Enhancing Firms' Financial Support Decision-Making with Predictions of Technological Resilience to Economic Crises

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ABSTRACT

Economic crises of different durations, intensities and geographic scopes are often appearing in market-based economies, while at the same time the economic stability periods become shorter. They have several negative impacts on firms, which include a decrease of their technological investments in various technological resources (e.g., production equipment, ICT, etc.). This can result in firms' technological backwardness and obsolescence, and finally lower competitiveness and growth, or even threaten the survival of many firms. At the same time, economic crises can have some positive impacts on firms as well, as they put pressure on them to exploit more efficiently their resources by rationalizing and improving the relevant processes and practices they follow for using and exploiting their resources, including the technological ones, which can have positive impacts on their competitiveness and growth. Therefore, institutions that provide financial support to firms, such as government agencies (through various government firms' financial support programs), banks (through the provision of various kinds of loans), and institutional investors, in their relevant decision-making should take into account not only criteria concerning firms' economic performance during normal economically stable periods but also criteria concerning their 'technological resilience' (with respect to their main production technologies, ICT, etc.) during economic crises periods as well. This is important because low technological resilience in economic crisis periods can result in severe technological backwardness and obsolescence, and finally lower future competitiveness and growth, and even threaten their survival. This paper proposes a methodology for enhancing government agencies', banks' and, institutional investors' decision-making concerning the financial support of firms by adding to pre-existing relevant criteria predictions of firms' technological resilience to economic crises. Having as theoretical foundation the resources and capabilities theory from the strategic management domain, we view technological resilience as a two-dimensional concept, which consists of a) the extent of reduction of technological investments during economic crises, and b) the extent of rationalization and improvement of their technological resources' exploitation processes and practices during economic crises. These predictions are based on existing data from government agencies (Statistical Authorities), which are used to construct relevant prediction models through artificial intelligence techniques from the area of machine learning. Also, an application of this methodology is described, which gives satisfactory results.

KEYWORDS

economic crisis, technological resilience, technological investment, technological rationalization, artificial intelligence, machine learning

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1 INTRODUCTION

Economic crises that result in recessions (=contractions of economic activity) of different intensities are repeatedly appearing in market-based economies, while at the same time, the economic stability periods become shorter [1]-[6]. In [2] are mentioned the numerous significant economic crises that have appeared in the last century; a decade ago, we experienced the severe 2007 Global Financial Crisis, which had quite negative consequences for economies and societies worldwide, while recently, we experienced the economic crisis caused by the COVID-19 pandemic [7], and currently, we are at the beginning of another economic crisis caused by significant increases in the prices of energy and other important essential goods. Economic crises have severe negative consequences for firms: a) decrease in firms' production, procurement, and personnel employment, which have severe negative short-term impacts on firms; and b) decrease of their technology investments in various important technological resources (e.g., production equipment, ICT, etc.), which have severe medium- and long-term impacts on firms, as they can result in firms' technological backwardness and obsolescence, leading to lower competitiveness and growth, and can even threaten the survival of many firms. At the same time, economic crises can have some positive impacts on firms as well [1][2][4][5], as they put pressure on them to exploit more efficiently their resources, including the technological ones (e.g., production equipment, ICT, etc.), by rationalizing and improving the processes and practices they follow for using and exploiting these resources and generating value from them, which can have positive impacts on their competitiveness and growth. In particular, during economic crises, the market demand for most products and services decreases, so the competition among firms increases for this reduced market demand, and the most efficient competitors, who

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exploit their inputs and resources more efficiently, and can therefore offer to customers products and services with higher ‘value for money’, will gain larger shares of this reduced market and survive; on the contrary, the remaining and less efficient competitors will gain only small shares of this reduced market and will experience a large decrease of their sales revenue, and some of them might even not survive. Therefore, firms strive to become more efficient and competitive during tough times of economic crises in order to be among the former and not among the latter firms. The above economic crisis impacts are stronger in high-tech sectors, as well as for sectors characterized by higher levels of technological change and evolution; however, these impacts will be strong for all sectors concerning the ICT, as there is a wide adoption of and reliance on ICT throughout the economy, as well as a strong tendency for ‘digital transformation’ [8], and exploitation of some disruptive ICT, such as artificial intelligence (AI) [9].

The intensity of the above technology-related negative as well as positive impacts of economic crises differs significantly among firms [2]-[4],[6]: some firms manage to cope better with the crisis and have minimal (or even not at all) decrease of their technological investments, and at the same time can exploit more efficiently their technological resources, by rationalizing and improving the processes and practices they follow for using and exploiting their technological resources, during the crisis, so they exhibit ‘higher technological resilience to economic crises’ (being the ‘technological winners in economic crises’); on the contrary some other firms cannot cope with the crisis and have to resort to drastic decrease of their technological investments during economic crises periods, and at the same time are not able to exploit better their technological resources, by significantly rationalizing and improving the efficiency of processes and practices they follow for using and exploiting their technological resources, so they exhibit ‘lower technological resilience to economic crises’ (being the ‘technological losers in economic crises’); furthermore, there will be also ‘intermediate’ firms, which exhibit ‘moderate technological resilience to economic crises’. Strategic management literature [10] has traditionally emphasized the importance of both resources acquisition and capabilities development for firms: it has theorized that it is necessary not only to acquire resources but also to develop appropriate processes and practices for using and exploiting these resources efficiently, in order to create higher levels of capabilities for performing their main tasks and functions, and finally achieve higher levels of performance; this holds even more for firms’ technological resources (e.g., production equipment, ICT, etc.), since their efficient use and exploitation, is more complex and sophisticated, and requires significant effort and extensive knowledge.

The importance of firms’ resilience, defined as their capacity to ‘survive, adapt and grow in the face of turbulent change’ [11], has been widely recognized by management literature due to the rapidly changing firms’ economic environment in the last decades (due to technological change, economic crises, etc.). Particularly important is a firm’s ‘technological resilience’ to economic crises, defined as the degree of maintaining its technological capacity and level with respect to the main technologies it employs (e.g., the main production technologies and ICTs it uses) during economic crises. Based on the abovementioned resources and capabilities theory [10] from the strategic management domain, we regard the technological resilience of a firm to economic crises as a two-dimensional concept, having as main components:

- the extent of decrease of a firm’s technological investments during economic crises (higher levels of it indicate lower technological resilience),
- the extent of rationalization and efficiency improvement of the processes and practices the firm follows for using and exploiting its technological resources during economic crises (as higher levels of it indicate higher technological resilience).

The levels of firms’ technological resilience to economic crises should be taken seriously into account by public and private institutions that provide various forms of financial support to firms, such as government agencies (running various kinds of firms’ financial assistance, support, and subsidy programs), banks (providing various kinds of loans), or institutional investors (making investments in various kinds of firms) in their relevant financing decision-making. As economically stable periods become shorter and economic crises periods longer, the above public and private institutions should enhance their decision-making about firms’ financial support by taking into account not only the usual criteria concerning firms’ economic performance during normal economically stable periods but also criteria concerning their ‘technological resilience’ (with respect to their core production technologies, ICT, etc.) during economic crises periods as well. This is quite important since a firm’s low technological resilience in such economic crisis periods can result in severe technological backwardness and obsolescence, and finally lower future competitiveness and growth, even threatening its survival.

This paper proposes a methodology for enhancing government agencies’, banks’, and institutional investors’ decision-making about financial support of firms by adding to pre-existing relevant criteria, which concern mainly economic performance during regular economically stable periods), some additional criteria concerning firms’ predicted technological resilience to economic crises. The predictions of the above two dimensions of technological resilience are based on data from government agencies, mainly Statistical Authorities, which are used to construct relevant prediction models through AI techniques from the area of machine learning (ML) [9, 12-14]. Also, a first application of this methodology is described, which gives satisfactory results.

The proposed methodology will be pretty valuable to all government agencies running various kinds of firms’ financial assistance, support, and subsidy programs (e.g., central, regional, local economic development agencies), as well as all banks and institutional investors, for making better decisions concerning the financing of firms. It can also be more widely beneficial to all firms for enhancing their decision-making concerning strategic medium- or long-term co-operations with important partners, suppliers, or even customers, by taking into account their technological resilience as well (among the other criteria they usually take into account); if such strategic partners, suppliers, and customers exhibit low levels of technological resilience to economic crises that will appear in the future, this is going to result in technological backwardness and obsolescence of them, with negative impacts on the success of these strategic co-operations.

Initially, we present the background of our methodology in section 2, then the methodology in section 3, and the abovementioned application in section 4, while section 5 summarizes our conclusions.

2 BACKGROUND

As mentioned in the Introduction, during economic crises, firms usually reduce their technological investments in production equipment, ICT, and other technological resources, which in the medium- and long-term results in technological backwardness and obsolescence, leading finally to lower competitiveness and growth, while it can even pose threats to the survival of many firms, especially in high-tech sectors [1-6]. At the same time, economic crises can have some positive impacts on firms as well [1, 2, 4]: during economic crises there is an increase in the competition among firms for the reduced market demand for most products and services, and this puts pressure on the firms to exploit better and more efficiently their resources, by rationalizing and improving the processes and practices they follow in order to use and exploit their resources, including the technological ones, so that they can finally offer to their customers (who become more 'price sensitive' during economic crises) products and services with higher 'value for money'; this can have positive impacts on their efficiency, competitiveness, and growth after the crisis.

However, the above impacts of the economic crises differ considerably among firms. Some firms can cope better with the crisis, have a higher capacity to make the required adaptations to the special crisis conditions, and offer higher value-for-money products and services (which are highly valued by the numerous customers who experience a severe drop in their income due to the crisis), and therefore have minimal (or even not at all) decrease of their sales revenue so they can afford only a minimal (or even not at all) decrease of their technological investment. On the contrary, some other firms cannot cope with the crisis, as they cannot make the required adaptations to the special conditions it gives rise to, and offer appropriate products and services with higher value-for-money, so they have a severe decrease in their sales revenue, and therefore have to make drastic decrease of their technological investment. Furthermore, some firms are able to significantly rationalize and improve the efficiency of the processes and practices they follow for using technological resources during the crisis, so they can extract more benefits and value from them in order to address the increasing competition and the special conditions of the economic crisis, while some other firms cannot. Therefore, based on the abovementioned resources and capabilities theory [10], we can distinguish between four categories of firms concerning their technological resilience to economic crises:

- Firms exhibiting a small extent of decrease of technological investments during crises, and at the same time a large extent of rationalization and efficiency improvement of their technological resources' use and exploitation processes and practices during economic crises; these firms exhibit a high level of technological resilience to economic crises and can maintain their technological capacity, so they can be called 'technological winners in economic crises'.
- Firms exhibiting a large extent of decrease of technological investments during crises, but at the same time a small extent of rationalization and efficiency improvement of their technological resources' use and exploitation processes and practices during economic crises; these firms exhibit a low level of technological resilience to economic crises, so they experience major reduction of their technological capacity and can be called 'technological losers in economic crises'.
- Firms exhibiting a large extent of decrease of technological investments during crises, but at the same time a large extent of rationalization and efficiency improvement of their technological resources' use and exploitation processes and practices during economic crises; these firms exhibit a moderate level of technological resilience to economic crises, as on the one hand, they decrease technological investments, but on the other hand they can extract more benefits and value from their existing technological resources, so they experience a moderate loss of their technological capacity.
- Firms exhibiting a small extent of decrease of technological investments during crises, but at the same time a small extent of rationalization and efficiency improvement of technological resources' use and exploitation processes and practices during economic crises; these firms exhibit a low level of technological resilience to economic crises as well, on the one hand, they do not decrease significantly technological investments, but on the other hand they cannot extract more benefits and value from their technological resources, so they experience a moderate loss of their technological capacity.

As discussed in more detail in section 3, we expect that the individual characteristics of a firm, such as human resources, technological resources, processes, structure, etc., will determine the category to which the firm will belong with respect to technological resilience to economic crises.

3 THE PROPOSED METHODOLOGY

Previous economic as well as management science research, has identified the main elements of a firm that determine its performance; we can expect that these elements might determine to a considerable extent firm's performance during a crisis in coping with the difficult economic crisis conditions, and therefore the degree of its resilience to the economic crisis, including its technological resilience. Economic research traditionally identifies the main production factors of a firm that determine its output and performance: a) its capital (meant as the different kinds of production equipment it uses), and b) its labor (Cobb – Douglas production function), while later, the wide use of ICT lead to discrimination between non-computer capital and computer capital, and also between non-computer labor and computer labor; subsequently the importance also of firm's 'organizational capital' (meant as processes and structures adopted by the firm) as well as 'human capital' (meant as the skills and knowledge of firm's human resources) for its output and performance were recognized [15-17]. At the same time, management science research has developed several conceptualizations of the main elements of a firm that determine its performance; the most widely recognized one is the 'Leavitt's Diamond' framework [18]. According to it, the most critical elements

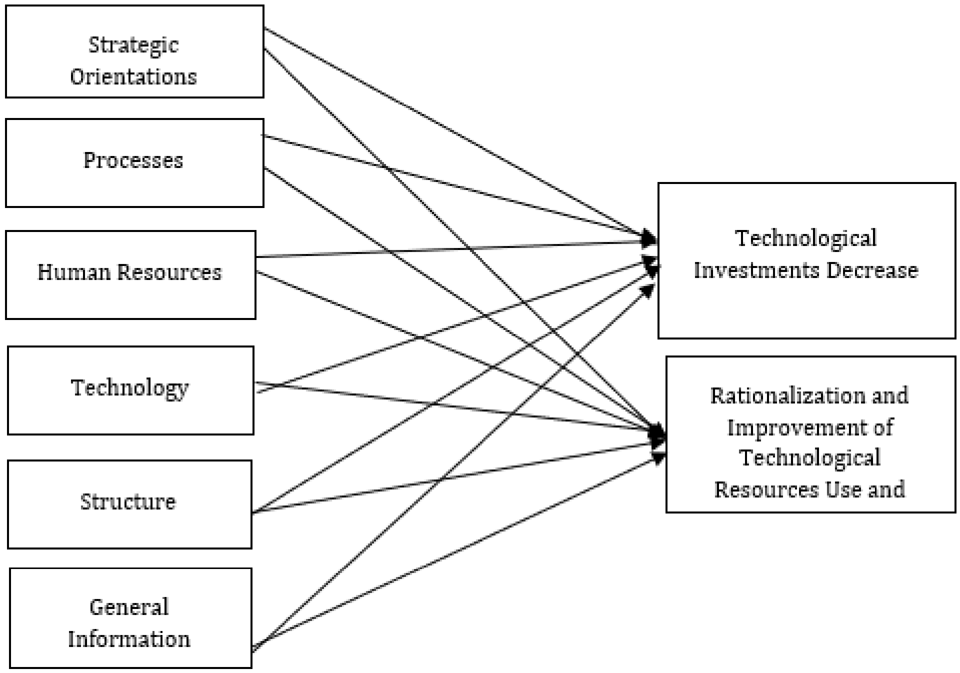

Figure 1: Structure (dependent and independent variables) of models of technological resilience to economic crises

of a firm that determine its performance are: a) its task (strategies and processes); b) people (skills of human resources); c) technology (= the technologies used for implementing administrative and production tasks); and d) structure. An extension of it has been developed subsequently, which analyses the above 'task' element into the 'strategy' and 'processes' elements [19]. We remark that most of the above five main elements of a firm that determine its performance according to this framework correspond at least to some extent to those determined by relevant economic research: the 'technology' corresponds to capital (non-computer and computer one), the 'people' correspond to labor - human resources, the 'structure and the 'processes' part of the 'task' correspond to organizational capital. Therefore, we expect that firm's characteristics concerning the above five main elements (strategy, processes, people, technology, and structure) might be good predictors of its performance and resilience, including its technological resilience, during economic crises.

The proposed methodology is using/leveraging existing government firm-level data for large numbers of firms from an economic crisis period (which in most countries are possessed by the Statistical Authority) concerning, on the one hand, the above five principal firm elements that determine its performance (to be used as independent variables):

- strategies: the extent of adoption of the main strategies described in relevant strategic management literature [10], such as cost leadership, differentiation, focus, innovation, export, etc.
- processes: characteristics of a firm's processes, such as complexity, formality, flexibility, etc.
- human resources: characteristics concerning the education and skills level of a firm's human resources
- technology: characteristics concerning the use of various essential production technologies, ICT, etc.
- structure: characteristics concerning various aspects of the structure of the firm, such as its main structural design [20],
- and also, we can include general information about each firm, such as sector, level of firm's comparative performance in this sector, etc.

moreover, on the other hand, data (to be used as dependent variables) about:

- the extent of a firm's technological investments decreases during economic crisis,
- the extent of rationalization and efficiency improvement of technological resources' use and exploitation processes and practices of the firm during an economic crisis.

Using the above data, we can construct prediction models of these two dimensions of a firm's technological resilience to economic crises (extent of decrease of technological investments, the extent of rationalization and efficiency improvement of technological resources' use and exploitation processes and practices), based on the above characteristics of it, using ML algorithms (e.g., Decision Trees, Random Forests, Gradient Boosted Trees, Support Vector Machines, Generalized Linear Modelling, etc.) [9, 12-14]. The structure (dependent and independent variables) of these models of technological resilience to economic crises are shown in Fig. 1

We can construct either overall firm's technological resilience models or more specialized ones focusing on the main production technologies used by the firm, ICT, etc.

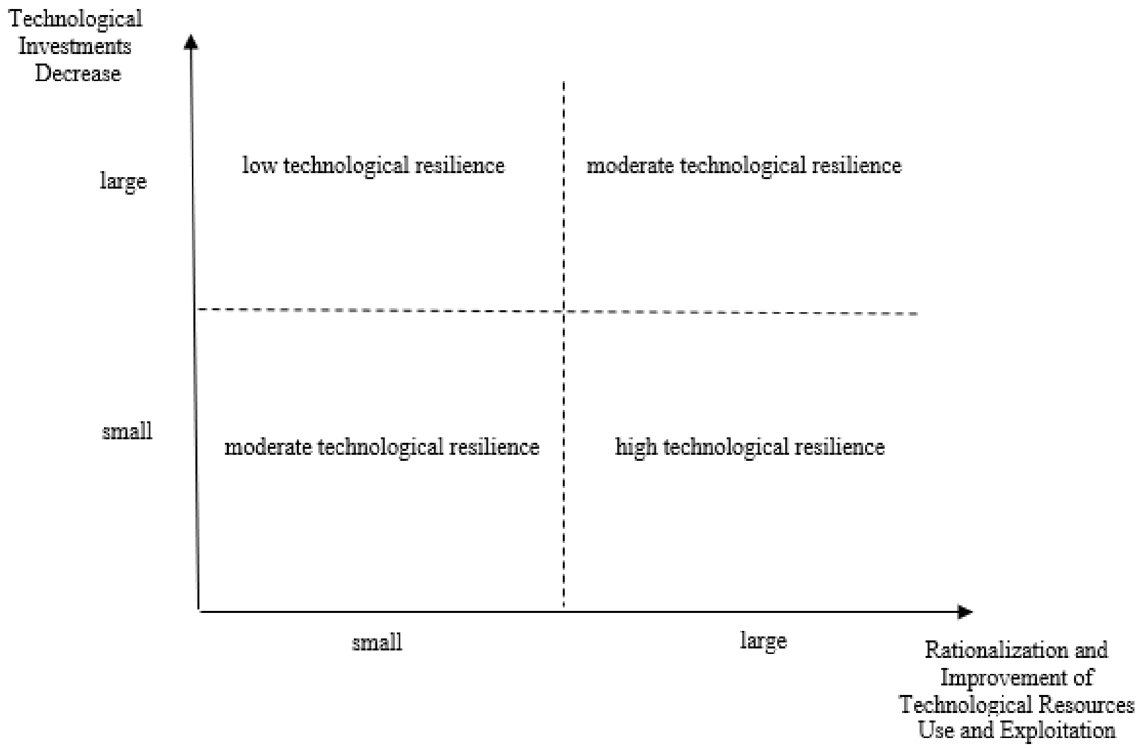

Figure 2: Categories of firms with respect to technological resilience to economic crises

The predictions of these two dimensions of the technological resilience to economic crises we can estimate for a firm using the above-constructed prediction models can be used: a) for classifying it in one of the four categories of firms with respect to technological resilience to economic crises, which have been defined at the end of section 2 (see Fig. 2); and b) as additional criteria for making decisions concerning the provision of financial support to the firm (in addition to the usual 'traditional' criteria used for this purpose, which concern mainly firm's economic performance during normal economically stable periods).

4 APPLICATION

We applied the proposed methodology using data concerning 363 Greek firms for the economic crisis period of 2009-2014 from the Greek Statistical Authority in order to construct prediction models of the two dimensions of firm's technological resilience concerning the ICT (ICT investment reduction and ICT exploitation processes rationalization and improvement due to economic crisis), based on firm's characteristics. In particular, we used data regarding the ICT investment reduction and ICT exploitation processes rationalization and improvement due to the economic crisis in the period 2009 – 2014 of 363 Greek firms. For the former, we used four ordinal variables: (1) the extent of reduction of investments in ICT hardware during the economic crisis (ICT_H_INV_RED), (2) the extent of reduction of investments in ICT software during the economic crisis (ICT_S_INV_RED), (3) the extent of reduction of investments in ICT training of personnel during the economic crisis (ICT_T_INV_RED), and (4) the extent of reduction of investments in ICT consulting services during the economic crisis (ICT_C_INV_RED); these five variables were measured in a common six levels scale (increase, no change, small reduction, moderate reduction, large reduction, very large reduction). Based on these four variables, the ICT investment reduction variable (ICT_INV_RED) was calculated as their average, which was our first dependent variable. For the latter, we used four ordinal variables: (a) the extent of rationalization/improvement of the processes and practices the firm follows for the development of ICT strategies and plans linked to the overall business strategies and plans (ICT_STR_PR_RAT), (b) the extent of rationalization/improvement of the processes and practices the firm follows for the implementation and management of ICT projects (ICT_PM_PR_RAT), (c) the extent of rationalization/improvement of the processes and practices the firm follows for the operation and support of its information systems (ICT_OP_PR_RAT), (d) the extent of rationalization/improvement of the processes and practices the firm follows for the support of ICT users (ICT_US_PR_RAT). These five variables were measured in a common five levels scale (not at all, to a small extent, to a moderate extent, to a large extent, to a very large extent). Based on these four variables, the ICT processes rationalization variable (ICT_PR_RAT) was calculated as their average, which was our second dependent variable.

We also used as data about 40 characteristics of these 363 firms, which involve their strategic orientations (12 variables concerning the extent of adoption of cost leadership, differentiation, export as

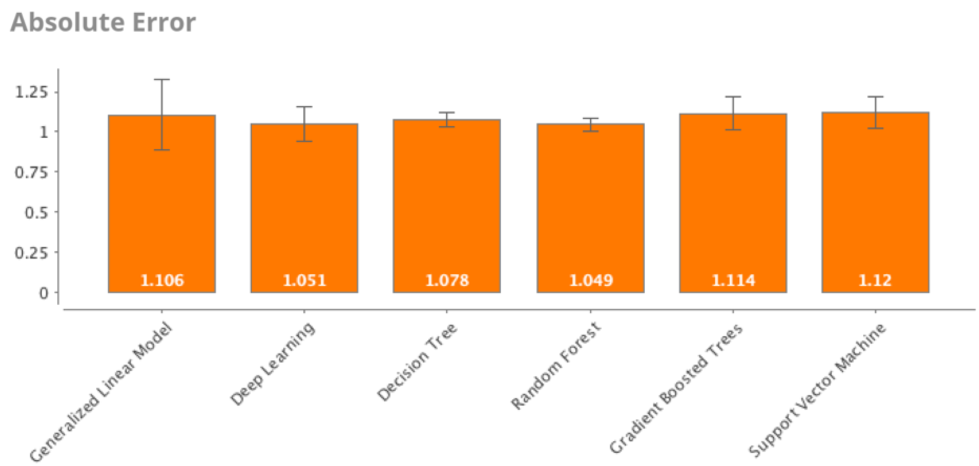

Figure 3: Mean absolute prediction errors of the five ML algorithms for the prediction model of ICT_INV_RED.

well as products/services and process innovation strategies), human resources (9 variables concerning shares of firm's employees of various educational levels, as well as shares of firm's employees using computers and having access to firm's Intranet as well as the Internet, and share of ICT personnel), technology (13 variables concerning the extent of use of ERP, CRM, SCM, Business Analytics (BA), Collaboration Support (CS) and e-sales systems, as well as social media and cloud), structure (1 variable concerning the use of 'organic structural forms of work organization, such as teamwork and job rotation), and also general characteristics (5 variables concerning size, sector as well as comparative performance in the sector); these 40 variables were used as independent variables in both models. These 363 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.

Using the above data, we constructed prediction models for the ICT_INV_RED and ICT_PR_RAT variables based on the 40 firm characteristics mentioned above, using the RapidMiner software, with five different ML algorithms for the case of continuous dependent variable: Generalized Linear Modelling, Deep Learning, Decision Trees, Random Forest, Gradient Boosted Trees, and Support Vector Machines. Fig. 3 shows the prediction performance of the five models for the ICT_INV_RED variable, evaluated through the mean absolute prediction error. Similarly, Fig. 2 depicts the mean absolute prediction error of the models for the ICT_PR_RAT variable. The mean absolute error of each predictive model was calculated by dividing the data set is divided randomly into two parts. The first part includes 90% of the records and is used to train the prediction model, while the second part includes the remaining 10% of the records and is used to test the model. The model trained by the first portion of the input data (the initial 90%) is then used to predict the dependent variables ICT_INV_RED and ICT_PR_RAT on the second part of the data (the remaining 10%). The absolute difference between each record's predicted and actual value (error) is calculated. This value represents the absolute prediction error. The process is repeated ten times, and the mean value of the absolute error over all ten iterations is calculated as a measure of the prediction performance of the algorithm. This value represents the mean absolute prediction error shown in Fig. 3 and Fig. 4

We can see in Fig. 3 that these five prediction models for the ICT_INV_RED have similar levels of prediction performance, with error rates ranging from 1.049 to 1.114. The Random Forest algorithm exhibits the lowest mean absolute error (1.049). In Fig. 4, we can see that the five prediction models for the ICT_PR_RAT also have similar levels of prediction performance ranging from 0.842 to 0.891. The Gradient Boosted Trees algorithm exhibits the lowest mean absolute error (0.842). The above results are satisfactory with respect to prediction performance, given the small size of the dataset we have used (data from 363 firms).

5 CONCLUSIONS

In the previous sections has been described a methodology for enhancing government agencies', banks', and institutional investors' decision-making concerning the financial support of firms by adding to pre-existing relevant criteria (concerning firm's economic performance during normal economically stable periods) predictions of firm's technological resilience to economic crises. This is quite useful, taking into account that economic crises of different durations, intensities, and geographic scopes are appearing with increasing frequencies in market-based economies, while at the same time, the economic stability periods become shorter. In our analysis, we adopt an approach based on 'resources and capabilities' theory [10] from the strategic management domain and include both the negative impacts of the economic crises on firms' technological level (decrease of investments in technological resources) and also the positive ones as well (rationalization and improvement of the exploitation of technological resources). This is done by conceptualizing a firm's technological resilience to economic crises as a two-dimensional concept, which consists of a) the extent of decrease of technological investments during economic crises (higher levels of it indicate lower technological resilience); b) the

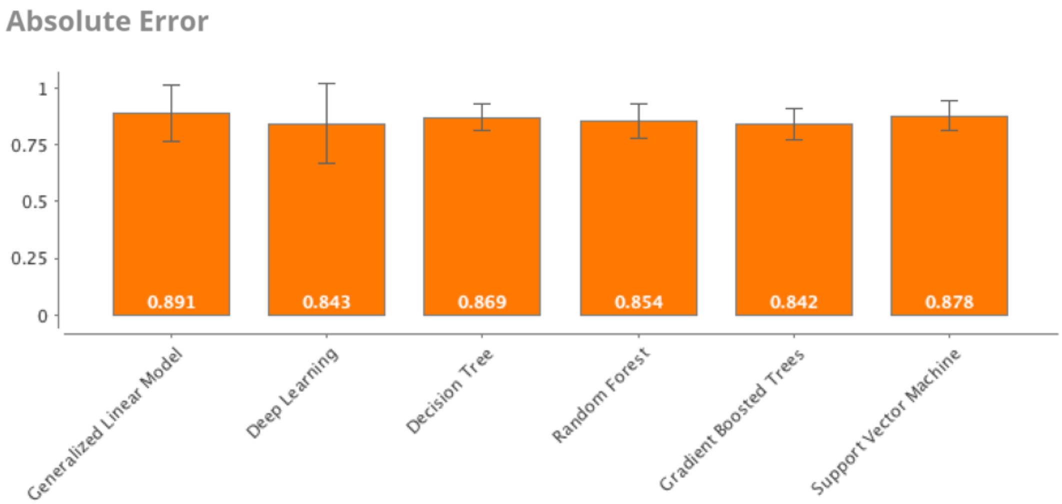

Figure 4: Mean absolute prediction errors of the five ML algorithms for the prediction model of ICT_PR_RAT.

extent of rationalization and efficiency improvement of technological resources' use and exploitation processes and practices during economic crises (higher levels of it indicate higher technological resilience). The prediction of these two aspects of a firm's technological resilience to economic crises is based on a wide range of firm's characteristics (concerning firm's strategies, processes, technology, structure, and general information). For estimating these prediction models are used existing government data for economic crisis periods from Statistical Authorities.

The study described in this paper has interesting implications for both research and practice. With respect to research, it creates new knowledge in the highly important and rapidly growing area of government AI exploitation [21-23], which has attracted recently quite high interest from both academics and practitioners, and also in the areas of government data analytics and evidence-based decision-making, concerning a quite important type of decisions that government agencies, and also banks and institutional investments, have to make: the selection of firms that will receive some kind of financial support. The proposed methodology allows enhancing this type of financial decision-making by taking into account not only the normal economically stable periods, but also the quite threatening recessionary economic crises that repeatedly appear in market-based economies and have quite negative impacts (among others) on firms' technological level, which can result in technological backwardness and obsolescence, leading to lower competitiveness and growth, and can even threaten the survival of many firms. With respect to practice, it proposes a methodology of using existing historic government data for constructing prediction models of the abovementioned two aspects of firms' technological resilience to economic crises, which can be quite useful to public and private institutions that provide various forms of financial support to firms, in order to direct their scarce financial resources to firms that have not only good economic performance during normal economically stable periods, but also high technological resilience during economic crises periods. In particular, our methodology can be quite useful to government agencies running various kinds of firms' financial assistance, support and subsidy programs, to banks providing various kinds of loans and to institutional investors who make investments in various kinds of firms. It can also be more widely useful to all firms for enhancing their decision-making concerning strategic medium- or long-term co-operations with important partners, suppliers or even customers, by taking into account their technological resilience as well (among the other criteria they take into account).

Future research is required for further application of the proposed methodology using larger datasets, possibly with wider sets of independent variables (firms' characteristic), and for different kinds of technologies (e.g. various production technologies). Also, it is necessary to investigate the prediction performance of other ML algorithms, such as Deep Learning ones. Finally, the proposed methodology has to be extended and include more dimensions of technological resilience.

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