ANALYSIS AND EVALUATION OF SATISFACTION AND PREFERENCES REGARDING THE USE OF ARTIFICIAL INTELLIGENCE IN EDUCATION

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Abstract: This study presents a study aimed at analyzing and evaluating the satisfaction and preferences of students and teachers regarding the use of artificial intelligence (AI) in the educational process. Surveys and interviews were conducted to collect data on the perception of various AI-based solutions, focusing on factors such as usefulness, ease of use, interaction quality, and trust in outcomes. An adapted ranking method based on weight coefficients was applied to assess preferences for specific AI tools, enabling the analysis of trends over time. The results provide an objective basis for optimizing the integration of AI in education and formulating recommendations for educational institutions to enhance the effectiveness of the learning process. The findings are expected to contribute to a better understanding of AI's impact on education and support future initiatives for its integration.

Key words: Artificial Intelligence, Educational Technology, Preference Analysis, Weighted Ranking, Multi-criteria Evaluation.

1. INTRODUCTION

In recent years, the use of Artificial Intelligence (AI) in education has evolved from a hypothetical possibility to a reality that is actively changing the way learning content is designed, delivered and perceived [1-3]. Technological advances, combined with global challenges facing education systems, have brought to the fore the need for more flexible, personalized and effective solutions, which AI tools promise to deliver.

Recent global reports by UNESCO and the European Commission emphasize that AI is no longer a complementary tool but a key driver of digital transformation in education [4]. Its integration is linked not only to pedagogical innovation but also to broader societal goals such as accessibility, inclusiveness, and lifelong learning. These perspectives further highlight the urgency of developing methodological approaches to evaluate and guide the adoption of AI in education.

Despite growing attention to the integration of AI in the educational process (EP), there is a lack of empirical clarity on how these technologies are perceived by the directly involved actors - students and faculty [5]. Neither the degree of satisfaction with the use of specific AI solutions nor preferences for particular tools or features have yet been well researched. This creates a knowledge gap that hinders the optimal implementation and adaptation of AI to the needs and expectations of users in education.

The aim of the present study is to analyze and evaluate the satisfaction and preferences of students and lecturers towards the use of AI in EP. By means of a survey and the application of an adapted preference ranking method, it seeks to answer the question of which factors - efficiency, convenience, and trust - matter most in the adoption of AI solutions.

The study aims not only to identify the leading AI tools in terms of user attitudes, but also to outline trends and opportunities for their effective implementation in the context of modern education. The results are expected to assist educational institutions in making informed decisions about digital transformation tailored to the real needs of learners and learners.

2. ANALYSIS AND EVALUATION OF DEGREE OF PREFERENCE REGARDING THE USE OF AI IN EP

Determining the degree of preference (DP) for different AI-based solutions in education (AISE) requires a complex evaluation approach combining quantitative analysis of empirical data with formalized processing of subjective evaluations. This entails determining the relative importance of each solution in relation to the others, based on the opinions of participants in the EP.

A commonly applied approach within multi-objective optimization and rational decision-making is the Stoyanov method [6–8], which determines weighting coefficients (WC) through the ranking of target parameters. To obtain the WCs, respondents engaged in the educational process are asked to rank the studied elements according to their perceived importance. This procedure yields objectively grounded values for their relative weights [6].

Grounded in rank-correlation concepts, Stoyanov's approach has shown consistent effectiveness for establishing priorities and guiding optimal choices in numerous contexts [5, 9–11]. In the framework of the present study, this conceptual foundation is applied to determine the DP of the AISE, using real AI solutions instead of classical parameters that can be applied in modern educational environments.

An essential feature of the present study is that preferences are not assessed uniformly, but through separate ranking on four distinct criteria: efficiency, convenience, communication, and trust. For each of these, a separate ranking matrix is formed, which allows for a more precise and multilayered assessment of participants' perception of AISE.

Given the specificity of the study – namely the need to track preferences over time and analyze their dynamics – Stoyanov's method [6] is not applied in its classical form but is modified and adapted to the specific context of evaluating AI-based solutions in education. The adaptation introduces two key extensions: structuring of rankings across four distinct criteria – efficiency, convenience, communication, and trust; and incorporation of a dynamic component that enables the method to be applied in successive periods and to predict future values while preserving its essential logic. Unlike classical applications, these extensions enable the method to be applied specifically in the educational context, which defines the novelty of the present approach. The algorithm in Figure 1 illustrates this adapted version. Recent studies of AI adoption in educational settings provide contextual support for this dynamic, multi-criteria approach [5].

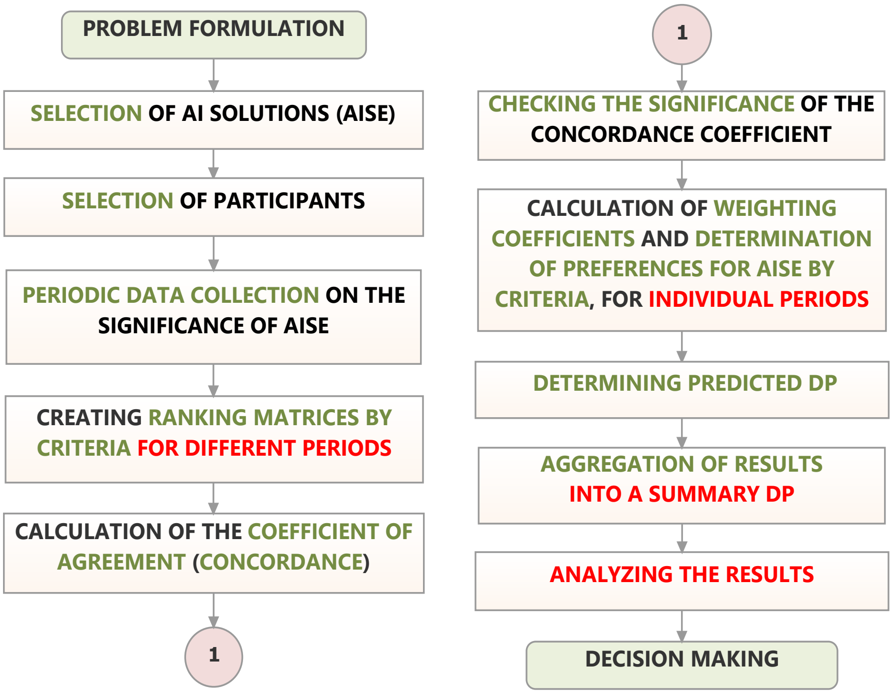

Figure 1. Stages of the algorithm applied to determine the degree of preference for AISE

Figure 1 outlines the stages of problem formulation, selection of AI solutions, periodic data collection, construction of rank matrices by individual criteria, calculation and verification of the consistency coefficient, determination of preferences for each criterion, aggregation of the results into an overall DP, and subsequent analysis. The algorithm allows for application both in one-off surveys and in the framework of a dynamic analysis tracking preferences over different time periods.

2.1. Problem formulation

The initial stage identifies the need to assess preferences for different AISE. The aim is to build an objective basis for comparison between the AI solutions that are or can be used in training, regarding their effectiveness, convenience, quality of communication and perceived trust by the participants in the EP.

2.2. Selection of AI solutions (AISE)

At this stage, the set of AISE to be included in the evaluation is determined. The selection is based on their relevance, applicability to the training and the interest of the participants. Each solution is conventionally denoted by an index (y_1, y_2, ... , y_m), where m is the number of evaluated AISE.

2.3. Selection of participants

At this stage, a sample of participants is identified who will provide their ratings of preference for the selected AISE. The larger the number of respondents and the more frequent the surveys, the more reliable the calculated and estimated WC values become. Larger biases may be observed in the initial periods, but as data accumulate, the accuracy of the analysis increases.

Depending on the objectives of the study, respondents may be students, faculty, or other participants in the EP. The group should be homogeneous in terms of context of decision use but can be heterogeneous in demographic or role characteristics when seeking a broader perspective on preferences.

2.4. Collection of estimates

In this stage, each respondent individually ranks the selected AISE in terms of predefined evaluation criteria - effectiveness, convenience, communication and trust. In the context of this study, these criteria are defined as follows:

- Efficiency - the extent to which the AI solution contributes to achieving learning outcomes effectively and saving time during the educational process;
- Convenience - the perceived ease of use, accessibility, and integration of the AI solution into routine educational activities;
- Communication - the quality and clarity of interaction between the user and the AI solution, including responsiveness, adaptability, and the ability to provide meaningful feedback;
- Trust - the level of confidence of users in the reliability, accuracy, and fairness of the outputs generated by the AI solution.

This allows for a multi-layered consideration of preferences and a more accurate interpretation of attitudes towards individual AISE. For each criterion, the respondent assigns a unique rank from 1 to m with rank 1 referring to the most preferred solution and rank m to the least preferred. No duplicate ranks are allowed within the same criterion. The resulting scores are subjective but are subject to formalized processing to derive objective dependencies and generalizations.

2.5. Creation of rank matrices

After collecting the rank scores, the data are structured into a rank matrix that reflects the individual preferences of each of the R respondents towards m number of AISE alternatives for each criterion. For each criterion, a separate matrix of size $R \times m$ is created, where the value $a_{ij}^{(k)}$ represents the rank score given by the i-th respondent for the j-th AISE on the k-th criterion. This structure allows systematic storage of the data and facilitates the subsequent computation of summary metrics such as sum of ranks, variances and WC.

2.6. Calculation of WC - separately for each criterion

Each of the steps, described below, applies separately to each of the selected criteria: efficiency, convenience, communication, and trust

- Calculate the sums of the ranks for each of the *m* AISE assessed in each period (1÷n):

$$\mathrm{A}_{\boldsymbol{j}}^{(\boldsymbol{k})} = \sum_{\boldsymbol{i}=1}^{\boldsymbol{R}} \boldsymbol{a}_{\boldsymbol{ij}}^{(\boldsymbol{k})}, \quad \boldsymbol{j} = \mathbf{1}, \mathbf{2}, \ldots \boldsymbol{m}. \tag{1}$$

- Derive the average value of the ranks, denoted as *S*, corresponding to period *n*:

$$\boldsymbol{S}^{(\boldsymbol{k})} = \frac{\mathbf{1}}{\boldsymbol{m}} \sum_{\boldsymbol{j}=1}^{\boldsymbol{m}} \boldsymbol{a}_{\boldsymbol{j}}^{(\boldsymbol{k})} = \frac{\boldsymbol{R}(\boldsymbol{m}+\mathbf{1})}{\mathbf{2}}, \tag{2}$$

where *R* corresponds to the number of participants in that period.

- Compute δ_j as the difference between the aggregated rank value of each AISE and the average sum *S*:

$$\boldsymbol{\delta}_{\boldsymbol{j}}^{(\boldsymbol{k})} = \mathrm{A}_{\boldsymbol{j}}^{(\boldsymbol{k})} - \boldsymbol{S}^{(\boldsymbol{k})} \tag{3}$$

- Computation of the concordance coefficient:

$$\boldsymbol{w}^{(\boldsymbol{k})} = \frac{12 \sum_{\mathrm{j}=1}^{\mathrm{m}} (\boldsymbol{\delta}_{\boldsymbol{j}}^{(\boldsymbol{k})})^2}{\mathrm{R}^2(\mathrm{m}^3 - \mathrm{m})} \tag{4}$$

- An additional step involves testing whether the concordance coefficient ($w^{(k)}$) is statistically significant. In situations where at least seven AISE are ranked, the χ^2 test is employed. Should the coefficient prove insignificant, $w^{(k)}$ is taken as zero and equal weights ($WC_j^{(k)} = 1$) are assigned to all solutions. When the ranked set consists of fewer than seven AISE, the assessment is carried out using Fisher's *Z*-criterion [6].
- Obtain WC values for each AISE during a certain period *n*, conditional on the significance of $w^{(k)}$:

$$\boldsymbol{WC}_{\boldsymbol{j}}^{(\boldsymbol{k})} = \frac{\boldsymbol{V}_{\boldsymbol{j}}^{(\boldsymbol{k})}}{\sum_{\boldsymbol{j}=1}^{\boldsymbol{m}} \boldsymbol{V}_{\boldsymbol{j}}^{(\boldsymbol{k})}}, \qquad \boldsymbol{j} = \mathbf{1}, \mathbf{2}, \ldots, \boldsymbol{m}, \quad \sum_{\boldsymbol{j}=1}^{\boldsymbol{m}} \boldsymbol{WC}_{\boldsymbol{j}}^{(\boldsymbol{k})} = \mathbf{1}, \tag{5}$$

where

$$\boldsymbol{V}_{\boldsymbol{j}}^{(\boldsymbol{k})} = \frac{\boldsymbol{Rm} - \sum_{\boldsymbol{i}=1}^{\boldsymbol{R}} \boldsymbol{a}_{\boldsymbol{ij}}^{(\boldsymbol{k})}}{\boldsymbol{Rm} - \boldsymbol{R}} \tag{6}$$

2.7. Determination of DP

After the calculation of the WC for each of the assessed AISE, a ranking is performed in descending order of the values obtained. This ranking represents the DP that reflects the comparative importance of each AISE according to the respondents' scores on the respective criterion. In case of equal WC values for two or more AISE, the equal ranking rule applies. In case the coefficient of agreement is not statistically significant, and no WCs are calculated, the DP for all AISE is assumed to be the same. The DP shall be determined separately for each criterion.

2.8. Storage of results

The calculated values of ranks, WC and DP are stored in a specific database organized by relational structures. The main tables include:

- Ranking - includes the individual rank scores of respondents;
- Weighting coefficients - includes WC for each AISE by criteria and periods;
- Preferences - reflects the ranking of the AISE by DP.

Data structured in this way allows both static analysis and dynamic tracking over time.

2.9. Determination of the predicted DP

Where data are available for at least three consecutive assessment periods, a projection of future WC and DP values is made for each AISE. Time series methods can be used for this purpose, such as:

- Least squares method - to calculate a linear prediction with variance minimization [12];
- Regression model - in the presence of complex or non-linear dependencies between periods. Linear regression can be used when a stable linear trend is assumed.

The prediction values support decision making on the sustainability and future relevance of specific AI solutions in the EP.

2.10. Aggregation of results into a summary DP

After determining the DP for each of the four criteria (effectiveness, convenience, communication, trust), the results are aggregated to form an aggregated DP for each of the AISE studied. The aggregation can be done in two ways:

- Equal averaging where all criteria are considered equally significant:

$$\boldsymbol{AW_j = \frac{1}{F}\sum_{k=1}^{F} WC_j^{(k)}} \ , \tag{7}$$

Where F is the number of criteria, and $WC_j^{(k)}$ is the DP value for the j-th AISE on the k-th criterion.

- Weighted averaging, given predefined weights w_k for each criterion:

$$\boldsymbol{AW_j = \sum_{k=1}^{F} w_k W_j^{(k)}, \ \sum_{k=1}^{F} w_k = 1}, \tag{8}$$

where w_k is the weight of the k-th criterion determined based on expert judgment, strategic priority, or another methodological basis.

The aggregated DP allows for an unambiguous ranking of the AISE according to the combined perception of the participants and serves as the basis for the final analysis.

2.11. Analysis of preference dynamics (DP) over time

When data from consecutive assessment periods are available, a qualitative analysis of the change in the DP to each AISE is performed. Based on the DP values over at least three periods, the following types of behavior can be distinguished:

- A preference is considered sustained when the following conditions hold:
  $S_{ij} - S_{(i+1)j} \leq 1, for\ i = m-2, m-1$
  $and\ (S_{ij} - S_{(i+1)j}) \neq S_{(i+1)j} - S_{(i+2)j}\ or\ S_{mj} = S_{(m-1)j}$
- An increasing preference trend is identified when the following requirement is fulfilled:
  $S_{(i-1)j} - S_{ij} \geq 1,\ for\ i = m-1, m$
- Sustained growth of preference occurs if the stated requirement is met:
  $S_{(i-1)j} - S_{ij} > 1,\ for\ i = m-1, m$
- A declining tendency in preferences is identified when the specified condition holds:
  $S_{(i+1)j} - S_{ij} \geq 1,\ for\ i = m-2, m-1$
- Permanent preference reduction if the condition is met:
  $S_{(i+1)j} - S_{ij} > 1,\ for\ i = m-2, m-1$
- A hesitant or unstable preference is identified when the corresponding conditions are fulfilled:
  $\left(S_{ij} - S_{(i+1)j}\right) \neq \left(S_{(i+1)j} - S_{(i+2)j}\right),\ for\ i = m-2$
  and for any $i = m-2, m-1\ is\ true\ \left|S_{ij} - S_{(i+1)j}\right| > 1,$

where S_{ij} is the DP for AISE j in period i, m is the number of the last period. All values are interpreted relative to the ranking order.

In the educational context, the ability to trace dynamic changes in preferences is of particular importance. Unlike static evaluations, which provide only a snapshot, longitudinal analysis can reveal emerging trends, identify early shifts in student or faculty attitudes, and support timely interventions. This dynamic perspective is essential for ensuring that the integration of AI solutions remains aligned with evolving educational needs and expectations.

3. APPLICATION OF THE METHOD

In the framework of the educational activities at the Technical University of Gabrovo, annual surveys are conducted among students in the discipline "Programming of mobile devices" to study the preferences towards the technological solutions used in the training. In 2025, the survey was adapted to collect opinions on the AISE, allowing the full implementation of the proposed method for determining the DP. A total of 34 students participated in the survey. Seven AISE are studied, conventionally labeled as follows: ChatGPT (y_1), Microsoft Copilot (y_2), Grammarly (y_3), Google Bard (y_4), Khanmigo (y_5), AI search engines (y_6), and Other AI tools (y_7). Each respondent performed ranking on four criteria: efficiency, convenience, communication, and trust. The gathered responses are organized following the algorithm and represented within the relational structure termed “Ranking Matrix”. Table 1 displays the aggregated DP values for all seven AISE, obtained through uniform averaging across the four evaluation criteria. The table includes simulated data for two consecutive academic years (2023÷2024) as well as real data for 2025, allowing not only the determination of current WC but also the analysis of preference dynamics.

Table 1. Aggregated preferences of AISE

m	A_1	A_2	A_3	A_4	A_5	A_6	A_7
2023	1	3	2	4	5	6	7
2024	1	2	3	4	5	6	7
2025	1	2	3	5	4	7	6
Prediction (2026)	1	2	4	5	3	7	6

According to the calculations for 2025 (Fig. 2), the three AISE with the highest aggregated DP are: ChatGPT, Grammarly and Microsoft Copilot, while the lowest value is reported for AI search engines.

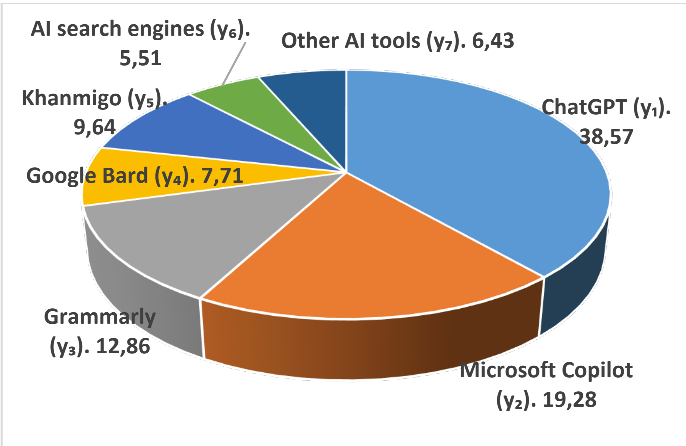

Fig. 2. Ranking of WC for 2025.

A linear regression based on the simulated results of the previous three periods (2023÷2025) was used to calculate projected DP values for 2026. The aim is to assess the trend in the dynamics of preferences towards each of the AISE considered, reflecting changes in participants' judgements.

After analyzing the DP values for each AISE by the algorithm, the following types of preferences are identified:

- Sustained preference - ChatGPT, Microsoft Copilot;
- Increasing preference trend - Khanmigo;
- Sustained increase in preference - not reported;
- Declining preference trend - Grammarly;
- Permanent preference reduction - AI search engines;
- Hesitant preference - Google Bard, Other AI tools.

According to the rules of the dynamic analysis algorithm, the classification was derived by examining the changes in DP values over the successive periods from 2023 to 2026. The 2026 projection is included to provide a preliminary assessment of persistence and trends, which provides an objective basis for drawing conclusions about the relevance and prospects for the implementation of the relevant AISE in educational practice.

The results obtained are in line with international studies reporting similar preferences among students, where general-purpose tools such as ChatGPT and Grammarly often receive the highest ratings, while more specialized or less familiar tools demonstrate lower acceptance. For instance, a large-scale survey in 2024 revealed that 66% of students most frequently use ChatGPT, followed by Grammarly and Microsoft Copilot (25% each) [13]. Similarly, recent research published in an ACM conference proceeding, confirms that ChatGPT, Grammarly, and Turnitin are among the most popular AI tools adopted by students and faculty in higher education [14]. This convergence suggests that the observed trends are not isolated to a single institution but reflect broader patterns in higher education worldwide.

4. CONCLUSION

The presented method provides the possibility to systematically assign DP to different AISE. The method combines quantitative and qualitative assessment of subjective opinions through rank scores, considering the influence of several criteria - efficiency, convenience, communication, and trust.

The obtained results provide an objective basis for optimizing the implementation of AI in educational practice, as well as for formulating institutional recommendations aimed at increasing the effectiveness of the learning process and learner satisfaction. The inclusion of a dynamic component in the algorithm allows tracking changes over time and building a predictive model of the future relevance of AISE.

Beyond this specific context, the proposed approach can be extended to a wider range of applications in education, including the evaluation of e-learning platforms, the prioritization of digital resources, and the design of curricula. At a strategic level, the method can provide decision support for university management and policy-makers engaged in digital transformation. Nevertheless, potential limitations remain, such as the need for sufficiently representative respondent groups and possible bias in subjective rankings. Future research could therefore explore the integration of the method with machine learning techniques, enabling large-scale data analysis and more accurate forecasting of preference trends.

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