The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/1750-6166.htm

Predicting firms' resilience to economic crisis using artificial intelligence for optimizing economic stimulus programs

Niki Kyriakou
Department of Information and Communication Systems Engineering, University of the Aegean, Mytilene, Greece

Euripidis N. Loukis
Department of Information and Communication Systems Engineering, University of the Aegean, Karlovassi, Greece, and

Manolis Maragoudakis
Department of Information and Communication Systems Engineering, University of the Aegean, Mytilene, Greece

Received 20 August 2022
Revised 2 January 2023
23 February 2023
2 June 2023
6 July 2023
1 August 2023
Accepted 2 August 2023

Abstract

Purpose – This study aims to develop a methodology for predicting the resilience of individual firms to economic crisis, using historical government data to optimize one of the most important and costly interventions that governments undertake, the huge economic stimulus programs that governments implement for mitigating the consequences of economic crises, by making them more focused on the less resilient and more vulnerable firms to the crisis, which have the highest need for government assistance and support.

Design/methodology/approach – The authors are leveraging existing firm-level data for economic crisis periods from government agencies having competencies/responsibilities in the domain of economy, such as Ministries of Finance and Statistical Authorities, to construct prediction models of the resilience of individual firms to the economic crisis based on firms' characteristics (such as human resources, technology, strategies, processes and structure), using artificial intelligence (AI) techniques from the area of machine learning (ML).

Findings – The methodology has been applied using data from the Greek Ministry of Finance and Statistical Authority about 363 firms for the Greek economic crisis period 2009–2014 and has provided a satisfactory prediction of a measure of the resilience of individual firms to an economic crisis.

Research limitations/implications – The authors' study opens up new research directions concerning the exploitation of AI/ML in government for a critical government activity/intervention of high importance that mobilizes/spends huge financial resources. The main limitation is that the abovementioned first application of the proposed methodology has been based on a rather small data set from a single national context (Greece), so it is necessary to proceed to further application of this methodology using larger data sets and different national contexts.

Practical implications – The proposed methodology enables government agencies responsible for the implementation of such economic stimulus programs to proceed to radical transformations of them by predicting the resilience to economic crisis of the firms applying for government assistance and then directing/focusing the scarce available financial resources to/on the ones predicted to be more vulnerable, increasing substantially the effectiveness of these programs and the economic/social value they generate.

Originality/value – To the best of the authors' knowledge, this study is the first application of AI/ML in government that leverages existing data for economic crisis periods to optimize and increase the effectiveness

Since acceptance of this article, the following author has updated their affiliation: Manolis Maragoudakis is at the Department of Informatics, Ionian University, Corfu, Greece.

Transforming Government: People, Process and Policy
© Emerald Publishing Limited
1750-6166
DOI 10.1108/TG-08-2022-0112

of the largest and most important and costly economic intervention that governments repeatedly have to make: the economic stimulus programs for mitigating the consequences of economic crises.

Keywords Economic crisis, Machine learning, Artificial intelligence, Digital government, Electronic government, Transformational government

Paper type Research paper

1. Introduction

Economic crises often appear in market-based economies, initiated by various types of events, such as banking crises, health-related crises (such as the COVID-19 one) and increases in the prices of essential goods (e.g. oil or gas), and resulting in economic recessions (meant as severe contractions of economic activity), which have quite negative consequences for the economy and society (Keeley and Love, 2012; Knoop, 2015; Allen, 2017; Vartanian, 2021; Loukis *et al.*, 2021). During the past century, numerous economic crises have appeared with quite negative consequences [a good review of them is provided in Knoop (2015)], while a decade ago, we had the severe 2007 Global Financial Crisis, and recently we experienced an economic crisis caused by the COVID-19 pandemic (Baldwin and Di Mauro, 2020); furthermore, the Ukraine war, and the significant increases in the prices of oil, gas, wheat and other goods it gives rise to, is expected to spark another economic crisis.

Because of the severe negative consequences of economic crises for the economy and society, governments undertake large-scale economic stimulus programs, spending vast amounts of financial resources, which can have orders of magnitude between 3% and 6% of GDP, or even more, to mitigate these negative consequences (such as the recent American Recovery and Reinvestment Act in the United States and the European Economic Recovery Plan in the European Union) (European Commission – Directorate-General for Economic and Financial Affairs, 2009; Khatiwada, 2009; Coenen *et al.*, 2012; Kalinowski, 2015; Taylor, 2018). These economic stimulus programs include many different types of actions, aiming mainly at the provision to firms of tax rebates, financial assistance, subsidies and low-interest (or even no-interest) loans to strengthen their overall financial position and liquidity. These programs, on the one hand, are of critical importance for mitigating the negative consequences of economic crises, but on the other hand, they result in considerable increases in national debts, which cause big macroeconomic problems in the post-crisis periods. So, it is necessary to design and implement carefully and rationally these extensive and costly economic interventions governments undertake to use these vast financial resources effectively and finally generate a high positive impact on the economy and society in these challenging crisis periods. In this direction, considerable research has been conducted for the assessment of the effects of such economic stimulus programs, which have been designed and implemented for addressing previous economic crises, such as the 2007 Global Financial Crisis, to draw valuable conclusions, insights and knowledge that can be used for designing and implementing economic stimulus programs for addressing future crises (Khatiwada, 2009; Coenen *et al.*, 2012; Kalinowski, 2015; Taylor, 2018). However, there is a lack of research concerning the exploitation and leveraging of the extensive firm-level data that government agencies have collected during previous economic crises, using highly sophisticated processing techniques, such as artificial intelligence (AI) – and especially machine learning (ML) – ones, for the optimization of these large and highly important for the economy and the society economic stimulus programs, to increase their effectiveness, economic/social value and positive impact.

This paper contributes to filling the abovementioned research gap. It proposes a methodology for leveraging existing firm-level data for economic crisis periods from government agencies with competencies/responsibilities in the domain of the economy, such as Ministries of Finance and Statistical Authorities, using AI/ML techniques to construct prediction models of individual firms' resilience to economic crisis; for this purpose, we are using as predictors (independent variables) a wide range of firms' characteristics, such as human resources, technology, strategies, processes and structure. These prediction models enable government agencies responsible for economic stimulus programs, implemented at the beginning of such economic crises or even earlier, to proceed with radical transformations of them by directing/focusing their scarce available financial resources on the firms predicted to be more vulnerable to the crisis, which will increase substantial the effectiveness of these programs. In particular, they enable predicting the resilience to an economic crisis of all the firms applying to such government assistance/support actions that aim to strengthen firms' overall financial position and liquidity, and then using these predictions (possibly in combination with other established criteria, which however usually concern mainly firm's performance during "normal" economically stable periods) to direct/focus the available financial resources to/on the ones predicted to exhibit lower overall economic resilience/higher vulnerability to an economic crisis.

Our study makes a significant contribution to the significant and growing stream of research about the exploitation of AI in government (briefly reviewed in Subsection 2.3); it is widely recognized that this research has revealed only a small part of the large potential of AI use in government, and extensive further research is required to exploit more this potential, developing new ways and methodologies of using AI in government, especially in its more critical and costly activities for increasing their efficiency and effectiveness (Medaglia *et al.*, 2021; Zuiderwijk *et al.*, 2021; Van Noordt and Misuraca, 2022). This study contributes to this direction by proposing a novel methodology of using AI/ML for optimizing and increasing the effectiveness of one of the most critical for the economy and society and, at the same time, the most costly and financially resource-consuming activity/intervention that governments repeatedly has to make: the economic stimulus programs for mitigating the consequences of economic crises. To the best of our knowledge, this is the first study that investigates the use of AI on such a large scale, sizeable financial magnitude and highly important for the economy and the society activity/intervention of government, for addressing one of the most severe crises our economies and societies repeatedly face, and proposes a sound and practically applicable methodology of AI exploitation for increasing the economic and social value generated by the economic stimulus programs undertaken for mitigating the consequences of economic crises.

In the following Section 2, the background of our methodology is outlined, while in Section 3, the conceptual framework of the methodology is described, and then in Section 4, the construction and possible use of the prediction models, followed by a first application of the methodology in Section 5. The final Section 6 summarizes conclusions and proposes directions for future research.

2. Background

2.1 Economic crises

In market-based economies, economic activity exhibits instabilities, which can take the milder form of "business cycles" (mild ups and downs of economic activity) or the more severe form of recessionary economic crises, defined as serious contractions of economic activity that have quite negative consequences for the economy and the society (Keeley and Love, 2012; Knoop, 2015; Allen, 2017; Vartanian, 2021; Loukis *et al.*, 2021). These economic crises decrease the demand for firms' products and services, and this results in a decrease in firms' sales and sales revenue; firms react by reducing their production, as well as personnel employment (and this increases unemployment and poverty, causing big social problems and unrest), materials' procurement (and this results in the propagation of the economic crisis to suppliers) and also capital investment (leading to technological backwardness); these result also in a decrease of firms' profits or even in losses, liquidity problems as well as increase of debts.

However, the above impacts of the economic crises differ considerably among firms. Some firms can cope better with the crisis, as they have higher abilities to make the required adaptations to these special crisis conditions and can offer higher value-for-money products and services (which are highly valued by the customers who experience a severe drop in their income due to the crisis), and therefore, have minimal (or even not at all) decrease in their sales revenue and profits, as well as in their overall financial position and liquidity; on the contrary, some other firms cannot cope sufficiently with the crisis and have a severe decrease in their sales revenue and profits, as well as severe deterioration of their overall financial position and liquidity. Therefore, firms differ significantly in their resilience to economic crises (Arvanitis and Woerter, 2014; Allen, 2017; Vartanian, 2021). The extent of an individual firm's resilience to the economic crisis is determined by its characteristics concerning human resources, technologies used for its activities, etc., as discussed later in Subsection 2.2.

Governments, to mitigate the abovementioned severe negative consequences of the economic crises, which can give rise to social unrest and political extremism, undertake large-scale economic stimulus programs, spending vast amounts of financial resources (European Commission – Directorate-General for Economic and Financial Affairs, 2009; Khatiwada, 2009; Coenen *et al.*, 2012; Kalinowski, 2015; Taylor, 2018). These economic stimulus programs vary in size [e.g. the stimulus program of the EU for addressing the 2007 Global Financial Crisis amounted to 5% of GDP in the EU (European Commission – Directorate-General for Economic and Financial Affairs, 2009), while the corresponding program of China was much bigger, reaching an estimated 12.5% of its GDP (Kalinowski, 2015)], and also vary in composition (i.e. in the specific actions they include). In general, they include two main categories of actions:

(1) demand-side oriented ones, which aim to stimulate consumption of various products and services by citizens, such as the provision of unemployment assistance, nutritional aid, health and welfare payments and tax cuts; and

(2) supply-side oriented ones, which aim to provide firms tax rebates, financial assistance, subsidies or low-interest (or even no-interest) loans to strengthen their overall financial position and liquidity in these challenging crisis periods (Kalinowski, 2015).

It is widely recognized that to maximize the effectiveness and positive impact of the above supply-side actions, the latter have to be highly focused on the firms that have the highest need for support of their overall financial position and liquidity. For this purpose, it is useful to develop predictions of the resilience to economic crisis of the individual firms that apply to these government support actions and then use these predictions, possibly in combination with other established criteria, to improve and rationalize the focusing of these support actions on the less resilient and, therefore, more vulnerable firms. Our study contributes to this direction by exploiting AI/ML techniques using existing historical government data.

2.2 Determinants of firm performance

Previous economic and management science research has dealt with the identification of the main elements of a firm that determine its performance; the conclusions of this research can be useful for our study, as we can expect that these elements might determine, to a considerable extent, the performance of a firm during an economic crisis in coping with the difficult and complex external conditions that these crises give rise to, and therefore, the degree of firm's resilience to economic crises.

Economic research has concluded that the main factors of a firm that determine the value of the output it produces and its economic performance are: its capital (meant as the different kinds of production equipment it uses) and its labor (meant as the personnel of different educational levels and specialties it employs) (Cobb – Douglas production function), while later, the wide use of ICT lead to discrimination between noncomputer capital and computer capital, and also between noncomputer labor and computer labor; subsequently the importance also of firm's "organizational capital" (meant as processes and structures of the firm) as well as "human capital" (meant as the skills and knowledge of firm's personnel) for its output and performance were recognized (Pilat, 2005; Arvanitis and Loukis, 2009).

At the same time, management science research has developed several conceptualizations of the main elements of a firm that determine its performance [a good review of them is provided in Král and Králová (2016)]; the most "classical" and widely recognized and used one is the "Leavitt's Diamond" framework (Leavitt, 1970). According to it, the most important elements of a firm that determine its performance are:

- its task (strategies and processes);
- people (skills of human resources);
- technology (technologies used for implementing administrative and production tasks); and
- structure.

An extension of it has been developed subsequently, which analyses the above "task" element into the "strategy" and "processes" elements (Scott-Morton, 1991).

We remark that most of the above five main elements of a firm that determine its performance according to the "Leavitt's Diamond" framework correspond – at least to some extent – to those determined by relevant economic research: the "technology" corresponds to capital (noncomputer and computer one), the "people" correspond to labor – human resources, the "structure" and the "processes" part of the "task" correspond to organizational capital; so "Leavitt's Diamond" framework incorporates the main determinants of firm's performance identified by economic research. Therefore, we can expect that the firm's characteristics concerning the above five main elements of a firm (strategy, processes, people, technology and structure) defined by "Leavitt's Diamond" framework might be good predictors of the performance and resilience of the firm exhibits during economic crises; for this reason, we have used this framework as theoretical foundation of the prediction models of resilience to economic crises our methodology is based on Section 3.

2.3 Artificial intelligence in government

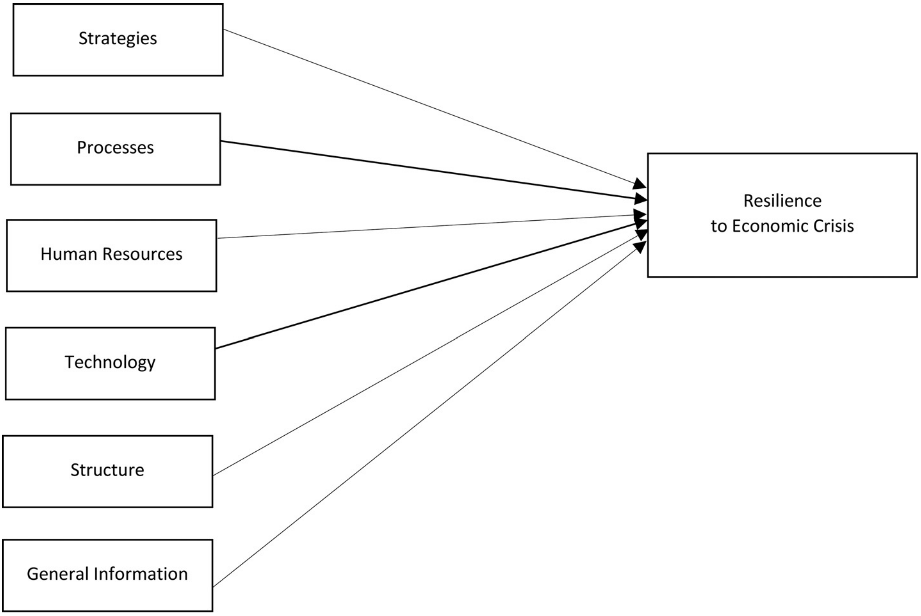
The success stories of the "real life" applications of AI in the private sector (Correia Loureiro *et al.*, 2021) generated a strong interest in using AI techniques in the public sector as well to exploit the vast amounts of data possessed by government agencies for automating or supporting, and/or enhancing, more sophisticated mental tasks than the simpler routine ones automated or supported by the traditional information systems of government agencies (Sun and Medaglia, 2019; DeSousa *et al.*, 2019; Misuraca and Van Noordt, 2020; Van Veenstra *et al.*, 2021; Medaglia *et al.*, 2021; Zuiderwijk *et al.*, 2021; Van Noordt and Misuraca, 2022; Manzoni *et al.*, 2022).

Considerable research has been conducted concerning the exploitation of AI in various government activities, for instance in education, for the prediction of applicants for teacher positions who will be more effective and successful, to support making the optimal recruitment decisions (Rockoff *et al.*, 2010); in social policy, for the prediction of higher risk youth concerning criminal activity, to target prevention interventions (Chandler *et al.*, 2011); in restaurant hygiene inspections, for harnessing the social media on-line reviews to discriminate severe offenders from the restaurants with no regulation violations, for optimizing inspections (Kang *et al.*, 2013); in tax administration for the detection of tax evasion (Matos *et al.*, 2014; De Roux *et al.*, 2018); in health care, for supporting diseases' diagnosis and treatment planning (Sun and Medaglia, 2019); and also for sustainable city planning as well as city infrastructures maintenance, congestion control and analysis of smart meter information about households' electricity/gas/water usage to design and support energy saving actions (Matsuo and Iwamitsu, 2022). Comprehensive reviews of the research that has been conducted concerning the exploitation of AI in government are provided by DeSousa *et al.* (2019), Zuiderwijk *et al.* (2021), Noordt and Misuraca (2022) and Manzoni *et al.* (2022).

However, it is widely recognized that this research stream has revealed only a small part of the large potential of AI use in government. Extensive further research is required in this area to explore and exploit this potential more and develop new ways and methodologies of using various AI techniques in a wide range of government activities, especially in the most important and costly ones that aim to address the most severe and complex problems modern economies and societies. Our study makes an important and highly beneficial for the economy and the society contribution to this research stream by developing a methodology of using AI/ML techniques and leveraging existing government data to optimize and increase the effectiveness of the largest and most important and costly economic activity/intervention that governments repeatedly have to undertake: the economic stimulus programs for mitigating the consequences of economic crises. Though there have been several studies investigating the use of AI in various activities of government (see previous paragraph), most of them deal with low or medium scale and financial magnitude, and also low or medium ones; our study is, to the best of our knowledge, the first one that investigates the use of AI in such a large scale, large financial magnitude and high importance activity of government, and proposes a sound and practically applicable methodology of exploiting AI for increasing the economic and social value generated by the economic stimulus programs undertaken for mitigating the consequences of economic crises.

3. Conceptual framework

In this section, we describe the conceptual framework of the proposed methodology. It is based on the construction of prediction models of the resilience of an individual firm to economic crisis, meant as the extent of deterioration of its financial position and liquidity during an economic crisis, using as predictors a wide range of firm's characteristics. The theoretical foundation of these models, and our methodology in general, is the "Leavitt's Diamond" framework (Leavitt, 1970) described in Subsection 2.2. According to this framework, the main elements of a firm that determine its performance are its strategy, processes, people, technology and structure; so, we can expect that these five elements will be the main determinants and predictors of the performance and resilience the firm exhibits during economic crises. So, the conceptual framework of our methodology (structure of the prediction models of a firm's resilience to an economic crisis) is shown in Figure 1. These



Source: Authors' own creation

Figure 1. Conceptual framework structure (dependent–independent variables) of prediction models of resilience to economic crises

models will include five groups of independent variables concerning the firm's strategy, processes, people, technology and structure as well as general characteristics of it.

4. Prediction models' construction and use

For the construction of these prediction models, having the abovementioned structure, we can use/try the main alternative AI/ML algorithms proposed/described in the relevant literature (Witten *et al.*, 2017; Tan *et al.*, 2019; Russell and Norvig, 2020; Blum *et al.*, 2020), as we do not know beforehand which of them is going to exhibit the highest prediction performance, such as Decision Trees, Random Forests, Deep Learning, Gradient Boosted Trees, Support Vector Machines and Generalized Linear Modeling (a detailed description of them is provided in this literature); then we select the one that exhibits the highest prediction performance (which can be different in different applications of our methodology, having different dependent and independent variables and in various national contexts).

For their training, we can use/leverage existing firm-level government data for economic crisis periods, which are possessed by Ministries of Finance (mainly Taxation Authorities) and Statistical Authorities, concerning:

- on the one hand, our dependent variable, the resilience to the economic crisis, can be operationalized as a composite variable, based on (e.g. calculated as the average of) several individual variables measuring the extent of decrease in the firm's sales revenue, profits, personnel, liquidity, etc., during the whole economic crisis period; and
- on the other hand, our independent variables, which concern the abovementioned five main elements of the firm that determine its performance (their values at the beginning of the economic crisis period):

- strategies – we can have several individual variables concerning the firm's strategies, such as the extent of adoption by the firm of the main strategies described in relevant strategic management literature (Whittington *et al.*, 2020), such as cost leadership, differentiation, focus, innovation and export;
- processes – we can have several individual variables concerning characteristics of a firm's processes, such as complexity, formality and flexibility;
- human resources – we can have several individual variables concerning the education and skills level of firm's human resources (e.g. share of firm's employees having tertiary education);
- technology – we can have several individual variables concerning the use by the firm of various important production technologies, ICT, etc.; and
- structure – we can have several individual variables concerning various aspects of the structure of the firm, the extent of use of organic forms of work organization (such as teamwork and job rotation), etc.

Also, we can have additional independent variables providing general information about the firm, such as its sector and the level of the firm's comparative performance in this sector.

These prediction models of an individual firm's resilience to the economic crisis based on its characteristics can have a wide range of uses by the management of government agencies, banks and firms of all sectors in general. In particular, it can be used by government agencies responsible for the design and implementation of economic stimulus programs for predicting the overall economic resilience of all the firms applying to government support actions that aim to strengthen firms' overall financial position and liquidity in general (through tax rebates, financial assistance, subsidies or low-interest [or even no-interest] loans, etc.); these predictions can be used, possibly in combination with other established criteria (which however usually concern mainly firm's performance during "normal" economically stable periods), to direct/focus the available financial resources to/on the firms predicted to exhibit lower overall economic resilience/higher economic vulnerability to the economic crisis. Furthermore, based on these predictions, we can group the applicant firms into two categories: the lower economic resilience/higher economic vulnerability firms (i.e. the ones having predicted economic resilience value higher than the median value over all the applicant firms) and the higher economic resilience/lower economic vulnerability firms or even into more categories (e.g. the top 25% firms, the bottom 25% ones and the remaining "intermediate" ones, concerning economic resilience). Then, we can allocate a specific share of the budget for each category for the action and possibly provide different kinds of assistance/support. This can lead to radical transformations of these economic stimulus programs, which can increase substantially their effectiveness and positive economic and social impact. Our methodology can also be used for policy design at the beginning of such an economic crisis, or even earlier when an economic crisis is in sight, for the prediction of the resilience of all the firms of a specific geographic region or a specific sector that belong to/fall within the competence of a government agency, to identify the firms likely to be highly vulnerable and be hit strongly by the crisis, and based on the produce an estimate of the financial resources that will be required for supporting them.

Furthermore, our methodology will be useful to all banks and institutional investors for making better decisions concerning the financing of firms, taking into account, in addition to other established criteria they use for making firms' financing decisions, their predicted resilience to economic crises; also, banks can predict the resilience to economic crisis of all the firms they have financed (i.e. granted loans to), and based on these predictions produce an estimate of the financial risk they will be exposed to in case of a possible future economic crisis. Moreover, our methodology can be more widely useful to firms of all sectors for improving their decision-making about the strategic medium- or long-term co-operations/networks with important partners, suppliers, or even customers by taking into account (in addition to other established criteria they use for this purpose) their resilience to recessionary economic crises as well; if such strategic partners, suppliers and customers exhibit low levels of resilience to economic crises that will appear in the future, this is going to have negative impacts on the success of these strategic co-operations with them.

5. Application

We applied the proposed methodology to construct prediction models of the resilience of Greek firms based on their characteristics concerning the above main elements. For this purpose, we used data from the Greek Ministry of Finance (the Taxation Authority) and Statistical Authority about 363 Greek firms concerning the deterioration of their main economic figures during the Greek economic crisis period 2009–2014, as well as some important characteristics of them concerning their strategies, human resources, technology, structure as well as some general characteristics at the beginning of the crisis (2009). These firms cover a wide range of sectors and sizes: 40.2% of them are in the manufacturing sector, 9.4% in construction and 50.4% in the services sector; also, 52.6% of them are small, 36.1% medium and 11.3% large businesses. For these firms, we used data concerning the following variables:

- the measure of the resilience of an individual firm to economic crisis (actually measuring its vulnerability) has been calculated as a composite variable equal to the average of six ordinal variables measuring the extent of decrease of its domestic sales (DSAL_RED), foreign sales (FSAL_RED), profits (PROF_RED), personnel (PER_RED) and liquidity (LIQ_RED) and the increase of its debts (DEBT_INC) during the economic crisis, all measured in a five-level Likert scale (not at all, to a small extent, to a moderate extent, to a large extent, to a very large extent);
- while as independent variables were used, 40 variables – firms' characteristics, which involve:
  - strategies (12 variables): the extent of adoption of strategies of cost leadership (STRAT_CL), differentiation (STRAT_DIF), innovation (STRAT_INNOV) (ordinal variables in the above five-levels Likert scale), introduction during the past three years of product/service innovations (INNOV_PRS), process innovations (INNOV_PROC), innovations in the goods' production or services' delivery processes (INN_PRSD), innovations in the sales, shipment or warehouse management processes (INN_SSWM), innovations in the support processes (e.g. in the equipment maintenance processes) (INN_SUPP) (binary variables), percentage of total sales revenue (turnover) coming from new products/services that were introduced in the market during the three previous years (NEW_PS_P), percentage of total sales revenue (turnover) coming from products/services that were improved significantly over the past three years (but were introduced previously (IMPR_PS_P) (continuous variables), existence of research and development in the past three years (R&D) (binary variable) and percentage of exports in firm's sales revenue (EXP_P) (continuous variable);

- human resources (eight variables): shares of firm's employees having tertiary education (EMPL_TERT), vocational/technical education (EMPL_VOCT), high school education (EMPL_HIGH), elementary school education (EMPL_ELEM) and also user computers for their work (EMPL_COM), use firm's intranet for their work (EMPL_INTRA), use the internet for their work (EMPL_INTER), and finally a percentage of qualified ICT personnel in the workforce of the firm (EMPL_ICT) (continuous variables);
- technology (13 variables): the extent of use of ERP, CRM, SCM, business intelligence/business analytics, collaboration support (CS) (D_ERP, D_CRM, D_SCM, D_BIBA, D_CS – ordinal variables in the above five-levels Likert scale), the conduct of e-sales (ESAL) (binary variable), the extent of use of social media for sales promotion (SM_SPRO), the collection of customers' opinions, comments and complaints about firm's products/services (SM_OPCO), the collection of ideas for improvements or innovations in firm's products/services (SM_IMPS), the searching for and finding personnel (SM_PERS), the support of the internal exchange of information and co-operation among firm's employees (SM_INTC), the support of the external exchange of information and co-operation with other firms (e.g. partners, suppliers, customers, etc.) (SM_IPAR) (ordinal variables in a three-levels Likert scale [not at all, to a small extent, to a large extent]) and use of cloud computing (CLOUD) (binary variable);
- structure (one variable): use of organic structural forms of work organization, such as teamwork and job rotation, in the past three years (ORG) (binary variable); and
- also, some general characteristics of the firm (six variables): number of firm's employees (EMPL), sector (SECT) (binary variable taking value 0 for service sectors' firms and 1 for manufacturing or construction sectors' firms) and firm's comparative financial performance in the past three years in comparison with competitors in terms of profitability (COMP_PROF), sales revenue (COMP_SALR), market share (COMP_MS) and return on investment (COMP_ROI).

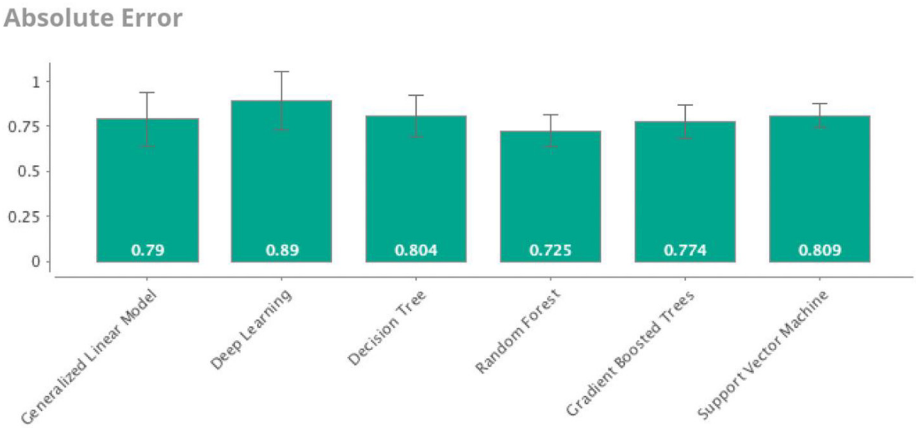
Using the above data, we constructed a prediction model of the firm's resilience (RES) based on the above 40 firm characteristics. Since, as mentioned above, our dependent variable is the average of six ordinal variables, with all of them being measured on a five-level Likert scale, it can be regarded as an "approximately continuous" variable (Sullivan and Artino, 2013; Robitzsch, 2020). So, for constructing the above prediction model, we used the six main alternative ML algorithms for the case of continuous dependent variable:

(1) Generalized Linear Modeling;
(2) Deep Learning (Multi-Layered Perceptron Neural Networks);
(3) Decision Trees;
(4) Random Forest;
(5) Gradient Boosted Trees; and
(6) Support Vector Machines (Witten *et al.*, 2017; Tan *et al.*, 2019; Russell and Norvig, 2020; Blum *et al.*, 2020).

The above were implemented using the Rapidminer® suite (www.rapidminer.com); optimization (tuning) of the hyperparameters for each algorithm was performed automatically using the automated machine learning feature (AutoML) provided by this suite. The choice of using AutoML, that is, exhaustively checking the hyperparameters' optimization process ensures that any additional hyperparameter tuning will have little to no effect on the accuracy of the predictions. In the Appendix are shown the hyperparameters that were optimized by the Rapidminer® suite for each of the abovementioned six ML algorithms.

In Figure 2, we can see the prediction performances of these six alternative ML algorithms. In particular, we can see each model's mean absolute error (MAE) of prediction, calculated using the "k-fold cross-validation procedure" recommended by relevant literature (Russell and Norvig, 2020), with $k = 10$. More specifically, according to this procedure, our data set is divided randomly into two parts: the first part includes 90% of the records and is used to construct (train) the prediction model, while the second part includes the remaining 10% of the records and is used to test the constructed prediction model: the model constructed (trained) using the first part of the data set is used to predict the value of the dependent variables for each of the records of the second (test) part of the data set, and then the absolute value of its difference from the actual value of the dependent value is calculated, termed as the "absolute error"; finally, the mean of the absolute errors over all the records of the test data set is calculated as a measure of prediction performance. The above process is repeated $k = 10$ times, and the mean value of the absolute error over all these $k = 10$ iterations is calculated as a measure of the prediction performance of the algorithm. The choice of MAE over root mean squared error (RMSE) as a measure of prediction performance is based on the fact that since in the RMSE, the errors are squared before they are averaged, it gives a relatively high weight to large individual errors, and MAE is easier to be interpreted.

As we can see in Figure 2, the algorithm exhibiting the highest prediction performance is the Random Forest (mean absolute error 0.725), followed by the Gradient Boosted Trees one (0.774). This is a satisfactory prediction performance, taking into account the small size of the data set we have used (data from 363 firms), and we expect that using a larger data set (as governments have such data for quite large numbers of firms) will result in an even smaller mean absolute error, and therefore, even more accurate prediction of firm-level resilience to an economic crisis. It provides first positive evidence concerning the value and usefulness of the proposed methodology, and especially the sufficiency of its conceptual framework (i.e. that it includes the main groups of independent variables that affect the resilience of a firm to economic crisis). It should be mentioned also that one of the advantages of this best-performing Random Forest algorithm is that it has a strong



Source: Authors' own creation

Figure 2.
Mean absolute prediction errors of the six ML algorithms for the prediction model of the economic resilience

mechanism for avoiding overfitting, provided that pruning is performed when building the trees and the leaf size parameter is properly tuned. Both these prerequisites were taken into account in the construction of the above Random Forest prediction model.

In the following Table 1, we can see the top ten predictors (independent variables) in terms of weight of the above best performing Random Forest algorithm, which have the highest influence on the predictions it produces, providing some "basic" level of "explainability" of the predictions (Meske *et al.*, 2022). Feature importance-influence, quantified through their weights, is an inherent functionality of Random Forests that is widely used by Business Analysts and Data Scientists when trying to explain the significant factors that affect most the dependent variables [their calculation is described in Sheppard (2017)].

We can see that the predictors (independent variables) influencing most the predictions are the extent of adoption of a differentiation strategy (STRAT_DIF), the share of employees having tertiary education (EMPL_TERT), followed by the extent of adoption of a cost leadership strategy (STRAT_CT) and the extent of use of social media for the collection of customers' opinions, comments and complaints about firm's products/services (SM_OPCO) and for the promotion of sales (SM_SPRO).

6. Conclusions

In the previous sections has been described a methodology of exploiting AI/ML to develop prediction models of the resilience to economic crisis of individual firms based on their individual characteristics, leveraging existing firm-level data for economic crisis periods from government agencies dealing with the economy, such as Ministries of Finance and Statistical Authorities. This methodology enables the prediction of the resilience to economic crisis of the individual firms applying for government support to various actions of the economic stimulus programs; these predictions can be used for optimizing these firms' support actions by focusing them on the less resilient and more vulnerable to the crisis firms. This methodology can result in radical and highly beneficial transformations of these economic stimulus programs. The first application of this methodology concerning the Greek economic crisis of 2010–2014 gave satisfactory results.

This study has interesting implications for research and practice. It contributes significantly to the highly important and growing stream of research about the exploitation of AI, concerning one of the most critical and costly activity/intervention that government repeatedly has to make. To the best of our knowledge, it is the first study that investigates

Table 1. Most influential predictors (having the highest weights)

Variable	Weight
STRAT_DIF	0.214
EMPL_TERT	0.210
STRAT_CL	0.148
SM_OPCO	0.116
SM_SPRO	0.105
COMP_PROF	0.078
EMPL_ELEM	0.074
EMPL_INTRA	0.069
INNOV_PRS	0.067
COMP_MS	0.058

Source: Authors' own creation

the use of AI on such a large scale, large financial magnitude and highly important for the economy and the society activity/intervention of government. It opens up new research directions concerning the exploitation of AI/ML for such highly important areas of government activity/intervention, and provides a framework and theoretical foundation for future research in this area. Furthermore, our study contributes to theory, as it provides evidence that our theoretical foundation, the "Leavitt's Diamond" framework, can provide a satisfactory prediction of a firm's performance not only in "normal" economically stable periods but also in recessionary economic crises ones. With respect to practice, the proposed methodology will be useful to all government agencies responsible for the design and implementation of actions of such economic stimulus programs that aim to mitigate the negative consequences of economic crises, optimizing them and increasing their effectiveness by predicting the resilience to the economic crisis of the firms applying to them for government assistance/support, and then direct/focus the scarce available financial resources to/on the ones predicted to be more vulnerable. Furthermore, as mentioned in the previous section, it will also be useful to all banks as an important criterion for selecting the firms to be financed (e.g. to be granted a loan) among their numerous applicants (to avoid long-term financing firms that will not exhibit resilience to future economic crises and will have difficulties in repaying their loans). Finally, it can be useful to firms of all sectors as an important criterion for the selection of important/strategic partners, suppliers or even customers who will be resilient to future crises. The possible ways of use of our methodology have been described in Section 4.

The main limitation of this study is that the abovementioned first application of the proposed methodology has been based on a rather small data set from a single national context (Greece), so it is necessary to proceed to further application and evaluation of this methodology using larger data sets, and also from different national contexts. Also, it is useful to investigate the sectoral use of this methodology: to examine to what extent if we use data from firms of a specific sector for constructing (training) resilience prediction models for firms of this sector, the prediction performance will increase substantially. Furthermore, it is interesting to investigate to what extent resilience prediction models that have been constructed (trained) using firm-level data from one country can be used to predict the resilience to economic crisis of firms from other countries (initially with similar level of economic development). Another limitation is that with respect to deep learning, we have used a rather simple structure/form of it (the "Multi-Layered Perceptron Neural Network"), so further research is required to examine the prediction performance that can be achieved by using other more sophisticated structures/forms of deep learning. Finally, it is necessary to research how we can organize the practical use of the proposed methodology by government agencies that are responsible for the implementation of various actions of these economic stimulus programs, as well as by banks, which are the preconditions for this, and the critical success factors, as well as the possible barriers (technological, legal, organizational, etc.).

References

Allen, R.E. (2017), *Financial Crises and Recession in the Global Economy*, 4th ed., Edward Elgar Publications, Cheltenham.

Arvanitis, S. and Loukis, E. (2009), "Information and communication technologies, human capital, workplace organization and labour productivity: a comparative study based on firm-level data for Greece and Switzerland", *Information Economics and Policy*, Vol. 21 No. 1, pp. 43-61.

Arvanitis, S. and Woerter, M. (2014), "Firm characteristics and the cyclicality of R&D investments", *Industrial and Corporate Change*, Vol. 23 No. 5, pp. 1141-1169.

Baldwin, R. and Di Mauro, B.W. (2020), *Mitigating the COVID Economic Crisis: Act Fast and Do Whatever It Takes*, Center of Economic Policy Research Press, London.

Blum, A., Hopcroft, J. and Kannan, R. (2020), *Foundations of Data Science*, Cambridge University Press, Cambridge.

Chandler, D., Levitt, S.D. and List, J.A. (2011), "Predicting and preventing shootings among at-risk youth", *American Economic Review*, Vol. 101 No. 3, pp. 288-292.

Coenen, G., Straub, R. and Trabandt, M. (2012), "Gauging the effects of fiscal stimulus packages in the Euro area", *Working Paper 1483*, European Central Bank, Frankfurt am Main, Germany.

Correia Loureiro, S.M., Guerreiro, J. and Tussyadiah, I. (2021), "Artificial intelligence in business: state of the art and future research agenda", *Journal of Business Research*, Vol. 129, pp. 911-926.

De Roux, D., Perez, B., Moreno, A.D., Pilar Villamil, M. and Figueroa, C. (2018), "Tax fraud detection for under-reporting declarations using an unsupervised machine learning approach", *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery and Data Mining*, pp. 215-222.

DeSousa, W.G., DeMelo, E.R.P., De Souza Bermejo, P.H., Sous Farias, R.A. and Gomes, A.O. (2019), "How and where is artificial intelligence in the public sector going? A literature review and research agenda", *Government Information Quarterly*, Vol. 36 No. 4, p. 101392.

European Commission – Directorate-General for Economic and Financial Affairs (2009), "Economic crisis in Europe: causes, consequences and responses", Office for Official Publications of the European Communities, Luxembourg.

Kalinowski, T. (2015), "Crisis management and the diversity of capitalism: fiscal stimulus packages and the East Asian (neo-)developmental state", *Economy and Society*, Vol. 44 No. 2, pp. 244-270.

Kang, J.S., Kuznetsova, P., Luca, M. and Choi, Y. (2013), "Where not to eat? Improving public policy by predicting hygiene inspections using online reviews", *Proceedings of Empirical Methods in Natural Language Processing Conference 2013*, pp. 1443-1448.

Keeley, B. and Love, P. (2012), "From crisis to recovery – the causes", *Course and Consequences of the Great Recession*, OECD Publishing, Paris.

Khatiwada, S. (2009), *Stimulus Packages to Counter Global Economic Crisis – a Review*, International Institute for Labour Studies, Geneva.

Knoop, T.A. (2015), *Recessions and Depressions: Understanding Business Cycles*, 2nd ed., Praeger Santa Barbara, CA.

Král, P. and Králová, V. (2016), "Approaches to changing organizational structure: the effect of drivers and communication", *Journal of Business Research*, Vol. 69 No. 11, pp. 5169-5174.

Leavitt, H.J. (1970), "Applied organizational change in industry: structural, technological and humanistic approaches", in March, J.G. (Ed.), *Handbook of Organizations*, 3rd ed., Rand McNally and Company, Chicago, IL, pp. 1144-1170.

Loukis, E., Arvanitis, S. and Myrtidis, D. (2021), "ICT-Related behaviour of Greek banks in the economic crisis", *Information Systems Management*, Vol. 38 No. 1, pp. 79-91.

Manzoni, M., Medaglia, R., Tangi, L., Van Noordt, C., Vaccari, L. and Gattwinkel, D. (2022), *AI Watch. Road to the Adoption of Artificial Intelligence by the Public Sector*, Publications Office of the European Union, Luxembourg.

Matos, T., de Macedo, J.A.F. and Monteiro, H.M. (2014), "An empirical method for discovering tax fraudsters", *Proceedings of the 19th International Database on Engineering and Applications Symposium (IDEAS)*, ACM Press, New York, NY, USA, pp. 41-48.

Matsuo, T. and Iwamitsu, S. (2022), "Sustainable city planning and public administration assisted by green AI: attendant legal challenges under Japanese law", *Transforming Government: People, Process and Policy*, Vol. 16 No. 3, pp. 334-346.

Medaglia, R., Gil-Garcia, R. and Pardo, T.A. (2021), "Artificial intelligence in government: taking stock and moving forward", *Social Science Computer Review*, Vol. 41 No. 1.

Meske, C., Bunde, E., Schneider, J. and Gersch, M. (2022), "Explainable artificial intelligence: objectives, stakeholders, and future research opportunities", *Information Systems Management*, Vol. 39 No. 1, pp. 53-63.

Misuraca, G. and van Noordt, C. (2020), *AI Watch—Artificial Intelligence in Public Services*, Publications Office of the European Union, Luxembourg.

Pilat, D. (2005), "The ICT productivity paradox: insights from micro data", *OECD Economic Studies*, Vol. 2004 No. 1, pp. 38-65.

Robitzsch, A. (2020), "Why ordinal variables can (almost) always be treated as continuous variables: clarifying assumptions of robust continuous and ordinal factor analysis estimation methods", *Frontiers in Education*, Vol. 5, p. 589965.

Rockoff, J.E., Jacob, B.A., Kane, T.J. and Staiger, D.O. (2010), "Can you recognize an effective teacher when you recruit one?", *Education Finance and Policy*, Vol. 6 No. 1, pp. 43-74.

Russell, S. and Norvig, P. (2020), *Artificial Intelligence (2020). A Modern Approach*, 3rd ed., Pearson, Essex, UK.

Scott-Morton, M.S. (1991), *The Corporation of the 1990s*, Oxford University Press, New York, NY.

Sheppard, C. (2017), *Tree-Based Machine Learning Algorithms: Decision Trees, Random Forests, and Boosting*, CreateSpace Independent Publishing, Austin, TX.

Sullivan, G. and Artino, G. Jr (2013), "Analyzing and interpreting data from Likert-type scales", *Journal of Graduate Medical Education*, Vol. 5 No. 4, pp. 541-542.

Sun, T.Q. and Medaglia, R. (2019), "Mapping the challenges of artificial intelligence in the public sector: evidence from public healthcare", *Government Information Quarterly*, Vol. 36 No. 2, pp. 368-383.

Tan, P.N., Steinbach, M., Karpatne, A. and Kumar, V. (2019), *Introduction to Data Mining*, 2nd ed., Pearson Education, USA.

Taylor, J. (2018), "Fiscal stimulus programs during the great recession", *Economics Working Paper 18117*, Hoover Institution, Stanford, CA.

Van Noordt, C. and Misuraca, G. (2022), "Artificial intelligence for the public sector: results of landscaping the use of AI in government across the European Union", *Government Information Quarterly*, Vol. 39 No. 3.

Van Veenstra, A.F., Grommé, F. and Djafari, S. (2021), "The use of public sector data analytics in the Netherlands", *Transforming Government: People, Process and Policy*, Vol. 15 No. 4, pp. 396-419.

Vartanian, T.P. (2021), *200 Years of American Financial Panics: Crashes, Recessions, Depressions, and the Technology That Will Change It All*, Prometheus Books, Guilford, CT.

Whittington, R., Regner, P., Angwin, D., Johnson, G. and Scholes, K. (2020), *Exploring Strategy*, 12th ed., Pearson Education Limited, Harlow, UK.

Witten, I.H., Frank, E., Hall, M.A. and Pal, C.J. (2017), *Data Mining - Practical Machine Learning Tools and Techniques*, Morgan Kaufmann, Amsterdam, London.

Zuiderwijk, A., Chen, Y.C. and Salem, F. (2021), "Implications of the use of artificial intelligence in public governance: a systematic literature review and a research agenda", *Government Information Quarterly*, Vol. 38 No. 3, p. 101577.

Appendix

ML algorithm	Parameters
Generalized linear modeling	Solver to be used Link function Maximum number of threads Beta constraints Use of regularization Lambda (it controls the amount of regularization applied) Alpha (it controls the distribution between the L1 [Lasso] and L2 [Ridge regression] penalties) Early stopping Stopping rounds Alpha Standardize Nonnegative coefficients Remove_collinear_columns Add intercept Missing values_handling Max iterations
Deep learning	Activation Hidden layer sizes Hidden_dropout_ratios Use_local_random_seed Compute variable importances Train_samples_per_iteration Adaptive rate Epsilon Standardize Learning rate Rate_annealing Loss function Distribution function Early stopping Stopping rounds Missing_values_handling
Decision trees	Criterion for splitting Tree maximal depth Apply pruning Confidence Apply prepruning Minimal gain Minimal leaf size Minimal_size_for_split
Random forest	Number_of_trees Criterion Apply pruning Confidence Apply prepruning Maximal_depth Minimal gain Minimal_leaf_size

(continued)

Table A1.
Hyperparameters optimized for each ML algorithm

ML algorithm	Parameters
Gradient boosted trees	Minimal_size_for_split Voting strategy Number_of_bins Number_of_trees Maximum_number_of_threads Maximal_depth Minimum rows Learning_rate: Sample rate Distribution Early stopping Stopping rounds
Support vector machines	Kernel_type Kernel gamma Kernel sigma1 Kernel sigma2 Kernel sigma3 Kernel degree Max iterations C (SVM complexity constant setting the tolerance for misclassification)

Source: Authors' own creation

Table A1.

Corresponding author
Niki Kyriakou can be contacted at: nkyr@aegean.gr