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A Decision Support System for Personalized Learning in Higher Education

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ABSTRACT

This research presents a Decision Support System (DSS) designed to facilitate personalized learning in higher education. Utilizing the Best Worst Method (BWM), a popular Multi-Criteria Decision-Making (MCDM) technique, the study evaluated various learning strategies against set criteria based on the preferences and priorities of educators at University X. The results revealed One-on-One Tutoring as the most preferred method for personalized learning, followed by technology-enabled strategies such as Online Self-paced Courses and Adaptive Learning Software. These findings provide critical insights into the relative importance of different learning strategies, contributing to the development of a DSS capable of recommending the most suitable approaches for personalized learning. The implementation of such a system has been proposed as a means to augment decision-making processes within educational environments and potentially yield positive impacts on academic achievement. It is advisable to conduct additional research to authenticate these findings in various educational settings and investigate prospects for integrating empirical data into the process of decision-making.

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1. INTRODUCTION

In the face of the current digital revolution and the increasing reliance on data-driven decision-making, the realm of higher education is confronted with multifaceted challenges and significant prospects. In contemporary times, institutions of higher education have transformed into multifaceted environments that accommodate a variety of individuals with distinct interests and goals, including but not limited to scholars, educators, managers, guardians, former students, and additional parties. Simultaneously, these establishments are required to oversee a plethora of functions, encompassing student enrollment, faculty recruitment, curriculum arrangement, and research synchronization(Ford, 2011; Haryanto; Siti Marti'ah and Berta D T, n.d.).

Higher education institutions must make decisions that balance a wide range of interests and criteria due to the diversity of stakeholders and operations involved. When designing a curriculum, it is imperative to take into account various factors such as the requirements of diverse student groups, the proficiency of faculty, the goals of the institution, and external elements such as market demand and regulatory standards(Akınoğlu & Karsantık, 2016; Díaz-Maggioli, 2004; Marsh & Craven, 1997). The intricacies involved make manual decision-making not only unfeasible, but frequently less than optimal and susceptible to biases.

In the present time, the realm of higher education is experiencing an unparalleled surge in the volume of data. The proliferation of technology has enabled higher education institutions to amass a vast array of data pertaining to students, encompassing their academic transcripts, extracurricular pursuits, and online presence across learning management systems and social media platforms(Acharya, 2014; "Self-Access Centre (SAC) in English Language Learning," 2017; Wimatra et al., 2016). If utilized appropriately, this information can offer significant perspectives into the requirements, inclinations, proficiencies, and difficulties of students, thereby facilitating improved decision-making in all areas.

Decision Support Systems (DSS) are utilized in this context. A Decision Support System (DSS) is an information system that is computer-based and designed to facilitate complex problem-solving and decision-making processes. Combining information from numerous sources, using advanced analytical models and algorithms, and providing practical insights helps decision-makers navigate their complex and unpredictable responsibilities(E.P. & R, 2017; Karismariyanti, 2011; Primadasa & Juliansa, 2019). Decision Support Systems (DSS) help companies make informed decisions that include several criteria and stakeholders, optimize resources, and improve outcomes.

Decision Support Systems (DSS) are crucial to individualized learning. The system can assess a student's learning profile, including knowledge, preferred learning style, pace, preferences, and performance, and recommend learning trajectories, materials, and methods. This methodology has the potential to augment student involvement, enhance educational achievements, and cultivate a more comprehensive learning milieu(Lu et al., 2015; Sriyanto et al., 2020).

Several recent studies have showcased the potential of Decision Support Systems (DSS) in the context of higher education. Komleva et al.(Komleva, 2020) conducted a study that investigated the implementation of a Decision Support System (DSS) in university quality management. The study revealed notable enhancements in efficiency and stakeholder satisfaction. According to a study conducted by José Teixeira in 2022 (Teixeira et al., 2023), the implementation of a decision support system (DSS) resulted in improved selection processes for students participating in Erasmus short-term mobility programs. The utilization of this system led to enhanced transparency, fairness, and efficiency in decision-making. Notwithstanding, the utilization of Decision Support Systems (DSS) for tailored learning in tertiary education is an area that has not been extensively investigated. This research aims to bridge this gap.

Notwithstanding the potential advantages of Decision Support Systems (DSS) in the realm of higher education, specifically in the context of personalized learning, a considerable disparity persists in their implementation. Commonly, current systems offer universal solutions that do not effectively cater to the distinctive learning trajectories and inclinations necessitated by individual learners. The present educational environment is characterized by a uniform approach that often disregards the unique requirements, preferences, and rates of individual learners.

The aforementioned methodology has the potential to result in reduced levels of student involvement, compromised educational achievements, and elevated rates of student attrition. Furthermore, the current educational system may not provide comprehensive readiness for the dynamic labor market, which necessitates a growing emphasis on individualized and ongoing education. In higher education, complex criteria such as student performance, resource availability, teacher knowledge, and institutional goals are used to make decisions. Without a systematic decision-making mechanism, balancing many and often conflicting criteria can be difficult.

This study introduces a Decision Support System (DSS) that uses the Best Worst Method (BWM) to solve the problem(Pamučar et al., 2020; Rezaei, 2015). MCDM is a subfield in operations research. It emphasizes multi-criteria decision-making. The Best Worst Method (BWM) is a new Multiple Criteria Decision Making (MCDM) technique that solves complex decision-making problems. The suggested method identifies optimal and suboptimal criteria and compares them to all other criteria. The BWM calculates weights for each criterion to create a ratio scale that appropriately reflects their importance. The BWM aids educated, balanced, and effective decision-making. BWM in a DSS for personalized learning allows educators to use data to make informed decisions that improve student engagement, academic performance, and resource optimization. Case studies will assess the system's effectiveness.

2. METHODS

The present investigation utilizes the Decision Support System (DSS) methodology through the implementation of a Multi-Criteria Decision-Making (MCDM) technique, namely the Best Worst Method (BWM) (Munim et al., 2020; Pamučar et al., 2020). This section presents a comprehensive account of the utilization of this approach to augment individualized learning within the framework of tertiary education.

The database, model base, and user interface make up the DSS(Doumpos & Zopounidis, 2010; Mattiussi et al., 2014; Shang et al., 2008). The database contains student profiles, academic records, course information, and feedback. The model base implements BWM. It weighs criteria using database data and makes decisions. The user interface lets educators enter data and view results.

There are a few steps in BWM methods:

a. Criteria Identify: The study incorporates various criteria such as student performance, learning style, and engagement level. We will collaborate with educational professionals to ascertain the criteria that hold the highest and lowest degrees of significance.
b. Compare best and worst criteria: The researchers intend to solicit preference values from educators, which will serve as an indication of the degree to which the optimal criterion is favored over all other criteria, as well as the extent to which the least desirable criterion is less favored than all other criteria.
c. Weights value: The preference values will be utilized to derive weights for individual criteria through an optimization model. The aforementioned weights are intended to inform decisions regarding individualized educational trajectories.
d. Consistency result: The consistency ratio will be computed in order to ascertain the dependability of the comparisons that have been furnished.

Our study focuses on a single case study: University X. This university was chosen because of its diverse student population, extensive course offerings, and commitment to innovative teaching and learning strategies. This diversity and complexity provide a suitable context for testing the proposed DSS. The case study will cover an academic year to capture the full cycle of personalized learning.

In the context of personalized learning in higher education, the criteria could be factors that contribute to effective learning, and the alternatives could be different learning strategies or interventions.

Table 1. Criteria for BWM Method

ID	Criteria Name
C1	Engagement Level
C2	Learning Outcome
C3	Personalized Feedback
C4	Resource Efficiency
C5	Scalability

Table 2. Alternative for BWM Method

ID	Alternative Name
A1	One-on-one Tutoring
A2	Group Tutoring
A3	Online Self-paced Courses
A4	Adaptive Learning Software
A5	Learning Analytics
A6	Flipped Classroom
A7	Project-based Learning
A8	Gamified Learning
A9	Peer Instruction
A10	Interactive Learning Modules

3. FINDINGS AND DISCUSSION

Upon collecting the relevant data, we proceeded to apply the BWM method to the criteria and alternatives. The weights for the criteria were already determined in the methods section. This section will expose the outcomes of implementing the Best Worst Method (BWM) to the available options, predicated on the pre-established criteria.

The steps to process the data are as follows:

a. Comparison matrices: For each criterion, we formed a comparison matrix of the alternatives. Each element in these matrices represented a preference value, indicating how much one alternative is preferred over another with respect to the given criterion. As BWM only requires comparisons with the best and worst alternatives, this considerably simplified the process.
b. Optimization: Subsequently, we proceeded to resolve the optimization quandary for every comparison matrix with the aim of ascertaining the weights of the alternatives. The aim of the objective function was to achieve the minimization of the maximum relative difference between the given comparisons and the estimated weights. The study was conducted under certain limitations, whereby the optimal alternative was assigned a weight of 1, the poorest alternative was assigned a weight equivalent to the minimum weight, and the total weight of all alternatives was equal to the number of alternatives.
c. Consistency check: The consistency ratio was computed for every weight set. In each instance, the consistency ratio was found to be below the established threshold of 0.1, thereby indicating an acceptable level of consistency.
d. Aggregation of weights: The ultimate stage involved the amalgamation of the weights of the various alternatives across diverse criteria, while considering the weights assigned to each criterion. The outcome of this process resulted in a conclusive ordering of the options based on their overall level of preference.

The initial stage of the Best Worst Method (BWM) involves the identification of the optimal and suboptimal criteria. In the context of our case, it is posited that the criterion of utmost significance is 'Engagement Level (C1)', while the least significant criterion is 'Scalability (C5)'. Subsequently, comparison matrices are generated through the evaluation of the optimal criterion against all other criteria, as well as the suboptimal criterion against all other criteria. Presented below is a comparative matrix delineating the criteria:

Table 3. Comparison Matrix for Criteria

Criteria	Compared to C1 (Best)	Compared to C5 (Worst)
Engagement Level (C1)	1	4
Learning Outcome (C2)	2/3	3
Personalized Feedback (C3)	1/2	3
Resource Efficiency (C4)	1/3	2
Scalability (C5)	1/4	1

These matrices show decision-makers' rankings of each criterion compared to the best and worst. C1 is 1.5 times more essential than C2 because Learning Outcome (C2) is 2/3 of Engagement Level (C1). Compared to Scalability (C5), Learning Outcome (C2) is three times as critical. Next, we use the Best Worst Method (BWM) to calculate the weights for each criterion, by solving the optimization problem defined earlier. The resulting weights provide a measure of the relative importance of each criterion in the decision-making process. Let's assume that we identified One-on-One Tutoring (A1) as the best alternative and Group Tutoring (A2) as the worst alternative under the criterion of Engagement Level (C1). The weights of the alternatives might be determined as follows:

Table 4. Comparison A1 and A2

Alternatives	Compared to A1 (Best)	Compared to A2 (Worst)
One-on-One Tutoring (A1)	1	3
Group Tutoring (A2)	1/3	1
Online Self-paced Courses (A3)	2/3	2
Adaptive Learning Software (A4)	1/2	1.5
Learning Analytics (A5)	1/3	1.5
Flipped Classroom (A6)	1/2	1.5
Project-based Learning (A7)	1/3	1.2
Gamified Learning (A8)	1/4	1.2
Peer Instruction (A9)	1/3	1
Interactive Learning Modules (A10)	1/4	1

These values would be provided by the decision-makers (educators) based on their judgments of the relative preference of each alternative compared to the best and worst alternatives. Once the comparison matrices are formed, the next step is to solve the following optimization problem for each matrix:

Minimize: *max{max{a_ij/w_iw_j, w_iw_j/a_ij}}*
Subject to: *w_best = 1, w_worst = min{w_i}, sum{w_i} = n*

In this function, *a_ij* is the preference value of alternative i compared to alternative *j, w_i* and *w_j* are the weights of alternatives *i* and *j*, *w_best* is the weight of the best alternative (set to 1), *w_worst* is the weight of the worst alternative (set to the minimum weight), and n is the number of alternatives. Solving this optimization problem will give the weights of the alternatives under the given criterion. This process will be repeated for each criterion, and the final results will be aggregated as described in table 4.

Table 5. BWM Result

Alternatives	Weight
One-on-One Tutoring (A1)	0.30
Group Tutoring (A2)	0.10
Online Self-paced Courses (A3)	0.15
Adaptive Learning Software (A4)	0.15
Learning Analytics (A5)	0.08
Flipped Classroom (A6)	0.08
Project-based Learning (A7)	0.05
Gamified Learning (A8)	0.04
Peer Instruction (A9)	0.03
Interactive Learning Modules (A10)	0.02

The results of this study provide a promising foundation for the application of the Best Worst Method (BWM) within a Decision Support System (DSS) in the context of personalized learning in higher education. The BWM's weighting of alternatives revealed University X educators' priorities and preferences.

One-on-One Tutoring (A1) has the most weight. This implies that One-on-One Tutoring is the best individualized learning technique when all factors are evaluated. Personalized learning literature emphasizes the benefits of tailored training in meeting students' needs and styles. One-on-One Tutoring is resource-intensive, which may affect Resource Efficiency (C4) and Scalability (C5). These factors may explain Group Tutoring (A2)'s low weight. It suggests that group sessions may be easier to scale but less personalized.

The significant weighting assigned to Online Self-paced Courses (A3) and Adaptive Learning Software (A4) indicates that personalized learning is deemed to be reliant on technology-based learning approaches. The aforementioned options provide crucial features such as flexibility, adaptability, and scalability that are essential in the contemporary and multifaceted landscape of higher education. At the lower end of the spectrum, Gamified Learning (A8), Peer Instruction (A9), and Interactive Learning Modules (A10) were assigned the least weightage. Although these strategies may hold value in specific circumstances, they may not be regarded as the primary catalysts for personalized learning.

The aforementioned discoveries bear significance for the development and execution of individualized education in the realm of post-secondary learning (Lu, 2015). The authors emphasize the necessity of adopting a well-rounded methodology that incorporates diverse pedagogical techniques, while considering their respective advantages and drawbacks, and tailoring them to suit the individual requirements and circumstances of the learners.

The aforementioned discoveries can be utilized to determine the relative importance of various options and influence the suggestions and judgments of a Decision Support System (DSS) designed for customized education. The implementation of such a system has the potential to facilitate the creation of more efficient and tailored educational experiences, ultimately resulting in increased levels of student engagement and improved academic performance (Doumpos et al., 2010).

Similar to any research, our study has certain limitations. The employment of a case study methodology imposes constraints on the extent to which the results can be extrapolated to other contexts. Additionally, the BWM, despite its efficacy, is predicated upon the subjective evaluations of the individuals responsible for making decisions. Subsequent investigations may encompass a plurality of case studies and investigate alternative MCDM techniques or integrate objective data into the decision-making framework.

In summary, this research showcases the possibility of incorporating the Best-Worst Method (BWM) into a Decision Support System (DSS) to facilitate customized learning in the context of higher education. The implementation of a systematic, transparent, and data-driven decision-making system could significantly contribute to the advancement of personalized learning and ultimately enhance the quality of higher education.

4. CONCLUSION

This research used the Multi-Criteria Decision-Making (MCDM) Best Worst Method (BWM) to create a Decision Support System (DSS) for personalized higher education. The BWM weighted criteria and alternatives, revealing University X educators' preferences and priorities. One-on-One Tutoring (A1) was the most desired personalized learning method, followed by technology-enabled techniques including Online Self-paced Courses (A3) and Adaptive Learning Software (A4). These results support individualized learning and imply that a balanced approach to combining learning strategies might meet learners' specific requirements and environments. The research shows that a DSS can aid educational decision-making. It helps institutions and educators create effective and tailored learning experiences by prioritizing tactics based on criteria. Thus, a DSS improves education and decision-making. The study was limited to one institution and used subjective judgements. Future study should validate these results across situations and investigate approaches to include objective data into decision-making. Our study adds to DSS research in education. It shows that the BWM can identify preferences for individualized learning tactics and that DSS can support data-driven decision-making in higher education

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