Advanced Leveraging of Government Data on Firms' Vulnerability to Crisis Using Artificial Intelligence

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Abstract. Government agencies possess large quantities of valuable data, which have to be leveraged to the highest possible extent, using the most advanced processing methods, in order to extract as much as possible the valuable knowledge they contain, in order to support future decisions, policies and programs. In this paper we develop a methodology for sophisticated advanced leveraging of data that government agencies possess concerning firms' behaviour during recessionary economic crises as well as firms' vulnerability to them, which is based on a combination of artificial intelligence (AI) techniques, both unsupervised and supervised ones. Economic crises are one of the most important significant challenges that market-based economies face, which has detrimental effects on businesses of most sectors. Governments employ diverse interventions, including extensive programs in order to mitigate the adverse effects of economic crises, which may include employment reduction, famine, public disturbance, and political instability. These government interventions, particularly the extensive economic stimulus programs during crises, can be rendered more efficacious by concentrating on the firms that are more vulnerable to economic crisis. In this direction the proposed methodology includes initially the use of unsupervised learning AI techniques (clustering) in order to identify based on the abovementioned government data the main typologies of firms with respect to the impacts of economic crisis they experience. Then it includes supervised learning AI techniques (classification) in order to predict based on these data the susceptibility/vulnerability of individual firms to future economic crises. Additionally, the authors present an initial implementation and substantiation (application) of the proposed methodology utilizing a dataset from the Greek Statistical Authority made available upon request, pertaining to 363 companies, data acquired during the Greek economic crises that occurred from 2009 to 2014. Satisfactory results were obtained from this first application.

Keywords. Artificial Intelligence, Government data, Machine Learning, Clustering, Economic Crises
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1. Introduction

Government agencies possess large quantities of valuable data, which have to be leveraged to the highest possible extent, using the most advanced processing methods, in order to extract as much as possible the valuable knowledge they contain, in order to supporting future decisions, policies and programs. In this paper we make a contribution towards this direction: we develop a methodology for sophisticated advanced leveraging of data government agencies possess concerning firms' behaviour during recessionary economic crises, as well as firms' vulnerability to them, using a combination of artificial intelligence techniques, both unsupervised and supervised ones. However, the proposed methodology has a wider applicability to a wide range of social and economic problems, for supporting the corresponding government decisions, policies and programs.

Economic crises are one of the most important significant challenges faced by market-based economies; they are caused by various events leading to instability of economic activities, which may cause recessions and result in economic crises of varying durations, geographical scopes, and intensities, (Allen, 2016; Keeley & Love, 2010; Knoop, 2010; Kottika et al., 2020; OECD, 2009a; Saifi & Horowitz, 2023). Economic crises that happened over the span of the previous century are succinctly outlined in (Knoop, 2010), along with their causes and detrimental effects on social and economic scales. In the beginning of the twenty-first century, there was an initial outbreak of the severe Global Financial Crisis in 2007 (Loukis et al., 2021; OECD, 2009a). Subsequently, the COVID-19 pandemic emerged, sparking an additional economic crisis (Baldwin & di Mauro, 2020). Most recently, the Ukraine conflict has led to substantial price increases for commodities including oil, gas, wheat, and others, which has led to another economic crisis. We generally observe that economic crises have become more frequent in this century and tend to propagate to wider geographic areas due to the internationalization of the economy, so periods of "normal" economic activity tend to become shorter, while periods of recessionary economic crisis tend to increase.

The society and the economy are profoundly impacted negatively by these economic crises (Dagoumas & Kitsios, 2014; Das, 2022; Keeley & Love, 2010; OECD, 2009a; Oliveras et al., 2021; Stylidis & Terzidou, 2014). As a consequence of economic crises, which are characterized by a decline in aggregate economic activity and incomes, the majority of firms encounter significant hindrances to their economic standing. These include a reduction in sales, which subsequently affects revenue and liquidity; an escalation in debts; a decrease in investments and personnel employment; and in certain cases, an inability to sustain operations and insolvency. Nevertheless, there is considerable variation in the adverse effects of economic crises among firms (Allen, 2016; Arvanitis & Loukis, 2023; Knoop, 2010; OECD, 2009a); certain firms demonstrate greater capacity to manage such crises and, consequently, are more susceptible/vulnerable to them; conversely, others lack the capability to do so effectively and are thus more susceptible/vulnerable.

These economic crises pose challenges to the governments, such as public disturbance, political instability, poverty and famine, and the governments struggle to minimize all these challenges and their destructive effects on the economy and the society. In order to achieve this objective, governments implement extensive interventions, including massive economic stimulus programs that provide firms with financial aid, tax rebates, subsidies, investment financial support, minor interest rate (or even interest less) loans, and so forth (Coenen et al., 2012; Kalinowski, 2015; Khatiwada, 2009; Taylor, 2018). For optimal efficiency and effectiveness of these interventions, particularly the extensive economic stimulus programs, it is important that they are accurately aimed and prioritized towards the most susceptible/vulnerable firms to the economic crisis.

In order to effectively allocate government support during an economic crisis, it is beneficial on one hand to understand the existing typologies of firms with respect to the impacts of economic crisis they experience, and on the other hand to be able to anticipate the multi-dimensional vulnerability to crisis of individual firms. The latter involves predicting their susceptibility/vulnerability to a recessionary economic crisis across various key aspects of their financial situation. By doing so, the government can concentrate its interventions, particularly the large-scale economic stimulus programs, on the firms that are most in need of this support: those that are most vulnerable to economic crises. The capacity to predict the susceptibility/ vulnerability of various firms to economic crises across multiple dimensions is additionally exceedingly beneficial for investment firms and institutions as well. This enables them to invest in and extend loans and other benefits to firms that will be more susceptible/vulnerable to subsequent crises, so that they endure and rebound once the crisis subsides. Further, this type of prediction will be beneficial for banks and investment firms (aiding them to avoid granting loans and investing in firms that might be quite vulnerable to future economic crises); and also to firms of all industries that rely heavily on extensive supply chains: it will aid them in selecting supply chain partners (including subcontractors, suppliers, wholesale and retail merchants, and others) that will exhibit a lower susceptibility/vulnerability to forthcoming economic downturns (supply chain partners that are more susceptible/vulnerable to such crises will consequently increase the vulnerability of a firm).

In this direction we propose a methodology for leveraging to the highest possible extent data that government agencies possess concerning firms' behaviour during recessionary economic crises, as well as firms' vulnerability to them; which is based on Artificial Intelligence (AI), and includes two main components: a) initially use of unsupervised artificial intelligence techniques (clustering) in order to identify, using the abovementioned government data, the main typologies of firms with respect to the impacts that economic crisis have on them; and b) a second component that includes use of supervised learning techniques (classification) in order to predict, based on the above data, the susceptibility/vulnerability of individual firms to future economic crises. This second component enables the prediction of the multi-dimensional "impact pattern" of a firm, which includes predicted impacts of economic crisis on several important aspects of the firm. For this purpose, using the above data a series of prediction models of various aspects of the vulnerability of an individual firm to economic crisis are constructed; as independent variables are used the characteristics of the firm, such as personnel, ICT infrastructure, innovation activities, exports, strategic standings, and economic performances as compared to competitors. To validate the proposed methodology a first application of it has been made, using open government data provided by the "Greek Statistical Authority" upon request, comprising of 363 firms' information that was collected during the Greek economic decline and crises from 2009 to 2014. The results of this validation/application were deemed satisfactory.

The rest of this research paper is structured as follows: the second section provides an overview of the background containing notions of economic crisis, open government data and AI utilization in government. Section 3 describes the proposed methodology, and then section 4 contains the validation application of the proposed methodology and the results; finally, the 5th section summarizes the conclusions.

2. Background

2.1 Economic crises

Many countries experience diverse economic crises over time, and considering the global economic landscape, all nations are vulnerable to encountering an economic crisis at some juncture in their history; in the present century we had several significant economic crises, as due to the internationalization of the economy crises appearing in one country can rapidly propagate to other countries (Allen, 2016; Baldwin & di Mauro, 2020; Keeley & Love, 2010; Knoop, 2010; Kottika et al., 2020; Loukis et al., 2021; OECD, 2009a; Saifi & Horowitz, 2023). Economic crises lead to recessions, which are significant downturns in economic activity, and can be triggered by various factors, such as: a) unstable and inconsistent long-term macroeconomic policies; b) emergence of unsustainable budgetary imbalance; c) significant inflationary pressures resulting in substantial price hikes for essential commodities such as oil and gas; d) misalignment of currency rates; e) retraction of foreign capital; f) crisis in the banking and financial institutions (Acemoglu et al., 2003). Firms are negatively affected by economic crises, as the latter result in economic recessions, leading to a decrease in the demand for most goods and services, as well as in their prices, decrease in liquidity provision by banks, etc.; so, firms react to the decrease of the demand for their products and services, and therefore of their sales revenue and liquidity, by reducing production and procurement, as well as personnel employment, with the latter leading to higher rates of unemployment, poverty, and social exclusion; furthermore, due to the reduced availability of financial resources, for the reasons mentioned above, resulting to an increase of their debts, and also higher difficulty to borrow from banks, firms decrease their capital expenditures for investments, including those in machinery, ICT, research and development, new products, etc. Possible negative consequences of this in the medium- to long-term include falling behind the technological trend, missing out on key growth opportunities, and slowing the rate of competitiveness progress. (Allen, 2016; Baldwin & di Mauro, 2020; Keeley & Love, 2010; Knoop, 2010; Kottika et al., 2020; Loukis et al., 2021; OECD, 2009a; Saifi & Horowitz, 2023).

Nevertheless, the adverse effects of economic crises vary considerably among firms (Allen, 2016; Arvanitis & Loukis, 2023; Knoop, 2010; OECD, 2009a). Certain firms have personnel with advanced educational backgrounds, with extensive expertise and experience, as well as more efficient production equipment and processes, and better digital infrastructures, so they can offer more attractive products/services of higher value-for money during the crisis, and in general adapt better to the tough crisis conditions, so they finally exhibit lower vulnerability to the crisis than other firms that are more vulnerable.

The frequent occurrence of economic crises, particularly in recent times, poses a significant and pressing challenge for governments. On one hand, they must strive to prevent these crises from happening, and on the other hand, they must take measures to mitigate their severity and the adverse outcomes they bring, such as widespread business closures, a sharp rise in unemployment, poverty, and social exclusion. These consequences can potentially lead to social unrest and political extremism. In regard to the latter, governments devise and execute enormous and expensive interventions, such as the expansive economic stimulus programs, which consume enormous quantities of financial resources (and can lead to substantial increases in public debt); they comprise (among others) a variety of financial support actions for firms, including rebates on taxes, monetary assistance, subsidies (aid), investment financial support, low-interest (or even no-interest) financing, and financial support for investments (Coenen et al., 2012; Kalinowski, 2015; Khatiwada, 2009; Taylor, 2018).

Significant governmental interventions, particularly expansive boost to the economy (stimulus) programs, are more economically viable when they are focused on the most susceptible/vulnerable businesses to the economic crisis rather than being "horizontal" (i.e., providing assistance to all firms), which can waste enormous financial resources. As stated in the Introduction, it would be extremely helpful if it was possible: a) to understand the main typologies of firms with respect to the impacts of economic crises on them; b) to predict the susceptibility/vulnerability of individual firms to future economic crises in light of their financial circumstances.

Especially with respect to the latter, it would be exceedingly practical to forecast the comprehensive "pattern" of a specific firm's susceptibility/vulnerability to economic crises. For these purposes pre-existing government data from economic crisis periods, processed through sophisticated AI, might be quite useful. In this direction our paper makes a contribution.

In the past, there has been some research that employs AI-based techniques in order to provide an early prediction and warning for economic crises. For instance (Wang & Zong, 2023), use AI/ML and currency data in order to assist private sector firms in China in early detection of crises. In (Samitas et al., 2020) is developed a method of using AI/ML and net-work analysis for creating an early-warning system for predicting financial crises, focusing on contagion risks. The benefits of using ML tools to assess the risk of fiscal crises are investigated in (Hellwig, 2021) , and a comparison is made with the standard econometric approaches that are usually employed for this purpose, concluding that the former outperform the latter. However, there is a lack of research concerning the use of AI for understanding and predicting the impacts of financial crises on firms, which constitute the primary actors of modern economies. The current investigation serves towards bridging this research gap.

2.2 Open Government Data

As mentioned in the Introduction government agencies possess large amounts of valuable data, usually developed through their operations of direct data collection from citizens and firms; for some of these data they decide to open them to the society, so that various actors (e.g. universities and research centres, firms, citizens communities, etc.) can process them, and extract additional useful insights from them as well as develop useful services; this has made a substantial contribution to the growth of the "data economy (Ali et al., 2022; Charalabidis et al., 2018; Gao et al., 2023; Van Loenen et al., 2021; Wirtz et al., 2022; Zuiderwijk et al., 2019). According to (Gao et al., 2023) “Open Government Data (OGD) refers to publishing public sector information in open and reusable formats, without restriction or monetary charge for use by society”. Most of these data are provided freely in government websites, but some sensitive data can be provided only upon request and subject to specific conditions. An increasing number of nations are formulating OGD policies and implementing targeted OGD initiatives with the following goals in mind: a) to promote economic activity that capitalizes on OGD (e.g., pioneering value-added e-services derived from the combination of diverse forms of OGD and potentially private data, and overall OG); and b) to advance social objectives (in-creased the government accountability and transparency, as well as citizen engagement and trust) (Official Journal of the European Union, 2019; Open, Useful and Re-Usable Data (OURdata) Index, 2020).

Despite the fact that these OGD initiatives have made available substantial quantities of public sector data, neither their use nor the social-political and economic value produced from them have met the initial expectations (Gao et al., 2023; Van Loenen et al., 2021; Zuiderwijk et al., 2019). This is quite negative given the large investments that have been made by governments for these OGD initiatives, as well as the loss of great opportunities that the utilization OGD could provide. As possible solutions of this problem have been proposed: a) on one hand the alignment of OGD supply with demand (i.e., the provision of the kinds of OGD that the public (citizens, firms, journalists, etc.) is really interested in), and the development of appropriate collaborations and ecosystems for the exploitation of OGD and the creation of significant societal and economical goals through these stakeholders (Van Loenen et al., 2021; Zuiderwijk et al., 2019); b) the more ‘intensive’ exploitation of the large quantities of public sector data that have been opened through the use of highly sophisticated processing techniques, such as AI techniques, in order to maximize the knowledge extraction and in general the value generation from them (Charalabidis et al., 2018; Gao et al., 2023). However limited is the research that has been conducted concerning the use of AI for increasing the generation of value from OGD. A good example of this research direction is the study described in (Tsagkis et al., 2023), which uses ML trained with OGD for the forecast of urban growth in order to improve city planning; in particular, an artificial neural network is constructed, which is used for five major Greek cities in order to make an urban growth prediction for each city for the following 12-years. Also, (Gao & Janssen, 2020) examines three instances of AI implementation for OGD, and concludes that it can lead to the generation of substantial innovation and efficiency related benefits. So, much more research is required concerning the more sophisticated and intensive utilization of the OGD using AI techniques for enhancing knowledge extraction and, in general, value generation from OGD; the current work provides a valuable addition to this particular area.

2.3 AI in Government

Over the course of the previous decade, AI has experienced significant growth in its implementation and exploitation beyond academic research centres; initially, private sector organizations and, more recently, government agencies have begun to utilize AI in their operations and decisions (European Commission. Joint Research Centre., 2022; Gomes de Sousa et al., 2019; Madan & Ashok, 2023; Medaglia et al., 2023; van Noordt & Misuraca, 2022; Zuiderwijk et al., 2021). The current automation in the government's processes and operations based on the utilization of traditional information systems methods can be extended and enhanced towards cognitive processes, through the exploitation of vast amounts of data available fed into AI algorithms, such as machine learning and deep learning ones.

Several highly beneficial applications of AI in government operations and decision making have been developed (European Commission. Joint Research Centre., 2022). For instance, the government in the fight against the tax evasion developed an automated ways to recognize citizens and businesses with a high risk of tax dodging. This application helps the governments to develop tax audits more precisely. Healthcare also utilizes AI to tackle several issues in the disease diagnosis-identification, prevention, as well as treatment of the patients. Healthcare also uses AI for clinical-related decision support systems and decision-making processes. In the social policy and crime prevention field, some of the AI uses, such as fraud identification, youth monitoring for prevention of any future risk and preventing any unwanted situation, identification of spatial crimes and patterns, face recognition from videos and images, and improving interaction with citizens through chatbots, are a few of the uses of AI, among others. In this direction the European Union initiative called "AI Watch" aims at recognizing the possible applications and goals of the AI utilization in the government's process, and disseminating them, aiming to increase the use of AI in governments (European Commission. Joint Research Centre., 2022). AI Watch highlights some specific uses of AI in the public sector; the first one is that the government uses it for the improvement in the public services provision by providing tailored and citizen-oriented services, information, and data; the second is that, governments use AI for improving the internal processes and administrative efficiencies by managing the available public resources as well as improving the quality of the process/service and reducing the overall cost of them. Moreover, there is high research interest in the AI's possible role in the government, which distinguished two possible roles:
a) Administration tasks automation through the utilization of AI, which can help in reducing the costs and increasing the efficiencies of these tasks.
b) Administration process enhancement through the use of AI augmentation, particularly duties related to top-level decision-making and policy devising, by providing AI with high-quality data to improve decision effectiveness and overall quality and performance.
There have been several studies discuss AI utilization and exploitation in the governments and their assessment methods (Gomes de Sousa et al., 2019; Madan & Ashok, 2023; Medaglia et al., 2023; van Noordt & Misuraca, 2022).

Nonetheless, it is widely acknowledged that the utilization of AI in government has only scratched the surface of its immense potential in automating, supporting, and enhancing various government functions. Furthermore, the majority of AI applications in government pertain to activities of low or medium administrative importance and financial significance (Gomes de Sousa et al., 2019), (Medaglia et al., 2023), and (van Noordt & Misuraca, 2022). As a result, substantial additional research is necessary to further exploit this enormous potential by developing new approaches and methodologies for utilizing AI in government, particularly in its most critical and expensive operations, with the aim of enhancing their efficacy and efficiency. This paper contributes in this direction towards increasing our knowledge about advanced utilization of AI in government in order to manage better one of the most important challenges it faces: the economic crises that frequently appear in this century in our economies and societies. In this direction we propose a methodology which combines the use of supervised machine learning (estimation of a prediction model of the value of a 'dependent variable' – outcome for a specific 'unit' (e.g. individual, firm, etc.) from the values of a number of 'independent variables' for the same unit, based on existing historic data for a number of units concerning both the value of the dependent variable and the values of the independent variables); with the use of unsupervised machine learning (use of existing historic data for a number of units concerning a number of variables, for the identification of possible clusters of 'similar' units, having similar values in these variables) (Russel and Norvig, 2020).

3. Proposed Methodology

The proposed methodology leverages existing data in government agencies about the behaviour of individual firms during economic crises and their vulnerability to them; these data include various aspects of impact of the economic crisis on these individual firms as main variables (e.g. impacts of various important economic aspects of the firms). Its structure is shown in Fig.1.

Initially it is important to use these data in order to understand the main typologies of firms with respect to the impact of economic crisis on them; if we find quite different typologies then we can design for each of them a different appropriate support policy and corresponding programs (mainly for the impact typologies that really require such support). For this purpose, we can use unsupervised learning techniques, such as clustering ones (e.g. k-means clustering) (Russel and Norvig, 2020), based on the above variables; the number of clusters can be identified through dendrogram or/and elbow techniques, and then in order to understand each cluster (typology) its centroid is calculated (=average values of all variables across all firms of the cluster).

Then we can proceed to the use of supervised learning techniques, such as classification ones (Russel and Norvig, 2020), based on the same data, in order to construct prediction models of the "vulnerability pattern" of an individual firm in the event of a future economic crisis. This pattern is represented as a vector, which has components the impacts of the crisis on various economic aspects of the firm (e.g. impacts on the decrease of domestic demand from other private sector firms and individual consumers, impact on the decrease of domestic demand from public sector, impact of the decrease of foreign demand, etc.):

$$IMP = [IMP_1, IMP_2, ..., IMP_N]$$

These N components can be measures in Likert scale with three or five levels of impact measurement (e.g. "not at all," "small impact", "moderate impact", "large impact" and "very large impact"); for each component a different prediction model is constructed using the available historic data.

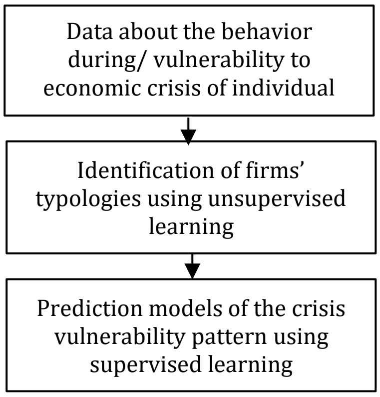

Fig.1. Structure of the proposed methodology

In particular, for each of the components of the "vulnerability pattern" IMPi we develop a predictive model that has this element as dependent variable. In order to define the independent variables of this model we have been based on theoretical foundations from economic and management science.

According to economic science, the main factors influencing a firm's output and overall performance are its labor force, which is made up of people with a variety of specializations and educational backgrounds, and its capital, which includes all types of equipment used for production and administrative tasks; the renowned production function of Cobb-Douglas is often used to quantify this connection (Douglas, 1976; Mahaboob et al., 2019; Pilat, 2004). Additionally, a variety of frameworks have been developed in the discipline of management science to outline the key elements of a firm that impact its performance. With five fundamental components—strategy, processes, people, technology, and organizational structure—the 'Leavitt's Diamond' framework is the most prominent among them (Leavitt, 1962; Scott Morton, 1991, p. 19). We can see that the 'people' and 'technology' components correspond broadly to the 'capital' and 'labour' ones of the Cobb-Douglas production function, so the other three 'strategy', 'processes' and 'structure' elements are additional (in comparison with the Cobb-Douglas production function). Therefore, the 'Leavitt's Diamond' framework is more comprehensive, so we have used it as basis and theoretical foundation for determining the independent variables of our prediction models, since it includes both the main production factors determined by the economic science and also the above three additional highly important management-oriented elements. It is reasonable to anticipate that these five pivotal components within the 'Leavitt's Diamond' framework will serve as primary determinants of a firm's performance in both typical economic conditions and during economic crises.

Therefore, each of these N prediction models (of IMPi, i=1…N) comprises five categories of independent variables:
a) Strategy: the first category of the independent variables comes from the strategy component of the 'Leavitt's Diamond' framework, and includes elements related to firm's adoption of key competitive strategies listed in strategic management literature studies, such as cost leadership, innovation, differentiation, and focus.
b) Process: the second category of independent variables covers process-related features of a firm's operations, such as complexity and flexibilities in operations.
c) People: it includes independent variables concerning the workforce of the firm in terms of education levels, particulars skills, certifications, and related attributes etc.
d) Technology: it refers to the utilization of various technologies for firm's manufacturing and administrative functions.
e) Structure: it refers to the fundamental elements of the company's organizational structure, such as the use of "organic" work organization techniques like cooperation, etc.
Additionally, a sixth category of independent variables is necessary concerning basic information about the firm, including its size, industry, and performance in comparison to rivals. Figure 2 shows the structure of these prediction models (dependent and independent variables).

For constructing each of these prediction models we can use several alternative widely used AI/ML algorithms, such as the decision tree (DT), random forest (RF), logistic regression (LR) and support vector machines (SVM) ones (Russel and Norvig, 2020), and determine the top performing one; they will be trained using available OGD (that might be freely available, or due to the sensitivity of these data available on request and under specific conditions) about individual firm's behaviour during and vulnerability to economic crisis, as well as main characteristics of them (including the ones of the main categories a) to e) mentioned above), from Statistical

Authorities or other government agencies collecting such data.

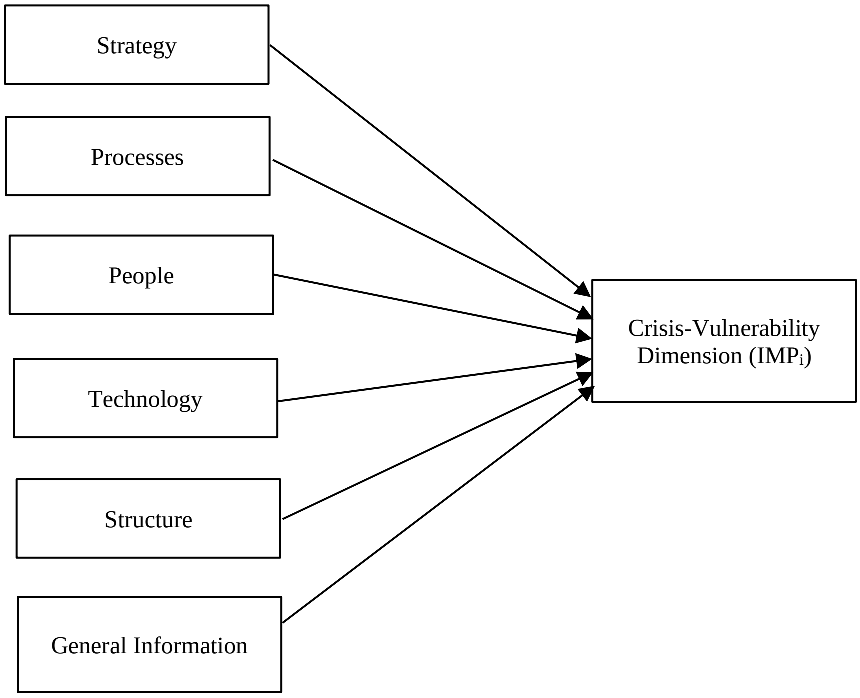

Fig. 2 - The structure for the prediction models of each of the elements of a firm's vulnerability pattern to economic crisis

Nonetheless, such datasets often exhibit several issues:
i) they tend to be noisy due to missing values;
ii) their size may not be sufficiently large to train robust and accurate machine learning models;
iii) and also, these datasets are frequently imbalanced, with some classes having a limited number of observations compared to others (this imbalance can lead to prediction models with reduced performance and potential bias).
In order to address problems ii) and ii), we include a preprocessing phase using the Synthetic Minority Over-sampling Technique (SMOTE) (Dudjak & Martinović, 2020). By filling in missing values, balancing the distribution of classes, and oversampling the dataset's existing samples, SMOTE allays these worries. This can improve the prediction model's performance and accounts for any possible bias.

Furthermore, our method starts with an exploratory data analysis (EDA) that incorporates data visualization to get a fundamental understanding of the dataset. This EDA step facilitates the necessary adjustments and informs the subsequent operations. Following the EDA, a Principal Component Analysis (PCA) is used to choose or exclude features according to their relative value (Mishra et al., 2017). This feature selection process reduces training time and enhances model performance.

4. Application

The proposed method was applied and validated using a OGD dataset obtained from the Greek Statistical Authority; it was provided to the authors upon request and with written authorization, in order to be used for research purposes, under a non-disclosure agreement. The dataset had 363 instances, each of which represented a distinct firm. It included a comprehensive list of traits and assessments for each firm, organized as follows:
- Vulnerability variables: Each firm's vulnerability to the economic crisis for the period 2009 to 2014, assessed through five variables: decrease of domestic demand from other private sector firms and individual consumers (IMP_DPRD), decrease of domestic demand from public sector (IMP_DPUD), decrease of foreign demand (IMP_DFOD), decrease of products/services prices (IMP_DPRI) and decrease of liquidity provision by banks (IMP_DLIQ). They were initially measured in a five levels Lickert scale ("not at all", "small", "moderate", "large" and "very large")
- Firm Characteristics: This part had forty variables that addressed various firm's characteristics: strategy, personnel, technology (especially digital technology), structure (including the use of "organic" forms of work organization, such collaboration), and general company information were some of these elements; this general information comprised the firm's size, as indicated by the number of employees, its industry (services or manufacturing), and a comparison of its financial performance over the last three years with that of its competitors.

All the processing of the above data described below was performed using Python language, specifically Python

3.11.7. For the machine learning tasks, we have used the open-source package within the Python environment — scikit-learn. This package contains the machine learning models and other data processing and splitting functions which are readily available to perform the supervised and unsupervised machine learning tasks, as we performed in our experimentation. Furthermore, scikit-learn supports parametric tuning; however, we used default parameters in all these experiments

The dataset's initial cause of noise was missing values; however, this was re-solved by replacing the missing values with the best values based on the variable type; for instance, the value with the highest relative frequency value was used to fill in the missing values for ordinal variables. The necessary visualizations and transformations were then used in an exploratory data analysis (EDA) to enhance data understanding. The size of the dataset—which, as previously said, included data for 363 firms—made it difficult to build a supervised ML prediction model of high prediction performance; so, as mentioned in the previous section 3, we used the oversampling and class-balancing method SMOTE to overcome this constraint.

After the above preprocessing we proceeded to the application of unsupervised learning to the above data; we conducted clustering, using the abovementioned five vulnerability variables (IMP_DPRD, IMP_DPUD, IMP_DFOD, IMP_DPRI, IMP_DLIQ), in order to examine if we can distinguish some distinct clusters – typologies of firms with respect to the above five kinds of impact of the economic crisis on them. Using both the dendrogram and the elbow techniques we identified the number of clusters; both techniques indicated the existence of three clusters. Then using this identified number of three clusters we performed k-means clustering. The results concerning the centroids of the three clusters are shown in Fig. 3 (we can see for each of the above five vulnerability variables (features) its average value over all firms of each class). We can distinguish one cluster (cluster 3 – it includes 78 firms) that experienced on average a negligible to small negative impact of the decrease of domestic public sector demand and foreign demand due to the crisis, and also a small to moderate negative impact of the decrease of domestic private sector and individual consumers' demand, as well as the decrease of products/services prices caused by the crisis; furthermore they experienced a small negative impact of the decrease of liquidity provision by banks during the crisis. We can characterize this cluster as 'low crisis-vulnerability firms' (the average value over all five vulnerability variables equals to 1,87). Also, we can distinguish another cluster (cluster 1 – it includes 118 firms) that experienced on average a moderate to large negative impact of the decrease of domestic private sector demand and the products/services prices caused by the crisis, a small to moderate negative impact of the decrease of the foreign demand, and a small negative impact of the decrease of domestic public sector demand; furthermore, they experienced a large negative impact of the decrease of liquidity provision by banks during the crisis. We can characterize this cluster as 'moderate crisis-vulnerability firms' (the average value over all five vulnerability variables equals to 2,9). Finally, we can distinguish another cluster experiencing even higher negative impacts (cluster 2 – it includes 167 firms): a high negative impact of the decrease of the domestic private sector and individual consumers' demand, as well as the domestic public sector demand, caused by the crisis; also a moderate to large negative impact of the decrease of products/services prices and the decrease of liquidity provision by banks during the crisis; and finally a small to moderate impact of the decrease of foreign demand. We can characterize this cluster as 'moderate to large crisis-vulnerability firms' (the average value over all five vulnerability variables equals to 3,45). The above clustering results indicate the existence of a large heterogeneity among the firms regarding the effects of the crisis, which necessitates the design and implementation of different policies and programs for each cluster-typology of crisis negative impacts, especially for clusters 1 and 2 (placing emphasis on supporting them to cope with the decrease of liquidity provision by banks during the crisis).

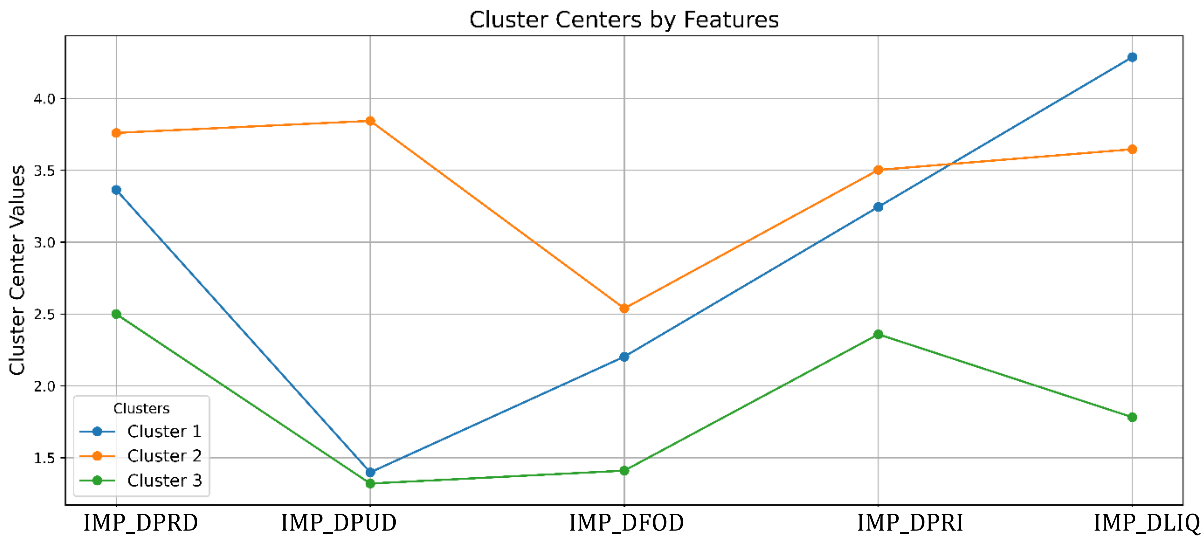

Fig.3. The centroids of the three clusters

Then we proceeded to the application of supervised machine learning to the above data: we used AI/ML algorithms in order to predict the 'vulnerability pattern' of an individual firm: we constructed for each of the five vulnerability variables one prediction models, having as independent variables the forty firm's characteristics mentioned in the beginning of this section (concerning firm's strategy, personnel, use of digital technologies, structure and general firm information). Due to the small size of our dataset (data for 363 firms) we focused on a less-detailed prediction of these five vulnerability variables, and for this purpose they were converted into binary form, with the first three values (not at all, small, moderate) being marked as "non-vulnerable" and the other two (large, very large) as "vulnerable". The dataset was divided into two subsets: a training dataset containing 70% of the samples and a testing dataset containing the remaining 30% of the samples; then another division of the dataset was made: a training dataset with 80% of the samples, and a test dataset with the remaining 20%. For both cases we used the training sets in order to construct AI/ML models, making use of four widely used algorithms: Decision Tree (DT), Random Forest (RF), Logistic Regression (LR) and Support Vector Machines (SVM). In each case the corresponding test set was used in order to evaluate the prediction performance of each of these AI/ML models. The results, including prediction accuracy, precision, recall, and F-score, are presented in Table 1, with bold highlights indicating the best-performing algorithm for each of the five crisis vulnerability variables. We have repeated the same for the prediction of firm's cluster membership (i.e. whether it will belong to cluster 1, 2 or 3 = whether in a future crisis it is going to exhibit low, moderate or moderate to large crisis-vulnerability) using the same firm's characteristics as independent variables.

Tab. 1 – Evaluation of Prediction Performance of the AI/ML models for each of the five crisis vulnerability variables

		Split Ratio							
Variable.e.	Algorithm	Performance with 70-30 (weighted average precision, recall, and F-score)				Performance with 80-20 (weighted average precision, recall, and F-score)			
		accuracy	precision	recall	F-score	accuracy	precision	recall	F-score
IMP_DPRD	DT	0.8165	0.83	0.82	0.82	0.7982	0.82	0.80	0.80
	RF	**0.9266**	**0.93**	**0.93**	**0.93**	**0.9083**	**0.91**	**0.91**	**0.91**
	LR	0.7431	0.74	0.74	0.74	0.7431	0.74	0.74	0.74
	SVC	0.8899	0.89	0.89	0.89	0.8899	0.89	0.89	0.89
IMP_DPUD	DT	0.7591	0.76	0.76	0.76	0.7810	0.78	0.78	0.78
	RF	**0.8686**	**0.89**	**0.87**	**0.86**	**0.8905**	**0.90**	**0.89**	**0.89**
	LR	0.6861	0.69	0.69	0.66	0.6861	0.69	0.69	0.66
	SVC	0.7810	0.80	0.78	0.77	0.7810	0.80	0.78	0.77
IMP_DFOD	DT	0.8050	0.80	0.81	0.80	0.7610	0.76	0.76	0.76
	RF	**0.8616**	**0.88**	**0.86**	**0.86**	**0.8742**	**0.89**	**0.87**	**0.87**
	LR	0.6792	0.68	0.68	0.68	0.6792	0.68	0.68	0.68
	SVC	0.7358	0.73	0.74	0.73	0.7358	0.73	0.74	0.73
IMP_DPRI	DT	0.8235	0.85	0.82	0.83	0.8039	0.83	0.80	0.81
	RF	**0.9216**	**0.93**	**0.92**	**0.92**	**0.9608**	**0.96**	**0.96**	**0.96**
	LR	0.7941	0.80	0.79	0.79	0.7941	0.80	0.79	0.79
	SVC	0.9020	0.91	0.90	0.90	0.9020	0.91	0.90	0.90
IMP_DLIQ	DT	0.7698	0.78	0.77	0.77	0.7770	0.78	0.78	0.78
	RF	**0.9065**	**0.91**	**0.91**	**0.90**	**0.9137**	**0.92**	**0.92**	**0.92**
	LR	0.7338	0.73	0.73	0.73	0.7338	0.73	0.73	0.73
	SVC	0.7626	0.78	0.76	0.75	0.7626	0.78	0.76	0.75
Cluster	DT	0.6500	0.66	0.65	0.65	0.6400	0.65	0.64	0.63
	RF	**0.7600**	**0.76**	**0.76**	**0.75**	**0.7400**	**0.74**	**0.74**	**0.73**
	LR	0.5500	0.54	0.55	0.55	0.5500	0.54	0.55	0.54
	SVC	0.6900	0.70	0.69	0.69	0.6900	0.70	0.69	0.69

We can see that for all the crisis vulnerability variables the highest prediction performance is achieved through the Random Forest (RF) algorithm; these prediction performances are high (especially if we take into account the small size of the available dataset), ranging (for the 70-30 training-test set case) from an accuracy of 0.9266 for IMP_DPRD and 0.9216 for IMP_DLIQ, to 0.8616 for IMP_DFOD. For the cluster membership again the RF algorithm achieves the highest prediction performance, which is however lower, with an accuracy equal to 0.76 (which was expected as now the prediction provided by this model is more detailed than in the previous ones: it has to predict one out of three possible values, while the previous models had to predict one out of two possible values); nevertheless it is satisfactory, taking into account the small size of the available dataset.

5. Conclusion

In the preceding sections of this paper, we have developed a methodology for sophisticated advanced leveraging of data that government agencies possess concerning firms' behaviour during and vulnerability to recessionary economic crises, using a combination of AI techniques, both unsupervised and supervised ones, the latter in conjunction with the Synthetic Minority Oversampling Technique (SMOTE) to optimize their performance. The primary goal of the proposed methodology is to provide valuable support and enhance the crucial and resource-intensive types of interventions undertaken by governments during economic crises, in order to mitigate their adverse consequences on firms (including large-scale economic stimulus programs). It quite important to bolster the effectiveness of such interventions and focus them on the most susceptible businesses affected severely by the economic crisis, thereby reducing the detrimental impact of economic crises.

From the two main roles that AI can play in government discussed in Section 2.3, namely automation and augmentation, our methodology aligns with the latter. Its primary objective is to augment and enhance the decision-making processes of competent government agencies when it comes to identifying firms to be supported through extensive and costly programs and interventions implemented during economic crises. This is particularly crucial in the context of large-scale economic stimulus programs. By offering an additional input, specifically the typologies of firms with respect to their behaviour in/vulnerability to economic crises, and the prediction of the vulnerability pattern of individual firms to economic crises, our methodology proves highly valuable for facilitating the critical decisions involved in designing and implementing policies and programs for mitigating the consequences of economic crises for firms, as well as in selecting firms to support, especially when numerous firms submit applications for such assistance.

The proposed methodology is useful not only to government agencies, but also to banks and investment firms as well, as it strengthens and improves their decision-making procedures when it comes to identifying firms eligible for loans or investments; our methodology enables them to identify firms that will be particularly vulnerable to future economic crises (which have become frequent in this century), which makes granting loans to or investing in them highly risky (this predicted vulnerability to future crises can be one of the criteria they use for selecting firms eligible for loans or investments). Our methodology also extends its utility to firms across various sectors that heavily rely on extensive supply chains: it improves and supplements the process of choosing supply chain partners, by enabling them to take into account their predicted vulnerability to future crises and avoid supply chain partners (e.g. suppliers, wholesalers, etc.) exhibiting high risk of vulnerability to future economic crises.

Furthermore, OGD provided on request from the Greek Statistical Authority, which includes data from 363 firms for the turbulent 2009–2014 period of the severe Greek economic crisis, has been used for a first application and validation of the suggested methodology, which gave satisfactory results.

The research presented in this paper carries substantial implications for both research and practice. In the realm of research, it offers significant contributions to two crucial research streams. Firstly, it enriches the ever-expanding research on the utilization of AI in government by introducing a novel approach that leverages AI/ML to bolster a vital government activity of high economic, social, and financial significance: government intervention for mitigating the impacts of crises on firms. Secondly, it extends the OGD research by presenting a methodology that enhances the economic and social value derived from OGD through advanced processing of them through AI-based processing techniques (unsupervised and supervised ML). In the context of practical applications, this research equips government agencies, and also banks, investment firms, and businesses across various sectors heavily reliant on extensive supply chains, with a valuable tool for augmenting and enhancing highly important decision-making.

Nonetheless, further research is warranted in several critical directions. Firstly, there is a need for expanded application of the proposed methodology, encompassing larger datasets from diverse national and sectoral contexts that have encountered varying types and intensities of economic crises. This will enhance the methodology's robustness and applicability. Secondly, exploration of alternative pre-processing algorithms, such as over-sampling and class-balancing algorithms, missing data treatment techniques, as well as more advanced AI/ML algorithms, including deep learning ones, is essential to broaden the methodology's capabilities. Lastly, investigating the integration of OGD with data from other sources, such as data from other government agencies and private firms, including private business information databases, is vital to enrich the information available about firms. This expanded data could potentially enhance the prediction performance of a firm's vulnerability pattern to economic crises, as well as provide deeper insights concerning heterogeneities among firms with respect to their behaviour in/vulnerability to economic crises.

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- **Data/Software Access Statement** (if applicable): The data we have used for the application described in section 4 have been provided by the Greek Statistical Authority upon request and under a non-disclosure agreement.
- **Contributor Statement**: The first author has been involved mainly in sections 1,2 and 3, the second has been involved mainly in sections 3 and 4, while the thid author has been involved mainly in the section 1, ans in general in developing the main research objectives and directions of the paper, as well as in the conclusions presented in section 5.
- **Use of AI***: No AI tool has been used the preparation of this work.
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