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Modelling Accelerating Acquisition of Teamwork Competences with Transversal Competences and Artificial Intelligence

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ABSTRACT

Objective: The purpose of this paper was to develop a model for accelerating the acquisition of the selected transversal competence of teamwork. Based on data from four EU countries, four models were developed and the best of them was selected, describing the results and variables relevant to that model.
Research Design & Methods: Data on improving transversal competences were collected from students in four countries, i.e. Poland, Slovakia, Slovenia and Finland. 26 variables were taken into account in the modelling which was based on four methods. They included the Multiple Linear Regression Model, Multivariate Adaptive Regression Splines, Support Vector Machine and two Artificial Neural Network methods.
Findings: The analyses show that the method of educating students and young employees, e.g. during training courses, can be a catalyst for accelerating teamwork competence acquisition. Other transversal competences including creativity, communicativeness and entrepreneurship correlate positively with growth in teamwork competence.
Implications/Recommendations: The study was conducted on an international group, also taking into account cross-cultural variables. However, to deepen the results, it is suggested that the sample size be increased and the research updated. The ranking of the education method is indicated to have an impact on the growth of transversal competences, including teamwork.
Contribution: New approaches in the paper include the analytical approach to modelling the growth in teamwork competence in relation to many variables describing students and young workers in the labour market in the UE. The use of multiple analytical and statistical methods allows the most fitting model to be selected and the error to be minimised.

Article type: original article.

Keywords: teamwork, creativity, communicativeness, entrepreneurship, transversal competences, competencies.

JEL Classification: O15, M52, M2, M12.

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1. Introduction

Ongoing technological developments and changes in the economy are forcing employees to continuously improve their competences (Jakubiak, 2017). The process of improving competences is directly linked to formal and informal education. Therefore, acquisition of skills should be planned and rationally implemented, for example, within the framework of education and training courses, a career path, or an employee competence development plan (Nosalska & Gracel, 2019) that are in place in the company. Knowledge of how to improve and accelerate competence enhancement is key in this area.

In the context of human resource management in companies, the assessment of employee competences is an essential part of the process of improving employee skills and, consequently, it is crucial in developing human potential in the organisation (Jędrzejczyk, 2017). It is important not only to be aware of one's competences but also to deepen one's knowledge of the competence-related needs in the labour market and to continuously improve them. Therefore, concepts that are currently relevant include lifelong learning. It represents a new perspective on an employee's career development (Solarczyk-Ambrozik, 2016). The idea sets new paths and directions for the development of the individual's competences. In addition, the competences that enable cooperation among many people, i.e. the ability to work in a team, are gaining in importance (Krawczyk-Blicharska, 2021). What employers currently desire most is the improvement of transversal competences (Graczyk-Kucharska *et al.*, 2019) as that has an important link with employability, especially for young people who are entering the labour market (Calero López & Rodríguez-López, 2020). Even though transversal competences contribute to future career success, their development is not an easy process (Sá & Serpa, 2018). At the beginning of the century, Wood and Payne (2006) pointed out that competences that are useful in the workplace include communication skills, the ability to work in a team, the ability to think analytically or the ability to solve problems. If these skills are important, how can we accelerate their development?

The issue of teamwork is important in the context of current social challenges in the context of management (Dimdiņš, Miltuze & Oļesika, 2022). Teamwork allows people with different skills and viewpoints to work together on modern problems, it utilises and merges the abilities of team members. Teamwork demands utilisation of a social skill (Goliński, Spychała & Miądowicz, 2022) and often requires face to face interactions and alignments regarding time and space (Wildman *et al.*, 2021). These circumstances can force employees to quickly improve their competences and can also influence other skills (Huang, 2022). There is a lack of analyses of teamwork competences in the context of other transversal competences (Graczyk--Kucharska *et al.*, 2020). There is also a shortage of methods used such as AI in researching this issue.

The Poznan University of Technology's Technical Knowledge Accelerator initiative aims to undertake and initiate actions meant to accelerate the development of the professional competence of employees. The initiative saw the launch of a project entitled "Method for accelerating the development of transversal competences in the process of practical education of students" for the purposes of the analysis of and research into the improvement of competences such as entrepreneurship, communicativeness, teamwork and creativity (Graczyk-Kucharska *et al.*, 2019). Research into the project was conducted with partners from Poland, Finland, Slovakia and Slovenia (Graczyk-Kucharska *et al.*, 2020). The project developed and tested five selected processes for accelerating the acquisition of transversal competences as described in more detail in other publications (Szafrański, Goliński & Simi, 2017).

This paper aims to develop a mathematical model for accelerating the acquisition of the transversal competence of teamwork. An additional objective is to verify different statistical analysis methods for the development of a model explaining the acceleration of the development of teamwork competences. Methods that were used to analyse the impact of and interdependence between factors influencing the rate of acceleration of the acquisition of this competence included the Multiple Linear Regression Model (MLRM), Multivariate Adaptive Regression Splines (MARS), Support Vector Machine (SVM) and Artificial Neural Network (ANN).

The chosen methods are popular statistical methods which will enable reliable development of models created using data from four countries (Poland, Slovakia, Slovenia and Finland) and 26 variables analysed in the process of improving and accelerating competence acquisition. The specifics of the data are described in the later part of the paper. Using the multiple linear regression method, it is possible to analyse to what extent different data are interrelated. The MARS method is a regression method that can be considered an extension of the linear model – it makes it easier to understand the behaviour of complex systems and to analyse and interpret the results of analyses. In recent years, MARS has been increasingly used in many fields of science, finance and economics. Therefore, a decision was made to test the possibility of using it in the area of competence management. The SVM method consists of models with learning algorithms that analyse the data for classification and regression analyses. ANN is a system designed to process information. Its most important feature is its ability to learn from data and generalise knowledge.

The development of the model for teamwork competence is intended to answer the following research problem: which variables influence the acceleration of the development of the transversal competence of teamwork? The 26 variables that were collected and classified during the study were included in further analyses. They are discussed in detail in the further part of the article. The results of the study present and compare four selected models that were developed using the various aforementioned methods. The further part of the paper discusses them, summarises the research work and identifies directions for further research.

2. Literature Review

2.1. Characteristics of the Term "Competence"

Literature offers many definitions of the term "competence", as is frequently the case with concepts that derive from social fields (Springer, 2018). Competences can be defined as a combination of knowledge, skills and attitudes appropriate to the situation and necessary to achieve societal goals (European Parliament and Council, 2006). Mansfield defines competences as the set of qualities that an employee possesses by which he or she achieves the intended outcomes at work

(Mansfield, 1999). Competences are also understood as personal qualities that contribute to the adequate performance of work and the proper functioning of the organisation (Dudzińska-Głaz, 2012). According to Filipowicz, competences are dispositions in terms of knowledge, skills and attitudes that enable one to perform professional tasks at an appropriate level (Filipowicz, 2019).

Competences are most often classified into two groups (Jagodziński, 2013):

– soft competences, also known as social competences, which include interpersonal skills, personality traits, approaches and attitudes,

– hard competences, also known as specialised competences, which include industry knowledge and knowledge and skills in the practical application of programmes and tools.

There are two perspectives on the perception of competences. The first (the behavioural one) refers to skills and dispositions that go beyond cognitive abilities, i.e. self-awareness and social skills. Unlike intelligence or personality, they can be acquired through exercise and development (Le Deist & Winterton, 2005). The second perspective (the functional one) defines competences as the characteristics of people who perform particular work or activities effectively and correctly. It is worth noting that it is a very broad definition as it includes traits, social roles, motives or knowledge resources, therefore it is not clear what it specifically refers to (Elkin, 1991; Robotham & Jubb, 1996). In the context of competences, there are many instances of adding further detail to the concept. One of them refers to transversal competences.

2.2. Transversal Competences

Another division of competences according to their typology distinguishes between transversal and technical competences (Sá & Serpa, 2018). Technical competences include the specialist knowledge and skills required for a particular job (Szafrański, Goliński & Simi, 2017). As the requirements may be different in different workplaces, these skills cannot always be used in every workplace. Transversal competences do not have a fixed definition, however, they can be described as those required for different jobs, in different industries and fields (Muhidova, 2022). Defined competences make it easier for us to find employment and function more easily in society. It is pointed out that the development of transversal competences is crucial as they are the ones that make it possible to form relations with the environment, an entrepreneurial attitude, and an ability to work creatively and solve problems (Szafrański, Goliński & Simi, 2017). In 2013, transversal competences were described by UNESCO as skills such as critical thinking, interpersonal skills and innovative thinking. Pârvu and Ipate believe that transversal competences also include values and attitudes that are appreciated in different fields and at each stage of a career (see: Sá & Serpa, 2018). Transversal competences are skills that anyone can acquire and those that can later be continuously improved (Belchior-Rocha, Casquilho-Martins & Simões, 2022). Increasingly, transversal competences such as good work organisation and self-discipline are required of employees by prospective employers. An employee with transversal competences can adapt more easily to a new job and their daily tasks. Other important competences are teamwork, creativity and problem solving (Sá & Serpa, 2018). Specific skills make it easier to work or carry out tasks and that allows companies to derive additional benefits. Teamwork is one of the most important skills for employers who are looking for employees (Graczyk-Kucharska *et al*., 2020).

There is a very large gap between the expectations of future employers and the opportunities for students to learn and develop transversal competences at universities (Serrano *et al*., 2011). Most universities focus on technical competencies, which are still very important and appreciated, however, without transversal competences they are not as attractive in themselves (García-Álvarez *et al*., 2022). Often, due to the lack of or limited budget for further training of new employees, companies are only interested in workers who already have transversal competences (Diaconu, Dutu & Georgescu, 2015). Such an employee can adapt to a new workplace, easily start working in a team and, in conjunction with other competences like creativity, offer many ideas and new solutions (Diaconu, Dutu & Georgescu, 2015). The literature indicates and emphasises the importance of improving transversal competences during education, in parallel with the development of technical competences using various educational methods. However, literature sources lack mathematical models to describe the dependencies inherent to students' transversal competences (Graczyk-Kucharska *et al*., 2020). This paper seeks to fill that research gap.

3. Methodology

3.1. Research Methodology

The first stage of the research was a literature analysis in the context of the research gap analysis defined in the first part of the article. Next, the research objective, which is to assess the growth of cross-cutting competencies among students participating in the testing of the new processes using practical training methods at universities in Finland, Poland, Slovakia and Slovenia, was defined. The objects of the study were transversal competences such as entrepreneurship, creativity, communicativeness, and teamwork. Further, the research sample was characterised, data was collected and analysed. The research methods were selected so that different variables could be included in the analysis of the impact on the studied variable, i.e. group work. The rest of the article describes them in detail. Finally, the results were analysed taking into account previous research. The diagram of the research methodology consists of several steps shown in Figure 1.

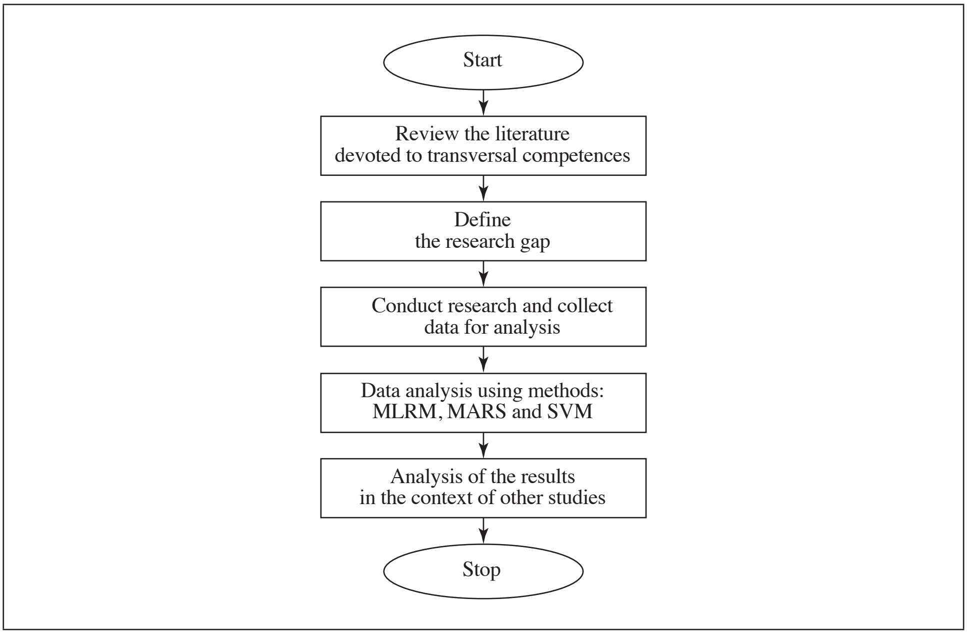

Fig. 1. Graphic Scheme of Research Methodology
Source: the authors.

3.2. The Multiple Linear Regression Method

This section briefly characterises each of the methods that were used to develop the models. Multiple linear regression is a tool that can be used to analyse how different variables are interrelated with one another. Linear regression analysis explains how the value of the response variable is affected by the explanatory variable (Piłatowska, 2006). When there are more than two explanatory variables, we are dealing with multiple regression analysis (Greń, 1984) which is the case of the analysis in this paper. The multiple (also known as multivariate) regression model involves using multiple explanatory variables to predict the value of the response variable (Aczel & Sounderpandian, 2018). We introduce additional explanatory variables into the basic regression model when regression with one explanatory variable does not reach a sufficient value of determination coefficient R^2. It is meant to reduce residual variability, however, it is only justified when each successive explanatory variable introduced into the model increases the value of the determination coefficient (Iwasiewicz & Paszek, 2004). Multiple linear regression can be used to predict future values of the dependent variable based on the values of the independent variables. It can also be used to determine which independent variables are most important in predicting the dependent variable.

3.3. Multivariate Adaptive Regression Splines

The MARS method aims to combine the method of recursive division and the method of interpolation with splines. The recursive division is a statistical method for the analysis of multiple variable functions. The use of the method results in the development of a decision tree that divides the adopted group according to the selected variables. The spline interpolation method is a numerical method that involves approximating an unknown function with low-degree polynomials (Friedman, 1991).

The MARS method consists of two sub-algorithms known as the forward and the backward stepwise algorithms. The first part involves looking for the main function and then each subsequent step expands the function. The process ends when the model has reached the M_{max} value which was previously set by the person who applied the method. The backward stepwise option reduces the complexity of the function, i.e. it simplifies it. Principal functions that cause an incremental squared residual error are excluded from the model. When all such errors are eliminated, an optimally approximated model is obtained (Weber *et al*., 2012).

3.4. Support Vector Machine

Machine learning is referred to as a sub-discipline of artificial intelligence that is responsible for a system's ability to augment knowledge resources, improve behaviour and make its own decisions based on experience. Induction, i.e. the ability to derive generalisations from observations, is responsible for the basis of that skill (Somvanshi *et al*., 2016).

There are three main types of machine learning, i.e. supervised and unsupervised learning and learning by reinforcement (Pisner & Schnyer, 2020). Sub-disciplines of supervised machine learning include classification, which involves assigning input to output data based on the numerous input-output examples identified during the learning phase (Pisner & Schnyer, 2020). The Support Vector Machine is an abstract machine model which is a classification and algorithm learning model. It uses a simple mathematical model and manipulates it to enable a linear division of the domain (Suthaharan, 2016).

The support vectors are the coordinates of individual observations while the SVM is the hyperplane separating the two classes and maximising the distance between the support vectors of each of them. The SVM decision-making process involves identifying a reproducible boundary, i.e. a hyperplane (Pisner & Schnyer, 2020).

3.5. The Artificial Neural Network Method

A neural network is a system designed to process information. The structure of the system is modelled on the functioning of the human biological nervous system.

One of the features of a neural network is the ability to learn from examples and automatically generalise acquired knowledge. All neural networks consist of three types of neurons, i.e. input, hidden and output neurons which are interconnected by synapses (Abraham, 2005).

There are two stages that make calculating final neuron value possible (Stęgowski, 2004). Firstly, the inserted vectors are multiplied by the synapse's weights and substituted to a given function. Most often, this function is scalar. Secondly, the function output is subject to the input-output activation function (Stęgowski, 2004; Graczyk-Kucharska *et al*., 2020).

4. Results and Developed Models

4.1. Data Collection

The study was conducted in six Europeans universities in four EU member states, i.e. Poland, Slovakia, Finland and Slovenia. The study ran from February to October 2017, using 10 teaching methods on a sample of 113 students divided into groups of 5 to 15.

The study sample consists of selected students, and the selection should be regarded as purposive-typical. Purposive selection is related to securing full groups for the study, while typicality is related to securing the identifiability of individuals as students. It is therefore required that survey participants be identified, for example, on attendance records. To secure the comparability of the data, it is assumed that groups of full-time students will be included in the survey. The basis for the selection of data was provided by the document "The development of principles for the selection of practical education methods for reference process models" which had been approved by university representatives as part of the ongoing project "Method for accelerating the development of transversal competences in the process of practical education of students". Based on the collected data, several dozen models were developed, some of which are presented in *The Acceleration of Development of Transversal Competences* (Szafrański, Goliński & Simi, 2017).

The project developed an educational methods matrix (Szafrański *et al*., 2017) that is relevant to the analyses in this paper. After diagnosing the educational methods, each of the 85 methods was evaluated in terms of its impact on the development of transversal skills. This made it possible to calculate the relevance of the educational method for each transversal competence.

During formal education, instructors used 3 educational methods from the available list of 85. After each of them was applied, students completed survey questionnaires regarding changes in their transversal competences. Based on their self-assessment, each of them determined, on a scale of 0–5, to what level their competences increased after a given method had been applied. The difference between the initial and the final assessment of a skill determines the rate of growth of a given competence.

To develop the model, teamwork skills were chosen as the independent variable. Subsequently, the efficiency of the model was improved by extending the scope of data, using time values as well as ANN, MARS, SVM and multiple regression methods. The input data are shown in Table 3 in the article by Graczyk-Kucharska *et al*. (2020, p. 659). A validation technique was used to compare the methods. Importantly, the amount of training data was 80% while the amount of test data was 20%.

That table incorporates the 26 variables that were included in the analysis. Among other things, it includes the cultural variables described by the Hofstede index, the start and end time of the process, the number of meetings with students, the size of the group, and the year of study.

4.2. Results

The Multiple Linear Regression Model

The study analysed the key variables for the development of the model. The analyses were conducted using STATISTICA software. Figure 2 presents the relevant variables that were included in the further development of the models. These include the average acceleration in Communicativeness (X_9), average acceleration in Creativity (X_8), average acceleration in Entrepreneurship (X_{10}), number of students (X_1) and the rank of the method in the matrix (X_2).

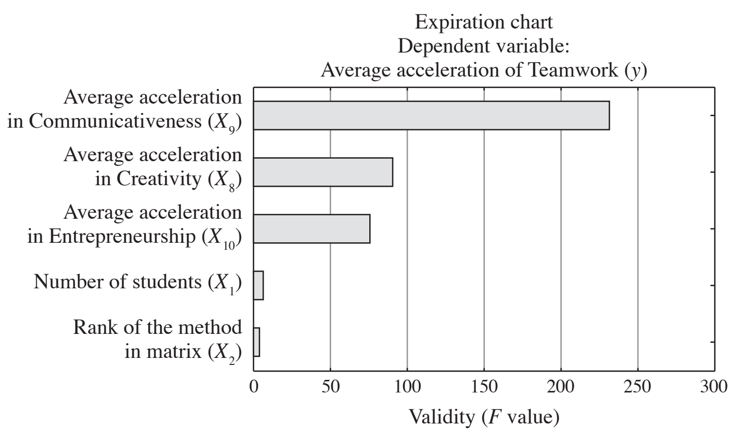

Fig. 2. The Dependent Variable in Modelling Teamwork Competence

Source: the authors.

Table 1 provides the results of the teamwork competence enhancement for the MLRM method. It details the coefficients, standard errors, *t*-values, and *p*-values for each variable, highlighting their significance in the model. Notably, the average acceleration in Communicativeness (X_9) and in Creativity (X_8) reveal significant positive effects on teamwork competence.

Table 1. Results of Teamwork Competence Enhancement for the MLRM Method (N = 339)

Specification	b^x	The Standard Error from b^x	b	The Standard Error from b	$t(333)$	p
Average acceleration of Teamwork (y)	–	–	0.2965	0.0809	3.6646	0.0003
Number of students (X_1)	–0.0133	0.0201	–0.0005	0.0007	–0.6593	0.5101
Position of the method in the matrix (X_2)	0.012	0.02	0.0008	0.0014	0.5977	0.5504
Average acceleration in Creativity (X_8)	0.1105	0.0443	0.1134	0.0455	2.4921	0.0132
Average acceleration in Communicativeness (X_9)	0.753	0.0398	0.7403	0.0391	18.9377	0.0000
Average acceleration in Entrepreneurship (X_{10})	0.0978	0.0443	0.0995	0.0450	2.2091	0.0278

Source: the authors.

Furthermore, Figure 3 illustrates the baseline function and regression for the teamwork competence using the Multiple Linear Regression Model. This figure helps visualise the relationship between the dependent variable and the predictors, showcasing the effectiveness of the model in capturing these changes.

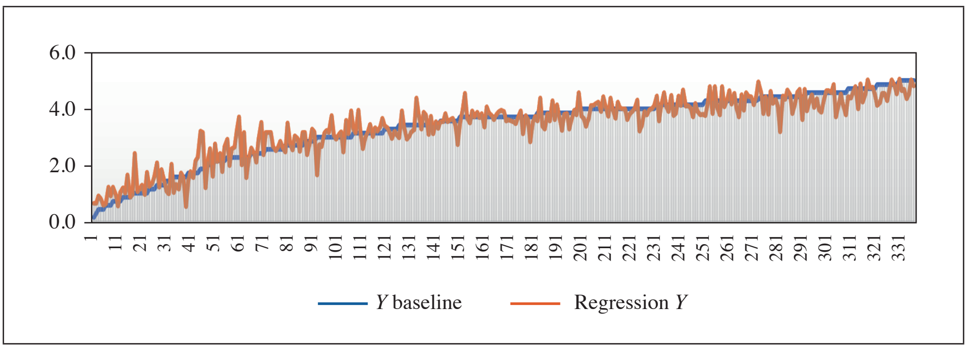

Fig. 3. Baseline Function and Regression for the Teamwork Competence Using the MLRM Method

Source: the authors.

Multivariate Adaptive Regression Splines

Generalised cross-validation was used to develop the model (1) with the best predictive fit. The teamwork competence acceleration function was calculated from the following formula:

$$(y) = 3.4514e{+}000 + 4.9196e{-}001{*}\max(0; (X_9){-}3.6667e{+}000) - 8.3755e{-}001{*}\max(0; 3.6667e{+}000{-}(X_9)) + 1.5593e{-}001{*}\max(0; (X_8){-}2.3333e{+}000) + 1.0646e{-}001{*}\max(0; (X_{10}){-}1.5e{+}000), \quad (1)$$

where:

y – average acceleration in Teamwork,
X_1 – number of students,
X_2 – position of the method in matrix,
X_8 – average acceleration in Creativity,
X_9 – average acceleration in Communicativeness,
X_{10} – average acceleration in Entrepreneurship.

The calculation error for this model was calculated at $R^2 = 0.8748$, adjusted $R^2 = 0.8729$, the standard error of estimation: 0.40. R^2 is about 87%. Therefore, we have a level of explanation as in the case of multiple regression with an accuracy of 1%. The results in the form of a baseline function and a predictive function calculated using MARS are shown in Figure 4.

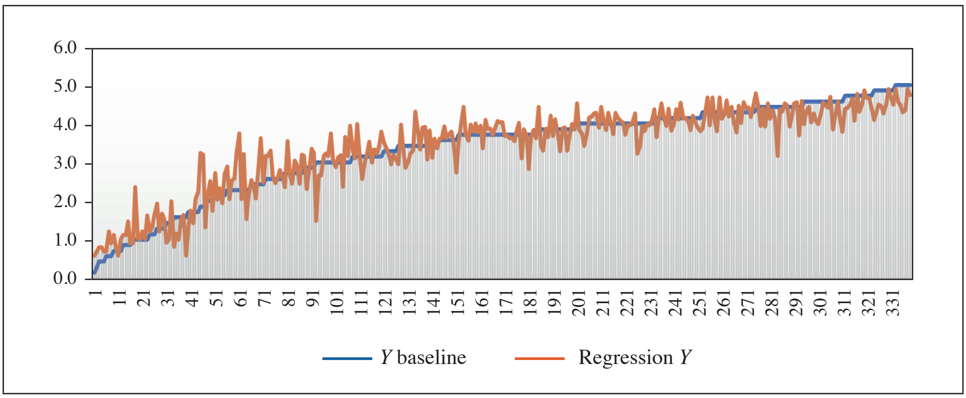

Fig. 4. Baseline and Predictive Function Model for Teamwork Competence Using the MARS Method

Source: the authors.

Support Vector Machine

The SVM model incorporated previously selected relevant variables. Calculations show that for this model the error is $r = 0.938$, adjusted $R^2 = 0.88$ and the standard error of estimation: 0.4. R^2 is about 88%. In relation to regression or MARS, we gained about 1% of the quality of the model as shown in Figure 5.

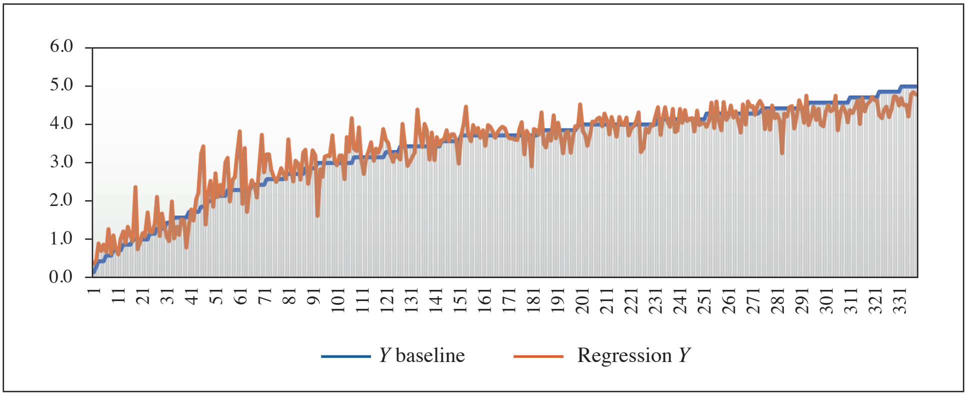

Fig. 5. Baseline and Predictive Function Model for Teamwork Competence Using the SVM Method

Source: the authors.

Artificial Neural Network

To create the model, the authors chose appropriate parameters such as the right kind of algorithm, the right kind of network, the number of hidden layers, the number of neurons in each layer and the kind of transfer function between coats.

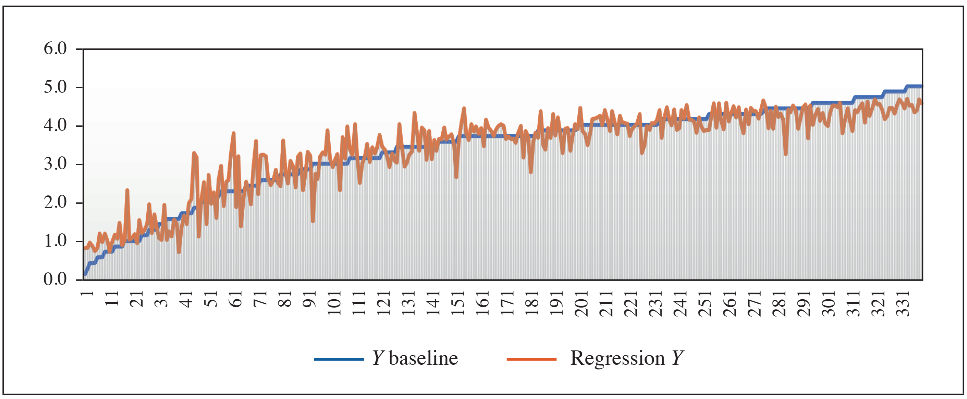

Fig. 6. Baseline and Predictive Function Model for Teamwork Competence Using the ANN MLP Method

Source: the authors.

Feed-forward models and multilayer neural network meta-models were then "trained" in STATISTICA, so that a teamwork prediction could be provided. For ANN Multilayer Perceptrons (MLP) on 88 neurons in the "hidden" layer gives us a modified R^2 of around 92%. In relation to regression or MARS, we gained about 5% of the quality of the model. On 33 neurons in the "hidden" layer – it gives us a modified R^2 of around 91%. These results are presented in Figure 6.

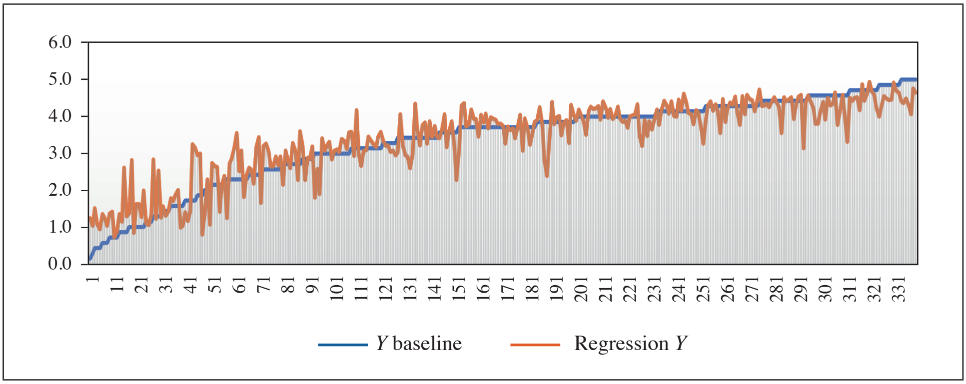

Fig. 7. Baseline and Predictive Function Model for Teamwork Competence Using the ANN RBF Method

Source: the authors.

In addition, a model was developed and results were verified using the ANN Radial Basis Function Networks (RBF) method. The analyses show that about 28 neurons in the â layer – hidden nonlinear layer gives us the modified R^2 of around 90%. In relation to regression or MARS, we gained about 3% of the quality of the model. These results are presented in Figure 7.

5. Comparison of the Models

Comparing the results from the models taking into account the same key variables for improving teamwork competence, it must be stated that the presented models make it possible to explain almost 92% of the variability of the phenomenon described by the collected data. The highest adjusted R^2 value was shown for the ANN MLP model (0.92), followed by ANN RBF (0.898), SVM (0.88), MARS (0.873) and MLRM (0.869) – see Table 2.

The obtained results unequivocally point to the dependence of all the studied transversal competences on the competence of teamwork. An earlier study on the same research sample analysed another key transversal competence, i.e. entrepreneurship (Graczyk-Kucharska *et al.*, 2020). That research reveals that the acceleration in obtaining the competence of entrepreneurship is also influenced

Table 2. Performance Measures of Models

Specification	Name of the Method				
	MLRM	MARS	SVM	ANN MLP	ANN RBF
R^2	0.871	0.875	0.880	–	–
Adjusted R^2	0.869	0.873	0.88	0.92	0.898
r	0.933	0.9354	0.938	–	–
The standard error of estimation	0.416	0.4	0.4	0.34	0.32

Source: the authors.

by other competences. The ranking of the educational method in learning is also important. It can therefore be concluded that this research confirms the direction and interdependence of all competences. However, it must be verified further by analysing and developing models for the competences of creativity and communicativeness.

6. Summary and Conclusions

In partnership with six universities, it was possible to develop a method for advancing the procurement of a chosen transversal competence. The analysis used MARS, ANN (MLP and RBF), SVM and MLRM methods. The studied competence was the transversal competence of teamwork. The results of accelerating the acquisition of the competence were analysed taking into account the effect of the reliant variables such as evidence accumulated throughout the trial process and hand-picked transversal competences.

The study makes it possible to select the most relevant variables that enable the acquisition and development of teamwork competence. The analysis and calculations help to compare the effectiveness of the separate methods. They show that the MLRM method is the least accurate but can be best explained by indicating the relevance of individual variables. In this case, the highest dependence is found with the communicativeness competence (X_9). The other methods confirm the relevance of these variables, but their interdependence cannot be easily explained. It is especially true of neural networks. These models, both the ANN MLP and the ANN RBF, explain the largest amount of the studied dataset. However, it should be pointed out that the differences in results between them are not large. The ANN MLP model makes it possible to explain almost 92% of the variability in the phenomenon described by the collected data. Following data collection and analysis and based on the developed models, it can be concluded that entrepreneurship and teamwork strongly influence each other and, in addition, all four transversal competences (entrepreneurship, teamwork, creativity, communicativeness) influence one another.

Transversal competences, including teamwork, are used in many jobs. All competences are interrelated. It can be concluded that if one of them is improved, the other transversal competences are also enhanced at the same time. This has been proven for the competence of entrepreneurship. Further research that confirms this hypothesis in relation to the competences of communicativeness and creativity must be undertaken. Increasingly, employers are looking for employees with developed transversal competences, therefore the results of the study should have implications for the field of education at all levels, including at universities, as well as in companies providing training for employees. The results can be used to inform decisions on the best teaching methods for students, thus helping to accelerate the development of transversal competences, including teamwork.

The study was limited to selected competences and countries. Which means that the possibility of influencing the development of selected competences by other competences was limited. Additionally, the sample was relatively small, so it was not possible to conduct statistical analysis with a small margin of error. Suggestions for further research directions include expansion of the dataset with additional data from other EU countries, expansion of the research sample and continuing research on developing models for the competences of communicativeness and creativity, and expanding the area of analysis to include professional competences. Moreover, future research may focus on transversal competences related to digital competences as relevant in the context of technological change and artificial intelligence.

Authors' Contribution

The authors' individual contribution is as follows: Magdalena Graczyk-Kucharska 30%, Robert Olszewski 30%, Joanna Przybyła 10%, Julia Łuszkiewicz 10%, Klaudia Hojka 10%, Małgorzata Spychała 10%.

Conflict of Interest

The authors declare no conflict of interest.

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