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Research Article

The AHP-TOPSIS Integration of a Decision Support System to Analyze and Enhance Student Engagement Based on Customer Relationship Management Approach

Trias Pungkur Kusumaningrum [1]*, Andjar Hernanto [2], Danik Riawati [3]

[1] Politeknik AKBARA Surakarta, Indonesia; e-mail : pungkur.trias@gmail.com
[2] Politeknik AKBARA Surakarta, Indonesia; e-mail: andjar.hernanto76@gmail.com
[3] Politeknik AKBARA Surakarta, Indonesia; e-mail: riawatidanik81@gmail.com
* Corresponding Author : Trias Pungkur Kusumaningrum

Abstract: Student engagement has become an important issue in higher education because it is closely related to academic achievement, learning effectiveness, and student retention. In digital learning environments, institutions require a systematic and data-driven approach to evaluate student engagement and support strategic academic decision-making. However, most previous studies still focus on descriptive and predictive analysis without providing structured decision support mechanisms integrated with relationship management strategies. Therefore, this study aims to develop an integrated Decision Support System (DSS) by combining the Analytical Hierarchy Process (AHP) and Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) methods within a Customer Relationship Management (CRM) approach to analyze and enhance student engagement. The study was conducted at Politeknik AKBARA Surakarta involving 47 students as respondents. The evaluation criteria consisted of Behavioral Engagement, Emotional Engagement, Cognitive Engagement, LMS Interaction, and Academic Participation. The AHP method was applied to determine the priority weights of the criteria, while TOPSIS was used to rank and classify student engagement levels. The results showed that the proposed framework successfully classified students into high, medium, and low engagement categories objectively and systematically. The CRM approach further translated these classifications into strategic academic actions such as retention programs, engagement improvement, and intensive intervention strategies. The integration of AHP-TOPSIS and CRM provides a comprehensive framework for transforming student engagement data into actionable academic decision support, enabling institutions to implement more personalized, adaptive, and data-driven student engagement management.

Keywords: Student Engagement; Decision Support System; AHP; TOPSIS; Customer Relationship Management.

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1. Introduction

Student engagement in higher education has become a major issue because it's closely related to academic achievement, learning effectiveness, and student retention. In the digital transformation context, student engagement extends beyond classroom participation and includes interactions through Learning Management Systems (LMS), online discussions, and technology-based academic collaboration activities. This condition encourages higher education institutions to adopt data-driven approaches to monitor and enhance student engagement systematically.

Student engagement is a multidimensional term consisting of behavioral, emotional, and cognitive dimensions. Previous research shows that student engagement is influenced by teaching methods, technological infrastructure, academic interaction quality, and a supportive learning environment. The development of learning analytics allows institutions to analyze student engagement patterns through data collected from digital learning platforms. However, most existing research still focuses on descriptive and predictive analysis, which has not been able yet to systematically support strategic decision-making.

To solve these restrictions, Customer Relationship Management (CRM) has been adopted in higher education as a strategic method to managing relationship between institutions and students. CRM enables institutions to provide personalized services, enhance student satisfaction, and strengthen student retention. Additionally, CRM helps institutions identify students with low engagement levels and supports targeted intervention strategies. Nevertheless, CRM implementation in higher education remains largely administrative and has not been integrated with analytical decision-making models capable of handling multi-criteria data objectively.

Decision Support Systems (DSS) have been widely used to assist in decision-making including multiple criteria and alternatives. In education, DSS is used for student evaluation, academic performance analysis, and learning systems optimization. Among Multi-Criteria Decision Making (MCDM) method, the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) are widely used due to their ability to handle complex decision structures.

The AHP method is effective in determining the relative importance of criteria through pairwise comparison [16], while TOPSIS ranks alternatives according to their distance from the positive and negative ideal solution. The integration of AHP and TOPSIS has proven capable of improving decision-making accuracy and consistency in various domains, including higher education. However, previous research generally applied these methods without integrating CRM as part of student engagement management strategy [20], [21].

Although there has been significant progress in student engagement and DSS research, there remains a research gap in integrating CRM with multi-criteria decision-making methods to analyze and enhance student engagement. Most previous studies have only focused on analyzing student engagement using learning analytics or applying DSS without considering the relational aspects in student management. This gap indicates the need for a comprehensive framework that integrates analytical decision-making with strategic student relationship management.

Furthermore, modern learning approaches such as hyflex learning and LMS gamification have shown positive impact on student engagement in digital learning environments. Evective utilization of digital learning technologies can create a more interactive, flexible, and student-oriented learning experience. Therefore, a decision-making model capable of integrating engagement factors, learning technology, and student relationship management strategies into a single integrated framework is required.

In order to examine and improve student engagement, this research proposes an integrated model combining the AHP-TOPSIS method with a CRM approach to analyze and enhance student engagement. The research was conducted at Politeknik AKBARA Surakarta with 47 students participated. The purpose of this research is to provide a systematic and data-driven approach to identify the level of student engagement and support strategic decision-making in the higher education environment.

The main contribution of this research is to develops a CRM-based decision support system for a more objective and structured student engagement analysis. Additionally, this research integrates AHP and TOPSIS methods to handle multi-criteria decision-making, providing a ranking-based classification of student engagement levels, and bridging the gap between DSS and CRM approaches in higher education.

2. Related Work

Student Engagement

Student engagement is a fundamental concept in higher education because it is related to academic achievement, learning effectiveness, and student retention. Theoretically, student engagement consist of behavioral, emotional, and cognitive dimensions. Behavioral engagement reflects participation in academic activities, emotional engagement relates to students' affective responses to learning, while cognitive engagement represents the level of investment in understanding complex concepts.

Recent studies emphasize the role of learning analytics in identifying student engagement through digital footprints. Johar et al. demonstrate engagement data obtained from learning systems can be used to predict academic performance, while Bergdahl et al. explain the importance of integrating engagement dimensions to achieve a comprehensive understanding. However, despite the availability of extensive data on student engagement, most studies

remain descriptive and predictive, lacking a structured framework for prioritized decision-making.

Digital Learning Environment and Engagement Measurement

The rapid utilization of digital learning platforms has transformed the way student engagement is measured and analysed. Learning Management Systems (LMS) provide facilities for interaction, collaboration, and access to learning resources. Empirical findings show that the use of LMS positively affects the level of student participation and engagement.

Recent learning approaches such as hyflex learning contribute to improving flexibility and student engagement in digital learning environments. On the other hand, LMS with gamification framework can enhance student motivation and interaction more actively [24]. Furthermore, Sharma et al. explain that modern technology-based LMS creates adaptive and student-centric learning environment.

The effectiveness of LMS depends not only on system availability but also on how data are utilized for institutional decision-making. Previous research has focused on system evaluation and usage patterns rather than transforming student engagement data into actionable insights. This creates a gap between the availability of data and the decision-making capability in Educational Institutions.

Customer Relationship Management in Higher Education

In higher education, CRM is used as a strategic approach to build long-term relationships between institutions and students. CRM supports decision-making, loyalty, and student retention through personalized and data-driven services. Additionally, CRM helps institutions identify students with low engagement risk so that academic interventions can be more precisely targeted.

Despite its strategic role, the CRM implementation in higher education is still largerly operational and administrative. Most systems focus on communication and service delivery, without integrating analytical decision support mechanisms. As a result, CRM lacks the ability to process complex multi-criteria data, such as student engagement indicators, objectly and systematically.

Multi-Criteria Decision Making using AHP-TOPSIS

Decision Support System are designed to support decision-making involving complex problems with multiple criteria. Among Multi-Criteria Decision Making (MCDM) methods, AHP and TOPSIS are widely used because of their ability to systematically handle complex decision structures.

The AHP method determines criteria importance through pairwise comparison and improves decision consistency [16]. While, TOPSIS ranks alternatives according to their distance to positive and negative ideal solution. The combination of these two methods has proven effective in improving decision-making accuracy in various domains.

Previous studies by Wang et al. and Sharmin et al. demonstrated that the AHP-TOPSIS hybrid approach enhances evaluation capabilities in complex systems. Hermansyah et al. emphasized its application in ranking alternatives in educational context.

However, existing application of AHP-TOPSIS are still limited to domains such as employee selection, system evaluation, or institutional ranking. Its application for student engagement analysis, particularly when combined with CRM, remains underexplored.

State of the Art and Research Positioning

Several relevant previous studies were taken as references for this research. To better understand the overview of the conducted research, a summary of these studies is presented in Table 1.

Table 1. Relevant previous research as a reference in determining the State of the Art.

Study	Domain	Methodological Approach	Key Contribution	Critical Limitation
Shafiq et al. (2022)	Engagement/Retention	Predictive analytics	Predicts student dropout	No prescriptive decision model
Johar et al. (2023)	Engagement	Learning analytics	Identifies engagement patterns	No ranking mechanism
Bergdahl et al. (2024)	Engagement theory	Systematic review	Defines engagement dimensions	No implementation
Sanchez et al. (2024)	LMS	Comparative analysis	Evaluates LMS effectiveness	No decision framework
Shalihati et al. (2025)	CRM	Bibliometric	Maps CRM trends	No analytical integration
Akbar et al. (2025)	CRM	Literature review	Improves customer loyalty	Not engagement-oriented
Wang et al. (2022)	DSS	AHP-TOPSIS hybrid	Improves evaluation accuracy	Not applied to engagement
Hermansyah et al. (2025)	DSS	AHP-TOPSIS	Effective ranking model	Limited scope
Sharmin et al. (2025)	DSS	AHP-TOPSIS	Accurate decision-making	Context-specific
Ikhsan (2023)	CRM + DSS	TOPSIS	Integrates CRM with DSS	Not in education domain

Table 1 shows that studies on student engagement focus on analysis and prediction, without providing a structured decision-making mechanism. This method is helpful in discovering trends of student engagement but does not support ranking.

Research on LMS and digital learning shows the importance of technology in enhancing student engagement. Unfortunately, those studies do not provide an analytical model to transform engagement data into strategic decisions.

CRM-related studies emphasize relationship management and student retention but they are not integrated with quantitative decision-making methods. This can limit their ability to support data-driven strategy development.

The AHP-TOPSIS method has proven to be effective in supporting decision-making. However, its application in analysing student engagement in learning has not been widely discussed. Including how it integrates with the CRM approach.

Research Gap and Contribution

Recent studies emphasize the significance of student engagement as a critical factor in determining academic achievement and retention in higher education. Advance in learning analytics enable institutions to capture and analyze engagement data across behavioral, emotional, and cognitive dimensions. However, most existing approaches are still descriptive and predictive, focusing on identifying patterns and projecting results rather than supporting structured and actionable decision-making. At the same time, CRM implementation in higher education has improved student interactions and service quality, but its implementation remains operational and lacks analytical capabilities for processing multi-criteria engagement data.

These limitations reveal a fundamental gap in the absence of an integrated framework connecting engagement analytics, decision-making models, and strategic implementation. Therefore, this study proposes an integrated AHP-TOPSIS model within a CRM framework to transform student engagement data into structured, objective, and actionable decision support, enabling more effective and data-driven engagement management in higher education. To understand the research gaps and contributions of this study, please refer to Figure 1.

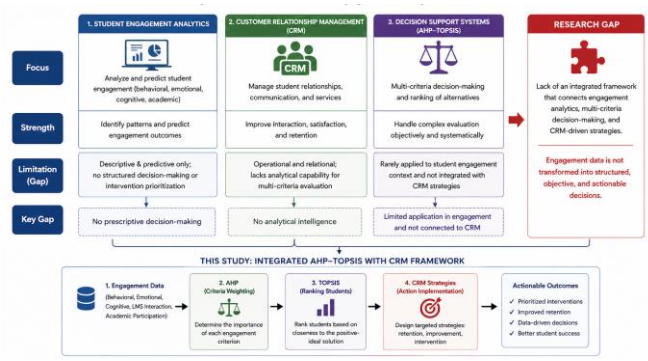


Figure 1. Research gap between learning analytics, CRM, and AHP-TOPSIS method for student engagement analysis in higher education.

3. Proposed Method

This study proposes an integrated Decision Support System (DSS) that combines the Analytical Hierarchy Process (AHP) and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) with a Customer Relationship Management (CRM) approach to evaluate and enhance student engagement. The integration of AHP and TOPSIS has been popular for its effectiveness in multi-criteria decision-making problems, while CRM provides a strategic layer for implementing data-driven decisions. Figure 2 presents the research flow framework as a diagram

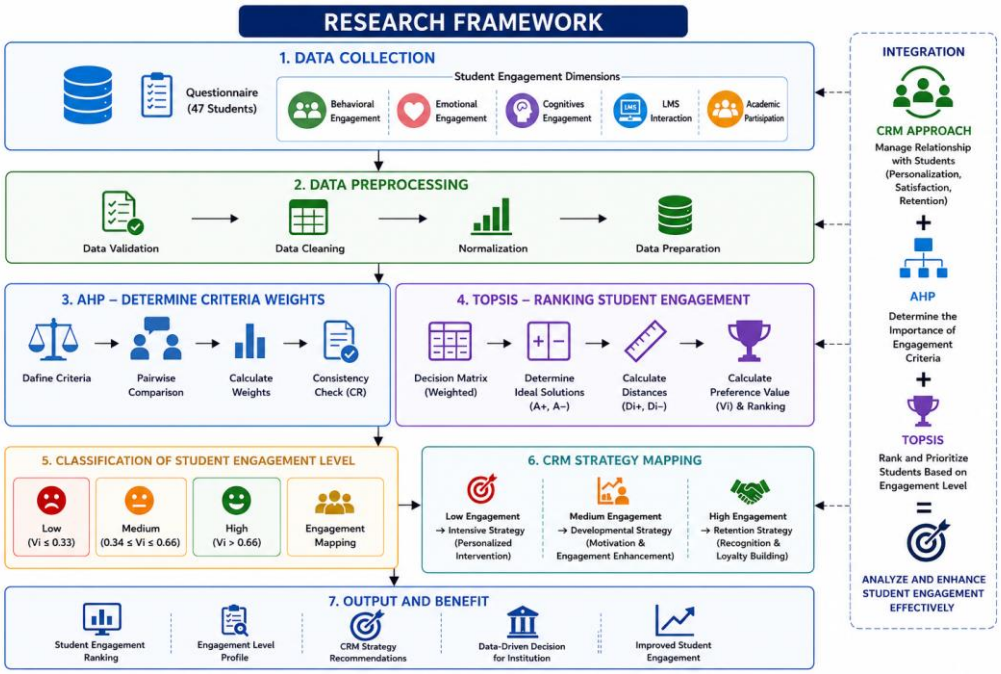


Figure 2. Research framework AHP-TOPSIS integration with CRM approach to analyzed and enhanced Student Engagement.

The research framework describes a systematic process for developing a decision support system to enhance student engagement in higher education. The first step in this study begins with the identification of the research problem which is the lack of organized decision-making processes and poor student engagement. This issue was then explored through literature review analysis three main domains: student engagement, Customer Relationship Management (CRM), and Decision Support Systems (DSS) using the AHP-TOPSIS method. Based on the latest analysis, previous studies tended to focus on these domains separately, creating a research gap due to the lack of an integrated framework connecting engagement analysis, decision-making models, and strategic implementation. This study proposes an integrated model that combines the dimensions of student engagement, AHP-TOPSIS as a decision support method, and CRM as a strategic framework. A systematic questionnaire is used to gather data from 47 students at Politeknik AKBARA Surakarta at the first step. The

collected data is then transformed into evaluation criteria consisting of behavioral engagement, emotional engagement, cognitive engagement, LMS interaction, and academic participation. The AHP method is applied to determine the weight of each criterion through pairwise comparisons and consistency testing, ensuring reliable weights. Next, the TOPSIS method is used to rank students according to how close they are to the ideal solution, generating preference scores for each student.

The ranking results are then classified into three categories: high, moderate, and low engagement. These categories are further mapped into CRM-based strategies, where highly engaged students are retained through retention strategies, moderately engaged students are supported through improvement strategies, and targeted intervention techniques for low engaged students. Finally, the results are analysed to determine the effectiveness and robustness of the proposed model. This framework provides a structured and data-driven strategy that transforms student engagement data into actionable decisions, contributing to better engagement management and institutional decision-making.

Data Collection

The primary data used in this study obtained from questionnaire responses by students of Politeknik AKBARA Surakarta. The questionnaire distributed using Google Form tools, making it easier to gather the answers. The list of incoming responses is then saved in Microsoft Excel format (*.xls) for further analysis. Several questionnaire items based on a Linkert scare from 1 (strongly disagree) to 5 (strongly agree) are used to measure each criterion.

The research dataset consisted of 47 respondents in total. The collected dataset includes demographics data and student engagement variables that were taken from relevant academic publications on student engagement and learning analytics. The criteria used in this study are shown in Table 2.

Table 2. Criteria of student engagement used in this study.

Code	Criteria	Description
C1	Behavioral	Student participation and academic behavior
C2	Emotional	Student motivation and emotional involvement
C3	Cognitive	Student learning effort and critical thinking
C4	LMS	Student interaction with LMS
C5	Academic	Student participation in academic activities

Data Preprocessing

Data preprocessing plays an important role in ensuring the reliability, consistency, and analytical validity of the proposed AHP-TOPSIS method. Because the raw questionnaire data is collected in Microsoft Excel format (*.xls) through Google Form, preprocessing is used to transform the unstructured data into a standardized decision matrix suitable for multi-criteria decision analysis. Previous research has explained that preprocessing is essential for improving data quality and reducing analytical bias in educational analytics and decision support systems. The preprocessing phase in this research consists of four processes: data cleaning, data transformation, criteria aggregation, and decision matrix construction.

Data Cleaning

Data cleaning is performed to improve the quality of the dataset by identifying and addressing incomplete responses, data duplication, or inconsistent data. In order to maintain data integrity and minimize noise in the analysis process, responses that show invalid patterns in their completion are eliminated.

Additionally, a consistent check of demographic data is conducted to validate respondents' information such as semester and study program. This process is carried out to ensure that the dataset represents the target population of respondents and to minimize the risk of biased decision-making. Data cleaning holds a crucial position because inaccurate educational data mining can affect the weighting and ranking results in multi-criteria decision-making models.

Data Transformation

After the data cleaning process, the qualitative questionnaire responses were converted into quantitative numerical values using a 5-point Likert scale. The AHP-TOPSIS method of statistical processing and mathematical computations are made possible by this conversion

The numerical conversion process standardizes respondents' perceptions into measurble engagement indicators. The same approach is widely used in the creation of engagement analysis and decision support systems in the education domain because it enables objective comparisons between alternatives.

Criteria Aggregation

Each dimension of engagement consists of several questionnaire indicators that represent similar behavioral constructs. In order to generate a representative engagement value for each student, aggregation is performed by computing the average score of all indicators within the same criteria. The aggregation process can reduce dimensional complexity and maintain the essential characteristics of each engagement dimension. The constructed criteria are presented in the table 3.

Table 3. the constructed criteria description used for to aggregation process of this study.

Criteria Code	Engagement Dimension	Questionnaire Indicator
C1	Behavioral Engagement	Class attendance consistency
		Assignment submission discipline
		Participation during learning activities
		Participation in academic discussions
C2	Emotional Engagement	Learning motivation
		Interest in course materials
		Sense of belonging to the institution
		Satisfaction with learning process
C3	Cognitive Engagement	Critical thinking during learning
		Independent learning effort
		Problem-solving capability
		Understanding of learning materials
C4	LMS Interaction	Frequency of LMS access
		Participation in online discussions
		Utilization of LMS learning resources
		Online assignment interaction
C5	Academic Participation	Participation in seminars/workshops
		Participation in collaborative learning
		Participation in campus academic programs
		Communication with lecturers

This procedure makes the AHP-TOPSIS model easier to apply and improve computational efficiency. The simplification of indicator values used in the data aggregation stage in this study was performed using equation (1).

$$C_i = \frac{\sum_{j=1}^{n} x_{ij}}{n} \quad (1)$$

Where :
C_i = aggregated value of the i criterion.
X_{ij} = value of the j indicator in the i criterion.
n = number of indicators within one criterion

Decision Matrix Construction

The primary input for the AHP-TOPSIS computation process is the decision matrix construction. Equation (2) represents the decision matrix as follows :

$$X = [x_{ij}] \quad (2)$$

Where:

X_{ij} = the engagement score of student i on criterion j.

The aggregate engagement values from all respondents across all engagement categories are included in the final matrix. In the ensuring AHP-TOPSIS stage, this matrix facilities a methodical evaluation procedure, weighting, normalization, and ranking [16], [19].

Formatting of Mathematical Components

In quantitative research, mathematical formulas serve as the core analytical foundation of the AHP-TOPSIS-based decision framework. The mathematical formulas in this study are divided into two computational steps : criteria weighting using AHP, and alternative ranking using TOPSIS. These formulations are adopted from MCDM models that have been widely applied in educational analysis and previous decision support systems [15], [16], [19] .

The formula used in this study presented in table 4.

Table 4. The formula used in this study with AHP-TOPSIS method

Step		Formula	Explain
AHP Weighting	Pairwise comparison matrix	$A = [a_{ij}]$ (3)	A = pairwise comparison matrix a_{ij} = relative importance of criterion i compared to criterion j.
	Pairwise comparison normalization	$\boldsymbol{n_{ij}} = \dfrac{\boldsymbol{a_{ij}}}{\sum_{\boldsymbol{i=1}}^{\boldsymbol{n}} \boldsymbol{a_{ij}}}$ (4)	n_{ij} = normalized comparison value
	Criteria weighting priority	$\boldsymbol{w_i} = \dfrac{\boldsymbol{1}}{\boldsymbol{n}} \sum_{\boldsymbol{j=1}}^{\boldsymbol{n}} \boldsymbol{n_{ij}}$ (5)	w_i = the weight of the priority of criterion i, n = indicates the number of criteria.
	Consistency Index (CI) & Consistancy Ration (CR)	$CI = \dfrac{\lambda_{max} - n}{n - 1}$ (6) $CR = \dfrac{CI}{RI}$ (7)	λmax = the maximum eigenvalue of the comparison matrix. RI = the random index value
	Decision matrix normalization	$r_{ij} = \dfrac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}}$ (8)	r_{ij} = the normalized value of alternative criterion i on j x_{ij} = represents the value of the original decision matrix.
	Normalized matrix weighting	$v_{ij} = w_j \cdot r_{ij}$ (9)	v_{ij} = weighted normalized value w_j = criterion weight obtained from AHP
TOPSIS alternative ranking	Ideal positive & negative solution	$A^+ = \{\max(v_{ij}) \mid j \in J\}$ (10) $A^- = \{\min(v_{ij}) \mid j \in J\}$ (11)	A+ = optimal alternative condition A- = least desirable alternative condition
	Distance value data from ideal positive & negative solution	$D_i^+ = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^+)^2}$ (12) $D_i^- = \sqrt{\sum_{j=1}^{n} (v_{ij} - A_j^-)^2}$ (13)	Di+ = distance to the positive ideal solution Di- = distance to the negative ideal solution
	Final preference value	$V_i = \dfrac{D_i^-}{D_i^- + D_i^+}$ (14)	V_i = final preference value The larger the value of V_i, the higher the level of student engagement.

Algorithm Pseudocode

The algorithm presented in this study provides an overview of the sequence of computational processes in evaluating student engagement and generating CRM-based strategy recommendations. This algorithm integrates three main analysis stages: data preprocessing, criterion weighting using AHP, and alternative ranking using TOPSIS. The application of similar algorithms has been widely used in MCDM research to enhance computational transparency

and facilitate system implementation. The computational flow of the proposed framework is presented in Algorithm 1.

Algorithm 1. AHP-TOPSIS Based on Student Engagement Evaluation

INPUT:
Student engagement dataset Respondent (*xlsx)
Criteria C = {C1, C2, C3, C4, C5}

OUTPUT:
Begin
1: Import dataset Responden.xlsx
2: Data Preprocessing :
- Remove incomplete and duplicate data
- Transform Likert responses into numerical values
- Aggregate indicators into engagement criteria
- Construct decision matrix X

3: Apply AHP weighting:
- Construct pairwise comparison matrix A
- Normalize comparison matrix
- Calculate criteria weights W
- Compute consistency ratio CR

4: Validate consistency :
if CR $\geq$ 0.1
then revise comparison matrix
else continue process

5: Apply TOPSIS ranking :
- Normalize decision matrix X
- Calculate weighted normalized matrix V
- Determine positive ideal solution A^+
- Determine negative ideal solution A^-
- Calculate separation distances
- Compute preference value V_i

6: Rank student based on V_i
7: Classify engagement level
if $V_i > 0.8$
then high engagement
else if $0.5 \leq V_i \leq 0.79$
then moderate engagement
else low engagement

8: Map engagement level into CRM strategy
- High = retention strategy
- Moderate = improvement strategy
- Low = intervention strategy

9: Generate final decision support output
End

4. Results and Discussion

Data Collected Result and Data Characteristic Analysis

This study used primary data collected through questionnaire distribution to students of AKBARA Surakarta using Google Forms. After the data cleaning process as described in the proposed method section, a total of 47 valid respondent data were obtained and used in the analysis process. The respondent data consisted of students from different study programs and semesters, enabling the dataset to represent the condition of student engagement within the digital learning environment.

The questionnaire used in this study measured five main dimensions of student engagement, namely Behavioral Engagement, Emotional Engagement, Cognitive Engagement, LMS Interaction, and Academic Participation. Each dimension was measured using several indicators based on 5 point Likert scale. This approach was selected because that Likert scale is

capable of quantitatively representing respondents' perceptions and experiences, allowing the data to pro be processed using the AHP-TOPSIS method.

Based on the preprocessing results, all data were successfully transformed into a decision matrix that was ready to be used in the weighting and ranking process. This stage is important because data quality greatly influence the final results of the decision support system, especially in Multi-Criteria Decision Making (MCDM) models that rely on data consistency and objectivity.

This study also collected demographic information from respondents. The respondents consisted of 59.6% male and 40.4% female. In term of semester level, 36% of respondents were from second semester, 48.9% from fourth semester, 12.8% from sixth semester, and 2.1% from eighth semester. Furthermore, the respondents came from several study programs, namely D3 Teknologi Bank Darah (14.9%), D4 Manajemen Penanggulangan Bencana (38.3%), D4 Bisnis Digital (46.8%).

Based on the demographic information, the respondent distribution was highly diverse. This indicates that the research dataset was able to represent student characteristics from different gender groups, semester levels, and study programs proportionally. The diversity of respondents is important in this study because the level of student engagement may be influenced by difference in academic experience, semester level, and learning environment within each study program.

Data Preprocessing

Data Cleaning

Data cleaning was conducted to obtain a consistent dataset. Several processes were performed, including removing incomplete data, eliminating duplicate records, validating the consistency of respondents' answers, and standardizing the data format into numerical values so that it could be computationally processed using the AHP-TOPSIS method.

From the data cleaning process, a total of 47 respondent record were considered valid and suitable to be used as the dataset in this study. The dataset used in this study is presented in the table 5.

Table 5. The respondent data were collected using Google Forms. R = Respondent, G = Gender, M = Male, F = Female, MPB = Manajemen Penanggulangan Bencana, BD = Bisnis Digital, TBD = Teknologi Bank Darah, BE = Behavioral Engagement, EE = Emotional Engagement, CE = Cognitive Engagement, LI = LMS Interaction, and AP = Academic Participation.

R	G	Smt	Study Program	BE 1	BE 2	BE 3	BE 4	EE 1	EE 2	EE 3	EE 4	CE 1	CE 2	CE 3	CE 4	LI 1	LI 2	LI 3	LI 4	AP 1	AP 2	AP 3	AP 4
M1	M	4	D4 MPB	5	5	4	5	4	5	4	5	5	5	5	4	4	4	5	5	4	4	4	5
M2	M	2	D4 MPB	5	5	5	4	5	5	5	5	5	5	5	5	5	3	5	4	4	3	5	4
M3	M	2	D4 MPB	5	5	4	5	5	4	3	3	5	4	4	4	3	3	3	3	5	5	5	4
M4	M	4	D4 BD	5	5	3	5	5	5	5	5	4	4	3	5	5	5	5	4	3	5	4	3
M5	M	6	D4 BD	4	4	3	4	4	4	4	4	4	4	4	4	3	4	4	2	4	4	4	3
M6	M	4	D4 BD	2	3	3	3	3	3	3	3	3	2	2	2	3	3	3	3	2	3	3	2
M7	F	2	D4 BD	4	4	4	5	4	4	5	5	5	4	5	2	3	5	4	3	4	5	5	5
M8	M	2	D4 BD	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	4	3	4	4	3	3
M9	M	4	D4 MPB	5	5	5	4	5	5	5	5	5	5	5	5	5	5	5	4	3	3	3	3	3
M10	F	6	D4 MPB	4	5	4	5	4	4	4	4	5	5	4	4	2	4	4	4	5	5	5	5

Data Transformation

Data transformation was conducted to convert qualitative questionnaire data into numerical data so that it could be processed using the AHP-TOPSIS method in the Decision Support System.

This study used a 5-point Likert scale to measure the level of student engagement. The use of Likert scale transformation has been widely applied in educational analytics and engagement evaluation studies because it allows quantitative perceptions to be converted into measurable quantitative values.The data conversion using the Likert scale is presented in the table 6.

Table 6. Likert scale for converting qualitative data to quantitative data.

Response	Score
Strongly Disagree	1
Disagree	2
Neutral	3
Agree	4
Strongly Agree	5

Criteria Aggregation

This study used multiple indicators for each established criterion. To simplify the large number of indicators within each criterion, an aggregation process was performed for each criterion. The criteria aggregation was calculated using equation (1). An example of the aggregation calculation for respondent M1 is presented as follows :

$$BE = \frac{5+5+4+5}{4} = 4.750$$

$$EE = \frac{4+5+4+5}{4} = 4.500$$

$$CE = \frac{5+5+5+4}{4} = 4.750$$

$$LI = \frac{4+4+5+5}{4} = 4.500$$

$$BE = \frac{4+4+4+5}{4} = 4.250$$

Decision Matrix Construction

The final stage in data preprocessing is the construction of decision matrix. The decision matrix was formed based on the results of the criteria aggregation calculations, as presented in the table 7.

Table 7. The result of criteria aggregation for each criterion

R	BE	EE	CE	LI	AP
M1	4,75	4,50	4,75	4,50	4,25
M2	4,75	5,00	5,00	4,25	4,00
M3	4,75	3,75	4,25	3,00	4,75
M4	4,50	5,00	4,00	4,75	3,75
M5	3,75	4,00	4,00	3,25	3,75
M6	2,75	3,00	2,25	3,00	2,50
M7	4,25	4,50	4,00	3,75	4,75
M8	4,00	4,00	4,00	3,75	3,50
M9	4,75	5,00	5,00	4,25	3,00
M10	4,50	4,00	4,50	3,50	5,00

AHP Weighting Analysis

The AHP method was used to determine the relative importance level among the dimensions of student engagement so that the decision-making process could be conducted in a more systematic and objective manner. In this study, the AHP method was applied to generate the priority weights of the criteria used, including Behavioral Engagement, Emotional Engagement, Cognitive Engagement, LMS Interaction, and Academic Participation.

Pairwise Comparison Matrix

The first stage of the AHP method is constructing the pairwise comparison matrix. This process is carried out to determine the relative importance level among criteria using the Saaty scale. The table 8 shows the Saaty scale values used in this study.

Table 8. Saaty scale used in this pairwise comparison matrix

Scale Value	Definition
1	Equal Importance
3	Moderate Importance
5	Strong Importance
7	Very Strong Importance
9	Extreme Importance
2, 4, 6, 8	Intermediate Values

The Saaty scale is used in the AHP method to determine the relative importance between criteria through pairwise comparison. A scale value of 1 indicates that two criteria have equal importance in the decision-making process. A value of 3 represents moderate importance, where one criterion is considered slightly more important than another. A value of 5 indicates strong importance, meaning that one criterion has a significantly greater influence compared to another criterion. Furthermore, a value of 7 represents very strong importance, while a value of 9 indicate extreme importance, where one criterion is considered absolutely dominant over other. Intermediate values such 2, 4, 6, and 8 are used when the decision maker's judgement falls between two adjacent levels of importance. The use of the Saaty scale enables decision makers to systematically and consistently quantify adjective judgments into numerical values for further analysis in the AHP process.

Behavioral engagement has the highest level of importance because it is considered to most directly represent student engagement through learning activities, attendance, and assignment completion. Emotional engagement and Cognitive Engagement are also considered important because they are related to students' learning motivation and their ability to understand learning materials. Meanwhile, LMS Interaction is considered a supporting factor in digital learning; therefore, it has a lower level of importance compared to the other criteria.

Based on these considerations, the pairwise comparison matrix used in this study is presented in the table 9.

Table 9. Pairwise comparison matrix among criteria.

Criterion	BE	EE	CE	LI	AP
BE	1	3	5	5	7
EE	0,33	1	3	5	5
CE	0,20	0,33	1	3	5
LI	0,20	0,20	0,33	1	3
AP	0,14	0,20	0,20	0,33	1
Total	1,88	4,73	9,53	14,33	21,00

Normalization of the Pairwise Comparison Matrix

The result of the pairwise comparison matrix were then normalized into a proportional scale to determine the priority weights of each criterion. The normalization process was carried out using calculations based on equation (4).

$$n_{11} = \frac{1}{1.88} = 0.53 \quad ; n_{21} = \frac{0.33}{1.88} = 0.18 \quad ; n_{31} = \frac{0.20}{1.88} = 0.11 \quad ; n_{41} = \frac{0.20}{1.88} = 0.11 \quad ; n_{51} = \frac{0.14}{1.88} = 0.08$$

The normalization results are presented in the table 10.

Table 10. Normalization results of the pairwise comparison matrix.

Criteria	BE	EE	CE	LI	AP
BE	0,53	0,63	0,52	0,35	0,33

EE	0,18	0,21	0,31	0,35	0,24
CE	0,11	0,07	0,10	0,21	0,24
LI	0,11	0,04	0,03	0,07	0,14
AP	0,08	0,04	0,02	0,02	0,05
Total	1	1	1	1	1

Criteria Priority Weighting

The next stage is calculating the priority weight of each criterion by computing the average value of each row in the normalized matrix. Table 11 presents the results of the criteria priority weight calculation.

Table 11. Criteria priority weighting of normalization result.

Criteria	BE	EE	CE	LI	AP	Priority weighting
BE	0,53	0,63	0,52	0,35	0,33	0,475
EE	0,18	0,21	0,31	0,35	0,24	0,258
CE	0,11	0,07	0,10	0,21	0,24	0,146
LI	0,11	0,04	0,03	0,07	0,14	0,079
AP	0,08	0,04	0,02	0,02	0,05	0,042

Consistency Index and Consistency Ratio

The final stage in the AHP method is the consistency index (CI) and consistency ratio (CR) testing. The purpose of this stage is to ensure that the pairwise comparison results are consistent and valid for use in the decision-making process. In the calculation process, the maximum eighen value obtained was 5.362. this value is considered consistent because it is close to the total number of criteria used, which is 5. Furthermore, this value was used to calculate the consistency index based on the formula (6) and consistency ratio using formula (7).

$$CI = \frac{5.362-5}{5-1} = 0.09$$

$$CR = \frac{0.09}{1.12} = 0.08$$

From the consistency ratio calculation results, a value of CR<0.1 was obtained, indicating that the constructed matrix is consistent and acceptable for further analysis in the decision-making process.

TOPSIS Ranking Result

After obtaining the criteria priority weights from the AHP process, the next step was performing alternative ranking using the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) method. This method was used to determine the level of student engagement based on the closeness of each alternative to the positive ideal solution and negative ideal solution. The decision matrix used in the TOPSIS process was derived from the aggregated criteria values obtained during the data preprocessing stage.

Calculating the Normalized Matrix

The normalization process was conducted to standardize the scale among criteria so that all criteria could be compared proportionally. This normalization calculation was performed using equation (8) based on the previously aggregated criteria data. An example of the normalization calculation is presented as follow :

$$r_{11} = \frac{x_{11}}{\sqrt{\sum_{i=1}^{47} x_{11}^2}} = \frac{4.75}{29.72} = 0.16$$

$$r_{12} = \frac{x_{12}}{\sqrt{\sum_{i=1}^{47} x_{12}^2}} = \frac{4.50}{29.16} = 0.15$$

$$r_{13} = \frac{x_{13}}{\sqrt{\sum_{i=1}^{47} x_{13}^2}} = \frac{4.75}{27.95} = 0.17$$

$$r_{14} = \frac{x_{14}}{\sqrt{\sum_{i=1}^{47} x_{14}^2}} = \frac{4.50}{26.65} = 0.17$$

$$r_{15} = \frac{x_{15}}{\sqrt{\sum_{i=1}^{47} x_{15}^2}} = \frac{4.25}{27.18} = 0.16$$

Based on these calculations, the resulting normalized aggregation matrix is presented in the table 12.

Table 12. normalized matrix of aggregated respondent data.

R	BE	EE	CE	LI	AP
M1	0,16	0,15	0,17	0,17	0,16
M2	0,16	0,17	0,18	0,16	0,15
M3	0,16	0,13	0,15	0,11	0,17
M4	0,15	0,17	0,14	0,18	0,14
M5	0,13	0,14	0,14	0,12	0,14
M6	0,09	0,10	0,08	0,11	0,09
M7	0,14	0,15	0,14	0,14	0,17
M8	0,13	0,14	0,14	0,14	0,13
M9	0,16	0,17	0,18	0,16	0,11
M10	0,15	0,14	0,16	0,13	0,18

Weighting the Normalized Matrix

The next step is weighting the normalized matrix by multiplying each normalized values of every respondent with the corresponding priority weights obtained from the AHP process. The weighting process produces a weighted normalized matrix that represents the contribution level of each criterion in determining the final TOPSIS ranking result. The corresponding priority weights obtained from the AHP process were Behavioral Engagement (0.475), Emotional Engagement (0.258), Cognitive Engagement (0.146), LMS Interaction (0.079), and Academic Participation (0.042). The weighting process was calculated using equation (9) with the calculation details presented as follow :

$$v_{11} = 0.475 \cdot 0.16 = 0.076$$

$$v_{12} = 0.258 \cdot 0.15 = 0.040$$

$$v_{13} = 0.146 \cdot 0.17 = 0.025$$

$$v_{11} = 0.079 \cdot 0.17 = 0.013$$

$$v_{11} = 0.042 \cdot 0.16 = 0.007$$

Based on the calculations, the weighted normalized matrix was obtained, as presented in table 13.

Table 13. Weighted matrix based on normalized respondent data.

R	BE	EE	CE	LI	AP
M1	0,076	0,040	0,025	0,013	0,007
M2	0,076	0,044	0,026	0,013	0,006
M3	0,076	0,033	0,022	0,009	0,007
M4	0,072	0,044	0,021	0,014	0,006
M5	0,060	0,035	0,021	0,010	0,006
M6	0,044	0,027	0,012	0,009	0,004
M7	0,068	0,040	0,021	0,011	0,007

M8	0,064	0,035	0,021	0,011	0,005
M9	0,076	0,044	0,026	0,013	0,005
M10	0,072	0,035	0,023	0,010	0,008

Determination of Positive and Negative Ideal Solutions.

The positive ideal solution (A^+) represents the best value for each criterion, while the negative ideal solution (A-) represents the worst value for each criterion. Using equation (10) and (11), the calculations are performed as follows :

Ideal positive solution :

$$A^+ = \{\max(v_{BE}) \mid j \in J\} = 0.08$$
$$A^+ = \{\max(v_{EE}) \mid j \in J\} = 0.044$$
$$A^+ = \{\max(v_{CE}) \mid j \in J\} = 0.026$$
$$A^+ = \{\max(v_{LI}) \mid j \in J\} = 0.015$$
$$A^+ = \{\max(v_{AP}) \mid j \in J\} = 0.008$$

Ideal negative solution :

$$A^- = \{\min(v_{BE}) \mid j \in J\} = 0.032$$
$$A^- = \{\min(v_{EE}) \mid j \in J\} = 0.009$$
$$A^- = \{\min(v_{CE}) \mid j \in J\} = 0.005$$
$$A^- = \{\min(v_{LI}) \mid j \in J\} = 0.003$$
$$A^- = \{\min(v_{AP}) \mid j \in J\} = 0.002$$

Measurement of Relative Separation Distance of Alternatives

The next step is calculating the separation distance of each alternative from the positive ideal solution and the negative ideal solution using equation (12) and (13). An example of the weighting calculation for each respondent based on the corresponding AHP priority weights is presented as follow :

Distance from the positive ideal solution :

$$D_1^+ = \sqrt{(0.076-0.080)^2 + (0.040-0.044)^2 + (0.025-0.026)^2 + (0.013-0.015)^2 + (0.007-0.008)^2}$$

Distance from the negative ideal solution :

$$D_1^- = \sqrt{(0.076-0.032)^2 + (0.040-0.009)^2 + (0.025-0.005)^2 + (0.013-0.003)^2 + (0.007-0.002)^2}$$

Final Preference Value Measurement

The final step of the TOPSIS method is measuring the final preference value of each alternative. The calculation was performed using equation (14). An example of the alternative preference value calculation is presented as follows :

$$V_1 = \frac{D_1^-}{D_1^- + D_1^+} = \frac{0.058}{0.058 + 0.006} = 0.901$$

The result of the calculation are presented in table 14.

Table 14. Final preference value calculation results for each respondent.

R	D+	D-	V
M1	0,006	0,058	0,901
M2	0,005	0,061	0,927
M3	0,014	0,054	0,796
M4	0,010	0,057	0,853
M5	0,023	0,042	0,646
M6	0,043	0,023	0,349
M7	0,014	0,051	0,781
M8	0,019	0,045	0,699
M9	0,006	0,061	0,917
M10	0,013	0,052	0,800

CRM-Based Student Engagement Strategy Mapping

After obtaining the final preference value from TOPSIS calculation process, the next step was mapping the student engagement levels using a Customer Relationship Management (CRM) approach. This process aims to help higher education institutions understand students' engagement levels so that they can determine appropriate strategies for student approaches, academic services, and retention improvement.

In this study, the TOPSIS ranking results were used to classify students based on their engagement levels into three main categories : high engagement, medium engagement, and low engagement.

Determination of Engagement Levels

The determination of engagement levels was carried out using the interval values of the final preference scores obtained from the TOPSIS calculation, as presented in table 15.

Table 15. The determination of engagement levels using interval values from TOPSIS calculation

Preference Value	Engagement Level
0.80 – 1.00	High Engagement
0.50 – 0.79	Medium Engagement
0.00 – 0.49	Low Engagement

The establishment of these engagement level categories was intended to simplify the institution's process of identifying student engagement conditions based on the results of the multi-criteria evaluation. Based on the preference value calculations using the TOPSIS method, the student engagement levels obtained are presented in table 16.

Table 16. The level of student engagement was determined based on the final preference value calculation results using the TOPSIS method

R	V	Level
M1	0,901	High
M2	0,927	High
M3	0,796	High
M4	0,853	High
M5	0,646	Medium
M6	0,349	Low
M7	0,781	Medium
M8	0,699	Medium
M9	0,917	High
M10	0,800	High

The results indicate that the students categorized as having high engagement demonstrated very strong academic involvement across behavioral engagement to academic participation aspect. Student in this category tended to actively participate in learning activities, possess high learning motivation, maintain consistency in academic activities, and actively use the LMS.

Meanwhile, students categorized as having medium engagement showed relatively good involvement but still required improvement in several engagement dimensions. On the other hand, students categorized as having low engagement demonstrated low levels of academic participation, which may potentially lead to decreased academic performance and lower student retention rate.

CRM Approach Based on Engagement Levels

The engagement mapping results were then used as the basic for implementing educational CRM strategies. Each engagement level has a different academic service approach according to student's needs and engagement characteristics.

Students categorized as having engagement shown strong academic participation, active in use of the Learning Management System (LMS), and active engage in learning activities. Therefore, the CRM-based strategy implemented for this category focuses on retention and

relationship strengthening, institutions can develop academic achievement recognition programs, provide rewards, offer opportunities for leadership involvement, monitoring activities, and participation in institutional academic programs. These strategies are expected to maintain student innovation and encourage sustainable academic performance.

Students with moderate engagement tend to demonstrate stable participation; however, several criteria still show variations in their level of engagement. The strategies implemented for this category focus on improvement and engagement enhancement. Institutions can provide personalized academic guidance, more interactive learning activities, collaborative learning programs, periodic academic monitoring, and motivational support through academic counseling services.

Meanwhile, students categorized having low engagement demonstrate limited participation in learning activities, low motivation, and insufficient academic interaction. This condition may negatively affect academic performance and increase the risk of student dropout. The CRM approach for this category focuses on intensive intervention and personalized support. Institutions can implement early warning system, academic counseling, personal monitoring, as well as psychological or motivational assistance programs.

Table 17 presents the CRM strategies based on students' engagement levels.

Table 17. CRM-based academic and institutional approaches according to student engagement levels determined from TOPSIS preference value classification.

Engagement Level	Student Characteristics	Recommended Institutional Actions
High Engagement	Students demonstrate strong academic participation, high learning motivation, active LMS usage, consistent assignment completion, and active involvement in learning activities.	Academic achievement recognition programs, rewards and appreciation, student leadership opportunities, academic mentoring, participation in institutional programs, and continuous engagement monitoring.
Medium Engagement	Students show relatively stable participation, but several engagement dimensions still fluctuate and require improvement.	Personalized academic guidance, interactive learning activities, collaborative learning programs, periodic academic monitoring, mentoring sessions, and motivational support through academic counseling services.
Low Engagement	Students demonstrate limited participation in learning activities, low motivation, weak academic interaction, and inconsistent LMS participation, potentially increasing dropout risk.	Early warning systems, academic counseling, personal monitoring, psychological and motivational assistance programs, remedial learning support, and intensive lecturer-student communication.

5. Comparison

The study proposes a Decision Support System framework for analyzing student engagement in higher education by integrating the AHP and TOPSIS method. Enabling more objective and accurate results. Additionally, the framework adopts a Customer Relationship Management (CRM) approach to support personalized academic service strategies based on students' engagement characteristics. As a result, the management of student engagement becomes more adaptive, individualized, and data-driven.

Previous study on student engagement have generally focuses on descriptive and predictive analysis. Shafiq et al. studied educational data mining technique to predict potential student dropout risk, while Johar et al. applied learning analytics to explore student engagement patterns. Unfortunately, these studies did not provide a structured mechanism for classifying engagement levels or formulating strategic actions based on the identified engagement categories.

Research on the topic of Customer Relationship Management in higher education mostly focuses on relationship management and student retention. Shalihati et al. mapped the research trends of CRM in higher education, while Akbar et al. analyzed the effectiveness of CRM in improving customer loyalty. However, these studies were still limited to CRM implementation from a managerial perspective and did not integrate analytical decision support mechanisms capable of processing student engagement data.

Several previous studies have combined the AHP and TOPSIS methods and demonstrated their effectiveness in improving decision-making accuracy. Research using the combination of AHP-TOPSIS methods in the various educational contexts has been conducted by Wang et al.; Hermansyah et al.; and Sharmin et al.. However, these research did not focused on student engagement management and the implementation of CRM-based academic service strategies.

Compared with previous study, this research combines multiple approaches previously applied separately by integrating the AHP-TOPSIS method within CRM-based decision support framework to analyze student engagement in a more systematic, objective, and personalized manner. The proposed model not only measures and classifies engagement levels but also translates the analytical outcomes into strategic recommendations for personalized academic services. Unlike previous studies that mainly stopped at engagement analysis or prediction, this research extends the framework toward CRM-based intervention strategies to support retention improvement and student-centered academic management. The framework developed contributes by providing a more comprehensive approach to transforming student engagement data into a strategic and data-driven academic decision-making process.

6. Conclusions

This study proposes an integrated Decision Support System framework that combines the AHP and TOPSIS methods with a Customer Relationship Management (CRM) approach to analyse and enhance student engagement in higher education. The proposed framework was developed to address the limitations of previous studies that primarily focused on descriptive and predictive engagement analysis without providing structured and actionable decision-making mechanisms.

The results demonstrate that the integration of AHP and TOPSIS successfully supports multi-criteria evaluation by determining the relative importance of engagement dimensions and ranking students based on their engagement levels objectively and systematically. The criteria used in this study include Behavioral Engagement, Emotional Engagement, Cognitive Engagement, LMS Interaction, and Academic Participation. The AHP method produced consistent priority weights, while TOPSIS effectively classified students into high, medium, and low engagement categories based on their preference values.

Furthermore, the CRM approach enabled the transformation of analytical results into strategic academic actions. Students with high engagement were directed toward retention and achievement development programs, students with moderate engagement received improvement and mentoring strategies, while students with low engagement were identified for intensive intervention and personalized academic support. This integration demonstrates that student engagement management can be implemented in a more adaptive, personalized, and data-driven manner.

The main contribution of this research lies in providing a comprehensive framework that bridges learning analytics, multi-criteria decision-making, and CRM-based academic strategies within a single integrated model. The proposed framework can assist higher education institutions in improving student engagement monitoring, supporting academic decision-making, and enhancing student retention strategies. Future research may expand this framework by integrating larger datasets, real-time LMS analytics, machine learning approaches, and broader institutional contexts to improve the scalability and predictive capabilities of the proposed system.

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References

D. A. Shafiq, M. Marjani, R. A. A. Habeeb, and D. Asirvatham, "Student Retention Using Educational Data Mining and Predictive Analytics: A Systematic Literature Review," *IEEE Access*, vol. 10, pp. 72480–72503, 2022, doi: 10.1109/ACCESS.2022.3188767.

N. A. Johar, S. N. Kew, Z. Tasir, and E. Koh, "Learning Analytics on Student Engagement to Enhance Students' Learning Performance: A Systematic Review," *Sustainability (Switzerland)*, vol. 15, no. 10, May 2023, doi: 10.3390/su15107849.

L. Sanchez, J. Penarreta, and X. Soria Poma, "Learning management systems for higher education: a brief comparison," *Discover Education*, vol. 3, no. 1, Dec. 2024, doi: 10.1007/s44217-024-00143-5.

P. D. Simon, J. Jiang, L. K. Fryer, R. B. King, and C. E. Frondozo, "An Assessment of Learning Management System Use in Higher Education: Perspectives from a Comprehensive Sample of Teachers and Students," *Technology, Knowledge and Learning*, vol. 30, no. 2, pp. 741–767, Jun. 2025, doi: 10.1007/s10758-024-09734-5.

N. Bergdahl, M. Bond, J. Sjöberg, M. Dougherty, and E. Oxley, "Unpacking student engagement in higher education learning analytics: a systematic review," *International Journal of Educational Technology in Higher Education*, vol. 21, no. 1, Dec. 2024, doi: 10.1186/s41239-024-00493-y.

F. Veiga *et al.*, "Higher education student engagement in learning activities: Clarifying concepts and introducing a short-scale," *PLoS One*, vol. 21, no. 2 February, Feb. 2026, doi: 10.1371/journal.pone.0340391.

L. Setiawan, R. Aprianto, and A. E. Mansurzade, "Management Dynamics: International Journal of Management and Digital Sciences Influence of Online Learning Platforms on Academic Performance and Student Engagement," 2025, doi: 10.70062/managementdynamics.v1i2.481.

Istijanto and C. C. Nathalie, "Factors influencing student engagement and intention to attend lectures," *Cogent Education*, vol. 11, no. 1, 2024, doi: 10.1080/2331186X.2024.2415287.

F. Shalihati, U. Sumarwan, H. Hartoyo, and L. N. Yuliati, "Mapping Customer Relationship Management Research in Higher Education: Trends and Future Directions," *Adm. Sci.*, vol. 15, no. 2, Feb. 2025, doi: 10.3390/admsci15020068.

A. S. Akbar, S. S. Iriani, and Sanaji, "A Systematic Literature Review on the Effectiveness of Customer Relationship Management in Building Customer Loyalty in the Digital Era," *JURNAL PENDIDIKAN EKONOMI*, vol. 9, no. 2, 2025, doi: 10.26740/jpeka.v9n2.p107-128.

M. N. Ikhsan, "Customer Relationship Management to Retain Customers with the Topsis Method," *Journal of Computer Scine and Information Technology*, pp. 112–118, Apr. 2023, doi: 10.35134/jcsitech.v9i2.73.

J. P. Nugraha, D. Surahmat, W. P. Astiyani, M. Tumpu, N. M. Tumanduk, and R. F. Larasati, "Decision Support System For Determining Smart Fishery Village Tourism Development Priorities Using Ahp And Topsis Methods," *Dinasti International Journal of Education Management and Social Science (DIJEMSS)*, vol. 6, no. 2, pp. 1129–1143, Dec. 2024, doi: 10.38035/dijemss.v6i2.

Vivek Sharma, N. A. Bangri, and A. Iskandar, "Decision Support System for Selection of Outstanding Students at Angkasa Maros High School Using the TOPSIS Method," *Ceddi Journal of Education*, vol. 3, no. 1, pp. 35–49, Jun. 2024, doi: 10.56134/cje.v3i1.92.

B. Đuričić and I. Medved, "Ranking Private Higher Education Institutions Based on Topsis Method," *Economic Themes*, vol. 62, no. 4, pp. 521–540, Dec. 2024, doi: 10.2478/ethemes-2024-0028.

N. Wang, Z. Ren, Z. Zhang, and J. Fu, "Evaluation and Prediction of Higher Education System Based on AHP-TOPSIS and LSTM Neural Network," *Applied Sciences (Switzerland)*, vol. 12, no. 10, May 2022, doi: 10.3390/app12104987.

M. Hermansyah, M. Mujiono, F. Fatimatuzzahra, K. Dedes, and M. F. Firdausi, "Integration of AHP and TOPSIS Methods in Decision Making Models to Identify High Achieving Students," *Journal of Informatics Development*, vol. 3, no. 2, pp. 7–19, Apr. 2025, doi: 10.30741/jid.v3i2.1547.

E. Lolang, M. Mutmainnah, H. Hafsah, I. Adhicandra, E. C. Avila, and R. Rahim, "Prioritizing Online Learning Platforms Based on Student Needs: A TOPSIS Analysis," *Journal of Applied Science, Engineering, Technology, and Education*, vol. 5, no. 1, pp. 8–14, Jun. 2023, doi: 10.35877/454RI.asci1587.

Y. A. Putri, Sumijan, and S. Enggari, "Implementation of the Topsis and AHP Methods in the Decision Support System for Determining the Best Employees," *Journal of Computer Scine and Information Technology*, pp. 60–65, Apr. 2024, doi: 10.35134/jcsitech.v10i2.103.

S. Sharmin, F. Tasnim, and S. J. Chowdhury, "Evaluating Online Learning Effectiveness Using AHP-TOPSIS: A Comprehensive Analysis of Student Feedback," in *2025 2nd International Conference on Next-Generation Computing, IoT and Machine Learning, NCIM 2025*, Institute of Electrical and Electronics Engineers Inc., 2025. doi: 10.1109/NCIM65934.2025.11159994.

M. H. Nasri, R. Hammad, and P. Irfan, "Selection of Outstanding Students Using AHP and Profile Matching," *Paradigma - Jurnal Komputer dan Informatika*, vol. 26, no. 1, pp. 38–43, Mar. 2024, doi: 10.31294/p.v26i1.3189.

A. Khoidir, F. Ama Bili, and A. K. Garside, "Prioritizing Critical Success Factors in Humanitarian Supply Chains: A Hybrid Intuitionistic Fuzzy AHP-TOPSIS Approach," *Jurnal Teknik Industri*, vol. 26, no. 2, pp. 221–238, Aug. 2025, doi: 10.22219/jtiumm.vol26.no2.221-238.

N. F. Husnaini, "Sistem Pendukung Keputusan Berbasis Web dengan Metode AHP-TOPSIS untuk Pengukuran Tingkat Kesejahteraan Masyarakat Pesisir di Kabupaten Pidie," *Computer Journal*, vol. 3, no. 1, pp. 51–60, Feb. 2025, doi: 10.58477/cj.v3i1.204.

M. M. Mahmud, J. K. L. Teh, and S. N. Azizan, "Hyflex learning and student engagement in higher education: a systematic literature review," *Front. Educ. (Lausanne).*, vol. 11, Apr. 2026, doi: 10.3389/feduc.2026.1773704.

M. M. Amin, S. N. W. Shamsuddin, and W. M. A. F. W. Hamzah, "Enhancing Engagement in Learning Management Systems using Gamification Framework," *The International journal of Multimedia & Its Applications*, vol. 16, no. 5, pp. 21–31, Oct. 2024, doi: 10.5121/ijma.2024.16502.

A. Sharma, Bharti, and A. Pandey, "Unleashing the Potential of Technology-Driven Learning Management Systems for Student-Centric Excellence to Empower Higher Education," *Engineering Proceedings*, vol. 59, no. 1, 2023, doi: 10.3390/engproc2023059195.