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Modeling Fiscal Pressure for Economic Resilience: An Intelligent Information System Approach Based on J48 Trees

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Abstract: The economic resilience of a state is directly influenced by its authorities' ability to manage fiscal pressure, a crucial factor in maintaining financial independence and macroeconomic stability. Within this framework, the present paper highlights the strategic importance of information systems in supporting fiscal decision-making and proposes an original predictive model for estimating aggregate fiscal pressure. The research employs a methodology based on decision tree regression, specifically the J48 algorithm, using Eurostat fiscal data across multiple categories (consumption, labor, property, and environmental taxes). The data was pre-processed through cleaning, interpolation of missing values, and normalization to ensure consistency and comparability across EU member states. Two categories of explanatory variables were included: historical fiscal data and macroeconomic indicators such as GDP, inflation, and unemployment. The predictive model achieved a high level of accuracy (98.62%), identifying significant nonlinear relationships and classification rules among fiscal indicators. The obtained results confirm the model's performance, revealing key connections between fiscal components and providing institutional actors with robust tools for anticipating and mitigating fiscal risks. In conclusion, the integration of information systems with advanced predictive algorithms proves essential for strengthening economic security and developing forward-looking, coherent fiscal policies.

Keywords: Fiscal Pressure; Economic Security, Decision Support Systems; Predictive Modeling; Decision Trees

JEL Classification: C53, E62, H21, H68, O21

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1. Introduction

In a global economic climate characterized by instability, fiscal volatility and macroeconomic uncertainties, ensuring economic security has become a central concern for decision-makers. Efficient tax management is an essential strategic tool for strengthening financial autonomy and protecting national economies against systemic risks. In particular, monitoring and controlling aggregate fiscal pressure are crucial for maintaining financial balance and promoting sustainable economic development.

Anticipating and accurately assessing aggregate fiscal pressure allows for the adoption of proactive policies aimed at preventing financial crises and ensuring a stable and predictable economic environment. This approach balances the need for budget financing with stimulating economic development.

In this context, modern information systems play a vital role through their ability to collect, integrate and analyze large volumes of fiscal and economic data. These systems provide strategic decision-making support, facilitating rapid and accurate predictive analyses of critical fiscal indicators. Thus, they directly contribute to strengthening economic security by improving the capacity for anticipation and reaction in the fiscal field.

The purpose of this article is to develop and apply an innovative predictive model, based on decision trees, to anticipate the evolution of the aggregate fiscal pressure. The model uses data from EUROSTAT, including consumption, labor, property and environmental taxes. The relevance of this approach lies in highlighting how information systems integrated with predictive techniques can strategically support the consolidation of financial autonomy and the assurance of sustainable economic security.

2. Information Systems Approaches to Economic Security

The ability of states to effectively anticipate and manage fiscal pressure is becoming a central element in ensuring economic stability and budgetary sustainability. The specialized literature increasingly emphasizes the importance of advanced analytical technologies, especially models based on machine learning, in modeling and predicting economic and fiscal phenomena (Masini, Medeiros & Mendes, 2020). In this direction, decision tree algorithms, such as the J48 model, have been recognized for their ability to manage nonlinear relationships and provide interpretable results, adapted to decision-making contexts (Nawaz & Sofiyan, 2024). The application of these models within decision support systems (DSS) allows the integration of complex and heterogeneous data sets, leading to rigorous and anticipatory assessments of fiscal risks (Bank of Canada, 2023). Moreover, international institutions such as the International Monetary Fund emphasize the analytical role of information technologies in tax administration and in the development of effective mechanisms for managing compliance risks (International Monetary Fund, 2024). In the same sense, the use of machine learning methods in supporting public policies has been validated by recent research on the personalization of interventions and the allocation of resources based on robust predictive models (World Economic Forum, 2018). Therefore, the integration of intelligent information systems with predictive algorithms, such as decision trees, provides a solid methodological framework for the analysis of aggregate tax pressure. These technological solutions not only facilitate a thorough understanding of the interdependencies between tax variables, but also contribute to strengthening the institutional capacity for anticipatory reaction, supporting the foundation of coherent and proactive tax policies. The architecture of an information system dedicated to the assessment of aggregate tax pressure assumes an integrated approach, in which the stages of collection, processing, analysis and dissemination of information are interconnected in a continuous and automated flow. At the heart of this architecture are data sources, mainly represented by public and institutional databases, such as EUROSTAT and national tax bases. They provide a standardized framework for monitoring the main fiscal indicators, including taxes on consumption, labor, property and environmental taxes. According to Eurostat (2024), detailed statistics on environmental tax revenues, structured by economic sectors, constitute a fundamental source for the analysis of environmental taxation and its impact on national budgets. For these data to be analytically useful, they need to be integrated into a platform capable of automatically managing the preliminary processing steps, including validation, cleaning and standardization. Modern data management practices, such as those highlighted by Codasol (2025), emphasize the importance of implementing clear procedures for ensuring data quality, eliminating errors and unifying formats from different origins. The quality of the processed data directly conditions the validity of the analytical results and the robustness of the predictive model subsequently applied. Next, the processed data is transmitted to the analytical component of the system, where advanced machine learning algorithms are applied, among which models based on decision trees, such as J48, stand out for their efficiency and interpretability. According to Aunalytics (2025), decision trees allow data to be segmented into homogeneous groups and the construction of explicit prediction rules, which makes them extremely valuable in economic contexts where decision-making transparency is essential. In the financial sector, such algorithms are frequently used to evaluate fiscal scenarios, estimate the impact of policies and support strategic planning (Investopedia, 2025). The information generated by the analytical modules is subsequently transformed into reports, interactive graphs and scenario simulations, accessible through visual interfaces dedicated to decision-makers. The role of this component is to facilitate the rapid interpretation of results, to support the decision-making process and to allow the evaluation of fiscal alternatives in real time. According to ScienceDirect (2025), interactive decision support systems offer the possibility of simulating multiple scenarios and testing their impact on macroeconomic indicators, thus strengthening the basis for adopting proactive measures.

The predictive and visual integration of results in a direct interface with decision-makers ensures the transition from retrospective to anticipatory analysis. In this way, the proposed information system becomes a strategic monitoring and reaction tool, contributing to the early identification of fiscal imbalances, the assessment of the impact of proposed policies and the formulation of rapid and substantiated responses. In an increasingly volatile economic context, the consolidation of financial autonomy and institutional resilience depends essentially on the state's capacity to integrate such advanced technological solutions into the fiscal decision-making process.

2.1. The Structure of the Aggregate Tax Burden as an Indicator of Fiscal Sustainability

The aggregate tax burden is an essential macroeconomic indicator, reflecting the proportion of tax revenues and social contributions in the gross domestic product (GDP) of an economy. This indicator provides an insight into the capacity of a state to generate the revenues necessary to finance public spending, without compromising economic competitiveness or social equity (Eurostat, 2024). According to the Eurostat methodology, the aggregate tax burden is composed of several categories of taxes and contributions, each having a distinct impact on the economy:

Consumption taxes (CT): include VAT and excise duties, representing a major source of tax revenues, but having a regressive nature, disproportionately affecting households with lower incomes (Eurostat, 2024).

Labor taxes (LT): include social contributions and income taxes, influencing the cost of labor and, implicitly, the level of employment and the competitiveness of the labor market (Eurostat, 2024).

Property taxes (PT): target real estate assets and other forms of wealth, having a redistributive potential and contributing to tax equity (Eurostat, 2024).

Environmental taxes: these are subdivided into:

- Energy taxes (ETE): represent over 75% of all environmental taxes in the EU, targeting energy consumption and having the role of discouraging the use of polluting sources (Eurostat, 2024).

- Transport taxes (ETT): apply to the use of vehicles and transport infrastructure, contributing to reducing emissions and financing infrastructure (Eurostat, 2024).

- Pollution and resource taxes: although they represent a smaller proportion of tax revenues, they are essential for promoting the sustainable use of resources and for environmental protection (Eurostat, 2024).

The analysis of the structure of the aggregate tax burden allows the assessment of the sustainability of tax policies and the identification of potential imbalances that may affect economic stability. For example, an excessive reliance on labour taxes may discourage employment, while a low share of environmental taxes may indicate an underuse of fiscal instruments in achieving environmental objectives (Eurostat, 2024). The integration of fiscal components into a single analytical framework allows for a comprehensive assessment of the fiscal impact on the economic environment and the effectiveness of the overall fiscal structure. This holistic approach provides decision-makers with a valuable strategic tool for formulating and adjusting fiscal policies in real time, contributing to optimizing the fiscal structure, reducing economic vulnerabilities and ensuring long-term financial stability (HighRadius, 2023). In the specialized literature, methods of fiscal and economic analysis range from classical techniques, such as descriptive statistical analysis and simple linear regression, to complex prediction models, including ARIMA models, advanced econometric models, and machine learning methods, such as artificial neural networks and decision trees (IABAC, 2023). In particular, decision trees are appreciated for their ability to identify nonlinear relationships between variables and to efficiently process complex and large data sets, providing clear interpretations of the determining fiscal factors and quickly generating alternative scenarios regarding the evolution of the aggregate fiscal pressure (Investopedia, 2025). The use of advanced predictive models thus responds to the current needs of economic security, directly contributing to the substantiation of proactive and sustainable fiscal policies. By anticipating fiscal and economic trends, these models allow authorities to implement preventive measures and adapt fiscal strategies according to economic dynamics, ensuring effective anticipatory governance (Strategy Software, 2025).

3. Methodology

3.1. Data Source and Processing

The present research adopts a quantitative and exploratory approach, based on machine learning methods, with the aim of estimating the aggregate fiscal pressure and identifying significant patterns between fiscal indicators at the level of the European Union member states. The proposed model integrates an intelligent information system that allows the automatic collection, processing and analysis of fiscal data, following a specific architecture of decision-making systems. The choice of the decision tree regression method is based on its ability to handle nonlinear relationships, to produce transparent decision rules and to provide increased interpretability – an essential aspect in the analysis of fiscal policies. The study uses data from the official Eurostat databases, which provide comparable fiscal and economic indicators at the European Union level. The selected indicators include: consumption taxes (TC), specific taxes on products such as tobacco and alcohol (TV), labor taxes (TL), environmental taxes on energy (ETE), transport taxes excluding fuels (ETT) and property taxes (TP).

To ensure data quality, preliminary processing procedures were applied, including data cleaning, filling in missing values by linear interpolation and normalization of variables for comparability across Member States.

3.2. Aggregate Fiscal Pressure Modeling

The dependent variable, aggregate fiscal pressure, is defined as the sum of the previously mentioned fiscal components, according to the relationship:

Fiscal pressure = TC + TV + TL + ETE + ETT + TP.

This formulation allows for a unitary assessment of the total fiscal burden borne by the economy, providing a comprehensive measure of the degree of fiscal intervention exercised by the state on the main sources of income and economic activity.

Explanatory Variables and Analytical Structure

The proposed analytical model integrates two categories of explanatory variables:

1. Historical values (lags) of fiscal indicators, to capture the inertia of the fiscal system.

2. Additional macroeconomic indicators, such as Gross Domestic Product (GDP), the unemployment rate and the inflation rate, to capture the general economic dynamics.

This structure allows for both a descriptive and predictive analysis of the fiscal pressure, facilitating the anticipation of future developments and the assessment of the sustainability of public finances.

Predictive Modeling Methods

To capture the complexity of the relationships between variables, advanced machine learning methods were used:

• Decision tree regression: chosen for its ability to handle nonlinear relationships and provide transparent interpretations of the determinants.

• J48 algorithm: used complementary to reduce the risk of overfitting and to increase the accuracy of predictions by aggregating the results of multiple decision trees.

These techniques allow the estimation of non-linear relationships between predictors and the dependent variable, the identification of significant thresholds and the assessment of the relative importance of each predictor in explaining the variation in the aggregate fiscal pressure.

4. Results and Discussion

The research has as its first result, in the first figure, a composite visual representation of the variation of the tax burden on the main tax categories, in a time interval covering at least the period 2016–2023. The presented bar graphs synthesize quantitative data on the tax contributions from taxes on consumption, labor, energy, transport and property, each indicator being treated separately, but in relation to a common temporal dynamic. From an analytical point of view, the image reflects a multidimensional approach to the aggregate tax burden, allowing a comparative assessment between years and types of taxation.

The central graph, structured by reference years (2018, 2021, 2023), highlights a significant decrease in the tax aggregate, from a cumulative level of 20.8 to 5.6 and then 5.5, which suggests a downward trend in the total tax intensity or a structural change in the sources of tax revenue. This trend can be associated either with fiscal relaxation policies or with changes in the tax base, in the context of economic adjustments generated by crises or budgetary transitions.

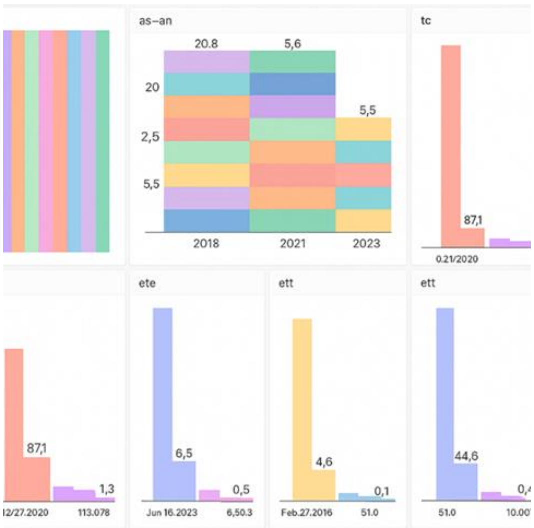

Fig. 1. Distribution of tax indicators

In particular, strong variations are noted in consumption taxes, where 2020 highlights a peak of 87.1, followed by a sharp decline in the immediate period. A possible interpretation is related to exceptional fiscal measures or changes in consumer behavior, determined by the pandemic context. Similarly, the high values of environmental and transport taxes in 2023 can be associated with the acceleration of ecological transition policies and infrastructure investments, in line with the guidelines of the European Green Deal.

Overall, the picture reflects not only the value distribution of tax indicators, but also the analytical capacity of an information system to provide visual support to decision-makers in interpreting and anticipating fiscal dynamics.

In an academic context, this model highlights the potential of decision trees to decompress the inherent complexity of the fiscal decision-making process by structuring data in a clear hierarchical format, in which each level of the tree corresponds to a logical condition applied to a specific variable. Through this mechanism, the model manages to segment the decision space into a set of homogeneous subdomains, each associated with a particular combination of fiscal indicator values. Each decision path resulting from the tree provides an explicit and easy-to-follow interpretation of how the interaction between the different fiscal components – such as consumption, property or excise taxes – determines the positioning of a state in a specific class of aggregate fiscal pressure.

This feature transforms decision trees into a tool of great analytical utility, as it allows not only classification, but also a deep understanding of the causal mechanisms between variables, through transparent decision-making rules, formulated on the basis of concrete and statistically justifiable thresholds. Thus, within applied economic research, decision trees not only synthesize the hidden knowledge in the data, but also formalize it in the form of explanatory models that can guide the foundation of public policies.

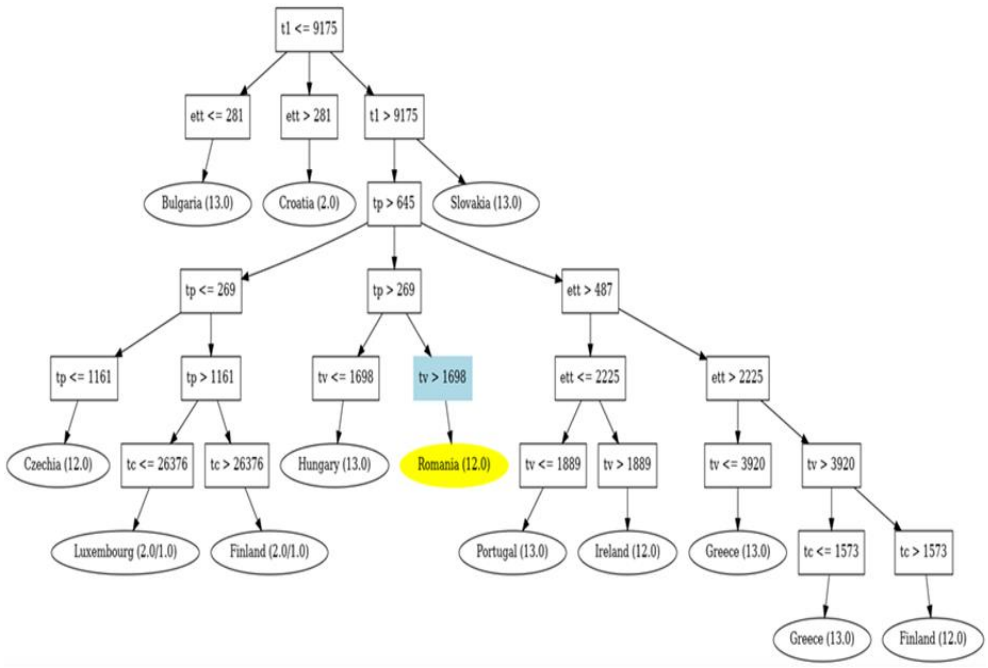

Fig. 2. Decision tree J48 for public policies. Realization of the author in Weka 3.8.6. software

The tree provides an explicable logic for classifying countries according to their fiscal profile.

Romania is located on the right side of the tree, being classified based on a sequence of conditions: t1 > 9175, tp > 269, tv > 1698. This positioning suggests that the value of the tv indicator (tobacco and alcohol taxes) above 1698 is a significant determinant of its classification in the fiscal pressure category estimated as 12.0. This can be interpreted as an indication of high selective taxation applied to the consumption of excisable products, in a context in which tp (property taxes) and t1 (probably a general fiscal aggregate or GDP per capita) exceed certain relevant thresholds.

In comparison, other countries are classified on distinct branches, depending on other critical conditions, such as ett (transport taxes), tc (consumption taxes) or tp (property taxes). For example, Greece is found twice, depending on the level of the tc tax, which indicates significant internal variations or possible registered tax subcategories.

The model highlights not only the membership of each country to a predictive class, but also the decision-making path based on which this classification was reached. This feature transforms decision trees into a valuable tool for decision-making transparency and interpretability in the analysis of tax policies. Therefore, the use of this type of model in a decision-making information system provides robust support for the formulation of differentiated public policies, depending on the specific tax profile of each country. As for Romania, the decision tree built based on the J48 algorithm allows the extraction of a clear classification rule, which differentiates it from other European countries according to the levels of specific tax indicators. According to this rule, Romania is identified as belonging to a distinct class if the following conditions are met: the value of transport taxes (ett) is initially below the threshold of 487, while tobacco and alcohol taxes (tv) exceed the value of 837; subsequently, a high level of property taxes is recorded (tp > 645), followed by a return of the ett value above the threshold of 269, and finally, the level of tv taxes continues to be high, exceeding 1698. This logical sequence of conditions can be formally expressed by the relationship:$ett \leq 487 \rightarrow tv > 837 \rightarrow tp > 645 \rightarrow ett > 269 \rightarrow tv > 1698 \Rightarrow$ Romania. This rule highlights the specific fiscal profile of Romania, characterized by a high level of taxation of excise goods and property taxes, as well as a medium to high value of transport taxes (excluding fuels), which differentiates Romania in the European fiscal landscape. This profile can be used for comparative analysis of the fiscal structure and for formulating public policies adapted to national characteristics.

The illustrated decision tree has considerable explanatory value, as it summarizes the criteria for differentiating between European states according to the key components of the tax burden: taxes on tobacco and alcohol consumption, property taxes and those related to transport. In this context, Romania is found in a median area of the ranking, with an aggregate tax burden of 2.850, which places it above states such as Hungary, Slovakia, the Czech Republic and Bulgaria, but below the average of Western and Nordic countries. In contrast, Germany and France occupy the first positions, with significantly higher tax burden levels (26.300 and 23.000), followed by Italy and Spain, with values of 15.150 and 14.100, respectively. This distribution highlights the major discrepancies between the major economies of the European Union and the states of Central and Eastern Europe.

Romania's lower ranking suggests moderate to low fiscal pressure, which may reflect a narrower tax base but also a conservative approach to expanding direct taxation. This reality may have direct implications for fiscal sustainability, public investment capacity, and redistribution and social protection policies. The performance of the J48 model in classifying European states based on these fiscal indicators is remarkable. The model achieves an overall accuracy of 98.62%, with only 1.38% of instances incorrectly classified. The Kappa coefficient value of 0.9857 indicates an almost perfect agreement between the classification made by the model and the actual classification, while the absolute and squared errors (0.0015 and 0.0273) are extremely low, reflecting a very good quality of the prediction.

Regarding the performance at the class level, Romania is correctly identified in 92.3% of the cases, with a precision of 100%. The only erroneous instance was misclassified as belonging to Luxembourg, a minor confound compared to the full set. This level of accuracy confirms the robustness of the model and its relevance in comparative fiscal analysis. The confusion matrix supports this conclusion, highlighting an almost perfect distribution of classifications along the main diagonal.

Therefore, the J48 algorithm applied in this context demonstrates not only a high degree of accuracy, but also an excellent capacity to interpret the European fiscal structure. The model can be used as a decision-making tool in the substantiation of public policies and in the design of fiscal strategies adapted to each state, depending on its taxable profile.

4.1. Study Limitations and Future Research Directions

The present study, although offering a coherent and applicable perspective on the modeling of aggregate tax burden through machine learning methods, presents a series of methodological and empirical limitations that must be mentioned in order to correctly interpret the results. One of the most important limitations is the uneven availability of historical tax data for certain countries or periods of analysis. In particular, discrepancies between national data sources and European databases, such as EUROSTAT, may affect the consistency of the data set and, implicitly, the accuracy of the model. Also, the aggregate data used for consumption, labor or property taxes do not always reflect the structural particularities of national tax systems, which may lead to a slight loss of analytical granularity.

Another important limitation is the absence of complementary macroeconomic indicators that may influence the tax burden, but which have not been integrated into the current model. For example, inflationary developments, labor market dynamics, the level of public investment or the efficiency of tax collection are variables with a potentially significant role, which, if included, would allow a more complete estimate of the real tax burden and the degree of financial sustainability.

Regarding future research directions, it is necessary to expand the predictive architecture by integrating more comprehensive data sets, including essential macroeconomic indicators such as the unemployment rate, inflation, GDP per capita and the level of public debt. This integration would contribute to increasing the robustness and accuracy of the models, allowing for a contextualized and dynamic analysis of taxation. In parallel, deep learning methods should also be explored, including artificial neural networks and LSTM (Long Short-Term Memory) models, which can capture temporal relationships and complex interdependencies between fiscal and macroeconomic variables. Such approaches can effectively complement decision tree-based models, providing a more complex and adaptive view of the evolution of the tax burden.

Furthermore, future research should address the integration of alternative scenarios and sensitivity analysis within predictive systems. This direction is essential for providing more sophisticated decision-making tools, capable of anticipating not only central trends, but also possible deviations resulting from economic shocks, legislative changes or external disturbances. Counterfactual scenarios could allow the simulation of alternative fiscal policies, thus supporting strategic fiscal governance in uncertain and volatile contexts. In addition, the extension of these models into an interactive platform for decision-makers in public administration could transform the proposed model into an operational, adaptable and replicable tool at regional or national level.

5. Conclusions and Recommendations

The present study confirms the strategic value of using modern information systems and advanced predictive methods in the analysis and anticipation of aggregate fiscal pressure. The application of machine learning techniques, in particular decision tree regression and the Random Forest algorithm, has demonstrated high efficiency in managing nonlinear relationships between fiscal indicators and relevant macroeconomic variables. Through the ability to provide clear and structured interpretations of data, these methods support the development of evidence-based fiscal policies, adapted to real economic dynamics.

The J48 algorithm, used as a classification model in the comparative analysis between European states, stood out for its excellent predictive performance, accurately identifying the fiscal profiles of the analyzed countries. In the case of Romania, the model managed to extract a specific decision rule, validating the usefulness of the predictive approach in supporting the strategic decision-making process. The model indicated that Romania is characterized by relatively high excise and property taxes, along with moderate taxation in the field of transport, which provides concrete directions for the formulation of adapted fiscal policies. The integration of these tools into decision-making information systems allows for continuous and rigorous monitoring of the main fiscal indicators, contributing to the consolidation of financial autonomy and national economic security. By providing relevant information in real time, predictive systems become essential in anticipating fiscal imbalances and in the preventive adjustment of policies, supporting adaptive and responsible fiscal governance.

Based on the conclusions obtained, it is recommended that public authorities strengthen the digital infrastructure necessary for the implementation of these predictive models within fiscal and economic institutions. It is imperative to develop a robust and interoperable information architecture, capable of integrating data flows from multiple sources and allowing for real-time analysis. In this sense, the complete digitalization of the processes of collection, validation and processing of fiscal data is an essential condition for increasing administrative efficiency and strategic response capacity.

At the same time, it is necessary to institutionalize mechanisms for continuous updating and maintenance of the systems, in order to maintain the accuracy of the models and the relevance of the interpretations. The transparency of the decision-making process and open access to the data and results generated by these models must become standards, in order to increase public trust and facilitate inter-institutional and intersectoral dialogue. It is also recommended that the staff involved in fiscal analysis and in the operation of information systems benefit from continuous training and specialization in emerging analytical technologies, so that they can fully capitalize on the strategic potential of these tools.

Following the modeling carried out, a series of recommended fiscal policies are outlined, which can be adapted to the national fiscal profile. In the case of Romania, it is appropriate to maintain a competitive level of general consumption taxes, but also to rebalance the fiscal structure by reconsidering property taxation, as the model suggests a positive correlation between this component and fiscal stability. Also, the level of taxation of excise products (tobacco and alcohol), located in the upper part of the distribution, can be used as a fiscal policy instrument with a dual role – generating budget revenue and discouraging harmful consumption, with positive effects also on public health costs.

At the same time, the relatively moderate level of transport taxes highlighted in the model can constitute an opportunity for fiscal adjustment in the direction of supporting the ecological transition, by introducing differentiated taxation components for vehicles depending on emissions, or through fiscal incentives for green mobility. These structural adjustments can contribute to expanding the tax base, without generating additional pressures on general consumption, and can support the objectives of budgetary sustainability and sustainable development.

In conclusion, the integrated use of intelligent information systems and advanced predictive methods proves indispensable for the formulation of efficient, proactive and sustainable fiscal policies. This approach allows not only to anticipate fiscal risks, but also to adapt economic policies to the structural and conjunctural challenges of the contemporary European.

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