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Application of Soft Computing Techniques in the Analysis of Educational Data Using Fuzzy Logic

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Abstract

The application of soft computing techniques, with a special emphasis on fuzzy logic, represents a modern approach to analyzing complex educational data. This paper explores the possibilities of applying soft computing to identify and interpret factors that influence the motivation and educational achievement of students in academic and professional studies, with special reference to the differences between these two groups of students in experienced subjects. Fuzzy logic enables more detailed processing of educational parameters that are subject to subjective interpretations and are often not clearly defined. By using this approach, decision support systems are developed that facilitate the understanding of students' motivational patterns, their preferences, and challenges in mastering different types of content. Analyzing educational data seeks to identify relevant motivational factors that can contribute to shaping more effective and personalized teaching strategies. The goal of the work is to improve the quality of the educational process through the integration of soft computing methods, to raise the level of engagement and success of students in various fields of study.

Keywords: soft computing; fuzzy logic; Anfis; education; student motivation

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1. Introduction

In the modern educational system, higher education institutions play a key role in forming future experts, not only through the transfer of theoretical knowledge but also through the development of practical skills [1]. To respond to the growing demands for an individualized approach, educational institutions are intensively exploring the possibilities of adapting their teaching methods [2]. This research is focused on the analysis of input factors that influence the level of students' motivation, to improve their achievements in professional subjects. Special attention is paid to the differences between academic and vocational studies, to identify specific elements that contribute to more effective learning in different educational contexts. Recognizing these motivational factors enables the creation of customized educational strategies that encourage the engagement and progress of students within professional disciplines. The analysis of motivational factors through soft computing techniques can significantly contribute to the personalization of education, better support for students, and improvement of their academic results [3].

The application of advanced software solutions in the analysis of motivational factors within the higher education system represents an important step toward shaping educational approaches that are aligned with the individual characteristics and needs of students. This integration of modern technologies into the educational process contributes to increasing the quality of teaching, creating a more stimulating environment for learning and better preparing students for the professional challenges of modern society. In today's educational environment, understanding the motivations that drive students to learn is crucial to improving academic performance and the effectiveness of the education system. Motivation appears as a multi-layered phenomenon that shapes the approach to learning, the degree of engagement and persistence in achieving educational goals [4]. Research has pointed to several factors that can positively influence motivation, among which interest in teaching content, the perception of tasks as challenging, a sense of personal relevance of the material, and the support provided by teachers stand out.

Motivation, as a key driver of learning, has a direct impact on educational outcomes and personality development [5]. In this process, schools and teachers have an important role through the way of communication, methods of work and evaluation of knowledge. Understanding the factors that influence students' motivation enables the improvement of teaching practice and the achievement of better results [6–8]. Soft computing, especially fuzzy logic, offers modern methods for analyzing complex and imprecise educational data [9]. These techniques, which rely on artificial intelligence, enable finding approximate solutions and are increasingly being used in education, especially in processing complex data and adapting the educational process to the real needs of students.

The novelty of this research lies in the application of the ANFIS method to analyze motivational factors and academic performance, combining the advantages of artificial neural networks and fuzzy logic in processing educational data. The study is based on real survey data collected from students of both academic and vocational programs and includes a comparative analysis of motivation in professional and general education subjects. Unlike prior research that mainly relies on traditional statistical approaches, this study applies soft computing techniques to identify the most influential factors, enabling predictive modeling and a deeper understanding of the educational process from the perspective of student motivation.

This paper presents a novel application of the Adaptive Neuro-Fuzzy Inference System (ANFIS) for identifying and predicting the key motivational factors that influence academic performance, with a focus on comparing vocational and academic study programs. The originality lies in the integration of fuzzy logic and neural networks to analyze student motivation through real-world data collected via a specially designed Likert-scale questionnaire. By transforming questionnaire responses into input variables for a soft computing model, this research enables deeper insights into how specific factors such as classroom atmosphere, employment perspective, and prior knowledge contribute to learning outcomes. The proposed approach advances previous studies by offering a predictive, data-driven framework that can be used to support personalized learning strategies and institutional decision making in higher education.

2. Literature Review

The theoretical basis of student motivation research includes the analysis of traditional and modern motivational theories that enable a deeper understanding of the factors that influence students' educational behavior [10,11]. Among the most represented approaches are Maslow's theory of the hierarchy of needs and Herzberg's two-factor theory, which provide a basis for considering the relationship between external conditions, internal needs, and the degree of commitment to learning [12].

According to these theories, satisfying basic needs—from physiological to self-affirmation needs—can significantly influence the level of academic aspirations and motivation in students. Although several psychological factors are relevant for shaping student behavior, motivation stands out as a central factor in their academic development. Numerous studies in the field of educational psychology confirm its key importance for understanding academic success, especially in the context of higher education [13].

In addition, modern technological development encourages the ever-increasing importance of the concept of lifelong learning and continuous personal improvement. The Internet and digital technologies are becoming an indispensable part of everyday life, including the educational process. It is expected that the wider application of information and communication technologies (ICT) will improve the presentation of educational content and contribute to greater teaching efficiency [14].

The application of soft computing technologies in modern education enables the development of generations that, in addition to technical competence, also possess the ability to think creatively, solve complex problems, and adapt to the dynamic labor market. Thus, innovations in the field of soft computing become an important factor in the modernization of the educational system and the preparation of personnel for the challenges of the digital society. The use of advanced software tools in the analysis of motivational factors in higher education contributes to the formation of educational models that are adjusted to the individual needs of students.

Current research on the application of soft computing techniques shows a wide range of possibilities in the analysis of human behavior. When it comes to education, these methods enable the discovery of hidden patterns and connections within complex data sets, which is particularly important in researching student motivation. Also, predictive models based on previous patterns of student behavior can contribute to better planning of teaching activities and personalization of educational approaches.

The application of the soft computing approach in modern education represents an important step towards the modernization of teaching processes, as it enables intelligent data processing, content adjustment and decision making based on specific information. These techniques, based on artificial intelligence, are increasingly used in educational technologies and analytical systems to increase the effectiveness of teaching, through a better understanding of the individual needs and educational styles of each individual [15].

One of the key advantages of soft computing is the possibility of personalizing teaching content, which is most effectively achieved through adaptive learning systems that use neural networks and genetic algorithms [16]. These systems analyze previous interactions and user results to adapt materials and recommend optimal tasks, methods, and resources for further progress.

In the context of digitization of education, digital tools play a significant role in increasing student motivation. By providing access to interactive and flexible platforms, online courses and multimedia resources, students have the opportunity to learn at their own pace and affinities, which further affects their engagement. Participation in forums, solving tasks in real time, simulations and tools for creative expression further stimulate cognitive processes and motivation.

Techniques such as fuzzy logic and neural networks are also applied in the analysis of large educational databases in order to identify patterns of behavior and predict learning outcomes. This kind of analysis allows educational institutions to identify students who need extra help in time and thus develop more effective support and intervention strategies [17].

Various studies have examined the influence of motivational factors on learning and academic success through quantitative and qualitative approaches. In South Africa, research was conducted among 380 ninth-grade students from three racial groups, where the impact of six motivational factors (e.g., self-efficacy, learning strategies, science appreciation) was analyzed using the SMLS questionnaire via a Likert scale [18]. In Iran, a total of 800 students participated in a survey of motivation for learning English. A two-stage instrument was used to check validity, and various statistical methods were used, including CFA and SEM. At a Midwestern college in the USA, 236 students were assessed for ability, achievement, self-regulation, and motivation using tests and questionnaires, while course grades served as a measure of success [10]. In Germany, 345 high school students were tested through questionnaires and an intelligence test to assess self-awareness, subject evaluation and learning goals, using standardized scales and motivational questionnaires [19]. One study examined the impact of educational software on mathematics instruction using the ANFIS model. The results showed positive effects on motivation, knowledge and objectivity of assessment. Another study used multiple regression analysis to identify which motivational variables best predicted success on final exams in 377 students [20–22]. Future perspective and self-confidence proved to be the strongest predictors. At Margalla University, Pakistan, dental students' motivation was measured using a customized SMDS questionnaire. A weak correlation was found between motivation and academic success [23].

3. Materials and Methods

The subject of the research is the analysis of factors that influence the motivation of students of academic studies at the University of Novi Pazar and vocational students at the Academy of Vocational Studies Šumadija Department Trstenik, with a focus on vocational subjects. Motivation is a complex aspect of human behavior and plays a crucial role in the educational process. When a student experiences a certain goal as personally significant, an inner strength is activated that enables overcoming average abilities and achieving high academic results. On the other hand, lack of motivation often leads to reduced engagement, procrastination, and failure to achieve educational goals.

In the context of higher education, motivation directly affects the level of engagement, interest, and academic achievement of students. Understanding the factors that encourage or hinder motivation enables the creation of a stimulating educational environment, both for teachers and for educational institutions.

The main goal of the research is to recognize and analyze the key determinants that influence the motivation of academic students, with the application of the adaptive neuro-fuzzy inference method, ANFIS [24–33], as part of the soft computing approach. The research aims to contribute to a better understanding of the relationship between educational strategies and motivation, as well as to enable the formulation of guidelines for personalized support in learning, to improve educational achievements.

Based on the defined goal and tasks of the research, the initial assumption is that the application of the ANFIS method will enable a reliable prediction of the factors that influence the motivation of students in academic and professional studies. The research is based on the following hypotheses:

- Hypothesis 1: Soft computing methods, specifically the ANFIS model, can successfully reveal patterns in the behavior and attitudes of students of academic and professional studies that are related to their motivation and level of learning achievement.

- Hypothesis 2: The quality of interaction during the teaching of academic subjects, including clarity of presentation, teacher engagement and active student involvement, positively correlates with the degree of student motivation.
- Hypothesis 3: Students' belief about future employment opportunities in the field of study has a direct impact on their internal motivation and academic commitment.
- Hypothesis 4: Students who have prior knowledge of professional academic areas show a higher level of engagement and motivation for additional learning within the same areas.

Anfis Methodology

As part of the conducted research, the model includes a total of 12 input variables, with three bell-shaped membership functions defined for each variable. Theoretically, this would result in a total of 3^{12} = 531,441 fuzzy rules in the ANFIS rule base, which is practically infeasible for training and implementation. Therefore, in this study, a reduction in input features and rules was applied by selecting the most relevant parameters based on input variable significance analysis, resulting in an optimized set of rules tailored to the specific model and the available experimental data.

The architecture of the ANFIS model consists of five layers: the input layer, the membership function layer, the rule layer, the inference layer, and the output layer. Each layer has its specific role in the process of fuzzy inference and model adaptation.

The first layer receives the input variables and transforms them into fuzzy values according to the membership functions. There are various types of membership functions; in this study, the bell-shaped membership function was used due to its superior capability in modeling nonlinear data. The bell-shaped membership function is defined as follows, known as the Bell function:

$$\mu(x) = bell(x; a_i, b_i, c_i) = \frac{1}{1 + \left[\left(\frac{x - c_i}{a_i} \right)^2 \right]^{b_i}}$$

where x is the input variable, and a_i, b_i and c_i are the given parameters.

The second layer multiplies the fuzzy signals from the first layer and, according to the rules, produces the activation strength w_i. The third layer, which is the rule layer, normalizes all signals from the second layer. The fourth layer is adaptive and generates the rule conclusions, converting all signals into precise values, while the fifth layer is fixed and sums all the signals, producing the final output value.

The fuzzy inference system model uses neural networks to determine membership function parameters based on available input–output data. During the forward pass of the ANFIS algorithm, signals propagate to the fourth layer where consequent parameters are estimated using the least squares method, while during the backward pass, premise parameters are updated through gradient descent. Training and testing of the ANFIS network were performed in the Matlab environment. Based on experimental results, the model can identify the most influential parameters for a given output, with prediction accuracy evaluated using the root mean square error (RMSE):

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (P_i - Q_i)^2}{n}}$$

Data processing in this study was performed using Matlab's neuro-fuzzy logic tools. Before training, the following steps were carried out: loading the dataset with input and output variables (output in the last column); loading the initial model structure—Sugeno-type FIS with a single output (ANFIS); selecting the hybrid optimization method combining least squares and gradient descent for training membership functions; and setting training parameters such as number of epochs and error tolerance, with training stopping once either is met. After training, model validation was conducted using separate test data, followed by analysis of all data. Results are graphically presented later in the dissertation.

The ANFIS network was trained for each input separately to determine mean error (ME), standard deviation (SD), mean squared error (MSE), root mean squared error (RMSE), and Pearson's correlation coefficient (R). Hypotheses were confirmed using RMSE and R values. Input relevance was assessed by RMSE, where the input with the lowest RMSE during training had the greatest influence on output. Monitoring RMSE helped detect overfitting between training and testing data. The correlation coefficient R measures linear dependence between training and testing outputs, with values from 0 to 1. A model with R above 0.8 is considered reliable, confirming the validity of the hypotheses.

The ANFIS model training process begins with defining fuzzy sets, determining the number of sets for input variables, and selecting the membership function. All training data pass through the neural network, where input parameters are adjusted to optimize the relationship between inputs and outputs, minimizing the error. In the ANFIS model, each input variable is treated as independent while examining its influence on the output. The fuzzification of input variables is performed using the bell-shaped membership function, which was used to develop a total of four models. Key characteristics of these models include fuzzification of inputs with the bell function, a total of 200 training epochs (iterations), and the use of root mean square error (RMSE) to identify the most influential input.

4. Results and Discussion

The research was conducted on a sample of students attending academic studies at the University of Novi Pazar; the total number of respondents is 131. The second group of respondents was conducted on a sample of 155 students of vocational studies from the Academy of Vocational Studies Šumadija Department Trstenik. Based on long-term involvement in teaching and daily interaction with students, differences were observed in the level of their motivation and success depending on the type of subject they studied.

The selection of the twelve input factors was based on a detailed analysis of the survey results conducted among students of both academic and vocational studies. The original questionnaire contained 13 items rated on a ten-point Likert scale, designed to capture a wide range of motivational influences. After collecting the data, a combination of expert evaluation, correlation analysis, and the assessment of response consistency was used to identify the most relevant factors. These twelve factors showed the strongest influence on motivation and academic achievement across both student groups. The selection was also guided by previous literature in the field of educational psychology and motivation, ensuring that the input variables reflect both empirical relevance and theoretical grounding.

These observations prompted the idea of conducting research to gain a deeper understanding of the factors that influence students' motivation and academic achievement. The research was designed as a survey aimed at identifying the motives that encourage greater engagement and success in professional subjects that are closely related to the future professional direction of students, compared to general education subjects that develop general competencies.

The research was conducted among students of academic studies at the University of Novi Pazar and students of vocational studies from the Academy of Vocational Studies in Šumadija, Trstenik Department, and the sample included students from different years of undergraduate studies. Special emphasis is placed on the comparative analysis of motivation in the context of professional and general education subjects that students attend as part of their study programs. The questions in the survey were adapted to the level of study and included subjects that the students had already taken and passed, which enabled the answers to reflect real experiences.

The survey consisted of 13 questions, where the answers were given on a ten-point Likert scale. The students, that is, the respondents, are from different departments and modules, which contributed to diversity in insights into motivational factors.

Motivation is influenced by many different factors, the most relevant of which are selected and shown as input variables in Table 1.

Table 1. Input and output factors.

Inputs and Output	Description of Parameters	Min–Max
Input 1	Foreknowledge	1–10
Input 2	Innovative technologies	1–10
Input 3	Attitude towards the subject	1–10
Input 4	Grade or knowledge	1–10
Input 5	Personal development—employment perspectives	1–10
Input 6	Financial support—scholarship	1–10
Input 7	Understandability	1–10
Input 8	Applicability	1–10
Input 9	Quality of teaching and teaching material	1–10
Input 10	Teacher commitment	1–10
Input 11	Working atmosphere	1–10
Input 12	Objectivity of assessment	1–10
Output	Student motivation	1–10

4.1. Analysis of Results for Professional Subjects in Vocational Studies

The motivation of vocational school students for professional subjects such as computer science, programming, and computer architecture significantly affects their success and future professional development. Practical application of this knowledge, interest in technology and awareness of high demand in the labor market are the key drivers of learning. Also, the teacher's support and the possibility to immediately apply what has been learned in practice further boost motivation.

Table 2 presents the performance results of the ANFIS model configured with the most relevant input variables, selected based on prior input significance analysis. This configuration uses bell-shaped membership functions (three per input), the hybrid training method (a combination of least squares and gradient descent), and 200 training epochs. In the revised version of the paper, we will include a clearer statement specifying that Table 2 refers to this optimized ANFIS model configuration, along with a brief explanation of the key parameters used.

Table 2 shows the results of training, testing and analysis of the entire data set for the factor with the greatest impact on motivation—input 5 (employment perspective, i.e., personal development). In addition, the reliability of the model is presented in the table, to see the assessment of how well the model fits the real data and how much can be relied on its prediction.

Input number 5 has the smallest error, that is, the biggest impact on motivation, where the RMSE values for different data sets are as follows: training data: RMSE = 0.307478, test data: RMSE = 0.359521, all data: RMSE = 0.31597.

Table 2. The impact of one entry on the exit for vocational subjects in vocational studies.

Input	The Input with the Least Error
One Input	Input no. 5 TRAINING—ERROR SV = 0.000000 SD = 0.308508 MSE = 0.094543 RMSE = 0.307478 TEST—ERROR SV = −0.029481 SD = 0.365136 MSE = 0.129255 RMSE = 0.359521 ALL DATA SV = −0.004497 SD = 0.31684 MSE = 0.099838 RMSE = 0.31597
Reliability of the model	Training data: R = 0.99513 Test data: R = 0.99269 All data: R == 0.99478

The perspective of employment has a strong influence on the motivation of students in vocational schools. When they see that education can directly help them find a job and develop their career, students are more inclined to engage more and achieve better results. Vocational programs, due to their compliance with the requirements of the labor market, further strengthen this motivation. The awareness that specific skills and certifications can provide them with better chances of employment often encourages them to work hard, improve and strive for success. The support of professional teachers and administration also plays an important role in that process, which facilitates connection with employers and thus additionally strengthens the perspective of employment as a motivational factor.

Figures 1–3 show in detail the results of error analysis during the training process, testing and the entire data set using the ANFIS methodology, with a focus on one achievement factor. These visuals allow for a deeper understanding of how errors change during different stages of the analysis, providing insight into the stability and reliability of the model. The displayed data offer a complete picture of the model's performance in different situations, enabling the identification of patterns and trends that may be key to further improving the methodology or data analysis for a given achievement factor.

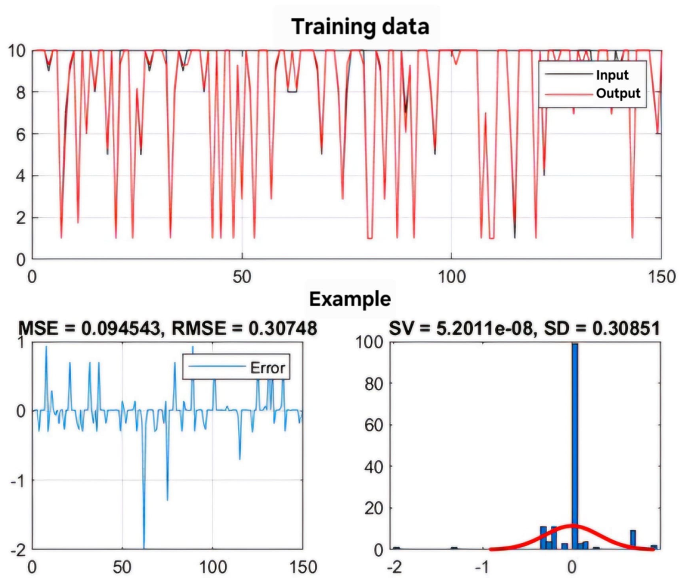

Figure 1. ANFIS network training—influence of one input on motivation, input number 5.

The error histogram shows the distribution of deviations between the predicted and actual values generated by the model. The blue bars represent the frequency of individual error values for each sample from the training dataset, while the red line indicates the fitted normal distribution (Gaussian curve) based on the same statistical parameters, primarily the standard deviation (SD = 0.30851). The purpose of this analysis is to assess whether the model errors are evenly distributed around zero, which would indicate good generalization capability and the absence of systematic bias in the predictions. The shape of the red line helps in the visual assessment of the normality of the error distribution, serving as an important indicator of the model's reliability and stability.

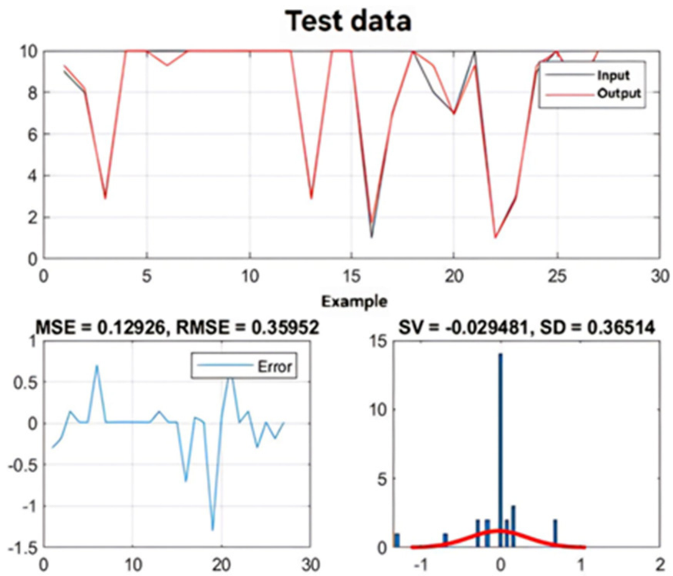

Figure 2. ANFIS network test—influence of one input on motivation, input number 5.

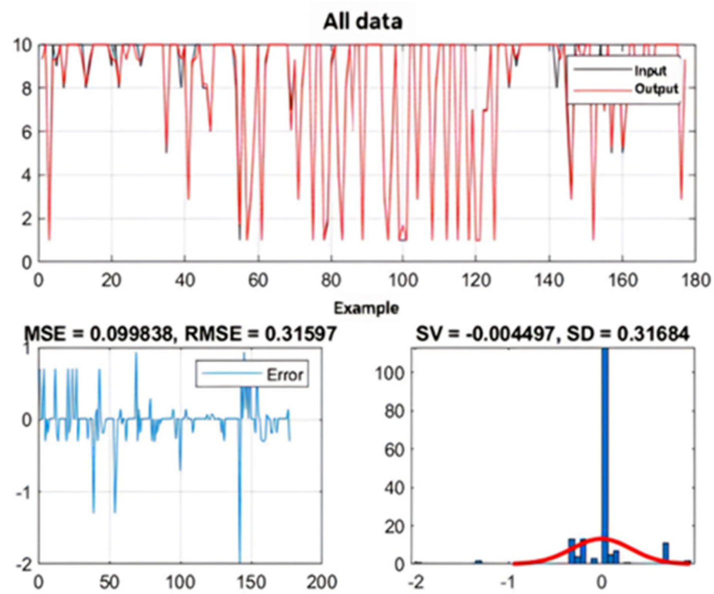

Figure 3. All ANFIS network data—influence of one input on motivation, input number 5.

In Figure 4, the regression analysis and degree of reliability of the model are shown in detail, which is a key stage in evaluating the efficiency and accuracy of the model. This analysis provides a deeper understanding of how the model behaves in relation to real data and how reliably its predictions can be relied upon. For training data, linear correlation coefficient R = 0.99513, test linear correlation coefficient R = 0.99269, while all data for linear correlation coefficient R = 0.99478. In addition, Figure 5 shows a graphical interpretation of the training data, which allows an intuitive overview of the data distribution and the identification of possible patterns or anomalies. The red stars indicate the data used for training, while the blue dots represent the output values generated by the ANFIS model. The graph clearly shows that the outputs of the ANFIS model (blue dots) closely follow the data from the training set (red stars). This indicates successful training of the model, allowing it to accurately predict the corresponding output values. This graphical interpretation helps us recognize patterns or irregularities in the data, which can contribute to further improving the quality of the model or better understanding the data. Overall, such visual representations allow deeper research and better understanding of the process and results of applying the ANFIS methodology in data analysis.

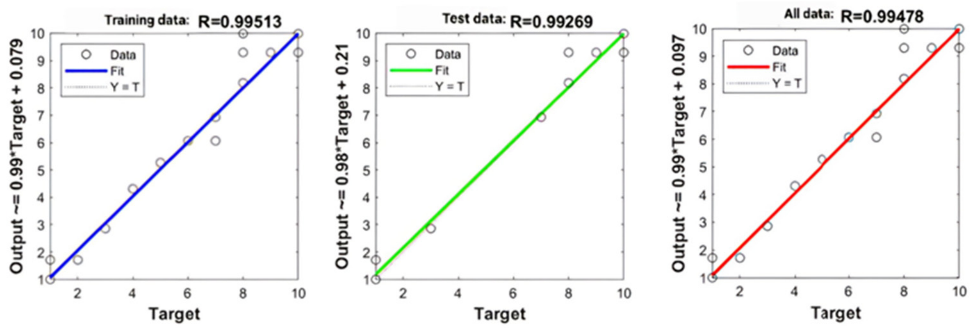

Figure 4. Linear regression of training, test and all data—influence of one input.

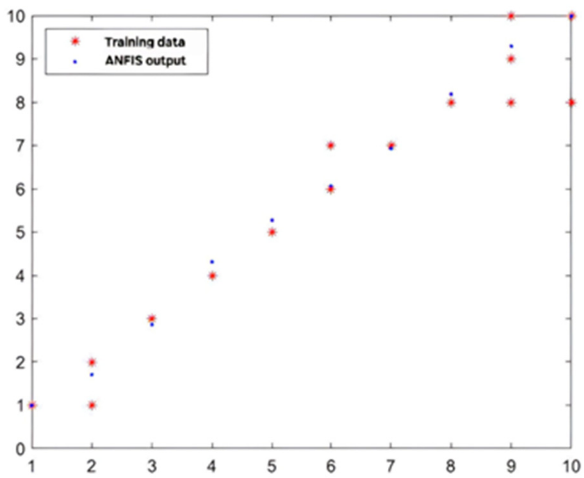

Figure 5. Graphical interpretation of training data—influence of one input.

The analysis of the research results highlights the importance of two factors that in combination contribute to the greatest motivation of students in professional subjects in vocational schools, where their combination gives the smallest RMSE error, where the RMSE values for different data sets are as follows: training data: RMSE = 0.094490, test data: RMSE = 0.082781, all data: RMSE = 0.092799.

The first key factor is employment perspectives, which represent students' perceptions of employment opportunities and career advancement after graduation. Students who recognize that their education directly contributes to their future career opportunities are often more motivated to learn. Another important factor is the working atmosphere in the class, which refers to the atmosphere created by teachers and students during classes. A positive, supportive and inspiring work atmosphere can significantly influence student motivation. The combination of these factors creates a stimulating learning environment, where students feel that their efforts are valued, while at the same time, they have a clear picture of their future career prospects. Integrating these factors into pedagogical strategies and learning practices can be key to achieving the best results in motivating students for vocational subjects in vocational schools.

Table 3 shows the data obtained as the best result for the combination of two factors that together have the greatest influence on the motivation of students in professional courses, as well as the reliability of the model for training, test and all data.

Table 3. The impact of two entrances on the exit for vocational subjects in vocational studies.

Input	The Input with the Least Error
Two Input	Input no. 5 and 11 TRAINING—ERROR SV = −0.000005 SD = 0.094807 MSE = 0.008928 RMSE = 0.094490 TEST—ERROR SV = 0.003170 SD = 0.084296 MSE = 0.006853 RMSE = 0.082781 ALL DATA SV = 0.00047892 SD = 0.093061 MSE = 0.0086117 RMSE = 0.092799
Reliability of the model	Training data: R = 0.99955 Test data: R = 0.99953 All data: R == 0.99955

Figures 6–8 provide an in-depth analysis of error data through the various stages of the process, particularly highlighting the impact of two key factors acting together. This detailed analysis allows us to gain a holistic perspective on how the errors evolve over time, in different scenarios, which is essential for understanding the stability and reliability of the model. The displayed error data during training, testing, and the entire data set allows us to identify patterns and trends, providing valuable insights into student achievement across the model when these combined factors are involved.

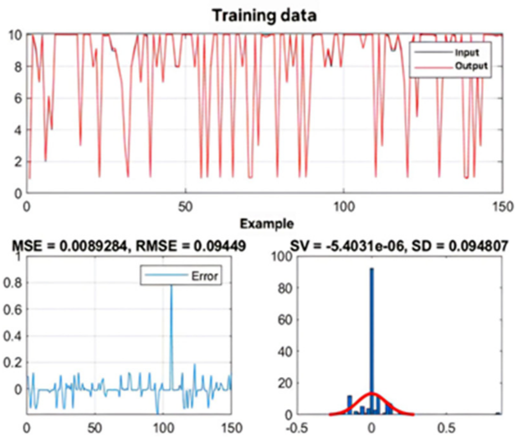

Figure 6. ANFIS network training—influence of two inputs on motivation, inputs number 5 and 11.

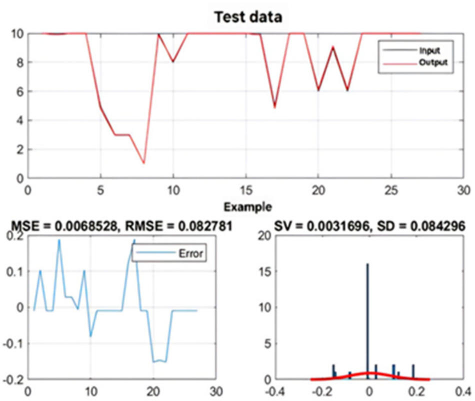

Figure 7. ANFIS network test—the influence of two inputs on motivation, inputs number 5 and 11.

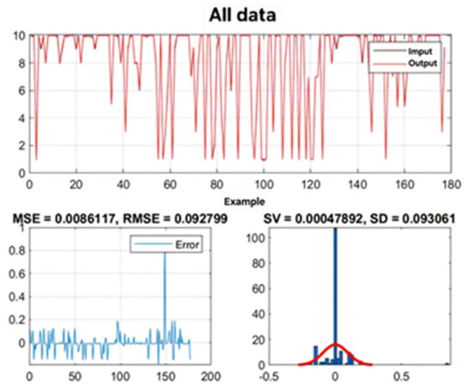

Figure 8. All data of the ANFIS network—the influence of two inputs on motivation, inputs number 5 and 11.

Figure 9 provides a regression analysis and an assessment of model reliability, which is crucial for assessing the accuracy and utility of the predictions obtained using the combined factors. This analysis makes it possible to assess the degree of agreement of the model with real data and the extent to which we can rely on its predictions. For training data, linear correlation coefficient R = 0.99955, test linear correlation coefficient R = 0.99953, while all data for linear correlation coefficient R = 0.99955. Also, Figure 10 offers a visual interpretation of the training data, which is essential for an intuitive understanding of the data distribution and the identification of possible deviations or patterns. Figure 10 shows a 3D graph that visualizes the dependence of student motivation (output) in relation to two inputs, for inputs number 5 and 11, which have the greatest impact on motivation when combined. The inputs were randomly combined in order to identify the two most significant factors influencing student motivation. This methodology makes it possible to extract key factors from a large amount of data, which have the greatest impact on motivation. The colors on the graph represent different levels of motivation; blue indicates the lowest values of motivation, green the middle values, and yellow the highest values of motivation. This chart provides a visual understanding of how combinations of inputs 5 and 11 affect student motivation levels, with changes in color used to quickly identify areas of low, medium and high motivation. These visual representations allow a deeper exploration of the influence of the combined factors on the final results, which contributes to concluding about their significance in the data analysis.

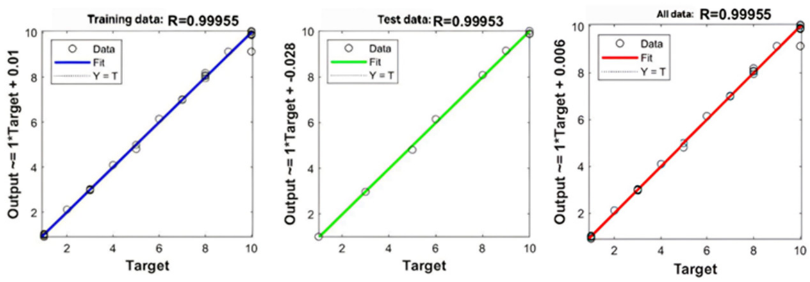

Figure 9. Linear regression of training, test and all data—influence of two inputs.

The analysis of the obtained results on the motivation of students in professional subjects in vocational schools highlights the combination of three key factors that give the smallest RMSE error and the best results in encouraging student motivation, where the RMSE values for different data sets are as follows: training data: RMSE = 0.067414, test data: RMSE = 0.260738, all data: RMSE = 0.11926. The first factor is prior knowledge, that is, the level of existing knowledge and experience that students bring to a specific subject. Students with more prior knowledge usually show more motivation to learn, which makes them more ready to face the challenges of teaching. Another key factor is innovative technologies in teaching that enable interactive learning, and practical application of knowledge and strengthening the creative learning process. Integrating these technologies into the classroom provides a stimulating learning environment and encourages student engagement. The third factor is the working atmosphere in the class, which implies the support of the teacher, openness to discussion, cooperation and teamwork. Creating a positive and supportive atmosphere in the classroom can significantly influence student motivation. The combination of these three factors creates optimal conditions for achieving the highest motivation of students in vocational courses while ensuring quality learning and development of key skills needed for a future career.

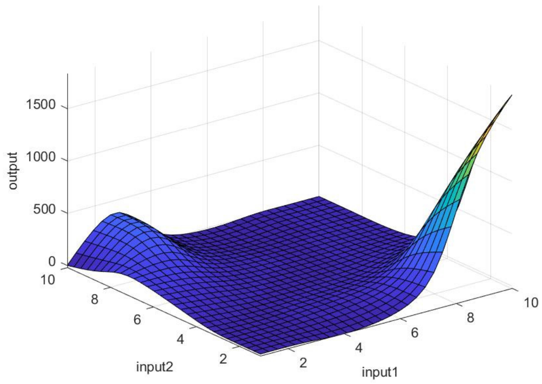

Figure 10. Graphical interpretation of training data—the effect of two inputs.

Table 4 details the results of the application of the ANFIS method, providing information on the mean error, mean deviation, root mean square error, and root mean square error for the training and test data. It is significant to point out that the smallest error was achieved when three factors were combined: inputs 1, 2, and 11, which are related to prior knowledge, innovative technologies, and work atmosphere. This combination of factors gives the best results, which indicates their significant contribution in the analysis and prediction of results.

Table 4. The impact of three inputs on output for vocational subjects in vocational studies.

Input	The Input with the Least Error
Three Input	Input no. 1, 2 and 11 TRAINING—ERROR SV = −0.000002 SD = 0.067640 MSE = 0.004545 RMSE = 0.067414 TEST—ERROR SV = −0.040010 SD = 0.262558 MSE = 0.067984 RMSE = 0.260738 ALL DATA SV = −0.0061053 SD = 0.11944 MSE = 0.014222 RMSE = 0.11926
Reliability of the model	Training data: R = 0.99976 Test data: R = 0.99693 All data: R == 0.99926

Figures 11–13 provide an in-depth analysis of error data through the various stages of the process, particularly highlighting the impact of two key factors acting together. This detailed analysis allows us to gain a holistic perspective on how errors evolve over time and in different scenarios, which is essential for understanding model stability and reliability. The displayed error data during training, testing, and the entire data set allows us to identify patterns and trends of the model when it comes to these combined factors.

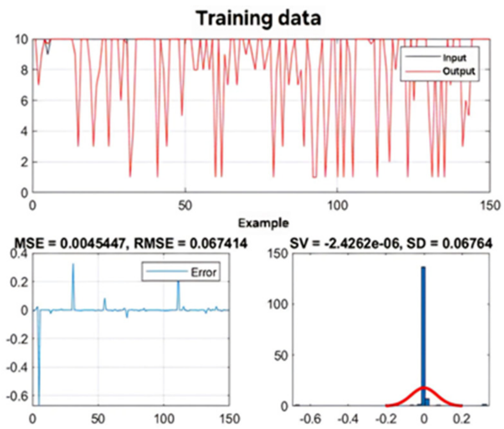

Figure 11. Training of the ANFIS network—the influence of three inputs on motivation, inputs number 1, 2 and 11.

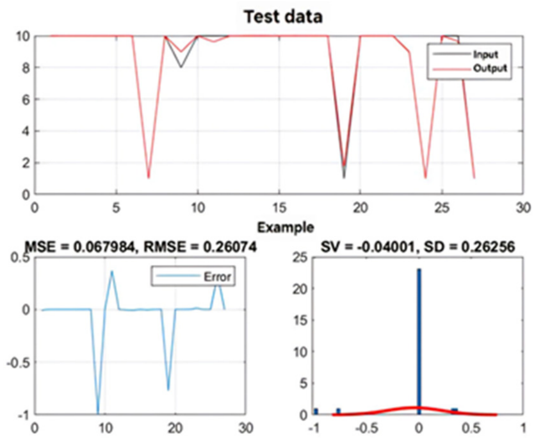

Figure 12. ANFIS network test—the influence of three inputs on motivation, inputs number 1, 2 and 11.

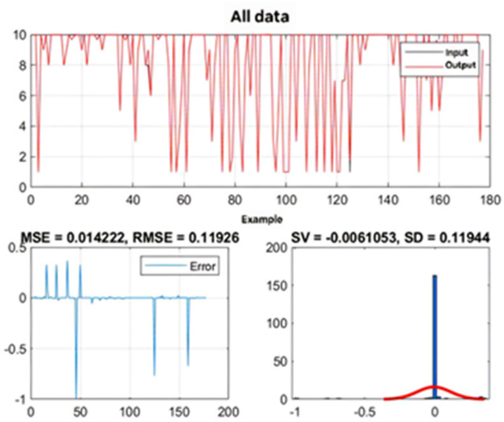

Figure 13. All data of the ANFIS network—the influence of three inputs on motivation, inputs number 1, 3 and 7.

Figure 14 provides an in-depth regression analysis and model reliability assessment, which is key to assessing the accuracy and utility of the predictions obtained by combining the three factors. This analysis allows measuring the degree of conformity of the model with real data and assessing the reliability of the projections provided by the model. For training data, the coefficient of linear correlation is R = 0.99976, the test coefficient of linear correlation is R = 0.99693, while all the data for the coefficient of linear correlation are R = 0.99926. Also, Figure 15 provides a graphical interpretation of training data, which is important for an intuitive understanding of data distribution and identification of possible deviations or patterns. The figure shows how different random combinations of the three input values 1, 2 and 11 affect the output. The colors on the graph represent different levels of output; blue indicates low values, green means medium, and yellow the highest values of output. This visualization enables quick recognition of key areas on the graph, providing insight into the combinations of input values that most significantly affect the output. Each combination of input values is shown individually, which allows detailed analysis of the impact of each of the three most important factors on the output. These visual representations allow for a deeper exploration of the influence of the combined factors on the final results, which helps in concluding about their significance in the data analysis.

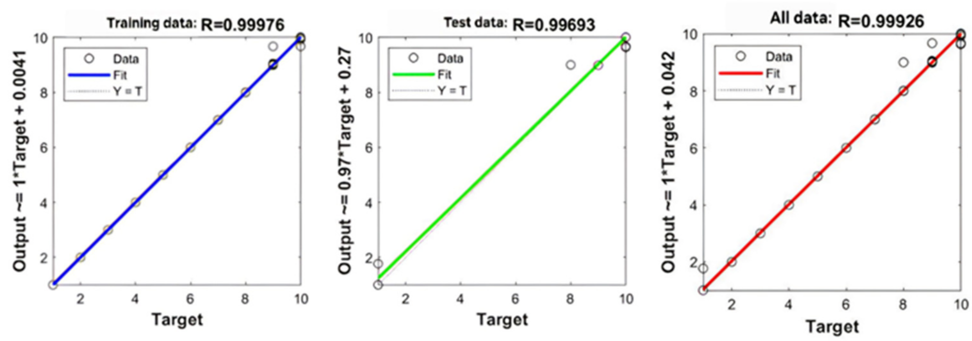

Figure 14. Linear regression of training, test, and all data—influence of three inputs.

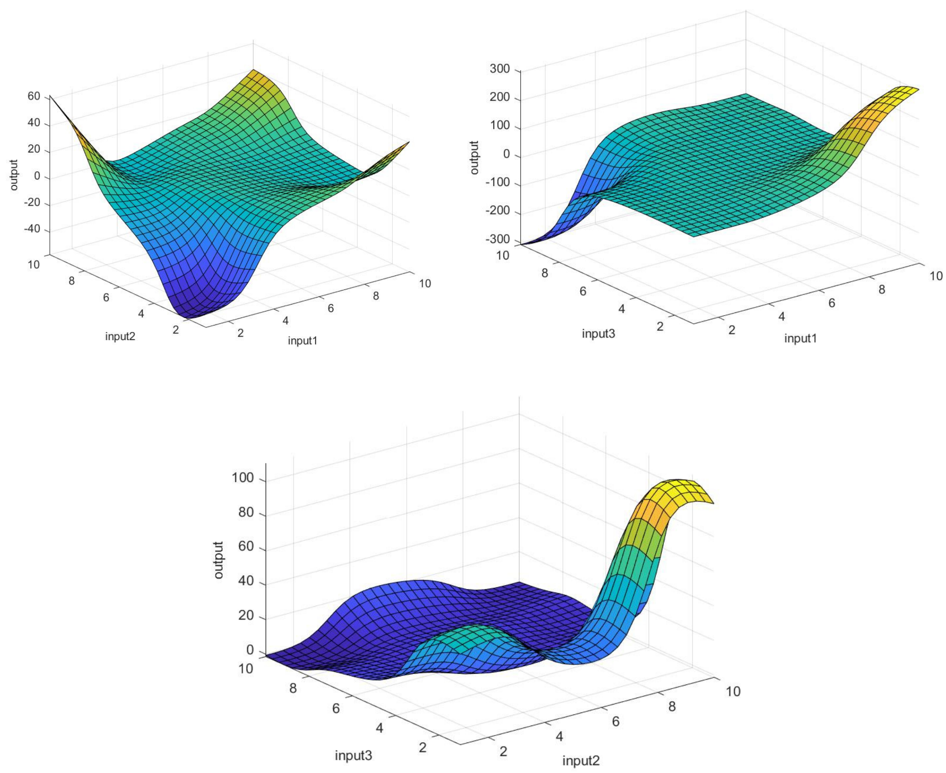

Figure 15. Graphical interpretation of training data—impact of three inputs.

4.2. Analysis of Results for Professional Subjects in Academic Studies

The data analysis highlights the importance of the prior knowledge factor as a key indicator that directly affects the motivation of students in vocational courses in academic schools. The RMSE values for different data sets are as follows: training data: RMSE = 0.243932, test data: RMSE = 0.230879, all data: RMSE = 0.24203. Prior knowledge, that is, the level of knowledge and experience that students bring at the beginning of their studies, shows a strong connection with motivation for learning. Students who already have a certain prior knowledge in the field covered in the study are often more motivated to further research and deepen their knowledge. This prior knowledge enables them to be more confident and confident in dealing with complex concepts and challenges that arise within the study program. Consequently, students who already have some prior knowledge often show greater motivation to engage in lectures, study and actively participate in discussions. Students' prior knowledge allows teachers to adapt teaching material and learning strategies to support and strengthen students' motivation in professional subjects, which further leads to better results and success in studies.

Table 5 shows statistical indicators such as mean error value, mean deviation, mean squared error and root mean squared error for training data, test data and all data together, as well as the reliability coefficient of the model for the input that has the greatest influence on the output size.

Table 5. The impact of one entry on the exit for professional subjects in academic studies.

Input	The Input with the Least Error
One Input	Input no. 1 TRAINING—ERROR SV = 0.000000 SD = 0.245199 MSE = 0.059503 RMSE = 0.243932 TEST—ERROR SV = −0.012634 SD = 0.237629 MSE = 0.053305 RMSE = 0.230879 ALL DATA SV = −0.0018839 SD = 0.24309 MSE = 0.058579 RMSE = 0.24203
Reliability of the model	Training data: R = 0.99632 Test data: R = 0.96785 All data: R == 0.99591

Input 1 shows the lowest value for RMSE, which means that prior knowledge has the greatest impact on the output size, that is, on the motivation of students in professional subjects in academic studies.

Figures 16–18 show all the results of errors during the process of training, testing and analysis of combined data, obtained by applying the ANFIS methodology in the Matlab software package, version 2018. Figure 19 shows the regression analysis and reliability of the model. For training data, linear correlation coefficient R = 0.99632, test linear correlation coefficient R = 0.96785, while all data for linear correlation coefficient R = 0.99591.

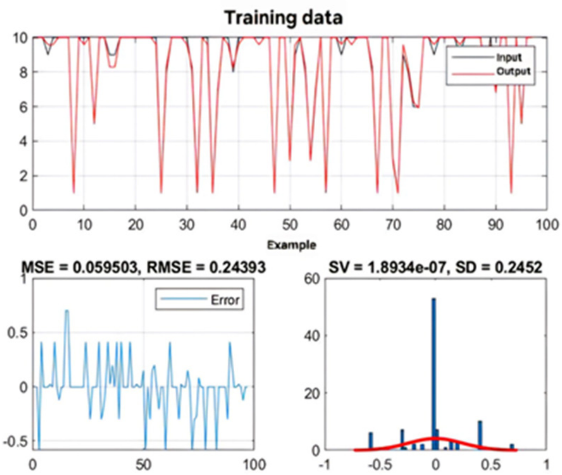

Figure 16. ANFIS network training—influence of one input on motivation, input number 1.

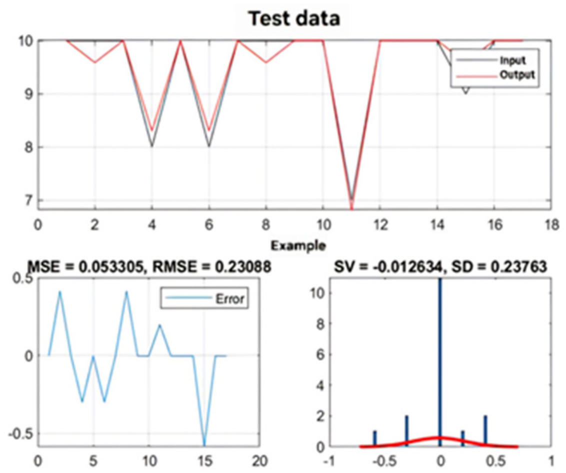

Figure 17. ANFIS network test—influence of one input on motivation, input number 1.

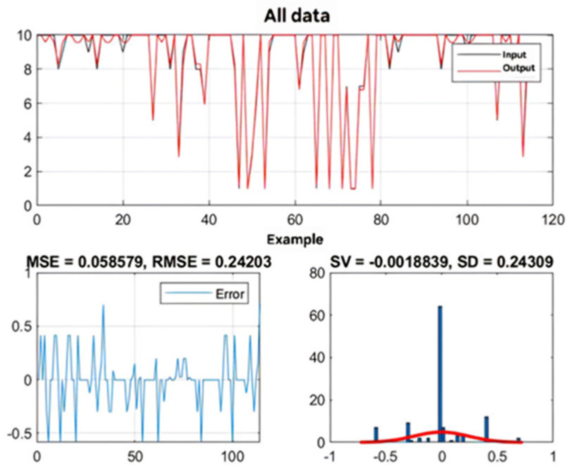

Figure 18. All data of the ANFIS network—the influence of one input on motivation, input number 1.

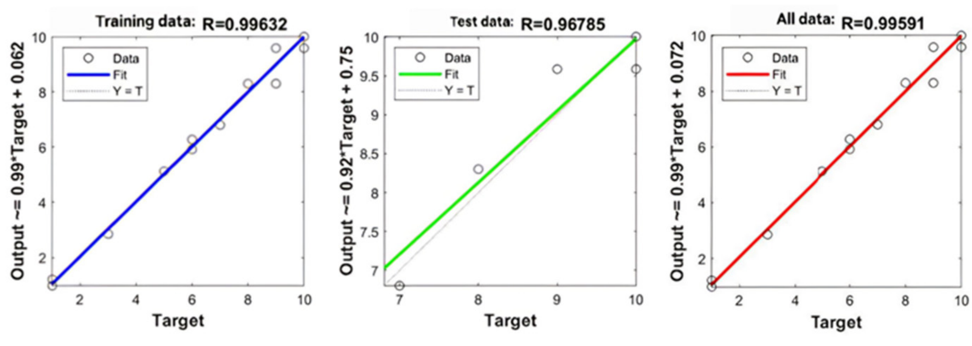

Figure 19. Linear regression of training, test and all data—influence of one input.

In Figure 20 there is a graphical approximation of the input data with the output ANFIS function. All results shown are centered on input 1, which has the greatest impact on the output size. The red stars indicate the data used for training, while the blue dots represent the output values generated by the ANFIS model. The graph shows that the ANFIS outputs (blue dots) track the data from the training set (red stars) very accurately. This indicates successful training of the model, which can accurately predict the output values. Visual interpretation allows us to identify patterns or irregularities in the data, which can help further improve the model or better understand the data.

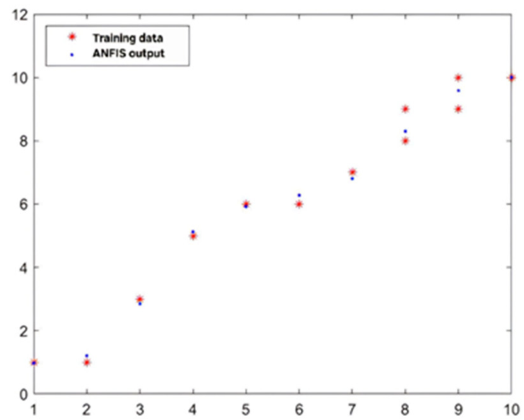

Figure 20. Graphical interpretation of training data—influence of one input.

The analysis of the results shown below highlights the combination of two key factors that have the lowest RMSE value and give the best results, and the highest motivation of students in vocational courses at faculties is achieved. The RMSE values for different data sets are as follows: training data: RMSE = 0.162314, test data: RMSE = 0.224256, all data: RMSE = 0.17296. The first factor is prior knowledge, which indicates the level of prior knowledge and experience that students bring with them at the beginning of their studies. Students who come with a solid prior knowledge in the field of study are often characterized by greater motivation to learn. This prior knowledge gives them confidence and a sense of competence when facing the challenges of subject content, which further motivates them to engage in learning. Another key factor is employment perspectives, that is, students' perception of how the acquired knowledge and skills will contribute to their opportunities for employment and career development. When students recognize that the material they study in the study program has direct application in the labor market and will enable them to achieve their professional goals, it further motivates them to devote themselves to learning and achieve outstanding results. The combination of these factors creates a stimulating learning environment, encouraging students to focus on their goals and develop skills critical to success in their future careers.

Table 6 shows the values for training, test and all data for inputs 1 and 5, which in combination give the greatest impact on the output size, as well as the reliability of the model.

Table 6. The impact of two inputs on output for professional subjects in academic studies.

Input	The Input with the Least Error
Two Input	Input no. 1 and 5 TRAINING—ERROR SV = 0.000000 SD = 0.163158 MSE = 0.026346 RMSE = 0.162314 TEST—ERROR SV = 0.016343 SD = 0.230543 MSE = 0.050291 RMSE = 0.224256 ALL DATA SV = 0.0024371 SD = 0.17371 MSE = 0.029917 RMSE = 0.17296
Reliability of the model	Training data: R = 0.9981 Test data: R = 0.99705 All data: R == 0.99791

Figures 21–23 show a graphical interpretation of the results for training, test and all data for the two combined factors that give the best result, i.e., the lowest RMSE value.

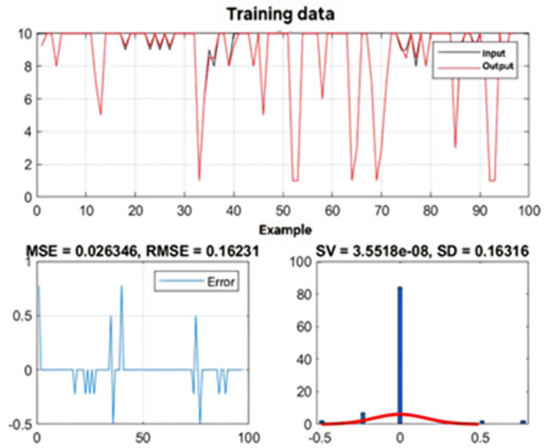

Figure 21. Training of the ANFIS network—the influence of two inputs on motivation, inputs number 1 and 5.

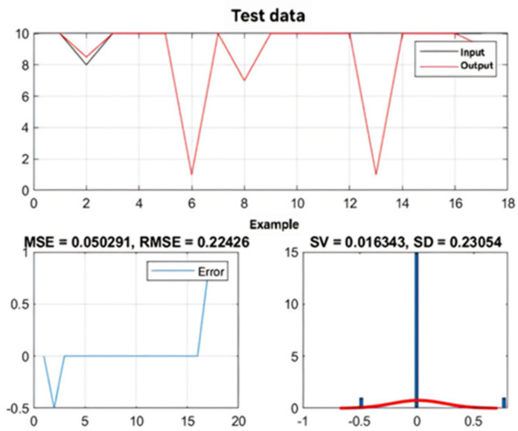

Figure 22. ANFIS network test—the influence of two inputs on motivation, inputs number 1 and 5.

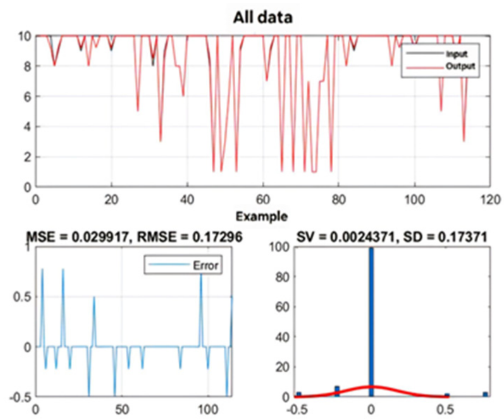

Figure 23. All data of the ANFIS network—the influence of two inputs on motivation, inputs number 1 and 5.

Figure 24 shows the regression analysis and reliability of the model. For training data, linear correlation coefficient R = 0.9981, test linear correlation coefficient R = 0.99705, while all data for linear correlation coefficient R = 0.99791. In Figure 25 there is a graphical approximation of the input data with the output ANFIS function. All these results are centered on inputs 1 and 5, which have the greatest impact on the output size. Figure 25 shows a 3D graph showing how combinations of two key inputs affect student motivation. The inputs are randomly combined to reveal the most important motivational factors.

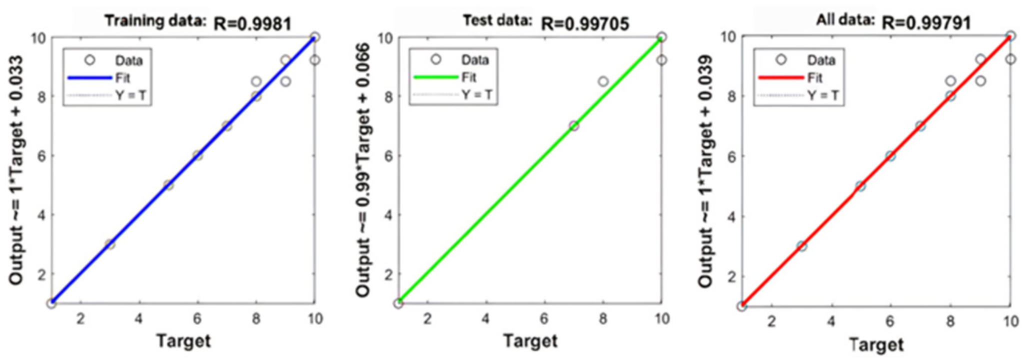

Figure 24. Linear regression of training, test and all data—influence of two inputs.

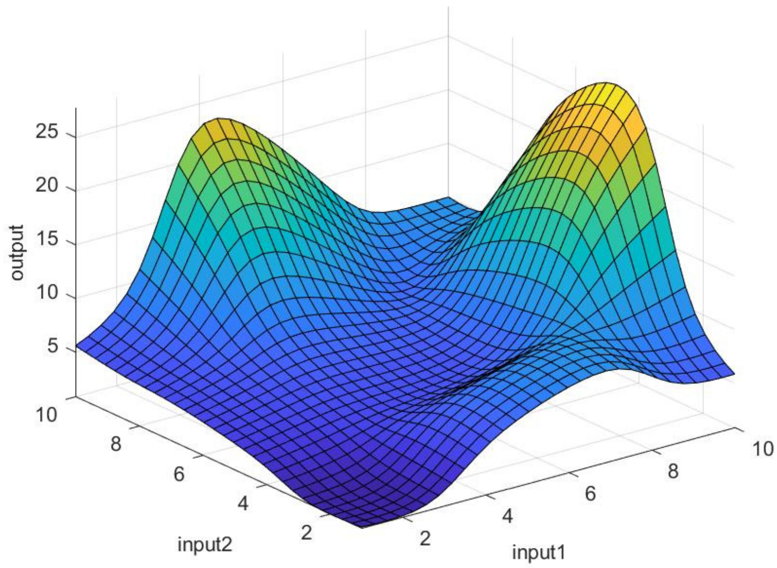

Figure 25. Graphical interpretation of training data—the effect of two inputs.

The analysis of the results highlights the combination of three key factors that provide the best results in the smallest RMSE error and achieve the highest motivation of academic students in vocational courses. The RMSE values for different data sets are as follows: training data: RMSE = 0.000010, test data: RMSE = 0.337550, all data: RMSE = 0.13035. The first factor is prior knowledge, which represents the level of prior knowledge and experience students bring at the beginning of their studies. Students with solid prior knowledge in the field covered in their studies often show greater motivation to study, because they feel more confident and competent in mastering the material. Another key factor is employment prospects, where students consider how the acquired knowledge and skills will contribute to their chances of employment and career progression. When students recognize the connection between their academic achievements and future professional opportunities, it further motivates them to engage and achieve success in their studies. The third factor is the working atmosphere of the class, which includes teacher support, interactive discussions, collaboration among students, and an inspiring learning environment. A quality working atmosphere creates a positive learning experience and encourages students to be engaged and motivated during classes. The combination of these factors creates optimal conditions for achieving high motivation of students in vocational courses, thus ensuring their success and future professional development.

After presenting the two combined factors, the influence of the combination of three input variables on the output size was examined. Inputs 1, 5 and 11 showed the lowest value for RMSE, implying that their combined presence has the most significant impact on the output. Specifically, prior knowledge from high school, employment prospects, and the working atmosphere of the class combined have the greatest influence on motivation. Table 7 shows the errors during training, testing and analysis of all data for these three most influential input variables on the output, as well as the reliability coefficient of the model.

Table 7. The impact of three inputs on output for professional subjects in academic studies.

Input	The Input with the Least Error
Three Input	Input no. 1, 5 and 11 TRAINING—ERROR SV = −0.000000 SD = 0.000010 MSE = 0.000000 RMSE = 0.000010 TEST—ERROR SV = 0.081869 SD = 0.337550 MSE = 0.113940 RMSE = 0.337550 ALL DATA SV = 0.012209 SD = 0.13035 MSE = 0.016991 RMSE = 0.13035
Reliability of the model	Training data: R = 1 Test data: R = 0.99524 All data: R == 0.99889

Figures 26–28 provide a detailed insight into all the errors that occurred during the different stages of data processing—training, testing and analysis of all data. In Figure 29, we focus on the reliability of the model resulting from the three most influential input variables on the output size, for all stages of the process. For training data, linear correlation coefficient R = 1, test linear correlation coefficient R = 0.99524, while all data for linear correlation coefficient R = 0.99889. Figure 30 shows a graphical interpretation of the approximation of the training data resulting from the influence of the three most significant input variables on the output of the ANFIS model. The graph shows how different random combinations of inputs, input 1, 5 and 11, affect the output, motivation. This visualization enables quick identification of key areas and insight into which input combinations have the most significant impact on output. Each combination of input values is presented separately, which facilitates the analysis of the effects of each of the three key factors on the final result, i.e., student motivation.

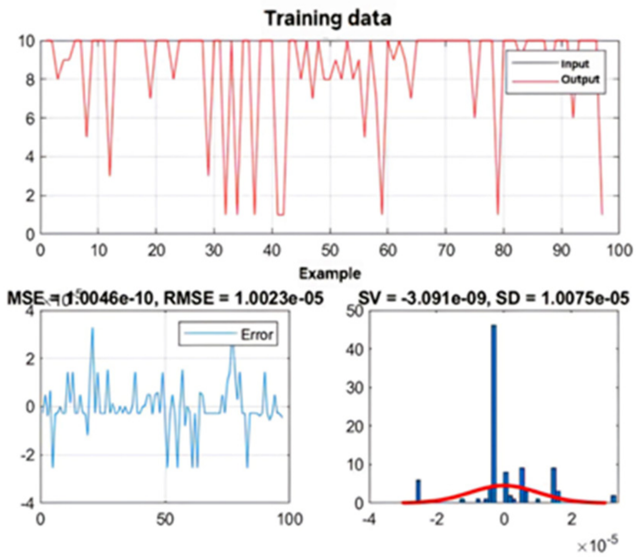

Figure 26. Training of ANFIS network—influence of three inputs on motivation, inputs number 1,5 and 11.

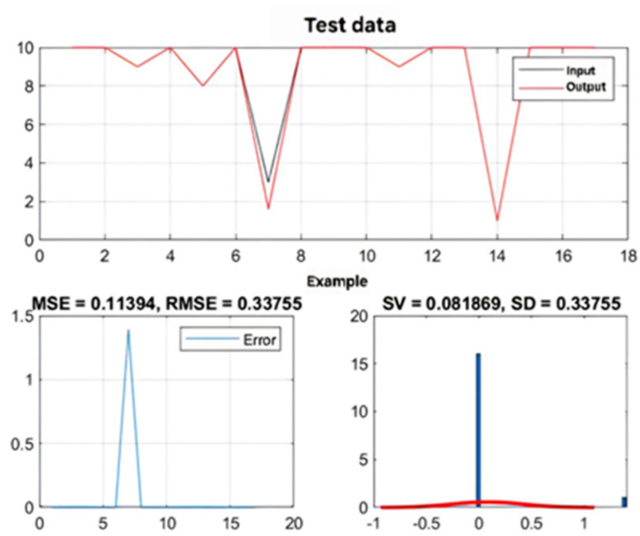

Figure 27. ANFIS network test—the influence of three inputs on motivation, inputs number 1,5 and 11.

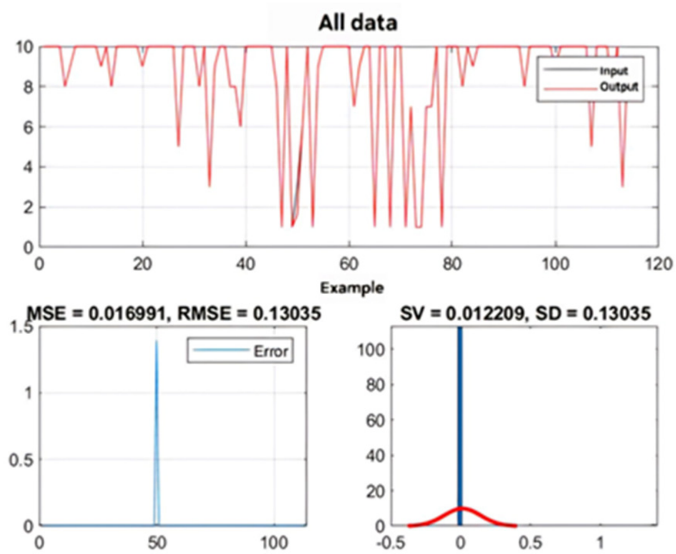

Figure 28. All data of ANFIS network—influence of three inputs on motivation, inputs number 1,5 and 11.

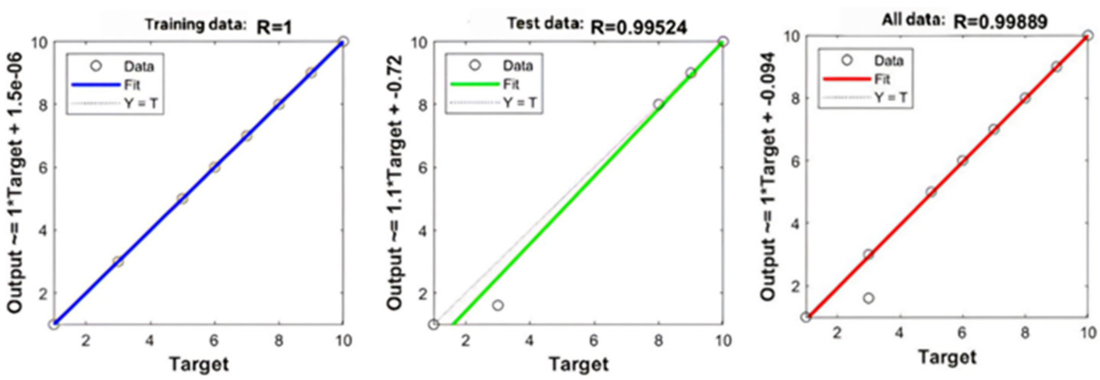

Figure 29. Linear regression of training, test, and all data—influence of three inputs.

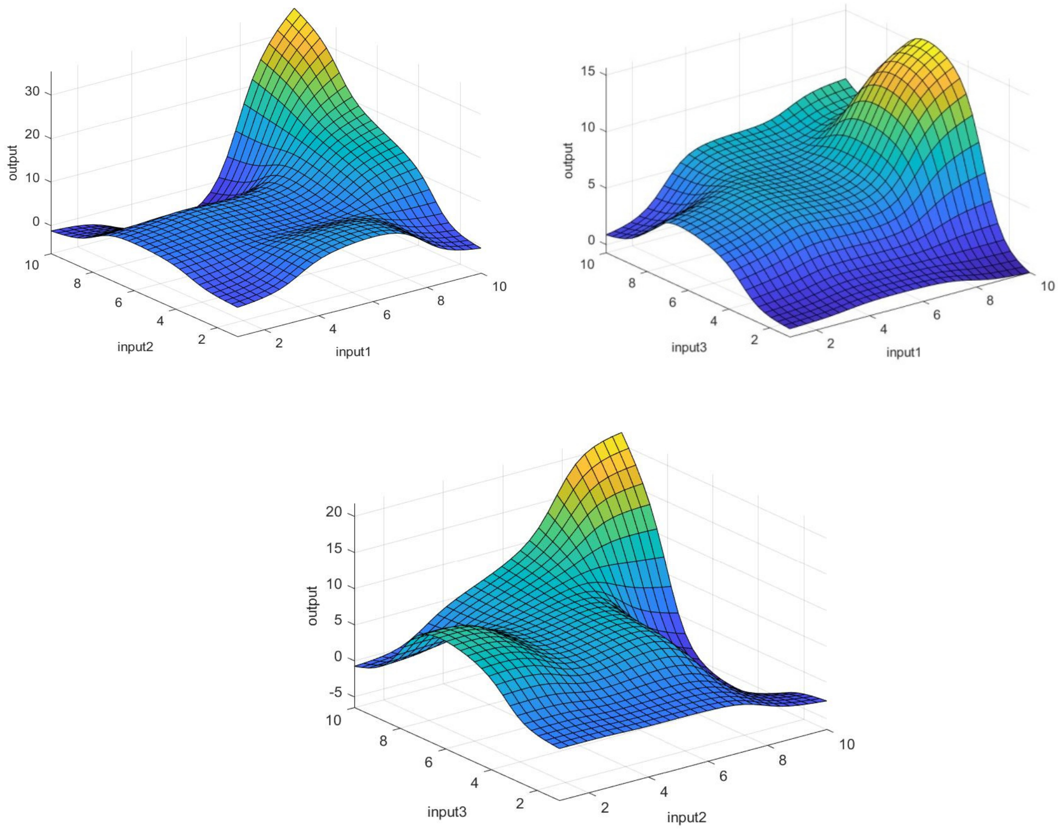

Figure 30. Graphical interpretation of training data—impact of three inputs.

5. Comparative Analysis

The analysis of the motivation of students of professional and academic studies in the field of professional subjects provides insight into their different approaches to learning and professional expectations. Vocational school students most often show a higher level of motivation in professional subjects that are closely related to the practical application of knowledge and future occupation. For example, students from majors such as road traffic or computer science excel in subjects such as transport, engines and motor vehicles, parking, programming and databases, because in these areas they clearly recognize the connection between what they learn and what they will do in practice.

In contrast, students of academic studies also achieve high results in professional subjects, but their motivation often stems from an interest in theoretical processing of content, research work and a deeper understanding of the field, and not necessarily from immediate practical application. Their commitment is often part of a broader academic strategy that includes an analytical approach to learning and the pursuit of high educational achievement.

By comparing these groups, it is possible to see different sources of motivation which, although they lead to success in professional subjects, stem from different educational goals and expectations. These insights can help tailor teaching methods and materials to the needs of a specific group of students, thereby encouraging even better performance and professional development.

By analyzing the achievements of both types of students, several key educational trends can be identified:

- Students in professional studies show greater engagement and success in subjects that are directly related to their future profession, emphasizing the importance of practical application of knowledge, which can be described as their practical orientation.

- Students in academic studies show consistently good results in a wide range of subjects, which reflects their ability to adapt to different educational requirements and achieve the high academic standards they set for themselves, emphasizing their theoretical and research orientation.
- Motivation stands out as a key factor in the achievements of students in vocational studies because they are motivated by concrete professional outcomes, while students in academic studies strive for long-term goals and are guided by an interest in theoretical knowledge and research.

Based on this analysis, Table 8, several recommendations can be made for the improvement of educational programs. It is recommended to increase the focus on practical aspects of professional studies to further motivate students through concrete professional outcomes. For students in academic studies, it would be useful to improve support for theoretical research and provide access to resources that will encourage them to engage more deeply in topics of their interest. The integration of modern technologies and innovative teaching methods can contribute to improving educational experiences for all students, while a more flexible approach to evaluation can be adapted to different learning styles and student goals.

Table 8. Comparative results.

	Academic Studies	**Vocational Studies**
The influence of one factor	Input no. 1	Input no. 5
Root mean square error RMSE	RMSE = 0.243932 RMSE = 0.230879 RMSE = 0.24203	RMSE = 0.307478 RMSE = 0.359521 RMSE = 0.31597
The influence of two factors	Input no. 1 and 5	Input no. 5 and 11
Root mean square error RMSE	RMSE = 0.162314 RMSE = 0.224256 RMSE = 0.17296	RMSE = 0.094490 RMSE = 0.082781 RMSE = 0.092799
The influence of three factors	Input no. 1, 5 and 11	Input no. 1, 2 and 11
Root mean square error RMSE	RMSE = 0.000010 RMSE = 0.337550 RMSE = 0.13035	RMSE = 0.067414 RMSE = 0.260738 RMSE = 0.11926

A comparative analysis of the factors that influence the motivation of students attending vocational and academic studies indicates significant differences in the factors that most influence the motivation of students in these two educational groups. Based on the results of the research, it can be concluded that the lowest value for RMSE for academic studies is input factor 1, while for vocational studies it is input 5. The results show that among vocational students, the attitude towards the subject has the greatest influence on motivation, while for academic students, prior knowledge is the key motivation factor. This is also a logical conclusion, because students who have achieved better success and greater prior knowledge in secondary schools generally opt for academic studies.

Among vocational students, the attitude towards the subject proved to be the most important motivational factor. This implies that the way students perceive the importance, relevance and usefulness of the subject directly affects their motivation to learn. This finding is significant because it suggests that vocational students value subjects that have a clear and immediate application in their future professional life more highly. If students believe that a particular subject will provide them with practical skills that are necessary for their career development, their motivation to study that subject will be significantly higher.

Understanding how various motivational factors affect vocational and academic students is critical to creating effective educational programs. In professional studies, prior knowledge, innovative technologies, and the working atmosphere in lectures and exercises are key for motivation, while in academic studies, prior knowledge, personal development and employment perspectives, and the working atmosphere are key factors. Educational institutions need to use these insights to adjust their curricula and teaching strategies to maximize student motivation, improve engagement, and achieve academic goals.

We applied fuzzy logic in soft computing for the detection of motivation factors with the aim of improving student achievement, through a comparative analysis between students of professional and academic studies in professional subjects. Through theoretical research, methodological approach and analysis of results, the research provided a deeper insight into the motivational dynamics of students and their impact on academic results.

Analyzing traditional theories of motivation and specific theories relevant to education, the research identified a wide range of factors that influence student motivation, including prior knowledge, innovative technologies, attitude towards the subject, priority goals, personal development, financial support, comprehensibility of the subject, applicability of the subject, quality of teaching, teacher's commitment, working atmosphere in the class and objectivity of assessment. Through the integration of fuzzy logic into the research methodology, significant results were achieved in the analysis of these factors and the identification of key links with academic success.

Based on the goals and objectives of the research, through the application of the ANFIS (Adaptive Neuro-Fuzzy Inference System) method, the set hypotheses were proven. By using the ANFIS method for analyzing large data sets, the factors that influence the motivation of students at university and college are predicted.

The results of the research showed that soft computing, through the analysis of large data sets, can identify complex patterns of student behavior and predict the factors that most influence their motivation and achievements. In particular, it was determined that the working atmosphere in the class, both for professional subjects and for general education, greatly affects the motivation of students. A positive, supportive and interactive atmosphere contributes to greater engagement and better achievements. The prospect of employment has also been shown to be a significant motivational factor, with students who perceive greater employment opportunities in their field of study showing greater motivation and better achievement. In addition, students with more prior knowledge in the subject area achieve better results and show greater motivation to learn compared to students with less or no prior knowledge. Similarly, students who have more prior knowledge of a particular general education subject express a more positive attitude towards that subject, which positively affects their motivation for learning and achievements in that subject.

These results indicate the importance of applying the ANFIS method in educational research for the identification and prediction of motivation factors. This research provides valuable insights that can contribute to the improvement of educational processes and student achievement, and represents a significant step towards more effective use of artificial intelligence in education.

One of the key contributions of the research is the identification of specific motivational factors that differ between vocational and academic students in professional and general education subjects. It has been shown that vocational students often show greater motivation for practical skills and application of knowledge, while academic students tend towards research work and theoretical understanding. These results have important implications for developing personalized support strategies and improving educational practice in both types of studies.

The integration of soft computing into the analysis of motivational factors has proven to be an effective approach for identifying hidden patterns in data and personalizing interventions. Through the application of algorithms for data analysis, such as neural networks, fuzzy logic and genetic algorithms, significant results have been achieved in predicting academic performance and identifying personalized support strategies for each student.

6. Conclusions and Future Research

This paper provides a deeper insight into the differences in the motivation of students of professional and academic studies when studying professional subjects, using soft computing methods to analyze the collected data. Specific factors influencing motivation were identified depending on the type of study, whereby students of vocational schools showed higher motivation for subjects with clear practical application, while students of academic studies showed stable motivation based on theoretical interest and research approach. Based on these findings, personalized strategies were proposed for improving the motivation and success of students in professional disciplines.

Research results can contribute to a better understanding of educational needs and the development of more effective teaching methods in higher education. Future research should be extended to a larger number of higher education institutions in order to enable wider application of the obtained results and validation of the proposed strategies in different educational contexts. It would be especially useful to conduct longitudinal research, in order to monitor changes in motivation during the entire educational process.

The research results showed that soft computing, through the analysis of large datasets, can identify complex patterns in student behavior and predict the factors that most significantly influence their motivation and achievement. Specifically, it was found that the classroom atmosphere greatly affects student motivation. A positive, supportive, and interactive environment contributes to increased engagement and improved academic performance. Employment prospects also proved to be an important motivational factor—students who perceive greater job opportunities in the field they are studying demonstrate higher motivation and better achievement. Furthermore, students with more prior knowledge in professional subjects tend to achieve better results and show greater motivation to learn compared to those with little or no prior knowledge.

The improvement of the methodology can be achieved by combining the ANFIS model with advanced artificial intelligence techniques, such as deep learning and big data analytics, which would further improve the accuracy of recognizing motivational patterns. Also, testing personalized support approaches in practice could contribute to the construction of more flexible and effective educational strategies, which are aligned with the specifics of students of different educational profiles.

Based on the obtained results, it is possible to propose specific measures for improving the learning environment and integrating technology into the teaching process in accordance with students' profiles. By identifying motivational factors that influence engagement and achievement, teachers can adapt their instructional approach—for example, by creating a stimulating, interactive, and supportive classroom atmosphere that aligns with different learning styles. Additionally, the introduction of tailored digital tools and platforms, matched to students' prior knowledge and interests, can further enhance motivation and teaching effectiveness. In this way, the research findings serve as a foundation for differentiated planning of the educational process, aiming to improve the overall quality of education.

Author Contributions: Conceptualization, M.M. and S.P.; Methodology, M.M., S.P., G.P. and D.K.; Software, M.S.; Formal analysis, M.S.; Investigation, G.P.; Writing—original draft, M.M., S.P. and G.P.;

Writing—review & editing, M.S. and D.K.; Supervision, D.K.; Project administration, D.K. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest: The authors declare no conflicts of interest.

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