IMPLEMENTATION OF THE KNN ALGORITHM FOR THE ANALYSIS OF STUDENT PREFERENCES TOWARDS INNOVATIVE TECHNOLOGIES IN EDUCATION

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Abstract: This paper deals with the implementation of the K-Nearest Neighbors (KNN) algorithm for the analysis of student preferences towards innovative technologies in education. Considering the rapid development of digital technologies and their impact on the educational system, the tendency of students to apply innovative methods in learning was investigated. The survey collected data on student attitudes and experiences regarding the use of digital tools and technologies in the learning process. The KNN algorithm was applied to classify students according to their preferences and recognize patterns that indicate groupings of students with similar attitudes. The aim of this research is to provide insight into how students accept new technologies in education and to identify key factors that influence their motivation and success in learning. The results can contribute to a better understanding of students' needs and help in the development of strategies for the effective integration of innovative technologies in teaching.

Key words: K-Nearest Neighbors, Classification, Student preferences, Innovative technologies, Education

1. INTRODUCTION

The development of digital technologies has transformed many aspects of society, including education [1]. The modern educational process is increasingly dependent on innovative technologies, such as virtual classrooms, adaptive learning, artificial intelligence and various digital tools [2]. These technologies not only enable easier access to knowledge, but also improve the interactivity and personalization of teaching methods. Nevertheless, the acceptance of innovative technologies in education largely depends on user preferences and attitudes towards the application of such tools [3].

Understanding those preferences is key to successfully integrating new technologies into the education system. Traditional approaches often ignore individual differences among users, while the use of machine learning algorithms, such as KNN, allows for more detailed analysis and discovery of patterns of behavior and attitudes. The KNN algorithm, known for its simplicity and efficiency, is ideal for data classification and recognition of groups of users with similar characteristics [4].

In this research, the focus is on the analysis of students' preferences towards innovative technologies in education using the KNN algorithm. The survey collected data on the attitudes, experiences and motivation of users regarding the use of digital tools in the learning process. The aim of the work is to provide insight into the factors that influence the acceptance of new technologies and contribute to the development of strategies for their effective application in teaching.

Based on the obtained results, the research aims not only to identify key patterns and groups of users, but also to offer concrete recommendations to educational institutions for the improvement of teaching processes.

2. RESEARCH METHODOLOGY

The modern education system increasingly relies on innovative technologies, which bring significant changes in the learning and teaching process [5]. Technologies such as virtual reality (VR), augmented reality (AR) and digital platforms enable personalization of content, greater interactivity and availability of educational materials [6]. However, their implementation faces challenges such as lack of digital literacy, inadequate technical infrastructure and resistance to change. Despite these challenges, innovative technologies offer the potential to improve students' motivation and performance in the educational process [7].

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Machine learning provides powerful tools for the analysis of educational data [8], including methods such as regression, clustering, and classification algorithms [9]. The K-Nearest Neighbors (KNN) algorithm, known for its simplicity, is used for data clustering and pattern identification [10]. Its application in education enables user classification according to preferences, performance prediction and personalization of teaching content. However, KNN is sensitive to noise in the data and requires careful preprocessing for optimal results.

Previous research has shown that the KNN algorithm achieves high accuracy in the classification of educational preferences, especially when the data is clearly structured [11]. For example, in the analysis of learning styles, KNN enabled the identification of key groups of users with similar preferences [12]. These results confirm the potential of the algorithm for improving educational strategies, but also indicate the need for parameter optimization and a more detailed analysis of the key factors that influence the results.

3. RESULTS AND DISCUSSION

3.1. Description of variables

The data for the analysis was collected through a survey that was used to investigate students' preferences for innovative educational technologies. The survey questions were formulated according to the Likert scale, which allows the respondents' attitudes to be quantified on a scale from 1 to 10, where 1 means "disagree" and 10 means "completely agree". This scale enabled a detailed measurement of students' perceptions regarding various aspects of educational technologies.

In total, 177 respondents filled out the survey, which enabled the collection of a significant amount of data for analysis. The survey explored three key variables that influence students' preferences for innovative technologies: interactivity, personalization and resources. Each of these variables was evaluated by respondents based on their experiences and attitudes towards the educational technologies they use or find useful.

Preferences towards innovative technologies depend on various factors, some of which are selected as input variables and shown in Table 1.

Table 1 – Influential variables on the application of innovative technologies

Parameters	Range
Resources	0 – 10
Personalization	0 – 10
Interactivity	0 – 10
Preferences	0 - 1

The three key variables that significantly influence students' preferences for innovative educational technologies are:

- Interactivity - Interactivity refers to the level of engagement that technologies enable students to have while learning. Technologies with a high degree of interactivity, such as simulations, dynamic activities and real-time feedback, often increase students' interest and motivation, making the learning process more effective. Students who prefer these technologies usually seek opportunities for active participation and direct interaction with the content, which contributes to better understanding and application of the material.
- Personalization - Personalization refers to the ability of educational technologies to adapt to the needs, interests and pace of the learner. Personalized platforms allow students to choose learning paths, adjust the speed of progress and select content relevant to their individual goals. Such technologies often lead to greater user satisfaction, as they allow students to learn in a way that best suits their specific needs.
- Resources – Resources include all materials and tools available within educational technologies, such as video lessons, interactive tutorials, quizzes, e-books and other forms of

learning support. The quality and availability of these resources often influence students' preference for certain technologies. Students who prefer technologies that offer a wealth of educational resources are likely to opt for platforms that provide them with a wide range of learning materials, allowing them to explore different aspects of the material.

3.2. Discussion

The graphic visualization shows the 3D distribution of the data used in the KNN model for the classification of student preferences, where three input features are represented: resources, personalization and interactivity. The colors on the graph play a key role in indicating the different classes: the training data are shown using circles in the color corresponding to the actual classes (y_train), while the test predictions are shown as triangles in the color indicating the predicted classes (y_pred). This 3D chart allows a visual analysis of the relationship between the three key features and how they affect the preference classification. The different colors on the test and training data help to spot the differences between the actual and predicted values, providing a clear idea of the model's accuracy in recognizing patterns in the data, Figure 1.

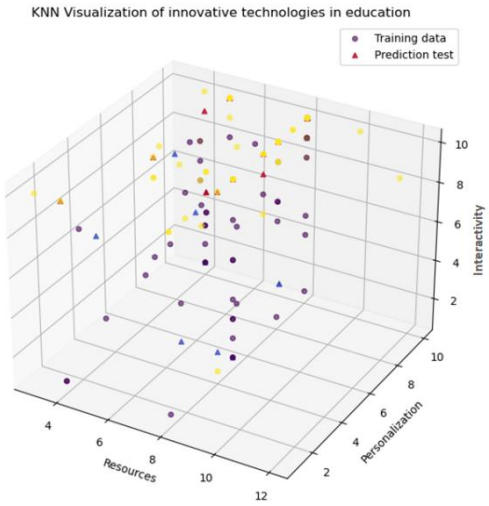

Figure 1 –3D visualization of the KNN model for the classification of preferences in educational technologies

Based on the obtained results, shown in Figure 2, the model achieved a high accuracy of 94.4%, which means that it successfully classified students' preferences towards innovative technologies in 94.4% of cases. The precision for class 0 was 0.90, indicating that the model correctly predicted class 0 in 90% of the cases, while for class 1 the precision was 0.96, indicating exceptional accuracy for this class.

Similarly, the recall for both classes was 0.90 for class 0 and 0.96 for class 1, which means that the model successfully identified 90% and 96% of the real examples for each class, respectively. The F1-score, which represents the balance between precision and responsiveness, was 0.90 for class 0 and 0.96 for class 1, which confirms a good balance. Macro and weighted average values for precision, recall and F1-score were 0.93 and 0.94, which indicates a good performance of the model in the overall classification.

These results suggest that the model well recognizes student preferences in the context of interactivity, personalization and resources in education, and can be used for further analysis and optimization of educational methods.

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Classification report:
              precision    recall  f1-score

           0       0.90      0.90      0.90
           1       0.96      0.96      0.96

    accuracy                           0.94
   macro avg       0.93      0.93      0.93
weighted avg       0.94      0.94      0.94

Model accuracy: 0.9444444444444444
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Figure 2 – Model reliability

A heatmap of the correlation between factors such as resources, personalization, interactivity and student preferences provides a visual representation of the strength and direction of the relationship between these variables, Figure 3. Correlation values displayed within map cells indicate mutual relationships between factors, with high values (close to + 1 or -1) indicate strong positive or negative correlations, while values close to 0 indicate weak or no association. This approach makes it possible to identify factors that have a significant impact on student preferences towards innovative technologies in education. For example, a high correlation between personalization and preferences may indicate that students who favor personalized approaches to learning are more likely to choose technologies that allow for easier customization. By analyzing these correlations, researchers can gain a deeper understanding of how different factors influence students' attitudes toward digital tools and technologies, which can contribute to the development of more effective educational strategies and approaches to implementing innovations in the educational system.

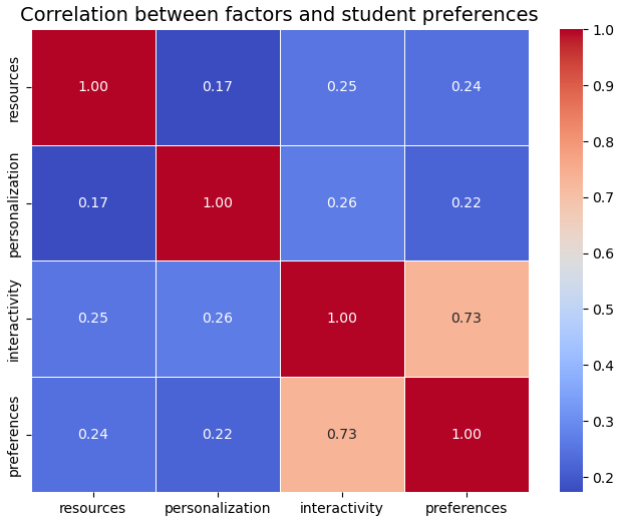

Figure 3 – Correlation between factors and student preferences

4. CONCLUSION

In this research, the K-Nearest Neighbors (KNN) algorithm was implemented for the analysis of student preferences towards innovative technologies in education. The results of the research showed that students show different preferences towards the application of digital tools and technologies in the learning process, where the key factors are interactivity, personalization and resources. Through the application of the KNN model, patterns were identified that enable the classification of students according to their preferences and needs.

This work enabled a better understanding of the impact of innovative technologies on student motivation, as well as on their success in learning. Using data collected through surveys, the research indicated that students who have a greater degree of interactivity, personalization and access to

resources show a greater interest in using digital technologies. These findings may be of importance to teachers and educational institutions, as they provide insight into what factors should be taken into account when implementing new technologies in the teaching process.

Further steps include the application of other machine learning models and the expansion of research to gain deeper insight into various aspects of student preferences, and the results of this research can contribute to the improvement of educational practices through better adaptation of technologies to the needs of students.

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