extreme social vulnerability [Medeiros and Diniz 2006]. To be eligible, a person must prove a per capita household income below one-quarter of the national minimum wage, which entitles them to a monthly benefit equivalent to the minimum wage [Presidência da República 1993]. In 2021 the monetary threshold was alleviated, under some circumstances, to one-half of the national minimum wage [Presidência da República 2021]. Since its implementation, BPC has played a central role in reducing extreme poverty, particularly among groups historically excluded from formal labor markets.

The two main types of BPC benefits include the Social Assistance for the Elderly (code 88), granted to individuals aged 65 or older, and the Social Assistance for Persons with Disabilities (code 87), intended for those considered unable to fully engage in work life [Ministério do Desenvolvimento Social 2003]. The analyzed data was obtained from SUIBE (Sistema Único de Informações de Benefícios – Unified Information System for Social Security Benefits), a comprehensive administrative database that records the outcome of benefit claims processed by the Brazilian social security system. The data spans from June to October 2024 and includes detailed information on BPC requests that were either granted, denied, or suspended. Among the granted benefits, it is possible to distinguish between those approved through regular administrative channels — including initial requests (known as "normal concessions"), administrative reviews, and appeals — and those granted via judicial rulings. In the case of denied benefits, the dataset includes the specific reason for rejection, allowing further analysis of systemic barriers to access. This classification enables a nuanced analysis of how different types of concession pathways reflect underlying patterns of access, efficiency, and procedural burden across regions.

To account for regional disparities in the administration of BPC benefits, this study also considers the six Superintendências Regionais (Regional Superintendencies, or SRs) of the INSS, which are the federal divisions responsible for managing social security operations across Brazil. These SRs correspond to broad geographic areas: SR North- Central-West (including AC, AM, AP, PA, RO, RR, TO, DF, GO, MS and MT), SR Northeast (AL, BA, CE, MA, PB, PE, PI, RN, and SE), SR Southeast I (SP), SR Southeast II (ES and MG), SR Southeast III (RJ), and SR South (PR, RS, and SC). Throughout this study, we refer to these divisions using the abbreviation "SR" to assess and compare patterns of benefit access, denial, and administrative performance across regions.

Despite its relevance as a social protection policy, BPC faces challenges in effectiveness, particularly due to the complexity of eligibility verification, high denial rates, and unequal access across Brazilian regions. Brazil ranks as the 9th most unequal country in the world, with extreme income concentration severely limiting access to social benefits for millions of citizens [Alcoforado and dos Reis 2021]. In this context, analyzing the relationship between socioeconomic variables, administrative processes, and territorial patterns of BPC access is essential to reinforcing the program's redistributive function.

This research contributes to a systemic understanding of Brazil's social assistance landscape through statistical analyses and geographic visualization techniques applied to large administrative datasets. The central objective is to evaluate regional heterogeneities and the correlation between socioeconomic factors and patterns of approval, denial, and suspension of BPC benefits based on national data from June to October of 2024. Specifically, the study aims to identify territorial patterns of approvals and denials by benefit type (B87 and B88) and federal unit; map the leading causes of denial and their regional distribution; analyze average processing times by decision type and state; assess the extent of judicial dependence for access to the benefit; apply clustering techniques to build state-level profiles based on administrative and clinical characteristics of beneficiaries; and propose recommendations to improve BPC management and effectiveness while accounting for demographic and regional disparities.

This article is structured as follows: Section 2 reviews the related literature, presenting prior studies on the judicialization of the BPC as well as recent applications of data analysis and computational methods in the context of social benefit systems. Section 3 describes the methodology applied in this study, including the data sources, preprocessing steps, and analytical approaches. Section 4 presents a descriptive overview of the distribution of BPC requests, highlighting regional patterns in approvals and denials. Section 5 explores the primary reasons for denial by benefit type and federal unit. Section 6 analyzes the processing times associated with different concession types, comparing administrative and judicial pathways. Section 7 investigates the extent of judicialization in BPC access across states. Section 8 addresses the issue of benefit suspensions and their geographic distribution. Section 9 applies K-Means clustering to identify state-level profiles based on denial reasons, ICD codes, and concession patterns. Section 10 discusses the limitations of this work and its underlying data. Finally, Section 11 offers concluding remarks and discusses implications for public policy and future research.

2 Related Work

This section reviews the literature related to the judicialization of the BPC and to data-driven approaches in the analysis of social benefit systems. It then situates the present study within this context, highlighting its contribution to a comprehensive, data-oriented examination of BPC provision across Brazil.

2.1 Judicialization of the BPC

The judicialization of access to the BPC has been widely examined, mostly in legal and public policy research. [Jasmin et al. 2024] argues that the lack of information regarding the accessibility of the benefit, bureaucratic complexity, and long administrative processing times are the main reasons that contribute to the growth of court cases related to the benefit. Similarly, [COSTA et al. 2025] concludes that the rigidity of eligibility criteria regarding per capita household income and a narrow interpretation of disability are key factors driving people to seek judicial paths.

Other authors,including [Neto et al. 2025] and [Silva 2012] frame judicialization as a response to social vulnerability, highlighting the use of court actions as a means of securing access to social rights. However, [Silva 2012] also emphasizes that, while judicial intervention plays an important role in guaranteeing these rights, it also reinforces inequalities, since access to the courts is uneven across regions. These works interpret judicialization not merely as a legal phenomenon, but as a reflection of structural challenges in the implementation of social protection policies.

However, most of this literature relies on qualitative or legal-normative approaches. There is still limited quantitative evidence, based on nationwide administrative data, on how judicialization is distributed across regions and how it affects processing times and the overall flow of benefit concessions.

2.2 Data-Driven Approaches to the Analysis of Social Benefit Provision

The use of administrative data and data-driven methods in public policy research has grown substantially in recent years, including in the study of social benefit systems. By exploring large-scale governmental records, these approaches make it possible to examine how decisions are made in practice, detect inefficiencies, and generate evidence to support improvements in policy implementation.

In this context, [Barchilon and Escovedo 2021] employ supervised machine learning models to predict approval and denial outcomes in INSS benefit requests. Their work illustrates how predictive techniques can be incorporated into social security administration, focusing primarily on individual-level classification and model performance rather than on broader systemic or territorial dynamics.

Looking at the issue from a wider institutional angle, the effects of artificial intelligence and automation on the provision of social benefits in Brazil is analyzed by [Nicolás and Sampaio 2024]. They discuss the balance between gains in administrative efficiency and the need to safeguard the public interest, drawing attention to potential risks of exclusion and to governance challenges associated with automated decision-making. Their contribution is therefore conceptual and policy-oriented, rather than centered on large-scale empirical analysis of administrative data.

Taken together, these studies point to the increasing importance of computational and data-analytic approaches in the management of social policies. However, there remains limited research that uses nationwide administrative microdata to simultaneously examine territorial disparities, reasons for denial, processing times, and the interaction between administrative and judicial pathways in access to benefits such as the BPC. Addressing this gap, the present study adopts a data-oriented perspective, combining descriptive statistical analysis and clustering techniques to provide a systemic view of how the program operates in practice.

2.3 Contribution of This Study

Existing literature provides important insights into the BPC as a social protection policy, the judicialization of access to social assistance, and the use of data-driven and automated methods in the administration of public benefits. However, these topics are typically addressed separately, either from legal and institutional perspectives or from predictive and technological standpoints.

There remains a lack of studies that leverage nationwide administrative microdata to analyze, in an integrated manner, approval and denial patterns, clinical and administrative reasons for rejection, processing times, territorial disparities, and dependence on judicial channels in accessing the BPC. This study addresses this gap by combining descriptive statistical analysis and clustering techniques to produce a comprehensive, data-driven assessment of how the benefit operates across Brazil.

3 Methodology

This study employed a data-driven approach to analyze the patterns of approval, denial, and suspension of the BPC in Brazil. The dataset was obtained from the SUIBE, managed by the INSS. It includes detailed records of BPC applications processed between June and October 2024, covering both types of benefits: for elderly individuals (B88) and for persons with disabilities (B87).

All data preprocessing, statistical analyses, and clustering procedures were conducted using the `R` programming language. The analysis followed the steps below:

- **Data Cleaning and Preprocessing:** The raw data were filtered, structured, and validated to remove inconsistencies and missing entries. Specific variables were selected to represent denial reasons, benefit types, decision times, and clinical codes (ICD).

- **Descriptive Analysis:** Aggregated statistics were calculated to explore patterns of benefit approval and denial across regions and states. Visualizations such as bar charts, heatmaps, and geospatial maps were used to highlight regional disparities.

- **Age Distribution and Processing Times:** Boxplots were created to analyze the age distribution of applicants by benefit type and decision outcome. Average processing times were computed and compared for different concession types, including normal administrative processing, judicial decisions, appeals, and administrative reviews.

- **Clustering:** The K-Means algorithm was applied to group Brazilian states based on selected features such as the most frequent ICD codes, top denial reasons, average grant and denial times, and the proportion of judicial concessions. Clustering was performed both in aggregate and separately for each benefit type (B87 and B88).

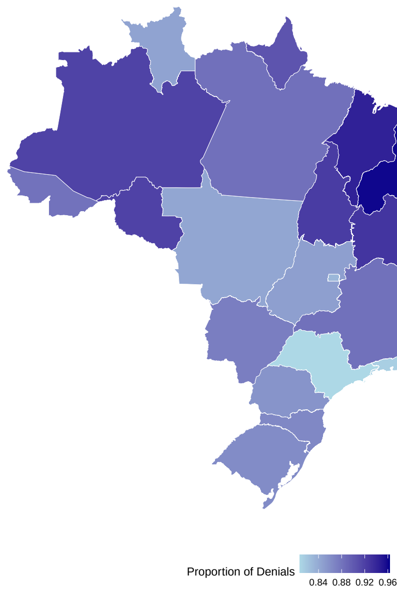
This methodological approach enabled a comprehensive exploration of key aspects of the BPC system. The following sections present the identification of regional patterns in approvals and denials, an analysis of the main reasons for benefit rejections by type and location, and a comparison of processing times across different decision pathways. Furthermore, the upcoming sections explore the investigation of the different pathways towards benefit access, the geographic distribution of suspended benefits, and the grouping of states according to administrative and clinical characteristics through clustering techniques.

4 Where Are the Requests Concentrated?

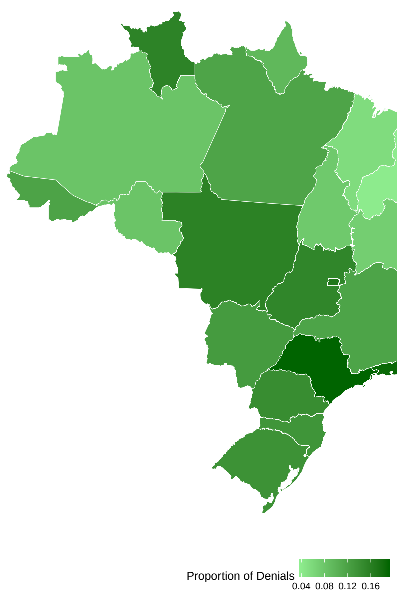
Among both denied and granted requests, a total of 892,591 BPC applications were analyzed, with approximately 63.6% resulting in denial. Figure 1 displays the proportional distribution of each benefit type within denials, whilst Figure 2 displays approvals.

Denials related to people with disabilities are more frequent in the Northeast, particularly in the states of Piauí and Paraíba, while denials associated with elderly applicants are more common in the Southeast, especially in Rio de Janeiro and São Paulo. On the other hand, approvals show a more balanced distribution between the two groups. The closest ratio observed is approximately 53% to 47%, still in favor of people with disabilities.

This suggests that while disability-related requests represent the majority in both approval and denial categories, they are more likely to be denied. One possible explanation is the frequent occurrence of a key rejection reason—"Does not meet the disability criteria"—which will be discussed in a later section.

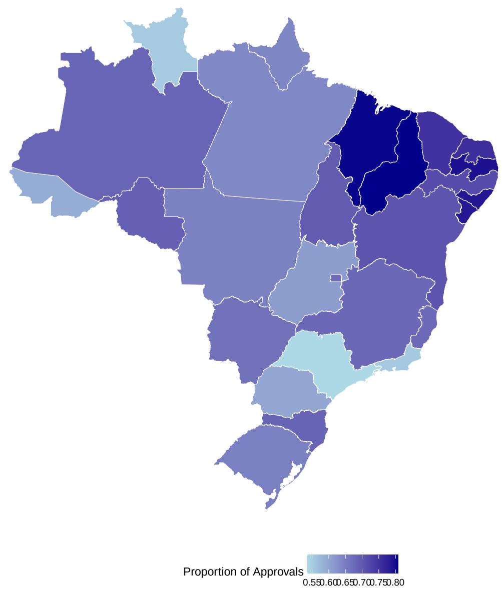


(a) B87 (Disability)

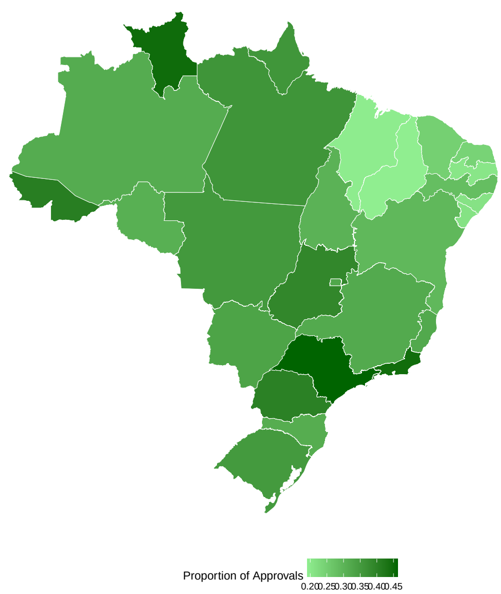


(b) B88 (Elderly)

Figure 1: Proportion of denials by benefit type



(a) B87 (Disability)



(b) B88 (Elderly)

Figure 2: Proportion of approvals by benefit type

5 Why Are Requests Denied?

The denial of the BPC negatively impacts both the applicants and the administrative system. Each denial represents not only an individual who remains without essential support, but also the use of institutional resources to process and reach that decision.

Between June and October 2024, a total of 567,647 benefit applications were denied. Understanding the reasons behind these denials is crucial for identifying systemic inefficiencies and developing strategies to reduce their recurrence. These reasons can be analyzed in three categories:

1. General denial reasons (aggregated across all benefit types)
2. Denial reasons specific to benefits for persons with disabilities
3. Denial reasons specific to elderly applicant

5.1 General Denial Reasons

Figure 3 presents the top reasons for BPC denial. The most frequent reason across all Brazilian states is "Does not meet the disability criteria for access to BPC-LOAS." This suggests that the eligibility criteria may not be clearly understood, leading individuals who are not eligible to apply.

The second most common reason is "Failure to attend the required medical examination." While miscommunication between the agency and the applicant can occur, this issue often stems from the applicant's actions.

The third prevalent reason is "Does not meet the requirements of Article 20 of Law 8.742/93." Similar to the first reason, this indicates that applicants may believe they are eligible when they are not, resulting in unnecessary efforts for both the applicant and the agency.

Figure 4, which displays the top reasons for BPC denial by state, largely reflects the same patterns observed in the overall analysis, with "Does not meet the disability criteria for access to BPC-LOAS" being the most frequent reason for denial ranking first in every state. "Failure to attend the required medical examination." and "Does not meet the requirements of Article 20 of Law 8.742/93." are again number 2 and 3 respectively. Even though not every state has them in this order, their overall ranking remains consistent.

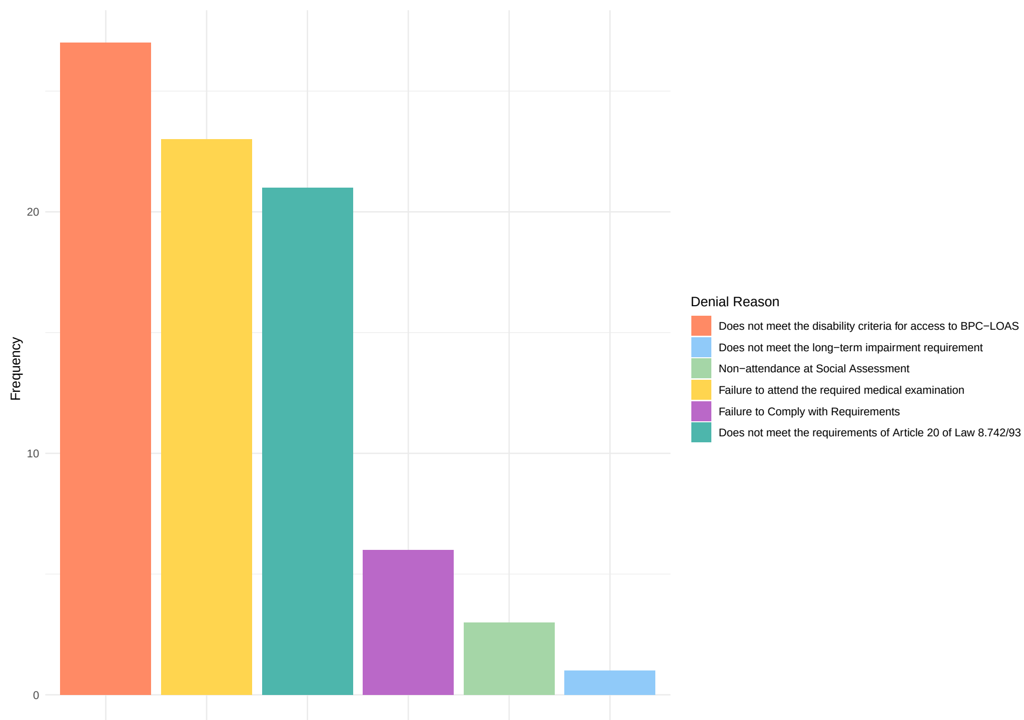


Figure 3: Top reasons for BPC denial (overall)

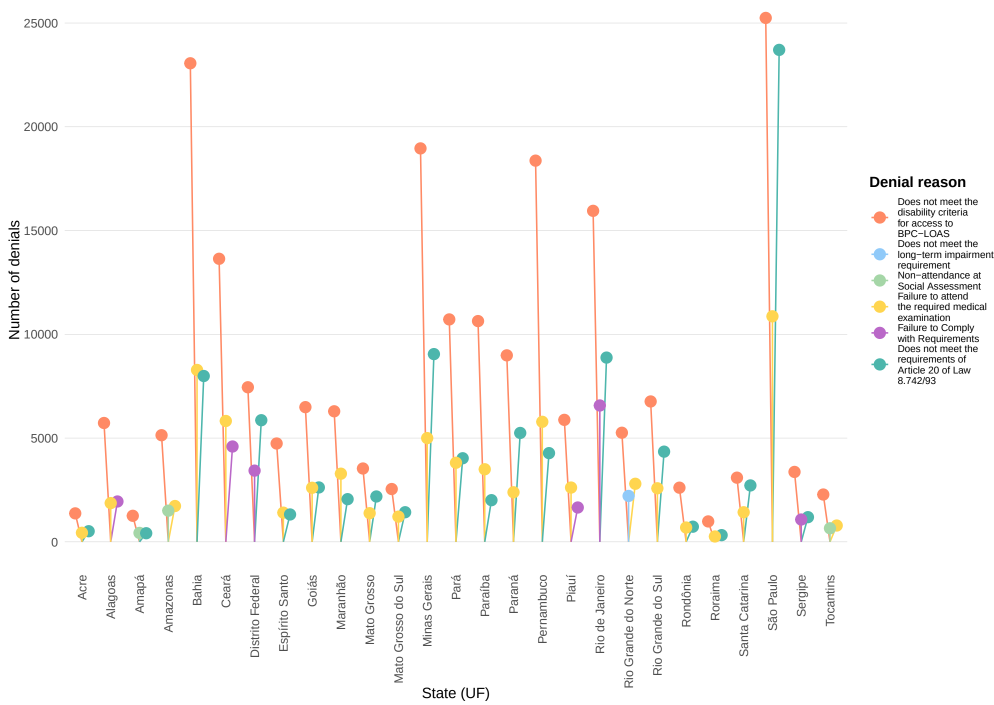


Figure 4: Top reasons for BPC denial per State (overall)

5.2 Denial Reasons for Persons with Disabilities

When focusing on denials for persons with disabilities, the ranking of reasons closely mirrors the general pattern as demonstrated by Figure 5. This similarity is due to the higher proportion of denials in this category compared to those for the elderly. Therefore, the analysis of occurrences is analogous to the general analysis.

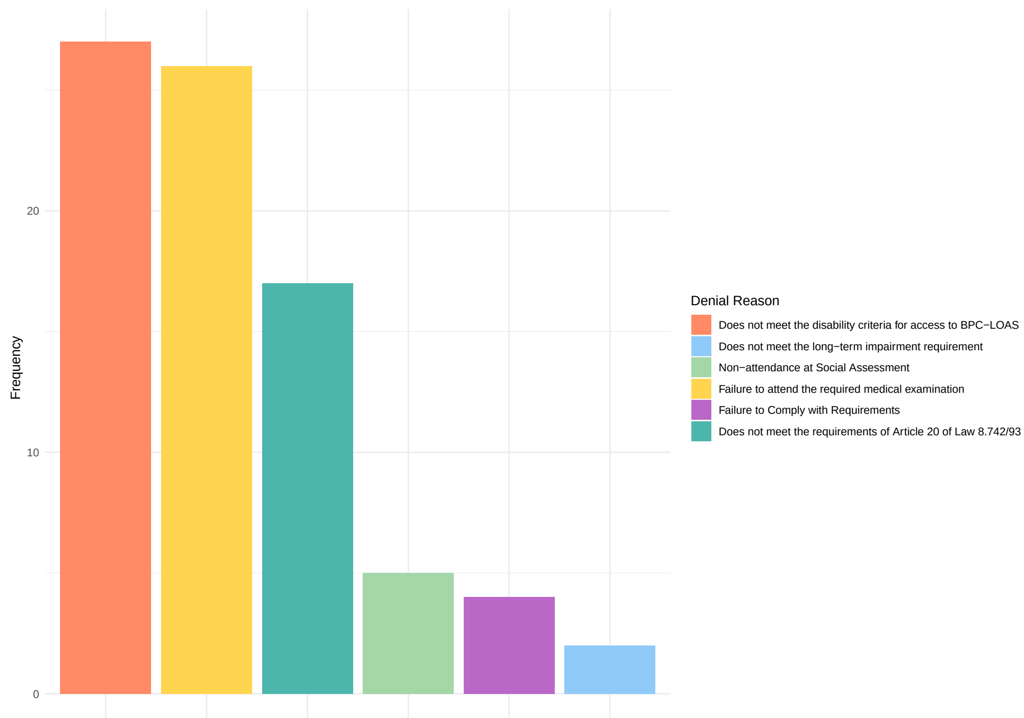


Figure 5: Top denial reasons for B87 (Disability) benefit

Figure 6 provides a more detailed view of each state. While some states may show slight variations, the overall trend observed earlier remains consistent at the state level.

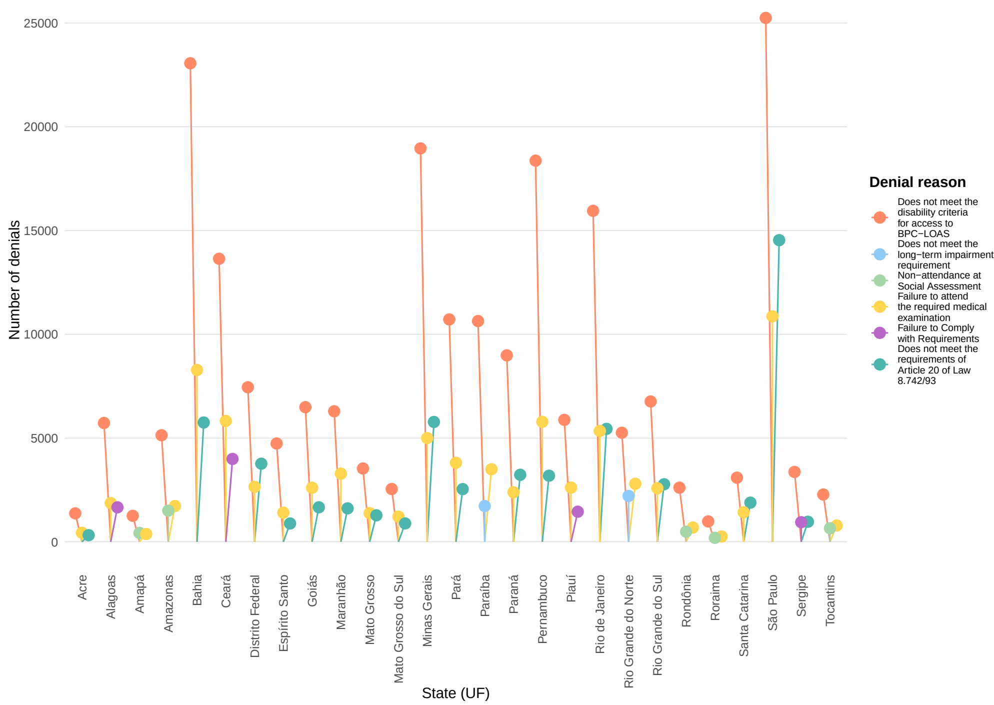


Figure 6: Top denial reasons for B87 (Disability) benefits per state.

5.3 Denial Reasons for the Elderly

In contrast, Figure 7 demonstrates that the reasons are more homogeneous across the country. All states and the Federal District share the same three reasons for denial, though not necessarily in the same order, as seen on Figure 8.

Two of these reasons can be attributed to potential miscommunication between the agency and the applicant: "Does not meet the requirements of Article 20 of Law 8.742/93" and "Failure to fulfill requirements." The lack of registration or enrollment in the CadÚnico (Unified Registry), as evidenced by [Marinho and Grigorio 2025], is indeed a critical issue when it comes to elderly people since they struggle to update their information or even navigate applications like "Meu INSS". Although digitalization is a strategy adopted to increase efficiency, the population in need of help often lacks the necessary digital skills to keep up with the digital transformation of everyday life.

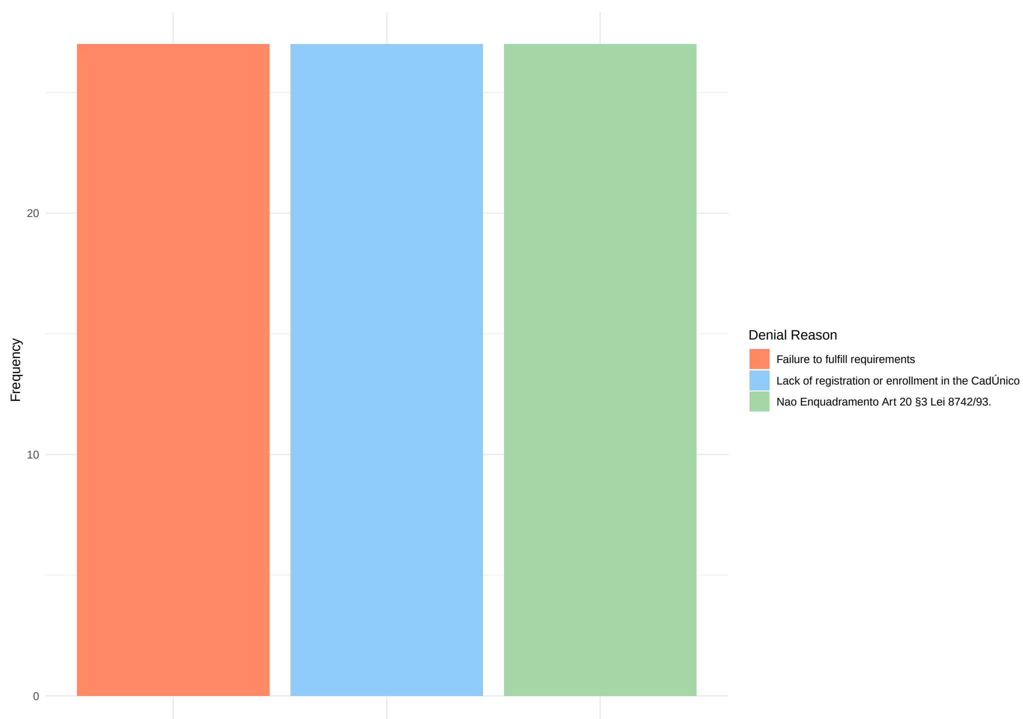


Figure 7: Top denial reasons for B88 (Elderly) benefit.

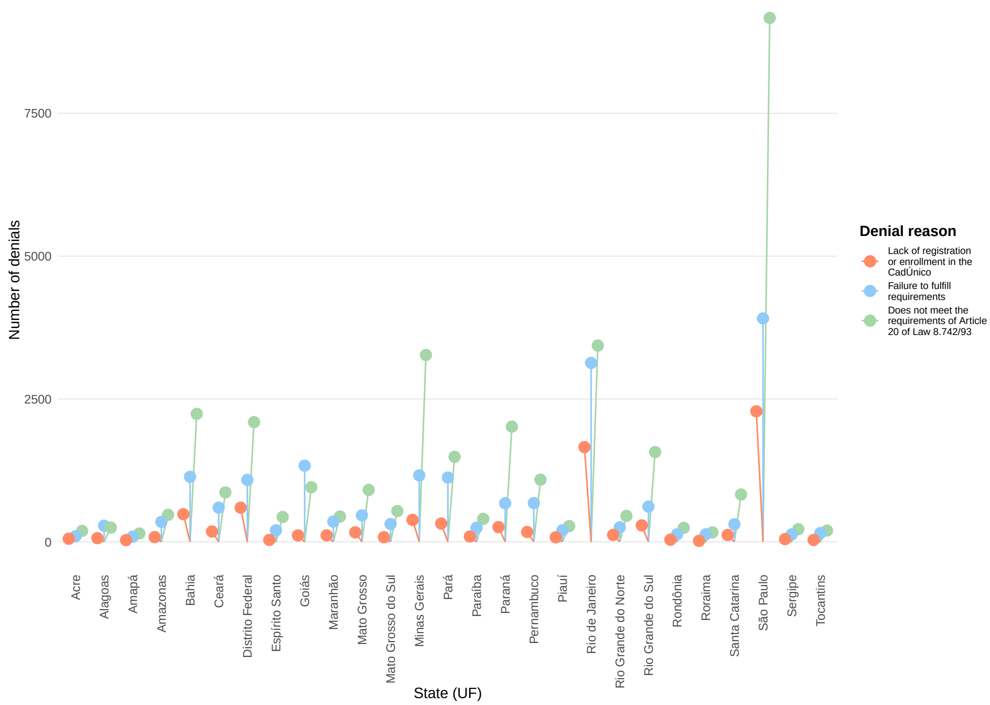


Figure 8: Top denial reasons for B88 (Elderly) benefits per state.

By analyzing Figure 8 it becomes evident that although only these 3 options are present they are not evenly distributed among Brazilian states. The reason that leads to the most denials is "Does not meet the requirements of Article 20 of Law 8.742/93" which further corroborates the lack of proper communication claims. The "lack of registration or enrollment in the CadÚnico" is usually the reason that leads to the least amount of denials, this is partially due to local governments' outreach efforts to assist the population with creating and updating their CadUnico, bridging the gap between the people and technology.

5.4 Age Distribution by Benefit Type and Decision Outcome

In addition to the analysis of denial reasons, we examined the age distribution of claimants using boxplots separated by benefit type and decision outcome. When analyzing denied benefits (Figure 9), we observe a clear distinction: code 87 denials exhibit wide variability (median around 35 years), while code 88 denials remain clustered near the elderly eligibility threshold. These contrasts suggest that age behaves differently as a predictor of outcome depending on the benefit type — with approvals for code 88 being more strongly tied to age compliance, whereas code 87 decisions involve broader assessments of disability status and socioeconomic context.

Among the approved benefits (Figure 10), claimants under code 87 (persons with disabilities) display a broad age range, with a median age of 27 and interquartile range spanning from early childhood to middle age. In contrast, those approved under code 88 show a sharply concentrated distribution around the minimum legal age of 65, with very limited dispersion.

Notably, both distributions include a small number of individuals under the age of 65 registered under code 88. While this may initially appear anomalous, it likely reflects specific administrative and legal situations — such as judicial rulings that allow children to receive pension benefits derived from BPC entitlements of deceased adult beneficiaries, or cases where guardianship rights are attached to BPC claims. These entries underscore how data irregularities or particular legal arrangements can introduce exceptions in otherwise well-defined eligibility categories. Such observations reinforce the importance of combining statistical analysis with institutional knowledge when interpreting social program data.

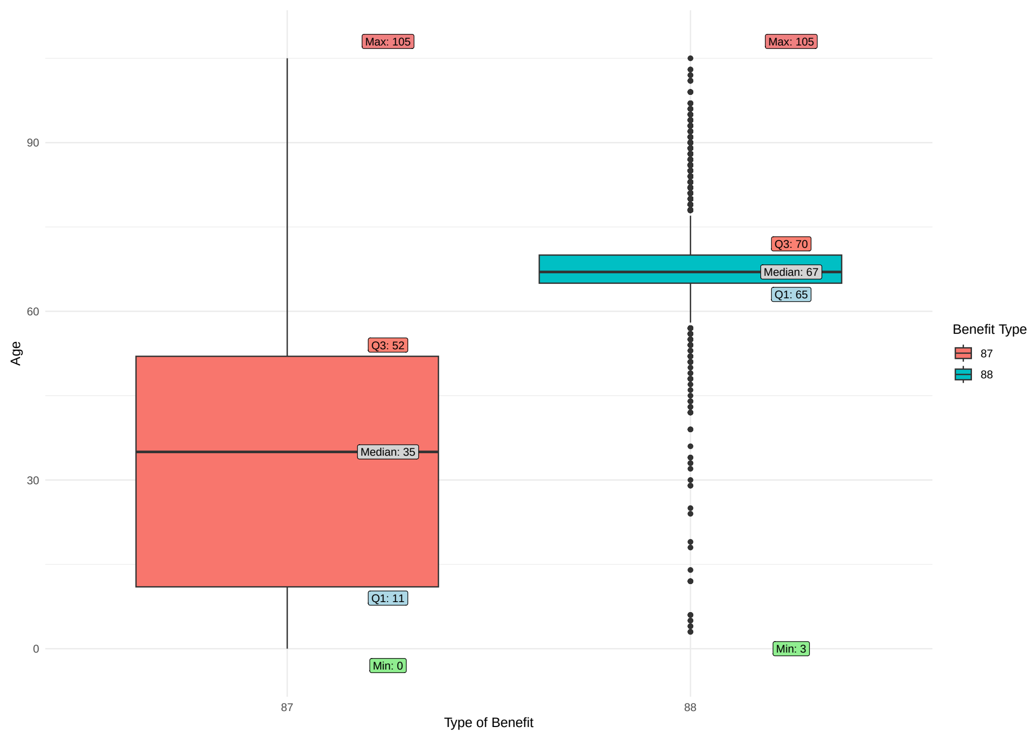


Figure 9: Distribution of the age of denied beneficiaries, by type of benefit

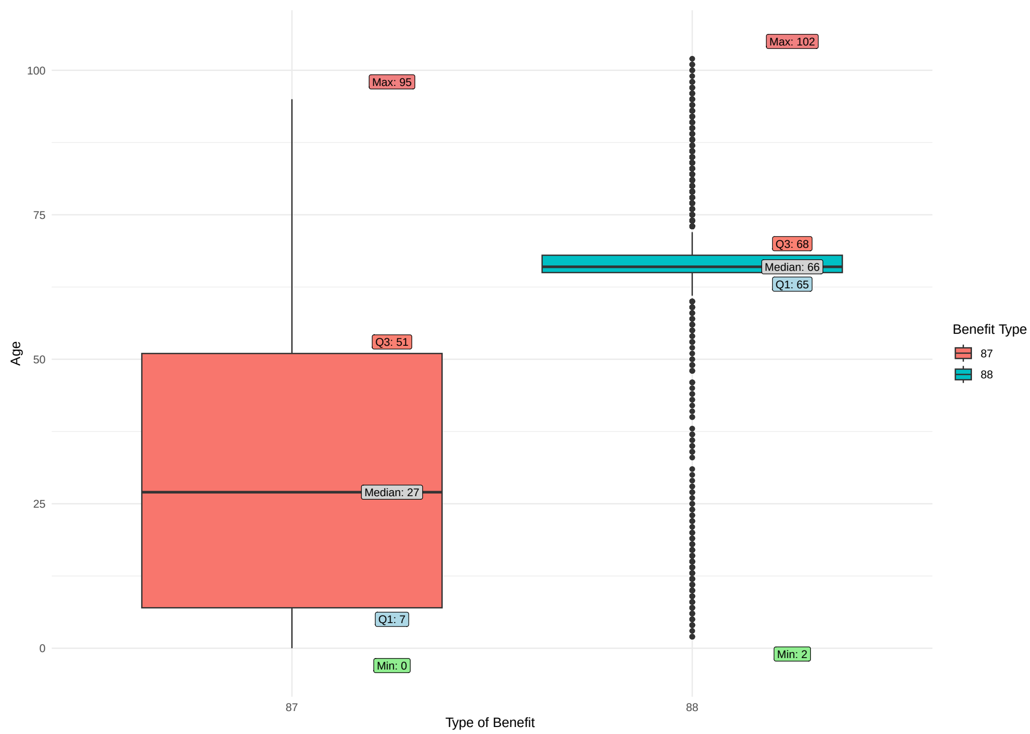


Figure 10: Distribution of the age of granted beneficiaries, by type of benefit

6 Waiting for Approval: Time Comparisons

Figure 11 highlights what is generally already expected. When the process follows its natural course, the granting time is faster. However, when the process takes alternative paths, we see a considerably large increase in the granting time — with durations three times longer for Grants Resulting from Judicial Actions, 15 times longer for Grants During the Appeals Phase, and up to 24 times longer for Grants Resulting from Administrative Review. These finding directly support the argument by [de Melo and Hecktheuer 2024] that the judicialization of administrative demands places an additional burden on the judiciary, decreasing the efficiency of benefit granting.

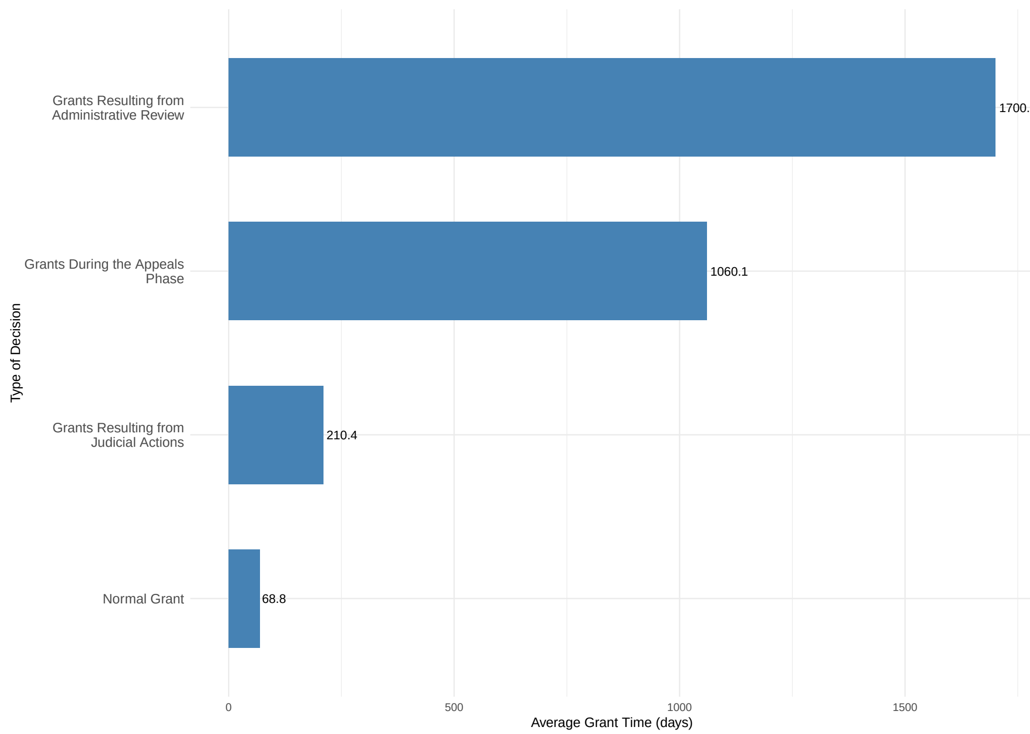
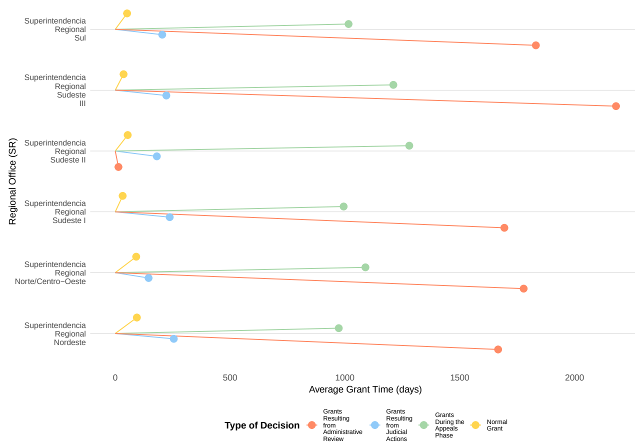


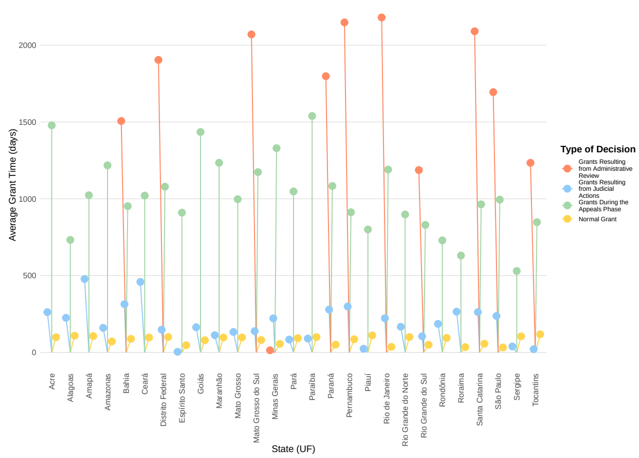
Figure 11: Average time to concession by type of approval

Figure 12a provides a regional breakdown of these results, revealing that this trend is mostly consistent across all SRs, the only exception being SR Sudeste III . While the absolute values vary slightly, every SR shows the same ranking of granting times by decision type, indicating that the delays caused by judicialization, appeals, and administrative reviews are not an isolated phenomenon but rather a widespread issue.

Similarly, Figure 12b views the data by state, showing that even at this more detailed level, the same pattern persists. Grants Resulting from Administrative Review happen in 11 states, among those, only Minas Gerais does not have it as the type of concession that takes the longest.



(a) SR



(b) State

Figure 12: Average time of grant by type of approval per SR and State

When we look at the SRs, we observe that the North/Central-West and Northeast regions have notably poor granting and denial times, while the Southern SR shows an average granting time and a relatively good denial time. In contrast, all SRs in the Southeast grant benefits faster than the national average and also deny requests in less time than average, as illustrated in Figure 13.

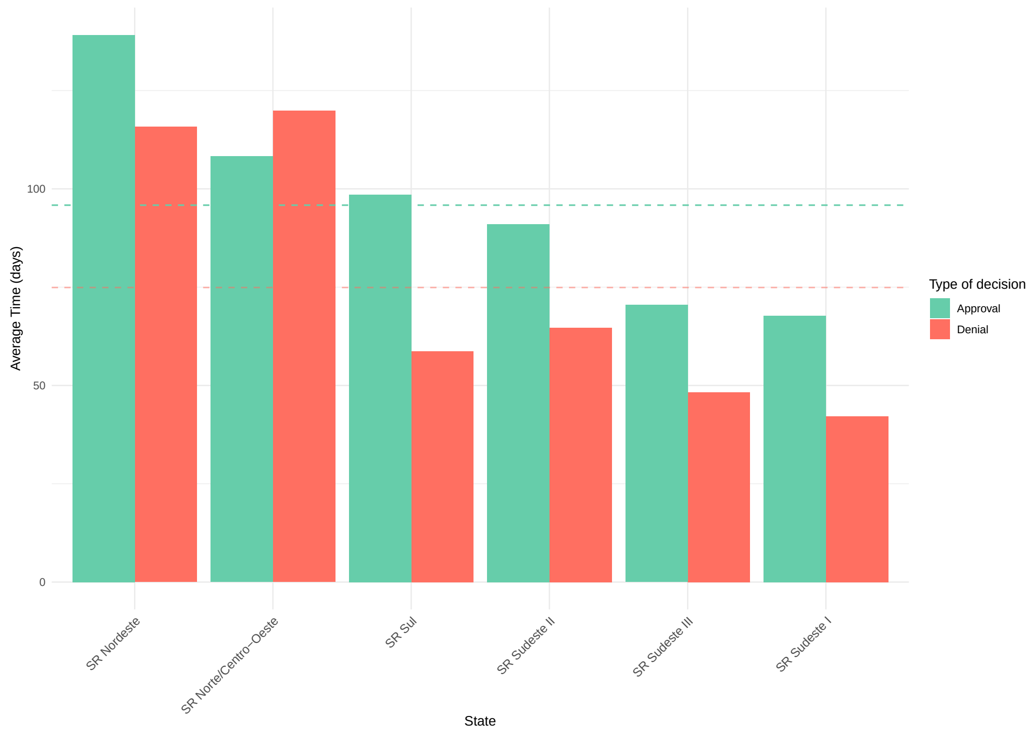


Figure 13: Average concession vs. denial time by regional superintendency

At the state level, it becomes clear that the main contributor to the Northeast's poor average granting time is the state of Ceará. On the other hand, Espírito Santo significantly contributes to the Southeast's lower average granting time. Regarding denials, Tocantins stands out with the worst denial time, while São Paulo is the state that denies requests the fastest, as shown in Figure 14.

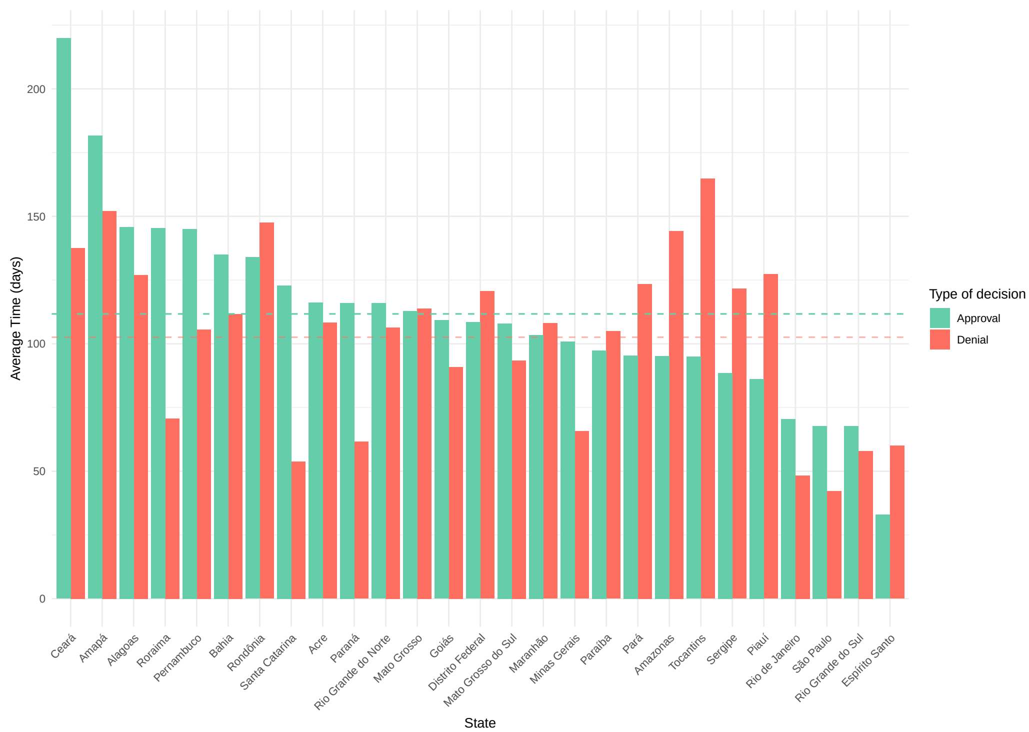


Figure 14: Average concession vs. denial time by state

7 Judicial Pathways to Access

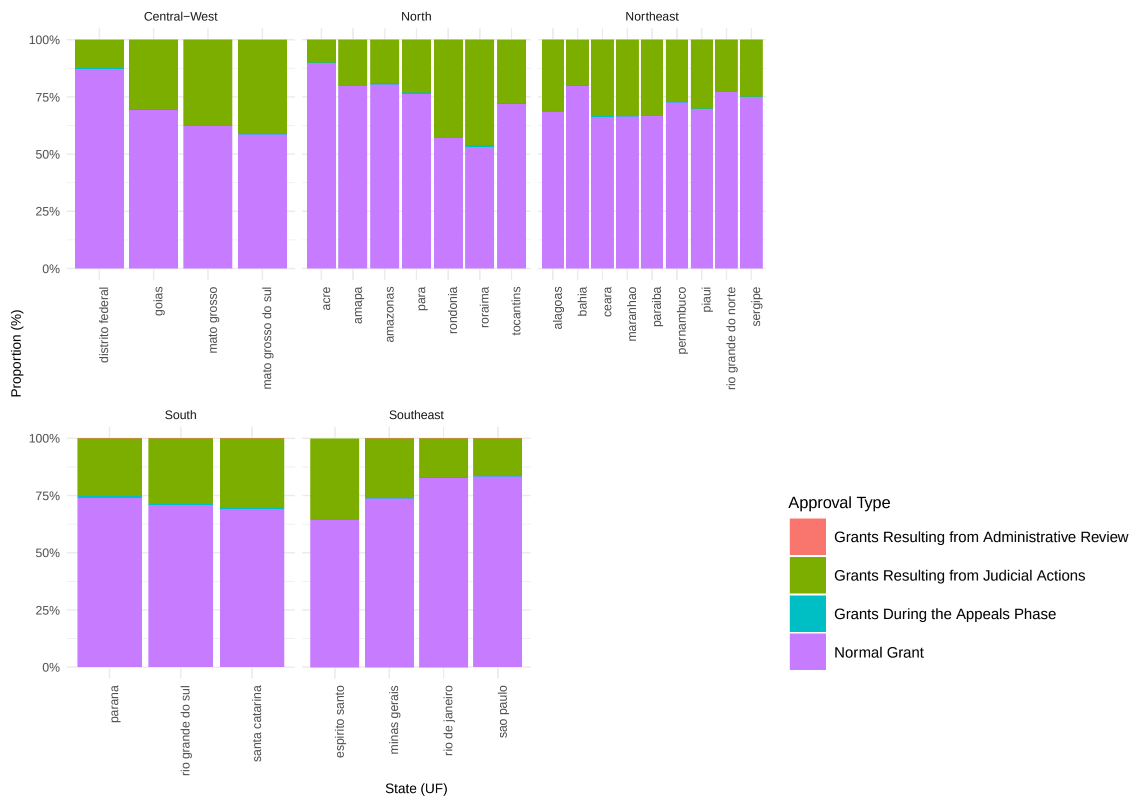


Figure 15: Types of benefit concession by state and region

Judicial concession is an alternative for when the standard concession does not work. When the person disagrees with whatever result came from INSS, be it an approval or denial , they can try to gain the benefit through legal means. This pathway is also supported by Article 203 of Brazil's Federal Constitution, which affirms that social assistance is a right for those in need, regardless of their contribution to social security[Presidência da República 1988]. Based on this principle, individuals may be granted the benefit through the courts even if they do not meet the formal eligibility criteria established by the INSS.

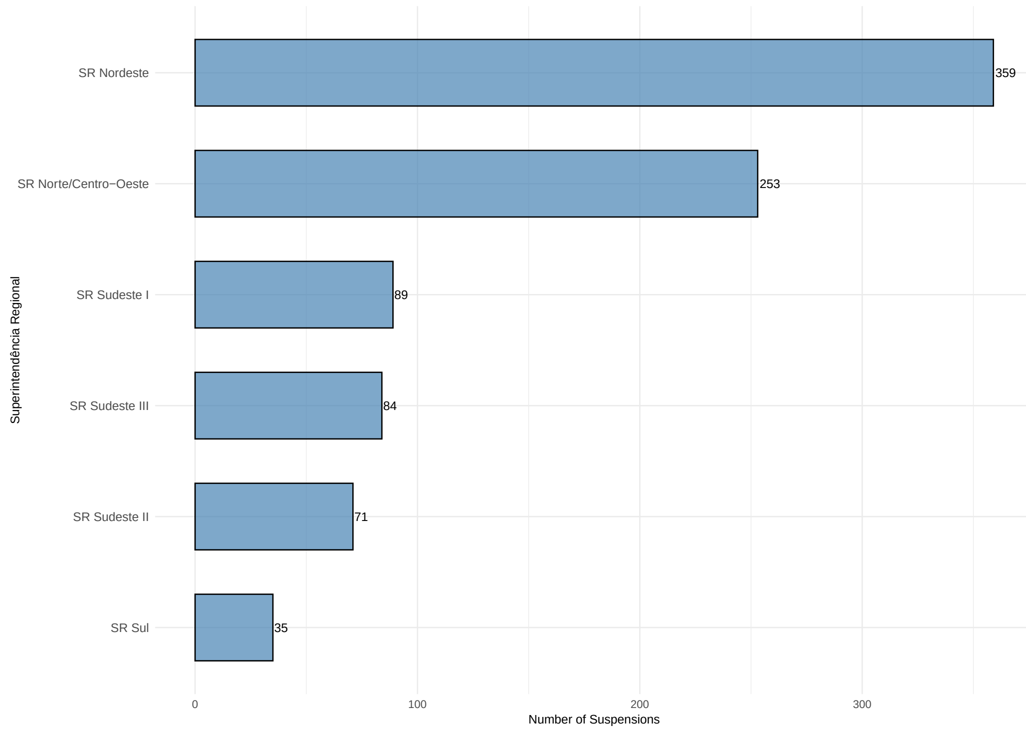
One of the main factors driving applicants to seek the benefit through legal means is the rigidity with which the BPC eligibility criteria are applied. Since 2012, judicial claims for the benefit have increased due to disagreements to these criteria, as the INSS applies them strictly, whereas the courts adopt a more flexible and subjective interpretation of social vulnerability[Lima 2023].

It is evidenced by Figure 15 that no state had more than 50% of its benefits granted through litigation. Although in 2020, 13% of all benefits in Brazil were granted through litigation[Executivo et al. 2021], there are several states that breach over 25%. Out of those cases, the most outstanding ones were Roraima with 46.2% and Rondonia with 42.7%, both of these States are from the North region. There were only 2 Federative Units that had a lower percentage than that of 2020, those being Acre and Distrito Federal with 9.9% and 12.5% respectively. The country's average was 27.6%, meaning that in the time of this study the BPC average was twice as much as the average for all benefits in 2020, which indicates inefficiencies in administrative pathways.

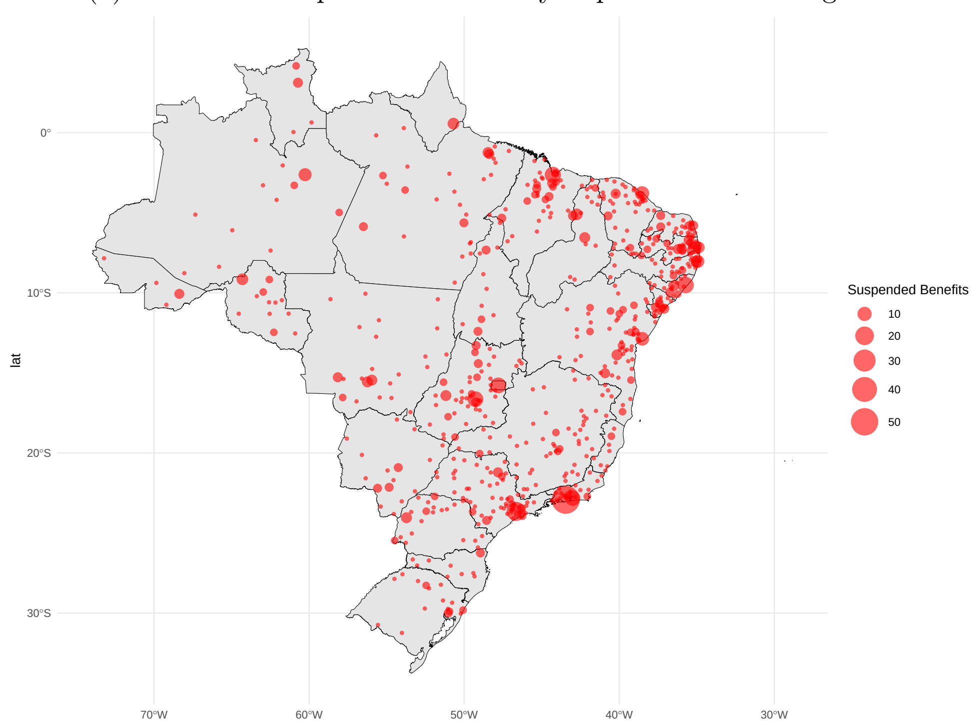
8 The Invisible Problem: Where Are Benefits Suspended?

The suspension of the BPC can occur for various reasons, predominantly related to the beneficiary no longer meeting the established eligibility criteria. For instance, if a beneficiary secures formal employment or if the per capita household income surpasses one-quarter of the minimum wage, the benefit may be suspended. Additionally, prolonged inactivity in withdrawing the benefit can lead to suspension. Therefore, maintaining compliance with all eligibility requirements is essential to ensure the continuity of the benefit.

As presented in Figure 16, we identified 891 benefit suspensions, representing 0.27% of all granted benefits. Although the overall number is low, the cases are concentrated primarily in two Regional Superintendencies: the Northeast (40%) and the North/Central-West (28%). In the Northeast, these occurrences are distributed across all states, whereas in the North/Central-West, most are concentrated in the state of Goiás.



(a) Number of suspended benefits by Superintendêncial regional



(b) Suspended benefits by municipality

Figure 16: Top grant reasons by benefit type

9 Identifying State Profiles Through Clustering

Clustering is a technique used in data science to identify groups in data such that elements in the same group have very similar characteristics while different groups are as different as possible [Sinaga and Yang 2020] . K-means is an unsupervised learning algorithm frequently used for clustering tasks. It works by partitioning a dataset into k clusters assigning each observation to the cluster with the nearest centroid based on some sort of distance, Euclidean distance is commonly used [Steinley 2006].

Given that this analysis aims to explore potential homogeneity in the data without predefined labels, the K-Means algorithm was selected. The clustering process was based on a set of carefully chosen features, including the three most frequent ICD codes, the top three reasons for benefit denial, average denial and grant processing times, and the proportion of benefits granted through judicial decisions.

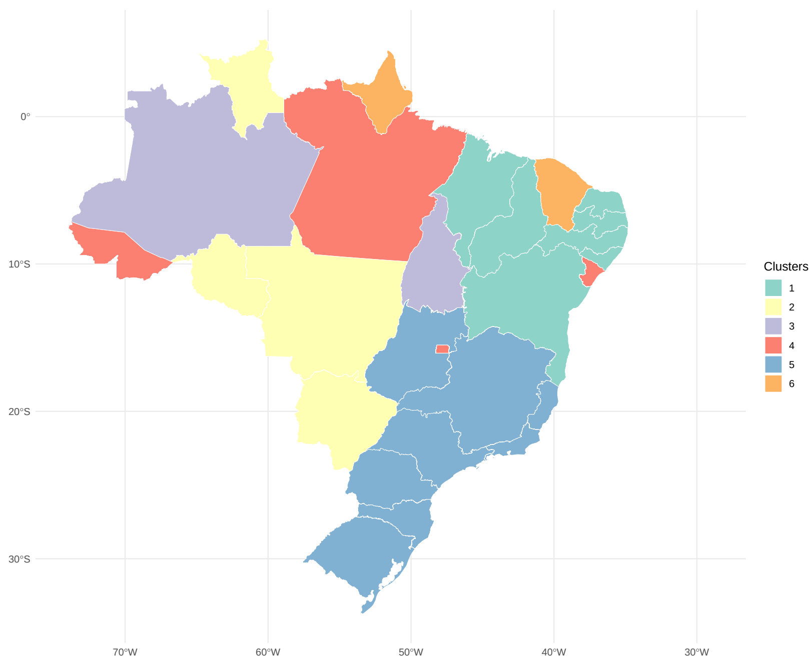


Figure 17: State clusters based on benefit characteristics (general case)

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
MA, PI, RN, PB, PE, AL BA	RO, RR, MS, MT	AM, TO	AC, PA, SE, DF	MG, ES, RJ, SP, PR, SC, RS, GO	AP, CE

Table 1: Distribution of Brazilian states by cluster (general scenario)

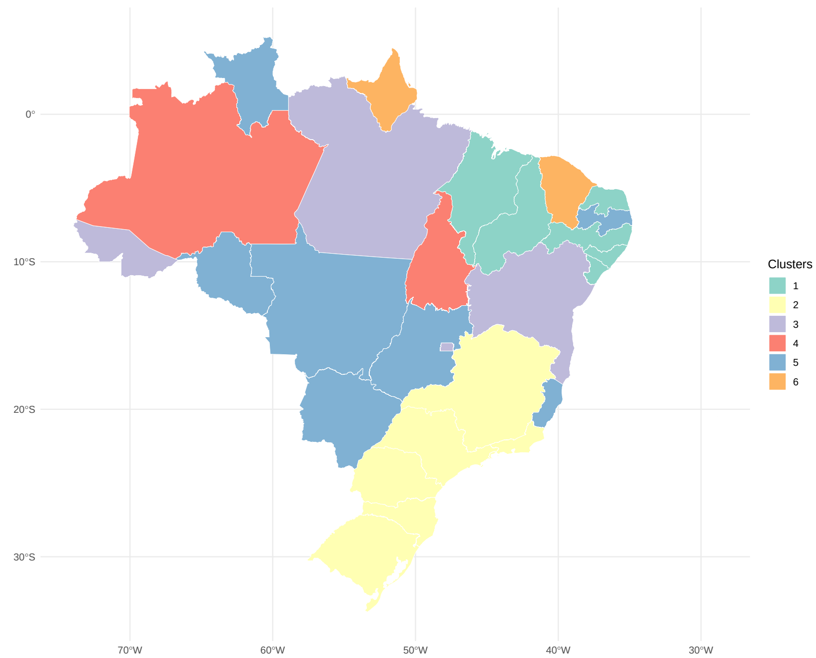


Figure 18: State clusters based on benefit characteristics (87)

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
MA, PI, RN, PE, AL, SE	MG, RJ, SP, PR, SC, RS	AC, PA, BA, DF	AM, TO	RO, RR, PB, ES, MS, MT, GO	AP, CE

Table 2: Distribution of Brazilian states by cluster (87)

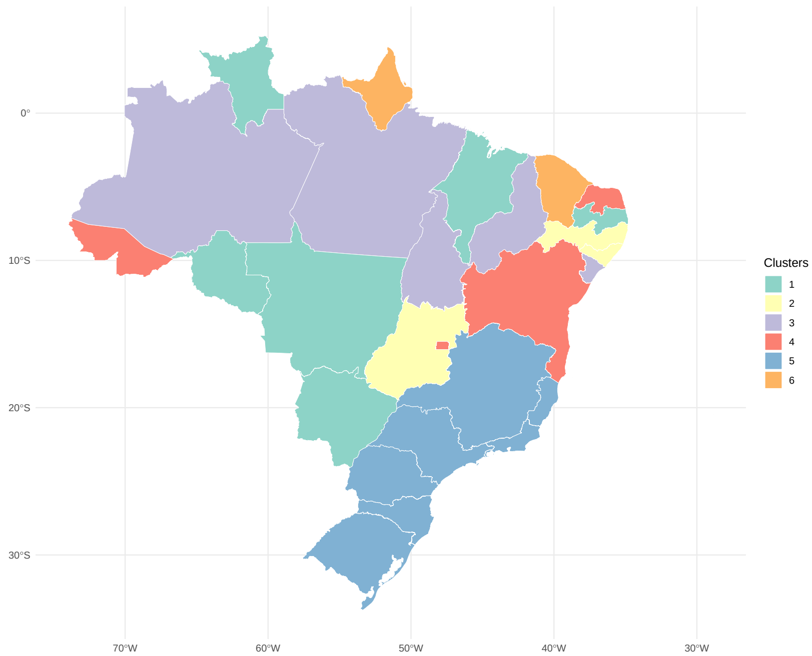


Figure 19: State clusters based on benefit characteristics (88)

Cluster 1	Cluster 2	Cluster 3	Cluster 4	Cluster 5	Cluster 6
RR, RO, MA, PB, MT, MS	PE, AL, GO	AM, PA, TO, PI, SE	AC, RN, BA, DF	MG, ES, RJ, SP, PR, SC, RS	AP, CE

Table 3: Distribution of Brazilian states by cluster (88)

Figure 17 and Table 1 show the result of applying K-means clustering to Brazilian states using the aforementioned features. Each color corresponds to one of six clusters. Considering K-means is an unsupervised learning method, each cluster represents groups of states with similar characteristics. Geographically speaking, we can see that the Northeast mostly only aligns with itself, whilst the South and Southeast generally behave as one.

Figure 18 and Table 2 were produced using only data related to BPC benefits of type 88, which correspond to claims made by elderly individuals aged 65 or older. As these benefits are not associated with medical diagnoses, the clustering excluded ICD codes and focused solely on variables relevant to this group.

Figure 19 and Table 3 were made by using only information relevant to BPC of type 88, that means no ICD (International Classification of Diseases) and data filtered to benefits of type 88. When compared to the previous 2 clusterizations, we can see that this time the South and Southeast are homogeneous. Meanwhile, the Northeast becomes very disjointed, which highlights the heterogeneity for benefits of this type.

Across all 3 clusterings, what was always constant was the fact that Mato Grosso and Mato Grosso do Sul were always grouped together, almost behaving like one big State. Likewise, Ceará and Amapá, even though they belong to different geographical regions, were always grouped together, showing their similarity.

10 Threats to Validity

Several potential threats to the validity of this study exist, primarily related to the data and methodology:

1. **Generalizability Threat:** The dataset, extracted from SUIBE, covers only a five-month period (June to October 2024). As such, it may not reflect broader, long-term trends or seasonal effects in the granting and denial of BPC benefits. Regional policy shifts, administrative changes, or extraordinary events (e.g., pandemics, federal budget restrictions) during or after this period could significantly alter observed patterns.

2. **Methodological Limitations:** The K-Means algorithm used for clustering assumes spherical clusters and equal variance, which may not

accurately represent the true structure of the data. Additionally, the clustering results are influenced by the initial feature selection, normalization choices, and the number of clusters defined. Although the selected features were based on domain knowledge, other potentially relevant variables (e.g., household composition, type of municipality) were not included due to data limitations.

3. **Omitted Contextual Variables:** Socioeconomic or infrastructural differences between states (such as the presence of digital literacy initiatives, healthcare accessibility, or legal aid availability) may partially explain the observed disparities in denial rates, judicial concessions, and processing times. However, these contextual factors were not directly modeled in this analysis due to lack of available data.

4. **Interpretation of Judicialization:** While the study quantifies judicial concessions, it does not explore the underlying causes of judicialization in depth—such as regional variation in legal advocacy networks, local interpretations of social vulnerability, or strategic litigation by public defenders. As a result, the increasing trend of judicial approvals is treated as a symptom rather than a fully explained phenomenon.

11 Final remarks and future considerations

This research aimed at mapping and analyzing the geographic, demographic, and clinical aspects underlying the approval, denial, and suspension of Brazil's Continued Provision Benefit, using data science, statistical models, and clustering methods. All goals were achieved: we identified the SRs and states with the largest amount of applications, deferrals, and denials; we investigated the main motivations for denial across regions; we documented the effect of judicial grants and delay; and we clustered states, which were determined using multiple indicators, such as ICD codes, reasons for denials, and average processing time.

In addition to satisfying these goals, this study provides arguably the largest data-based analysis of the BPC thus far. The vast majority of studies that have been conducted to date have merely examined the benefit from either legal or socioeconomic perspectives. In contrast, this analysis employed national-level administrative microdata, combined with unsupervised statistical methods, that identify hidden structures to unfold associations between attainment of benefits. This unique combination of scale, specificity, and method rigor proposes the potential for a replicable approach for studying other large-scale social assistance programs.

Our research documents systemic problems like high levels of rejection related to fuzzy disability definitions, big geographic variation in processing times, and states with deep dependence on courts. Importantly, unsupervised clustering (with K-Means) was particularly useful in identifying geographical similarities that are often missed in typical descriptive approaches.

Future research could expand upon this by integrating supervised learning methods to provide statistical predictions of the risk of denial or processing delays, in advance of interventions. Also, our approach could be used to evaluate the impact of policy changes, assess equity of service delivery, and compare the operational effectiveness of social programs over time.

Finally, we hope this work contributes to an ongoing discussion not only in the academic literature on social protection, but to the ongoing agenda of reforming public administration through evidence-based decision-making and transparency.

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