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ALOCAÇÃO ORÇAMENTÁRIA INTELIGENTE DE RECURSOS PÚBLICOS

Saulo de Oliveira Nonato

Brasília, DF

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Dissertação apresentada ao Curso de Mestrado Profissional em Administração Pública da Faculdade de Economia, Administração, Contabilidade e Gestão de Políticas Públicas, como requisito parcial para obtenção do título de Mestre em Administração Pública.

Orientadora: Marina Figueiredo Moreira

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"'Aprendi que a coragem não é a ausência do medo, mas o triunfo sobre ele. ’’

Nelson Mandela

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RESUMO

Este trabalho explora a alocação eficiente de recursos públicos orçamentários por meio de três componentes interligados: uma revisão integrativa da literatura, um estudo empírico e um Produto Técnico-Tecnológico (PTT). A revisão de literatura examina como as funções estatais — alocativa, distributiva e estabilizadora — se manifestam em diferentes setores, identificando nove categorias que influenciam essa alocação. Com base nesses achados, o estudo empírico apresenta um modelo híbrido de inteligência artificial, que integra aprendizado de máquina e otimização bayesiana, aplicado a dados orçamentários do Brasil entre 2000 e 2023, para simular alocações que otimizem indicadores socioeconômicos. O PTT materializa essa abordagem por meio de uma plataforma interativa, permitindo que gestores públicos ajustem despesas por função orçamentária e visualizem os impactos simulados nos indicadores, fornecendo uma ferramenta prática e replicável para apoiar a tomada de decisão.

Palavras-chave: Alocação de Recursos Públicos; Orçamento Público; Inteligência Artificial

ABSTRACT

This work explores the efficient allocation of public budgetary resources through three interconnected components: an integrative literature review, an empirical study, and a Technical-Technological Product (PTT). The literature review examines how the state's functions—allocative, distributive, and stabilizing—manifest in different sectors, identifying nine categories that influence this allocation. Based on these findings, the empirical study presents a hybrid artificial intelligence model that integrates machine learning and Bayesian optimization, applied to Brazilian budget data from 2000 to 2023, to simulate allocations that optimize socioeconomic indicators. The PTT materializes this approach through an interactive platform, allowing public managers to adjust expenditures by budgetary function and visualize the simulated impacts on the indicators, providing a practical and replicable tool to support decision-making.

Keywords: Public Resource Allocation; Public Budgeting; Artificial Intelligence

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INTRODUÇÃO GERAL

A alocação de recursos públicos orçamentários, conhecida como o "problema básico do orçamento", é um desafio central para a administração pública, pois envolve a distribuição de recursos limitados entre demandas concorrentes (Fozzard, 2001; Key, 1940). Essa complexidade é intensificada por variáveis multidisciplinares e transversais, incluindo fatores sociais, econômicos, ambientais e tecnológicos, que dificultam a tomada de decisões eficazes na área (Amin, 2020; Medema, 2023; Valle-Cruz et al., 2022). Para enfrentar essa complexidade crescente, a evolução das tecnologias digitais tem promovido uma transformação do governo eletrônico para o governo inteligente, caracterizado pelo uso de ferramentas como a IA para apoiar a tomada de decisão baseada em evidências e melhorar a eficiência na alocação de recursos públicos (Fernandez-Cortez et al., 2020; Gil-Garcia et al., 2014, 2016; Harsh & Ichalkaranje, 2015).

No Brasil, as pesquisas sobre a aplicação de IA na alocação orçamentária permanecem incipientes. Este estudo propõe-se a contribuir para o início dessa discussão, explorando o potencial da tecnologia como uma ferramenta de suporte à tomada de decisão, enquanto reconhece as limitações e os desafios específicos envolvidos em sua aplicação no contexto do sistema orçamentário nacional.

Diante desse contexto, esta dissertação investiga a temática por intermédio de três estudos inter-relacionados: um artigo de revisão integrativa da literatura, um estudo empírico e um Produto Técnico-Tecnológico (PTT). De maneira integrada, os trabalhos abordam tanto os aspectos teóricos quanto os práticos da alocação de recursos públicos, analisando áreas de interesse identificadas na literatura, simulando cenários de alocação ótima com o uso de IA e propondo um modelo para apoiar a tomada de decisão orçamentária.

O primeiro estudo, "*Where Do Public Resources Go? An Integrative Literature Review on Budget Allocation*", realiza uma revisão integrativa da literatura sobre alocação orçamentária, examinando trabalhos publicados entre 2014 e 2023. O artigo busca compreender como a alocação de recursos públicos reflete as prioridades do Estado em diversos setores, identificando fatores que influenciam esse processo. Além disso, analisa como as características das funções do Estado na economia (Musgrave, 1959, 2008) — alocativa, distributiva e estabilizadora — se manifestam nas tendências atuais de pesquisa (Kenno et al., 2018; Medema, 2023). A relevância desse estudo reside na necessidade de fornecer uma visão abrangente dos temas que orientam a alocação orçamentária, contribuindo para o avanço teórico na área.

O segundo artigo, "*Let's Spend Smarter: How Artificial Intelligence Can Help Us Better Allocate Public Budgetary Resources*", é um estudo empírico que propõe e testa um modelo híbrido de IA para otimizar a alocação de recursos públicos orçamentários no Brasil. Reconhecendo que os modelos tradicionais de orçamento apresentam limitações para absorver as mudanças no ambiente econômico e são criticados por sua lentidão e falta de precisão (Galdino & Andrade, 2020; Lindblom, 1981; Zatonatska et al., 2023), o estudo adota uma abordagem quantitativa e algorítmica. Para tanto, utiliza-se dados orçamentários como variáveis independentes e indicadores socioeconômicos como variáveis dependentes para simular um cenário de alocação ótima de recursos.

O modelo relatado no trabalho foi desenvolvido com base em um espelho metodológico adaptado do estudo de Valle-Cruz et al. (2022), mas integrando, de maneira inovadora, um algoritmo de aprendizado de máquina, o *Gradient Boosting* implementado pela biblioteca *XGBoost* (Chen & Guestrin, 2016; XGBoost developers, 2022), e um algoritmo de otimização bayesiana, o *Tree-structured Parzen Estimator* (TPE), utilizando a biblioteca *Optuna* (Akiba et al., 2019; Optuna Contributors, 2020). O objetivo é investigar como um modelo híbrido de IA pode apoiar a definição de alocações orçamentárias no Brasil, fornecendo subsídios para a tomada de decisão, sem substituir a análise humana.

Entende-se que o modelo proporciona suporte aos gestores públicos na busca por uma alocação mais eficiente de recursos, alinhada aos objetivos governamentais. Sem a pretensão de estabelecer relações causais diretas, sua finalidade é integrar-se aos instrumentos tradicionalmente empregados para subsidiar o processo decisório na área orçamentária, ampliando a capacidade analítica que auxilia na tomada de decisão.

O terceiro trabalho, o PTT intitulado "Modelo Híbrido de Inteligência Artificial na Alocação de Recursos Públicos", baseia-se nos fundamentos do segundo estudo para desenvolver uma ferramenta prática de apoio à decisão. Classificado como "processo/tecnologia e produto/material não patenteável" pela CAPES, o PTT se materializa em uma plataforma interativa que permite simular cenários de alocação orçamentária e visualizar os impactos sobre os indicadores socioeconômicos escolhidos. O modelo foi testado com dados de execução orçamentária federal do Brasil do período de 2000 a 2023, com o objetivo de otimizar, de forma simultânea, o PIB, a inflação e o índice de Gini. A aplicação seguiu uma abordagem quantitativa, empregando uma metodologia, como já dito, adaptada de estudo anterior (Valle-Cruz et al., 2022).

A integração desses três trabalhos justifica-se pela necessidade de explorar metodologias interdisciplinares e inovadoras no processo de alocação de recursos públicos, diante dos desafios históricos e das dinâmicas globais e locais emergentes. Parte-se da premissa de que o uso de técnicas de IA pode superar as limitações dos métodos tradicionais de alocação orçamentária, permitindo identificar padrões complexos que métodos estatísticos convencionais podem não detectar (Chi & Shen, 2022; Katharina Dhungel et al., 2024). Ao não buscar substituir a inteligência humana, mas sim oferecer suporte quantitativo ao processo decisório, a dissertação contribui para o avanço teórico e prático na alocação de recursos públicos, estabelecendo uma base para futuras pesquisas na intersecção entre administração pública, economia e tecnologia.

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PAPER 1. WHERE DO PUBLIC RESOURCES GO? AN INTEGRATIVE LITERATURE REVIEW ON BUDGET ALLOCATION

ABSTRACT

This paper examines the allocation of public budgetary resources through the lens of public administration, focusing on how state functions—allocative, distributive, and stabilizing—manifest across different sectors. Based on an integrative literature review, we classify the findings into nine cross-cutting categories: Economic Development; Sustainable Development and the Environment; Social Inequality; Influence-Based Distribution; Emergency Management; Participatory Management; Public Policy and Fiscal Management; Innovation, R&D, and Technology; and Public Health. The analysis reveals that these functions are mobilized independently or in combination, depending on sectoral demands, reflecting the dynamic and adaptive nature of budget management. By aligning resource allocation with varying priorities across sectors, this study advances public administration theory and provides practical insights for policymakers. Future research should explore the trade-offs inherent in prioritizing certain functions, refine analytical methods, conduct comparative studies, and adapt frameworks to emerging contexts in public budgeting.

Keywords: Allocation of Public Budgetary Resources, State Functions; Integrative Review.

INTRODUCTION

The allocation of public budget resources has long been of interest to public administrations and remains a persistent challenge in government management (Brumby, 2007; Medema, 2023; Valle-Cruz et al., 2022). The "basic budget problem" refers to the challenge of distributing limited resources among competing needs and demands (Fozzard, 2001; Key, 1940). The complexity of this problem is intensified by the influence of cross-cutting, multidisciplinary and complex variables, such as social, economic, environmental, and technological factors, as evidenced by more recent studies (Buffart et al., 2020; Ghazinoory & Hashemi, 2023; B. Guo et al., 2023; Musgrave, 2008; Pradhan, 1996; Valle-Cruz et al., 2022; Zawalińska et al., 2018).

In the pursuit of a cohesive theory of public expenditure, a theoretical framework is employed that emphasises the role of public administration in the efficient allocation of resources, income distribution, and economic stabilisation, grounded in the correction of market failures, such as the provision of public goods and the mitigation of externalities (Fozzard, 2001; Medema, 2023; Pradhan, 1996). Such analysis derives from welfare economics and regards public administration as an instrument for maximising social welfare by balancing the benefits of public spending with fiscal costs and establishing normative criteria for government decisions (Fozzard, 2001; Keynes, 2018; Medema, 2023). Therefore government, acting as the manager of a 'public household', should integrate the state's budgetary functions — resource allocation, income distribution, and economic stabilisation — to promote equity and economic efficiency (Musgrave 2008; Case 2008; Medema 2023).

Studying how these functions manifest themselves in the budget process allows the development of theoretical models that guide public administration practices (Desmarais-Tremblay, 2021; Medema, 2023; Musgrave, 2008). The transversality and multidisciplinarity of the subject become evident in its relevance to fields such as economics, law, political science, and health sciences (Kenno et al., 2018; Medema, 2023; Musgrave, 2008). However, there is a gap in the literature due to the absence of studies that integrate these different perspectives into a unified analysis (Kenno et al., 2018; Medema, 2023). This fragmentation limits theoretical advancement in public administration, as it hinders the construction of comprehensive conceptual frameworks that reflect the complexity of public resource allocation across different sectors.

To this end, we conducted an integrative literature review (Cooper, 1989; Russell, 2005) of papers published between 2014 and 2023 to examine how public budget allocation reflects the state's priorities across various sectors, such as economic, social, political, technological, and environmental domains. This study provides a comprehensive overview of the key factors driving budget allocation, maps recent research topics, analyzes how the state's functions — allocative, distributive, and stabilizing — manifest in current trends, and identifies directions for future research.

Complementing the integrative literature review, the content analysis (Bardin, 2015) of each selected paper enabled the systematic classification of the studies into thematic categories, reflecting the current areas of research interest.

This study presents the following structure: the Background outlines the theoretical framework and context. The Methods cover the research design, including the literature review and content analysis. The Content Analysis details the thematic categorization of the studies. The Results present the main findings of the literature review. The Agenda for Future Studies compiles key research suggestions from the selected papers. The Conclusion summarizes the study's contributions and implications.

BACKGROUND

The evolution of state functions in the economy, from classical liberalism to contemporary approaches, reflects a change in the role of the state. Initially, the market was seen as capable of regulating itself, with state intervention restricted to areas such as defence and infrastructure (Medema, 2023; Smith, 2002, 2007). However, economic crises and conflicts in the 19th and 20th centuries revealed the limitations of this approach, leading to the defence of more active state intervention to correct market failures and promote economic stability (Keynes, 2018; Medema, 2023). Musgrave (1959) expanded this vision, defining the functions of the state in a tripartite way: allocative, distributive, and stabilizing (Table 1), emphasizing that a comprehensive budgetary policy should address all three functions in a balanced manner to ensure effective public resource management and economic stability.

Considering the multiple functions that the budget plays in the economy, the role of the public sector involves balancing economic efficiency and equity in budget policies (Musgrave, 2008). In operational terms, it often means setting budgetary priorities. In addition, social, political and historical contexts shape the formulation of these policies, with an emphasis on the importance of integrating the allocation, distribution and stabilisation functions of the budget, recognising that these functions are interdependent and mutually influential (Musgrave, 1959, 2008; Musgrave & Musgrave, 1989).

Musgrave (1959) proposed a theoretical framework for allocating resources to public goods, highlighting the need for government intervention to align their provision with societal preferences, especially when private goods fail to meet collective needs effectively (Case, 2008). The framework expands to include a system of simultaneous equations that examines the interactions between public budget functions, helping to understand how changes in one function can influence others to maximize social welfare (Medema, 2023). This approach emphasises the need to focus on allocative efficiency, understood as the optimal distribution of government resources according to priorities, something complex that requires allocation strategies that constantly adjust to the government's evolving needs (Brumby, 2007).

Table 1. Main characteristics of state functions in the economy via the budget

Function	Key features
Allocative Function	It addresses market failures in the provision of non-rivalrous and non-excludable public goods, such as national defence, and encompasses investments in infrastructure and merit goods, such as health and education (Musgrave, 1959, 2008; Musgrave & Musgrave, 1989).

Function	Key features
Distributive Function	It corrects imbalances in the distribution of income and wealth through budgetary policies. It uses, for example, progressive taxes and social transfers to promote equity (Musgrave, 1959, 2008; Musgrave & Musgrave, 1989)
Stabilising function	It corrects macroeconomic imbalances by managing inflation, unemployment and economic growth through fiscal policies (Alem & Giambiagi, 2018; Musgrave, 1959, 2008; Musgrave & Musgrave, 1989)

Although not explored in depth in this study, it is important to acknowledge the existence of other theories that address budgeting, particularly in the fields of economics, psychology, and sociology (Kenno et al., 2018). Musgrave's (1959) theoretical framework was chosen for its relevance in addressing the relationship between public resource allocation and state priorities, providing a robust foundation for the objectives of this research.

METHODS

Integrative Literature Review

This integrative review identifies, interprets and synthesis the results of previous published research to identify thematic categories and trends in the literature on public budget resources allocation. The review connects theory to empirical practices, demonstrating how contemporary research considers the state's functions in the economy.

The integrative literature review is a method that summarises past research, consolidating the conclusions of various studies (Cooper, 1989; Russell, 2005). First, researchers must formulate a problem to guide the integrative review and delimit its scope (Cooper, 1989; Mendes et al., 2008; Russell, 2005). Next, the inclusion and exclusion criteria stipulated the filtering of relevant studies during the identification of the literature (Botelho et al., 2011; Russell, 2005). Researchers must next assess the quality of the selected studies systematically and objectively (Botelho et al., 2011; Mendes et al., 2008; Russell, 2005). The data is then extracted and synthesized, leading to the interpretation of results and the presentation of conclusions, aligned with the review's objectives and the established research questions (Botelho et al., 2011; Cooper, 1989; Mendes et al., 2008; Russell, 2005; Whittemore & Knafl, 2005).

Following this methodology, the research used the process described in Table 2 for the final selection of the papers of interest:

Table 2. Phases of the Integrative Review

Phase	Research Application
Formulating the research question	Central question: - How does contemporary academic literature explore the manifestation of the state's economic functions (allocative, distributive, and stabilizing) in the allocation of public budgetary resources across different sectors? Secondary questions: - What characteristics of the state's economic functions are identified as priorities in public budget allocation within different sectors? - What are the possible research directions for future investigations into the allocation of public resources?
Definition of Inclusion and Exclusion Criteria	Inclusion criteria: The inclusion criteria for the selection of papers focussed on publications from 2014 to 2023, restricting them to peer-reviewed journals in the areas of public policy, administration, economics and social sciences. The researchers selected studies using a specific set of keywords to ensure accuracy and thematic relevance. The initial search identified **133 papers** in the databases. Exclusion criteria The exclusion criteria in the integrative review involved assessing the quality of the journals, the thematic relevance of the papers, the presence of duplication between the databases and the availability of access to the full content of the studies. In all, **the authors excluded a total of 74 papers**.
Identifying the literature	Main search criteria**:** - Databases searched: CAFe/CAPES, ProQuest, Scopus and ScienceDirect. - Time: Papers published between 2014 and 2023. - Type of Publications: Peer-reviewed papers only. The authors used filters and Boolean searches to identify relevant papers in the databases. Keywords and themes: - Budget allocation: "budget allocation function", "allocation of resources" and similar. - Public Governance: "government", "public management", "public governance" and the like. - Methodologies and instruments: "methodology", "method", "technique" etc. - Institutional Objectives: "Aims", "Goals", "Objectives" etc. - Public spending: "Public budget", "Public spending", "Financial assistance" etc.
Study Quality Assessment	Journals Impact Factor: Exclusion based on metrics such as Qualis, CiteScore and JCR. Only higher stratum journals were considered. Thematic Relevance (carried out in two stages): - Reading the title and abstract: papers that did not adhere to the object of study (allocation of public budget resources). - Complete reading of the rest: exclusion of papers with low thematic relevance.

Phase	Research Application
	Duplication: Elimination of repeated papers in different databases. Access to Content: The authors excluded papers without access to the full text. The authors considered only papers that described methodological aspects (qualitative, quantitative, and mixed), excluding purely theoretical studies.
Data extraction and synthesis	The information was managed using Zotero, Obsidian and Excel software. The authors catalogued each paper in detail, including title, author, database, DOI, year, abstract, objectives, findings and the role of resource allocation in the research. In addition, two different classifications were applied: a content analysis that categorised the studies into nine thematic categories and a classification according to Musgrave's allocation, distribution and stabilisation functions.
Interpretation of results and presentation	After selection and analysis, **59 papers** were included in the integrative review, distributed into **nine categories**. The analysis examined the allocation of public budget resources in different contexts, using Musgrave's functions and identifying the main suggestions for future research in each thematic area.

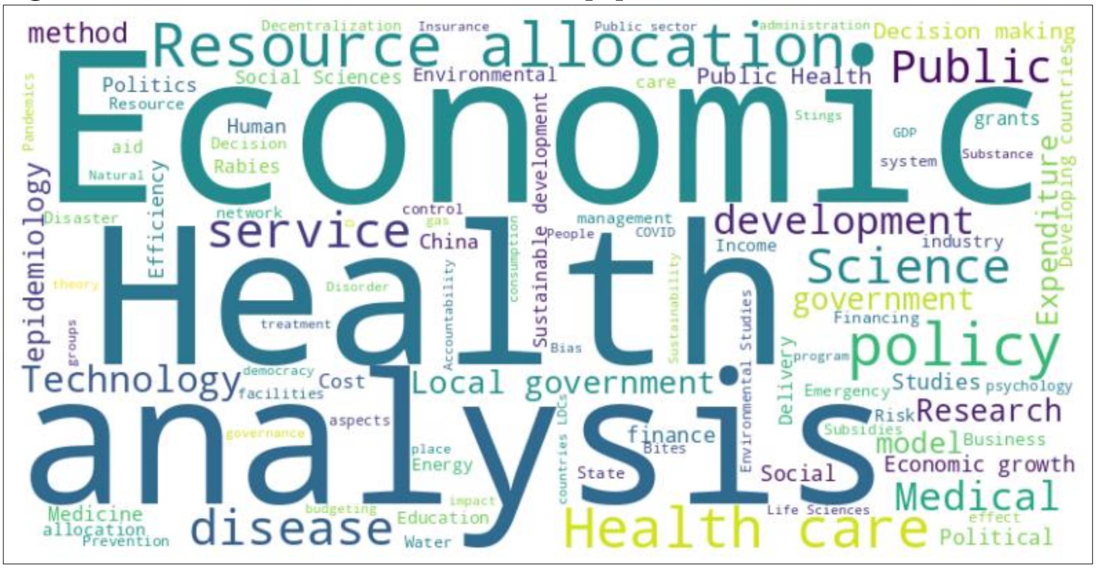
Content Analysis

After identifying the relevant papers, the authors extracted data, analysed and categorised it to synthesise information on public resource allocation, focusing on abstracts, conclusions, and keywords. This process highlighted current practices, persistent challenges, and opportunities for future research. The authors applied content analysis to interpret both explicit and implicit meanings of the texts, structuring the process into three phases: pre-analysis, material exploration, and treatment of results (Bardin, 2015).

For the thematic categorisation, a coding method was used which allowed the categories to be continuously adapted as the analysis progressed (Dey, 1993). The use of a word cloud (Figure 1), generated from the paper *tags* in Zotero[1](Zotero, 2022) provided a visualisation of the most recurrent themes, guiding the subsequent stages of data analysis and synthesis[2].

[1] Reference manager database available at < https://bit.ly/46w1Hft>.
[2] In Zotero, tags are customizable labels used to organize and categorize references. In this research, the tags were automatically imported from the metadata assigned by the original sources, such as library catalogs or databases. Unlike scientific keywords, tags offer greater flexibility for managing workflows and organizing content by topics, methodologies, or other criteria (Zotero, 2022).

Figure 1. Word Cloud - metadata of selected papers

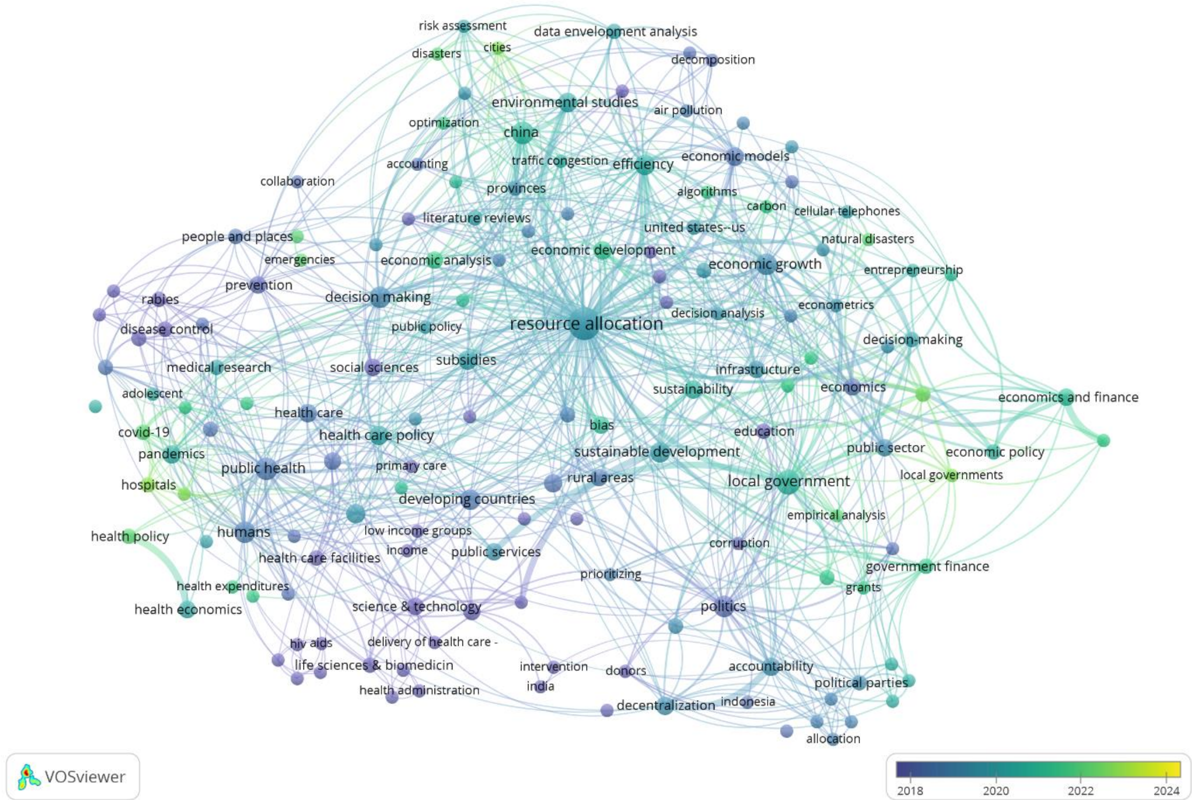


The image in question used *Python*'s '*WordCloud*' library[3] to create a word cloud that visually illustrates the prevalence of terms in a collection of texts. In the representation, the words are sized according to their frequency, highlighting central terms such as "Resource allocation", "Economic", "Health" and "Politics". Other themes such as "Science", "Development" and "Local Government" also emerge as focuses, illustrating that the allocation of public budget resources is part of a transversal and multidisciplinary approach.

Figure 2 shows a bibliometric map of co-occurrence of terms generated by the *VOSviewer software*, using data from Zotero, such as titles and abstracts, to examine the interrelationship of keywords in the literature on resource allocation. The colour scale ranges from blue to yellow, representing the period from 2018 to 2023, where blue indicates the beginning and yellow the end, showing the temporal evolution of the relevance of the terms. Topics such as "resource allocation", "public health", "economic growth", "local government", "politics" and "subsidies" emerge as particularly relevant, reflecting areas of focus in academic research on the allocation of public budget resources over time.

[3] Code available at < https://bit.ly/4flavsE >.

Figure 2. Bibliometric map



After visually analysing the frequency and interrelationships of the terms, the research moved on to a complete reading of the selected texts, identifying complementary themes that were not initially evident but were relevant to the study. This detailed observation made it possible to classify the papers into consistent thematic categories, defined organically from the content analysed, enriching the research with detailed information and contextual nuances.

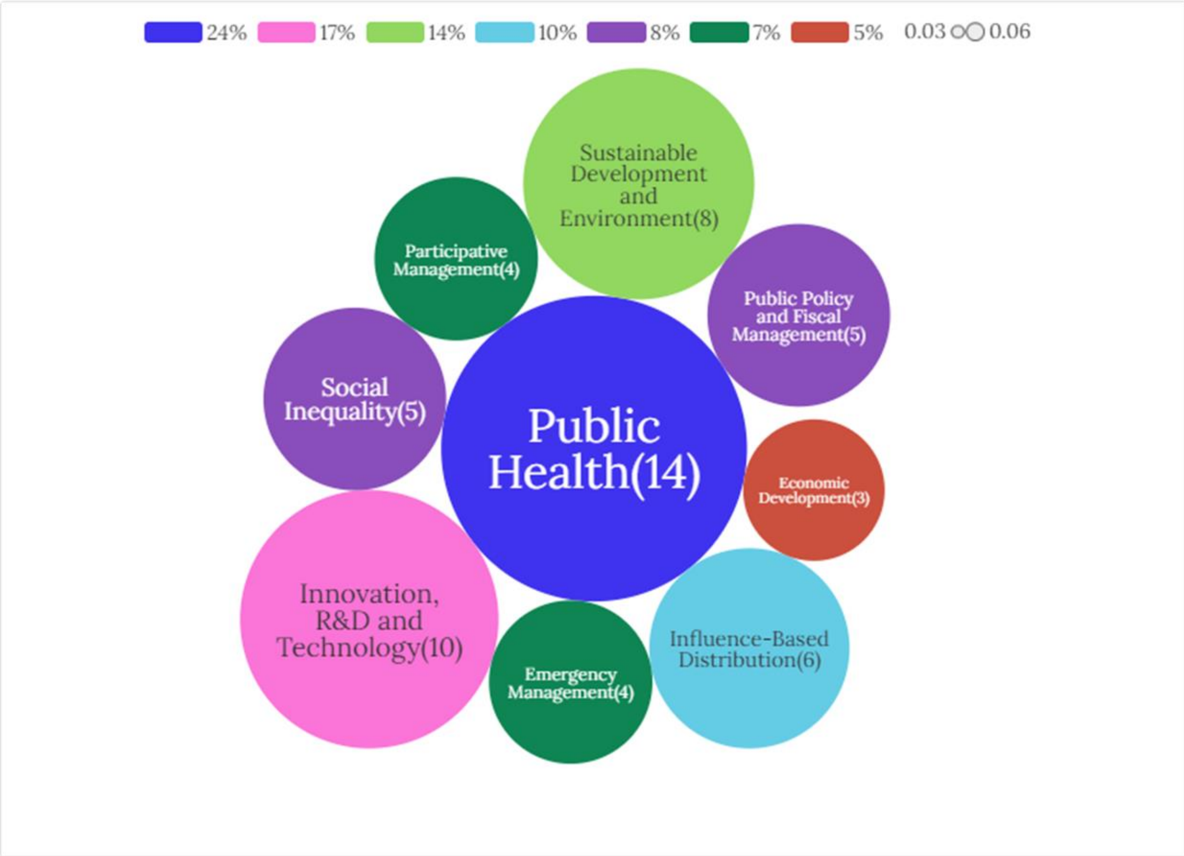
To ensure the reliability of the categorization, two independent researchers conducted a double-coding procedure, achieving an inter-rater reliability exceeding 95%, meeting the quality benchmark established by McAlister *et al.* (2017).

The result of this analysis process was the identification of 9 (nine) distinct thematic categories of interest: Economic Development; Sustainable Development and the Environment; Social Inequality; Influence-Based Distribution; Emergency Management; Participatory Management; Public Policy and Fiscal Management; Innovation, R&D and Technology; and Public Health.

As illustrated in Figure 3, each "bubble" has the name of the category and the number of papers in brackets, highlighting the proportion each category contributes to the total data set.

The graph also includes a coloured legend at the top, indicating the percentages associated with each bubble size, ranging from 5% to 24%.

Figure 3. Categories of resource allocation studies public budgets



In order to provide a more structured understanding of the areas impacted by the allocation of public budget resources, Appendix A summarises the central ideas and references associated with each category, allowing for an integrated and grounded analysis of the approaches discussed in the literature.

RESULTS AND DISCUSSION

This integrative literature review deepens the theoretical understanding of public budget resource allocation, contributing to both theory and practice in public administration, as well as empirical knowledge in the field. By evaluating a cross-cutting agenda that connects the classical functions of the state in the economy (Musgrave, 1959) — allocative, distributive, and stabilising — to the themes addressed in the reviewed studies, we establish a conceptual framework that integrates different perspectives of public administration. Although the original studies do not detail this connection, the authors of this research established it through a careful interpretation of the available data, aiming to clarify underlying concepts and theoretical mechanisms relevant to public management. We therefore present our results considering each thematic category.

Appendix B presents the distribution of 59 studies across nine thematic categories, indicating how Musgrave's (1959) allocative, distributive, and stabilizing functions were applied, either individually or in combination, based on the analysis of characteristics observed in each study. The data highlight the prominence of the characteristics of the allocative function, which appear independently in 64% of the papers, particularly in sectors such as Public Health and Sustainable Development and the Environment, where resource allocation is guided by the efficient provision of public goods and services.

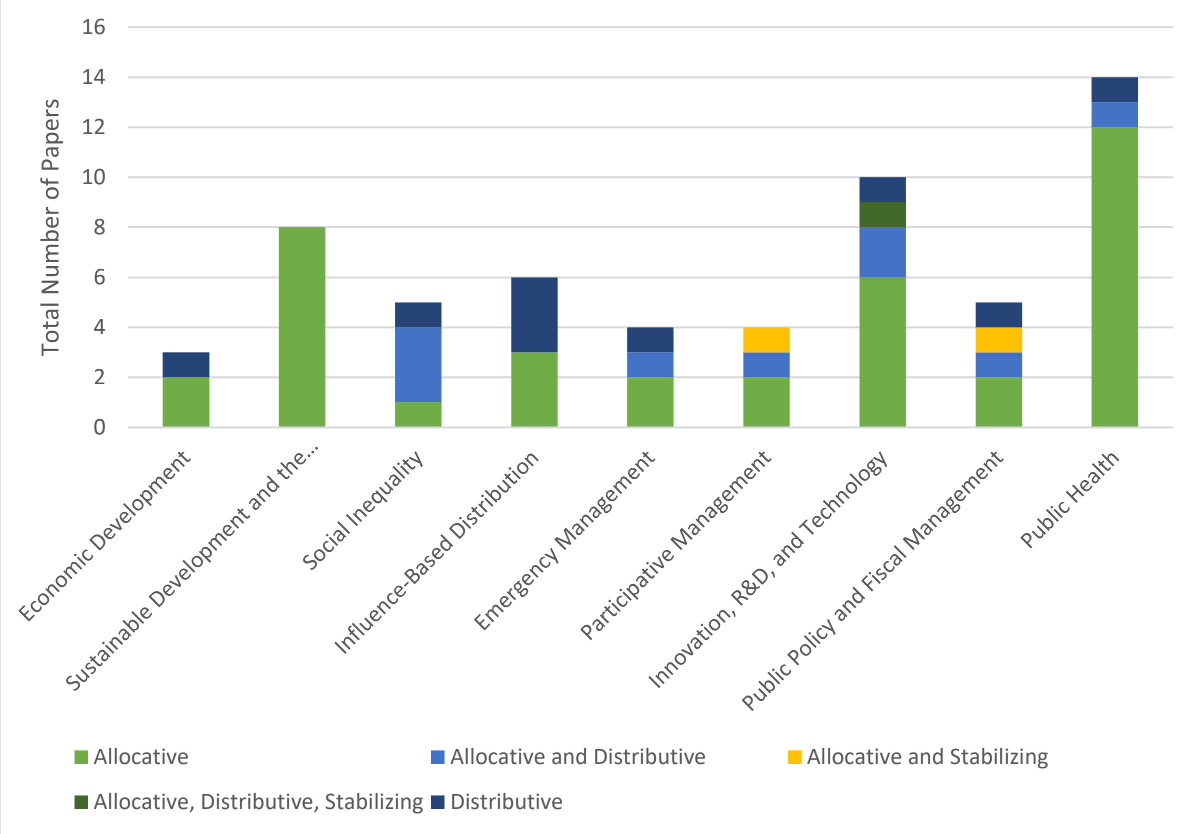
Beyond its isolated application, the characteristics of the allocative function are also present in combination with other state functions in 20% of the papers. The most frequent combination is between the characteristics of the allocative and distributive functions (15%), identified in categories such as Social Inequality and Innovation, R&D, and Technology, where resource efficiency is accompanied by concerns about equitable distribution. One study (Valle-Cruz et al., 2022), also within the category of Innovation, R&D, and Technology, exhibits characteristics of all three state functions, suggesting an integrated approach to address interdependent demands and varied economic and social impacts.

The authors identified the characteristics of the distributive function, when observed independently, in 15% of the studies, particularly within the category of influence-based distribution. When combined with characteristics of other functions, especially the allocative function, it appears in an additional 32% of the studies, covering nearly all categories except Sustainable Development and the Environment.

The authors did not identify the characteristics of the stabilising function in isolation in any study but found them strategically combined with other functions in studies classified under Participative Management, Innovation, R&D, and Technology, and Public Policy and Fiscal Management.

Figure 4 summarizes the findings in a graphical representation that integrates both perspectives: categorisation and the functions of the state in the economy.

Figure 4. Integration of State Economic Categories and Functions: A Synthesis of Both Perspectives



In the "Economic Development" category, elements of the state's allocative function directly relevant to public administration are identified. The analysed studies discuss the distribution of resources to stimulate strategic sectors, such as industrial development and institutional innovation, highlighting the role of public administration in correcting market failures and promoting economic efficiency (Song & Simpson, 2018; C. Wang & Yang, 2022). This approach reinforces the importance of state intervention, through effective public policies, in allocating resources to areas not adequately served by the market, contributing to sustainable economic growth. The literature also highlights the distributive function by analysing the adjustment of subsidies in times of crisis to meet diverse economic needs equitably, as seen in the distribution of financial support during the COVID-19 pandemic (Rocha et al., 2021). This demonstrates how public administration operationalises the allocative and distributive functions in budgetary practice to achieve socio-economic objectives.

In the context of "Sustainable Development and the Environment," the studies explore the allocation of public resources to practices that integrate economic growth with environmental protection, reflecting challenges and responsibilities of public administration. Allocating resources to clean technologies and natural resource management, such as the biomass industry and water management, requires coordinated actions by public bodies to reduce negative environmental externalities and promote efficient resource use (Dong et al., 2017; Graversgaard et al., 2018; Yan et al., 2017). This perspective incorporates sustainability as an essential dimension in budget allocation decisions by public administration, clarifying mechanisms by which public managers can balance economic and environmental objectives. The need to adapt public resources to address environmental and climatic risks (Feindouno et al., 2020) emphasises the strategic role of public administration in promoting sustainable practices, enriching the theoretical basis of environmental governance within the context of public management.

The "Social Inequality" category addresses the allocation of public resources as an instrument to mitigate economic and social inequalities, highlighting the allocative and distributive functions of the state within public administration. The literature reveals elements of the allocative function in correcting market failures, especially in the provision of basic infrastructure and essential services not offered by the private sector, which is a central responsibility of public administration (Karnam & Acharya, 2018; Solaymani, 2016). Simultaneously, the distributive function is observed in works that discuss the redistribution of resources to vulnerable groups, such as subsidies to small farmers and transfers to low-income families — policies formulated and implemented by public administration aiming to promote equitable distribution (Aaberge et al., 2019; Nkhoma, 2018). These findings clarify how public managers can structure policies to promote social justice, providing a conceptual framework for analysing and implementing strategies to reduce inequalities.

In "Influence-Based Distribution," the literature demonstrates how resource allocation can be influenced by political and social factors, challenging the principles of necessity and justice that ought to guide public administration. The allocative function is activated when public administration must correct distortions caused by favouritism or political influence, ensuring that resource distribution is based on objective and transparent criteria (Carlitz, 2017; Scott et al., 2020). The identification of the distributive function in studies examining how political influences can direct resources unequally (Flink & Molina, 2017; Gonschorek, 2021) clarifies the mechanisms by which politics interferes in resource distribution—a constant challenge for public administration. These insights are fundamental for public management, as they highlight the importance of governance models that minimise political capture and promote equity in resource allocation.

In the "Emergency Management" category, the allocative function is observed when the literature focuses on the efficient distribution of resources to maximise the state's response to crises, such as natural disasters and public health emergencies — a crucial role of public administration. The studies emphasise the importance of optimising the allocation of emergency resources to meet the most urgent needs (B. Guo et al., 2023; Y. Wang, 2021), contributing to theory in crisis management and institutional resilience within public administration. Elements of the distributive function are observed in studies advocating for resource allocation that ensures support reaches the most affected communities (Hong Boyeong et al., 2021; Mogge et al., 2023), enriching the debate on equity and social justice in emergency contexts—central themes for public managers. The integration of the allocative and distributive functions in crisis situations provides a conceptual basis to enhance public policies directed at disaster management by public administration.

The category “Participatory Management” analyses citizen participation in budget decisions, as a mechanism to enhance the state's allocative function, aligning resources with community needs — a practice relevant to contemporary public administration. This focus demonstrates how the inclusion of citizens in decision-making processes conducted by public administration can improve the efficiency and legitimacy of public policies (Calabrese et al., 2020). Additionally, the distributive function is highlighted in studies emphasising the importance of aligning resource distribution with community demands (Molina et al., 2016; Nadeem et al., 2020), contributing to the development of models that incorporate social participation as a central element in policy formulation and implementation by public administration.

In the "Innovation, R&D, and Technology" category, the allocative function is associated with allocating public resources for technological development and research, aiming to boost economic growth and national competitiveness — challenges faced by public administration. The review suggests that investments in innovation and state incentives promote technological advances and strengthen the economy (Bahrini & Qaffas, 2019; Zawalińska et al., 2018). These findings clarify mechanisms by which strategic allocation of resources in R&D by public administration can generate positive externalities and competitive advantages. The distributive function is relevant when the literature discusses resource allocation to support green technologies and small businesses, contributing to sustainable development and equity (Ghazinoory & Hashemi, 2023; Shaverdi et al., 2020). The integration of the allocative, distributive, and stabilising functions is illustrated by the use of artificial intelligence to optimise the distribution of public spending, aiming to promote economic growth, control inflation, and reduce income inequalities (Valle-Cruz et al., 2022). These insights broaden the foundation for incorporating emerging technologies into public administration to enhance decision-making.

In "Public Health" the allocative function is highlighted in the allocation of resources to maximise the quality of health interventions — a fundamental responsibility of public administration. The literature demonstrates that directing resources to priority areas allows for more effective responses in facing challenges such as pandemics, contributing to health policies and health system management by public administration (Fronczak et al., 2016; Prinja et al., 2015). The distributive function appears when analysing the need to ensure that health financing promotes equitable access to services, addressing social inequalities (Zhong & Wang, 2022). These findings clarify how the allocation and distribution of health resources can be structured by public administration to promote social justice and efficiency.

Finally, in "Public Policies and Fiscal Management," characteristics of the allocative function are observed in applying resources to correct market inefficiencies and improve public policies — central tasks of public administration. The review emphasises the importance of proper fiscal management to ensure that resource allocation meets fiscal and governance objectives (Reiling et al., 2021; Wu & Divigalpitiya, 2022), contributing to theory on public financial management and fiscal responsibility within public administration. The distributive function is explored in promoting equitable distribution of resources among municipalities, using models that ensure appropriate fiscal management (Arocena et al., 2022; Jaaidane & Larribeau, 2023). These studies clarify how fiscal and budgetary mechanisms can be employed by public administration to promote intermunicipal equity and territorial cohesion.

The analysis indicates that public resource allocation reflects both state priorities and societal demands, shaped by political, economic, and institutional factors. The predominance of the allocative function across various sectors, such as public health and sustainability, demonstrates a focus on the efficient provision of public goods and services. However, the distributive and stabilizing functions appear as complementary, mobilized according to the specific demands of areas such as innovation, emergency management, and fiscal policies.

The findings suggest that resource allocation does not follow a fixed hierarchy among the state functions but adopts an adaptive structure in which efficiency, equity, and stability are prioritized according to the context and sectoral objectives. The simultaneous presence of multiple functions in several studies reflects the complexity of public governance and the need for integrated strategies. This approach contributes to both theory and practice by providing a conceptual framework for developing budgeting strategies that address the interconnected and multifaceted realities of public administration.

AGENDA FOR FUTURE STUDIES

This section consolidates suggestions from the literature reviewed on the allocation of public budget resources, identifying four main perspectives: improving methods and analytical models; delving deeper through comparative studies; investigating the influence of external factors; and expanding methodologies to new contexts.

The future research agenda to **improve analytical methods and models** in the allocation of public budget resources suggests:

- The expansion of economic analysis in the energy sectors, with a focus on biomass, by means of Data Envelopment Analysis (DEA) models to include more industries and extend the periods of analysis, with the aim of providing more comprehensive data on costs and benefits to support policy decisions. (Yan et al., 2017).
- Improving resource allocation modelling in emergencies, taking into account factors such as the vulnerability of the location, the urgency of the demand and the specificities of the victims, in order to develop more complete and inclusive models. (Y. Wang, 2021).

The future research agenda in the approach of **deepening through comparative studies** includes:

- The evaluation and comparison of different analytical methodologies to improve the identification of critical industries, with the aim of increasing accuracy in the identification of priority areas for public investment, with direct implications for the efficiency and strategy of budgetary and fiscal management. (C. Wang & Yang, 2022).
- The comparison between AI techniques and traditional statistical models to evaluate their effectiveness and results in the context of budget allocation, with a view to a more efficient application of these technologies in public policies. (Valle-Cruz et al., 2022).

The future research agenda focussing on the **influence of external factors** on resource allocation includes:

- Examining the role of representative bureaucracies in influencing budget outcomes and minority groups' access to public budget resources (Flink & Molina, 2017).
- Research into the role of the media in formulating financial aid policies for democracies, considering the effects of media attention on political decisions and how different geopolitical and historical contexts alter these impacts (Scott et al., 2020).
- The study of patronage networks and their influence on the allocation of public budget resources, evaluating the *trade-offs* between political benefits and efficiency costs, including protection against illicit behaviour. (J. Jiang & Zhang, 2020).

Finally, from the perspective of **"Expansion of Methodologies and Application in New Contexts",** the future research agenda suggests:

- To study the influences of different forms of participatory budgeting on financial results and citizen satisfaction, and how these practices affect the redistribution of public spending, with a focus on urban contexts. (Calabrese et al., 2020).
- Analysing the impacts of R&D funding sources, both private and public, on productivity growth, especially in regional contexts and economies in transition. (Zawalińska et al., 2018).
- Explore the use of AI technologies to improve budget allocation and the efficiency of public spending, adapting these tools to the needs of different government contexts. (Valle-Cruz et al., 2022).
- Analyse and expand methods for evaluating urban indicators, with a particular focus on Transport Oriented Developments (TODs), and the proposal to expand these methods to other cities to improve urban and fiscal planning (Wu & Divigalpitiya, 2022).

Identify the types of spending that promote effective improvements in the health of the population (Micah et al., 2020).

CONCLUSION

The paper conducted an integrative literature review on the allocation of public budget resources in papers published between 2014 and 2023, examining how different allocation approaches impact key areas of public management, such as Economic Development, Sustainable Development and the Environment, Social Inequality, Influence-Based Allocation, Emergency Management, Participatory Management, Public Policy and Fiscal Management, Innovation, R&D and Technology and Public Health.

This analysis shows that public resource allocation reflects the predominant characteristics of state functions, varying according to the specific demands of each sector. Through an integrative literature review, this study identified how the allocative, distributive, and stabilizing functions manifest within individual papers. Characteristics of the allocative function, focused on addressing market failures and ensuring the provision of public goods, are prevalent in studies categorized under Public Health and Sustainable Development and Environment. Distributive function characteristics, aimed at correcting income and wealth disparities through budget policies, are prominent in studies categorized under Social Inequality and Influence-Based Distribution. Stabilizing function characteristics, which involve managing inflation, unemployment, and economic growth, are identified in studies on Public Policy and Fiscal Management, Innovation, R&D, and Technology, and Emergency Management, though always in combination with other functions.

Overall, this integrative review demonstrates that the functions of the state in the economy are interconnected and shaped by various factors, including political, institutional, economic, social, environmental, and technological elements, among others. This study contributes to the literature by showing that public budgeting does not follow a rigid structure but dynamically adapts to sectoral needs. The findings reveal that public administration mobilises state functions independently or in combination to address complex governance challenges. This framework enhances the understanding of how resource allocation aligns with the specific priorities of each area, providing a foundation for future research and practical strategies that respond to the multifaceted realities of public administration.

In summary, these findings highlight that budgeting strategies must be adapted to context, balancing efficiency, equity, and stability according to sectoral needs.

Integratively, the literature review suggests that subsequent studies should refine analytical methods, conduct comparative analyses across different contexts, consider external factors, and adapt methodologies to new scenarios of public resource allocation.

In addition to the identified recommendations, future research in public administration can explore how trade-offs emerge when certain state functions are prioritized in resource allocation. Although the allocative, distributive, and stabilizing functions are not mutually exclusive, their prominence varies across sectors, as demonstrated by the results of this study. Frequent emphasis on the allocative function, for example, may limit the attention given to redistributive or stabilizing concerns. Understanding these trade-offs is essential for assessing whether budgeting practices are effectively balancing efficiency, equity, and stability. Future studies could further investigate whether the predominance of certain functions reflects strategic decisions aligned with sectoral demands or unintended omissions, contributing to the development of budgeting frameworks that better address the interconnected nature of public policies.

DISCLOSURE STATEMENT

The authors reported no potential conflict of interest.

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Appendix A. Thematic Categories identified in the Integrative Review

Category	General idea	Full list of selected references
Economic Development	It can be understood as the direct impact of the allocation of public resources in areas that are vital for the growth of the economy.	(Rocha et al., 2021; Song & Simpson, 2018; C. Wang & Yang, 2022)
Sustainable Development and the Environment	Strategic application of resources to promote a balance between economic growth, environmental protection and sustainability	(Chai et al., 2021; Chen et al., 2023; Dong et al., 2017; Feindouno et al., 2020; Graversgaard et al., 2018; Guerrero et al., 2022; Thiene et al., 2017; Yan et al., 2017)
Social Inequality	A phenomenon that reflects the discrepancies in access to and distribution of resources between different social groups, regions and population categories.	(Aaberge et al., 2019; Bechtel, 2018; Karnam & Acharya, 2018; Nkhoma, 2018; Solaymani, 2016)
Influence-Based Distribution	A practice in which decisions about the distribution of resources are influenced by factors other than objective needs, such as politics, personal connections or media attention.	(Carlitz, 2017; Flink & Molina, 2017; Gonschorek, 2021; J. Jiang & Zhang, 2020; Mok & Wen, 2022; Scott et al., 2020)
Emergency Management	Set of practices and strategies employed by government entities to manage public resources during emergency situations.	(B. Guo et al., 2023; Hong Boyeong et al., 2021; Mogge et al., 2023; Y. Wang, 2021)
Participatory management	A mechanism that gives citizens an active role in deciding how public resources are spent.	(Calabrese et al., 2020; Losada Maestre et al., 2021; Molina et al., 2016; Nadeem et al., 2020)
Innovation, R&D and Technology	Directing public budget resources towards the development and improvement of new technologies, research and innovations. It also covers the use of emerging technologies in the evaluation of budgetary policies.	(Bahrini & Qaffas, 2019; Buffart et al., 2020; Ghazinoory & Hashemi, 2023; Y. Guo et al., 2023; Shaverdi et al., 2020; Valle-Cruz et al., 2022; Vasconcelos & Silva, 2019; Yang et al., 2019; Zawalińska et al., 2018; Zhang et al., 2020)
Public Health	The "Public Health" category is justified by the relevance of the topic and the significant volume of publications, requiring a detailed focus on the allocation of public budget resources in this category.	(Barbosa et al., 2020; Fronczak et al., 2016; Hongoh et al., 2016; Y. Jiang et al., 2023; Masaba et al., 2020; Micah et al., 2020; Munyua et al., 2016; Prinja et al., 2015; Tran et al., 2018; Venkatesh et al., 2022; Vernazza et al., 2023; Waring & Jones, 2023; Zhong & Wang, 2022; Zhou et al., 2020)
Public Policy and Fiscal Management	The residual studies included in this category investigate the distribution and management of public resources, examining their impact on public	(Arocena et al., 2022; De La O et al., 2023; Jaaidane & Larribeau, 2023; Reiling et al.,

Category	General idea	Full list of selected references
	policies. Although they do not fit into the other categorisations, these studies share a focus on the proper management of resources, highlighting the importance of oversight, efficiency and equity in the implementation of public policies.	2021; Wu & Divigalpitiya, 2022)

Appendix B. Classification of Studies by Musgrave's Functions

Category	Allocative	Allocative and Distributive	Allocative and Stabilizing	Allocative, Distributive, Stabilizing	Distributive	Total Number of Papers
Economic Development	2	-	-	-	1	3
Sustainable Development and the Environment	8	-	-	-	-	8
Social Inequality	1	3	-	-	1	5
Influence-Based Distribution	3	-	-	-	3	6
Emergency Management	2	1	-	-	1	4
Participative Management	2	1	1	-	-	4
Innovation, R&D, and Technology	6	2	-	1	1	10
Public Policy and Fiscal Management	2	1	1	-	1	5
Public Health	12	1	1	-	1	14
Total	38	9	2	1	9	59
%	64%	14%	3%	2%	15%	100%

PAPER 2. LET'S SPEND SMARTER: HOW ARTIFICIAL INTELLIGENCE CAN HELP US BETTER ALLOCATE PUBLIC BUDGETARY RESOURCES

ABSTRACT

This study addresses the optimization of public budgetary resources allocation in Brazil using artificial intelligence algorithms. Confronting the challenges presented by traditional budget systems, this research proposes the application of a hybrid artificial intelligence model. Using budget expenditure data and socio-economic indicators from 2000 to 2023, the model employs Machine Leaning and Bayesian Optimization techniques to simulate optimal resource allocation scenarios, aiming to improve socio-economic indicators. The results demonstrate the model's potential to provide forecasts and make efficient allocations, despite the limitations related to dependence on historical data and the explainability of the algorithms.

Keywords: Artificial Intelligence; Resource Allocation; Public Budget; Machine Learning; bayesian optimization

INTRODUCTION

Since seminal works (Key, 1940; Musgrave, 1959), the literature has explored how to distribute public resources to meet the economic and social needs of nations. More contemporary studies emphasize that the persistent complexity of decisions in this area stems from the interaction between various economic, social, and contextual variables (Amin, 2020; Esnaashari et al., 2023; Fozzard, 2001; Katharina Dhungel et al., 2024; Medema, 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Valle-Cruz, Fernandez-Cortez, López-Chau, et al., 2022). Among the initiatives to deal with this this diversity proposals are emerging for integration of new technologies into allocation of public budget resources (Esnaashari et al., 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Valle-Cruz, Fernandez-Cortez, López-Chau, et al., 2022).

Traditional budgeting models, often based on incremental updates to spending grounded in historical values with minor annual adjustments, have been criticised for their inability to adapt to changes in the economic environment. They are frequently characterised as slow, rigid, and lacking precision (Galdino & Andrade, 2020; Ghiassi & Simo-Kengne, 2021; Kunnathuvalappil Hariharan, 2017; Lindblom, 1981; Nonato, 2024; Zatonatska et al., 2023).

Thus, considering the dynamism of the current scenario, there is a clear need to review and adapt traditional budgeting methods in the public sector (Kunnathuvalappil Hariharan, 2017; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Zatonatska et al., 2023). Of particular note is the availability of algorithmic technologies, such as AI, which are potentially applicable to the government budget process. In addition, it is noted that the application of AI can optimize the distribution of public resources, reduce waiting times and increase success rates by up to 50% compared to traditional methods (Esnaashari et al., 2023).

However, although the adoption of these technologies is expanding in the public sector, their use is still limited, especially in the budgetary context (Valle-Cruz et al., 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Zuiderwijk et al., 2021). It is important to note that there is a scarcity of academic studies investigating the use of AI in the allocation of public budget resources (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Valle-Cruz, Fernandez-Cortez, López-Chau, et al., 2022), highlighting a gap in the literature that this study seeks to begin addressing. This research aims to initiate a focused discussion on the application of AI in public budgeting, acknowledging the specific limitations and challenges inherent to its use in this context.

To contribute to this emerging field, the paper presents an empirical study utilizing a hybrid AI model specifically designed to support decision-making in the formulation of the Federal Budget Law and potential adjustments through supplementary appropriations, with the goal of optimizing the allocation of federal public resources in Brazil. In 2024, the country had a total expenditure set in the Fiscal and Social Security Budgets of almost R$ 5.5 billion and Social Security Budgets of almost R$ 5.5 trillion reais (Senado Federal, 2024) including that relating to the Refinancing of the Federal Public Debt, both internal and external. Given this volume, minimal efficiency gains could free up significant resources for other priority areas.

The justification for using a hybrid AI model lies in the potential of this technology to transform public administration governance (Valle-Cruz et al., 2024; Zuiderwijk et al., 2021). This technology, which is capable of identifying complex relationships and uncovering non-obvious patterns, offers opportunities to improve predictive analysis in response to socio-economic changes, including in the management of public budget resources (Esnaashari et al., 2023; Katharina Dhungel et al., 2024; Valle-Cruz et al., 2024; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Zatonatska et al., 2023)

Thus, this study proposes and tests a hybrid artificial intelligence model that integrates two algorithms: a machine-learning (ML) algorithm and an optimization algorithm. The research employs a methodological benchmarking replicating method implemented in previous studies but adapting them to the reality of the data available for Brazil (Jang, 2019; Pinheiro & Becker, 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022).

Therefore, the central problem of this study is: how can the use of a hybrid model, which integrates machine learning algorithms and optimization techniques, contribute to the definition of an optimal budget allocation in Brazil?

In methodological terms, a quantitative and algorithmic approach was adopted. Budget data served as independent variables, while socio-economic indicators (GDP, inflation, and the Gini index) were used as dependent variables. This approach simulated alternative scenarios for the optimal allocation of resources, functioning as a decision-making support tool. However, it does not provide definitive solutions to the complexities of the budget process and the country's socio-economic context (Esnaashari et al., 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Valle-Cruz, Fernandez-Cortez, López-Chau, et al., 2022).

Specifically, the selected methodology uses the Gradient Boosting algorithm, implemented by the XGBoost library in Python, to analyze historical data on federal budget execution. This machine-learning algorithm creates predictive models by combining multiple decision trees sequentially, in which each new tree corrects the errors of the previous ones, resulting in more accurate forecasts (Parsa et al., 2020; XGBoost developers, 2022). In addition, the research employs Bayesian Optimization with the Tree-structured Parzen Estimator (TPE) algorithm, using the Optuna library (Optuna Contributors, 2020; Parra-Ullauri et al., 2023) to automatically adjust the model's hyperparameters and optimize the allocation of public budget resources considering the chosen objective function (improvement of selected socioeconomic indicators).

This hybrid approach has the potential to contribute to more informed decisions in public policy, demonstrating the ability to adapt to a wide range of data patterns (Ghiassi & Simo-Kengne, 2021, Jang, 2019; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022)

The paper presents the following structure: initially, we present a theoretical-conceptual framework that explores the allocation of public budget resources. Next, we detail the methodological approach used. It presents and discusses the results obtained, considering the relevant theories and the identified methodological limitations. Finally, in its conclusion, the paper summarizes the main findings and future directions for research.

BACKGROUND

From Classical Theories to the Algorithmic Allocation of Public Budgetary Resources

The allocation of public budget resources is a process that directly impacts the state's ability to perform its fundamental functions, such as promoting social welfare, maintaining economic stability and correcting market failures (Medema, 2023; Musgrave, 1959; Musgrave & Musgrave, 1989). By directing resources to different areas, the state influences the distribution of income and the provision of essential goods and services, affecting the lives of citizens (Amin, 2020). In this context, the theory of public finance proposed by Musgrave (1959), which identifies three main functions of the state in the economy - allocative, distributive and stabilizing - provides a theoretical framework for understanding how these functions interact and how they can be optimized in the public budget to maximize social welfare (Medema, 2023; Musgrave, 1959; Musgrave & Musgrave, 1989).

The state's allocative function seeks to correct market failures, ensuring the provision of non-rival and non-excludable public goods, such as national defense and public infrastructure (Case, 2008; Musgrave & Musgrave, 1989). The distributive function aims to correct imbalances in the distribution of income and wealth, using fiscal policies such as progressive taxes and social transfers (Case, 2008; Musgrave, 1959; Musgrave & Musgrave, 1989). The stabilizing function, on the other hand, aims to correct macroeconomic imbalances, such as inflation and unemployment, through appropriate fiscal policies (Alem & Giambiagi, 2018; Case, 2008; Musgrave, 1959; Musgrave & Musgrave, 1989). Although these functions are theoretically relevant, their practical application presents challenges, especially when considering the interdependence between them and the need for an integrated analysis of public policies (Case, 2008; Medema, 2023; Musgrave, 2008).

Despite the theoretical relevance of Musgrave's (1959) model, its applicability is often limited by factors such as politics (Flink & Molina, 2017; Jiang & Zhang, 2020) economic crises, pandemics and natural disasters (Mogge et al., 2023; Rocha et al., 2021) which change budget priorities and make it difficult to implement proper management of public resources. Effective management requires the ability to respond rapidly to changes in the economic and social environment, relying on accurate and up-to-date data to inform decision-making (Brumby, 2007; Waring & Jones, 2023). This need for adaptation and flexibility reflects a criticism of Musgrave's normative approach, which, although solid in its theoretical basis, lacks a positive foundation that makes it more applicable in dynamic and varied contexts (Desmarais-Tremblay, 2021).

Thus, it is understood that allocative efficiency requires that resources be distributed in such a way as to maximize social benefits, adjusting allocations according to the needs and priorities of the State (Brumby, 2007). The complexity of the task involves accurately measuring both social preferences and the real costs of public services (Brumby, 2007). Thus, the adoption of data-based predictive practices, which consider both the costs and the output of public services, emerges as an approach that can better align government priorities with allocative efficiency (Esnaashari et al., 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Valle-Cruz, Fernandez-Cortez, López-Chau, et al., 2022). This approach enables the identification of priority areas and the reallocation of resources to optimize the use of available public funds (Brumby, 2007; Esnaashari et al., 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022).

Since the 1960s, attempts to improve budgeting in the public sector, such as the Planning, Programming, and Budgeting System (PPBS), have aimed to improve government decision-making, but they have faced barriers, such as bureaucratic dysfunctions and incentive problems, compromising the achievement of state objectives (Brumby, 2007; Kunnathuvalappil Hariharan, 2017; Zatonatska et al., 2023). The more traditional budgeting models, based on historical spending from an incrementalist perspective, have proved inadequate in the face of constant changes in the economic environment, and are often criticized for their slowness, rigidity and lack of precision (Galdino & Andrade, 2020; Kunnathuvalappil Hariharan, 2017; Lindblom, 1981; Nonato, 2024).

The transition to algorithmic approaches in the allocation of public resources, although promising, brings with it some challenges (Esnaashari et al., 2023; Valle-Cruz et al., 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022). Implementing these methods requires an advanced technological infrastructure and qualified personnel to interpret and apply the data effectively (Zatonatska et al., 2023). Furthermore, the accuracy of these approaches depends on the quality of the input data and the transparency of the algorithms used (Ghiassi & Simo-Kengne, 2021; Goodman & Flaxman, 2017; Valle-Cruz et al., 2023; Zatonatska et al., 2023; Zuiderwijk et al., 2021). In emerging contexts, where budget data may be limited or inconsistent, the effectiveness of predictive models may be compromised (Ghiassi & Simo-Kengne, 2021). Therefore, these technologies need to be adapted to the specific context of the public sector, considering its particularities and challenges (Esnaashari et al., 2023; Zuiderwijk et al., 2021).

AI Algorithms in the Allocation of Public Budgetary Resources

AI is a technology that integrates the algorithmic approach and can be defined as a set of systems that process information and simulate human intelligent behaviors, such as reasoning, learning, perception, prediction, planning and control (Nonato et al., 2024; Unesco, 2020; Zuiderwijk et al., 2021). These systems use models and algorithms to perform cognitive tasks, supporting decision-making in real and virtual environments, with operational autonomy that includes techniques such as machine learning, automated reasoning, optimization and cyber-physical systems, such as the Internet of Things (IoT) and robotics. (Unesco, 2020; Valle-Cruz et al., 2024).

In the public sector, AI is used to improve government performance in areas such as urban infrastructure, public safety and health, as well as specific activities such as predicting natural disasters, optimizing traffic, auditing and allocating public budget resources (Abu Huson et al., 2024; Valle-Cruz et al., 2024; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Zuiderwijk et al., 2021). The application of these technologies enables the government to make more decisions that are informed, promote transparency and agility in public responses and transform government operations into more agile and resilient structures (Valle-Cruz et al., 2024; Zuiderwijk et al., 2021). However, the implementation of AI in the public sector also faces challenges, including ethical and governance issues, such as the opacity of algorithms, biases in data and automated decisions, and the possibility of inadvertent discrimination (Livingston, 2020; Nonato et al., 2024; Valle-Cruz et al., 2023; Zuiderwijk et al., 2021).

In the context of public resource allocation, AI offers substantial advantages compared to conventional statistical models, such as the Auto Regressive Integrated Moving Average with Exogenous variable – ARIMAX (Ghiassi & Simo-Kengne, 2021). Artificial neural networks, for example, capture complex relationships between economic and financial variables, including non-linear ones, where changes in one variable do not result in proportional changes in another, allowing for more accurate and reliable forecasts (Ghiassi & Simo-Kengne, 2021; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022).

This capability to uncover hidden patterns enables policymakers to make more informed decisions, optimize fiscal management, and allocate resources more effectively (Ghiassi & Simo-Kengne, 2021; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Valle-Cruz, Fernandez-Cortez, López-Chau, et al., 2022; Zatonatska et al., 2023). In addition, the automation of bureaucratic tasks and the detection of relevant patterns in financial and accounting data result in improvements in financial management and risk assessment (Abu Huson et al., 2024; Zuiderwijk et al., 2021).

The use of hybrid AI modeling in public budget management has been shown to improve forecast accuracy and optimize resource allocation. This approach integrates multiple forecasting methods, combining ML and optimization algorithms, which improves the ability to adapt to changes and reduces the incidence of errors (Jang, 2019; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022). An example of the application of this approach is the framework developed for R&D budget allocation in Korea, which integrated ML and optimization techniques to maximize results, achieving a performance 13.6% higher than the actual budget (Jang, 2019). Similarly, the combination of machine learning and optimization in public policy can improve the distribution of public spending, positively affecting economic indicators such as GDP, inflation and the Gini index, which measures income inequality (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022).

In this work, a hybrid AI model will be used, employing the Gradient Boosting algorithm, implemented by the XGBoost library, and Bayesian Optimization with Optuna's TPE algorithm.

The Brazilian Public Budget System: Structure, Dysfunctions and Technologies

The Brazilian public budget system is structured around three main instruments: the Multi-Year Plan (PPA), the Budget Guidelines Law (LDO) and the Annual Budget Law (LOA). The PPA defines the goals and objectives for a four-year period, guiding the government's medium-term actions. The LDO establishes the guidelines for drawing up the LOA, which specifies the revenue and expenditure planned for the following fiscal year. These instruments are interlinked and form the basis for the allocation of public resources in Brazil (Giacomoni, 2021; Júnior et al., 2022; Lima, 2022).

However, the system faces dysfunctions, such as budgetary rigidity, resulting from the high level of revenue and expenditure linkage, which limits the ability to reallocate resources according to new needs (Giacomoni, 2021; Oliveira et al., 2022). In addition, fiscal rules such as the "golden rule", the Fiscal Responsibility Law and the debt ceiling further restrict this flexibility, making it difficult to respond to crises, such as the Covid-19 pandemic (Couto & Rodrigues, 2022).

The fragmentation of the budget process, with the participation of multiple actors, contributes to the dispersion of resources and hinders the efficient implementation of public policies (Baptista et al., 2012; Couto & Rodrigues, 2022). The relationship between the executive and legislative branches is another complicating factor, especially due to mandatory parliamentary amendments that often prioritize local interests, hindering the strategic allocation of resources (Baptista et al., 2012; Couto & Rodrigues, 2022).

To tackle these issues, new institutions, such as the Independent Fiscal Institution and the Budget Execution Board, have sought to increase transparency and accountability in the management of public accounts. These entities aim to improve budgetary governance, acting as control mechanisms to mitigate existing dysfunctions in the system (Couto & Rodrigues, 2022).

In addition, the implementation of electronic technologies such as Finanças do Brasil (Finbra), which centralizes accounting and fiscal data from federal entities, and the Public Health Budget Information System (Siops) have improved the management of budget information in a context of decentralization of public policies. (Medeiros et al., 2014).

These systems, however, face challenges related to the distance between managers and information systems, which often leads to the outsourcing of data entry and limits the strategic use of information (Silva et al., 2010). The demand for transparency and efficiency in public management stimulates the use of tools such as the Integrated Financial Administration System of the Federal Government (Siafi) and the Managerial Treasury, which are important for recording, monitoring and controlling the budgetary, financial and accounting execution of federal public administration entities. (Fonseca et al., 2020).

With regard to the use of AI in Brazilian public administration, especially in budgetary processes, there is no centralized mechanism for monitoring AI initiatives[4] . This indicates that each government body has the autonomy to adopt and manage its own AI systems according to its needs and institutional competencies.

The investigation into the application of AI in Brazilian budget administration included a survey by the Federal Court of Auditors (2021) which highlighted the "PropLegis" initiative. Developed by the National Treasury Secretariat (STN) in partnership with the Federal Data Processing Service (Serpro), this tool uses AI techniques to identify patterns in legislative proposals that could affect the public budget.

In addition, the Budget, Oversight and Control Consultancy of the Federal Senate has developed a pilot project that uses the AdaBoost model (machine learning algorithm) to improve the classification of the Primary Result in the budget, demonstrating high effectiveness in managing class imbalance (Neto & Sá, 2022). Another study evaluated the use of the Random Forest machine-learning algorithm to classify accounts payable in the Federal Public Budget (Santos, 2023).

METHODS

This study uses a hybrid AI model that integrates two different algorithms. The first is *Gradient Boosting*, a machine-learning algorithm implemented in Python using the XGBoost library. The second is the Tree-structured Parzen Estimator (TPE), a Bayesian optimization algorithm also implemented in Python using the Optuna library. The model replicates the methodology of previous studies, adapted to the allocation of public budget resources at the federal level in Brazil (Jang, 2019; Pinheiro & Becker, 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022).

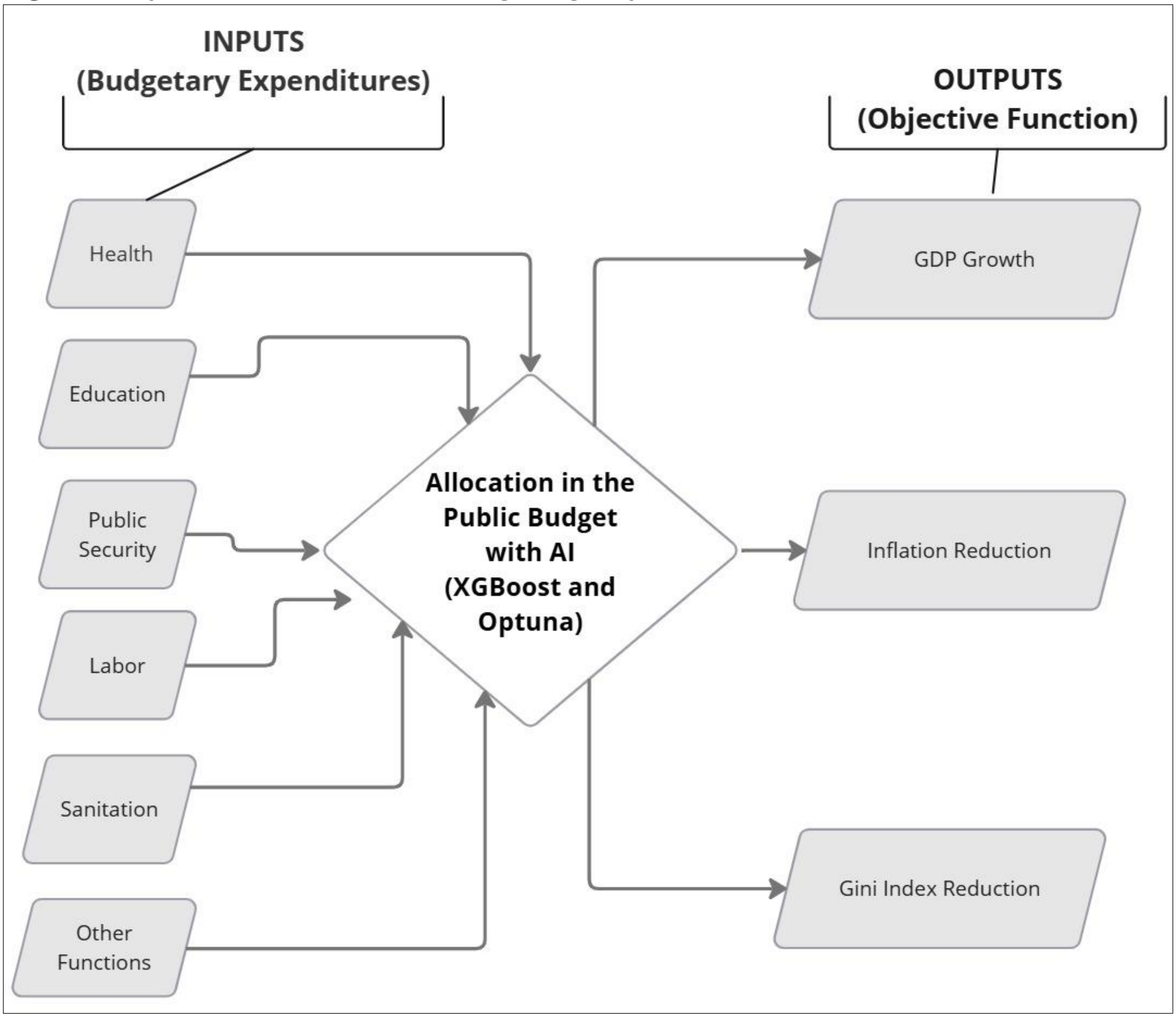
The hybrid model focuses on simulating alternative budget allocation scenarios (Figure 5), using Brazil's federal spending by budget function as input (independent) variables. In this research, three socio-economic indicators were used as output (dependent) variables, the same ones used and tested in a previous study, which considered their relevance in assessing the impact of budget allocations (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022). The data collected refers to the period from 2000 to 2023, reflecting the stabilization of budget function classifications after the publication of Ordinance nº 42 of 1999 (Ministério de Estado do Orçamento e Gestão, 1999). This standardization provided a consistent basis for comparison over time.

However, the dataset has a limitation: with only 24 years of observations, the sample size is relatively small, which may influence the robustness of the findings. This constraint stems from the

[4] Information obtained through a request to the Ministry of Science, Technology and Innovation, filed under number 18002.000022/2023-10 on 05/04/2023, via the Access to Information Act.

lack of compatibility with pre-2000 data, as earlier classifications followed entirely different methodologies.

Figure 5. Hybrid AI model for allocating budgetary resources



Below, Table 3 presents a detailed description of the variables selected for the simulation carried out by the hybrid model:

Table 3. Description of variables

Variable	Constitutive Description	Operational Description	Data Source
Expenditure by Budget Function	It represents the budget classification of government spending, which reflects the areas in which the public sector operates, such as health, education, security, national defense, social assistance, among others (Ministry of State for Budget and Management, 1999; OECD, 2021).	Measured by the sum of liquidated (executed) expenses in each budget function. Data taken from the "Transparent Treasury" platform. The time cut-off began in 2000 due to the stabilization of the classification of budget functions with the publication of Ordinance nº 42 of 1999, which provided a more consistent basis for the longitudinal comparison of government spending on the various functions. (Ministry of State for Budget and Management, 1999).	https://www.tesourotransparente.gov.br/publicacoes/despesas-da-uniao-series-historicas/2023/8-2?ano_selecionado=2024 A detailed list of budget functions can be found at in Table 4.
Gross Domestic Product	Indicator of the total value of goods and services produced in an economy during a specific period, reflecting the level of economic activity. (Wang & Alvi, 2011).	Measured by the annual GDP growth rate in percent, based on data from the World Bank's *DataBank*.	https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.MKTP.KD.ZG
Inflation	It reflects the general and continuous increase in the prices of goods and services in an economy over time, indicating the loss of purchasing power of the currency (Aladejare, 2020; Fonchamnyo & Sama, 2016)	Measured by the implicit GDP deflator, in annual percentage, as provided by the World Bank's DataBank.	https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.DEFL.KD.ZG
Gini Index	Index that measures inequality in income distribution within an economy, ranging from 0 (perfect equality) to 100 (perfect inequality). (Afonso et al., 2010).	Calculated based on income distribution data obtained from the World Bank's DataBank.	https://databank.worldbank.org/metadataglossary/world-development-indicators/series/SI.POV.GINI

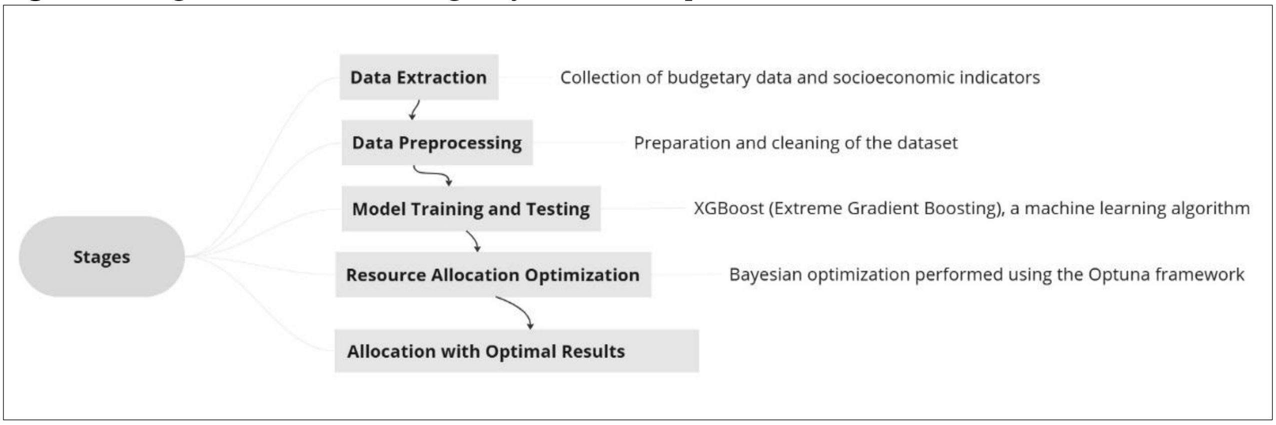
Table 4. Budgetary Functions

Cod.	Expense	Cod.	Expense
1	Legislative	16	Housing
2	Judiciary	17	Sanitation
3	Essential to Justice	18	Environmental Management
4	Administration	19	Science and Technology
5	National Defense	20	Agriculture
6	Public Safety	21	Agrarian Organization
7	Foreign Relations	22	Industry
8	Social Assistance	23	Services and Commerce
9	Security	24	Communications
10	Health	25	Energy
11	Labor	26	Transportation
12	Education	27	Sports and Leisure
13	Culture	28	Special Charges
14	Citizenship Rights	29	Refinancing
15	Urbanism		

Source: Adapted from Ordinance No. 42/1999

Figure 6 below illustrates the methodological steps adopted in this research to develop a hybrid model of optimized public resource allocation, in line with the objectives of the study.

Figure 6. Stages of the Public Budgetary Resource Optimization Process with AI



It should also be noted that the tests were carried out on a computer with an Intel Core i5-7200U processor and 8 GB of RAM, operating on the Windows 10 64-bit system. We used *Jupyter Notebook*, a *web* application for creating and sharing code and visualizations, installed via *Anaconda*, a platform for managing packages and environments for data science.

Machine Learning Algorithm - *Gradient Boosting*

We selected the Gradient Boosting algorithm, implemented through the XGBoost library, due to its capacity to capture complex interactions between variables (Chen & Guestrin, 2016; Montomoli et al., 2021; Vaid et al., 2020). For comparison purposes, we also tested the Multilayer Perceptron and Random Forest algorithms. We evaluated the performance of the models using three metrics: mean square error (MSE), sum of squared errors (SSE) and coefficient of determination (R^2).

It can be said, based on previous studies, that a model is considered adequate if it has a low MSE, indicating accuracy in the forecasts (James et al., 2023; Kumar et al., 2023; Pu et al., 2023; Segovia et al., 2023). In turn, a low SSE suggests consistency and little variability in the errors (James et al., 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022). An R^2 close to 1 shows that the model can explain a large proportion of the variance observed in the data (Gao et al., 2023; Hoiem et al., 2020; James et al., 2023; Nguyen et al., 2021).

As seen in Table 5, Gradient Boosting showed the best performance, with greater accuracy and ability to explain the variability of the data compared to the other models.

Table 5. Performance of machine learning models

Machine Learning Models	SSE	MSE	R^2
MLP	14,67	0,61	0,08
Random Forest	8,07	0,54	0,24
Gradient Boosting (*XGBoost*)	3,20	0,21	0,69

XGBoost is a machine-learning library used to solve supervised learning problems. It uses training data with multiple features to predict target variables and applies the *Gradient* Boosting algorithm (Chen & Guestrin, 2016; Friedman, 2001; XGBoost developers, 2022).

In this algorithm, each decision tree is made up of nodes, which represent decision points that divide the data based on specific characteristics, and leaves, which contain the final predictions. The model builds these trees iteratively, continually adjusting the parameters to improve the accuracy of the predictions. This adjustment is carried out through the use of gradients, which measure the rate of change of the prediction error as the model parameters are altered, and Hessians, which assess how these rates of change, providing an analysis of the curvature of the error function (Chen & Guestrin, 2016; XGBoost developers, 2022).

According to the library's documentation, the model's objective function includes two main components: the training loss and the regularization term. The training loss $(\mathrm{L}(\theta))$ assesses how well the model fits the training data and is usually measured by the MSE. The regularization term $(\Omega(\theta))$ controls the complexity of the model to avoid overfitting, which occurs when the model overfits the training data and loses the ability to generalize to new data (XGBoost developers, 2022).

The iterative approach of adding trees allows XGBoost to refine its predictions systematic, ensuring better generalization in diverse environments. In practical terms, the algorithm makes predictions by combining various characteristics of the data (DMLC XGBoost developers, 2022). The basic formula for these predictions is:

$$\hat{y}_i = \sum_j \theta_j x_{ij}$$

where $\hat{y}_i$ is the prediction for the i-th sample, x_{ij} are the characteristics of the data and θ_j are the parameters that the model adjusts during training. The θ parameters are coefficients that determine the relationship between the data characteristics and the target variable, and are adjusted to minimize the difference between the predictions $\hat{y}_i$ and the actual values.

According to the library documentation (DMLC XGBoost developers, 2022), XGBoost uses an ensemble of decision trees, known as Classification and Regression Trees (CART). Each tree in the ensemble contributes to the final prediction, which is the sum of the predictions of all the trees:

$$\hat{y}_i = \sum_{k=1}^{K} f_{k(x_i)}$$

where K is the number of trees and $f_k$is the function represented by each tree. During training, 'XGBoost' iteratively adds new trees, each one adjusting to improve the accuracy of the predictions made by the previous trees. This process is guided by the objective function, which includes gradients and Hessians of the loss function.

In addition, the document states that regularization in XGBoost helps to avoid overfitting by controlling the complexity of the model. Regularization parameters are used to penalize excessively complex models and ensure that the model remains simple and predictive. The formula for controlling model complexity is:

$$\omega(f) = \gamma \mathrm{T} + \frac{1}{2}\lambda \sum_{j=1}^{T} \omega_j^2$$

where $\omega(f)$ represents the regularization function, γ and λ are regularization parameters, T is the number of leaves in the tree and ω_j are the weights assigned to each leaf j.

As previously mentioned, this research utilized a machine learning algorithm as a regressor to simultaneously predict three socio-economic indicators—GDP, inflation, and the Gini index—using normalized budget data. The model was configured to minimize squared error and was implemented with the data divided into training (80%) and testing (20%) sets.

Specifically, the division of 80% of the data for training and 20% for testing was used as it yielded the best performance in terms of MSE and R^2 in the conducted analysis. This approach is also exemplified in applications such as predicting occupations using demographic variables and modeling median housing values, highlighting its use in practical machine learning problems (Hastie et al., 2009).

For more details on the XGBoost library, we recommend consulting the official documentation (https://xgboost.readthedocs.io/en/stable/index.html), which offers a complete explanation of its components, operation and implementation (XGBoost developers, 2022).

Enhancing Model Reliability

The model implementation incorporated several practices designed to mitigate the risks of overfitting and underfitting. Specifically, a low learning rate (0.002) was configured to enable gradual learning, and a high number of estimators (n_estimators=980) was used to ensure controlled and incremental adjustments during training. These configurations aim to balance the model's learning process, reducing the likelihood of overfitting by preventing the model from becoming overly complex and tailored to the training data. However, while these adjustments provide some level of control, they do not guarantee the complete avoidance of overfitting or underfitting.

To further enhance generalization and assess the model's robustness, the code applied K-Fold cross-validation, dividing the dataset into four subsets (folds) and alternating between training and validation phases. This technique helps identify whether the model is consistently learning patterns or overfitting specific subsets of the data. By calculating performance metrics, such as MSE and R^2, across multiple folds, this approach allows for a broader evaluation of the model's performance and reduces the influence of specific data splits on the results.

While these practices are established methods for improving model reliability, their effectiveness depends on the dataset's characteristics. In this case, the code integrates these strategies to manage potential risks, but the limited dataset size (n=24) imposes inherent challenges that no single technique can fully address.

Optimization Algorithm - *Tree-structured Parzen Estimator (TPE)*

TPE is a Bayesian optimization algorithm often used to adjust hyperparameters in machine learning models (Frazier, 2018; Joy et al., 2020; Ozaki et al., 2022; Rajalakshmi & Sulochana, 2023). Hyperparameters are parameters defined before the model is trained, such as the learning rate, which affect the model's performance (Optuna Contributors, 2020). TPE works by classifying hyperparameters into two groups: "good", which have a high probability of improving the model, and "bad", which are less likely to contribute to improvement (Rajalakshmi & Sulochana, 2023). This probabilistic approach allows the algorithm to concentrate its search on the most promising regions of the hyperparameter space, making the optimization process more efficient (Ozaki et al., 2022; Rajalakshmi & Sulochana, 2023).

We opted for TPE, via the Optuna library, due to its good performance in scenarios where adjusting hyperparameters is costly (Akiba et al., 2019; Optuna Contributors, 2020; Pinheiro &

Becker, 2023). It allows dynamic hyperparameter adjustments during execution and supports parallelization, a feature that makes it possible to perform several optimization operations simultaneously (Akiba et al., 2019; Frazier, 2018; Optuna Contributors, 2020; Parra-Ullauri et al., 2023). These features increase the efficiency of the process and improve the stability of the results (Akiba et al., 2019; Optuna Contributors, 2020; Pinheiro & Becker, 2023) (Optuna Contributors, 2020).

In this research, we used TPE to optimize the model that simultaneously maximizes GDP growth and minimizes inflation and the Gini index (Objective function: *score* = *gdp_growth* - *inflation* - *gini_index*).

The selection of TPE as the optimization algorithm is also partly due to the fact that, compared to the genetic algorithm initially tested, it showed greater consistency in the results. In contrast, the genetic algorithm showed considerable fluctuations in the results between different runs, even using a fixed random seed, as illustrated in Table 6.

Table 6. Result of the fitness values of the optimization models (Normalized Values)

Model	*GDP growth*	*Inflation*	*Gini index*
Bayesian optimization (Optuna)	0.9802	-1.1611	-0.7541
Genetic Algorithm (DEAP)	Varies between runs in Jupyter Notebook		
Execution 1	1.1110	-0.2816	0.2190
Execution 2	0.9076	-0.5053	-1.2442

Note: fitness values are metrics that quantify the quality of solutions in optimization models, guiding the algorithm in the search for the best solution that meets the defined objectives (Eiben & Smith, 2015).

RESULTS

Machine Learning Model Results - XGBoost

For the simulation, the data was pre-processed, organized in tabular format with years in rows and variables in columns. Missing data, such as the Gini indices for the years 2000 and 2010, were linearly interpolated, and the 2023 entries for GDP (Agência Brasil, 2024) inflation (IpeaData, 2024b) and Gini (IpeaData, 2024a) were updated with data from the Brazilian federal government. The data was then normalized with the `*StandardScaler* function of the `sklearn.*preprocessing*` module in Python, adjusting it to zero mean and 1 (one) standard deviation (Raju et al., 2020; Singh & Singh, 2020). The descriptive statistics confirm the normalization (Table 7), which ensures that all the variables make a balanced contribution to training the model.

Table 7. Descriptive Statistics (Normalized Values)

Expense	count	mean	std	min	25%	50%	75%	max	kurtosis	skewness
Legislative	24	0,00	1	- 2,05	- 0,61	0,10	0,89	1,63	- 0,72	- 0,44

Expense	count	mean	std	min	25%	50%	75%	max	kurtosis	skewness
Judiciary	24	0,00	1	- 1,46	- 0,86	- 0,13	0,97	1,77	- 1,31	0,13
Essential to Justice	24	0,00	1	- 1,66	- 0,75	0,01	0,88	1,87	- 0,97	- 0,01
Administration	24	0,00	1	- 1,49	- 0,97	0,05	1,05	1,64	- 1,43	0,03
National Defense	24	0,00	1	- 1,07	- 0,85	- 0,39	1,02	1,68	- 1,30	0,64
Public Safety	24	0,00	1	- 1,38	- 0,98	0,03	0,69	2,17	- 0,69	0,30
Foreign Relations	24	0,00	1	- 1,53	- 0,85	- 0,24	0,86	1,68	- 1,14	0,39
Social Assistance	24	0,00	1	- 0,79	- 0,62	- 0,30	0,07	3,56	6,00	2,34
Security	24	0,00	1	- 1,30	- 0,87	- 0,22	0,85	2,03	- 1,02	0,47
Health	24	0,00	1	- 1,25	- 0,83	- 0,20	0,62	1,94	- 0,78	0,62
Labor	24	0,00	1	- 1,30	- 0,98	- 0,19	0,88	1,75	- 1,53	0,15
Education	24	0,00	1	- 1,20	- 1,02	- 0,14	0,93	2,04	- 1,34	0,29
Culture	24	0,00	1	- 1,10	- 0,50	- 0,21	0,39	3,96	9,66	2,55
Citizenship Rights	24	0,00	1	- 1,27	- 0,67	- 0,22	0,38	2,99	1,99	1,28
Urbanism	24	0,00	1	- 2,09	- 0,32	- 0,07	0,58	1,76	- 0,13	- 0,29
Housing	24	0,00	1	- 0,53	- 0,52	- 0,49	- 0,17	3,57	6,92	2,64
Sanitation	24	0,00	1	- 1,31	- 0,93	- 0,03	0,62	1,88	- 1,04	0,36
Environmental Management	24	0,00	1	- 1,54	- 0,97	0,03	0,91	1,61	- 1,54	- 0,02
Science and Technology	24	0,00	1	- 1,52	- 0,71	0,08	0,45	3,00	1,94	0,85
Agriculture	24	0,00	1	- 1,32	- 0,76	- 0,33	0,68	2,11	- 0,49	0,72
Agrarian Organization	24	0,00	1	- 1,35	- 0,84	- 0,15	0,51	2,60	0,52	0,94
Industry	24	0,00	1	- 2,10	- 0,14	0,10	0,66	2,01	0,53	- 0,81
Services and Commerce	24	0,00	1	- 0,84	- 0,59	- 0,22	0,09	4,27	13,90	3,39
Communications	24	0,00	1	- 0,91	- 0,74	- 0,44	0,27	3,10	2,90	1,71
Energy	24	0,00	1	- 0,62	- 0,56	- 0,36	0,14	4,14	12,25	3,27
Transportation	24	0,00	1	- 1,61	- 0,82	- 0,07	0,86	1,77	- 1,23	- 0,05
Sports and Leisure	24	0,00	1	- 1,25	- 0,71	- 0,29	0,25	2,47	0,67	1,22
Special Charges	24	0,00	1	- 1,45	- 0,78	- 0,25	0,83	1,79	- 1,21	0,30
Refinancing[5]	24	0,00	1	- 0,92	- 0,56	- 0,26	0,10	2,58	2,57	1,87
GDP growth	24	0,00	1	- 2,08	- 0,40	0,20	0,62	1,84	0,18	- 0,57
Inflation	24	0,00	1	- 1,75	- 0,49	0,05	0,34	2,96	2,18	0,80
Gini index	24	0,00	1	- 2,22	- 0,55	- 0,30	0,68	1,92	- 0,05	0,33

The data was split into training and test sets using scikit-learn's '*train_test_split*' function, with a proportion of 80% for training and 20% for testing, guaranteeing randomness through a fixed '*random_state*'. For the simulation, the XGBoost model was configured with the following parameters:

- *objective*: reg:squarederror, for regression with quadratic error.

[5] Expenditure on debt refinancing is part of the 'Special Charges' budget function. They were segregated due to the materiality and relevance of the matter.

- *n_estimators*: 980, which determines the number of trees to be built.
- *learning_rate*: 0.002, to control the impact of each individual tree.
- *random_state*: 42, to ensure reproducibility.
- *n_jobs*: -1, for full utilization of available processing resources.

These parameters were selected empirically, through manual adjustments, in order to achieve the best results in the performance metrics (MSE, SSE and R^2).

The XGBoost machine-learning model was used to predict three socio-economic indicators: GDP growth, inflation and the Gini index, based on budget data.

In addition, learning curves were generated using cross-validation ('K-Fold' with 4 divisions) to monitor the model's performance during training and validation. The learning curves provided information on possible overfitting (failure to generalize to new data) or *underfitting* (failure to capture data patterns), allowing fine adjustments to be made to the model's training.

In summary, XGBoost performed satisfactorily for GDP and the Gini index, but encountered challenges in predicting inflation. Overall, Table 8 shows that XGBoost has an overall R^2 of 0.69, indicating that it explains 69% of the variability in socioeconomic indicators. The remaining 31% of uncaptured variability can be attributed to the complexity of the factors influencing the selected socioeconomic indicators.

Specifically, the model was more accurate in predicting GDP growth, with an R^2 of 0.8789, explaining 87.89% of the variance. For the Gini index, the model explains 82% of the variance (R^2 = 0.8252). However, in predicting inflation, performance is more limited, with an R^2 of 0.3793, reflecting the model's difficulty in capturing the full complexity of this indicator. The overall MSE of 0.21 and the SSE of 3.20 confirm that, despite the good overall performance, there is greater difficulty in predicting inflation.

Table 8. XGBoost Performance Metrics

Metric	*GDP growth*	*Inflation*	*Gini index*	General
MSE	0.1406	0.3629	0.1366	0,21
R^2	0.8789	0.3793	0.8252	0,69
SSE	0.7032	1.8145	0.6832	3,20

The importance metrics of the variables' characteristics - '*weight*', '*gain*' and '*cover*' - were used to assess which budget variables most influenced the algorithm's performance (Table 9). '*Weight*' indicates how many times a variable is used in the divisions of the decision trees; '*Gain*' measures the improvement in accuracy when using that variable; and '*Cover*' represents the proportion of samples impacted by the variable (XGBoost developers, 2022). Budget functions such as "Energy", "Public Security" and "Citizenship Rights" stood out as the most influential in the model.

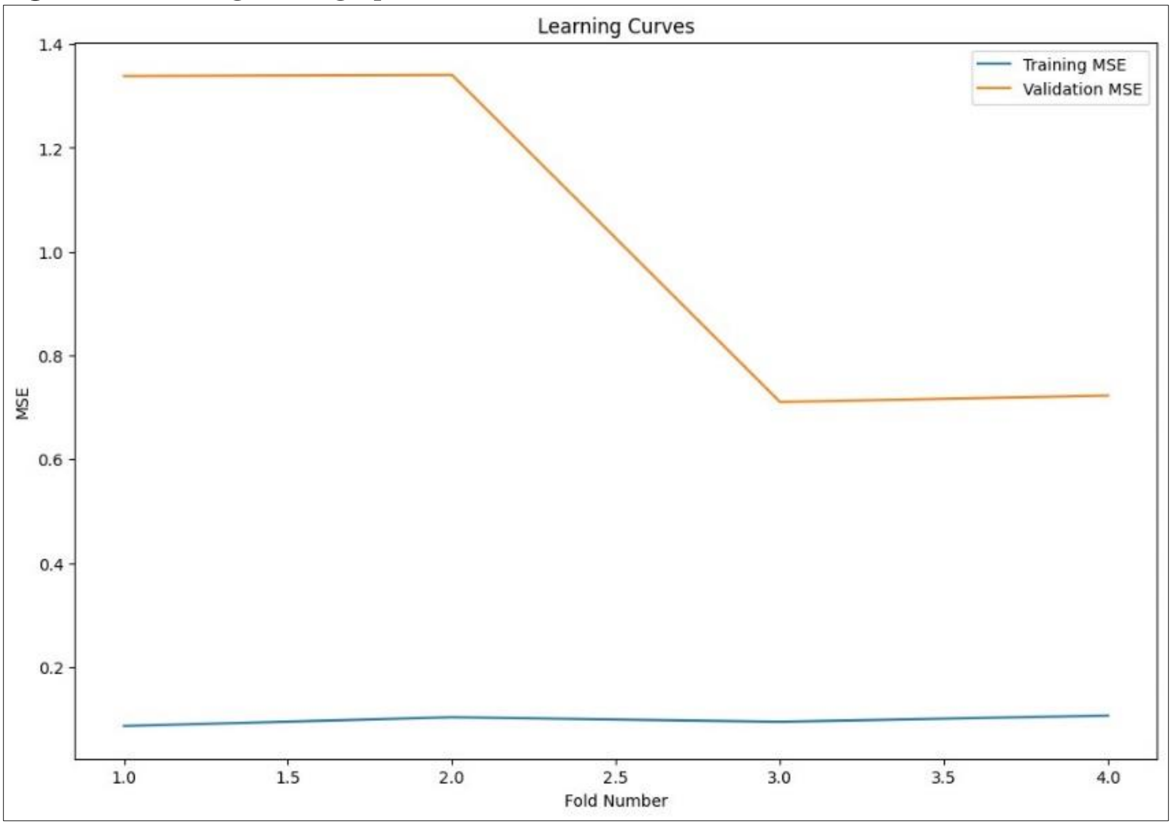
Table 9. Importance of Input Variables in XGBoost

Expense	*Cover*	*Weight*	*Gain*
Energy	18.344515	1431.0	1.612654
Public Safety	11.703369	1217.0	0.478419
Citizenship Rights	11.672556	2547.0	1.207250
Social Assistance	11.441296	741.0	0.247432
Communications	11.425197	381.0	0.501928
Housing	9.822534	1713.0	0.497706
Transportation	7.484127	126.0	0.008372
Science and Technology	7.035524	563.0	0.002693
Administration	6.400687	2039.0	0.456954
Environmental Management	6.257549	563.0	0.085920
Legislative	5.682010	8277.0	0.531682
Essential to Justice	4.945602	864.0	0.074656
Urbanism	4.628114	1124.0	0.108848
Judiciary	4.263959	788.0	0.017775
Health	3.746753	1078.0	0.019005
Culture	3.591727	556.0	0.017212
Foreign Relations	3.312057	282.0	0.002119
Labor	17.0	15.0	0.235357
Sanitation	9.5	30.0	0.010769
Services and Commerce	13.0	514.0	1.178998
Agrarian Organization	12.0	172.0	0.078991
Sports and Leisure	11.0	124.0	0.013858

These results highlight that budget areas had the greatest impact on the algorithm's accuracy and performance.

The learning curves in Figure 7 illustrate the model's performance during training and validation. The training error (blue line) remains consistently low across all folds, indicating that the model effectively fits the training data. The validation error (orange line) starts at a relatively high level, decreases sharply after the second fold, and stabilizes at a lower but still distinct level compared to the training error. This pattern suggests that while the model improves its predictions for unseen data during the process, the gap between training and validation errors indicates potential limitations in generalizing to entirely new datasets. It is also important to note that the small dataset size (n=24) likely amplifies variability in the validation error, as smaller datasets can make the model more sensitive to differences between training and validation splits.

Figure 7. Learning curve graph



These results were essential for the next stage, where the optimization algorithm refined the forecasts and allocation of public resources.

Results of the Optimization Algorithm - Tree-structured Parzen Estimator (TPE)

The results obtained from the optimization *script* offer another approach to the allocation of budgetary resources and their impact on socio-economic indicators. The study was run with 1000 *trials*. To ensure the reproducibility of the results, the parameter '*seed=42 in the sampler'* was used.

In this way, the comparison between actual and predicted values provides a basis for assessing the algorithm's accuracy, as shown in Table 10.

Table 10. Comparison of Actual and Predicted Values - Optimization (Normalized Values)

Sample	GDP growth (Real)	GDP growth (Predicted)	(%)	Inflation (Real)	Inflation (Predicted)	(%)	Gini index (Real)	Gini index (Predicted)	(%)
0	0,73	0,10	86,38%	-0,88	0,62	170,34%	1,92	1,26	34,20%
1	-0,33	-0,27	17,41%	0,31	0,22	28,47%	1,79	1,26	29,55%
2	0,26	0,21	18,45%	1,02	0,80	21,36%	1,66	1,26	24,19%
3	-0,42	-0,32	24,93%	2,96	1,83	38,15%	1,45	1,24	14,37%
4	1,22	1,02	16,37%	0,09	0,08	13,82%	0,99	0,80	18,87%

Table 10 presents the performance of the forecasting model across five subsets of data (samples), each reflecting different scenarios. The results highlight variations in the model's ability to predict the three socio-economic indicators under evaluation. For GDP growth, the percentage differences between actual and predicted values were below 25% in four of the samples, indicating relatively close predictions in those scenarios. However, sample 0 showed a discrepancy of 86.38%, suggesting that the model faced challenges in accurately capturing the patterns in this specific subset of data.

For inflation, the results exhibit greater variability across the samples, with discrepancies ranging from 13.82% in sample 4 to 170.34% in sample 0. These differences indicate inconsistencies in the model's ability to generalize predictions for this indicator, which may stem from the inherent complexity of inflation dynamics or limitations in the available data. This variability suggests the need for further investigation into how inflation-related data is represented and modeled.

The Gini index predictions were relatively more stable across the samples, with percentage differences ranging from 14.37% to 34.20%. This consistency indicates that the model performs more uniformly for this variable, although the level of error observed still suggests the potential for further improvement to enhance the precision of these predictions.

Overall, the results indicate that the model's predictive performance varies depending on the indicator and data subset. While the model demonstrates some capacity to generalize predictions, particularly for GDP growth and the Gini index in specific scenarios, the discrepancies observed — especially for inflation — underscore the need for refinements.

As can be seen in Figure 8 and Table 11, the best simulated budget allocation prioritizes spending on "Public Security", "National Defense" and "Services and Trade". On the other hand, it proposes reducing spending on functions such as "Foreign Affairs", "Energy" and "Transportation".

Figure 8. Optimized Distribution of Budget Allocation by Budget Function

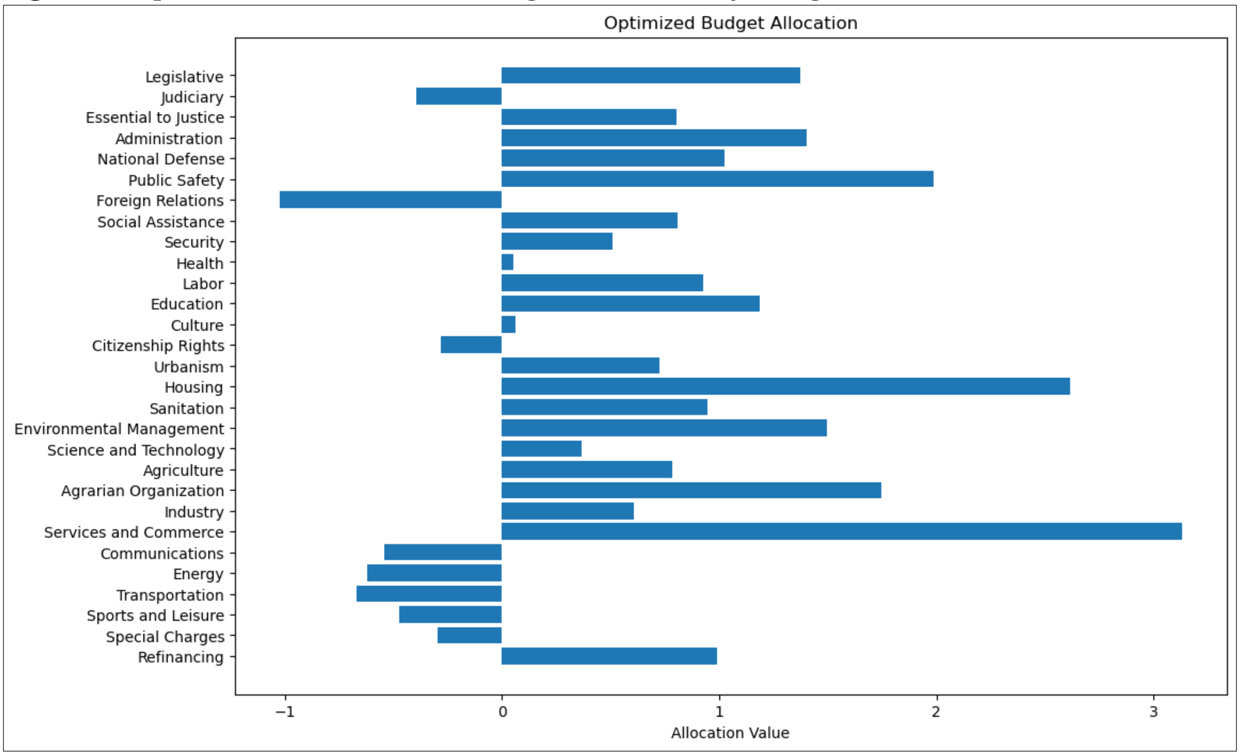


Table 11. Best Allocation for Different Expenses by Budget Functions (Normalized Values)

Expense	Value	Expense	Value
Legislative	1,370748	Housing	2,616916
Judiciary	-0,39336	Sanitation	0,94688
Essential to Justice	0,803417	Environmental Management	1,493447
Administration	1,4037	Science and Technology	0,3657
National Defense	1,024561	Agriculture	0,781334
Public Safety	1,987079	Agrarian Organization	1,746737
Foreign Relations	-1,02345	Industry	0,606013
Social Assistance	0,806531	Services and Commerce	3,129045
Security	0,507696	Communications	-0,5414
Health	0,053357	Energy	-0,61924
Labor	0,924915	Transportation	-0,66871
Education	1,184879	Sports and Leisure	-0,47516
Culture	0,063421	Special Charges	-0,2982
Citizenship Rights	-0,28372	Refinancing	0,991842
Urbanism	0,725448		

Note. The values in the table represent the best normalized budget allocation for each function, as determined by the optimization model.

The socio-economic results predicted with the optimized allocation of resources, in normalized data, were:

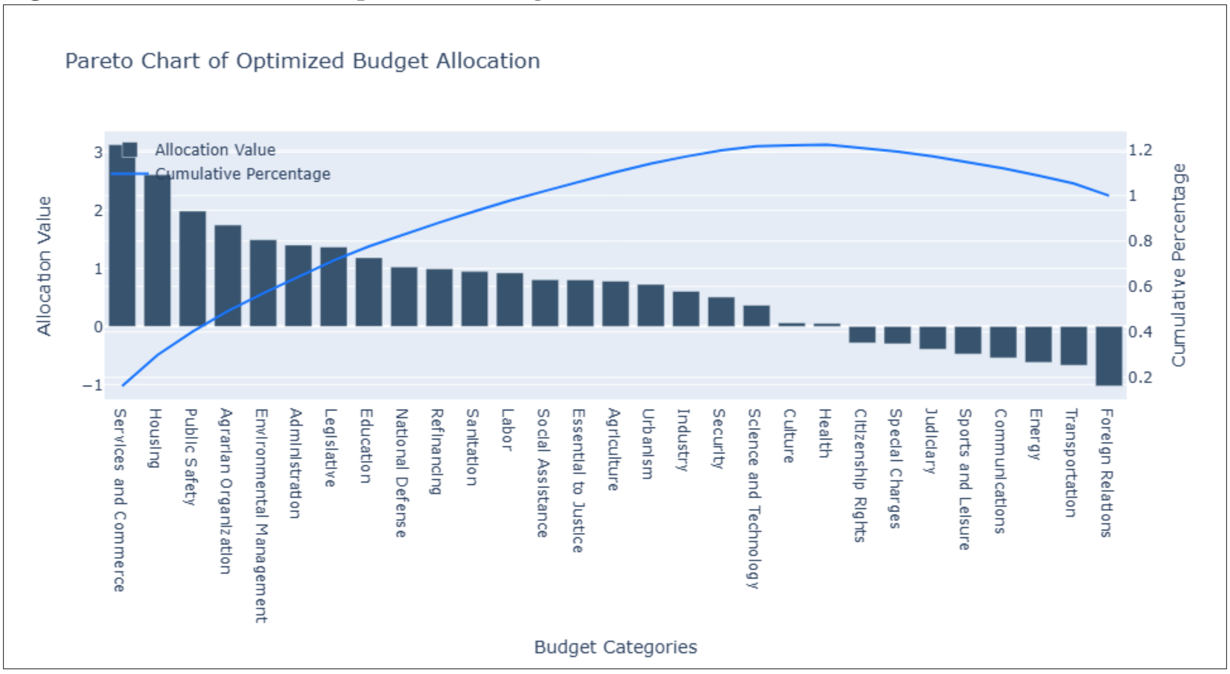
- GDP: 0.98 standard deviations above the average value.
- Inflation: -1.16 standard deviations below the mean value.

- Gini Index: -0.75 standard deviations below the average value.

These results indicate that the Objective Function has been met: an increase in GDP, a reduction in inflation and an improvement in income distribution, via a reduction in the Gini index.

The graph in Figure 9 illustrates the distribution of the normalized allocation values for the various expenses by budget function, highlighting that a few functions accumulate most of the total impact. The "Services and Trade" function received the largest allocation, followed by other important expenses such as the "Housing" and "Public Security" functions. The cumulative line indicates that around 20% of the highest priority categories explain approximately 80% of the total impact of the allocations, according to the Pareto principle. The rapid initial increase followed by stabilization suggests that most of the desired effects are achieved through a small number of categories, while the remaining allocations have only a marginal impact.

Figure 9. Pareto Chart of Optimized Budget Allocation



DISCUSSION

The hybrid model adopted is based on a combination of machine learning (Gradient Boosting) and bayesian optimization (TPE), reflecting an advance over traditional resource allocation methodologies, and extending its applicability to dynamic and complex contemporary contexts (Ghiassi & Simo-Kengne, 2021; Kunnathuvalappil Hariharan, 2017; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Zatonatska et al., 2023).

The results of the model indicate a prioritization of spending on "Services and Trade", "Housing" and "Public Security", while suggesting reductions in spending on "Foreign Affairs", "Energy" and "Transport". These findings are in line with public finance theory, which highlights the allocative function in correcting market failures and promoting social welfare (Case, 2008; Musgrave & Musgrave, 1989). For example, increasing resources in "Public Security" and "National Defense" can be seen as a response to the need to provide public goods that are typically under-provided by the market (Musgrave & Musgrave, 1989; Zatonatska et al., 2023).

In the optimization model implemented, examples of the application of the distributive function include the proposed increase in categories such as "Social Assistance" and "Housing", representing efforts to improve social equity, among other possible areas of intervention. The stabilizing function, responsible for maintaining macroeconomic stability, manifests itself in the management of expenses such as "Debt Refinancing", illustrating the concern with fiscal sustainability. As Brumby (2007) points out, allocative efficiency requires the maximization of social benefits, adapting allocations to the real needs and costs of public services.

The use of AI in the budget allocation process has the potential to improve operational efficiency by optimizing the distribution of public resources. This approach aims not only to make the process more precise, but also to support the commitment to a fairer society and the maintenance of economic stability, by aligning allocations with the distributive and stabilizing functions of the state.

However, the practical application of the model is constrained by certain limitations, primarily stemming from the characteristics of the dataset and the complexity of the relationships it aims to capture. The dataset spans only 24 years (2000–2023), which restricts the capacity of the model to generalize, particularly for long-term projections or scenarios significantly different from historical patterns. Furthermore, while measures such as cross-validation, K-Fold techniques, and hyperparameter tuning (e.g., low learning rate, controlled n_estimators) were applied to mitigate overfitting and ensure better generalization, these strategies cannot entirely guarantee the avoidance of overfitting or underfitting, especially with a limited dataset.

Another limitation is the model's reliance on historical data, which may introduce bias into the forecasts and restrict the generalizability of the results to different or future contexts. As observed in previous studies (Ghiassi & Simo-Kengne, 2021; Zuiderwijk et al., 2021) the accuracy of predictive models is sensitive to the quality of the input data, and in emerging contexts such as Brazil, where budget data can be inconsistent, this dependence can jeopardize the quality of the suggested allocations. In addition, public spending is influenced by a wide range of multifaceted factors - economic, demographic, social, environmental and political – which makes predicting it especially challenging (Ghiassi & Simo-Kengne, 2021).

In addition, the "black box" of machine learning algorithms limits the transparency and explainability of the decisions generated. Although these models have demonstrated technical capability in identifying complex patterns, the lack of clarity about how allocations were determined can reduce the confidence of policymakers and the public (Valle-Cruz et al., 2023; Zuiderwijk et al., 2021).

Another aspect to consider is that the model's objective function, defined as the difference between GDP growth, inflation and the Gini index (score = gdp_growth - inflation - gini_index), seeks to balance these three socio-economic dimensions without assigning specific weights to each one. Although this approach, inspired by previous studies (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022) allows for a direct and simplified evaluation, the absence of differentiated weights can limit the model's ability to reflect the relative importance of each variable in the context of public policies. The lack of adjustments to the weights can result in resource allocations that do not fully capture specific economic and social priorities. Therefore, it is recommended that future studies take into account an objective function with adjustable weights.

The results also indicated that while the model performed better in promoting GDP growth and reducing the Gini Index, it faced difficulties in accurately predicting inflation, especially in some subsets/samples of data. This variation in accuracy suggests that the model is not equally robust in all scenarios, which may limit its applicability.

Finally, the practical implementation of the allocations suggested by the model must take into account the restrictions and challenges faced by the Brazilian budget system. Budgetary rigidity, the fragmentation of the allocation process, the quality of the data made available and bureaucratic dysfunctions are barriers that can make it difficult to achieve the benefits expected from optimized allocations (Baptista et al., 2012; Couto & Rodrigues, 2022; Giacomoni, 2021).

In summary, while the application of AI in public budget allocation provides a promising tool to complement decision-making, this study highlights several limitations that must be addressed for practical implementation. These include the reliance on historical data, which may introduce bias and limit generalizability, as well as challenges related to the transparency of algorithms and the inherent constraints of the public budgeting system. Additionally, the model's quantitative nature does not account for contextual social, political, and economic dynamics, emphasizing the need for qualitative analyses to complement the results. Beyond the findings and limitations discussed, this study aimed to initiate a broader conversation about the potential use of AI in public budgeting as a decision-support tool—a field that remains underexplored both in research and in practice.

CONCLUSION

This study used a hybrid AI model combining machine learning and optimization to generate a simulated budget allocation scenario in Brazil. The results indicate that the model can improve socio-economic indicators by proposing allocations that increase GDP, control inflation and reduce income inequality, as demonstrated by the standard deviations observed in the simulation.

This study showed that the machine-learning model, using the Gradient Boosting algorithm, obtained an overall R^2 of 0.69. This result indicates that the model was able to explain 69% of the variability in the selected socio-economic indicators. In practical terms, this means that the model captured the relationships between budget variables and socioeconomic outcomes, although there is still 31% of the variability unexplained, possibly due to the complexity of the indicators and external factors not taken into account by the model.

The optimization algorithm, in turn, directed budget allocations to budget expenditures such as "Services and Trade", "Housing" and "Public Security", demonstrating its potential for use in efficient public budget management. The integration of TPE with Gradient Boosting resulted in a budget simulation that demonstrated greater stability and consistency compared to the other AI algorithms tested. This suggests that AI can complement traditional methodologies in the allocation of resources, making budget decisions more aligned with the desired socio-economic objectives.

Despite the advances demonstrated by the hybrid AI model adopted in this research, several limitations were identified that warrant attention. The reliance on historical data may have introduced biases into the forecasts, limiting the model's ability to generalize its results to different contexts. Additionally, the absence of differentiated weights in the objective function assumes equal importance for all indicators, which may not align with real-world priorities. The model also struggled to predict certain indicators, such as inflation, reflecting challenges in handling highly volatile or complex variables. Furthermore, the small sample size (n=24 years) limits the robustness of the findings and underscores the challenges of applying AI to datasets with constrained time spans.

Acknowledging these constraints, the simulation provides an innovative perspective on public budget allocation, highlighting the potential of AI to enhance decision-making. Future applications could benefit from refined adjustments, including the incorporation of qualitative variables and a better integration of contextual factors to complement the model's quantitative approach.

Given these conclusions, we suggest that future research expand the application of this hybrid methodology to state and municipal contexts, allowing for a more comprehensive analysis of resource allocation policies. In addition, we recommend exploring other machine learning algorithms and optimization techniques to increase forecast accuracy. Other performance metrics and hyperparameter adjustments could also be incorporated to better evaluate the performance of the algorithms used. Finally, quantitative analyses should be complemented with qualitative approaches that take into account the economic and social context, offering a more complete view adapted to the complexity of public finances.

In summary, this study initiates the exploration of AI applications in public budgeting within the Brazilian context, addressing a gap in existing research. Despite the limitations identified, the work offers a methodological contribution to public policy analysis and demonstrates the potential of AI as a tool to support resource allocation processes, encouraging further investigation and development in this area.

REPLICATION STATEMENT

All the materials needed to reproduce the results presented in this research are available in the public repositories listed on the GitHub account (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/tree/main).

Data without treatment of input and output variables
(https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/Raw_Data_Input_Output_Variables.xlsx).

Preprocessed and normalized data
(https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/Processed_Normalized_Data.csv).

Script 1: The script used to normalize the data can be accessed at (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/data_normalization_script.ipynb).

Script 2: The script for calculating the descriptive statistics of the normalized data is available at (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/descriptive_statistics_scripts.ipynb).

***Script 3*:** The complete script for training and evaluating the XGBoost model can be found at (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/xgboost_model_pipeline.ipynb).

Script 4: The script for optimizing the allocation of budget resources using Bayesian Optimization is available at (https://github.com/Saulo113z\\40/Public_Resource_Allocation_Analysis/blob/main/budget_optimization_pipeline.ipynb).

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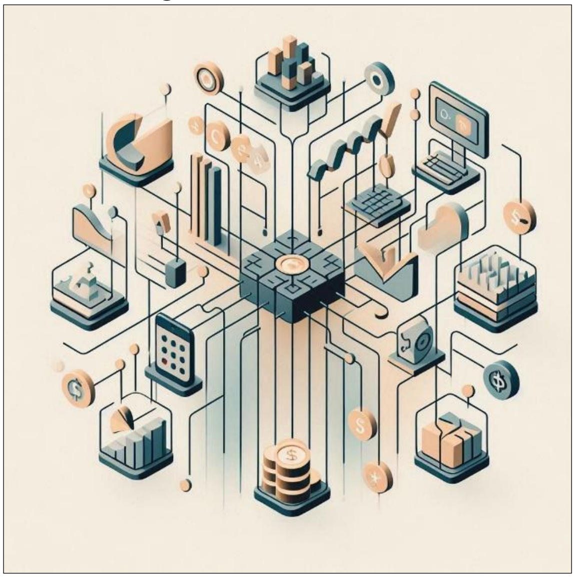
PRODUTO TÉCNICO-TECNOLÓGICO

ORÇAMENTAÇÃO ALGORÍTMICA
MODELO HÍBRIDO DE INTELIGÊNCIA ARTIFICIAL NA ALOCAÇÃO DE RECURSOS PÚBLICOS

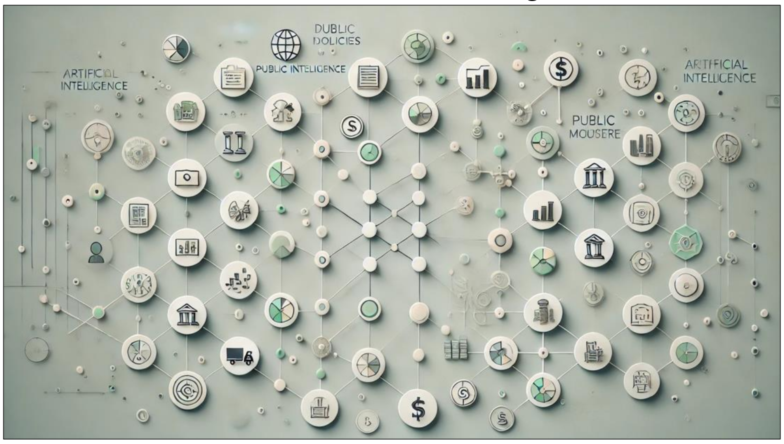
Prompt utilizado em duas plataformas geradoras de imagem com IA, Designer (Microsoft) e DALL·E (OpenAI), com o seguinte comando:
-A minimalist image suggesting an algorithmic system that uses automated artificial intelligence to generate financial flows to meet society's demands.
- Use icons that represent public policies and public money.
-The image cannot contain letters, text or words. Use icons and images.
-The design should balance structure (suggesting complexity of the model) and simplicity (to align with the minimalist and academic purpose).
- The color palette should be neutral, with soft/clean tones (green, whites and soft blues), suitable for a scientific presentation.

Figura 1. Resultado OPENAI. Imagem gerada por inteligência artificial via DALL·E



Nota: Disponível em: https://chatgpt.com/; 2024.

Figura 2. Resultado MICROSOFT. Imagem gerada por inteligência artificial via Microsoft Designer



Nota. Disponível em: https://designer.microsoft.com; 2024.

INTRODUÇÃO

O Produto Técnico-Tecnológico (PTT) intitulado "Modelo Híbrido de Inteligência Artificial na Alocação de Recursos Públicos" enquadra-se na categoria de "Processo/tecnologia e produto/material não patenteável", conforme definido pela CAPES, por desenvolver um modelo de orçamentação algorítmica sem a necessidade de proteção legal por patentes. Baseado em tecnologias de Inteligência Artificial (IA) de código aberto, o PTT pode ser adaptado e implementado por diferentes organizações públicas, caracterizando-se como um modelo replicável e aplicável sem restrições de propriedade intelectual.

De maneira mais específica, o Produto propõe a implementação de um modelo híbrido de orçamentação inteligente, que combina o potencial preditivo do aprendizado de máquina com a eficiência da otimização, com o objetivo de auxiliar o processo decisório na alocação de recursos públicos. Embora incipiente e com limitações identificadas, o modelo tem o potencial de melhorar a precisão e a eficácia dessas decisões, oferecendo suporte aos gestores na busca por uma distribuição mais eficiente e alinhada aos objetivos governamentais.

Para testar o modelo, simulou-se cenários alternativos de alocação de recursos públicos entre as funções orçamentárias do orçamento federal brasileiro, utilizando dados de execução orçamentária do período de 2000 a 2023. O modelo visou otimizar simultaneamente três indicadores socioeconômicos — Produto Interno Bruto (PIB), Inflação e índice de Gini[6] — por meio de uma abordagem estritamente quantitativa, utilizando uma metodologia previamente validada em estudo anterior (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022), adaptada para as especificidades da orçamentação pública brasileira.

O modelo foi treinado com o algoritmo de regressão *XGBoost*, que é uma técnica de aprendizado de máquina supervisionado, capaz de identificar padrões nos dados históricos. Para a etapa de otimização, foi utilizado o algoritmo de otimização bayesiana do *Optuna*, que busca encontrar as melhores combinações de alocação de recursos orçamentários, maximizando simultaneamente os três indicadores escolhidos para fins de simulação sem a necessidade de estabelecer relações causais diretas, mas visando melhorá-los de forma integrada.

Reitere-se que o modelo foi desenvolvido com base em resultados comprovados por pesquisas anteriores e adaptada para atender ao escopo e às necessidades do contexto brasileiro, aproveitando os resultados promissores já observados (Jang, 2019; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022). Neste relato, apresenta-se o desenvolvimento e teste da tecnologia aqui ofertada. Além deste

[6] O Índice de Gini é uma medida de desigualdade econômica que varia de 0 a 1, onde 0 representa perfeita igualdade e 1 representa máxima desigualdade na distribuição de renda (Afonso et al., 2010; Wolffenbüttel, 2004).

relato, este PTT também contém uma plataforma de visualização interativa implementada através de um *dashboard*. Trata-se de ferramenta que permite aos usuários ajustar categorias de despesa por função orçamentária e visualizar, em tempo real, os impactos da alocação sobre os indicadores socioeconômicos escolhidos para simulação, facilitando a análise de dados e a tomada de decisões de forma prática, intuitiva e acessível. O Produto pode ser visualizado no seguinte endereço eletrônico: https://meu-projeto-dash-7.onrender.com/.

DESCRIÇÃO GERAL DO PRODUTO

Com o objetivo de auxiliar o processo de alocação de recursos orçamentários federais no Brasil, o modelo híbrido de IA é composto por dois componentes principais: (1) o algoritmo de regressão *XGBoost*, que aplica o método de *Gradient Boosting* para analisar dados históricos da execução orçamentária e prever indicadores selecionados; e (2) um algoritmo de otimização bayesiana, implementado com a biblioteca *Optuna*, que utiliza a técnica *Tree-structured Parzen Estimator* (TPE), que simular diferentes cenários de alocação de recursos, buscando a configuração que maximiza simultaneamente os resultados dos indicadores previstos.

O *XGBoost* é uma versão avançada do método *Gradient Boostin*g, que constrói árvores de decisão de forma sequencial para corrigir erros anteriores, otimiza o uso de memória e processamento, e inclui técnicas para evitar o *overfitting* (quando o modelo se ajusta demais aos dados), melhorando a precisão das previsões em modelos de aprendizado de máquina (Parsa et al., 2020; XGBoost developers, 2022). Já a Otimização Bayesiana é utilizada para ajustar automaticamente os hiperparâmetros do modelo, que são parâmetros que controlam seu funcionamento, como a taxa de aprendizado e o número de árvores, facilitando assim a otimização da alocação de recursos públicos com base na função objetivo escolhida (melhoria de indicadores socioeconômicos selecionados, por exemplo) (Optuna Contributors, 2020; Parra-Ullauri et al., 2023).

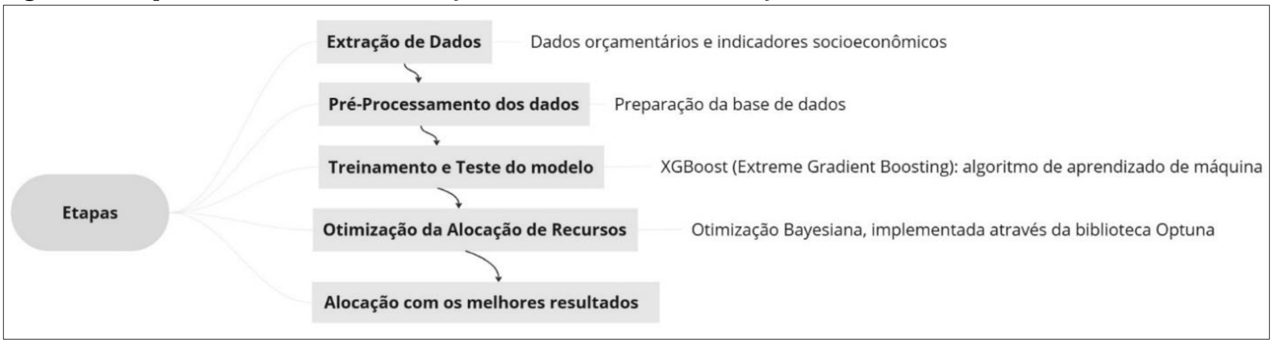
A escolha desse modelo híbrido de IA é justificada pela sua capacidade de identificar padrões complexos que não são óbvios, o que é adequado para a análise preditiva necessária na gestão de recursos públicos (Esnaashari et al., 2023; Katharina Dhungel et al., 2024; Valle-Cruz et al., 2024; Zatonatska et al., 2023). Além disso, estudos indicam que a aplicação de IA pode aumentar as taxas de sucesso na alocação de recursos em até 50% em comparação aos métodos tradicionais (Esnaashari et al., 2023).

Ressalta-se que o modelo utilizado funciona como apoio à tomada de decisão, sem oferecer soluções definitivas para a complexidade do processo orçamentário e do contexto socioeconômico.

Além disso, é importante destacar que este modelo serve como ponto de partida para futuras investigações e aprimoramentos. O código-fonte do modelo está disponibilizado à comunidade para que outros pesquisadores e profissionais possam realizar ajustes, evoluções e refinamentos. Essa abertura visa facilitar a colaboração contínua e o desenvolvimento do modelo, permitindo que ele se adapte e responda melhor às complexidades inerentes ao processo orçamentário público. Assim, enquanto a ferramenta proposta oferece um arcabouço útil para a simulação de cenários, ela deve ser vista como uma ideia em evolução, que requer validações e melhorias contínuas para atingir seu potencial pleno.

A seguir, a Figura 3 ilustra as etapas metodológicas adotadas no desenvolvimento e simulação do Produto:

Figura 3 - *Etapas do Processo de Otimização de Recursos Públicos Orçamentários com IA*



Por fim, as instruções, arquivos e endereços de acesso à solução pela *internet* estão no subtópico 4.3 deste trabalho.

Benefícios Esperados

A implementação do modelo híbrido de IA proposto na gestão orçamentária pública brasileira pode proporcionar alguns benefícios:

- Otimização da alocação de recursos: a utilização de IA tem o potencial de oferecer suporte na análise detalhada das necessidades de alocação de recursos, ajudando a orientar o processo de decisão e a promover uma distribuição mais alinhada aos objetivos governamentais (Ghiassi & Simo-Kengne, 2021; Jang, 2019; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022).
- Redução de tempos de resposta: A automação de processos complexos por meio de IA pode reduzir o tempo necessário para a tomada de decisões orçamentárias, aumentando a agilidade do processo de gestão orçamentária (Valle-Cruz et al., 2024; Zuiderwijk et al., 2021).
- Melhoria nas previsões e planejamento: O modelo híbrido permite melhorar a previsão de resultados a partir de diferentes cenários de alocação, fornecendo suporte para a tomada de decisões baseadas em dados (Jang, 2019; Pinheiro & Becker, 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022).

Assim, espera-se que a implementação dessa solução não só melhore a eficiência e precisão da alocação orçamentária, mas também contribua para a transformação digital da administração pública no Brasil, alinhando-se com a evolução global do "governo eletrônico" para o "governo inteligente" (Eom et al., 2016; Gil-Garcia et al., 2014, 2016; Harsh & Ichalkaranje, 2015; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022).

Relevância do Produto

a) Complexidade e Aderência

O PTT desenvolvido integra disciplinas e metodologias, como administração pública, orçamentação aprendizado de máquina, otimização e visualização de dados. A complexidade técnica se evidencia pelo uso de algoritmos, como o *XGBoost*, para criar um modelo preditivo que otimiza indicadores socioeconômicos com base nos dados de execução orçamentária do Brasil. Além disso, a utilização da biblioteca *Optuna* permite simular cenários e realizar ajustes dinâmicos nas variáveis de entrada, otimizando o desempenho dos indicadores.

A construção de interfaces, por meio de um *dashboard* interativo na plataforma *Dash*, facilita a interação dos gestores com os dados, permitindo ajustes em tempo real nas categorias de despesa e visualização dos impactos projetados. Essa interface alia complexidade técnica à usabilidade prática, oferecendo uma ferramenta de apoio à decisão.

A complexidade conceitual do PTT decorre da necessidade de alinhar os resultados do modelo com objetivos de políticas públicas multifacetadas, como crescimento econômico sustentável, equidade de renda e controle da inflação. O modelo não apenas fornece previsões, mas também simula cenários que permitem avaliar diferentes alocações orçamentárias, servindo de suporte para uma gestão pública informada em um ambiente em constante mudança.

A aderência do PTT à administração pública está diretamente relacionada às práticas e aos desafios enfrentados pelos gestores no planejamento e execução orçamentária, oferecendo uma solução dinâmica de suporte à otimização da alocação de recursos públicos.

b) Potencial Inovador

O potencial inovador deste PTT reside na integração de técnicas de aprendizado de máquina e otimização, uma novidade em um campo que tradicionalmente depende de métodos estatísticos convencionais. Essa abordagem utiliza conhecimento inovador para formular uma função multiobjetivo que auxilia na otimização de indicadores socioeconômicos, adaptada especificamente para a administração pública. Ao fornecer uma ferramenta ajustável para simular diferentes cenários orçamentários, o PTT oferece suporte à tomada de decisão sem substituir o julgamento humano. O modelo propõe uma melhoria metodológica na orçamentação pública, com o potencial de apoiar os gestores no planejamento e na resposta às demandas, sem oferecer soluções definitivas, mas possibilitando análises mais flexíveis e ajustes oportunos na alocação de recursos.

c) Aplicabilidade

A aplicabilidade do PTT pode ser analisada em duas dimensões: potencial e realizada. Potencialmente, o modelo e o sistema de visualização são adequados a contextos diversos que demandem otimização na alocação de recursos, como ministérios, secretarias, órgãos e entidades governamentais. A utilização de tecnologias de código aberto permite que a solução seja empregada de forma flexível e replicável em diferentes ambientes, com facilidade de adaptação.

A aplicabilidade do modelo foi testada através de uma simulação utilizando dados da execução orçamentária, segmentados por funções do orçamento federal do Brasil. Apesar das limitações encontradas, o modelo demonstrou potencial para prever resultados e otimizar a alocação de recursos conforme os objetivos estabelecidos. Contudo, trata-se de uma abordagem inicial, que requer aprimoramentos e a consideração de variáveis adicionais para refletir com maior precisão a complexidade do processo orçamentário. Assim, entende-se que os resultados obtidos oferecem uma base relevante para futuros ajustes do modelo.

d) Impacto Potencial

O impacto potencial do PTT reside na possibilidade de auxiliar gestores públicos na tomada de decisões mais informadas sobre a alocação de recursos, contribuindo para uma administração mais eficiente. Embora o modelo ofereça uma abordagem estruturada para otimização de múltiplos objetivos, seu uso deve ser visto como um apoio à gestão, e não uma solução definitiva.

Apesar de limitações identificadas, no teste realizado com dados da execução orçamentária federal do Brasil, o modelo apresentou resultados que indicam seu potencial em contribuir para uma alocação mais eficiente dos recursos, com projeções que sugerem melhorias na gestão orçamentária. Embora esses resultados sejam promissores, sua aplicação em larga escala e em diferentes contextos deve ser avaliada com cautela, considerando sempre as especificidades de cada organização e suas demandas.

BASE TEÓRICA UTILIZADA

A alocação de recursos públicos é um desafio persistente para os governos, que precisam equilibrar demandas econômicas e sociais variadas com os recursos escassos disponíveis (Esnaashari et al., 2023; Fozzard, 2001; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022). Desde trabalhos seminais (Key, 1940; Musgrave, 1959), a literatura tem explorado a melhor forma de distribuir os recursos públicos para atender às necessidades de uma nação. Apesar dos avanços teóricos, os métodos tradicionais de orçamentação, frequentemente baseados em históricos de gastos e abordagens incrementalistas, apresentam limitações (Galdino & Andrade, 2020; Lindblom, 1981; Nonato, 2024). Esses métodos são frequentemente criticados por sua lentidão, rigidez e falta de precisão, especialmente em contextos de mudanças rápidas no ambiente econômico (Ghiassi & Simo-Kengne, 2021; Kunnathuvalappil Hariharan, 2017; Zatonatska et al., 2023).

Estudos contemporâneos reforçam a complexidade e a persistência desses desafios de alocação orçamentária de recursos públicos (Amin, 2020; Esnaashari et al., 2023; Fozzard, 2001; Katharina Dhungel et al., 2024; Medema, 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Valle-Cruz, Fernandez-Cortez, López-Chau, et al., 2022). Além disso, percebe-se uma lacuna na integração de novas tecnologias, como a IA, na gestão da alocação de recursos públicos orçamentários (Esnaashari et al., 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Valle-Cruz, Fernandez-Cortez, López-Chau, et al., 2022).

No Brasil, o orçamento federal para 2024 foi fixado em quase R$ 5,5 trilhões, abrangendo despesas significativas nos Orçamentos Fiscal e da Seguridade Social, incluindo o refinanciamento da dívida pública federal, tanto interna quanto externa (Senado Federal, 2024). Considerando o grande volume de recursos envolvidos, a aplicação de métodos de otimização na alocação orçamentária tem o potencial de aumentar o impacto socioeconômico dos gastos governamentais, especialmente por meio de soluções tecnológicas baseadas em dados. No entanto, o uso de tecnologias algorítmicas para aprimorar a eficiência e a precisão na alocação de recursos públicos permanece limitado, particularmente na gestão do orçamento público (Esnaashari et al., 2023; Valle-Cruz et al., 2024; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Zuiderwijk et al., 2021).

Nesse contexto, surge a possibilidade de utilização da IA, que pode ser definida como um conjunto de sistemas que processam informações e simulam comportamentos inteligentes humanos, como raciocínio, aprendizado, previsão e planejamento, utilizando algoritmos e modelos para realizar tarefas cognitivas de forma autônoma (Nonato et al., 2024; Unesco, 2020; Zuiderwijk et al., 2021). Esses sistemas, que integram aprendizado de máquina, otimização e raciocínio automatizado, têm sido aplicados em ambientes reais e virtuais, apoiando a tomada de decisões em diversos setores governamentais, como infraestrutura, segurança, saúde e, particularmente, na alocação de recursos públicos (Unesco, 2020; Valle-Cruz et al., 2024; Zuiderwijk et al., 2021). No contexto da gestão orçamentária, a IA permite a captura de relações complexas entre variáveis econômicas e sociais, o que torna as previsões mais precisas e a alocação de recursos mais eficiente (Ghiassi & Simo-Kengne, 2021; Katharina Dhungel et al., 2024; Valle-Cruz et al., 2024; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022; Zatonatska et al., 2023).

A aplicação dessas técnicas está alinhada com a governança baseada em evidências, que defende que as decisões políticas sejam fundamentadas em dados empíricos e análises rigorosas, promovendo uma melhor qualidade na alocação de recursos públicos (Boaz & Nutley, 2019; M et al., 2007). Essa abordagem reforça a necessidade de transparência e base empírica nas decisões, permitindo que a IA otimize a gestão fiscal ao identificar padrões ocultos e realizar previsões mais confiáveis (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022, 2022).

Além disso, a visualização dos dados gerados por esses sistemas, conforme os princípios da teoria de sistemas de informação, destaca a importância de apresentar informações de maneira clara e acessível para apoiar o processo decisório (Laudon & Laudon, 2017). Exemplos de ferramentas que utilizam IA, como o *Gradient Boosting* e a Otimização Bayesiana, são aplicáveis nesse contexto ao melhorar a precisão na alocação orçamentária, com o objetivo de proporcionar maior adaptabilidade às mudanças, com o potencial de reduzir ineficiências (Akiba et al., 2019; Chen & Guestrin, 2016; Esnaashari et al., 2023; Pinheiro & Becker, 2023; Valle-Cruz et al., 2024; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022).

MÉTODOS

Variáveis

Para testar e validar o PTT, o modelo híbrido de IA proposto simulou cenários alternativos de alocação de recursos orçamentários, utilizando como variáveis independentes os valores das despesas federais do Brasil na fase de liquidação (Quadro 1 e Quadro 2), organizados por função orçamentária. Como variáveis dependes, a simulação utilizou três indicadores socioeconômicos — PIB, inflação e índice de Gini (Quadro 2). Os dados levantados referem-se ao período de 2000 a 2023.

Os dados utilizados neste estudo têm como ponto de partida o ano 2000 devido a alterações nas classificações das funções orçamentárias realizadas anteriormente. Até 1999, as classificações seguiam critérios diferentes, o que dificultava a comparação e análise ao longo do tempo. Com a publicação da Portaria nº 42 de 1999, foi estabelecida uma padronização nacional para a classificação das despesas públicas, permitindo a construção de séries históricas consistentes a partir de 2000 (Ministério de Estado do Orçamento e Gestão, 1999). Essa uniformidade foi fundamental para assegurar que as análises realizadas neste estudo fossem metodologicamente consistentes e baseadas em dados comparáveis, ainda que o número de observações seja limitado (n = 24).

O Quadro 1 a seguir apresenta a classificação das funções orçamentárias utilizadas para a organização das despesas públicas, permitindo uma visão estruturada das áreas de atuação do governo.

Quadro 1 - Funções Orçamentárias

Cod.	Expense	Cod.	Expense
1	Legislative	16	Housing

Cod.	Expense	Cod.	Expense
2	Judiciary	17	Sanitation
3	Essential to Justice	18	Environmental Management
4	Administration	19	Science and Technology
5	National Defense	20	Agriculture
6	Public Safety	21	Agrarian Organization
7	Foreign Relations	22	Industry
8	Social Assistance	23	Services and Commerce
9	Security	24	Communications
10	Health	25	Energy
11	Labor	26	Transportation
12	Education	27	Sports and Leisure
13	Culture	28	Special Charges
14	Citizenship Rights	29	Refinancing[7]
15	Urbanism		

Fonte: Adaptado da Portaria n° 42/1999.

A escolha dos indicadores socioeconômicos neste trabalho foi fundamentada em sua relevância teórica e em seu uso em estudo anterior (Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022), que serviu como referência metodológica.

Os indicadores selecionados neste estudo relacionam-se às funções do Estado na economia (Musgrave, 1959): a **inflação** está associada à **função estabilizadora**, que se refere ao papel do Estado em manter a estabilidade econômica, controlando os níveis de preços e o ciclo econômico por meio de políticas fiscais e monetárias (Aladejare, 2020; Case, 2008; Musgrave, 2008); o **índice de Gini** reflete a **função distributiva**, que trata da redistribuição de renda, com o objetivo de reduzir as desigualdades sociais (Afonso et al., 2010; IpeaData, 2024a; Musgrave & Musgrave, 1989); o **PIB**, por sua vez, não se vincula diretamente a uma função específica, mas serve como um indicador macroeconômico abrangente que reflete o impacto agregado das políticas públicas (IpeaData, 2024b; Mankiw, 2019; Wang & Alvi, 2011). Já a **função alocativa** refere-se ao papel do Estado na alocação de recursos para a provisão de bens públicos e na correção de falhas de mercado, e, embora não possua um indicador específico neste estudo, permeia todo o processo orçamentário (Case, 2008; Musgrave & Musgrave, 1989).

A seguir, o Quadro 2 apresenta a descrição detalhada das variáveis selecionadas para a simulação realizada pelo modelo híbrido:

[7] As despesas com refinanciamento da dívida fazem parte da função orçamentária 'Encargos Especiais'. Foram segregadas em virtude da materialidade e relevância da matéria.

Quadro 2 - Descrição das variáveis

Variável	Descrição Constitutiva	Descrição Operacional	Fonte dos Dados
Despesas liquidadas por Função Orçamentária	Representa a classificação orçamentária das despesas realizadas pelo governo, que refletem as áreas de atuação do setor público, como saúde, educação, segurança, defesa nacional, assistência social, entre outras (Ministério de Estado do Orçamento e Gestão, 1999; OECD, 2021).	Medida pela soma das despesas liquidadas (executadas) em cada função orçamentária. Dados extraídos da plataforma "Tesouro Transparente". O corte temporal iniciou-se em 2000 devido à estabilização da classificação das funções orçamentárias com a publicação da Portaria n° 42 de 1999, que proporcionou uma base mais consistente para a comparação longitudinal das despesas governamentais nas diversas funções (Ministério de Estado do Orçamento e Gestão, 1999).	https://www.tesourotransparente.gov.br/publicacoes/despesas-da-uniao-series-historicas/2023/8-2?ano_selecionado=2024 A relação detalhada das funções orçamentárias encontra-se no Quadro 1.
Produto Interno Bruto	Indicador do valor total dos bens e serviços produzidos em uma economia durante um período específico, refletindo o nível de atividade econômica (Wang & Alvi, 2011).	Medido pela taxa de crescimento anual do PIB em percentual, com base nos dados do *DataBank* do Banco Mundial.	https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.MKTP.KD.ZG
Inflação	Reflete o aumento geral e contínuo dos preços dos bens e serviços em uma economia ao longo do tempo, indicando a perda de poder aquisitivo da moeda (Aladejare, 2020; Fonchamnyo & Sama, 2016)	Medida pelo deflator implícito do PIB, em percentual anual, conforme disponibilizado pelo *DataBank* do Banco Mundial.	https://databank.worldbank.org/metadataglossary/world-development-indicators/series/NY.GDP.DEFL.KD.ZG
Índice de Gini	Índice que mede a desigualdade na distribuição de renda dentro de uma economia, variando de 0 (igualdade perfeita) a 1 (desigualdade perfeita) - alguns apresentam de zero a cem (Afonso et al., 2010; Wolffenbüttel, 2004).	Calculado com base na distribuição de renda, utilizando os dados do *DataBank* do Banco Mundial.	https://databank.worldbank.org/metadataglossary/world-development-indicators/series/SI.POV.GINI

Síntese dos Scripts de IA utilizados

Seguindo a metodologia detalhadamente explicada no trabalho "Let's Spend Smarter: How Artificial Intelligence Can Help Us Better Allocate Public Budgetary Resources", apresentamos a seguir uma breve síntese dos *scripts* desenvolvidos no *Jupyter Notebook* para as soluções algorítmicas de IA utilizadas no modelo proposto:

1) Script de Aprendizado de Máquina

- Carregamento e Processamento de Dados: Utilização de dados normalizados de despesas orçamentárias e variáveis socioeconômicas.
- Divisão dos Dados: Separação dos dados em conjuntos de treinamento e teste.

- Modelagem: Treinamento de um modelo *XGBoost* de regressão *multi-output*, configurado para minimizar o MSE e maximizar o R^2.
- Avaliação: Cálculo das métricas de desempenho do modelo, incluindo MSE, R^2 e SSE, com análise detalhada para cada variável de saída.
- Visualização e Salvamento dos Resultados: Geração de gráficos comparativos entre valores reais e preditos, e análise da importância das características para cada variável de saída. Salvamento dos resultados para futura utilização no modelo de otimização.

2) Script de Otimização

- Carregamento do Modelo Treinado: Utilização do modelo previamente treinado com *XGboost* para realizar predições baseadas em novas alocações sugeridas.
- Definição da Função Objetivo: Implementação de uma função objetivo que maximize os resultados pretendidos. Na simulação em tela foi de, simultaneamente, maximizar o crescimento do PIB e minimize a inflação e o índice de Gini (**score = gdp_growth - inflation - gini_index**).
- Otimização Bayesiana: Emprego da biblioteca *Optuna* para realizar a otimização bayesiana, sugerindo novas alocações de recursos.
- Análise dos Resultados: Identificação da melhor alocação encontrada e avaliação dos impactos socioeconômicos correspondentes.
- Visualização e Salvamento dos Resultados: Criação de gráficos ilustrativos e salvamento dos resultados em arquivos CSV para posterior análise.

Aprimorando a Confiabilidade do Modelo

A implementação do modelo incluiu práticas para mitigar os riscos de *overfitting* e *underfitting*. Foi configurada uma taxa de aprendizado baixa (0,002) para permitir um aprendizado gradual e utilizado um número elevado de estimadores (n_estimators=980), garantindo ajustes controlados durante o treinamento. Essas configurações têm como objetivo equilibrar o processo de aprendizado do modelo e reduzir a probabilidade de *overfitting* ao evitar que o modelo seja excessivamente ajustado aos dados de treinamento. No entanto, essas medidas não garantem a eliminação completa de riscos.

Para avaliar a generalização e a robustez do modelo, o código utilizou validação cruzada K-Fold, dividindo o conjunto de dados em quatro subconjuntos (*folds*) e alternando entre fases de treinamento e validação. É uma técnica que identifica se o modelo está aprendendo padrões consistentes ou ajustando-se a subconjuntos específicos. Além disso, métricas de performance como o erro quadrático médio foram calculadas em vários *folds* para avaliar o desempenho do modelo de forma mais ampla e reduzir a influência de divisões específicas dos dados nos resultados.

Essas práticas são aplicadas no código para gerenciar riscos associados ao modelo, mas o tamanho reduzido do conjunto de dados (n=24) apresenta desafios que não podem ser plenamente resolvidos apenas com essas técnicas.

Documentação Comprobatória

Todos os materiais e instruções necessários para a reprodução dos resultados apresentados nesta pesquisa estão disponíveis nos repositórios públicos listados na conta do GitHub (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/tree/main).

- ***Dados sem tratamento das variáveis de entrada e saída*** (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/Raw_Data_Input_Output_Variables.xlsx).
- ***Dados pré-processados e normalizados*** (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/Processed_Normalized_Data.csv).
- ***Script 1:*** O script utilizado para normalização dos dados pode ser acessado em (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/data_normalization_script.ipynb).
- ***Script 2:*** O script para cálculo das estatísticas descritivas dos dados normalizados está disponível em (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/descriptive_statistics_scripts.ipynb).
- ***Script 3*:** O script completo para o treinamento e avaliação do modelo *XGBoost* pode ser encontrado em (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/xgboost_model_pipeline.ipynb).
- ***Script 4:*** O script para otimização da alocação de recursos orçamentários utilizando Otimização Bayesiana está disponível em (https://github.com/Saulo11340/Public_Resource_Allocation_Analysis/blob/main/budget_optimization_pipeline.ipynb).
- ***Script do Dashboard:*** Este script implementa um aplicativo interativo usando Dash para otimizar a alocação de recursos públicos orçamentários, utilizando um modelo de aprendizado de máquina pré-treinado para prever indicadores socioeconômicos, como PIB, inflação e índice de Gini, com base em diferentes alocações de orçamento, permitindo ajustes e simulações em tempo real através de uma interface gráfica.
  Disponível em: (https://github.com/Saulo11340/meu-projeto-dash/tree/main).

- ***Aplicação visual desenvolvida com auxílio da plataforma Render:*** O Render implantou a aplicação Dash, configurando o ambiente, instalando as dependências necessárias e executando o servidor para disponibilizar a aplicação online. Disponível em (https://meu-projeto-dash-7.onrender.com/).

Cumpre esclarecer, ainda, que a simulação foi realizada em um computador com processador *Intel Core* i5-7200U e 8 GB de RAM, operando no sistema *Windows* 10 de 64 bits. Utilizou-se o *Jupyter Notebook*, uma aplicação web para criação e compartilhamento de código e visualizações, instalado via Anaconda, uma plataforma de gerenciamento de pacotes e ambientes para ciência de dados.

RESULTADOS DA SIMULAÇÃO E EVIDÊNCIAS

Parâmetros de Desempenho - Aprendizado de Máquina

Avaliou-se o desempenho do modelo de aprendizado de máquina usando três métricas: erro quadrático médio (MSE), soma dos erros quadráticos (SSE) e coeficiente de determinação (R^2).

Pode-se afirmar, com base em estudos anteriores, que um modelo é considerado adequado se apresenta MSE baixo, indicando precisão nas previsões (James et al., 2023; Kumar et al., 2023; Pu et al., 2023; Segovia et al., 2023). Por sua vez, um SSE reduzido sugere consistência e pouca variabilidade nos erros (James et al., 2023; Valle-Cruz, Fernandez-Cortez, & Gil-Garcia, 2022). Já um R^2 próximo de 1 demonstra que o modelo consegue explicar uma grande proporção da variância observada nos dados (Gao et al., 2023; Hoiem et al., 2020; James et al., 2023; Nguyen et al., 2021).

Resultados do Modelo de Aprendizado de Máquina – *XGBoost*

Para a simulação, os dados foram pré-processados, organizando-se em formato tabular com anos em linhas e variáveis em colunas. Dados faltantes, como os índices de Gini dos anos 2000 e 2010, foram interpolados linearmente, e as entradas de 2023 para PIB (Agência Brasil, 2024), inflação (IpeaData, 2024b) e Gini (IpeaData, 2024a) foram atualizadas com dados do governo federal brasileiro.

Em seguida, os dados foram normalizados com a função `*StandardScaler*` do módulo `*sklearn.preprocessing*` em *Python*, ajustando-os para média zero e desvio padrão 1 (um) (Raju et al., 2020; Singh & Singh, 2020). A divisão dos dados em conjuntos de treinamento e teste foi realizada utilizando a função '*train_test_split*' do '*scikit-learn'*, com uma proporção de 80% para treinamento e 20% para teste, garantindo a aleatoriedade através de um "*random_state*" fixo. Para a simulação, a configuração do modelo *XGBoost* foi feita com os seguintes parâmetros:

- *objective*: reg:squarederror, para regressão com erro quadrático.
- *n_estimators*: 980, que determina o número de árvores a serem construídas.

- *learning_rate*: 0.002, para controlar o impacto de cada árvore individual.
- *random_state*: 42, para garantir reprodutibilidade.
- *n_jobs*: -1, para utilização completa dos recursos de processamento disponíveis.

Esses parâmetros foram selecionados empiricamente, através de ajustes manuais, de forma a alcançar os melhores resultados nas métricas de desempenho (MSE, SSE e R^2).

Especificamente, a divisão de 80% dos dados para treinamento e 20% para teste foi utilizada por gerar a melhor performance, em termos de MSE e R^2, na análise conduzida. Essa abordagem também é exemplificada em aplicações como a predição de ocupações com variáveis demográficas e a modelagem de valores medianos de habitação, destacando seu uso em problemas práticos de aprendizado de máquina (Hastie et al., 2009).

O modelo de aprendizado de máquina *XGBoost* foi utilizado para prever três indicadores socioeconômicos: crescimento do PIB, inflação e índice de Gini, com base em dados da execução orçamentária das despesas, por função orçamentária.

A Tabela 1 apresenta as métricas de desempenho do modelo XGBoost na previsão de crescimento do PIB, inflação e índice de Gini, bem como os valores gerais consolidados. O R^2 geral do modelo foi de 0,69, indicando que aproximadamente 69% da variabilidade dos indicadores foi explicada, enquanto os 31% restantes sugerem a influência de fatores não capturados pelas variáveis utilizadas no modelo.

Ao avaliar os indicadores individualmente, observa-se que o crescimento do PIB apresentou o maior R^2 (0,8789), indicando que essa variável foi a mais explicada pelo modelo. O índice de Gini também apresentou um R^2 relativamente elevado (0,8252), enquanto a inflação teve o menor R^2 (0,3793), sugerindo que o modelo encontra maior dificuldade em capturar os padrões associados a essa variável, possivelmente devido à sua natureza mais volátil e dependente de fatores exógenos não incluídos nos dados.

O MSE geral foi de 0,21, refletindo a média dos erros ao longo das previsões. Entre os indicadores, o MSE foi maior para a inflação (0,3629), enquanto PIB e índice de Gini tiveram valores mais baixos (0,1406 e 0,1366, respectivamente). Isso sugere que os erros relativos às previsões da inflação foram mais expressivos, o que também é refletido no SSE geral de 3,20, que representa o somatório dos erros quadráticos para todos os indicadores.

Esses resultados indicam diferenças na capacidade do modelo de prever os indicadores analisados, sendo que a inflação apresentou maior dificuldade, enquanto PIB e índice de Gini tiveram erros menores. Essas métricas refletem tanto a influência da qualidade e disponibilidade dos dados quanto a capacidade do modelo de capturar padrões complexos e não lineares. A análise sugere que ajustes futuros ou a inclusão de variáveis complementares podem ser necessários para melhorar a consistência das previsões, especialmente para indicadores mais sensíveis a variações contextuais

Tabela 1 - Métricas de Desempenho do XGBoost

Métrica	*GDP growth*	*Inflation*	*Gini index*	Geral
MSE	0.1406	0.3629	0.1366	0,21
R^2	0.8789	0.3793	0.8252	0,69
SSE	0.7032	1.8145	0.6832	3,20

Resultados do Algoritmo de Otimização – *Tree-structured Parzen* Estimator (TPE)

Os resultados obtidos a partir do *script* de otimização oferecem uma outra abordagem sobre a alocação de recursos orçamentários e seus impactos nos indicadores socioeconômicos. O estudo foi executado com 1000 tentativas (*trials*). Para garantir a reprodutibilidade dos resultados, foi utilizado o parâmetro '*seed=42 no sampler'*.

Os resultados socioeconômicos previstos com a alocação otimizada dos recursos, em dados normalizados, foram:

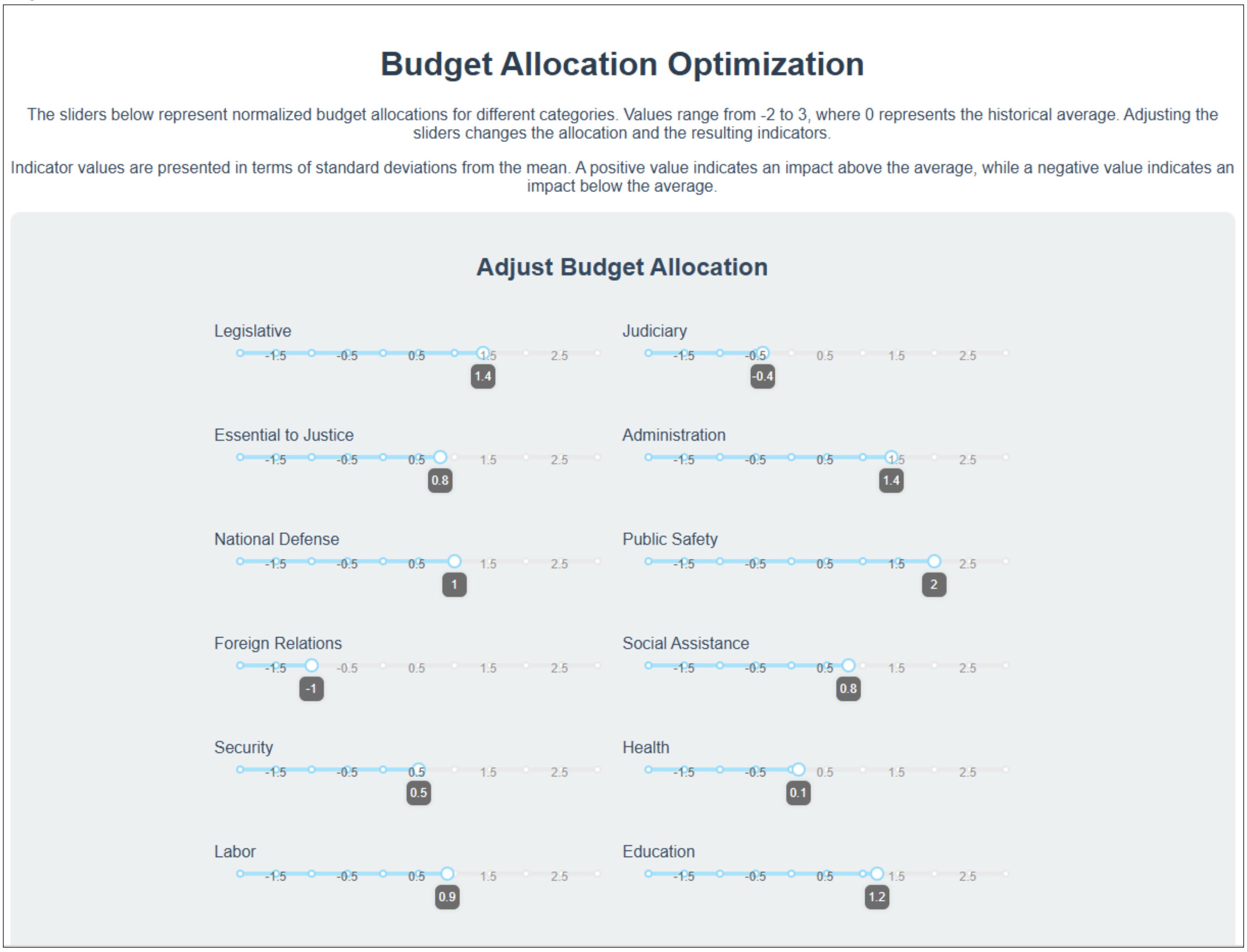
- PIB: 0.98 desvios padrões acima do valor médio.
- Inflação: -1.16 desvios padrões abaixo do valor médio.
- Índice de Gini: -0.75 desvios padrões abaixo do valor médio.

Esses resultados indicam o atendimento do definido pela Função Objetivo: **um aumento no PIB, uma redução na inflação e uma melhora na distribuição de renda, via diminuição do índice Gini.**

VISUALIZAÇÃO

A primeira parte do *Dashboard* **(Disponível em: https://meu-projeto-dash-7.onrender.com/)**, apresentada na Figura 2, contém *sliders* (controles deslizantes) que representam as alocações orçamentárias normalizadas para diferentes funções orçamentárias, como "Legislative", "Judiciary", e "Public Safety". Os valores dos *sliders* variam de -2 a 3, expressos em termos de desvio padrão, em que 0 corresponde à média histórica de alocação. Os ajustes na alocação impactam automaticamente os resultados dos indicadores, como visto na área representada na Figura 4.

Figura 4 - Primeira área do *Dashboard*: Controle Deslizante ajustáveis que simulam a alocação orçamentária

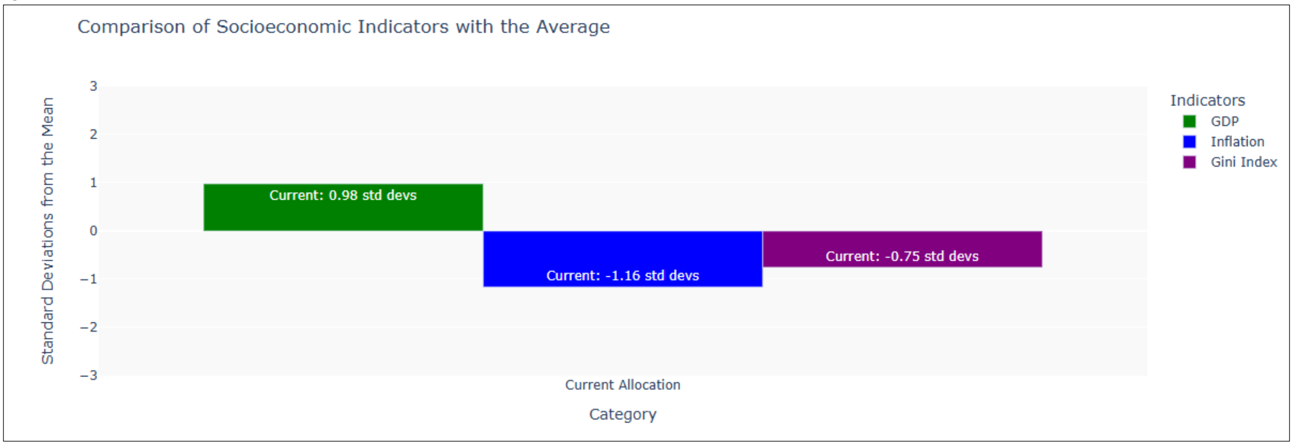


Como visto na Figura 5, a área "*Alternative Scenarios*" permite selecionar, de maneira exemplificativa, diferentes cenários de alocação orçamentária predefinidos (melhor otimização, valores médios, mínimos e máximos), atualizando automaticamente os *sliders* em cada função de despesa. Os resultados dos indicadores (PIB, inflação e índice de Gini) são exibidos em termos de desvios padrão em relação à média histórica. A opção "Best Optimization Result", representada pelo botão verde, mostra o resultado da aplicação do modelo híbrido de IA, enquanto as outras opções fornecem cenários alternativos para comparação.

Figura 5 - Segunda área do *Dashboard*: Cenários pré-definidos e resultados automáticos da alocação nos indicadores

Já o gráfico de barras constante da Figura 6 muda automaticamente conforme os *sliders* são ajustados, exibindo os impactos dos indicadores em relação à média histórica, medidos em desvios padrão. Ele mostra visualmente como as alterações na alocação orçamentária afetam esses indicadores.

Figura 6 - Terceira área do *Dashboard*: gráfico interativo com os resultados dos indicadores ajustados automaticamente



OBSTÁCULOS E LIMITAÇÕES

Ressalta-se que a implementação da IA no setor público enfrenta obstáculos de diversas naturezas. Tecnicamente, os principais desafios incluem a opacidade dos algoritmos, que dificulta a compreensão dos processos decisórios automatizados, e os vieses nos dados, que podem resultar em decisões injustas (Valle-Cruz et al., 2023; Zuiderwijk et al., 2021). Além desses fatores, a complexidade na interpretação dos resultados, frequentemente chamada de "caixa-preta" da IA, também compromete a transparência (Xie et al., 2023; Zuiderwijk et al., 2021).

Na simulação apresentada, com uma série histórica composta por apenas 24 observações anuais (2000-2023), o modelo enfrenta desafios relacionados à robustez estatística e à representatividade dos dados, o que pode comprometer a confiabilidade das previsões e a generalização dos resultados.

Nesse diapasão, a aplicação do aprendizado de máquina requer dados em volume suficiente e de alta qualidade, mas a obtenção de dados orçamentários que atendam a esses critérios ainda é um desafio (Katharina Dhungel et al., 2024). Além desses fatores, a resistência à mudança, a falta de conhecimento especializado e a relutância em adotar novas tecnologias são barreiras significativas à implementação da IA (Valle-Cruz et al., 2023; Zuiderwijk et al., 2021).

Já politicamente, o deslocamento de gastos entre rubricas orçamentárias e a redução da transparência podem ser estratégias políticas deliberadas e conscientes (Katharina Dhungel et al., 2024). Além disso, o processo de decisão política por trás dos valores orçamentários não é evidente a partir dos próprios valores (Katharina Dhungel et al., 2024; Zuiderwijk et al., 2021).

Com relação às limitações específicas do modelo híbrido apresentado, o **XGBoost**, como modelo de aprendizado de máquina, depende fortemente dos dados históricos. Isso implica que erros ou vieses nos dados podem afetar negativamente a precisão das previsões e comprometer a capacidade do modelo de generalizar para novos cenários (C. (Abigail) Zhang et al., 2022; Y. Zhang et al., 2023). Quanto à otimização, a utilização da biblioteca *Optuna* para ajuste de hiperparâmetros pode resultar em variabilidade nos resultados devido à natureza estocástica da otimização, o que pode comprometer a consistência das previsões (Parra-Ullauri et al., 2023). Além disso, o uso de algoritmos de IA, como o *XGBoost*, apresenta desafios de explicabilidade, uma vez que esses modelos funcionam como "caixas-pretas", dificultando a interpretação dos processos de tomada de decisão e limitando a transparência necessária para ajustes e validações em contextos orçamentários complexos (Valle-Cruz et al., 2023; Zuiderwijk et al., 2021).

A precisão dos modelos preditivos depende da qualidade dos dados de entrada, o que pode ser um problema em contextos emergentes, como o brasileiro, em que os dados orçamentários de entrada podem ser inconsistentes (Ghiassi & Simo-Kengne, 2021; Zuiderwijk et al., 2021). Além disso, as despesas públicas são influenciadas por diversos fatores — econômicos, demográficos, sociais, ambientais e políticos — que tornam a previsão orçamentária desafiadora (Ghiassi & Simo-Kengne, 2021).

Por fim, na simulação realizada, os erros observados podem ser atribuídos a limitações inerentes ao modelo e ao contexto dos dados utilizados. A dependência de uma série histórica reduzida, com apenas 24 observações anuais, aumenta os riscos de sub-representação. Além disso, o uso exclusivo de variáveis quantitativas ignora fatores qualitativos e contextuais — como mudanças políticas, econômicas e sociais — que têm impacto sobre os resultados orçamentários. Esses fatores, não modelados, introduzem incertezas e dificultam a generalização das conclusões para novos cenários. Para reduzir esses riscos, seria necessário incorporar dados adicionais, que aumentem a granularidade temporal ou abranjam variáveis qualitativas relevantes, assim como adotar estratégias para mitigar os vieses presentes nos dados históricos. A integração de múltiplas perspectivas é essencial para que as simulações avancem além das limitações atuais, permitindo análises mais confiáveis sobre a alocação orçamentária de recursos públicos.

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CONCLUSÃO GERAL

Esta dissertação articula três estudos interrelacionados: uma revisão integrativa da literatura, um estudo empírico e um PTT, que, em conjunto, abordam a alocação de recursos públicos orçamentários a partir de perspectivas teóricas, empíricas e práticas.

O primeiro estudo realizou uma revisão integrativa da literatura sobre alocação orçamentária de recursos públicos, abrangendo artigos publicados entre 2014 e 2023. A análise identificou áreas de interesse em setores como saúde, sustentabilidade, inovação e gestão fiscal, destacando como as características das funções alocativa, distributiva e estabilizadora do Estado na economia se manifestam nesses contextos. O levantamento revelou ainda uma lacuna específica relacionada ao uso da IA na alocação orçamentária, apontando para a necessidade de estudos que investiguem sua aplicação nesse campo.

No segundo estudo, foi implementado um modelo híbrido de IA para simular cenários de alocação orçamentária no Brasil. Esse modelo combinou o algoritmo *Gradient Boosting*, utilizando a biblioteca *XGBoost*, e um método de otimização baseado no algoritmo TPE. O modelo apresentou um R^2 de 0,69, indicando que explicou 69% da variabilidade nos indicadores socioeconômicos analisados – PIB, inflação e índice de Gini. Entretanto, a análise das métricas de erro demonstrou diferenças de desempenho entre os indicadores, com maior precisão para o PIB e o índice de Gini, enquanto a inflação apresentou erros mais elevados, refletindo sua complexidade e dependência de fatores externos não modelados. O TPE direcionou alocações para setores como "Serviços e Comércio", "Habitação" e "Segurança Pública", indicando potenciais impactos positivos nos indicadores analisados. No entanto, as limitações do modelo requerem uma interpretação criteriosa dos resultados obtidos.

Entre as limitações identificadas, destaca-se a dependência de uma base de dados históricos restrita a 24 observações anuais (2000–2023), consequência da ausência de padronização prévia nas classificações orçamentárias. Essa restrição pode comprometer a robustez estatística e a generalização dos resultados. Adicionalmente, a ausência de pesos diferenciados na função objetivo limitou a capacidade do modelo de priorizar setores estratégicos, e a não inclusão de variáveis qualitativas, como fatores políticos e institucionais, restringiu a abrangência das análises. Erros identificados nas previsões, especialmente para a inflação, sugerem a necessidade de ajustes nos hiperparâmetros e na estrutura do modelo para aprimorar sua aplicabilidade.

O PTT desenvolvido complementa os estudos empírico ao apresentar uma plataforma interativa que permite a simulação de alocações orçamentárias e seus impactos em indicadores socioeconômicos. A ferramenta oferece suporte à análise de cenários, possibilitando ajustes dinâmicos e visualização de resultados de maneira acessível, com o objetivo de auxiliar gestores públicos no processo decisório.

Esta dissertação investigou o uso da IA como ferramenta de apoio à alocação orçamentária no Brasil, contribuindo para o debate sobre sua aplicação no setor público, reconhecendo importantes limitações. Embora os resultados demonstrem o potencial da tecnologia para apoiar a eficiência no uso dos recursos públicos, eles não substituem a análise política nem consideram plenamente variáveis contextuais essenciais. O modelo proposto deve ser entendido como complementar, servindo para auxiliar na tomada de decisões, mas com a ressalva de que sua aplicação requer dados mais abrangentes, ajustes metodológicos e integração com fatores qualitativos. Frisa-se que as limitações percebidas ressaltam a necessidade de pesquisas futuras que ampliem o escopo analítico e considerem a complexidade dos sistemas orçamentários em diferentes contextos.