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FURTHER EDUCATION, ITS METHODS AND SELECTED CHARACTERISTICS OF ORGANISATIONS: AN EMPIRICAL STUDY OF THEIR ASSOCIATION WITH ORGANISATIONS PROFITABILITY

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Abstract. *Purpose* – The paper presents the results of the study based on a sample of 358 organisations that focuses on further education and training (FET) of their employees. It specifically investigates which specific educational methods and various characteristics of organisations are associated with their financial performance.

Research methodology – The Dependency Aware Feature (DAF) selection method from statistical pattern recognition has been used to identify which of the 37 considered variables are most associated with the profitability indicators (ROA, ROCE, ROS).

Findings – The profitability indices are significantly associated with some of the specific methods of FET. Organisations should pay attention particularly to instructing, coaching and mentoring. The results also confirm the importance of talent management for organisations to be successful.

Research limitations – The examined sample consists solely of organisations operating in the Czech Republic. Shortly, we plan to extend the selection by including organisations from abroad.

Practical implications – The study provides recommendations for HR managers for the goals they should focus on. Organisations should evaluate the impacts of FET; otherwise increasing investments in it may not have an effect.

Originality/Value – The originality of the current study lies in using a new methodology based on machine learning and respecting complex mutual relations among variables.

Keywords: further education and training, lifelong education, methods of education, organisations' profitability, human resource management.

JEL Classification: M12, M53, L20.

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Introduction

One way to increase an organisation's competitiveness and profitability is to focus on improving the value of its human capital, i.e., investing in employee development through further education to increase working skills, competences and knowledge. Research confirms that participation in further (lifelong) training organised by employers is beneficial not only for the staff involved but from an economic point of view, also for the organisations or companies (De Grip & Sauermann, 2013). However, the authors point out that the processes through which educational and development programmes in the organisation lead to higher employee productivity remain unclear. Furthermore, they state that research considering both the educational and economic perspectives should focus on multidisciplinary research projects. Considering both these perspectives together will help to clarify the aspects connected to the issue of transferring education into practice and enable to evaluate the benefits of educational events to organisations.

As this is the focus of our research, we also used a multidisciplinary approach. In the initial research, we used the classical regression analysis to identify the relations between the financial ratio indicators and the selected characteristics of organisations (Pudil et al., 2019). The study investigated six characteristics (regressors in the regression model), which had been chosen based on the literature search. There is no doubt that these six characteristics investigated in Pudil et al. (2019) represent only a small subset of those that are in some way related to further or continuing education and whose relation to organisation profitability is investigated. Therefore, in this follow-up research study, we explore a considerably enlarged set of variables, fully utilising the data from the questionnaire. Moreover, concerning the relatively high number of variables and properties, we employ completely different methods of analysing the data in comparison to the methods used in Pudil et al. (2019). The multidisciplinarity of our approach is shown by using statistical pattern recognition methodology, which is a discipline of machine learning, thus artificial intelligence (AI).

This paper aims:

- to conduct an empirical investigation of a large set of characteristics of organisations and education, together with all the investigated methods of further education and training (FET);
- to find their association with the profitability indicators, more specifically, to assess to what degree is each of the studied characteristics and methods associated with the profitability indicators and to rank them accordingly.

To respect the mutual relations of these variables (characteristics of organisations and FET methods), feature selection (FS) and classification methods are utilised, namely the DAF (Dependency Aware Feature) selection method (Somol et al., 2011).

The structure of the paper is as follows. The next section contains the theoretical background, divided into three parts:

- methods of further education and training and investigation;
- characteristics of organisations and education; their relation to profitability;
- methods of pattern classification and feature selection in the management.

Section 2 discusses the data and methods used in the study, particularly on the utilisation of feature selection methods, namely the DAF method and pseudo-kernel regression model. Section 3 is devoted to the results and their discussion. Then the limitations of the study, together with future research directions, are briefly discussed. The paper ends with the conclusions and the list of references.

1. Theoretical background

Since our study is essentially based on the interconnection of several seemingly unrelated areas, at this point, in the overview of the current state of knowledge, we should focus separately on all these areas, which are listed at the end of the Introduction. Accordingly, this section is divided into three subsections, as follows.

1.1. Methods of further education and training and investigation

According to Armstrong (2006), Bartonkova (2010), and others, FET cannot be effectively implemented without analysing and identifying educational needs, planning and selecting the appropriate training. Moreover, all these authors state that the training should be accompanied with the appropriately chosen forms and methods of learning through which the desired effects can be most easily achieved.

Mehrdad et al. (2009) divide training techniques into behavioural, also known as on-the-job methods (i.e. orientation, training, briefing, apprenticeship, internships and assistance, work rotation and coaching) and cognitive, also known as off-the-job methods (lectures, computer training, games and simulations, etc.). Alipour et al. (2009) state that cognitive techniques can be considered to be the most suitable for the development of knowledge, while behavioural techniques effectively develop skills. Further, behavioural techniques have a significant impact on employee performance and the organisation's prosperity, while cognitive training techniques lead to optimum performance and have a substantial impact on employee creativity (Falola et al., 2014). Both the behavioural methods and mental training enrich employees' potential by developing their skills and knowledge needed to optimise performance, increase efficiency, and promote the innovation and creativity that contribute to the organisation's competitive advantage. The choice between the methods depends on the type of training planned, the selected participants, the objectives of the training programme and the nature of the training, as confirmed by Alipour et al. (2009).

Grossman and Salas (2011) addressed the success of the transfer of skills and competencies acquired by training. They found that the factors related to trainees' characteristics, training design and the work environment are those with the closest and most consistent relationships with the transfer of training to employee activities.

It is apparent from this research survey that almost all the authors share the conviction of the need to use proper methods for further education, which would ensure the desired benefits for trainees and the effectiveness of the training for organisations. Therefore, our research study aims to analyse this issue and the situation in the Czech Republic, which is sometimes regarded as a post-transformation economy.

1.2. Characteristics of organisations and education; their relation to profitability

The importance of FET as an integral part of the HRM process in any organisation as emphasised by Armstrong (2006). HRM is defined as a strategic and logically thought-out approach to managing an organisation's most valuable asset – the people working there and contributing to its success. However, the influence of further professional education on the success of an organisation needs to be assessed. The first models for evaluating the effectiveness of FET were developed a relatively long time ago (Kirkpatrick, 1959; Hamblin, 1974; Simmonds, 2003).

Kirkpatrick's four-level model from 1994 (e.g., Kirkpatrick & Kirkpatrick, 2006) is considered the standard in evaluating the quality of education within HRM. This has been further enhanced by Jack Phillips (1996), who evaluated the financial benefits of continuing education by adding a fifth level. The resulting model is known as the Kirkpatrick/Phillips's model. The fifth level of the model concerns the return on investments (ROI). This indicator is even applicable to education.

The area of research concerning the impact of FET on an organisation's performance has been extensively covered by many authors, e.g. Barrett and O'Connell (2001), Chen et al. (2008), Nikandrou et al. (2008), Van de Wiele (2010), Rahimić and Vuk (2012), Beynon et al. (2015), Kaur (2016). Another area that has attracted attention in recent years is talent management, as discussed, among others, by Egerová et al. (2013), Baartvedt (2013), Dirani and Nafukkho (2018).

Pudil et al. (2019) investigate the relationship between the selected characteristics of organisations (existence of talent management, evaluation of education, investment into education, sector of activity, size and owner of an organisation) and their financial performance using a multiple median regression model. The variables associated with the majority of the considered financial indicators were the organisation's owner and the evaluation of the education.

1.3. Methods of pattern classification and feature selection in the management and education

In statistical pattern classification (e.g. Devijver & Kittler, 1982; Jain et al., 2000), the term "features" is used for variables or characteristics, the importance of which is investigated. The methodology of FS or more generally, dimensionality reduction in machine learning, is very extensive, and a detailed description is beyond the scope of this paper. The principal goal of FS is to select a small subset of the given problem characteristics or variables to optimise a model, typically to discriminate among classes of observations or to optimise any suitably defined criterion function (Pudil et al., 2003).

The main advantage of non-trivial FS methods is their ability to evaluate characteristics in context, possibly extracting more information than is customary with commonly used ranking methods. One of the more sophisticated methods is the DAF procedure (Somol et al., 2011), which has a favourable mix of properties. These are the ability to reveal contextual information, reasonable speed, generalisation ability, good results for the unfavourable ratio of sample size (training set) and dimensionality (the number of features). For these reasons, the DAF procedure was used in our study, together with a special *pseudo-kernel regression model*, first proposed by Pudil et al. (2013). Its idea is described in more detail in subsection 2.2 "Feature selection methodology – DAF and pseudo-kernel regression model". Here we should state that it helps to reveal the association of the considered features with the profitability indicators.

The statistical pattern recognition techniques, particularly FS methods, have been widely used in many diverse fields such as robotics, data mining, medicine, geology, banking, military applications, agriculture, information management systems, power networks, etc. The International Conference on Pattern Recognition, which has been organised biennially since 1980, has almost 1,000 active participants split into several tracks, including applications.

FS methods have also been used in research from the fields of economics and management. Their perhaps first use in management can be found in Pudil et al. (2002) whose research searched for the most informative factors, differentiating the successful merger and acquisition operations from those that were unsuccessful. Another paper by Pudil et al. (2012) discusses the methodology and the first results of identifying the competitiveness factors of companies in the Czech Republic. Further and more detailed results can be found in the monography by Pudil et al. (2014a). This publication addresses the issue of applying selected statistical methods to identify the competitiveness factors of companies to respect the synergistic effect of their influence. The classification-based approach that minimises the error of classifying the enterprises into two groups ("Under average ROA" and "Above average ROA") is described in Pudil et al. (2014b). The analysed dataset consisted of 260 enterprises in the Czech business environment and was taken from 2011 to 2013.

Contemporary research on pattern recognition and feature selection is very extensive. Therefore, to be in line with our study's topic, we concentrate only on the application in management, business and education. Arévalo et al. (2019) propose a reverse engineering approach, which uses patterns to transform software projects into software business processes. Bhatti et al. (2019) used feature extraction approach and pattern recognition and implemented it in Healthcare 4.0. The tool they developed is a complete package solution for the Enterprise Management System, which shows improvement in healthcare. Cervelló-Royo, Guijarro, and Michniuk (2015) used pattern recognition to build s stock market trading rule. Another trading rule based on pattern recognition was designed and validated by Arévalo et al. (2017).

Similarly, the k-nearest neighbour classifier was used by Naranjo and Santos (2019) to design a new fuzzy forecasting system for stock markets. Escobar and Morales-Menendez (2017) present the learning process and pattern recognition strategy for a knowledge-based intelligent supervisory system; the main goal is to detect rare quality events through binary classification. Paltrinieri et al. (2019) used machine learning for risk assessment in safety-critical industries, namely oil and gas. The oil industry was also the field where the machine learning technique was applied to investigate the oil well efficiency project (Bao et al., 2016).

The usage of pattern recognition can be found even in the field of education. Calderon, Crick, and Tryfona (2015) proposed that computational thinking skills can be taught to early year students and highlight a method for teaching a specific aspect, namely pattern recognition. Vieira, Magana, and Boutin (2017) proposed using computational tools and methods to analyse educational data. According to them, these tools can be used to visualise and characterise patterns within educational data, and validate them using statistical techniques. A very interesting paper was published by Viloria et al. (2018). The authors proposed a design methodology of a student pattern recognition tool to facilitate the teaching-learning process through Knowledge Data Discovery (Big Data). Their research aims to answer important issues like how the teacher can identify patterns in students' learning styles attached to their course, and in turn, to know which pedagogical techniques to use in the teaching and learning process to increase the probability of success in their classroom.

In a recent paper by Matusov (2020), pattern recognition is used to analyse students' proper meaning-making patterns. According to him, students are positioned to be recipients of ready-made knowledge and skills on teachers' demand, rather than being authors of their own education, learning, knowledge, and meaning. Pattern recognition involves the emergence of active production of diverse potential patterns that may or may not approximate well the targeted pattern. This process can be guided ("supervised") by an expert or unguided, mediated or unmediated.

2. Data and methods

This empirical study is based on the questionnaire data from 358 companies operating in the Czech Republic (CR). According to the Czech Statistical Office (2020), 1,475,207 organisations were active in the CR to the end of 2017. The data was collected from 2017–2019 using an online questionnaire. It was inspired by the validated Cranet Project questionnaire (Christensen et al., 2019) and was analogously designed from the questionnaire by Folwarczna (2010) for the CR environment. One respondent represented each company. The respondents were graduates of our faculty or were students in the last year of the management course in distance studies. Almost all the respondents currently hold a managerial position. This study extends the preliminary results presented by Pudil et al. (2019) based on the regression analysis of data from 142 companies concerning only six explanatory variables.

2.1. Data – utilisation of feature selection methods

Before proceeding to a closer characterisation of the data and selecting research methods, we should briefly point out how our study differs from previous research, both by ourselves and other authors.

To the best of our knowledge, no study has yet been conducted to analyse the association of profitability indicators with three groups of variables, namely the organisation characteristics, further education characteristics, and the FET methods group. Such an analysis is further complicated by the fact that there are links between the elements (variables) of these three seemingly unrelated groups, sometimes even strong ones. Our previous research demonstrates these facts (Pudil et al., 2014b, 2017, 2019; Mikova et al., 2019a, 2019b). Considering the relatively high number of variables and their specific properties such as a mix of nominal, ordinal and dichotomic variables, together with some missing values, we decided to use FS methods as described further on.

In particular, this study analysed the set of 37 variables (features). From these, 19 concern the specific techniques used for further education and 18 represent the various characteristics of organisations and the characteristics of education other than FET methods. The objective is to identify their association with the profitability indicators, more specifically, to what degree is each variable associated with these indicators. What should be emphasised is that we aim to assess the degree of this association for each of the 37 investigated variables not by considering them separately but considering their mutual links, which may be complex. For clarity, all the examined variables (features in terms of FS methodology), together with their description and characteristics, are listed in the following tables (Table 1 and Table 2).

Table 1. List of features representing the characteristics of an organisation and further education

No.	Feature (Abbrev.)	Description	Data type	Values
1	size	Number of employees	O	1 – Small (0 to 49) 2 – Medium (50 to 249) 3 – Large (250+)
2	investment	Into education	O	0 – Low 1 – Rather low 2 – Rather high 3 – High
3	owner	Majority owner	ND	1 – Foreign 0 – Domestic
4	sector	Economic sector	N	1 – Primary 2 – Secondary 3 – Tertiary
5	eval	FET evaluation	ND	1 – Yes 0 – No
6	talent	Special education for talents	ND	
7	evalcount	Number of Kirkpatrick model levels used	O	1; 2; 3; 4
8	fieldact	Field of activities	ND	1 – International 0 – Domestic
9	strategy	Education in strategy	ND	1 – Yes 0 – No
10	eduwom	Education for women	ND	
11	edu50+	Education for 50+	ND	
12	eduman	Education for managers	ND	
13	benefit	Education as part of employees' benefits	ND	
14	interenv	Training for the international environment	ND	
15	adapt	Adaptation of new employees	ND	1 – Yes 0 – No
16	qualif	Strengthening qualifications	ND	
17	requal	Requalification	ND	
18	personality	Further development of employees' personality and career	ND	

Note: O – ordinal; N – nominal; ND – nominal dichotomous.
Also note that only features 1–6 were used in the initial study (Pudil et al., 2019) as regressors in the multiple median regression model.

Table 2. List of features representing methods of further education

No.	Feature (Abbrev.)	Data type	Values
19	lectures	O	0 – Never 1 – Rarely 2 – Sometimes 3 – Often
20	discussions	O	
21	demonstrations	O	
22	case studies	O	
23	workshops	O	
24	brainstorming	O	
25	simulations	O	
26	managerial games	O	
27	assessment	O	
28	outdoor learning	O	
29	e-learning	O	
30	instructing	O	
31	coaching	O	
32	mentoring	O	
33	counselling	O	
34	assisting	O	
35	task assignment	O	
36	job rotation	O	
37	working meetings	O	

Note: O – ordinal; N – nominal; ND – nominal dichotomous.

Three financial indicators *ROA (Return on Assets, Return on Total Capital), ROCE (Return on Capital Employed), ROS (Return on Sales)* for 2017, available in the Albertina database of all the Czech organisations including their financial statements, were acquired from it and used one by one as a dependent variable in separate models. All these financial indicators are described in more detail in Pudil et al. (2019). Note that the ROCE indicator is closest to ROI (Return on Investment) considered in the Kirkpatrick/Phillips's model.

2.2. Feature selection methodology – DAF and pseudo-kernel regression model

As stated before, we should consider two aspects of our data. The first one is a high number of 37 investigated variables. The second one is a mix of nominal, ordinal and dichotomic variables, together with some missing values. Therefore, FS methods from statistical pattern recognition were employed. These methods, although from a completely different field of science and research, are known to have been successfully applied across vastly different scientific areas, including management (Pudil et al., 2014a; Khodaskar & Ladhake, 2014; Escobar & Morales-Menendez, 2017).

The methodology of FS or more generally, dimensionality reduction in machine learning, is very extensive and its detailed description is beyond the scope of this paper. The principal goal of FS is to select a small subset of given problem characteristics or variables to optimise a model, typically to discriminate among the classes of observations or to optimise any suitably defined criterion function (Pudil et al., 2003).

In machine learning, it is well known that the two best individual features may not be the best pair. The two best individual features can very often prove to be redundant (each provides almost the same information despite their seemingly different nature). Alternatively, neither of them proves sufficient to reveal the true data structure, or in our case, the ability to respect complex relationships between features (variables). For this reason, the DAF procedure (Somol et al., 2011) was used.

To be able to understand the results, it is necessary to mention the idea briefly and explain the basic principle of DAF. This is a highly robust FS procedure based on the idea that any feature importance should be investigated in the context of being or not being in the various subsets of other features. A DAF coefficient then measures this importance. The higher the DAF coefficient of a feature is, the more informative (thus more important) the element is in the general context. More precisely, the DAF procedure ranks the features according to the average benefit of including a feature in a high number of randomly generated feature subsets. The benefit is expressed as the difference of the mean criterion values computed for subsets that do and do not contain the feature, based on a suitably chosen feature selection criterion.

It should be noted that the DAF coefficient can even attain negative values for some features. It means that on average, such a feature does not increase the criterion value when included in the subsets with others. Contrarily, the criterion value decreases. This does not imply that the feature is useless, but rather that it may be slightly redundant in most contexts with the others. This simple idea is suitable for high dimensional FS problems where it is capable of considerably outperforming the commonly used individual feature ranking approaches due to its favourable mix of properties (Somol et al., 2011) as already stated in 1.3.

To reveal the association of the considered features with the profitability indicators, we used a special *pseudo-kernel regression model* (Pudil et al., 2013). The model does not place any assumptions on the space of feature vectors except that a distance measure must exist, which is capable of evaluating the distance between any two feature vectors (organisations). The model is applied in a leave-one-out fashion on the training data, i.e., the model is used to predict its value of the profitability indicator for each organisation, and the predicted value is compared to the known value. The average difference between the predicted and known values over all the analysed organisations is then used as the feature selection criterion. Those features that best predict the real profitability value (when included in various randomly generated subsets of features) can be regarded as well associated with the organisation profitability.

The proposed *pseudo-kernel regression model* is analogous to Parzen kernel models with Gaussian kernels, the main difference being that we assume only one-dimensional kernels. The unknown dependent value (of the profitability indicator) is predicted as the weighted average of the known values of the dependent variables (the profitability indicators) of all other organisations. In our case, the one-dimensional Gaussian kernel serves as the weight in the definition of distance between two organisations. The Gaussian kernel thus helps to progressively reduce the influence of more distant (not similar) organisations in the considered features subspace and emphasises the importance of close (similar) organisations when predicting the dependent variable.

3. Results and discussion

As explained above, the DAF ranking procedure using the special pseudo-kernel regression model facilitates assessing a measure of the association of features (variables) with a dependent variable, which is a profitability indicator. The principal virtue of this approach is that the assessment considers almost all possible contexts with other features in which the investigated feature may or may not occur and interact (about 40,000 subsets were randomly generated for each feature). Concerning this special methodology, we repeat that the higher the DAF value of a particular feature, then the higher its association with the profitability indicator (financial ratio index).

Three separate analyses were conducted for the three available financial ratio indices (ROA, ROCE, ROS). Although a somewhat different ranking was obtained for each of these indices, the basic pattern for the individual index is not too different. Therefore, we do not present the results separately for ROA, ROCE and ROS. However, as all these indices are important profitability indicators, we have introduced a "summary" measure for ranking. For each of the features, the values of the DAF coefficient for ROA, ROCE and ROS, denoted DAF_{ROA}, DAF_{ROCE}, and DAF_{ROS}, are calculated respectively. Then their average value

$$ADAF = \frac{1000\left(DAF_{ROA} + DAF_{ROCE} + DAF_{ROS}\right)}{3} \tag{1}$$

is used as a summary measure for ranking each feature.

The ranking of ADAF coefficients for all the analysed methods of FET (respecting their interactions with the characteristics of organisations and education) is illustrated in Figure 1. We can make several observations from these results:

- The three FET methods with the ADAF coefficient visibly higher than the rest of the methods are *instructing*, *coaching*, and *mentoring*. These are the methods that the organisations should pay increased attention to, as they are most associated with organisation profitability. Note that this does not mean they increase profitability, only that they are the most important for its value.
- This result is in absolute accordance with the ranking of the subjectively perceived effectiveness of particular methods, assessed by all the respondents. The results presented in Mikova et al. (2019b) rank *instructing*, *coaching*, and *mentoring* as the three most effective methods. It is of interest that as far as "the best" three methods are concerned, the subjective assessment by respondents coincides with a more objective assessment based on the calculation of ADAF with pseudo-kernel regression. Of course, "the best" in this context means something else for a subjective and the objective assessment.
- *Instructing* proved to be the method of FET most associated with the profitability in-

dicators. Its ADAF coefficient is more than twice higher than that of coaching, which is ranked second.
- Out of the 19 FET methods, 14 have a positive value of the ADAF coefficient. Starting from *brainstorming* (ranked 4th) to *assessment* (ranked 13th), the ADAF values are not too dissimilar.
- The FET methods least associated with the profitability indicators (in the context of all the others, including the characteristics of organisation and education) are *working meetings*, *job rotation*, *discussions*, *workshops* and also *lectures* and *managerial games*. It should be noted that particularly the first four of these were found to be at least partially effective when subjectively assessed by the respondents (Mikova et al., 2019b). This finding only confirms the assumption that, in general, the methods subjectively perceived as effective (at least partially) may not be well associated with the profitability indicator.

Most of the FET methods ranked in the top part are so-called modern methods. When adopting the division into on-the-job and off-the-job methods of FET (e.g. Folwarczna, 2010), it can also be observed that on-the-job methods generally have a higher ranking.

Similarly, Figure 2 illustrates the ranking of the ADAF coefficients for all the organisations and education characteristics, while respecting their interactions with the analysed methods of FET.

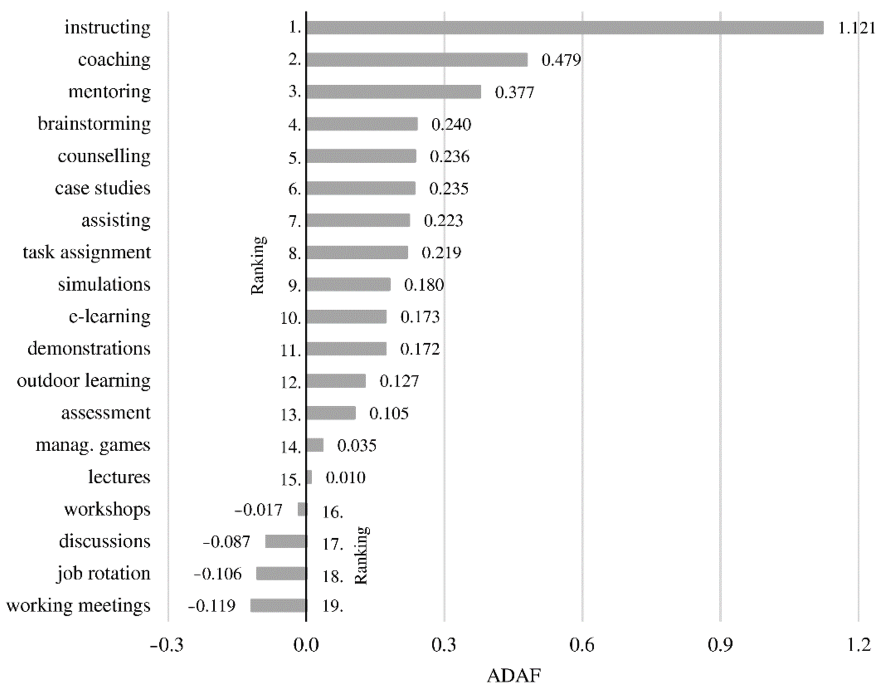

Figure 1. Ranking of the ADAF coefficients for the analysed methods of further education and training

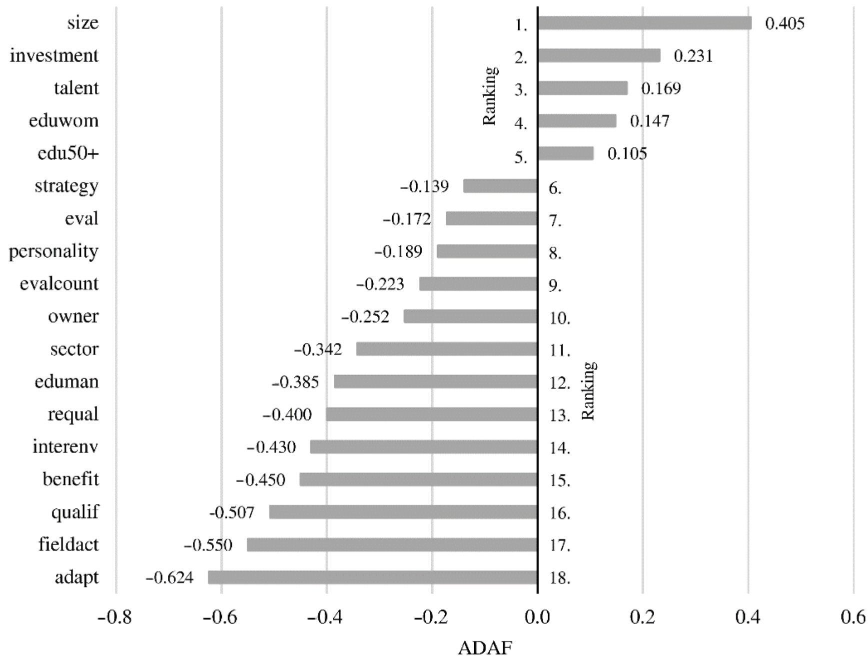

Figure 2. Ranking of the ADAF coefficients for the characteristics of organisations and education

Again, when interpreting these results, we have to be cautious. A lower value of ADAF does not mean that the particular feature is not important, only that its association with the profitability indicators is weaker (in the context of other features, which may provide similar information). Regardless, the following observations can be made from these results:

- Of the 18 analysed characteristics, five (*size*, *investment*, *talent*, *eduwom*, *edu50+*) have a positive value of the ADAF coefficient. Two of these (*investment* and *talent*) also proved to be significantly related to ROCE or ROA in the initial study (Pudil et al., 2019).
- Two characteristics with the highest value of ADAF, thus the most associated with the profitability indicators, are *size* and *investment*. Our previous research (2019a) also confirmed the significance of these two characteristics and their mutual relationship. Moreover, the result corresponds to the findings of Henderson (2003), who states that for programmes aimed at training and developing employees, the economy of scale must be taken into account. The fixed costs of starting training and education programmes are usually about the same regardless of the size of the organisation. He further argues that achieving an immediate return on investment in education is more difficult for a small organisation than for an organisation with a large number of employees.
- *Talent* is ranked relatively high (in third place) while the initial study found it had a negative relation to ROA in the median multiple regression model. This negative relation demonstrates the previously mentioned fact that a relatively high DAF ranking of any feature does not necessarily mean its positive relation to the corresponding profitability indicator. The DAF coefficient is a measure of association of a particular

feature with the considered profitability indicator regardless of the direction of relation (positive or negative). Therefore, a high ranking of ADAF for *talent* does not contradict its negative relation.

– *Eduwom* – special education for women is, perhaps surprisingly, also ranked rather high. This finding suggests the necessity to pay increased attention to this type of FET, particularly respecting the specific needs of women returning to the workplace after maternity leave or an extended stay with children at home. With the current shortage of qualified employees in the labour market, these special courses for women are gaining importance.

– A joint DAF analysis of all 37 investigated features (both the FET methods used and the characteristics of the organisation) show that the top places in the ranking are occupied by several FET methods (dominated by the "modern" ones), pushing characteristics such as *evaluation*, *strategy*, *owner* further down. On the one hand, this finding represents a possible discrepancy with previous results regarding FET evaluation and its importance, as confirmed by many studies, even in our research (Mikova et al., 2019b; Pudil et al., 2017). On the other hand, it also emphasises the importance of including the methods of FET used in the multivariate analysis (besides the characteristics of organisation and education used before). It is the extension of the set of variables included in the analysis that explains this apparent discrepancy with previous results. The reason is that a detailed analysis of the corresponding results shows that, for example, the evaluation of education is strongly related to using the so-called modern methods of FET. Therefore, when also taking the complex mutual links with all the methods used into consideration, it appears that *evaluation* was pushed further down the ranking by the relatively high ranking of the modern methods of FET (due to their strong relation). A similar argument could be used for other characteristics of organisations and education (*strategy* and *owner*).

It can be observed that using FS and dimensionality reduction methods may yield different results than the classical multiple median regression used in the initial study (Pudil et al., 2019). The initial study found no statistically significant relationship of the size with any of the considered profitability factors. On the other hand, using the DAF method, just the *size* was found to have the highest ADAF value of all the examined variables. There can be two reasons for this different result. The first is that the initial study used smaller sized data with fewer variables (regressors) and the variable *size* was dichotomic compared to the three categories of *size* used in this study. The second reason may be that the DAF method considers the complex interrelationships between all features (variables) and its algorithm analyses and compares the benefits of the individual features in a large number of different contexts. In our case, this was about 40,000 subsets randomly generated for each feature. The importance of *size* is confirmed by the findings of Henderson (2003) and Mikova et al. (2019a).

The results of the current study also confirm the importance of *talent* management for organisations to be successful. Its relatively high position in the ADAF ranking follows the findings of Baartvedt (2013), Egerová et al. (2013), Morley et al. (2016), and other authors. It should be noted that a negative relation between talent management and ROA was found in our initial study (Pudil et al., 2019). However, considering the direction of causality, the initial study also concludes that organisations, especially those less successful, should pay increased attention to talent management.

To conclude the discussion of the results, we can state that this study complements and extends the previous one (Pudil et al., 2019), the main findings of which are described in the Theoretical Background section. We should emphasise that this follow-up study takes into consideration the complex relations of organisation and education characteristics with the methods of FET.

As stated in the literature review, in the opinion of De Grip and Sauermann (2013), the processes through which educational and development programs in the organisation lead to higher employee productivity remain unclear. Furthermore, they point out the need to focus on multidisciplinary research projects, especially when considering both educational and economic perspectives. The approach we chose in our study, combining the areas of HRM, corporate financial performance and the field of FS from pattern recognition, made it possible to reveal at least partially those parts of educational and development programs that lead to higher efficiency. At the same time, our findings can help clarify aspects related to transferring education into practice and enable us to evaluate the benefits of educational events for organisations.

Our study and its results can be placed in the context of the overall current situation, significantly affected by Covid-19. The new situation has dramatically affected the labour market and transfers the labour force between economic activity sectors. Although not a long time has passed since its development in terms of research, a number of papers have been published in this area. Their analysis shows that virtually all of them emphasise the need to adapt the workforce to new conditions to a greater or lesser extent.

Some papers concern entrepreneurship education. Ratten (2020) emphasises that a relative lack of practical and real-life examples in the Covid-19 crisis causes difficulties for entrepreneurship education. In another paper, Ratten and Jones (2020) argue that besides its adverse effects, the Covid-19 crisis places increased attention on the importance of entrepreneurship education for society.

Some authors assume that a similar global crisis may be encountered in society in the near future, and therefore changes in education need to be considered. Zhu and Liu (2020) suggest that the change in learning infrastructure is only the first step. It should be followed by shifting from traditional lecture-based activities towards activities more focused on students. In their opinion, it should include group activities, discussions, hands-on learning activities, and the limited use of formal lectures. This shift is precisely in line with our study's findings, which found classical lectures as not being too effective.

The importance of talent management and special education for women found in our study is also in line with newly published studies during the Covid-19 crisis. Haak-Saheem (2020) discusses the importance of talent management in businesses in Dubai. Almeida and Santos (2020) analyse the effects of Covid-19 on job security and unemployment in Portugal. In particular, they found that the most affected by unemployment are young people and women. This finding is in accordance with the UK study by Mayhew and Anand (2020), who advocate the necessity of a more active workforce policy to assist young people who suffer most from the job recession. Of course, the need for training newly hired employees, especially young people, implies the necessity to introduce policies supporting FET at workplaces.

We should realise that jobs are not only changing in the current Covid-19 crisis, but that similar changes have a long history. Whether it is the first industrial revolution, the information age or the fourth industrial revolution, each new era ushers in changes. Some jobs become obsolete or disappear, and others emerge in response to the needs of the new era. Hite and McDonald (2020) explore the role of human resource development in the post-Covid-19 era and talk about career sustainability. According to Heslin, Keating, and Ashford (2020), learning will be crucial in adapting to new ways of working. Moreover, being in a continuous learning mode represents for individuals a "meta-competency" for achieving career sustainability. The learning process may involve various forms like cross-training, formal and informal learning, job sharing, coaching, and consulting. A new culture that promotes lifelong learning should be fostered. Davidović (2020) investigated motives for FET of adults in the current Covid-19 era. Specifically, he found that for almost 40% of respondents, these motives were related to professional needs, and for 27% it was a desire for learning and self-development. Alternative approaches to work were explored even before the pandemic era. Epstein (2019) discusses moving from job specialisation into more generalisation.

Recent data from the US Private Sector Job Quality Index (2020) indicate that 42% of all jobs lost will not return. On the other hand, this damage can be diminished by work reallocation as the same study suggests, having found three new hires for every ten positions lost due to the coronavirus. Work reallocation is also confirmed by Barrero et al. (2020), who point out that companies like Amazon and Walmart experienced a considerable increase while other businesses declined. Of course, all these work reallocations call for the necessary training of newly hired employees, increasing the importance of the findings related to FET.

4. Limitations and future research directions

The limitations of our research stem mainly from the fact that the examined sample consists exclusively of organisations operating in the Czech Republic, and also from the associated restriction of sample size. Another limitation is that we determine the financial performance of organisations for only one selected year. Therefore, in the continuation of the research, we plan to increase the sample size and monitor financial performance in the longer term. In cooperation with foreign partners, we would also like to include organisations from abroad in the study.

We also plan further development in the theoretical and methodological area. The DAF coefficients analysis and ranking that facilitated identifying the features most associated with profitability do not answer the critical question of whether their relationship is positive or negative. Therefore, one future direction of research will be to use the current results of the DAF ranking to prepare an extended set of potential regressors for the multiple regression analysis that should answer the question of the direction of the relations. This extended set will not be based on the literature review but on a more exact approach as presented here.

Finally, we plan to use other methods from machine learning, namely pattern recognition and classification to identify the key factors that differentiate organisations with an above-average financial performance from those with below-average performance.

Conclusions

Our study investigates the association of organisational financial performance with three groups of variables, namely 1) the characteristics of the organisation, 2) the characteristics of FET, and 3) specific FET methods. With its comprehensive concept and application of FS methods, it sought to contribute to research on the financial effects of FET in organisations.

The main conclusion from this study is that the methods of FET are in relation to the characteristics of organisations and education and, therefore, influence their relative importance for ranking the corresponding association with the profitability indicators. For this reason, organisations should also pay attention to the educational methods, particularly as methods such as *instructing*, *coaching* and *mentoring* appear to play an important role.

The study provides recommendations for HR managers on which goals to focus their attention on. A major conclusion is that the relative increase in investment in FET is very important but is not enough in itself. When not accompanied simultaneously by an evaluation of FET, increasing investment in further education may not have the desired effects on the organisation and so would essentially be a loss. Therefore, the evaluation of the impact of FET should be a necessary part of the measures to increase the financial performance of an organisation.

Finally, as discussed in more detail in the Results and Discussion section, we can state that the current coronavirus pandemic dramatically changes the structure of occupations, when some economic activity sectors lay off workers while others recruit them. Therefore, the need for retraining such workers moving from professions affected by the unfavourable epidemiological situation is significantly increasing. Even more, this fact highlights the importance of FET-related results for both the present and the near future.

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References

Alipour, M., Salehi, M., & Shahnavaz, A. (2009). A study of on the job training effectiveness: Empirical evidence of Iran. *International Journal of Business and Management*, *4*(11), 63–68. https://doi.org/10.5539/ijbm.v4n11p63

Almeida, F., & Santos, J. D. (2020). The effects of COVID-19 on job security and unemployment in Portugal. *International Journal of Sociology and Social Policy*, *40*(9/10), 995–1003. https://doi.org/10.1108/IJSSP-07-2020-0291

Arévalo, C., Ramos, I., Gutiérrez, J., & Cruz, M. (2019). Practical experiences in the use of pattern-recognition strategies to transform software project plans into software business processes of information technology companies. *Scientific Programming*, 7973289. https://doi.org/10.1155/2019/7973289

Arévalo, R., García, J., Guijarro, F., & Peris, A. (2017). A dynamic trading rule based on filtered flag pattern recognition for stock market price forecasting. *Expert Systems with Applications*, *81*, 177–192. https://doi.org/10.1016/j.eswa.2017.03.028

Armstrong, M. (2006). *A handbook of human resource management practice* (10th revised ed.). Kogan Page Ltd.

Baartvedt, N. (2013). *Talent management as a strategic priority for competitive advantage: A qualitative case study on talent management implementation within a Multinational Company* [PhD Thesis]. Umeå University, Department of Education. http://urn.kb.se/resolve?urn=urn:nbn:se:umu:diva-86472

Bao, S., Ding, Z., Wu, Y., & Shi, Y. (2016). Machine learning algorithm for efficiency management of oil well. In *Proceedings of the 2nd International Conference on Electronics, Network and Computer Engineering (ICENCE 2016)*. Yinchuan, China. https://doi.org/10.2991/icence-16.2016.136

Barrero, J. M., Bloom, N., & Davis, S. J. (2020). *COVID-19 is also a reallocation shock* (Working paper No. 2020-59). The Becker Friedman Institute. https://bfi.uchicago.edu/wp-content/uploads/BFI_WP_202059.pdf

Barrett, A., & O'Connell, P. J. (2001). Does training generally work? The returns to in-company training. *Industrial and Labor Relations Review*, *54*(3), 647–662. https://doi.org/10.2307/2695995

Bartonkova, H. (2010). *Firemní vzdělávání* [Corporate education] (1st ed.). Grada Publishing, a.s.

Beynon, M. J., Jones, P., Pickernell, D., & Packham, G. (2015). Investigating the impact of training influence on employee retention in small and medium enterprises: A regression-type classification and ranking believe simplex analysis on sparse data. *Expert Systems*, *32*(1), 141–154. https://doi.org/10.1111/exsy.12067

Bhatti, U. A., Huang, M., Wu, D., Zhang, Y., Mehmood, A., & Han, H. (2019). Recommendation system using feature extraction and pattern recognition in clinical care systems. *Enterprise Information Systems*, *13*(3), 329–351. https://doi.org/10.1080/17517575.2018.1557256

Calderon, A. C., Crick, T., & Tryfona, C. (2015). Developing computational thinking through pattern recognition in early years education. In *Proceedings of the 2015 British HCI Conference* (pp. 259–260). https://doi.org/10.1145/2783446.2783600

Cervelló-Royo, R., Guijarro, F., & Michniuk, K. (2015). Stock market trading rule based on pattern recognition and technical analysis: Forecasting the DJIA index with intraday data. *Expert Systems with Applications*, *42*(14), 5963–5975. https://doi.org/10.1016/j.eswa.2015.03.017

Chen, Y.-S., Chang, B.-G., & Lee, C.-C. (2008). The association between continuing professional education and financial performance of public accounting firms. *The International Journal of Human Resource Management*, *19*(9), 1720–1737. https://doi.org/10.1080/09585190802295363

Christensen, J., Bévort, F., & Rasmussen, E. (2019). The Cranet survey: Improving on a challenged research-practice? *International Studies of Management & Organization*, *49*(4), 441–464. https://doi.org/10.1080/00208825.2019.1646491

Czech Statistical Office. (2020). *Organisational Statistics*. https://www.czso.cz/csu/czso/organizational-statistics

Davidović, G. R. (2020, September). Lifelong learning in pandemic situation–challenge and need. In *8th International Scientific Conference Technics and Informatics in Education* (pp. 77–82). Faculty of Technical Sciences, Čačak, Serbia.

De Grip, A., & Sauermann, J. (2013). The effect of training on productivity: The transfer of on-the-job training from the perspective of economics. *Educational Research Review*, *8*, 28–36. https://doi.org/10.1016/j.edurev.2012.05.005

Devijver, P. A., & Kittler, J. (1982). *Pattern recognition: A statistical approach*. Prentice/Hall International.

Dirani, K. M., & Nafukho, F. M. (2018). Talent management and development: Perspectives from emerging market economies. *Advances in Developing Human Resources*, *20*(4), 383–388. https://doi.org/10.1177/1523422318803362

Egerová, D., Eger, L., Jirincova, H., & Ali Taha, V. (2013). *Integrated talent management challenge and future for organisations in Visegrad Countries*. NAVA.

Epstein, D. (2019). *Range: How generalists triumph in a specialised world*. Pan Macmillan.

Escobar, C. A., & Morales-Menendez, R. (2017). Machine learning and pattern recognition techniques for information extraction to improve production control and design decisions. In P. Perner (Ed.), *Lecture notes in computer science: Vol. 10357. Advances in data mining. Applications and theoretical aspects* (pp. 286–300). Springer, Cham. https://doi.org/10.1007/978-3-319-62701-4_23

Falola, H. O., Osibanjo, A. O., & Ojo, I. S. (2014). Effectiveness of training and development on employees' performance and organisation competitiveness in the Nigerian banking industry. *Bulletin of the Transilvania University of Braşov*, *7*(1), 161–170.

Folwarczna, I. (2010). *Rozvoj a vzdělávání manažerů* [Development and education of managers]. Grada Publishing a.s. (in Czech).

Grossman, R., & Salas, E. (2011). The transfer of training: What really matters: The transfer of training. *International Journal of Training and Development*, *15*(2), 103–120. https://doi.org/10.1111/j.1468-2419.2011.00373.x

Haak-Saheem, W. (2020). Talent management in Covid-19 crisis: How Dubai manages and sustains its global talent pool. *Asian Business & Management*, *19*, 298–301. https://doi.org/10.1057/s41291-020-00120-4

Hamblin, A. C. (1974). *Evaluation and control of training*. McGraw-Hill.

Henderson, A. J. (2003). *The e-learning question and answer book: A survival guide for trainers and business managers*. American Management Association.

Heslin, P. A., Keating, L. A., & Ashford, S. J. (2020). How being in learning mode may enable a sustainable career across the lifespan. *Journal of Vocational Behavior*, *117*, 103324. https://doi.org/10.1016/j.jvb.2019.103324

Hite, L. M., & McDonald, K. S. (2020). Careers after COVID-19: Challenges and changes. *Human Resource Development International*, *23*(4), 427–437. https://doi.org/10.1080/13678868.2020.1779576

Jain, A. K., Duin, R. P. W., & Jianchang Mao. (2000). Statistical pattern recognition: A review. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, *22*(1), 4–37. https://doi.org/10.1109/34.824819

Kaur, J. (2016). Impact of training and development programmes on the productivity of employees in the banks. *Journal of Strategic Human Resource Management*, *5*(1). https://doi.org/10.21863/jshrm/2016.5.1.023

Khodaskar, A. A., & Ladhake, S. A. (2014). Pattern recognition: Advanced development, techniques and application for image retrieval. In *2014 International Conference on Communication and Network Technologies* (pp. 74–78). Sivakasi, India. https://doi.org/10.1109/CNT.2014.7062728

Kirkpatrick, D. L. (1959). Techniques for evaluation training programs. *Journal of the American Society of Training Directors*, *13*, 21–26.

Kirkpatrick, D. L., & Kirkpatrick, J. D. (2006). *Evaluating training programs: The four levels* (3rd ed). Berrett-Koehler.

Matusov, E. (2020). Pattern-recognition, intersubjectivity, and dialogic meaning-making in education. *Dialogic Pedagogy: An International Online Journal*, *8*, 1–24. https://doi.org/10.5195/dpj.2020.314

Mayhew, K., & Anand, P. (2020). COVID-19 and the UK Labour Market. *Oxford Review of Economic Policy*, *36*(Supplement 1), S215–S224. https://doi.org/10.1093/oxrep/graa017

Mehrdad, A., Salehi, M., & Ali, S. (2009). A study of on the job training effectiveness: Empirical evidence of Iran. *International Journal of Business and Management*, *4*(11), 63–68. https://doi.org/10.5539/ijbm.v4n11p63

Mikova, I., Komarkova, L., & Pudil, P. (2019a). Support of development of non-profit organisations through special training programs for their managers. In *CIBMEE 2019: Proceedings of the Interna-*

tional Scientific Conference "Contemporary Issues in Business, Management and Economics Engineering'2019" (pp. 468–479). Vilnius Gediminas Technical University, Vilnius, Lithuania. https://doi.org/10.3846/cibmee.2019.048

Mikova, I., Komarkova, L., Pudil, P., & Pribyl, V. (2019b). Comparison of usage and effectiveness of methods for further education. In L. Gomez Chova, A. Lopez Martinez, & I. Candel Torres (Eds.), *11th International Conference on Education and New Learning Technologies "Edulearn19 Proceedings"* (pp. 4930–4937). Palma, Mallorca. IATED Academy. https://doi.org/10.21125/edulearn.2019.1230

Morley, M., Szlávicz, Á., Poór, J., & Berber, N. (2016). Training practices and organisational performance: A comparative analysis of domestic and international market oriented Organisations in Central & Eastern Europe. *Journal for East European Management Studies*, *21*(4), 1–27. https://doi.org/10.5771/0949-6181-2016-4-406

Naranjo, R., & Santos, M. (2019). A fuzzy decision system for money investment in stock markets based on fuzzy candlesticks pattern recognition. *Expert Systems with Applications*, *133*, 34–48. https://doi.org/10.1016/j.eswa.2019.05.012

Nikandrou, I., Apospori, E., Panayotopoulou, L., Stavrou, E., & Papalexandris, N. (2008). Training and firm performance in Europe: The impact of national and organisational characteristics. *International Journal of Human Resource Management*, *19*(1), 2057–2078. https://doi.org/10.1080/09585190802404304

Paltrinieri, N., Comfort, L., & Reniers, G. (2019). Learning about risk: Machine learning for risk assessment. *Safety Science*, *118*, 475–486. https://doi.org/10.1016/j.ssci.2019.06.001

Phillips, J. J. (1996). How much is the training worth? *Training and Development*, *50*(4), 20–24.

Pudil, P., Blazek, L., Castek, O., Somol, P., Pokorna, J., & Kralova, M. (2014a). *Identifying corporate performance factors based on feature selection in statistical pattern recognition: Methods, application, interpretation*. Munipress. https://doi.org/10.5817/CZ.MUNI.M210-7557-2014

Pudil, P., Komarkova, L., & Mikova, I. (2017). Link between financial performance of organisations and selected aspects of further education. In *European Conference on Management, Leadership & Governance* (pp. 402–407). London, UK. Academic Conferences International Limited.

Pudil, P., Mikova, I., Komarkova, L., & Pribyl, V. (2019). Relation of selected factors of further education in organisations development and profitability of organisations. In *CIBMEE 2019: Proceedings of the International Scientific Conference "Contemporary Issues in Business, Management and Economics Engineering'2019"* (pp. 247–254). Vilnius Gediminas Technical University, Vilnius, Lithuania. https://doi.org/10.3846/cibmee.2019.025

Pudil, P., Novovičová, J., & Somol, P. (2003). Recent feature selection methods in statistical pattern recognition. In D. Chen & X. Cheng (Eds.), *Pattern recognition and string matching* (pp. 565–615). Springer, Boston, MA. https://doi.org/10.1007/978-1-4613-0231-5_23

Pudil, P., Pirozek, P., & Somol, P. (2002). Selection of most informative factors in merger and acquisition process by means of pattern recognition. In *Signal Processing, Pattern Recognition, and Application* (pp. 224–229). Crete, Greece, IASTED. ACTA Press.

Pudil, P., Pirozek, P., Somol, P., & Komarkova, L. (2014b). Identification of key organization components influencing enterprises performance by means of non-linear regression model. In *European Conference on Management, Leadership & Governance* (p. 278). Zagreb, Croatia. Academic Conferences International Limited.

Rahimić, Z., & Vuk, S. (2012). Evaluating the effects of employees education in B&H companies. In E. Mehic (Ed.), *Conference Proceedings, 6th International Conference of the School of Economics and Business (ICES) "Beyond the Economic Crisis: Lessons Learned and Challenges Ahead"* (pp. 1044–1057). Sarajevo, Bosnia and Herzegovina.

Ratten, V. (2020). Coronavirus (Covid-19) and the entrepreneurship education community. *Journal of Enterprising Communities: People and Places in the Global Economy*, *14*(5), 753–764. https://doi.org/10.1108/JEC-06-2020-0121

Ratten, V., & Jones, P. (2020). Covid-19 and entrepreneurship education: Implications for advancing research and practice. *The International Journal of Management Education*, *19*(1), 100432. https://doi.org/10.1016/j.ijme.2020.100432

Simmonds, D. (2003). *Designing and delivering training*. Chartered Institute of Personnel and Development.

Somol, P., Grim, J., & Pudil, P. (2011). Fast dependency-aware feature selection in very-high-dimensional pattern recognition. In *2011 IEEE International Conference on Systems, Man, and Cybernetics* (pp. 502–509). Anchorage, AK, USA. IEEE. https://doi.org/10.1109/ICSMC.2011.6083733

US Private Sector Job Quality Index. (2020). *Statement #3 from the US Private Sector Job Quality Index ("JQI") Team on Economic Impacts of COVID-19 Related Unemployment.* https://www.jobquality-index.com/#flashsection

Van de Wiele, P. (2010). The impact of training participation and training costs on firm productivity in Belgium. *The International Journal of Human Resource Management*, *21*(4), 582–599. https://doi.org/10.1080/09585191003612083

Vieira, C., Magana, A. J., & Boutin, M. (2017). Using pattern recognition techniques to analyse educational data. In *2017 IEEE Frontiers in Education Conference (FIE)* (pp. 1–3). Indianapolis, IN, USA. IEEE. https://doi.org/10.1109/FIE.2017.8190592

Viloria, A., Lis-Gutiérrez, J. P., Gaitán-Angulo, M., Godoy, A. R. M., Moreno, G. C., & Kamatkar, S. J. (2018). Methodology for the design of a student pattern recognition tool to facilitate the teaching – learning process through knowledge data discovery (Big Data). In Y. Tan, Y. Shi, & Q. Tang (Eds.), *Lecture notes in computer science: Vol. 10943*. *Data mining and big data*. *DMBD 2018*. Springer, Cham. https://doi.org/10.1007/978-3-319-93803-5_63

Zhu, X., & Liu, J. (2020). Education in and after Covid-19: Immediate responses and long-term visions. *Postdigital Science and Education*, *2*(3), 695–699. https://doi.org/10.1007/s42438-020-00126-3