Multi-Criteria Decision Analysis in project procurement processes for learning management systems

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Abstract

Learning management systems (LMSs) have become a common practice in education delivery. The LMS market is growing rapidly, and the number of vendors offering diverse solutions is also growing. This raises the problem of selecting the optimal LMS. The choice of LMS is made using various criteria, both those related to the system itself and its technical parameters, as well as related qualitative criteria. The article addresses the problem of indicating the most optimal LMS, considering technical and cost parameters and user ratings. The most popular LMSs listed in the top LMS rankings were assessed.

Keywords: learning management system, LMS, e-learning, MCDA, TOPSIS

1. Introduction

In the era of digitalization, IT tools have become an essential driver of the development of education and teaching methods [13]. Currently, learning management systems (LMSs) are widely used in teaching. LMSs are "software systems designed to assist in the management of educational courses for students, especially by helping teachers and learners with course administration."[5]. The LMS market is growing dynamically. The global e-learning market is estimated to be worth 305.3 billion U.S. dollars by 2025 [16]. Over 1000 vendors on the market offer various services and platforms [7]. Due to the numerous and diverse LMS solutions and systems, the selection of a system for teaching remains essential. Multicriteria methods are helpful when making this choice, and selecting LMS systems using these methods is a significant research trend [25].

This article applies the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) method [14] to select the optimal LMS system. The original value of the study is expressed in the article's attempt to present an integrated approach to the selection criteria of LMSs, i.e., the system and user perspectives. The eleven most frequently listed LMSs were evaluated using seven decision-making criteria.

2. Literature review

The use of ICT in education has grown steadily in recent years, with LMSs playing a key role in supporting students' learning experiences by complementing traditional forms of teaching and increasingly being the only channel for knowledge acquisition. Mixed and online learning became particularly important during the pandemic and lockdowns. Although many online learning platforms are available, institutions and other stakeholders most often look for integrated comprehensive learning platforms such as LMSs. Currently, LMSs are becoming an integral part of the education system around the world.

Sanchez et al. (2024) [18] compare 45 LMSs based on six main criteria: interoperability, accessibility, productivity tools, communication tools, learning tools, and safety standards. They introduce the Software Quality and Teaching-Learning metric to rank the systems. A slightly different approach to comparing LMSs is used by Rabiman et al. (2024) [17]. They describe the process of evaluating a LMS through validation by media and learning material experts. Due to the specific nature of the evaluation and the selection of experts, such aspects as usability, functionality and visual communication turned out to be the most important; however, the authors point out that the study focuses on the evaluation of the existing or developed LMS rather than its selection.

Soko et al. (2023) [21] assess LMS use from students' perspectives. Key motivators include ease of use and enjoyment (hedonic motivation). Infrastructure, internet access, and the impact on academic performance also affect LMS usage. Hussein et al. (2024) [8], explore LMS effectiveness in similar way. They find that usability, ease of use, self-assessment, and student attitudes are critical to system success, reinforcing the importance of user-focused evaluation. Yet another approach is presented by Karadimas (2018) [10], who assumes that the active use of an LMS by students leads to its perception as an effective learning tool. The author compares 10 selected LMS platforms on the basis of thirty-eight key functional features and costs. The paper stresses that there is no single ‘best’ LMS, as each platform may suit different purposes and be chosen depending on the specific circumstances and preferences of the institution or organisation.

The process of choosing an LMS that meets the expectations of the institution while taking into account the features of systems goes far beyond the mere comparison of systems. The complexity of the LMS selection process is pointed out by Kasim and Khalid (2016) [11].These authors recommend choosing LMS based on the following key criteria: needs of users and courses, user friendliness, integration with other systems, accessibility, effective management, interactivity and adaptation to the needs of students. In addition, they mention open source as a feature of some platforms.

Blagoev and Monov (2018) [3], propose a comprehensive methodology involving 10 evaluation categories (including security, communication, content development, evaluation, reports, UX, integration, personalisation, support). This methodology uses an 11-point scale to assess the degree of impact of each criterion on the organization and a 6-point scale to assess the degree of compliance of the assessed LMS with a given criterion. The conclusion emphasises that the effective evaluation of LMSs requires the separation of functional and financial aspects and the consideration of the organisation's specific needs and goals.

A strategic approach to selecting an appropriate (LMS) in the context of open and distance learning is also described by Kant et al. (2020) [9]. These authors indicate that the main decision factors are licence, learning flexibility, security and market share, while the decision itself should take into account cost, quality, usability, capacity, budget and the priorities and goals of the institution. Abdennour et al. (2024) [1] list the evaluation criteria for LMS platforms, indicating their evolution between 2019 and 2022. While the set of LMS selection criteria itself does not differ from other papers, it is worth noting that a much greater emphasis was laid on collaborative learning in 2022.

Shehabat and Altarawneh (2021) [19] used a multi-criteria decision-making approach (MADM) to evaluate LMS platforms on the basis of 52 qualitatively selected features. Categories of criteria include usability (ease of learning, using and remembering, small number of errors, subjective satisfaction; user interface, table of contents, help system, language environment), instruction management, screen design, technology, interaction, evaluation, system quality, service quality and content quality. The authors emphasise the importance of a comprehensive set of technical and pedagogical criteria and those concerning users' perception for the evaluation and choice of an LMS.

Păvăloai and Stofor (2024) [15] identifies a coherent and comprehensive set of criteria for choosing an LMS. These include: Budget (cost of licensing, support, training), Customization and scalability, System integration, Technical support and user training, Data security, User experience (UX) and accessibility, Feedback and evaluation tools, and

Compatibility across devices. These authors also point out that the final choice should be based on a detailed analysis of the institution's needs and available resources.

While most authors describe the LMS selection process by means of qualitative criteria selection, there are relatively few papers based on quantitative methods. Cardenas (2018) [4] applies MCDA (Multi-Criteria Decision Analysis) to software selection. He argues that traditional measure selection methods may be subjective and proposes MCDA approach using a six-step process. He notes that MCDA allows us to take into account stakeholders' preferences, to effectively eliminate less important measures and to systematise and rank them. In addition, sensitivity analysis allows us to examine the impact of changes in criteria weights on the ranking of measures. In the author's opinion, the proposed method can serve as a guide for software evaluators, enabling them to make methodological, documented and transparent decisions regarding the selection of software measures.

Muhammad and Cavus (2017) [12] combine fuzzy logic with DEMATEL to evaluate LMS features. Their findings identify user satisfaction, ease of learning, and system usability as key factors. They recommend integrating fuzzy DEMATEL with other MCDA methods for broader decision-making applications. A fuzzy multi-criteria decision-making approach using fuzzy analytic process hierarchy (FAHP) for the selection of criteria for an e-learning platform is proposed by Güldeş et al. (2021) [6]. Their study identifies information security, system quality, and access to learning materials as top priorities based on student, academic, and IT expert input.

In the following paper, we attempt to select LMSs on the basis of quantitative analysis using the two most commonly used MCDA methods, i.e. TOPSIS and AHP (Analytical Hierarchy Process). An analogous methodology was used by Tairab (2020) [23] to assess e-learning success factors during the COVID-19 pandemic from the perspective of managers. The evaluation considered criteria related to the instructor's characteristics, students' characteristics, IT support technology, knowledge, course design, e-learning environment and level of collaboration.

3. Methodology

MCDA methods are used to find the optimal choice among options described by different and distinctive criteria. Among the techniques used in such an approach, TOPSIS method is a useful tool. A review of MCDA methods and their relative popularity is presented in [22]. The essence of TOPSIS is the evaluation of alternatives by calculating the distances of alternatives to virtual ideal and anti-ideal reference solutions in the multidimensional space of analysed options. The Euclidean distance is a standard distance measure used in TOPSIS, although there is no restriction on the use of alternative distance measures. It should be noted that a significant advantage of the TOPSIS method is its full flexibility in the selection of evaluation criteria for the analysis of a given problem. Originally, the criteria can be qualitative, binary and quantitative. Some of them can be positive evaluation criteria (increasing the position in the ranking), as well as negative criteria (decreasing the position in the ranking).

At the same time, it should be noted that TOPSIS does not provide an answer as to what the rational weights for individual options should be. For criteria that are intuitively similar in importance, or that are recalculated with respect to a common form (e.g., the present value of financial flows of all monetary criteria), an equal-weights approach can be used. In other cases, a structured process for determining the criteria should be used. For this purpose, we apply AHP. The TOPSIS method involves the following steps after the data for analysis have been collected - for a detailed description of the method, see [14].

Step T.1 - Normalization of the initial data set X, consisting of x_{ij} observations, in the decision matrix by columns. In this analysis, we used the normalization method presented in Equation 1, but other methods can be used. Another popular approach is the minimum-maximum normalization method.

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad \text{(Eq. 1)}$$

where:
x_{ij} – value of j-th criterion for i-th alternative analysed (in our case, i represents specific LMSs).
r_{ij} – normalized values for each x_{ij}, respectively.
i – index of analysed alternatives; $i = 1, \ldots, m$.
j – index of criteria; $j = 1, \ldots, n$.

Step T.2 - Calculation of the Weighted Normalized Decision Matrix v_{ij} where w_j are the weighting criteria obtained, for example, by the AHP method or determined subjectively.

$$v_{ij} = w_j r_{ij} \qquad \text{(Eq. 2)}$$

Step T.3 - Construction of Positive Ideal Solution (PIS), namely v_j^+ for benefit / profit criteria and Negative Ideal Solution (NIS) v_j^- for cost criteria. The determination of the nature of a given criterion (benefit or cost) is made by the decision maker. In our case, the first two criteria are cost, and the others are benefits – see also Table 1.

$$v_j^+ = \{v_1^+, v_2^+, \ldots, v_n^+\} = \{max_j(v_{ij})\},\ v_j^- = \{v_1^-, v_2^-, \ldots, v_n^-\} = \{min_j(v_{ij})\} \quad \text{(Eq. 3)}$$

Step T.4 - Calculation of the distance to both ideal solutions, i.e. from PIS denoted as $D+$ and NIS denoted as $D-$. Then, the overall preference score C_i is calculated - see Eq. 5 - which reflects the final ranking of alternatives (the higher C_i, the better). Note that Eq. 4 uses Euclidean distance. Other distance measures can be used. As [2] showed, there is little variation in the results when using different distance measures.

$$D_i^+ = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^+)^2}\ ,\ D_i^- = \sqrt{\sum_{j=1}^{n}(v_{ij} - v_j^-)^2} \qquad \text{(Eq. 4)}$$

$$C_i = \frac{D_i^-}{D_i^- + D_i^+} \qquad \text{(Eq. 5)}$$

As mentioned above, TOPSIS does not include a formal process for determining criteria weights. Therefore, it should be complemented by other relevant methods, such as the Analytical Hierarchy Process. AHP allows both the identification of weights and the verification of their correctness against a random selection of weights - see [20], [24]. AHP consists of the following steps.

Step A.1 - Construction of Pairwise Comparison Matrix A. The A matrix contains n rows and columns, where n represents the total number of criteria analysed and each matrix element a_{ij} represents the relative importance score of criterion i compared to criterion j on a scale from 1 (equal importance) to 9 (criterion i is extremely more important than criterion j).

Step A.2 - Normalization of the A matrix by division of each element by the sum of its column using equation 6.

$$a'_{ij} = \frac{a_{ij}}{\sum_{i=1}^{n} a_{ij}} \qquad \text{(Eq. 6)}$$

Step A.3 - Calculation of the priority vector w_i (criteria weights). By averaging the normalized values over each row (Eq. 7), the criterion weights are obtained. These weights, if verified to be consistent, are then used in TOPSIS in Eq. 2. (Note that in the A matrix, both columns and rows represent the same criteria, so the set of weights can also be used for w_j).

$$w_i = \frac{\sum_{j=1}^{n} a'_{ij}}{n} \qquad \text{(Eq. 7)}$$

Step A.4 - Consistency check of the computed weights. This step includes the calculation of the Consistency Index (CI) according to Eq. 8, where λ_{max} is the largest eigenvalue of the matrix A. Finally, the Consistency Ratio (CR) is computed (Eq. 9), where RI is the Random

Index, which depends on the size of the matrix. The RI values are obtained from simulations of random matrices. The criteria weights are considered consistent if a value of $CR < 0.10$.

$$CI = \frac{\lambda_{max} - n}{n-1} \quad \text{(Eq. 8)}$$

$$CR = \frac{CI}{RI} \quad \text{(Eq. 9)}$$

4. Discussion of results

The data for the study was obtained from the publicly available information of the individual providers. Websites containing comparisons of LMS offerings were also used [7]. A summary of the data collected is presented in Table 1.

Table 1. Original data collected for the software selection process

Software** ↓	annual cost thsd. USD	implementation cost thsd. USD	free trial days	compatibility* categorical	user rating from 1 to 5	user support categorical	mobile app. access categorical
A	32.0	5.00	14	1	4.6	0.5	1
B	15.0	5.00	30	0.7	4.6	1	0.5
C	4.2	1.00	14	0.35	4.6	1	0.5
D	65.4	0.00	14	0.7	4.6	0.5	0
E	9.0	5.00	14	0.7	4.3	0.5	1
F	25.0	5.00	14	1	4.3	0.5	1
G	35.3	5.90	30	1	4.7	0.5	1
H	120.0	0.75	45	1	3.0	0.5	1
I	80.4	5.00	14	1	4.8	1	1
J	36.0	9.50	30	1	3.0	1	1
K	45.0	5.90	14	0.35	4.8	0.5	0
Criteria type	- (cost)	- (cost)	+ (benefit)	+ (benefit)	+ (benefit)	+ (benefit)	+ (benefit)

* compatibility with SCORM, AICC and xAPI/Tin Can API; ** Software names are presented in Appendix A.

The results of the AHP and TOPSIS procedures are presented below. Table 2 shows the AHP pairwise comparison matrix designed by authors and the final criteria weights obtained via the AHP method, calculated based on Eq. 6 and Eq. 7. The consistency index for selected criteria weights amounted to 5.0%. Consequently, the consistency ratio (calculated with RI for $n = 7$) was 3.8%, which shows that the result of the AHP process is coherent and can be reliably used in the TOPSIS calculation.

Table 2. AHP pairwise comparison matrix and final criteria weights

	annual cost	implementation cost	free trial period	compatibility*	user rating	user support	mobile app. access
annual cost	1.00	4.00	5.00	5.00	2.00	3.00	6.00
implementation cost	0.25	1.00	2.00	4.00	1.00	2.00	6.00
free trial period	0.20	0.50	1.00	2.00	0.50	0.50	2.00
compatibility*	0.20	0.25	0.50	1.00	0.33	0.50	2.00
user rating	0.50	1.00	2.00	3.00	1.00	3.00	6.00
user support	0.33	0.50	2.00	2.00	0.33	1.00	6.00
mobile app. access	0.17	0.17	0.50	0.50	0.17	0.17	1.00
Final criteria weights:	**35.2%**	**17.2%**	**7.8%**	**5.5%**	**19.1%**	**11.8%**	**3.4%**

* compatibility with SCORM, AICC and xAPI/Tin Can API

Figure 1 shows the results of the TOPSIS ranking, calculated according to Eq. 1-4 using data from Table 1 and the weights from Table 2. The X and Y axes indicate the distance of each alternative from the virtual positive and negative solutions, respectively. The left panel of Figure 1 shows the baseline solution. It can be easily seen that System C was ranked highest, followed by Systems B and E. The C_i ratios (see Eq. 5) amounted to 0.874, 0.789 and 0.774, respectively. As shown in Figure 1 (the right panel), the results in this specific selection problem are remarkably different when equal weights of the criteria are used in TOPSIS instead of weights developed, for example, through the AHP process. Then, System B is slightly preferred over System C. In this case; $D_B^+ = 0.059$, $D_B^- = 0.107, C_B = 0.644$ and $D_C^+ = 0.071$, $D_C^- = 0.125, C_C = 0.636$, and the third place is taken by System G ($C_G = 0.598$). A conclusion at this stage is that it is critical to use well-designed weights.

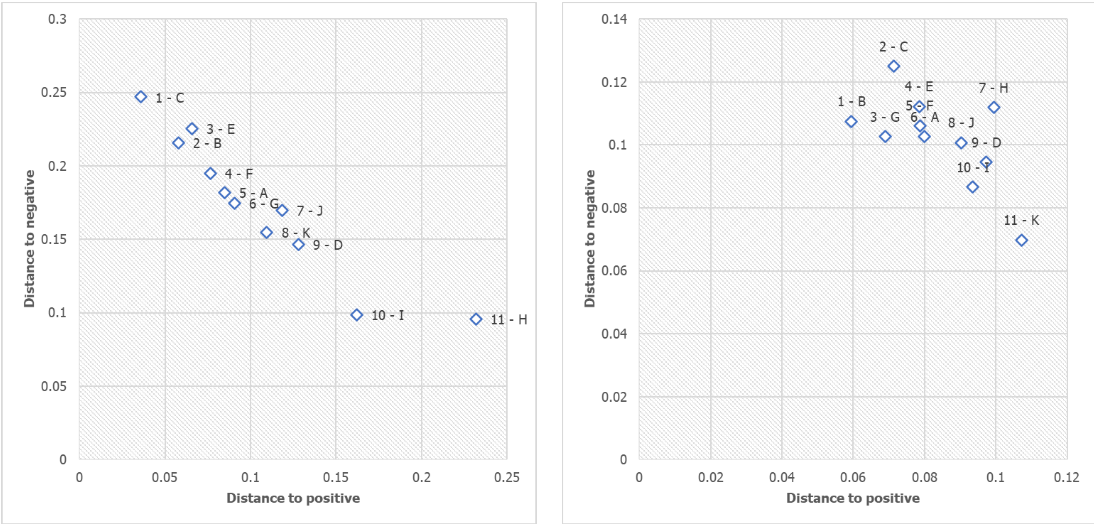

Fig. 1. Solution with the weights based on AHP process (left panel) and the equal weights (right panel)

Next, sensitivity analyses were conducted to verify the stability of the results obtained, with different weights assigned to the individual criteria. The results of the sensitivity analyses for the baseline solution are shown in Figures 2-4. The sensitivity analyses include testing the effect of changing the weights from 5% to 50% for the following criteria: annual cost and user rating. In the simulation, the weight structure for the remaining criteria is maintained and then scaled proportionally to the remaining total sum of weights. In addition, Figure 4 presents a sensitivity analysis that examines the impact of changing the overall weight structure for the financial (cost) criteria versus the remaining quality criteria. The top of the ranking is the most sensitive to overall changes in the weight structure between financial and qualitative criteria, as shown in Figure 4.

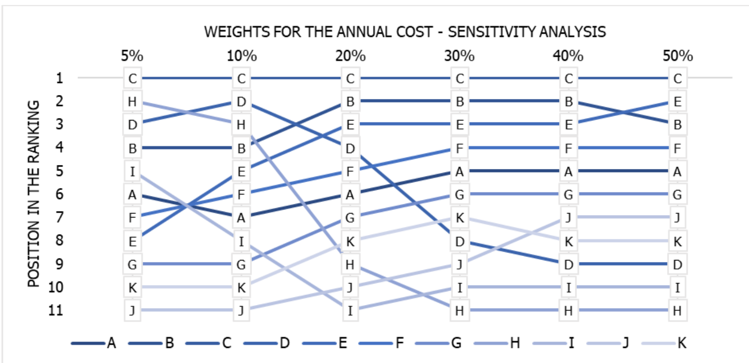

Fig. 2. Sensitivity analysis of different weights of the annual cost criterion – impact on TOPSIS results

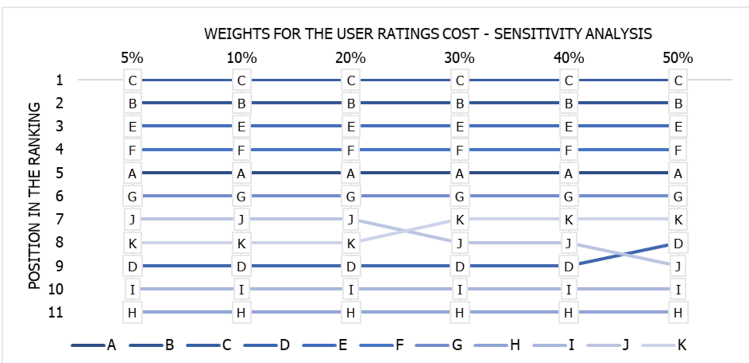

Fig. 3. Sensitivity analysis of different weights of the user rating criterion – impact on TOPSIS results

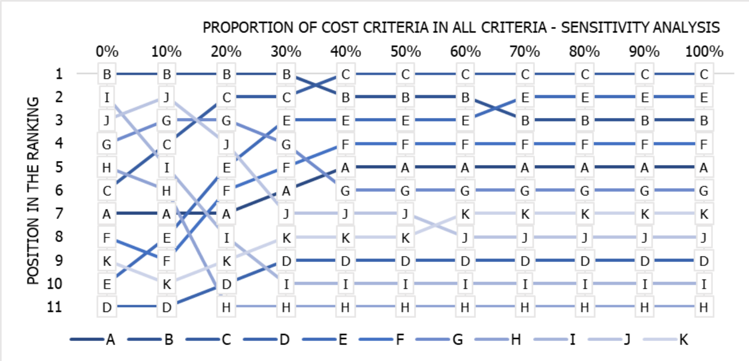

Fig. 4. Sensitivity analysis for different structure between cost criteria and qualitative criteria

The analyses carried out indicate that an important part of the analysis prior to the development of a request should be to what extent certain criteria are worthy of inclusion in the evaluation and to what extent they should be discriminatory parameters, the fulfilment of which is obligatory to a certain/minimum degree. This applies both to key binary factors, such as compatibility with a particular system, and to factors with a low degree of differentiation and sometimes without precise measurement. An example of such a criterion could be the user rating, which, as can be seen in this comparison, is not very differentiated and does not really affect the selection results, but increases the complexity of the analyses.

5. Conclusion

The growing number of solutions and services in the field of LMSs makes the selection a challenge. This article attempts to analyse and choose the optimal LMS from among the most popular solutions ranked on the top LMS lists. Cost and technical criteria were used for this purpose, including the often-raised problem of LMS system integration, as well as user opinions and system availability for the user, e.g., through mobile apps. Both implementation costs and subscription costs were taken into account. As a result of the study, a system was indicated that is user-friendly but also acceptable, cost-wise. The paper indicates the selection of the most optimal LMSs, which is a significant implication for potential decision-makers. The paper has several limitations; among them, it analyses only selected LMSs, and the analysis uses only one of many MCDA methods. However, future work is planned to apply more methods and deepen the evaluation criteria, e.g., to focus exclusively on the so-called technical criteria and evaluate them more comprehensively.

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Appendix A. A list of the analysed software.

ID in the analysis	Software name		ID in the analysis	Software name
A	Absorb LMS		G	iSpring Learn
B	LearnUpon		H	Moodle
C	360Learning		I	SkyPrep
D	TalentLMS		J	Blackboard
E	Litmos		K	CoreAchieve
F	Docebo			