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ORIGINAL PAPER

The use of machine learning techniques for assessing the potential of organizational resilience

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Abstract

Organizational resilience (OR) increases when the company has the ability to anticipate, plan, make decisions, and react quickly to changes and disruptions. Thus the company should focus on the creation and implementation of proactive and innovative solutions. Proactive processing of information requires modern technological solutions and new techniques used. The main focus of this study is to propose the best technique of Machine Learning (ML) in the context of accuracy for predicting the attributes of the organizational resilience potential. Based on the calculations, the research includes estimating them through the applications of regression and machine learning methods. The dataset is obtained from the results of the our survey based on the questionnaire consisting of 48 items mainly established on OR attributes formed on ISO 22316:2017 standard. Based on the outcomes of the study, it can be stated that the optimal technique in the context of accuracy for predicting the attributes of the organizational resilience potential is ensemble methods. The k-nearest neighbor (KNN) filtering-based data pre-processing technique for stacked ensemble classifier is used. The stacking is achieved with three base classifiers namely Random Forest (RF), Naive Bayes (NB), and Support Vector Machine (SVM). The chosen ensemble method should be implemented in an organization systemically according to the circle of innovation, and should support the quality of managerial decision-making process by increasing the accuracy of organizational resilience potential prediction, and indication of the importance of attributes and factors affecting the potential for organizational resilience.

Keywords Organizational resilience · Decision-making process · Regression · Machine learning · Artificial intelligence

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1 Introduction

Disruptions such as the COVID-19 pandemic and other crises can affect the organization's performance. In a crisis situation, managers must make rapid, high-risk decisions based on available information (Rauner et al. 2018). To be able to withstand any kind of disruption, an organization needs three essential components: organizational resilience (OR), crisis management (CM), and business continuity management (BCM). These components work together to create a comprehensive concept of integrating corporate recovery management systems. The foundation of this concept is the element of organizational resilience (Ewertowski 2022). The pandemic crisis revealed varying levels of organizational resilience of enterprises (Ewertowski and Butlewski 2021). Companies try to cope with increasing uncertainty to survive the crisis, adapt to a new situation and ensure stability and safety (Ma et al. 2018). To become more resilient, organizations should anticipate and respond to threats and opportunities arising from sudden or gradual changes in both the internal and external context. Effective risk management help to achieve it (Ewertowski and Butlewski 2022). Proper utilization of relevant information regarding past and current disruptions, as well as the perception of organizational resilience characteristics by employees, is crucial in effectively managing the risks linked with issues related to organizational resilience. The approach allows to set and modify properly the solution based on the obtained information (Nehézová et al. 2022). Enabling the refinement of the decision-making procedure in relation to amplifying the organizational resilience potential can be accomplished. It is possible to achieve this by employing innovative technological resolutions for the proactive handling of information. Technological innovations had been faster than social change. However, Philips maintained that the era is over (Phillips 2008). Subsequent events seemed to support this opinion. Philips creates so called "circle of innovations" and claimed that innovation creates not only new products and services, but new ways of using them. It is changing the ways we organize and interact with each other. Smart organizations generate new needs that are met by the next technical innovations (Phillips 2014). In the smart organization, increasing amounts of data need to be collected, analyzed, and interpreted in order to manage technology and innovation and to detect discontinuous changes. Data mining is the process of extracting knowledge from data using algorithms that identify hidden relationships that are usually not noticeable at first glance (Pejic et al. 2022). Data mining models based on artificial intelligence allow for greater automation of these activities (Mühlroth and Grottke 2022). The applications of regression is also widely being used for prediction and forecasting (Nalcaci et al. 2019). The numerous supervised regression models and algorithms used in artificial intelligence (AI) and machine learning (ML) call for a comparative examination of AI models, which can help managers select the most suitable model, as suggested by Elmousalami (2021). According to Valaskova et. al. the most important challenges in the implementation of intelligent production solutions are, inter alia, implementation of AI/ML (77% of responders) and internet of things (IoT) (74% of responders) technologies. The reasons why business organizations plan to use AI include, inter alia, innovation management (42% of responders) and data analysis (42% of responders) (Valášková et al. 2020). It has been observed that only a small number of methods are designed to specifically measure resilience, or more specifically, resilience potential (Tew et al. 2008). In addition, they point out that there is a significant gap in the assessment of resilience using quantitative methods. Another problem is which method is optimal to help predict the organizational resilience potential. From a managerial perspective, it is important to know how to predict the weakest points of the organizational resilience potential and what methods are best to do so. The use of machine learning to support analytical processes improves management decision making (Graczyk-Kucharska et al. 2022). This allows companies to implement effective preventive measures to reduce the likelihood of a recurrence of crises or incidents. According to Phillips and Linstone, the true objective of forecasting is to handle the future in an optimistic, safe, and cost-effective manner. Achieving this goal involves crafting the most promising visions for the future, and equipping our organization to grasp the potential outcomes and be responsive to both expected and unexpected events (Phillips and Linstone 2016).

The proposed research adopts a novel approach by addressing a cognitive gap in the existing literature. This gap pertains to the scarcity of findings from word search analysis of organizational resilience and machine learning in the Scopus database. Remarkably, this search yielded a mere 20 relevant documents. The main research hypothesis of the study concerns the possibility of optimizing the results of estimating the organizational resilience potential through the implementation of the most accurate technique of regression or ML to predict the importance of attributes of organizational resilience. Additionally, the second hypothesis concerns the possible difference between the importance of the surveyed variables influencing the potential of organizational resilience in the studied subscales. The dataset was obtained from the results of our survey based on the questionnaire consisting of 48 items mainly established on OR attributes formed on ISO 22316:2017 (2017) "Organizational Resilience—Principles And Attributes". The main objective of the research is to propose the best technique in the context of accuracy for predicting the attributes of the organizational resilience potential.

2 Literature review

Firstly, literature research explains different definitions and attributes of organizational resilience based on ISO 22316:2017 (2017) standard. In the second part, additional factors influencing organizational resilience, such as situational awareness and proactive attitude, are briefly characterized.

2.1 Organizational resilience

The concept of resilience was borrowed from physics, where it refers to the description of the properties of materials that are characterized by a return to their original shape after previous deformation resulting from pressure. This physical property, which is called resilience, is also being used in other sciences such as psychology and organizational management (Holling 1973; Xiao and Cao 2017). The concept of organizational resilience has also been included in international standards such as the ISO 22316:2017 (2017). Many authors have attempted to define this concept; some of those definitions are presented chronologically in Table 1.

In the scientific approach, they are blurred, therefore, for the purposes of the article, the definition of organizational resilience was adopted from ISO 22316:2017 (2017), which was defined as: "The organization's ability to absorb and adapt to a changing environment". According to this standard, organizational resilience consists of the following 9 attributes: The standard facilitates adaptability and stability, both of which are vital for the survival and growth of enterprises. This is achieved by fostering a shared vision and a clear sense of purpose (C1), comprehension and influence of the context (C2), effective and empowered

Table 1 Selected definitions of organizational resilience

Year	Author	Definition of organizational resilience
1973	C.S. Holling	"Resilience defines the persistence of relation in a system, and is a measure of ability of these systems to absorb changes of state variables, control variables and parameters until it continues to last" (Holling, 1973)
1992	S. Sitkin	"Effect of organizational learning" (Sitkin, 1992)
1998	L. Mallak	"The ability of an individual or organization to quickly design and implement positive adaptive behaviors suited to the current situation with minimal stress" (Mallak, 1998)
2003	K. Sutcliffe, T. Vogus	"Maintaining positive adaptation in difficult conditions so that the organization emerges from these conditions stronger and more resourceful" (Sutcliffe and Vogus, 2003)
2006	Ch. Perring	"The ability of the system to deal with disruptions without losing its functionality" (Perrings, 2006)
2007	D.R. Nelson, W.N Adger,K. Brown	"The number of changes an organization is able to experience while maintaining the same functions and structure" (Nelson et al. 2007)
2009	E.H. Powley	"Latent capability of an organization built through social interactions and relationships. It becomes to be felt when organizations face failure" (Powley, 2009)
2011	A. Masten	"The ability of a dynamic system to withstand significant challenges that threaten its stability, viability or development, or the ability to overcome those challenges" (Masten, 2011)
2011	K. Burnard, R. Bhamra	"Resilience on the organizational level is an emergent property which resides in units, systems, structures, infrastructure, procedures and parameters of an organization" (Burnard and Bhamra, 2011)
2013	P. Regibeau, K. Rockett	"The ability of the economy, society, organization or individual to a successful return to the state before the unexpected shock" (Régibeau and Rockett, 2013)
2017	ISO 22316:2017	"The organization's ability to absorb and adapt to a changing environment" (ISO 2017)

leadership (C3), a culture that promotes organizational resilience (C4), shared information and knowledge (C5), access to resources (C6), development and coordination of management disciplines (C7), support for continuous improvement (C8), and the capacity to anticipate and manage change (C9).

2.2 Situational awareness and proactive attitude

Two additional factors related to the concept of resilience are proactivity and situational awareness. Organizations looking to improve their resilience should proactively scan and monitor their environment as this supports the development of situational awareness and ultimately allows for a continuous exchange and review of information (Burnard et al. 2018). A proactive organization is an organization that puts the greatest emphasis on long-term strategic planning. Being a proactive organization has many benefits in terms of business and in dealing with potential problems. One cannot precisely predict future opportunities and threats to one's business, but one can make rational forecasts by performing an in-depth analysis. Skillful use of opportunities is a positive feature of being proactive. The awareness of the changes and the impact they may have on an enterprise will allow a proactive enterprise to plan an alternative strategy before the threats become real (Hill 2017). Another factor related to the concept of resilience is situation awareness. Resilience is a function of "situation awareness, management of keystone vulnerabilities and adaptive capacity" in a complex, dynamic and connected environment (Rzegocki 2015). According to Gilson, the concept of situation awareness was first formulated during World War I by Oswald Boelke, who realized "the importance of gaining enemy's awareness before the enemy gained similar awareness and devised methods of achieving it" (Woods 1988). Over the years, situation awareness has become a research topic in a variety of fields, where people perform tasks in complex and dynamic systems such as military operations, aviation, air traffic control, driving and the C4I systems (Salmon et al. 2006). There is no single measure that would define the level of organizational resilience. This is called a latent (unobservable) variable that cannot be directly measured. Likewise, situation awareness and proactive attitude cannot be measured directly. To describe them, we use a set of attitudes that indicate the presence of such a feature.

3 Materials and methods

Firstly, this section explains a data set structure, its reliability, and a sample method. In the second part, the applications of regression is characterized. In the third part machine learning and ensembling techniques are briefly characterized.

3.1 Data set and a sample method

In order to examine the organizational resilience potential, a questionnaire consisting of 48 questions has been developed on the basis of the presented 9 attributes (according to ISO 22316:2017 (2017)) and 2 additional factors, i.e. a proactive attitude and situation awareness. Each attribute and additional factor was assessed with the help of 4–6 questions. The answers in the questionnaire were given on a five-point Likert scale, where 1 means "I strongly disagree", and 5- "I strongly agree". The Likert scale can be treated as an ordinal variable, however, assuming that there are equal distances between the answers, it can be used as an interval variable (Joshi et al. 2015). Variables on an interval scale with a length of at least five degrees can be treated as continuous variables (Weziak-Bialowolska 2011). Such an assumption was made in the following analyses and quantitative methods were used. After the validation of the questionnaire, the main study was conducted, focusing specifically on production plants within the foundry industry operating in Poland. The selection of the sample was based on data obtained from the CEIDG (Central Register and Information on Economic Activity) Polish government database, where companies were searched by legal form (active legal entities), valid email addresses and by business sector. The authors opted for a non-probability sampling method known as purposive sampling selection. This approach was employed based on the researchers' discretion, taking into consideration the specific objectives of the study and their understanding of the target group. After screening the list of companies, the authors picked out those that fulfilled the criteria of company sector and size, and utilized them as the sampling frame. Out of a total of 233 companies in the sector, the authors narrowed down the selection to only medium and large companies. This decision was made because these companies were deemed to better represent the characteristics of the target group under investigation. Consequently, the inclusion criterion was met by a final count of 47 companies. The authors used a fixed periodic interval to select respondents from the companies listed in the sampling frame: starting with a random respondent between 1 and 9, followed by every 4th respondent thereafter (8, 12, 16, 20, 24, 28, 32, 36, 40, 44). From this process, data was collected from 10 units. The categorization of enterprise size as medium or large is based on the number of employees, which is universally applied throughout Europe as outlined in the Commission Recommendation of 6 May 2003 concerning the definition of micro, small and medium-sized enterprises (Journal of Laws UE L 124 of 20.05.2003, p. 36). Size categories are as follows: Medium (from 50 to 249 employees), and Large (more than 249 employees). The authors made an approximation of 250 as the average number of employees across all 47 companies, which allowed for the estimation of a total population of 11,750 employees. Using a sample size calculator (calculator.net, 2022)., the authors calculated that a sufficient sample size for the survey would be 373 responders, based on the number of employees, with a confidence level and interval of 95%.

The study took place from 27 January 2021 to 8 May 2021. During this time, 374 people correctly completed the questionnaires. It means that the authors got sufficient sample. The forms were sent electronically. The vast majority of people who completed the questionnaires were employees with more than 3 years of experience

(84%). This means that the study was mainly attended by experienced people who know well the enterprise in which they work. The diversity regarding the structure of the respondents who completed the questionnaires is presented in Table 2.

Table 3 presents the questionnaire structure used in this study. To evaluate the relationship between two continuous variables, the Spearman correlation coefficient was employed since the data set did not have a normal distribution, as confirmed by the Kolmogorov–Smirnov test with a significance level of 0.05. The item-total correlation values ranged from 0.21 to 0.68, indicating mainly a moderate or strong correlation strength, with a few weak and strong values. To assess the questionnaire's reliability and interval consistency of questions, the overall Cronbach's alpha coefficient was used, which was 0.94, indicating a high degree of internal consistency. This result confirms the questionnaire's reliability for data evaluation, with a Cronbach's alpha coefficient greater than the recommended threshold of 0.70 (Akoğlu 2018).

3.2 Regression techniques

Two well-known regression algorithms are employed in the analyses, namely, Multiple Linear Regression (MLR), and Multivariate Adaptive Regression Splines (MARS) as a more advanced and adaptable regression technique for high dimensional data.

3.2.1 Multivariate adaptive regression splines (MARS)

Introduced by Friedman (Friedman 1991), MARS allows user to model the nonlinear structures in the data by recursively assigning different piece-wise linear functions (i.e., basis functions—BFs) in individual intervals of the feature space defined by the knot locations. In MARS, the slopes of individual piece-wise BFs may change at knots without breaks and extreme jumps. By this way, the continuity of the fully fitted function is assured. Complex nonlinear relationships between predictors and their response are also considered by employing the tensor products of BFs in MARS. MARS model building process is controlled by two primary tuning parameters (Hastie et al. 2001): (i) max_{BFs}: this parameter determines the number of maximum BFs to be included in the forward step and adjusts the model's flexibility (also increasing its complexity) to penetrate the nonlinear structures in the input data space; and (ii) max_{DEG}: it allows the user to model the interactions and statistical dependencies between different predictor variables.

3.2.2 Multiple linear regression (MLR)

In this subsection, the basics of MLR is introduced based on Kelley and Bolin (2013). MLR is achieved by the generalization of simple linear regression. When assessing the relationship between two variables, i.e., a response and a predictor in MLR, the impact or contribution of other predictors are taken into consideration.

Table 2 Features of the studied employees

Feature	Possible answers	Number	%
Sex	Female	89	24
	Male	285	76
Age	<26	32	9
	26–40	155	41
	41–60	141	38
	>60	46	12
Education	Elementary/primary	29	8
	Vocational	80	22
	Secondary	109	29
	Higher	156	41
Work experience	<1	29	8
	1–3	31	8
	3–4	66	18
	5–6	69	19
	> 6	176	47
Post	Production worker	177	47
	Specialist	113	30
	Assistant	20	5
	Manager	54	15
	Director	10	3

By doing so, the effect imposed by other variables is dismissed to solely isolate and measure the relationship between the two variables of interest. The contribution (or impact) of each predictor (i.e., X) on the response (i.e., Y) is realized through a linear equation with regression coefficients, which is often expressed as:

$$Y_i = \beta_0 + \beta_1 X_{1i} + \cdots + \beta_K X_{Ki} + \varepsilon_i, \tag{1}$$

where Y_i is the i_{th} dependent variable ($i = 1, \ldots, N$), β_0 is the Y-intercept, β_K is the regression coefficient (i.e., slope) for the k_{th} predictor ($k = 1, \ldots, K$), and ε_i denotes the residual term.

3.3 Machine learning and ensembling techniques

In machine learning, classification algorithms predict class of labels according to input data. The conducted experiment is based on Likert-Scale and, these types of problems are separated from multi-class classification or regression models since there is not any ordering within the classes. In this study, Random Forests (RF), Naive Bayes Classifier (NBC) and Support Vector Machines (SVM) are also applied to estimate the organizational resilience potential.

Table 3 Questionnaire and evaluation of its individual indicators—Part I

Variable	Indicator			Mean	SD	Item-total correlation
Situation averaness (A)	A1		The current epidemiological situation is very serious	4.01	1.07	0.21
	A2		The crisis always surprises	3.93	1.09	0.28
	A3		We need a long time to recover from the coronavirus pandemic	4.08	0.86	0.26
	A4		Our company monitors the level of acceptable risk associated with a pandemic crisis	3.52	1.08	0.59
	A5		Crises will always happen	4.18	0.85	0.33
Proactive attitude (B)	B1		I like my job even when I face difficulties	4.19	0.94	0.44
	B2		When I encounter a difficult situation, I actively seek help from others	3.62	1.14	0.32
	B3		I am committed to my work	4.35	0.72	0.49
	B4		I have the courage to overcome difficulties and problems	4.37	0.70	0.39
	B5		The current pandemic situation is stressful	3.68	1.16	0.33
Potential of an OR (C)	Shared Vision and Clarity of Purpose (C1)	C11	I have clear goals and precise responsibilities	4.35	0.64	0.36
		C12	My personal development goals align with the company's goals	3.64	1.02	0.61
		C13	Production is always my supervisor's first and most valuable priority	3.91	0.99	0.30
		C14	My goals and the company's goals are monitored and reviewed periodically for possible discrepancies and adjusted to changes	3.48	1.03	0.57

Table 3 (continued)

Variable	Indicator			Mean	SD	Item-total correlation
	Understanding and influencing the context (C2)	C21	In my company, all initiatives in the field of innovation are promoted, consisting in the development and achievement of the strategic goals of the organization	3.50	1.02	0.62
		C22	In my workplace, employees can influence the decisions of their superiors	3.09	1.12	0.52
		C23	The company has identified all stakeholders and tries to maintain strong relationships with them	3.81	0.92	0.58
		C24	The company supports all activities at all levels in accordance with its goals andvision	3.48	0.97	0.68
	Effective and empowered leadership (C3)	C31	My supervisor appreciates my work	3.67	1.07	0.59
		C32	My supervisor is always aware of the organizational, human and technological risks that can threaten the company's operations	3.82	1.00	0.68
		C33	If I have concerns about my safety and work, I can consult them with my supervisor	4.17	0.96	0.60
		C34	My supervisor tolerates any news, including bad ones	3.76	1.12	0.46

Table 3 (continued)

Variable	Indicator			Mean	SD	Item-total correlation
	A culture supportive of organizational resilience (C4)	C41	Safety issues are continuously raised and investigated at senior management level (not just as a single case or only after accidents have occurred)	3.63	1.01	0.64
		C42	If I have concerns about safety of my task, I do not have to do it	3.66	1.21	0.51
		C43	Our safety meetings or workshops are a great way to better anticipate potential problems in the future	3.69	1.04	0.64
		C44	The company expects me to perform simultaneously several tasks that have conflicting goals	2.99	1.21	0.24
		C45	If there is a conflict between safety and production, safety comes first	3.96	1.07	0.54
		C46	I look for a learning opportunity to improve or gain new professional skills	3.86	1.04	0.40

Table 3 (continued)

Variable	Indicator			Mean	SD	Item-total correlation
	Shared information and knowledge (C5)	C51	I have completed the training necessary for the proper and safe performance of my work	4.52	0.75	0.51
		C52	Information on flaws and shortcomings of the system have to be reported to the appropriate persons in our company	4.09	0.92	0.59
		C53	Incidents occurring in the company should be thoroughly analyzed and their causes should be explained to other employees in order to learn from them and prevent their recurrence	4.23	0.77	0.42
		C54	In our company, communication is developed, and resources are provided in order to quickly respond to emergency situations	3.58	0.92	0.68

3.3.1 Random forests (RF)

As its name directly implies, an RF is composed of numbers of individual classification and regression trees (CARTs) (Breiman et al. 1983) that function as an ensemble and the main logic is based on the idea of bagging, which is also known as bootstrap aggregating (Breiman 2004a). Bagging concept is composed of two parts: (i) bootstrapping (i.e., sampling): Numbers of data subsets are randomly obtained from the training data with replacement, and then employed to train the trees, at the end of the training process, an ensemble of several different models is generated. (ii) Aggregation: a single estimate is obtained by combining the outputs from each individual model, two-stage process ensures the model's variance to be reduced by averaging multiple estimates that are measured from random samples of population data (Breiman 2004b).

The model building process in RFs is mainly controlled by a single parameter, i.e., the number of trees in the forest—N_{tree}. The other two parameters that involve in the model building are the number of potential directions to split at each node (i.e., M_{try}) and the numbers of examples at each tree leaf below which the split process is not allowed (i.e., L_{size}).

3.3.2 Naive Bayes classifier (NBC)

Basically, Bayes' Theorem attempts to find the probability of an event occurring given that another has occurred under the assumption of independence among the predictor variables. In case of a classification problem, NBC states that existence of a certain feature in a class is not linked (or related) to the existence of any other feature (Bhowmik 2015). The posterior probability of a data sample with attributes X (i.e., predictors) belonging to a certain class C_i can be calculated by NBC via the following expression (Bhowmik 2015):

$$P(C_i|X) = \frac{P(X|C_i)P(C_i)}{P(X)}, \tag{2}$$

where $P(C_i|X)$ is the posterior probability of class C_i (i.e., target) given predictors X, $P(C_i)$ denotes the prior probability of class C_i, $P(X|C_i)$ is the probability which is the probability of predictor given class C_i, and finally, $P(X)$ stands for the prior probability of predictor X. Since $P(X)$ is the constant for all classes, only the product $P(X|C_i)P(C_i)$ is maximized. The prior probabilities of the class are calculated as given below:

$$P(C_i) = \frac{\text{training samples of class } C_i}{m \text{ (total training samples)}}. \tag{3}$$

Using the *Conditional Independence* assumption between attributes, it can be written:

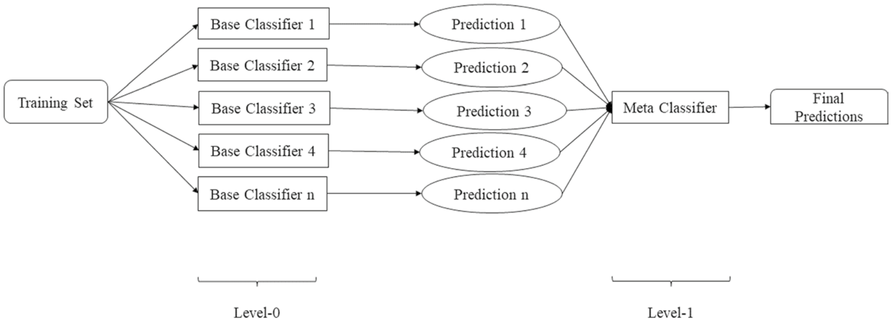

Fig. 1 A stacked generalization model

$$P(C_i|X) = \prod_{t=1}^{n} P(X_t|C_i), \tag{4}$$

where X_t are values for attributes in the sample X. The probabilities $P(X_t|C_i)$ can be estimated from the training dataset calculating for each attribute columns.

3.3.3 Support vector machines (SVMs)

The idea of support vector was initiated from the earlier studies of Vapnik (1982). General idea behind the support vector concept in classification, which is later improved to deal with regression problems (i.e., support vector regression—SVR) (Simionescu 2022), is to develop a decision function that depends on a certain set of data instances after introducing a test sample. These data points, upon which the decision surface (i.e., separating hyperplane) is founded, is referred as support vectors. When deciding the optimal separating hyperplane in a traditional binary classification case, SVM attempts to (i) find the margins with a maximum separating distance between two classes, and at the same time, (ii) decrease the number of misclassified instances (Vapnik 2000). The optimal separating hyperplane is expressed as:

$$\boldsymbol{w}^T\boldsymbol{x} + b = 0, \tag{5}$$

where $\boldsymbol{x}$ is the vector of predictor variables, $\boldsymbol{w}$ determines the direction of the hyperplane and b is the bias term. In the case of data that cannot be linearly separable, the input data is mapped into a higher-dimensional feature space by using soft margin and kernel methods. After introducing these conditions, the decision function takes the following form:

$$f(x) = \mathrm{sgn}\left(\sum_{i=1}^{r} \alpha_i y_i K(\boldsymbol{x}, \boldsymbol{x}_i) + b\right), \tag{6}$$

where $\boldsymbol{x}_i$ represents the vector of predictors for each of the r training cases with y_i defining the class membership, $\alpha_i (i = 1, \dots r)$ are Lagrange multipliers, $K(\boldsymbol{x}, \boldsymbol{x}_i)$

Table 4 Questionnaire and evaluation of its individual indicators—Part II

Variable	Indicator			Mean	SD	Item-total correlation
Potential of an OR (C)	Availability of resources (C6)	C61	My supervisor provides sufficient resources and facilities to maintain and raise the safety level of the company	3.76	1.03	0.60
		C62	My access to helping resources (equipment, time, etc.) is perfect for dealing with unexpected events	3.53	0.97	0.67
		C63	In my workplace, training and additional courses are held regularly and on time	3.87	1.08	0.51
		C64	If at a given moment an employee in the company is absent, there is always a replacement	3.55	1.05	0.51
	Development and coordination of management disciplines (C7)	C71	Employees of various departments and levels take part in occupational health and safety (OHS) meetings	4.07	1.08	0.53
		C72	In our company, managers of individual departments exchange information on changes taking place in the functioning of these departments	3.74	0.95	0.60
		C73	In our company, all departments develop ways to deal with undesirable changes in order to overcome them	3.62	0.93	0.61
		C74	In our company, all departments develop ways to deal with undesirable changes by adapting to them	3.52	0.86	0.63
	Supporting continuous improvement (C8)	C81	Workplace safety instructions and procedures are updated regularly	3.96	1.03	0.65
		C82	Employees who are able to detect occurrences or threats (sixth sense) are supported and encouraged to express their observations	3.22	1.13	0.65
		C83	Discussion and exchange of views on the risks in my workplace are very important to me	3.96	0.99	0.57
		C84	The company's continuous improvement mechanisms are monitored and assessed	3.58	0.97	0.66
	Ability to anticipate and manage the change (C9)	C91	The company I work in has the necessary facilities and procedures to respond to unforeseen and unexpected changes and disruptions	3.64	0.94	0.62
		C92	The company I work in has the ability to adapt to stressful situations caused by internal and external pressure	3.47	0.96	0.53
		C93	If the system collapses, the company has the ability to quickly return to its original (stable) state	3.36	0.97	0.57
		C94	The company has mechanisms to predict threats and changes, and reacts to them appropriately	3.55	0.93	0.68

Table 4 (continued)

Variable	Indicator		Mod (modal value)	Median	SD
Structure of responders (D)	D1	Gender	Male (285)	–	0.43
	D2	Age	26–40 (155)	36	0.82
	D3	Education	High (156)	Secondary	0.97
	D4	Experience in the company	> 6 (176)	5	1.23
	D5	Position	Production worker (177)	Specialist	1.16

specifies the kernel function that redistribute the data points allowing the insertion of a linear hyperplane. The magnitude of α_i is controlled by the constant $C > 0$ which is a "tuning parameter" to adjust the trade-off between the margin maximization and the rate of misclassification.

3.3.4 Ensemble methods

In ensemble learning, multiple instances of classical ML algorithms are combined to achieve a more feasible (i.e., optimal) solution to a specific engineering/scientific problem. Each individual ML method involved in the ensemble is a base learner, and the results obtained from these base learners are aggregated to generate more accurate and robust predictions. There are several ensemble learning techniques for classification and regression such as voting-majority voting, bagging, boosting, and stacking. Voting method combines the predictions of different classifiers to achieve better prediction performance for a classification or a regression problem. If voting is applied to regression task, averages of the predictions are taken. If the problem is a classification task, the predictions for every label are summed to predict the label which has the majority vote. Bagging is proposed by Breiman (2004a), which is an effective technique for regression and classification tasks. This technique increases the strength of each model while improving accuracy and decreasing variance to cope with over fitting. Boosting is another ensemble technique, which aims to minimize errors in the training such as decreasing both variance and bias by combining weak learners while adding them iteratively to generate a strong learner. This technique is proposed for classification problems, but it can also be used for regression problems (Schapire 2005). Stacking (stack generalization) combines the predictions of multiple machine learning algorithms. Before this combining step, all the algorithms are trained on training set and their predictions are given as inputs to a meta-classifier algorithm to make a final prediction. The meta classifier algorithm tries minimizing the instability while maximizing the strengths of models and any machine learning model can be used as a meta classifier such as k-nearest neighbors, random forests and SVM. A general illustration for stacked ensemble is shown in Fig. 1.

4 Results and discussions

The dataset contains 374 observations and 48 variables gathered in three subscales such as: dependent variables A, B, and C which is are given in Table 4. The variables indicating the degree (expressed in Likert scale) to which individuals believe in specific attributes and factors. The surveyed units (organizations) are measured on the scale of organizational resilience potential by the variable C. The dependent section variable C is the main response and consists of 38 independent variables described by 38 questions (items). Total organizational resilience potential consists of 9 attributes of C, where C1—shared vision and clarity of purpose (4 independent variables such as C11–C14), C2—understanding and influencing context (4 independent variables such as C21–C24), C3—effective and empowered leadership (4

Table 5 Results of multiple linear regression

Multiple linear regression	Res. std. err.	Multiple R^2	Adjusted R^2	p-value
Response C and C1–C9 training set	0.1472	0.9363	0.934	2.2e–16
Response C and C1–C9 testing set	0.1448	0.9447	0.9398	2.2e–16
Response C and A1–A5 training set	0.4339	0.3567	0.3441	2.2e–16
Response C and A1–A5 testing set	0.4630	0.4127	0.3852	3.631e–11
Response C and B1–B5 training set	0.4642	0.3561	0.3434	2.2e–16
Response C and B1–B5 testing set	0.5047	0.3019	0.2693	0.0000002401
Response C and D1–D5 training set	0.5565	0.0744	0.05625	0.001345
Response C and D1–D5 testing set	0.5902	0.04534	0.000727	0.4118

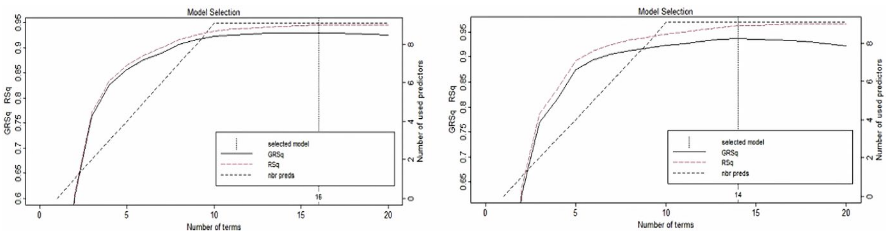

Fig. 2 Model summary of GCV R^2, where the x-axis is the number of terms retained, y-axis is the number of predictors used between C and C1-C9

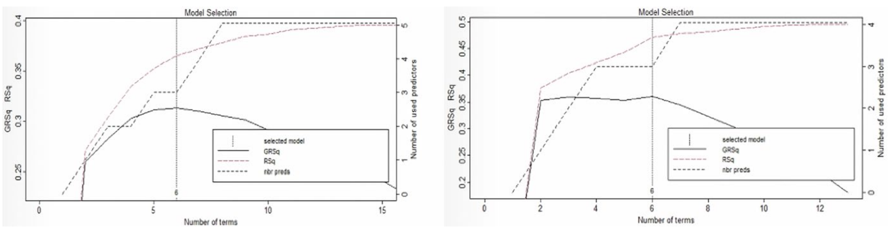

Fig. 3 Model summary of GCV R^2, where the x-axis is the number of terms retained, y-axis is the number of predictors used between C and A1–A5

independent variables such as C31–C34), C4—a culture supportive of organizational resilience (6 independent variables such as C41–C46), C5—shared information and knowledge (4 independent variables such as C51–C54), C6—availability of

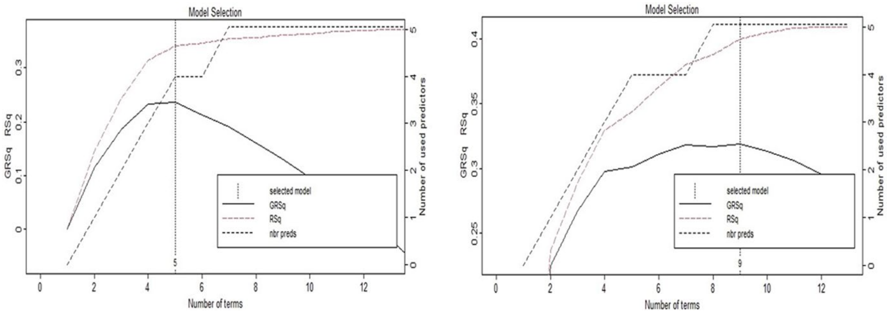

Fig. 4 Model summary of GCV R^2, where the x-axis is the number of terms retained, y-axis is the number of predictors used between C and B1-B5

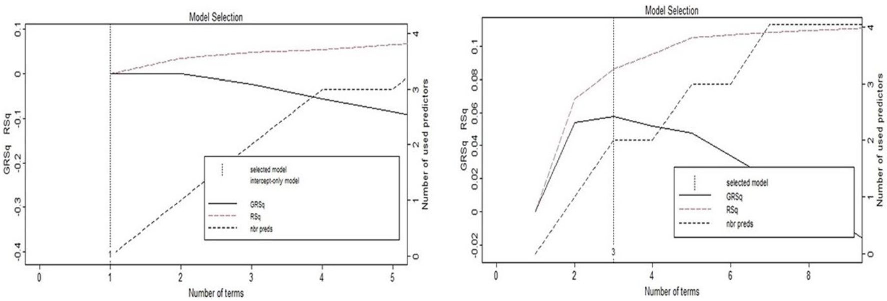

Fig. 5 Model summary of GCV R^2, where the x-axis is the number of terms retained, y-axis is the number of predictors used between C and D1–D5

Table 6 Accurracy (Acc) metrics of the machine learning algorithms and the stacked ensemble

	Acc. for C and C1–C9 (%)	Acc. for C and A1–A5 (%)	Acc. for C and B1–B5 (%)	Acc. for C and D1–D5 (%)
Random forest	89.38	65.48	**66.37**	59.29
Naive Bayes	84.07	63.71	65.48	50.44
SVM	88.49	64.60	61.94	56.63
Stacked ensemble (KNN-based)	**90.26**	**71.68**	62.83	**63.71**

Bold values indicate the best performance

resources (4 independent variables such as C61–C64), C7—development and coordination of management disciplines (4 items such as C71–C74), C8—supporting continual improvement (4 independent variables such as C81–C84), C9—ability to anticipate and managing change (4 independent variables such as C91–C94). Additionally, the questionnaire provides two subscales—dependent variables: variable A—the measure of situational awareness (5 independent variables such as A1–A5) and section variable B—measure of proactive posture (5 independent variables such as B1–B5). In addition to these variables, there is also a variable D. The subscale—variable D (5 items) is called "demographics" (D1—gender, D2—age, D3—education, D4—experience and D5—position of responders).Using regression analysis, machine learning algorithms, and ensemble technique it has been investigated: (i) the possibility of the optimization of the results of estimating the organizational resilience potential by an appropriate machine learning method, and (ii) the possible existence of the difference between the importance of the surveyed variables influencing the potential of organizational resilience in the studied subscales. A, B and C variables are in continuous form and interval scale. D variables are in categorical forms and both nominal and ordinal scales. When the Principal Component Analysis (PCA) is applied to combine different measures, it has been decided that the loss of information can be very high, and it may eliminate the variables with high importance. Therefore, A, B, C and D are introduced by taking the mean of their own items. The mean of independent variables "C11, C12, C13, C14" are calculated and defined as a new variable "C1". The same process is applied for all variables C2–C5. Hence, "C1, C2, C3, C4, C5" are added to the table, and the dependent variable "C" is introduced by taking the mean of these variables. The dataset is divided by taking 70% for training and 30% for testing. The questionnaire dataset is checked for multicollinearity, and variance inflation factor (VIF) is calculated since in case of VIF > 10, we can assume multicollinearity problem, then the process is continued in MLR. It has been found that there is a significant relationship between dependent variable "C" and its independent variables "C1–C9", where p-value < 0.001 for each by using MLR for both training and testing set. While MLR explains significance between continuous dependent with independent variables, the method fails to explain the relationship between continuous dependent variable C and categorical independent variable D in Table 5.

Since linear models make assumptions on linearity, the results can be poor if there is any nonlinear relationship within the dataset. Thus, within this perspective, MARS can be regarded as a useful method to reveal the nonlinear relationships in the dataset. The plots given below illustrates model selection showing the generalized cross validation (GCV) (Friedman 1991) R^2 (left-hand y-axis and solid black line) according to the number of terms retained in the model (x-axis) which are constructed from a fixed number of original predictors (right-hand y-axis). The vertical dashed line is the optimal number of terms retained, where marginal increases in GCV R^2 is less than 0.001. The *earth* package of *RStudio* (Milborrow 2011) is used to evaluate results and model summaries for both training and testing set are given below for C and its attributes C1–C9 in Fig. 2, C and A for Fig. 3, C and B in Fig. 4 and C and D in Fig. 5, respectively.

Additionally, RF, NBC, and SVM are applied and tested on the dataset for their predictions of scales. Also, the dependent variable is redefined by rounding its value to the closest integer to apply the chosen ensemble method. After rounding the column "C", instead of 5-point Likert Scale, it is recategorized as 4-point scale such that; Strong Disagree, Somewhat Disagree, Somewhat Agree, Strong Agree. As a meta-classifier KNN is chosen and fivefold cross validation is applied, where processes are repeated 10×. The performance metrics ofAccuracy (Acc) metrics of the machine learning algorithms and the stacked ensemble (Please note that the boldface numbers indicate the best performance) algorithms and KNN-based stacked ensemble are given in Table 6.

For determining the variable importance score, the varImp function of the caret package is utilized in the RF model. In cases where there are more variables than observations, the RF model is run on each variable individually. It should be noted that the magnitude of the variable importance values may change, but the order of importance remains the same. Furthermore, the relative values maintain a similar order, and they can still be differentiated from less relevant variables. Even when additional highly correlated variables are added to the most important variables, the prediction set for each RF model still displays the most important variable. This variable was already identified as the most important by Genuer et al. (2010). According to the RF with the response variable C, the most important variable between C1–C9 is C5, and the least important one is C1. For A1–A5, the best one is A4, while A5 is the worst. The most important variable for B1–B5 is B5, and the least important variable is B4. Between D1–D5, the best one is D4, whereas the worst one is D1. The study acknowledges certain limitations that should be taken into consideration. Firstly, the utilization of a non-probability sampling method, specifically purposive sampling selection, introduced subjectivity into the sample selection process rather than relying on random selection. However, it is important to note that companies were still drawn from this selected pool. Moreover, during the survey phase, the study focused on medium and large companies exclusively within the foundry industry, which may have introduced a potential selection bias. Nevertheless, the authors recognized these limitations and justified their choice by considering these companies as the target group for their research. To address these limitations, future studies should consider conducting additional surveys that encompass companies of different sizes and from various industries. This approach would allow for a more comprehensive analysis and enhance the generalizability of the findings.

5 Conclusions

The two main findings of the research are (i) it is possible to optimize the results of estimating the organizational resilience potential by an appropriate machine learning method and (ii) there exists a difference between the importance of the surveyed variables influencing the potential of organizational resilience in the studied subscales. The best technique in the context of accuracy is ensemble methods. Regression analysis is employed on numerical variables. When data in nominal or ordinal scale are used as predictors in a regression task, they are often replaced by numeric dummy variables, which may potentially fall short to accurately encode the inherent information represented in the original structure of the data. This situation often causes the regression models to misinterpret the relationship between these numbers and degrades their performance, as in the case of MARS and MLR, which are also prone to outliers. This paper uses a KNN filtering-based data pre-processing technique for stacked ensemble classifier. The stacking is achieved with three base classifiers (i.e., RF, NB, and SVM). KNN is chosen as meta-classifier, and then, a comparative analysis among 4 classifiers is performed. The proposed stacked ensemble classifier with KNN filtering performs best among all the techniques. As far as the importance of the surveyed variables is concerned the most important variable are C5, A4, B5, and D4 in the studied subscales, respectively.

The preferred technique should support the quality of managerial decision-making process by (i) increasing the accuracy of organizational resilience potential prediction, and (ii) indication of the importance of attributes and factors affecting the potential for organizational resilience. Attributes of the organizational resilience potential prediction is crucial for the corporate recovery management systems to enhance the ability of an organization to survive and cope with adversity and uncertainty during the disruption. It assists with crisis management and business continuity planning by identifying which attributes require additional attention and which aspects of organizational resilience are more susceptible to errors and weaknesses. This can lead to a reduction in the cost of crisis preparation, ultimately lowering the overall cost for the organization.

The potential of these solutions is good and continuously growing, which makes artificial intelligence a promising field for research and implementation. Before ML techniques for assessing organizational resilience potential can reach their full potential, there are problems to be resolved. The proposed innovations should be implemented systemically according to the circle of innovation. We should consider new requirements and problems, new ways to organize the organizational resilience assessment, new social interactions, and so on. For example, one new problem is the availability of skilled staff to implement these new techniques. Unfortunately, it will take time to find the right staff and train them. It is important to keep in mind that the value of a forecast is not solely determined by its accuracy, as there are other factors that influence its usefulness. Ultimately, the decision-makers who act upon the forecast must consider the potential consequences of any variance between the forecast and the actual outcome. This raises the question of how much discrepancy is required to warrant a change in decision, a topic that has been discussed (Phillips and Linstone 2016). This task will be accomplished by preparing the organization to understand the range of possibilities and flexibly respond to events within and beyond the prepared scope. As a future study, each category in the resilience questionnaire can be considered as an individual source of data, and to establish the similarity matrix in SVR, Multiple Kernel Learning (MKL) algorithm can be deployed into SVR so that each category of questions refer to a separate kernel function within the kernel combination. The next further step could be the generalization of MKL to Infinite Kernel Learning (IKL) (Ozögür-Akyüz and Weber 2010b, a; Özögür-Akyüz et al. 2016), which has been applied to various classification problems in the literature. Inspired by IKL approach, one can employ the IKL embedded SVR technique for the organizational resilience survey questions. Furthermore, it is also planned to use conic and robustified versions of MARS named RMARS (Özmen and Weber 2014), CMARS (Weber et al. 2012), and RCMARS (Özmen et al. 2014). Eventually, this paper also provides information on the benefits that companies can obtain by adopting the innovation technique, mainly by improving the quality of decision-making process associated with organizational resilience, and corporate recovery management systems.

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Code availability All of the codes are available at https://github.com/bscslotr/organizationalresilience.

Declarations

Conflict of interest The authors declare no conflicts of interest.

Ethical approval Due to the characteristics of the research and the provisions of the regulations on the work of the Commission on Ethics of Scientific Research conducted with the participation of people at Poznan University of Technology, research was not subject to opinion. Moreover, the research began before the commission was appointed by Rector's Order RO/IV/15/2022.

Informed consent Informed consent was obtained from all subjects involved in the study.

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