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From E-budgeting to smart budgeting: Exploring the potential of artificial intelligence in government decision-making for resource allocation

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ABSTRACT

Artificial intelligence has become an important tool for governments around the world. However, it is not clear to what extent artificial intelligence can improve decision-making, and some policy domains have not been the focus of most recent studies, including the public budget process. More specifically, budget allocation is one of the areas in which AI may have greatest potential. Therefore, this study attempts to contribute to this gap in our existing knowledge by answering the following research question: To what extent can artificial intelligence techniques help distribute public spending to increase GDP, decrease inflation and reduce the Gini index? In order to respond to this question, this article proposes an algorithmic approach on how budget inputs (specific expenditures) are processed to generate certain outputs (economic, political, and social outcomes). The authors use the multilayer perceptron and a multiobjective genetic algorithm to analyze World Bank Open Data from 1960 to 2019, including 217 countries. The advantages of implementing this type of decision support system in public expenditures allocation arise from the ability to process large amounts of data and to find patterns that are not easy to detect, which include multiple non-linear relationships. Some technical aspects of the expenditure allocation process could be improved with the help of these kinds of techniques. In addition, the results of the AI-based approach are consistent with the findings of the scientific literature on public budgets, using traditional statistical techniques.

1. Introduction

Traditionally, the role of fiscal policy has been summarized in three interrelated functions: resource allocation, income distribution, and stabilization of the economy (Adler, 2021). The expenditure distribution in the budget should be dynamic because economic events are dynamic. The economic crises, pandemics, inflation, exchange rates, and other factors require fiscal policy in order to achieve economic growth and well-being. In this regard, one of the main problems in public budgeting is to reach the right spending distribution to meet the population's needs. Therefore, it is important to better understand which categories of public spending are or should be priorities for the benefit of society.

Nowadays, AI has become an essential issue on the agenda of governments around the world (Dwivedi et al., 2019; Engin & Treleaven, 2019) due to its potential benefits and positive implications for efficiency, transparency, service quality, and public value (Corvalán, 2018; Valle-Cruz, 2019). However, the AI black box and the lack of explainability of some deep learning techniques could result in lack of trust, inequity, bias, the massive replacement of the workforce (particularly in routine tasks), and the increase in the digital divide (Engin & Treleaven, 2019; Wirtz, Weyerer, & Sturm, 2020). Despite the potential for positive or negative impacts in the use of AI in government, it seems clear that AI techniques could assist in decision-making by supporting public managers and government officials with simulations, new ideas, and innovative approaches to better understand data and the dynamics among multiple variables (Sun & Medaglia, 2019; Valle-Cruz, Criado, Sandoval-Almazán, & Ruvalcaba-Gomez, 2020).

Technology use in government (e-government) has enabled public services delivery through the Internet, fostered efficient capture, process, and report on data, and improved decision-making. However, advances in smart technologies, better informed and connected citizens, and globally connected economies have created additional

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opportunities. Governments have begun to take the concept of e-government to a new level as they realize the power of data and heuristic processing through artificial intelligence to improve their services, interact with citizens, develop policies and implement solutions for the welfare of the community and become a smart government (Gil-Garcia, Helbig, & Ojo, 2014; Harsh & Ichalkaranje, 2015). Smart government is considered one of the key trends that governments are following with the participation of the public and private sectors, as well as NGOs and members of civil society, boosted by technology, like the Internet, Big Data, open data, and AI, bringing the potential to improve planning and decision-making in governments (Mellouli, Luna-Reyes, & Zhang, 2014; Sun & Medaglia, 2019; Valle-Cruz, Criado, et al., 2020).

Budgeting cannot be left behind in this transformation because it is one of the most important financial activities of governments (Ayala, 1996; Buchanan, 2014; Dalton, 2013; Gruber, 2005). Without a comprehensive budget, it is challenging to monitor expenses or develop a growth plan. E-government has allowed reforming the functioning of public administrations (OECD, 2003), and digitalization has also affected the budgetary field. In this regard, scholars have addressed ICT applications used for budgetary functions, procedures, or services throughout the budget cycle (planning, programming, budgeting, appropriations, control, and evaluation of financial resources), using the term e-budgeting (Purón-Cid & Gil-García, 2004). E-budgeting refers to the digitalization of budgetary procedures, as well as the dissemination of open data and Big Data (Sgueo, 2015). It is also expected to develop a better accountability for government institutions (Puron-Cid & Gil-Garcia, 2008). E-budgeting will be more effective if integrated with financial management to achieve good governance (Gamayuni & Hendrawaty, 2020). In this regard, smart budgeting is a systematic process that collects pertinent information and uses algorithmic models to develop a budget. Smart budgeting, including historical data and intelligent algorithms, could make valuable predictions and produce different scenarios to support decision-making (Gil-Garcia et al., 2014).

Puron-Cid (2014) states that smart technologies and data integration are being adopted in complex contexts with unprecedented opportunities and challenges for new democratic forms of society. It seems clear that it is important to explore new methods and technologies, including AI, considering different government functions and programs. Research on public budgeting has evolved into increasingly sophisticated decision models. In a seminal paper, Hollander and Icerman (1991) propose using artificial intelligence techniques as a logical complement to mechanical decision modeling approaches. Dobrescu (2015) analyzed the public budget global output using different statistical and machine learning techniques. Anastasopoulos, Moldogaziev, and Scott (2020) assessed the relevance of organizational context to the budgetary functions of control, management, and planning in public documents in California county, using text mining tools. The authors found that turbulence, munificence, and complexity appear to be essential factors for county budget orientations in the micro-narratives and using untapped information found in the documents analyzed. Valle-Cruz, Gil-Garcia, and Fernandez-Cortez (2020), and Fernandez-Cortez, Valle-Cruz, and Gil-Garcia (2020) analyzed Mexico's public budget through artificial neural networks and genetic algorithms in an attempt to identify budget allocations potentially useful for decision-making. However, these are rare examples, and there is limited research on public budgeting and AI. Given the importance of public budgeting, we argue that more empirical evidence is needed on the potential of AI techniques to improve efficiency, effectiveness, and support government decision-making (Agrawal, Gans, & Goldfarb, 2018; Duan, Edwards, & Dwivedi, 2019; Raibagi, 2020).

Anastasopoulos and Whitford (2019) argued that supervised learning algorithms could be used for various applications in the public administration context when the theory is well-developed or when there is preexisting data that can be leveraged. We argue that this perspective could be extrapolated to the use of other AI techniques. This paper focuses better understanding the allocation of public budget expenditure through the multilayer perceptron and multiobjective genetic algorithms. The guiding research question is: To what extent can artificial intelligence techniques help distribute public spending to increase GDP, decrease inflation and reduce the Gini index? In order to answer this question, this study analyzes the allocation of the public budget expenditures using the World Bank Open Data, which includes 217 countries from 1960 to 2019. The study also provides some recommendations and identifies a few limitations related to the complexity of the public budgeting process. The authors propose a hybrid AI approach, based on the Kurzweil (1999, p. 281) perspective to build an intelligent machine in three easy paradigms.

Therefore, based on an algorithmic approach, this study analyzes the World Bank Open Data related to how certain public budget expenses increase GDP and reduce inflation and inequality (Gini Index). The following section presents our review of recent literature on artificial intelligence applied to decision-making and public budgeting, specifically identifying the inputs (specific expenses) and outputs (certain results) to be used in our AI-based data analysis. The third section describes the methods used in this study, based on a multilayer perceptron and multiobjective genetic algorithms. The fourth section shows and explains the results of the AI-based data analysis, suggesting the importance of a few public budget expenses categories. The fifth section discuss our results and systematically compares them with previous research. It also presents some implications of using AI for the public budgeting planning stage. Finally, the sixth section provides some conclusions, identifies the study's limitations, and suggests areas for future research about this topic.

2. State of the art

This section is twofold. First, we present the recent literature on the artificial intelligence applied to government decision-making. Second, we systematically analyze the existing research in the Web of Science and Scopus related to the study of public budget expenses and their social and economic results. This becomes the basis for the AI-based data analysis to understand the public expenditure categories that increase GDP and reduce inflation and the Gini index.

2.1. *Artificial intelligence into government decision making*

This subsection aims to present existing research related to artificial intelligence applied to government decision-making. AI is the science of knowledge representation and reasoning (Newell et al., 1972). It is known as the ability of a machine to learn from experience, adjust to new inputs, and perform human-like tasks to generate outputs (Russell & Norvig, 2002). Nowadays, AI techniques have become more powerful with the rapid advancement of Big Data technologies and increased computer processing power: government-decision making could benefit from this emerging technology.

The boom in the study of AI in government began in the second decade of the 21st century. Data science, machine learning, robotics, and expert systems are the most frequently mentioned terms. Many practical tools from leading technology providers and articles in top management magazines, like Harvard Business Review and MIT Sloan Management Review, provide strategic and practical guidelines for benefiting from AI. However, there is a lack of research in academia and the impact of AI on government decision-making (Duan et al., 2019). The scientific literature has converged in the study of the potential consequences of AI in different governmental sectors, contemplating the challenges, benefits, risks, ethical aspects, explainability, and trust, as well as intelligent automation and public policies (Sun & Medaglia, 2019; Valle-Cruz, Criado, et al., 2020; Wirtz et al., 2020; Wirtz, Weyerer, & Geyer, 2019). The results support the existence of different AI governance models and policy priorities in countries around the world. Computational power and AI techniques have led governments to rely on machines to perform public functions, for example, social welfare, law enforcement, and to combat the pandemic caused by COVID-19 (Lin & Hou, 2020; Valle-Cruz, Fernandez-Cortez, López-Chau, & Sandoval-Almazán, 2021). Complex statistical algorithms and artificial intelligence tools have started to be used to support decision-making, which has a significant impact on efficiency and accuracy, but with dilemmas in terms of explainability, rights, and obligations of individuals (Liu, Lin, & Chen, 2019). AI models approximate the real world like operations research models, but usually with more precision and detail. In this regard, the potential benefit of AI is based on heuristic searches performed in a more complex and less structured problem space. AI methods extend to all situations represented symbolically, i.e., verbally, mathematically, or diagrammatically (Duan et al., 2019; Simon, 1996).

The new wave of AI has improved the organization's ability in data management to make predictions and pattern recognition (Agrawal et al., 2018; Kassania, Kassanib, Wesolowskic, Schneidera, & Detersa, 2021). AI is positioned as the most important strategic and technological tool for organizations (Panetta, 2018). AI-based systems have the potential to assist decision-makers in identifying relevant criteria, evidence, or particular issues to consider, generating more accurate, consistent, cost-effective, and timely decision-making, as well as decreasing the risk of the decision being overruled due to individual motivations (Hogan-Doran, 2017). The AI functions to support/assist the human decision-makers assistance can be divided into critical situations, second opinion, expert consultant, tutor, and automaton (Bader, Edwards, Harris-Jones, & Hannaford, 1988; Edwards, Duan, & Robins, 2000). AI techniques are increasingly extending and enriching decision support through such means as coordinating data delivery, analyzing data trends, providing forecasts, developing data consistency, quantifying uncertainty, anticipating data needs, providing information, predicting, and suggesting courses of action (Duan et al., 2019; Phillips-Wren & Jain, 2006). AI can empower decision-making. First, by making it possible to use predictive analytics to enable much earlier intervention. Second, by forcing humans out of the loop, outperforming them in an increasing number of domains. Third, by providing correct but challenging to explain advice. Fourth, in the short term, driving unprecedented rigor in decision-making processes, forcing decision-makers to be more explicit about the mental models on which they base their decisions, enables comparison with automated analytics (Dear, 2019).

Davenport and Ronanki (2018) examined 152 artificial intelligence implementation projects, classifying artificial intelligence applications into three categories: 1) Cognitive Process Automation: automation of administrative and financial back-office activities. 2) Cognitive insights: patterns detection in data and interpretation of their meaning using statistics-based machine learning algorithms. 3) Cognitive engagement: engaging employees or customers (or both) through natural language processing chatbots, intelligent agents, and machine learning. Duan et al. (2019) examined AI functions using the three organizational decision-making levels (strategic, tactical, and operational decisions). They found that expert systems in a surrogate role are effective at the operational and tactical decision levels but have limitations at the strategic level. In addition to the fact that a support role can help users make better decisions at all three decision levels, but their effectiveness can only be fulfilled through their users. An expert system acting in a support role does not necessarily save the user's time, but an expert system in a replacement role improves decision-making efficiency. AI can help employees in organizations make better decisions by boosting analytical skills and increasing creativity (Daugherty & Wilson, 2018). AI can help government agencies solve complex public sector problems (Dhasarathy, Jain, & Khan, 2020). Although algorithms are becoming an important tool for policymakers, little is known about how they are used in practice and how they work, even among the experts charged with using them. Policy decision-making is increasingly deferring to algorithms, but surprisingly little is known about how this quantification is used in practice (Kolkman, 2020a).

Raibagi (2020) presented some examples of AI-based government decision-making. The first case is related to the Japanese government considering using AI for rapid policy decision-making with the exploitation of big data. Japan has started basic research and planning to implement policy decisions based on artificial intelligence for national strategies, such as defense, national security, business management, and controlling the spread of the novel coronavirus (Jiji, 2020). Also, one in three councils in the UK uses computer algorithms to help make decisions about benefit claims and other welfare issues (Marsh, 2020). Even in the US, several public organizations, including the Army Research Laboratory, Food and Drug Administration, and Centre for Disease Control, have also collaborated with Palantir, a silicon-valley-based data science company (Gordon, 2020).

Moreover, state governments in India use applications based on AI to locate hotspots that will help them in decision-making processes to control crime (Basu et al., 2018). Besides, they are using AI in education to monitor children and dedicate student-centered attention to identifying and curbing school dropouts (Pant, 2019). These algorithmic models are a subset of algorithms used in policy-making (Valle-Cruz, Criado, et al., 2020).

Kleinberg, Ludwig, Mullainathan, and Obermeyer (2015) discuss the policy implications that the application of machine learning techniques can have. For example, rulings in the criminal justice system depend on predicting the likelihood that the detainee will commit a crime. In regulation, they are guiding health inspections, among others. Related to labor market policy, the length prediction of the unemployment period helps workers decide on savings rates and job search strategies. In the public budgeting context, AI can help decide public spending categories and understand some consequences of such allocation on social welfare and economic growth. AI can make public spending more efficient. By creating scenarios and simulations, it may be possible to foresee the effects of a given allocation of public spending to improve government decision-making. In this regard, Kolkman (2020b) mentions that AI is used to forecast the future situation of the Dutch economy considering existing government policy. These forecasts are used as a legal basis for the Dutch government budget, subject to uncertainty. Considering this, AI has the potential to analyze data related to some government actions and economic growth, as well as evaluate some events that can affect public spending allocation. Some AI techniques can explore a large amount of data and find patterns to detect similar/different situations useful for budget allocation assistance.

As can be seen, for some, AI offers a transformative potential, as the first industrial revolution, for the augmentation and potential replacement of human tasks and activities across a wide range of industrial, intellectual, and social applications. Algorithmic evolution manifests itself with new advances in algorithmic machine learning and autonomous decision-making, creating new opportunities for continuous innovation (Dwivedi et al., 2019). Besides, the most recurrent technique in the studies investigated is artificial neural networks, which provide positive results in several application areas (de Sousa, de Melo, Bermejo, Farias, & Gomes, 2019). However, there is a need to analyze the application of AI techniques in the public sector, due to AI in government is widespread and underexplored. Although empirical studies are rising, there is a gap in studying the consequences and potential benefits of AI techniques for decision support in the public sector.

2.2. Public budget expenses and results

Public budgeting depends on public policies and adequate decision-making to have an impact on the economy and society. Different disciplines have studied public budgeting, such as economics (Baumol, 1967; Musgrave & Musgrave, 1984), political science (Gruber, 2005; Wildavsky & Caiden, 1988), and organization theory (Gil-García & Luna-Reyes, 2003). Spending review is, after all, the systematic search for areas where public spending can be cut. In this context, designing good spending review processes is essential (Robinson, 2014).

Over time, budgeting has undergone changes generated by the objective pursued. According to Schick (2014), there are three systems for deciding budget allocations:

1. Presentational: performance information is published in the budget but is not inputted into spending decisions.

2. Performance informed budgets (PIB): there is no prescribed or automatic link between performance and decisions, but performance information is considered in formulating the budget.

3. Direct public budgeting: budget allocations are based on actual or expected performance.

Theoretical approaches to budgeting have had varying degrees of impact on capital budgeting. In recent years, a trend has emerged towards comprehensive rational budgeting (conceptually similar to its predecessors). However, advances in capital budgeting have come primarily in increasingly sophisticated project selection/evaluation techniques and expanded notions of rationality (Hollander & Icerman, 1991). In this regard, AI has the potential to be a tool to support the allocation of public budget expenditure and examine the possible socio-economic consequences and effects.

Public budgeting involves knowledge of socio-economic conditions, public policies, and assertive decision-making. Socio-economic factors refer to macro variables related to a country or state's economic, demographic, and social conditions, also called environmental factors. Gross Domestic Product (GDP) per capita and the unemployment rate are the most widely used variables to measure economic conditions: the former indicates average productivity, and the latter indicates the overall quality of the economy. GDP per capita is positively associated with government spending (Tang, 2020). GDP represents the economic growth of a country and is affected by public spending. One way to understand GDP is the consumption by households and non-profit institutions, investment by firms and families, final consumption expenditure by the public sector, and exports minus imports. These series of chained events are called the "multiplier effect" and depend, fundamentally, on the propensity of spending of individuals and companies since an increase in government spending implies that both production and aggregate demand increase (Baumol, 1967; Ono, 2011). In contrast, inflation is generated by the abuse of policies that promote public spending, producing recession periods (Anderson, d'Orey, Duvendack, & Esposito, 2018). High inflation creates uncertainty about the future course of monetary policy, which adversely affects on domestic investment and foreign capital inflows; inflation also influences some other long-term economic growth determinants and the public budget allocation (Barro, 2013). This section presents some important inputs and outputs of the public budget process, resulting from the systematic literature review in Web of Science and Scopus (See Appendix A).

2.2.1. *The inputs: public budget expenses*

Development experts, advocacy organizations, researchers, and academics express their ideas on how to allocate public resources, and it is through the satisfaction of competing needs, based on the assumption that those who make decisions on the allocation of funds generally seek to maximize welfare, considering resource and information limitations (Mogues, 2015). The percentage of spending in the agricultural sector sheds light on how spending choices manifest themselves in public goods and services (Mogues, 2015). Hence, capital investment and the introduction of advanced technology in agriculture are good options for reducing inequality. The lack of capital is causing the labor force focused on this sector to migrate to the non-agricultural sector (Marsh, 2015). On the other hand, the saving rate indicates a country's capacity to finance the government's budgeted expenditures and shows the relationship between debt and income (Wang & Alvi, 2011). In this regard, Leiderman and Razin (1991) analyzed the factors that determine the evolution of savings to estimate the parameters that govern it. Their findings show that the incentive that raises savings is the rate of return contributing to improving the balance of external and domestic wealth.

Regarding investment in education, it is argued that good budgetary and financial management is positively related to efficiency scores of public spending focused on education (Fonchamnyo & Sama, 2016). Dragomirescu-Gaina (2015), based on Baumol's model, concluded that there is a relationship between education and economic development in the European Union. Their findings show that political commitment has been a determinant of the dynamics of public spending on education in Europe (Tang, 2020). Wang and Alvi (2011) used the secondary school enrollment rate to measure the level of education, finding that higher educational attainment is associated with greater efficiency of public spending and thus better economic conditions. In turn, Crenshaw (1992) argued that education provides individuals with the qualifications and skills needed to enter occupations in the modern economy, resulting in economic growth. Afonso, Schuknecht, and Tanzi (2010) stated that better education and institutions allow for better monitoring and control over the effectiveness and efficiency of public spending and more equitable distribution of revenues for certain public sector expenditures. Likewise, as measured by the average number of years of schooling in society, the improvement of human resources has a strong negative linear effect on educational inequality (Marsh, 2015). Thus, nations with higher levels of education show greater well-being and lower inequalities.

The population growth rate substantially affects the per capita spending that grows at the same rate or faster than the population (Aladejare, 2020). For this reason, fiscal authorities should incorporate population growth as a decision factor in budget planning. Another endemic problem linked to overpopulation is poverty. Population growth continues to be a condition for inequality and increases public spending (Marsh, 2015), hindering economic growth. Consequently, it is necessary to evaluate the efficiency of income distribution measures and improve the efficiency of public spending through the correct distribution of the public budget. In this regard, socio-economic vulnerability, uncertainty, and political economy considerations contribute to the government's funding decisions (Karim & Noy, 2020).

Public health influences social and economic conditions. In this regard, good budgetary and financial management is positively related to public spending and health sectors (Fonchamnyo & Sama, 2016). However, budget allocation in public health is narrow and not always aligned with policy-making efforts for the well-being of the population as a whole and health equity (McLaren & Dutton, 2020). They affirmed about negative consequences of not investing in preventing and protecting health emergencies, such as the pandemic caused by COVID-19. Several historical examples show that public health infrastructure was mobilized reactively and then decreased the amount allocated to this item, forgetting the negative consequences of potential pandemics. For this reason, health policies should focus on more significant investment in disease prevention, health promotion, and well-being.

McCausland and Theodossiou (2015) argued that when businesses recognize that the government's balance sheet is improving and public debt is decreasing, it is created greater confidence in the country's economic prospects, increasing investment. Government expenditures are necessary for normal government operations. This condition encourages economic growth and the path to economic recovery. However, the decline in public spending does not lead to a decrease in public debt as a percentage of GDP, implying that fiscal austerity exacerbates the lack of demand and deteriorates, rather than improving the prospects for economic recovery (De Haan & Sturm, 1997). Another significant budget expense is public safety. In this regard, Heim (2016) argued that government policies for stimulating the economy through tax cuts and decreased government operating expenditures are unlikely to improve the economy or reduce unemployment. In fact, such policies may make the situation worse, especially in recessions. Wassmer, Lascher, and Kroll (2009) gathered evidence that personal happiness and well-being can be increased by improving the percentage of the public budget-oriented to public safety. However, Russo and Verzichell (2016) found that changes in government ideology and political priorities are related to public spending on welfare and defense.

Subsidies and transfers are conceptualized as government grants, donations, and other benefits that include non-counterpart transfers. They are not reimbursable in current accounts to private and public enterprises; donations to foreign governments, international organizations, and other government units; and social security, welfare, and employer social benefits in cash and in-kind (The World Bank, 2020). Resources are considered part of the public expenditure budget and potentially affect economic growth as they are received. Moreover, the GINI index has been used to assess the equality of income distribution measures, which considers the following variables: social spending, transfers, and subsidies, spending on pensions, health and education, and fiscal and institutional indicators (Afonso et al., 2010).

Another part of the public budget expenditure is allocated to unemployment, which is considered an expense to increase the welfare of society. Fraile and Ferrer (2005) proposed two elements to explain public support for unemployment benefit cuts. The first is the specification of the institutional characteristics of the welfare regimes: the generosity of the protection against unemployment, while the second represents a structural characteristic of the policies considered: the seriousness of the unemployment problem. Furthermore, Wang and Alvi (2011) argued that the unemployment rate could represent the impact of the economic cycle on public expenditure. Meanwhile, Jensen (2012) suggested increasing welfare by increasing unemployment protection programs, family services, and old-age pensions.

2.2.2. The outputs: public budget results

According to Aladejare (2020), government revenues, the inflation rate, the exchange rate, the growth rate of the gross domestic product, and the international price of oil are affected by public budgeting allocations. The population growth rate substantially affects the per capita public expenditures, resulting in economic growth and inflation. Wang and Alvi (2011) mentioned that the per capita GDP indicated the country's degree of development and stated that higher income levels lead to better fiscal efficiency. Despite the theoretical foundation of the Keynesian multiplier effect, Heim (2016) found that the decrease in public spending has no statistically significant impact on GDP in times of no recession. However, adequate distribution of public spending reduces inflation and fosters economic development. Thus, growth in public spending results from increased government revenues, higher oil prices, and currency depreciation (Aladejare, 2019). In this regard, Fonchamnyo and Sama (2016) stated that it is necessary to stabilize the prices of goods and services to promote the economy, stability, and, therefore, public spending efficiency.

Crenshaw (1992) affirmed that economic growth, with its corresponding specialization and concentration of wealth among elites, is expected to benefit an entire national population since the elites provide the infrastructure that fosters the economy, benefiting many people. However, societies with less income inequality are much more economically developed than those with greater inequality, a situation that leads to an assessment of the efficiency of income distribution measures. The GINI index measures income distribution and provides evidence that the efficiency of public spending in income distribution is linked to the well-being of countries that make better use of public money to equalize income (Afonso et al., 2010). Facchini (2018) analyzed the literature on the determinants of public spending. The analytical consequence of this result is the excellent futility of the search for a general law of the dynamics of public spending, finding that it is not possible to do so through quantitative methods. A careful reading of the literature on the elements of public expenditure has led to a skeptical attitude regarding the predictive capacity of econometric models, considering the use of variables such as the GINI coefficient to describe society's welfare and make decisions about the distribution of public expenditure. In this regard, Marsh (2015) analyzed the variation of the GINI coefficients of 142 developing countries and obtained, as a result, that Kuznets' inverse relationship between economic development and inequality, understood as a cross-cutting relationship, is still valid, more than fifty years after it was first formulated.

Public budgeting is essential to understand public spending, as it affects economic growth. However, there are no strong arguments about the impact of public spending on economic performance due to circumstances in which low levels of public spending improve economic growth and other circumstances in which a higher level would be desirable (Mitchell, 2005). In general terms, decisions about public budgeting are fundamental for changing public spending, creating a multiplier effect (Ono, 2011) that results in economic growth or inflation. If government spending reduces helps and the unemployed gain jobs, they will have more income to spend, further increasing aggregate demand. In this spare capacity situation, government spending would potentially cause an increase in GDP. On the other hand, if all the economy's resources are occupied, there will be no momentum, producing higher inflation (Lin, 1994).

The analysis of public budgeting, from a classical approach, is coherent and clear. Based on the inputs and outputs of public budgeting, identified in the state of the art, this paper proposes an AI-based approach to identify which public spending categories could increase GDP, decrease inflation, and reduce the Gini index. Although some previous research addresses the application and implications of AI in public budgeting, this paper attempts to break new ground by applying a hybrid AI approach to public expenditure categories, potentially guiding decision-making at the beginning of the budget planning process. Summarizing public budget expenditures (inputs) and results (outputs), Fig. 1 shows the dynamic of the public budget inputs and outputs used in the AI-based analysis to allocate the public budget. From an algorithmic approach, the public budget's elements (inputs and outputs) are consistent with the basic functioning of computational systems, explaining how budget expenditures are processed (public budget allocation) to generate economic, political, and social results.

3. Methods

Breiman (2001) argues that there are two streams in using statistical models to draft conclusions from data. One assumes that the data are generated by a given stochastic data model, while the other uses algorithmic models and treats the mechanism of the data as unknown. This paper is based on the latter and the Kurzweil (1999, p. 281) approach, related to building an intelligent machine in three easy paradigms: recursion, neural networks, and evolutionary algorithms. For this reason, this section outlines the AI techniques used to analyze World Bank Open Data. The first part describes the artificial neural networks technique (particularly the multilayer perceptron). In this study, multilayer perceptron weights are used to design the fitness equations of the multiobjective genetic algorithm. The second part shows the evolutionary algorithm approach based on a multiobjective optimization. The aim here is to identify the public budget allocation to increase GDP, decrease inflation and inequality (GINI Index). The third part describes the hybrid AI approach for the data analysis process to perform a series of experiments that recursively lead to the study results.

3.1. The multilayer perceptron

Artificial Neural Networks (ANN) solve problems by simulating the human brain's behavior in an abstract and straightforward model. ANN can learn to perform certain tasks by training. ANN is the basis of machine learning. Some specific applications of ANNs relate to the design of predictive models, regression, recognition, pattern detection, classification, and the importance of explanatory variables (Anthony & Bartlett, 2009; Basheer & Hajmeer, 2000; Garson, 1991; Russell & Norvig, 2002). ANN does not need a priori modeling and inherently generates results with the simultaneous interaction of the input variables on the output variables (Azuaje, 2019; Jordan, 2019).

ANN is made up of processing elements called neurons that work together to solve a specific problem and are based on the mathematical model of McCulloch and Pitts. There are several connections between

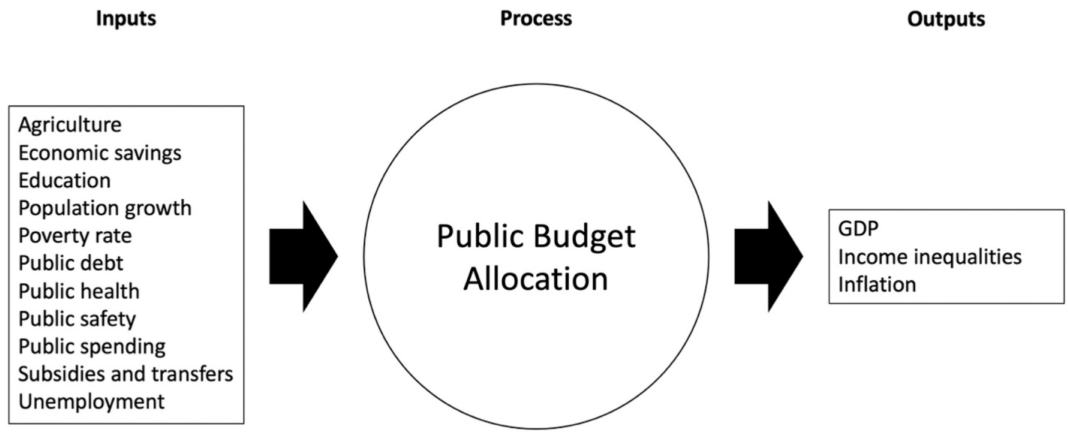


Fig. 1. Dynamics of the public budget inputs and outputs.

the different neurons within the ANN that make them up. These connections are established with different levels of intensity called synaptic weight (synapse), where each x_i input of a neuron is affected by a w_i weight. Each neuron receives a set of inputs and returns an output (Hopfield, 1988; McCulloch & Pitts, 1943; Negnevitsky, 2005). The activation of a neuron (a) is calculated as the weighted sum of the inputs:

$$a = \sum_{i=1}^{D} w_i x_i + w_0$$

where w_0 is a threshold or bias used to compensate the difference between the average value of the inputs. The output of the neuron (y) is then calculated from the value of a through activation or transfer function $g(a)$. There are different activation functions; among the most used are identity, step, sigmoid, hyperbolic tangent, and gaussian.

$$y = g(a)$$

The number of neurons in an ANN and how they are interconnected is called the topology or architecture. To measure the prediction error (E) between the difference of the calculated output (y^n) and the desired output (t^n) for each learning example n is determined by the mean square error:

$$E = \frac{1}{N}\sum_{n=1}^{N}(y^n - t^n)^2$$

The neural network trivial architecture is the simple perceptron. It is impossible to solve complex classification problems or implement functions with a higher degree of complexity with a simple perceptron. With the desired degree of accuracy, more complex functions can be implemented by adding more intermediate layers between the input and the output layers of ANN. The intermediate layers make a projection in which the input patterns are linearly separable. This way, the output unit can perform a better data classification or prediction (Minsky & Papert, 1969). Fig. 2 shows a multilayer perceptron architecture, which includes one or more intermediate layers of processing units, also called hidden layers.

The goal of machine learning is to estimate a function of the data that will make optimal predictions about some outcome (Anastasopoulos & Whitford, 2019). The multilayer perceptron defines, through its connections and neurons, a function where the y_j depend on the x_i simultaneously:

$$\boldsymbol{Z} = F(\boldsymbol{X}, \boldsymbol{W})$$

where:

$\boldsymbol{X}$ contains the n inputs of the ANN (x_i).
$\boldsymbol{Y}$ contains the m outputs of the ANN (y_j).
$\boldsymbol{W}$ represents the calculated weights of each layer.

$\boldsymbol{Z} = F(\boldsymbol{X}, \boldsymbol{W})$ is a matrix containing the relationship between inputs and outputs (applying matrix algebra).[1]

The weights connecting the variables in an ANN are similar to the coefficients of the parameters in a standard regression model. They can be used to describe the relationships between variables. However, ANN has an excessive number of weights, making ANN more flexible in modeling linear and nonlinear functions with multiple interactions (Garson, 1991). The relative importance of explanatory variables for particular response variables in a supervised ANN can be realized by deconstructing the model weights. This way, the relative importance of an explanatory variable to a response variable can be determined by identifying all the weights that connect an input node to a response variable. The connections are counted for each input node and scaled relative to all other inputs, thus yielding a single value for each explanatory variable that describes the relationship to the response variable in the ANN model (Garson, 1991; Goh, 1995).

3.2. Multiobjective genetic algorithms

Genetic algorithms (GA) are a type of evolutionary and metaheuristic search algorithms based on the theory of biological evolution developed by Charles Darwin. GA approaches the best solution inspired by the adaptive and evolutionary behavior and can provide feasible or near-optimal solutions (Swarnkar & Swarnkar, 2020). The main use of GA is to solve optimization problems and work based on adaptive processes in natural systems, find solutions in complex adaptive spaces, and use stochastic methods. Some advantages of GA are that it is not necessary to establish specific knowledge about the problem they are trying to solve. They are less affected, compared to traditional techniques, by local maxima (false solutions). However, depending on the configuration of their genetic parameters, they can take a long time to converge, fail to converge, or converge prematurely (Floreano, Mattiussi, & Arkin, 2008; Mitchell, 1998). GA requires fitness functions to optimize each generation's individuals to find a satisfactory solution (Mitchell, 1998; Yu & Gen, 2010). Designing a fitness function is often a complicated process. The total genetic package is called genotype. The interaction of the genotype with its environment is called phenotype and results in decoding the chromosome to obtain an alternative solution (Michalski, Carbonell, & Mitchell, 2013; Russell & Norvig, 2002).

$$X_i^t = \left(c_i^t, x_i^t, f_i^t\right)$$

where x_i^t is the decoding (phenotype) of the c_i^t chromosome and the f_i^t is the adequacy of the solution to the environment or fitness. The algorithm begins by creating a random population whose individuals are

[1] The calculation of Z is explained in section 4.

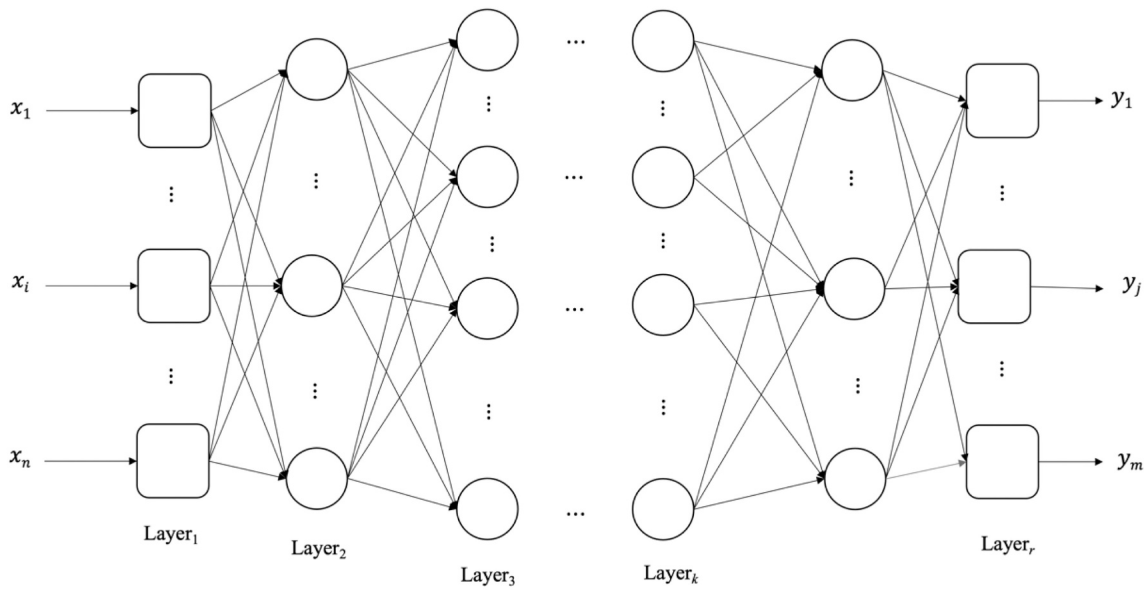


Fig. 2. Multilayer perceptron.

evaluated through the matching function, which usually coincides with the optimization problem's objective or fitness function. The algorithm is an iterative process, where a selection process of the best individuals of each generation is made. The iterative process ends when a termination condition is reached, depending on the number of generations or the error level between the new and previous generations (Floreano et al., 2008; McCall, 2005) (See Algorithm 1 in Appendix B). Many optimization problems are multiobjective in nature and contain functions that must be simultaneously satisfied with multiple optimal solutions and with constraints:

$$Optimize\, f_i(\vec{x}), i = 1, \cdots, n$$

$$subject\ to\ lower\ limit \leq g_j(\vec{x}) \leq upper\ limit\ j = 1, \cdots, m$$

The NSGA-II algorithm is a non-dominated sorting GA with elitism and an explicit diversity mechanism to solve multi-equation optimization problems. From a P_t population, a new population of Q_t descendants are created by applying binary tournament selection by fronts and niche, and the evolutionary operators of crossing and mutation. These two populations are mixed to form a new R_t population of size $2N$ ($N=$ size of the P_t population). The new $P_t + 1$ population is obtained from the R_t population, from which the best N individuals survive after applying fronts and niche sorting (Deb, Pratap, Agarwal, & Meyarivan, 2002; Dhanalakshmi, Kannan, Mahadevan, & Baskar, 2011; Zhou, Cao, Kosonen, & Hamdy, 2020) (See Algorithm 2 in Appendix B). The binary tournament selection based on fronts and niche compares two solutions and returns the best one according to the non-dominance and niche operator. Similarly, front and niche sorting, order individuals according to the conditions set by the non-dominance and niche operator (Deb et al., 2002; Wang, Zhao, Yuan, Li, & Gao, 2019).

3.3. Data analysis process using artificial intelligence techniques

This research proposes a mixed or hybrid AI approach, combining the advantages of ANN and GA, applied to the analysis of public budget allocation. We used the ANN weights to generate the multiobjective optimization equations for the GA (Garson, 1991). In this regard, data analysis consisted of seven steps supported by the R programming language.

First, due to the literature review on public budgeting inputs and outputs, we downloaded data related to each country's public budget expenses and social and economic conditions from the World Bank Open Data from 1960 to 2019 (The World Bank, 2020). Data included variables related to the government expenditure, research and design investment, government debt, education investment, agriculture, unemployment, government saving, population growth, poverty, commerce, public health, military investment, GDP growth, inflation, and the Gini Index. These data were used to design the multilayer perceptron to explore the effect of different public budget expenses on three social and economic results (GDP growth, inflation, and the Gini index).

Second, the World Bank Open Data can be downloaded in a non-tidy or wider format, where each year is a column, which makes it difficult to analyze. For this reason, the data were transformed to tidy or long format, where each year is transformed into a row. In this way, we obtain one observation for each year, each country, and each category.

Third, to design the AI-based model, we cleaned and normalized the data. Firstly, we grouped the data into a tidy format by country and category. Next, we identified and transformed the values into the corrected numerical format. Finally, we replaced all null values with the minimum value of the series to perform the calculations without errors or missing values.

Fourth, we used the cleaned and normalized data to test different multilayer perceptron architectures, with 70% of the data for the training phase and 30% for the test phase. We performed a standard score normalization for each of the variables of the World Bank Open Data. As a result, we obtained values without any type of scale, with a mean equal to zero and a standard deviation equal to one, which can be combined and operated for calculations in any mathematical model.

Fifth, we designed the fitness functions for the multiobjective genetic algorithm, applying matrix algebra to the resulting weights of the multilayer perceptron. Different multilayer perceptrons were tested to find the model with the lowest mean square error (as a goodness-of-fit measure).

Sixth, we performed different experiments with multiobjective genetic algorithms until we found the most feasible solution. Czarn, MacNish, Vijayan, Turlach, and Gupta (2004) explored some adjustments for genetic parameters. In this regard, we took advantage of ANN learning and the metaheuristic optimization of multiobjective genetic algorithms to find the public budget allocation.

Finally, we analyzed the results and interpreted them based on the state of the art of public budget expenses and results (Fig. 3).

4. Main results

Twelve different multilayer perceptron architectures were tested with the cleaned and normalized World Bank Open Data from 1960 to 2019 (See Appendix E for descriptive statistics of the data), based on the possible options when combining different activation functions. The architecture selected was number 6. This multilayer perceptron has a hidden ($\omega_{n\ h}{}^{hidden}$) and an output layer ($\omega_{h\ m}{}^{output}$), and it was selected due to the sum-of-squares error during training and testing and by the non-linear activation function in the layers: sigmoid (Table 1).

To establish the most feasible proportion of the public budget elements, ANN allows us to consider the simultaneous effect of all public budget expenses on the GDP growth, inflation, and the Gini index. At this stage, we found that in the selected multilayer perceptron model, the public budget expenses that have the most significant impact on the GDP growth, inflation, and the Gini index are poverty, population growth (as a control variable for increasing public spending), agriculture, and public debt. Other crucial public budget expenses are economic savings, education, public safety, and subsidies in the second stage. When considering our three social and economic results, public health, unemployment, and public spending were the least important public budget expenses. Nevertheless, these results do not mean that these public budget expenses do not affect GDP growth, inflation, and the Gini index or that they are unimportant. Fig. 4 shows the selected multilayer perceptron architecture; the calculated weights between each of the neurons in each layer are shown in Appendix D, which explains the activation of each neuron.

Based on Anastasopoulos and Whitford's (2019) perspective on the estimation of data functions for machine learning analysis and the relative importance of explanatory variables over response variables in ANN weights, proposed by Garson (1991), we designed the fitness functions. To achieve this, we calculated the activation of each input ($\boldsymbol{X}$) on the outputs ($\boldsymbol{Y}$) of the multilayer perceptron, based on matrix algebra. We calculated the matrix product between the weights of the hidden layer ($\omega_{n\ h}{}^{hidden}$), with the weights of output layer ($\omega_{h\ m}{}^{output}$) (for ANN weights, see Appendix D):

$$\boldsymbol{\omega}_{n\ h}^{\mathbf{hidden}} \times \boldsymbol{\omega}_{h\ m}^{\mathrm{output}}$$

obtaining the simultaneous effect or weighting of the n input variables on the m output variables (Table 2):

$$\boldsymbol{Z} = F(\boldsymbol{X}, \boldsymbol{W}) = \boldsymbol{\omega}_{n\ h}^{\mathbf{hidden}} \times \boldsymbol{\omega}_{h\ m}^{\mathrm{output}}$$

where:

$\omega_{n\ h}{}^{hidden}$ is the weight matrix of the hidden layer, with n rows and h columns.

$\omega_{h\ m}{}^{output}$ is the weight matrix of the output layer, with h rows and m columns.

The calculated values of the effect of the input variables ($\boldsymbol{X}$) on the

Table 1
Multilayer perceptron architectures tested.

Test*	Hidden layers	Activation function (hidden layer)	Activation function (output layer)	Sum-of-squares error (training)	Sum-of-squares error (testing)
1	1	Hyperbolic tangent	Identity	396.72	173.11
2	1	Hyperbolic tangent	Hyperbolic tangent	1630.88	703.55
3	1	Hyperbolic tangent	Sigmoid	434.20	188.19
4	1	Sigmoid	Identity	389.50	155.95
5	1	Sigmoid	Hyperbolic tangent	1549.35	659.44
6	1	Sigmoid	Sigmoid	366.92	158.37
7	2	Hyperbolic tangent	Identity	390.13	165.67
8	2	Hyperbolic tangent	Hyperbolic tangent	1484.97	640.66
9	2	Hyperbolic tangent	Sigmoid	403.81	182.78
10	2	Sigmoid	Identity	394.92	169.26
11	2	Sigmoid	Hyperbolic tangent	1517.03	621.64
12	2	Sigmoid	Sigmoid	374.62	165.61

Source: Authors' elaboration.
* 70% of the data were used for training and 30% for testing.

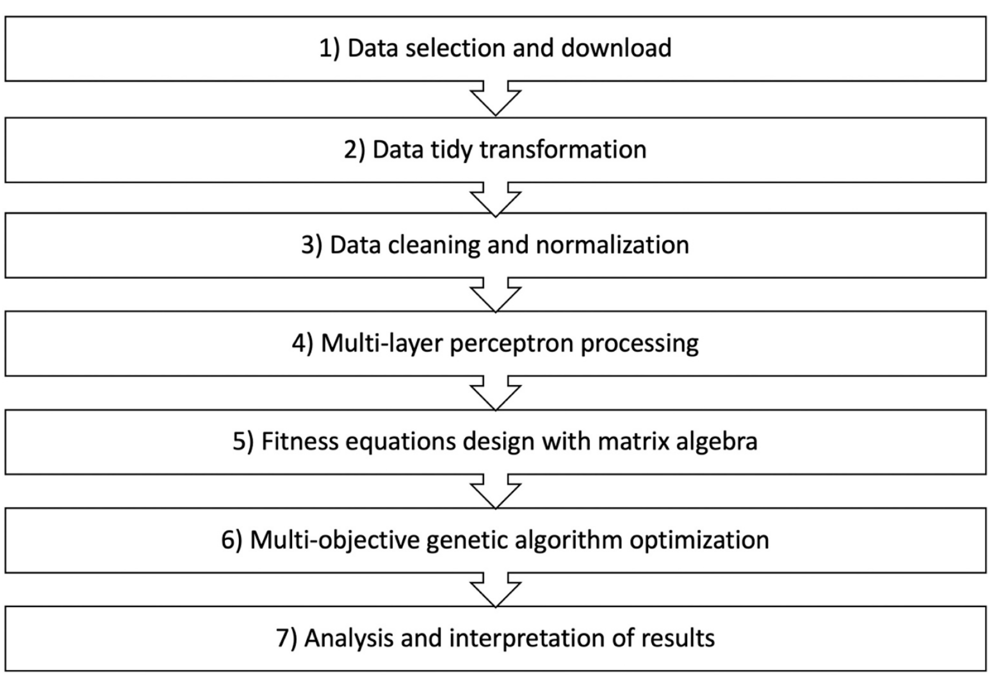


Fig. 3. Data analysis process with artificial intelligence techniques.

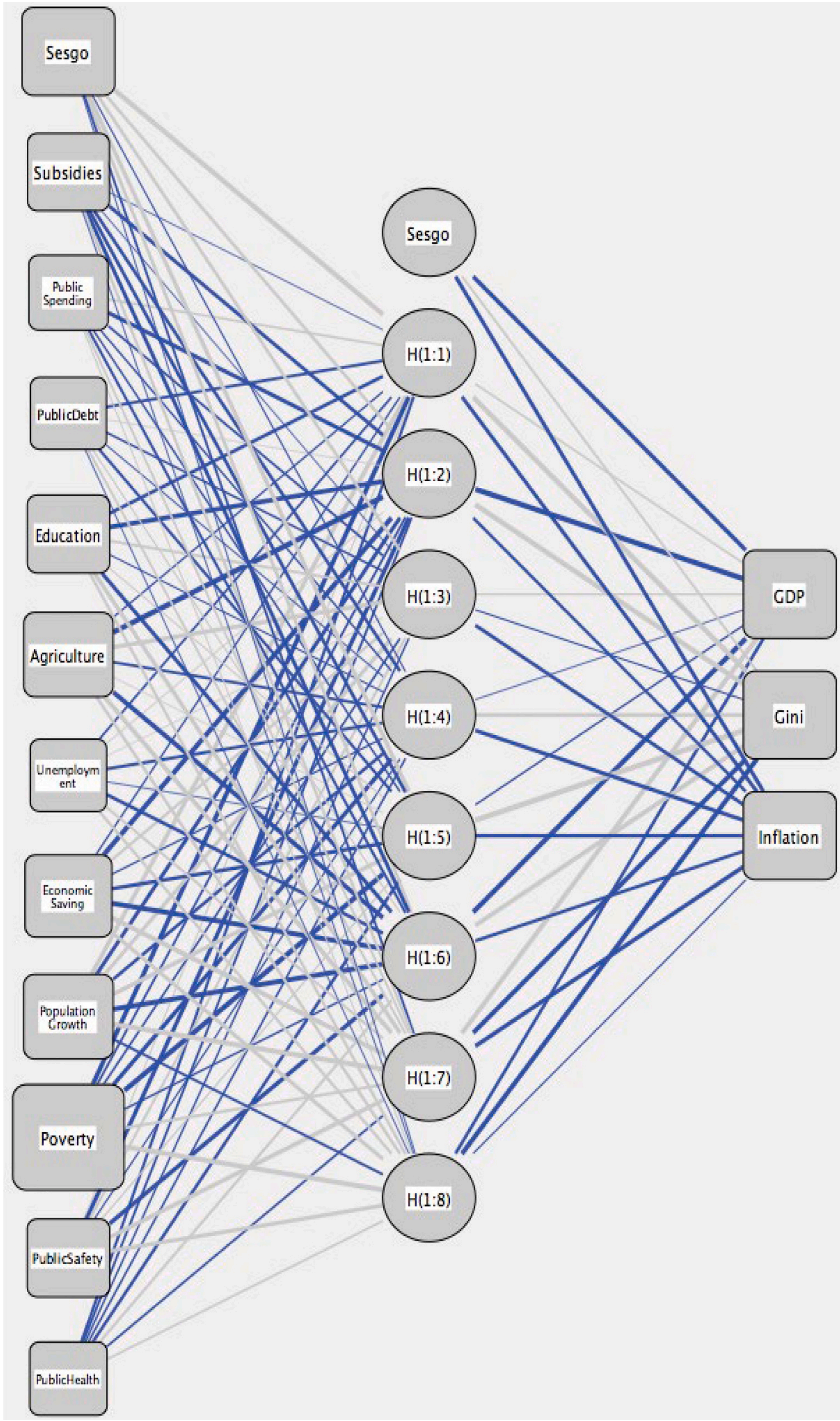


Fig. 4. Multilayer perceptron to design fitness functions. [Activation function in layers: sigmoid.]
The bias of each layer of the neural network allows the activation function to be shifted by adding a constant to the input. It can be considered analogous to the role of a constant in a linear function and has the effect of shifting the activation function by a constant amount.

Table 2
Effect of the input variables on the output variables.

Public budget expenses inputs (X)	Social and economic results outputs (Y)		
$n = 11$	$m = 3$		
	GDP growth (GDP)	Inflation (I)	Gini index (GINI)
Agriculture (A)	22.3585688	−18.63550913	0.725048346
Economic Saving (ES)	19.97877389	−20.89445112	1.392917549
Education (E)	11.35957087	−11.84701335	0.392167617
Population Growth (PG)	15.72405006	0.096845469	−3.584064366
Poverty (P)	2.40925214	−29.22804641	6.803888888
Public Debt (PD)	0.259145771	−4.09784408	0.867145612
Public Health (PH)	−1.072882803	−5.324115827	2.316976748
Public Safety (PSf)	11.84531977	−9.636044008	−0.649280141
Public Spending (PS)	6.702862783	−5.062750283	0.99674821
Subsidies (S)	8.532619399	−9.129243203	2.412916172
Unemployment (U)	2.244913957	−5.310131775	0.719639716

output variables (***Y***) represent the coefficients for each variable of the fitness equations for the multiobjective genetic algorithm ($\boldsymbol{Z} = F(\boldsymbol{X}, \boldsymbol{W})$). The constraints for the optimization process depend on the output variables (GDP, I, and GINI); the output variables cannot be negative or exceed the maximum value of the output variables of the countries analyzed in the study period (1960 to 2019). We present the equations designed with the weights of the multilayer neural network below. The result is an equation system with 11 independent variables and 3 dependent variables, subject to the fact that each variable can have a minimum value = 0 and a maximum value = 1,102,850,455,881.60, as an indicator to determine its importance. Consequently, the optimization problem has an infinity of possible solutions that were evaluated with the multiobjective genetic algorithm:

$$\begin{aligned} Max\ GDP = {} & 22.3585688\, A + 19.97877389\, ES + 11.35957087\, E + 15.72405006\, PG + 2.40925214\, P + 0.259145771\, PD - 1.072882803\, PH \\ & + 11.84531977\, PSf + 6.702862783\, PS + 8.532619399\, S + 2.244913957\, U \end{aligned}$$

$$\begin{aligned} Min\ I = {} & -18.63550913\, A - 20.89445112\, ES - 11.84701335\, E + 0.096845469\, PG - 29.22804641\, P - 4.09784408\, PD - 5.324115827\, PH \\ & - 9.636044008\, PSf - 5.062750283\, PS - 9.129243203\, S - 5.310131775\, \mathrm{U} \end{aligned}$$

$$\begin{aligned} Min\ GINI = {} & 0.725048346\, A + 1.392917549\, ES + 0.392167617\, E - 3.584064366\, PG + 6.8038888889\, P + 0.867145612\, PD + 2.316976748\, PH \\ & - 0.6492801411\, PSf + 0.99674821\, PS + 2.412916172\, S + 0.719639716\, U \end{aligned}$$

$$subject\ to\ 0 \le S, PS, PD, E, A, U, ES, PG, P, PSf, PH \le 1102850455881.60$$

We developed different experiments looking for the most feasible solution to solve the equation system simultaneously. The results of the multiobjective genetic algorithm indicate the public budget allocation. In optimization with multiple objective functions, it is necessary to decide which results to optimize. The objective of the genetic algorithms was to maximize GDP growth and reduce inflation and Gini index values. For this reason, the first model is the best (See the fitness in Table 3). This model has the best fitness values for inflation and Gini and the second-best fitness for maximizing economic growth. However, each model is a potential scenario with different indices for distributing the public budget and different results for prioritizing certain public budget expenditures. For example, the third and the fourth models contain many values equal to zero and the maximum possible values calculated, useful to understand what happens when increasing or decreasing certain public budget expenditures. The third model is the worst due to its fitness values, and it may represent the pessimistic scenario, with the worst results in GDP growth and inflation reduction. The second model is only suitable for improving GDP; however, that is not the aim of this research.

Table 3 shows values that can be interpreted as indicators to understand the importance of public budget expenses in fostering economic growth (GDP), reducing inflation, and improving income inequalities (GINI index). The calculated results are only indicators that have the potential to be useful in decision-making for the public policies in government and allow us to see the effects of increasing or decreasing some variables of the public budget. The AI-based analysis allows us to analyze the simultaneous effect of the public budget inputs on the GDP, inflation, and income inequalities (Gini Index) using the World Bank Open Data.

We used the results of model 1, ordering the values of each variable in ascending order for GDP and descending order for inflation and the Gini index, to understand the importance of the public budget allocation for each output variable. In this regard, the results of the multilayer artificial neural networks and the multiobjective genetic algorithm, found the importance of the public budget expenditures on GDP, Inflation, and Gini Index (Table 4).

5. Discussion and implications

This section is twofold. First, we presented the discussion of results and systematically compared them with previous public budgeting research. Second, we discuss the implications of using AI in the planning phase for public budget allocation. The tested model, based on multilayer neural networks and multiobjective genetic algorithms, showed

Table 3
Multiobjective genetic algorithm tests.

Public budget		Outputs in millions		
Inputs	Model*	Max GDP growth	Min inflation	Min GINI
Agriculture (A)	1	1,090,418	3,530	28,045
	2	1,102,789	1,102,494	1,102,655
	3	0	1,102,850	0
	4	1,102,850	0	0
Economic Saving (ES)	1	905,355	11,705	86,224
	2	1,102,656	1,102,273	1,048,968
	3	0	1,102,850	1,102,850
	4	1,102,850	0	1,102,850
Education (E)	1	972,554	111,219	1,102,741
	2	1,049,441	619	1,102,599
	3	1,102,850	0.00000007	0
	4	0.00000007	1,102,850	0
Population Growth (PG)	1	1,061,589	145,614	150,005
	2	1,099,662	37,083	1,096,611
	3	1,102,850	1,102,850	0
	4	1,102,850	1,102,850	0
Poverty (P)	1	964,443	12,354	186,738
	2	1,100,456	1,094,460	1,102,589
	3	0	1,102,850	0
	4	1,102,850	0	0
Public Debt (PD)	1	1,079,582	247,830	941,176
	2	1,102,833	974,821	1,101,091
	3	0	1,102,850	0
	4	1,102,850	0	0
Public Health (PH)	1	962,798	153,311	136,320
	2	1,094,502	1,100,482	1,098,359
	3	0	1,102,850	0
	4	1,102,850	0	0
Public Safety (PSf)	1	1,004,796	77,868	102,483
	2	1,102,528	1,085,580	1,102,697
	3	0	1,102,850	0
	4	1,102,850	0	0
Public Spending (PS)	1	1,090,437	47,910	19,738
	2	1,102,747	1,094,948	1,102,690
	3	0	1,102,850	0
	4	1,102,850	0	0
Subsidies (S)	1	1,086,210	113,836	181,165
	2	1,102,743	1,099,113	1,100,594
	3	0	1,102,850	0
	4	1,102,850	0	0
Unemployment (U)	1	1,064,954	876,891	266,407
	2	1,102,622	1,102,598	1,101,358
	3	0	1,102,850	0
	4	1,102,850	0	0
Fitness	1	102,648,923	7,978,770	21,272,762
	2	109,997,611	81,023,046	109,458,872
	3	29,869,183	98,134,527	22,033,599
	4	98,134,527	29,869,183	22,033,599

Source: Authors' elaboration.
* Model 1: generations = 10, popSize = 100.
Model 2: generations = 100, popSize = 100.
Model 3: generations = 1000, popSize = 100.
Model 4: generations = 10,000, popSize = 100.

indicators that have the potential to understand the importance of certain public budget expenses simultaneously. It is important to clarify that the equation that resulted in the optimization of inflation obtained negative coefficients in the public budget expenses because the objective of the AI-based model was to minimize it. Although the aim from an AI-based analysis of the optimization function related to the Gini index was also to minimize it, we obtained few negative coefficients, which could be at least partially explained by the fact that several countries, didn't have any data (nulls) during some years. The equations to optimize the GDP obtained positive coefficients, as expected.

Comparing the AI results with what has already been done on budgeting, we learned that the most important aspects that can generate an efficient public budget refer to policies that improve GDP, income inequality, and inflation reduction. These aspects are based on strategies

Table 4
Importance of public budget expenditure on GDP, inflation, and Gini index.*

Importance for increasing GDP		Importance for reducing inflation		Importance for improving Gini index	
1	Public Spending (PS)	1	Unemployment (U)	1	Education (E)
2	Agriculture (A)	2	Public Debt (PD)	2	Public Debt (PD)
3	Subsidies (S)	3	Public Health (PH)	3	Unemployment (U)
4	Public Debt (PD)	4	Population Growth (PG)	4	Poverty (P)
5	Unemployment (U)	5	Subsidies (S)	5	Subsidies (S)
6	Population Growth (PG)	6	Education (E)	6	Population Growth (PG)
7	Public Safety (PSf)	7	Public Safety (PSf)	7	Public Health (PH)
8	Education (E)	8	Public Spending (PS)	8	Public Safety (PSf)
9	Poverty (P)	9	Poverty (P)	9	Economic Saving (ES)
10	Public Health (PH)	10	Economic Saving (ES)	10	Agriculture (A)
11	Economic Saving (ES)	11	Agriculture (A)	11	Public Spending (PS)

Source: Authors' elaboration.
* Results based on Model 1.

focusing on improving public debt (McCausland & Theodossiou, 2016), fostering education and economic saving (Dragomirescu-Gaina, 2015; Wang & Alvi, 2011), investing in the agricultural sector (Marsh, 2015), and addressing the population growth and public health problems (Aladejare, 2020; Marsh, 2015; McLaren & Dutton, 2020). According to our AI-based analysis approach, the three most essential budget expenses that could improve the GDP are public spending, agriculture, and subsidies. This finding is consistent with previous research that indicates that agriculture and public spending have a significant and positive effect on the GDP, and health directly affects productivity (Bhattarai, Lee, & Park, 2014; Mogues, 2015; Ono, 2011). Additionally, we found that subsidies have the potential to activate the economy (GDP Growth).

Regarding reducing inflation, the most relevant expenses that may be considered in the public budget are related to implementing strategies against unemployment, reducing public debt, and fostering public health. Combating unemployment and incentivizing public health encourages economic development, investment, and welfare, raising the economy's income (McCausland and Theodossiou, 2016; Fonchamnyo & Sama, 2016). Lower public debt levels can reduce inflation, even though the economic growth would slow down (Bhattarai et al., 2014). According to our results based on the intelligent algorithmic analysis, economic inequality, measured by the Gini index, could be addressed mainly by considering policies focusing on incentivizing education and implementing strategies to address public debt and unemployment problems. In this regard, the GDP measures the total income, while the Gini index measures income inequality (Gastwirth, 1972). Inequality reduction could be addressed by generating employment policies that promote an efficient, productive, and competent labor market, which creates the need to generate strategies to support unemployment. Another way to combat inequality is by implementing free and high-quality public services (Solt, 2009).

Public health is a problem of inequality that has resulted in economic consequences. The COVID-19 pandemic has highlighted this situation; poverty and deficiencies in public health systems are interrelated phenomena (Devi, 2020; Karim & Noy, 2020; McLaren & Dutton, 2020). Emerging countries tend to have worse health outcomes, and poor people have more health problems than affluent people. For this reason, there is a need to design strategies to solve the complications of public health, poverty, and population growth. Agriculture is considered a relevant issue on the agenda of governments for reducing inequalities (Marsh, 2015; Mogues, 2015). Our model confirmed this situation for improving GDP growth. Education is a primary element for combating inequalities. Policies related to education can enhance economic development and greater efficiency of public spending (Dragomirescu-Gaina, 2015). It is also a relevant issue in the fourth industrial revolution era since more routine and less remunerative activities will be replaced by AI more quickly (Crenshaw, 1992).

Another topic of importance to the governments' agenda could be the fight against poverty since it represents an indicator of socio-economic vulnerability (Karim & Noy, 2020). Furthermore, McCausland and Theodossiou (2016) argued that reducing public debt and stability in a country's economy is synonymous with confidence in investment. Nevertheless, in our results, we only found that good public debt management may lead to an improvement in terms of the inflation rate. Expenditures for government operations are critical to economic development, as they can stimulate the economy. It has been argued that government subsidies and transfers can positively impact economic growth (The World Bank, 2020). However, our findings show no impact from these types of public budget expenses. Regarding public debt, according to our results, we found that it is an issue that could impact inflation (Wassmer et al., 2009).

What happens to algorithmic analysis when something changes in the allocation of public spending? Although the proposed algorithmic-analysis approach found the most feasible solution of public expenditure allocation to improve inflation and GINI index values. At first glance, it provides a scenario that provides indicators that can improve inflation conditions and decrease inequalities. One of the major limitations of our algorithmic model is that it failed to find a feasible solution to enhance GDP growth simultaneously. What is clear is that there is an inherent complexity in trying to solve this type of budgetary problem and any change or adjustment in the public budget allocation alters the expected results. The resulting models from the data analysis (Table 3), with the multilayer perceptron and the multiobjective genetic algorithms, offer different scenarios that could indicate the potential outcomes of changing the public budget allocation. This type of algorithmic analysis has the potential to allow decision-making based on previous scenarios generated by AI. Models three and four could help understand the effect of increasing or decreasing the allocation of public spending because they have zero values and the maximum possible values calculated (but this does not imply having the most satisfactory combination of all the budget expenses).

While the first model is the best, the third one is the worst - our initial discussion of the results revolved around the first model. However, analyzing the results of the third model allows understanding what could happen when changing the public budget allocation: potential risks in decision-making may be identified. Based on the zero-values of the third model, our algorithmic approach shows that investing less in agriculture could lead to a decrease in GDP and the GINI index, as well as an inflation increment. The same may happen when no initiatives are generated to combat poverty and policies to solve public debt and public spending. Something similar is found when health and public safety are not promoted and encouraged. Moreover, according to our algorithmic analysis, not implementing initiatives to combat unemployment and not encouraging subsidies could negatively affect the economy and inequality.

The findings described above are based on algorithmic analysis and do not imply that it must occur. With this type of approach, only practical simulations for decision-making are glimpsed. However, the advantages of implementing this type of decision-making system arise from the ease of processing large amounts of data and finding patterns difficult to detect. Specifically, the multilayer perceptron, a machine learning technique, learns from a large amount of historical data. Their results help generate predictions, detect patterns, or explain the simultaneous relationship between different variables. In turn, multiobjective genetic algorithms allow heuristically optimizing any type of problem (multiple variables and simultaneous equations), provided that the objective or fitness functions are available. One of the advantages of combining the multilayer perceptron with genetic algorithms is that the former learns from data to obtain the necessary optimization equations.

We assume that, although we have raised the possible advantages of using artificial intelligence techniques for decision-making, there is still distrust when using these algorithms due to their lack of transparency and explainability. Nevertheless, the combination of these techniques, and others that belong to the machine learning family, can support not only smart budgeting but also different areas of government automatically and intelligently in a strategic manner.

6. Conclusions

This article explores how AI techniques produce scenarios that could help the public spending allocation, specifically using the multilayer perceptron and multiobjective genetic algorithms. This is consistent with an algorithmic approach, as computational systems have inputs that are processed (public budgeting expenses) to generate outputs (economic, political, and social outcomes). Although this research could not be realistic in terms of including all the crucial aspects of the budgeting process, we argue that this kind of algorithmic approach has the potential to be useful to improve some technical aspects of decision-making. Specifically, this research provides an alternative to make decisions about allocations of public spending (for the planning stage) based on an algorithmic approach and data analysis.

Algorithms and artificial intelligence have the potential to support decision-makers in government, particularly in public budgeting. Consistent with previous literature, mostly based on statistical analysis, our AI-based data analysis recommended that the government should consider certain public budget expenses to improve economic growth, reduce inflation and decrease income inequality. More specifically, the findings suggest enhancing the allocation of public spending, improving public debt and public expenditure, fostering the investment in agriculture, education, and public health, and implementing strategies to address the problem of unemployment to boost economic growth, decrease income inequality and reduce inflation. The fact that our results are consistent with previous studies, shows that AI techniques have the potential to complement or substitute other analytical techniques used to make decisions about budget allocations.

Due to the inherent complexity of fiscal policy, caused by factors such as economic crises, pandemics, exchange rates, and political interests, we consider that the distribution of public expenditure should be dynamic, as the environment in which it is embedded is dynamic too. However, one of the main challenges in public budgeting is meeting all the population's needs to generate welfare and growth. Therefore, some of the main benefits from the use of AI in public spending allocation come from providing guidance or allocation criteria to leverage multiple, often conflicting, objectives. Despite the black box inherent in AI algorithms, such techniques can bring some degree of rationality to the budget process, which is not only technical, but also political in nature. AI in government can become a tool for data analysis and support better decision-making by reinforcing existing good practices and providing additional evidence to support them. In addition, these techniques could also uncover innovative approaches and produce new ideas for decision-makers in government. This could be done, for example, through advice based on different scenarios or models resulting from artificial intelligence simulations. In our view, government agencies should explore the potential of artificial intelligence techniques in the budgeting process. They should be aware that their potential might not always be realized as automatic decision-making, but in supporting creative ways to analyze and understand the data used for specific government programs and policies.

In addition to exploring the potential of AI in general, our contribution consists of proposing a hybrid artificial intelligence approach based on the learning capacity of artificial neural networks, combined with the optimization power of multiobjective genetic algorithms. This could be used, for example, to identify the public spending allocation that simultaneously promotes economic growth and reduces inflation and inequalities. Based on Kurzweil's approach, this could be called an intelligent budget machine. However, we know that using artificial intelligence does not always mean that human decision-makers are no longer needed and this is particularly true in political processes such as budgeting. Analyzing all available data makes it easier to detect which expenditure allocation strategies have been successful in the past and which have not. This could help to face the economic events and create a dynamic allocation of expenditures when such events occur. An automated AI system that makes technical decisions to be accepted by politicians or other decision-makers is still far from being technically possible and politically feasible. We think AI can be useful by providing information about alternative budget allocations and their potential effects on society to decision-makers or their staff. Once this information is generated, it becomes part of a more complex decision-making process, a highly political and sometimes even irrational process. In this regard, AI is no different from a decision support system or a statistical model since they provide helpful information. However, the final decision maker can still ignore their results. Despite this situation, we argue that all these tools and techniques are still relevant and useful for certain actors and situations within the budgeting process.

Regarding our research question, we argue that the combination of multilayer perceptron to learn from available data and multiobjective genetic algorithms has the potential to generate valuable scenarios for public budget allocation. The challenge is understanding how these algorithms exploit data and interpret their results to generate helpful information for decision-making. We argue that public spending allocation can be improved with the help of these kinds of techniques. However, we are aware that this algorithmic approach is still limited because it does not consider aspects inherent to the budgeting process, such as political, economic, and even corruption-related factors. We acknowledge that the budget process is complex but argue that artificial intelligence can assist in decision-making, particularly from a technical and rational point of view.

The potential benefits of AI in government could be mostly related to efficiency and effectiveness from a technical point of view and other perspectives are not necessarily considered. However, we argue that having this information could help some of the involved actors make better-informed decisions. As mentioned before, this would be like any other decision support system. The decision-maker is not given the solution but several alternatives and much information for her/him to make the final decision. More generally, some of the advantages that artificial intelligence techniques provide are related to their capacity to analyze any data, regardless of its distribution, size, or format. However, some limitations of AI-based decision-making are related to the computational capacity necessary to implement some of these techniques and the lack of algorithmic transparency. The former situation is a potential problem for government agencies, particularly at the local and state levels. They must have sound computational processing and storage infrastructure and staff trained in artificial intelligence and/or data science. Also, they require a significant amount of time to carry out these kinds of simulations before obtaining some potential benefits, particularly those related to improved decision-making. For these reasons, smart budgeting goes beyond just an algorithmic approach. It depends on many factors and diverse stakeholders for being truly smart. Therefore, AI is only a sophisticated computational tool and a potential part of smart budgeting that could improve decision-making in government.

The limitations of this research are related to the fact that we could not include in an algorithm all the complexity of the budget process in terms of economic, political, and human aspects. As mentioned before, the budgeting process is not a purely technical exercise, and there are many self-interested actors involved. Our approach analyzes budgeting allocation on economic development from an international comparative and longitudinal perspective. In this regard, this article aims to detect how countries allocate public spending, regardless of their specific characteristics and whether they are highly developed or not. A mixed AI approach could identify which budget expenditures have had the best impact on GDP, inflation, and inequality. One of the advantages of AI is finding patterns in the analyzed database and thus distributing the budget considering the public budgeting allocation that governments have implemented to achieve economic growth and reduce inflation and inequality. However, the analysis of a single country could allow understanding its context and particular situation in a deeper and more precise manner.

We argue that the results of this study are encouraging concerning the potential of conducting AI-based analyses to support government decision-making. We think AI can improve the budget process, but we also acknowledge that there are many non-technical factors to consider. We are also conscious that algorithmic approaches and AI techniques may result in bias, omissions, and errors. In addition, the analysis was conducted using the World Bank Open Data, and bias may exist in the datasets too. So, the ideas and policy recommendations suggested by the results obtained in this research should be seen with caution and not be generalized since each context is different. Some policies may be effective for certain nations and contexts but may lead to failure or harmful biases for others. For this reason, future research should evaluate these techniques in particular contexts, adapt to the specific needs of different nations and governments, and include other factors inherent to public budgeting. Another path for future research consists of simulating different scenarios with AI models to understand other potential relationships between public budget expenses and other social and economic outcomes useful for government decision-making. Finally, it would be very interesting to directly compare AI techniques with more traditional statistical models in terms of their results and potential recommendations for budget allocation.

Declaration of Competing Interest

The authors declare that they have no conflict of interest.

Appendix A. Article selection process

There is a lack of studies related to the analysis of the public budget with AI techniques. This section aims to find out the public budget expenses (inputs) and social and economic results (outputs) to be analyzed with an algorithmic approach. The process of identifying articles on the public budget elements (inputs and outputs) in the scientific literature consists of five stages described below.

A.1. Stage 1: thesaurus use

First, we identified synonyms and terms related to the words: 1) "elements", 2) "budget", 3) "government", and 4) "results", using a thesaurus. As a result, we found the related terms with the word "elements": "components" and "factors". The related terms with the word "budget": "allocation", "account", "bulk", "finance", "funds", "quantity", "expenses", "fiscal", "spending", "income", "fiscal year". The related terms with the word "government": "national" and "public". And the related terms with the word "results": "determinants", "consequences", "issue", "outcome", and "stimulus".

A.2. Stage 2: queries applied in web of science and scopus

In the second stage, with the terms found in Stage 1, we performed a logical search of the articles' titles on the Web of Science and Scopus to identify the scientific literature related to the analysis of the public budget elements. We filtered the documents considering only the economics, finance, social sciences, and public policy areas to refine the results. We found 66 articles in Web of Science and 93 in Scopus (Table 5).

Table 5
Queries applied in web of science and scopus.

Database	Queries applied in November 2020	Scientific articles
Web of Science	TI = ((“Elements” OR “Components” OR “Factors” OR “Determinants “OR “Consequences” OR “Issues” OR “Outcomes” OR “Stimulus” OR “Results”) AND (“Government” OR “National” OR “Public”) AND (“Budget” OR “Allocation” OR “Account” OR “Bulk” OR “Finance” OR “Funds” OR “Quantity” OR “Expenses” OR “Fiscal” OR “Spending” OR “Income “OR “Fiscal Year”))	66
Scopus	TITLE((“Elements” OR “Components” OR “Factors” OR “Determinants “OR “Consequences” OR “Issues” OR “Outcomes” OR “Stimulus” OR “Results”) AND (“Budget” OR “Allocation” OR “Account” OR “Bulk” OR “Finance” OR “Funds” OR “Quantity” OR “Expenses” OR “Fiscal” OR “Spending” OR “Income “OR “Fiscal Year”))	93

Source: Authors' elaboration.

A.3. Stage 3: removing repeated articles

In the third stage, we excluded 71 repeated papers. At this stage, we obtained 88 scientific articles related to the public budget elements in Web of Science and Scopus.

A.4. Stage 4: screening titles and abstracts

In the fourth stage, we screened titles and abstracts. We omitted 29 papers unrelated to the public budget elements, having 59 scientific articles that we downloaded to analyze in-depth.

A.5. Stage 5: reviewing the public budget elements in the articles

After analyzing downloaded documents, we discarded 38 unrelated to the central topic of this research. Therefore, the state of the art of public budget elements consisted of 21 scientific articles dealing with agriculture investment, economic savings, education investment, GDP, income inequalities, inflation, population growth, poverty rate, public debt, public health, public safety, subsidies, and transfers, and unemployment topics (Table 6).

Table 6
Public budget elements and authors identified in the state of the art.

Elements by name	Authors
Agriculture	Marsh, 2015; Mogues, 2015)
Economic savings	(Leiderman & Razin, 1991; Wang & Alvi, 2011)
Education	(Afonso et al., 2010; Crenshaw, 1992; Dragomirescu-Gaina, 2015; Fonchamnyo & Sama, 2016; Marsh, 2015; Russo & Verzichelli, 2016; Tang, 2020; Wang & Alvi, 2011)
GDP	(Aladejare, 2020; Dragomirescu-Gaina, 2015; Heim, 2016; Wang & Alvi, 2011)
Income inequalities	(Afonso et al., 2010; Crenshaw, 1992; Facchini, 2018; Marsh, 2015)
Inflation	(Aladejare, 2019, 2020; Fonchamnyo & Sama, 2016)
Population growth	(Aladejare, 2020; Marsh, 2015)
Poverty rate	(Karim & Noy, 2020)
Public debt	(De Haan & Sturm, 1997; McCausland & Theodossiou, 2015)
Public health	(Fonchamnyo & Sama, 2016; McLaren & Dutton, 2020)
Public safety	(Wassmer et al., 2009)
Public spending	(De Haan & Sturm, 1997; McCausland & Theodossiou, 2015)
Subsidies and transfers	(Afonso et al., 2010)
Unemployment	(Fraile & Ferrer, 2005; Jensen, 2012; Wang & Alvi, 2011)

Source: Authors' elaboration.

Appendix B

Algorithm 1. Genetic algorithm (GA)

Step 1: $t \leftarrow 0$; /* initial generation */

Step 2: initialize $P(t)$; /*create the initial population*/

Step 3: evaluate $P(t)$; /* Calculate fitness */

Step 4: While (generations) do

Step 5: select parents of $P\ (t)$;

Step 6: recombine parents and mutate $\Rightarrow C\ (t)$;

Step 7: evaluate $C(t)$; /* Calculate fitness */

Step 8: select survivors of $P\ (t)\ \cup\ C(t) \Rightarrow P\ (t\ +\ 1)$; /* generational replacement */

Step 9: $t\ \leftarrow\ t\ +\ 1$ /* next generation */

Step 10: End While

Algorithm 2. NSGA-II.

Step 1: $t \leftarrow 0$; /* initial generation */

Step 2: Initialize $P_0(t)$; /*create the initial population*/

Step 3: Create a new Q_t population of N individuals from the P_t population

Step 4: While (generations) do

Step 5: Combine the P_t and Q_t populations to create a new population: $R_t = P_t \cup Q_t$

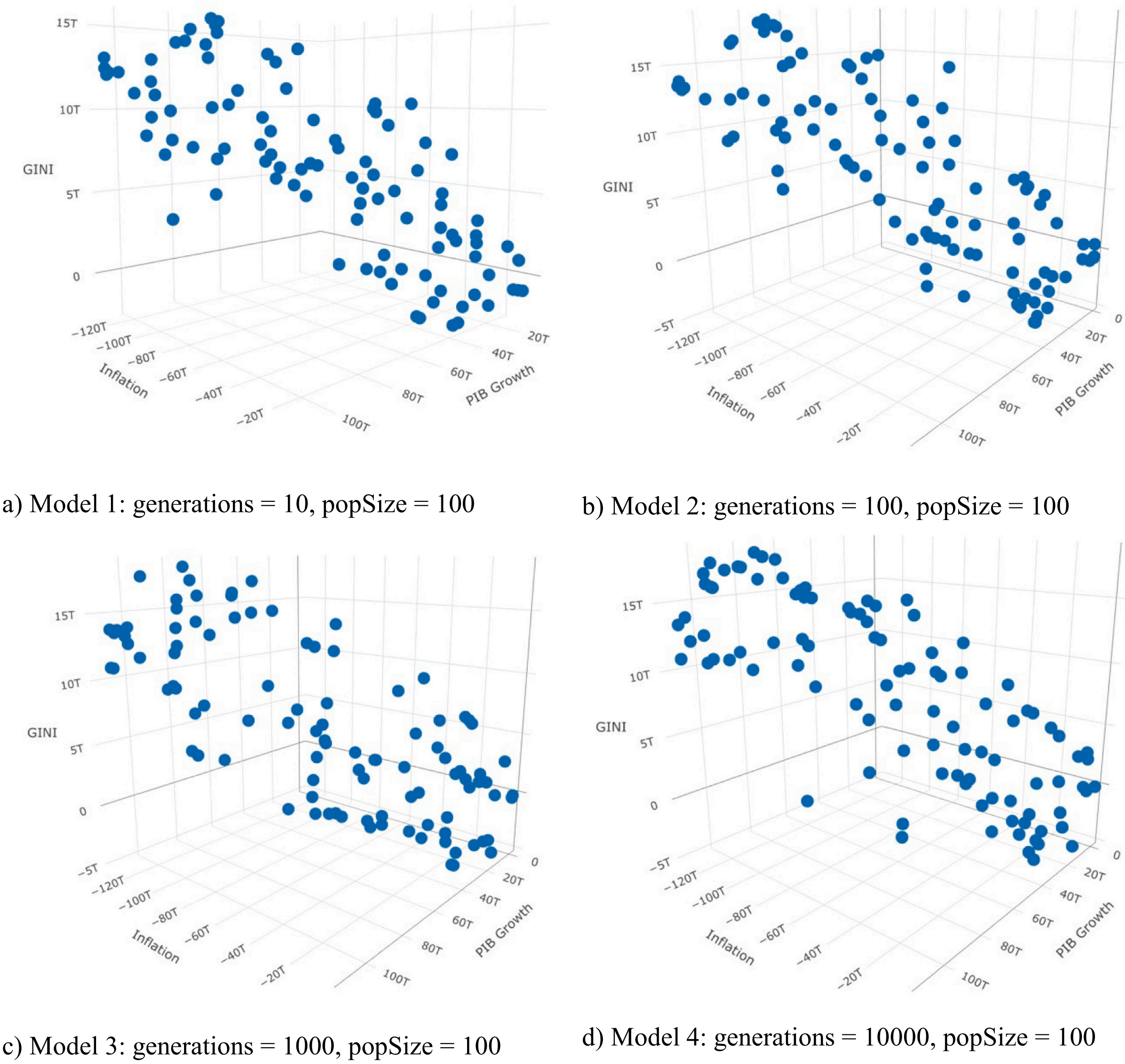
Step 6 Create a new $P_t + 1$ population by selecting N individuals from the R_t population using fronts and niche sorting

Step 7: $t\ \leftarrow\ t\ +\ 1$ /* next generation */

Step 8: End While

Appendix C. Objective values visualization

For these models, the non-dominated objective function values found in the adaptive landscape are similar in each simulation, despite the combination of genetic parameters (generations and population size). The simulations converge to similar objective values, despite the number of generations and population size. However, the heuristic optimization results in fitness that allows the decision-maker to choose GDP growth, inflation decrease, or GINI index values. The computations performed with the multiobjective genetic algorithm had a low computational load (Fig. 5).



a) Model 1: generations = 10, popSize = 100

b) Model 2: generations = 100, popSize = 100

c) Model 3: generations = 1000, popSize = 100

d) Model 4: generations = 10000, popSize = 100

Fig. 5. Non-dominated objective function values in the 3D-adaptive landscape.

Table 7
Multilayer perceptron weights.

		Hidden layer 1 ($\omega_{n\ h}^{hidden}$)								Output layer ($\omega_{h\ m}^{output}$)		
		$n = 11$, $h = 8$								$h = 8$, $m = 3$		
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	H(1:8)	GDP Growth (GDP)	Gini index (GINI)	Inflation (I)
Input layer	(Bias)	2.070	0.632	0.711	−0.243	1.518	0.846	−0.473	−0.156			
	Subsidies (S)	−0.051	−0.889	−0.090	−0.844	−0.883	−1.213	0.591	−0.149			
	Public Spending (PS)	0.365	−1.163	−0.401	−0.278	−0.305	−0.549	0.416	0.177			
	Public Debt (PD)	−0.525	0.026	−0.338	−0.162	−0.571	0.229	0.452	−0.141			
	Education (E)	−0.718	−1.532	0.483	−0.223	0.185	−1.206	1.280	0.590			
	Agriculture (A)	−0.266	−3.556	1.214	−0.503	0.032	−1.951	1.818	0.637			
	Unemployment (U)	−0.397	0.139	0.018	−0.595	−0.052	−0.719	0.461	0.564			
	Economic Saving (ES)	−0.276	−2.853	0.561	−0.260	−0.847	−2.051	1.834	0.978			
	Population Growth (PG)	1.620	−1.192	1.037	−0.692	1.240	−2.036	2.011	−0.452			
	Poverty (P)	−2.371	−0.438	−0.369	−1.348	−3.380	−0.293	0.522	1.909			
	Public Safety (PSf)	0.212	−1.577	0.485	−0.249	0.257	−1.326	1.258	0.950			
	Public Health (PH)	−0.599	−0.466	−0.301	−0.364	−0.706	0.521	−0.387	0.349			
	(Bias)									−1.391	0.431	−1.226

(*continued on next page*)

Table 7 (*continued*)

		Hidden layer 1 ($\omega_{n\ h}^{hidden}$)								Output layer ($\omega_{h\ m}^{output}$)		
		$n = 11$, $h = 8$								$h = 8$, $m = 3$		
		H(1:1)	H(1:2)	H(1:3)	H(1:4)	H(1:5)	H(1:6)	H(1:7)	H(1:8)	GDP Growth (GDP)	Gini index (GINI)	Inflation (I)
Output layer	H(1:1)									0.320	3.391	−1.124
	H(1:2)									−3.549	2.428	−0.625
	H(1:3)									0.264	−0.235	−0.855
	H(1:4)									−0.126	0.950	−0.996
	H(1:5)									−0.270	3.694	−0.933
	H(1:6)									−2.996	1.589	−0.640
	H(1:7)									2.244	−2.044	−1.276
	H(1:8)									−0.743	−2.573	−0.245

Table 8
Descriptive statistics of the world bank data set.

Statistic	World Bank indicator code*	Minimum	Maximum	Mean	Median	Standard deviation	Kurtosis	Skewness
Inputs								
Public Spending (PS)	GC.XPN.TOTL.GD.ZS	0.00	210.21	23.10	21.51	11.12	32.43	3.36
Agriculture (A)	NV.AGR.TOTL.ZS	0.03	89.41	16.43	12.86	13.86	1.19	1.11
Subsidies (S)	GC.XPN.TRFT.ZS	0.00	90.65	31.58	29.84	17.84	−0.59	0.44
Public Debt (PD)	GC.DOD.TOTL.GD.ZS	0.02	2002.51	56.12	48.25	77.48	451.98	19.11
Unemployment (U)	SL.UEM.TOTL.ZS	0.08	37.98	7.76	6.14	5.67	4.23	1.76
Population Growth (PG)	SP.POP.GROW	−10.96	28.06	1.77	1.74	1.55	26.33	2.47
Public Safety (PSf)	MS.MIL.XPND.GD.ZS	0.00	117.35	2.77	2.08	2.91	277.29	9.79
Education (E)	SE.XPD.TOTL.GD.ZS	0.00	44.33	4.33	4.24	1.79	56.82	3.29
Poverty (P)	SI.POV.NAHC	0.60	83.30	24.96	20.50	14.85	0.98	1.18
Public Health (PH)	SH.MED.BEDS.ZS	0.10	40.32	4.41	3.40	3.38	3.61	1.33
Economic Saving (ES)	NY.GNS.ICTR.ZS	−236.27	372.99	22.52	21.84	13.96	148.48	5.56
Outputs								
GDP	NY.GDP.MKTP.KD.ZG	−64.05	149.97	3.85	3.87	5.69	77.10	2.80
Gini Index	SI.POV.GINI	20.70	65.80	38.82	36.70	9.41	−0.55	0.56
Inflation	NY.GDP.DEFL.KD.ZG	−98.70	26,765.86	24.43	5.45	371.60	2931.08	48.80

* World Bank Open Data from 1960 to 2019, including 217 countries.

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