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Utilizing Machine Learning-Based Decision-Making to Align Higher Education Curriculum with Industry Requirements

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Abstract: The accelerating pace of industrial transformation necessitates a strategic reconfiguration of higher education curriculum to ensure alignment with dynamic labour market demands. This study introduces a hybrid decision-making framework that integrates Machine Learning with Multi-Criteria Decision Making techniques to evaluate and classify the readiness and relevance of academic programs. The methodological core includes the Step-wise Weight Assessment Ratio Analysis, Linguistic q-Rung Orthopair Fuzzy Numbers, and the Multi-Attributive Border Approximation Area Comparison method for criteria weighting, coupled with a classification model based on Support Vector Machine optimized using the Salp Swarm Optimization algorithm. The results demonstrate the framework's efficacy in identifying curriculum gaps and recommending adaptive enhancements, especially for programs categorized as "*Needs Improvement*" Beyond classification, the system facilitates strategic curriculum planning, fosters pedagogical innovation, and promotes industry-responsive learning pathways. This study highlights the transformative potential of machine learning in higher education, equipping students with the skills required to navigate an increasingly dynamic professional landscape, while offering actionable insights into instructional redesign, competency-based delivery, and industry-informed pedagogy. Future research will explore longitudinal impact assessment and broader stakeholder integration to enhance the framework's scalability and contextual adaptability.

Index Terms: Curriculum evaluation, machine learning, Lq-ROFNs, MCDM, SVM, SSO, higher education planning.

1. Introduction

The use of artificial intelligence in higher education institutions offers many benefits, including facilitating collaborative learning, improving safety, and supporting research [1, 2]. The application of Machine Learning (ML) technology in education includes personalized learning, predictive analytics, and automated evaluation systems [3]. Studies show that machine learning-based intelligent tutoring systems can adapt teaching to individual learning styles and needs [4]. Machine learning capabilities in big data allow for identifying success indicators supporting curriculum design and instructional strategies [5]. Predictive algorithms such as neural networks and support vector machines have effectively predicted academic outcomes, helping educators make better decisions [6]. For instance, research by Onyema et al. (2022) [7] stated that the KNN and Random Forest can accurately predict student performance. Analysis of data histories uncovering the determinants of academic success to support decision-making in curriculum design [8, 9].

Integrating machine learning in education management allows institutions to adapt to student needs and industry demands. Collaboration with industry in curriculum development can increase educational relevance [10]. Moreover, Holmes et al. (2022) [11] emphasized the need for a machine learning-based framework to address differences in the interpretation of ethical principles in the field of education, supporting adaptation to technological developments [12]. Machine learning technology also allows for the analysis of industry trends and skills needs to align educational programs [13]. By incorporating job market data and new technologies, institutions can design a curriculum that suits the needs of the dynamic world of work [14]. As Nauman et al. noted, integrating machine learning into curriculum development can result in adaptive programs ready to face future challenges. The machine learning-based Multi-Criteria Decision Making (MCDM) approach is proven to improve the effectiveness of curriculum alignment. Research by Cui et al. (2023) [15] also shows that combining MCDM techniques and machine learning models allows for a more holistic evaluation by considering the views of diverse stakeholders. This application requires strong analytical skills and a data-driven decision-making culture within educational institutions [16].

Machine learning-based decision-making frameworks can improve personalization and adaptability in learning, ensuring students receive learning experiences tailored to their needs [17, 18]. This improves student engagement, retention, and alignment of skills with industry requirements [19, 20]. However, its implementation requires special attention to ethical and technical challenges, such as fair use of algorithms and accurate interpretation of models [21]. In line with that, S. AL-Malaise AL-Ghamdi et al. (2022) [22] affirmed the importance of collaboration between researchers, industry, and education experts in developing a transparent framework that prioritizes the needs of students, employers, and society. Research by Hassan et al. (2023) [23] also highlights the importance of bridging the gap between the skills that the industry needs and those taught at universities. Below is a list of the main objectives of this study:

- Identifying and determining the weighting of criteria used to measure the alignment of the curriculum with industry needs is carried out through the collection of literature reviews and interviews with interested parties using the Step-Wise Weight Assessment Ratio Analysis (SWARA) method.
- Grouping the curriculum based on the level of curriculum alignment using the Linguistic q-Rung Orthopair Fuzzy Numbers (Lq-ROFNs) and Multi-Attributive Border Approximation Area Comparison (MABAC).
- Build a model to get curriculum user feedback that supports machine learning-based personalised learning experiences using hybrid Salp Swarm Optimization (SSO) and Support Vector Machine (SVM).

The alignment between the curriculum of higher education and the demands of the industrial world has become an important topic in academic research. Related literature is key in bridging the gap between theory and practical applications, providing insights into the challenges and best practices in leveraging technologies such as machine learning for responsive curriculum development [24]. Garousi (2020) [25] investigated the gap between software engineering education and industry needs, highlighting the importance of work-based learning as well as close collaboration between universities and industry sectors to reduce skills gaps. In a broader context, Sukackė et al. (2022) [26] emphasise the need for higher education institutions to adopt adaptive approaches that can respond to the demands of dynamic industries. This effort involves the development of a competency-based curriculum model strategically designed to meet the needs of the labour market [27]. Favaretto et al. (2023) [28] demonstrated that technologies such as big data analytics can be leveraged to strengthen collaboration between academia and industry [28], creating a learning environment that is more responsive to market changes.

Research by Heriyadi (2023) [29] explored important competencies in the mining sector and aligned them with industry needs through the Delphi techniques, underlining the importance of empirical data in curriculum reconstruction. This approach is supported by Bermejo et al. (2021) [30], who discussed the importance of university-industry collaboration in curriculum design and stated that such partnerships are essential to drive innovation and meet industry demands. Furthermore, research conducted by Oke and Fernandes (2020) [31] provided insight into pedagogical innovation in the context of the Industrial Revolution 4.0. Despite these contributions, gaps still exist in the literature regarding the practical implementation of this framework in various educational contexts. For instance, despite the suggestion of industry collaboration in certain research, the precise mechanisms and efficacy of such partnerships across various regions and disciplines are still unexplored. In addition, as discussed by Pereira (2024) [32], the role of technology in facilitating curriculum alignment demonstrated the need for further research on how technological advances can be integrated into curriculum development.

Data-based decision-making systems have significant advantages over traditional curriculum design and alignment methods. These findings are reinforced by Marsudi (2023) [33], which highlights the importance of understanding industry needs in the development of adaptive curriculum that include cross-sector collaboration and the application of innovative technologies. Such a data-driven approach allows for the creation of educational programs that are more relevant to the global job market. A commitment to continuous improvement is key to developing a competitive and adaptive curriculum [34]. As Tuğrul and Çitil (2021) [35] applied the MCDM as a structured approach to evaluate and prioritise curriculum components based on various criteria, such as industry relevance and student learning outcomes. This approach accommodates uncertainty and reduces subjectivity in the curriculum evaluation process. In a systematic literature review, Yüksel et al. (2023) [36] highlighted the importance of MCDM techniques in decision-making in higher education institutions. Previous research findings confirm that these techniques can help improve the quality of education by supporting more objective and data-driven decisions. Although previous studies have provided valuable insights, there are still gaps in the literature regarding the specific application of machine learning in supporting the decision-making process for aligning curriculum with industry needs. Some previous studies have tended to under-explore the potential of machine learning in informing curriculum development and adapting it to changes in the labour market [37].

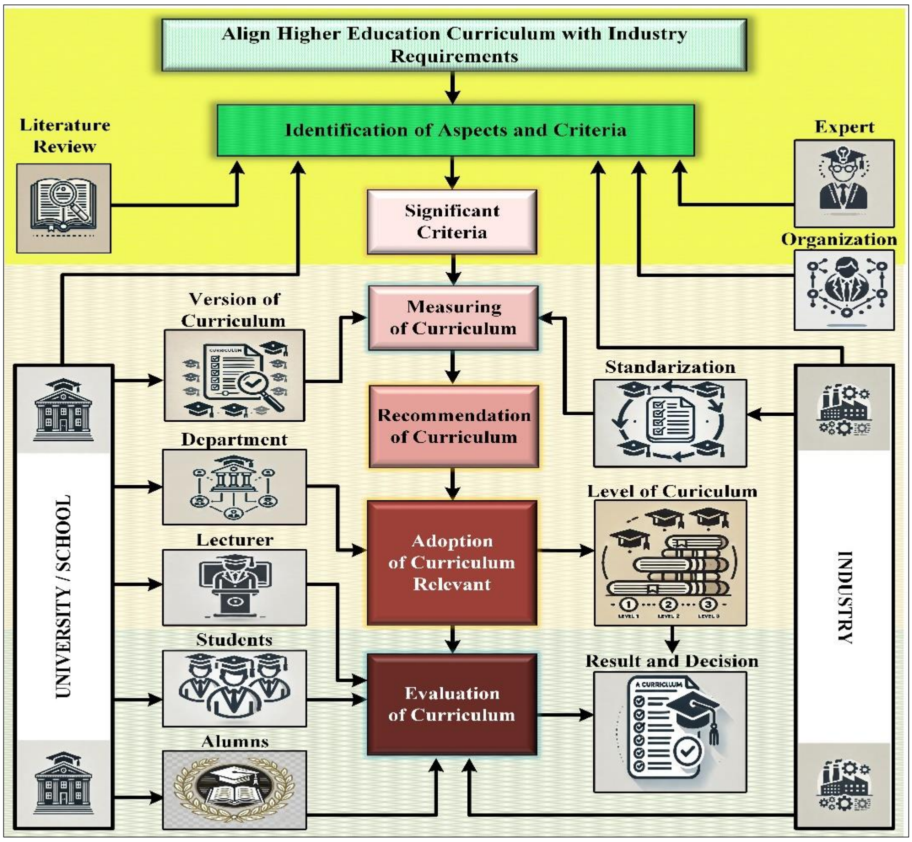


Fig. 1. Proposed framework

This study presents a framework for developing an innovative, relevant, and future-ready curriculum. The process begins with identifying key aspects and criteria through literature reviews and input from experts and relevant organizations. These criteria form the foundation for evaluating the existing curriculum and generating new or revised recommendations. Components such as curriculum versions, departments, faculty, students, and alumns play crucial roles in providing feedback on curriculum effectiveness. Simultaneously, industry stakeholders contribute through standardization efforts and by defining curriculum levels that meet workforce demands. The process concludes with adopting relevant curriculum and continuous evaluation to ensure compliance with standards and the production of competent graduates. The synergy between academia and industry is essential, with alumns serving as intermediaries who provide real-world insights into labour market needs, as illustrated in Figure 1.

Addressing this gap significantly contributes to advancing a more adaptive, technology-driven education model. This research supports the development of a curriculum model aimed at empowering education administrators to design frameworks that are both adaptive and responsive to the rapidly evolving demands and characteristics of modern industry.

2 Methodology

2.1. Data Collection

This study utilizes various sources, including academic data, student data, graduate data, universities/schools, and academic research. Additionally, it incorporates organizations that are organised around scientific fields. The following are some of the methods employed to collect data in particular:

- *Industry Data Collection.*

Surveys and Interviews: Direct feedback from industry professionals and recruiters to gather qualitative insights. This study collected feedback data from 17 participating industries, selected based on their relevance to the curriculum's focus areas and their active engagement in workforce development. The feedback, used as a basis for the scoring process, was centred on assessing curriculum relevance, graduate competencies, and industry alignment. The industry data is presented in Table 1 below.

Table 1. Industry participants and their roles in curriculum evaluation

No	Industry Name	Sector	Role in Feedback Process
1	PT. Berkarya Indo Celebes	Technology	Evaluated digital literacy, startup innovation, and software development integration
2	PT. Suraco Jaya Abadi	Automotive	Assessed alignment between curriculum and practical automotive engineering applications
3	PT. RAW Makassar	Expedition	Evaluated logistics, digital tracking systems, and graduate readiness for operational roles
4	PT. Pertamina	Energy	Provided input on safety protocols, energy sustainability, and industry-aligned competencies
5	PT. Quadra Dinamika Internasional	Consumer Goods	Reviewed marketing, branding, and product innovation elements within the curriculum
6	PT. Indofood Sukses Makmur	Food Industry	Evaluated curriculum relevance to food safety, quality control, and industrial standards
7	PT. Moladin Finance Indonesia	Financial Services	Provided insights on financial literacy, data analysis, and business process integration
8	PT. Delima Utama	Utilities	Assessed energy management
9	Padaidi Medical Center	Pharmaceuticals	Reviewed curriculum coverage of medical knowledge, diagnostics, and pharmaceutical ethics
10	PT. Angkasa Pura	Aviation	Provided feedback on aviation service management and logistics
11	PT. Kharisma Sentosa	E-commerce	Assessed the curriculum's relevance to online business, digital marketing, and UI/UX design
12	PT. Kalla Group	Construction	Reviewed competencies in project planning, structural design, and sustainable construction
13	PT. Bosowa Group	Mining	Evaluated curriculum against safety standards, mining operations, and environmental impact
14	IMedical Specialist Centre	Biotechnology	Assessed integration of biotech innovations, lab research skills, and health technology
15	PT. Pelindo IV	Transportation	Provided input on port logistics, transportation systems, and intermodal coordination
16	PT. Sistemindo Megarezst Utama	Software House	Evaluated software engineering practices, agile development, and system architecture content
17	PT. Karya Sindo Papua	Manufacturing	Assessed manufacturing processes, mechanical design, and industrial automation relevance

- *Academic Data Collection.*

Qualitative Methods: Conducting interviews or focus groups with educators and curriculum designers.

- *Student Data Collection.*

Surveys: Collecting students' perspectives on curriculum relevance.

Academic Records: Analyzing course enrollments, grades, and outcomes from learning management systems.

- *Feedback Collection.*

Alumns Tracking: Using tracer alumns insights to trace graduates' career trajectories.
Employer Surveys: Gathering hiring feedback from organizations to evaluate curriculum effectiveness.
Outcome Metrics: Analyzing placement rates, salary data, and skill alignment.

2.2. Finding of Aspects and Criteria

Aspects and criteria are systematically derived through a rigorous methodological approach [38], integrating expert interviews with comprehensive literature reviews to ensure the robustness and contextual relevance of the findings. The expert interviews provide practical insights and contextual nuance, while the literature reviews undertake a critical evaluation of prior research to identify key aspects and measurable criteria. This integrative approach facilitates cross-validation, culminating in the formulation of a structured and actionable framework for aspects and criteria. The detailed list, including aspects, criteria, and subcriteria, is presented in Table 2 below.

Table 2. List of aspects, criteria, and subcriteria

No	Aspect	Criteria	Subcriteria
1	Stakeholder Engagement [39, 40].	Industry Collaboration (IC).	1) Fully active partnerships 2) Frequent collaboration 3) Limited partnerships with occasional input 4) Minimal collaboration
		Feedback Mechanisms (FM).	1) Real-time feedback integration 2) Structured, regular feedback 3) Occasional, informal feedback 4) Feedback absent
2	Curriculum Relevance [41, 42].	Alignment with Industry Standards (AIS).	1) Fully aligned and regularly updated 2) Mostly aligned with standards 3) Partial alignment with limited updates 4) No alignment
		Interdisciplinary Approach (IA).	1) Fully interdisciplinary 2) Significant inclusion 3) Limited interdisciplinary elements 4) There is no interdisciplinary content
3	Skill Development [43, 44].	Soft Skills and Technical Skills (STS).	1) Fully integrated 2) Comprehensive skill balance 3) Partial balance between skills 4) Focus on only one skill type
		Work-Based Learning Opportunities (WLO).	1) Fully embedded 2) Structured, frequent opportunities 3) Limited or unstructured opportunities 4) No practical opportunities
4	Assessment Mechanisms [45].	Competency-Based Assessment (CBA).	1) Fully integrated 2) Mostly competency-based 3) Partial integration 4) No competency-based assessments
		Continuous Improvement (CI).	1) Real-time updates based on feedback 2) Regular updates 3) Infrequent updates 4) No updates to assessments
5	Innovation and Technology Integration [46, 47].	Adoption of Emerging Technologies (AET).	1) Fully integrated 2) Broad adoption 3) Limited adoption 4) No adoption of technologies
		Sustainability and Ethical Considerations (SEC).	1) Fully embedded 2) Mostly integrated 3) Limited inclusion 4) No consideration
6	Market Responsiveness [48].	Labour Market Analysis (LMA).	1) Real-time analysis 2) Regular analysis 3) Infrequent or limited analysis 4) No labour market analysis
		Flexible Curriculum Design (FCD).	1) Fully adaptable 2) Mostly flexible 3) Partially flexible 4) Rigid curriculum

2.3. MDCM Using Approach Hybrid SWARA, Lq-ROFNs, and MABAC

The MCDM used to solve complex real-life problems is finding the most suitable alternative based on various tangible or intangible criteria [49]. However, the traditional MCDM method, based on precise numerical values, is insufficient when considering inadequate information about the system, complex environment, and real-world conditions. Identification and assessment of decision-making using classical methods have various weaknesses, such as uncertainty in data, failure to give weight to criteria, to inconsistency with the use of predetermined data and tables [50].

The application of MCDM in this study was carried out by involving a hybrid method of SWARA, Lq- ROFNs, and MABAC methods to solve the weaknesses found. The stages are as follows:

Step 1: Assessments for each criterion by an expert to get the initial aggregate value ($\bar{t}_j$), which is expressed using:

$$\bar{t}_j = \frac{\sum_{k=1}^{r} t_{jk}}{r} \tag{1}$$

Step 2: Find the comparative (S_j) and value of the coefficient (K_j), which be expressed using:

$$k_j = \begin{cases} 1 & j=1 \\ S_j + 1 & j>1 \end{cases} \tag{2}$$

Step 3: Determine the criteria's weight again (q_j), which can be expressed using:

$$q_j = \begin{cases} 1 & j=1 \\ \frac{k_j - 1}{k_j} & j>1 \end{cases} \tag{3}$$

Step 4: Determine the weight of criteria (w_j) that can be expressed using:

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{4}$$

Next, the expert evaluations be aggregated based on the initial weights from the SWARA, and be expressed using:

$$Lq\_ROFN_{aggregated} = \sum (w_i - Lq\_ROFN_i) \tag{5}$$

For each criterion, multiply the fuzzy evaluation by its SWARA-derived weight. This gives us a refined fuzzy number for each criterion, accounting for importance and uncertainty.

Step 5: After assigning weights to each sub-criteria, the next stage is to defuzzify the aggregated Lq-ROFNs using a score function [51], which can be expressed using:

$$Lq\_ROFN_i = (\mu_i - v_i) \tag{6}$$

Step 6: Determine aggregation linguistic evaluations with different importance levels, be expressed using:

$$Final\_Weight_i = \alpha \times SWARA_i + (1 - \alpha) \times Lq\_ROFN_i \tag{7}$$

After incorporating subjective expert judgments and fuzzy logic evaluations, the $Final\_Weight_i$ reflects the importance or relevance of the criterion. The coefficient value (α) is a scaling coefficient (between 0 and 1) that controls how much influence each method has on the final weight. The $SWARA_i$ is the weight of the i-th criterion calculated using the SWARA method. Then, the function of (1 – α) reflects the complementary portion of the weight given to the Lq-ROFNs method. When α is small, (1 – α) becomes large, giving more weight to the Lq-ROFNs based evaluations. The $Lq\_ROFN\_Weight_i$ is the weight of the i-th criterion derived from the Lq-ROFNs method.

Step 7: Following the assignment of the weighted average for the alternative, the subsequent step is to format matrix (X) that categorises alternatives based on criteria [52] in the form of vectors $A_i = (x_{i1}, x_{i2}, \ldots, x_{in})$ where x_{ij} Is the value of the "I -th" alternative according to the "j -th" criterion ($i = 1,2,\ldots,m$; $j = 1,2,\ldots,n$), can be expressed using:

$$X = \begin{array}{c} \\ A_1 \\ A_2 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{cccc} C_1 & C_2 & \cdots & C_n \end{array} \\ \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{8}$$

Step 8: Normalisation of the elements from the initial matrix be expressed using:

$$N = \begin{array}{c|cccc} & C_1 & C_2 & \dots & C_n \\ \hline A_1 & t_{11} & t_{12} & \dots & t_{1n} \\ A_2 & t_{21} & t_{22} & \dots & t_{2n} \\ \dots & \dots & \dots & \dots & \dots \\ A_m & t_{m1} & t_{m2} & \dots & t_{mn} \end{array} \tag{9}$$

Step 9: The elements of the normalised matrix (N) can be articulated using:

$$\text{Cost: } t_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-}, \text{ Benefit: } t_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \tag{10}$$

Step 10: Calculate the elements from the weighted matrix (V), which can be expressed using:

$$v_{ij} = fw_i t_{ij} \tag{11}$$

where t_{ij} are the elements of the normalised matrix (N), fw_i, is the weight coefficients of the aspects and criteria.
Step 11: The calculation of the border approximation area "G" for each criterion can be expressed using:

$$g_i = \left(\prod_{j=1}^{m} v_{ij}\right)^{1/m} \tag{12}$$

Step 12: The calculation of the distance of the alternative from the boundary approximation region for the matrix elements (Q) can be expressed using:

$$Q = V - G \tag{13}$$

Step 13: Determine the curriculum into 3 levels of readiness, which can be expressed using:

$$Highly\ Recommended = S_i > k \tag{14}$$

All stages in the MCDM process produce outputs used as inputs for the classification process.

2.4. Machine Learning-Based Prediction Using Hybrid SVM - SSO

Hybrid SVM and SSO present a robust approach to improve classification, predictive modelling and optimisation tasks. As Zhang [53] noted, SSO is effective in global optimisation tasks, which can be leveraged to improve SVM performance in high-dimensional feature spaces. Yildiz and Erdaş also describe the application of hybrid optimisation techniques in engineering problems [54], emphasising the importance of robust design and optimisation in practical scenarios. SSO's ability to exit the local optima can result in improved feature selection and parameter customisation, thereby improving the overall performance of the SVM model.

SSO is a relatively recent meta-heuristic optimisation algorithm inspired by the foraging behaviour of salps, a type of marine organism [55]. The fundamental mechanism of SSO is based on the collective behaviour of salps, which form long chains while swimming through the ocean, thereby optimising their food search [56]. The basic mathematical representation of the SSO involves updating the position of each salp in the solution space based on its current position. Position updates on SSO are performed using:

$$y_j^{t+1} = \begin{cases} F_j + w_1\left(\left(ub_j - lb_j\right)w_2 + lb_j\right), & w_3 \geq 0.5 \\ F_j - w_1\left(\left(ub_j - lb_j\right)w_2 + lb_j\right), & w_3 < 0.5 \end{cases} \tag{15}$$

y_j^{t+1} and F_j Respectively, the coordinates of the initial salp position and the sustenance source's location in the j-th dimension are denoted. The upper and lower bounds are denoted by ub_j and lb_j, accordingly. Within the interval [0, 1], the two scales w_2 and w_3 are generated at random. Parameter w_1 is employed to ensure consistency during the exploitation and exploration process, as well as to serve as a critical point parameter that can be expressed using:

$$w_1 = 2e^{-\left(\frac{4t}{T}\right)^2} \tag{16}$$

A maximal number of iterations is represented by "T", and the current iteration is denoted as "t". Eq. 15 is then exclusively concerned with updating the dominant salp's position, as previously mentioned. The position update is determined concerning the follower salps using:

$$y_{j,i}^{t+1} = \frac{1}{2}\left(y_{j,i}^{t} + y_{j,i-1}^{t}\right) \tag{17}$$

$y_{j,i}^{t}$ Is the location of the i-th follower in the j-th dimension, $y_{j,i-1}^{t}$ is the location of the i-th leader in the j-th dimension. -1 follower in the j-th dimension using:

$$y_{j,i} = \frac{1}{2} a \times time^2 + u_0 \times time \tag{18}$$

$y_{j,i}$ Is the location of the i-th follower in the j-th dimension, variable $time$ denotes the time per iteration, u_0 is the initial speed, and "a" is calculated using:

$$a = \frac{u_{final}}{u_0} \tag{19}$$

Initial velocity is denoted by u_0, while the final velocity is denoted by u_{final}. Salp. Salps followers are required to replicate the leader's actions until the maximum number of iterations is attained, while the leader's salp is updated following the availability of food sources. During the iteration, the exploitative phase of the algorithm replaces the investigation phase, which is characterised by a downward trend in the w_1.

SVM classification methods are used in various applications to maximise margins between two sample classes to obtain optimal hyperplane values [57]. Continuing the stages that have been worked on in SSO, the role of the SVM method is to produce optimal values, where the stages consist of:

- Each salp represents a potential solution $[C, \gamma]$ in the search space using:

$$f(C, \gamma) = 1 - \text{Cross} - \text{Validation Accuracy} \tag{20}$$

- SSO iteratively improves $[C, \gamma]$ by minimising $f(C, \gamma)$.
  Using the optimal C, γ from SSO as the best $[C, \gamma]$ is passed to the SVM for training, which is these parameters influence the decision function of the kernel $(\alpha_i, K(x_i, x), b)$.
- Trained SVM decision function can be expressed using:

$$\hat{y} = sign\left(\sum_{i=1}^{n} \alpha_i \, y_i exp(-\gamma \parallel x_i - x \parallel^2) + b \right) \tag{21}$$

  The final SVM decision function uses:
  Optimal α_i: Computed using the optimal C.
  Optimal kernel function: Using the optimal γ.
- Calculate the stakeholder score to determine the result of the evaluation which can be expressed using:

$$S_i = \sum_{j=1}^{n} w_j * S_{ij} \tag{22}$$

  where, S_i is the stakeholder evaluation score, w_j is the weight of criteria, S_{ij} is stakeholder score against the criteria, and the number of criteria written "n".

SWARA, Lq-ROFNs, MABAC, SSO, and SVM methods establish a resilient and adaptive model that guarantees consistent performance in various educational settings.

3. Result and Discussion

3.1. MCDM Technique for Measuring Relevant Curriculum

In order to implement MCDM, the initial step is to ascertain the weight of each criterion using the SWARA method. The data is presented in Table 3 below.

Table 3. List of the initial weights of criteria

No	Aspect	Criteria	Initial Weight
1	Stakeholder Engagement	IC	0.0149
		FM	0.0422
2	Curriculum Relevance	AIS	0.0831
		IA	0.1255
3	Skill Development	STS	0.1540
		WLO	0.1589
4	Assessment Mechanisms	CBA	0.1415
		CI	0.1108
5	Innovation and Technology Integration	AET	0.0774
		SEC	0.0489
6	Market Responsiveness	LMA	0.0281
		FCD	0.0149

To refine these subjective weights and account for uncertainty and linguistic assessments, the company uses Lq-ROFNs. Each criterion is now evaluated by a panel of experts using linguistic terms, namely Very Agree (VA), Agree (A), Moderate (M), Disagree (D), and Very Disagree (VD). The following Lq-ROFNs are assigned to these linguistic terms in Table 4 below.

Table 4. Linguistic terms for evaluation

Linguistic Terms	Membership	Non-membership
Very Agree (VA)	0.9	0.05
Agree (A)	0.7	0.2
Moderate (M)	0.5	0.4
Disagree (D)	0.3	0.6
Very Disagree (VD)	0.3	0.85

Based on linguistic terms in Table 4, all experts evaluate the criteria as seen in Table 5 below.

Table 5. List of the final weights of criteria

No	Criteria	Membership (u)	Non-Membership (v)	Aggregation Value	Final Weight
1	IC	0.5038	0.4962	0.0075	0.0145
2	FM	1.4237	-0.4237	1.8473	0.1324
3	AIS	2.8042	-1.8042	4.6084	0.3093
4	IA	4.2389	-3.2389	7.4778	0.4931
5	STS	5.1986	-4.1986	9.3973	0.6161
6	WLO	5.3637	-4.3637	9.7273	0.6372
7	CBA	4.7759	-3.7759	8.5517	0.5619
8	CI	3.7401	-2.7401	6.4803	0.4292
9	AET	2.6141	-1.6141	4.2282	0.2849
10	SEC	1.6497	-0.6497	2.2993	0.1613
11	LMA	0.9489	0.0511	0.8978	0.0715
12	FCD	0.5015	0.4985	0.0029	0.0142

Table 5 shows the evaluation results, aggregation and decision weights for each criterion, as in the calculation process of the Lq-ROFNs method, the coefficient value (α) is set at 0.95. An example of weight calculation using SWARA and Lq-ROFNs is given as follows:

$$\text{FinalWeighti} = \alpha \times SWARA\_Weight_i + (1 - \alpha) \times LqROFN_i.$$
$$\text{FinalWeight}_{C1} = 0.95 * 0.0149 + (1 - 0.95) * 0.0075 = 0.0145.$$

In large-scale MCDM problems with many competing criteria, purely subjective methods may struggle to capture all the nuances of the problem [58]. The hybrid SWARA and Lq-ROFNs methods can scale effectively to handle more complex decision-making scenarios by incorporating qualitative and quantitative aspects. This study involved 10 curriculum as sample data collection areas for industry and university as representative respondents. Data is distributed through online questionnaires to make it easier for respondents to give answers faster. The type of curriculum is shown in Table 6 below.

Table 6. List of the curriculum

No	Curriculum	Characteristic
1	Competency-Based Curriculum (CBC) [59, 60].	• Focus on developing technical and soft competencies relevant to the world of work. • Based on specific "learning outcomes". • The curriculum is often designed in collaboration with industry players.
2	Dual Education System Curriculum (DESC) [61, 62].	• A combination of theory at the university and practice in the company (industry-based internships). • Students work in parallel in industry while attending lectures. • Strong in practical skills development and application of the latest technologies. • The industrial sector contributes greatly to curriculum planning.
3	Outcome-Based Education Curriculum (OBEC) [63, 64].	• Emphasis on desired learning outcomes in accordance with industry standards. • Have project-based assessments, capstone projects, and collaboration with companies. • Applied to many engineering and management programs.
4	Cooperative Education Curriculum (CEC) [65, 66].	• Students alternate between academic studies and work experience in industry. • This curriculum provides students with real-world experience from college.
5	Technology-Based Curriculum (TBC) [67, 68].	• Focus on advanced technologies such as AI, IoT, and robotics. • Close collaboration between universities, research centers, and technology companies.

6	Skills-Based Curriculum (SBC) [69, 70].	• Focus on developing communication, data analysis, and problem-solving skills. • The educational program includes on-the-job training, project-based learning, and additional certifications.
7	Merdeka Belajar Curriculum (MBC) [58, 71].	• Providing opportunities for students to participate in independent learning programs such as industrial internships, entrepreneurship projects, or independent off-campus study. • Improving industry engagement and graduate employability.
8	Polytechnic Education Curriculum (PEC) [72, 73].	• Offers advanced vocational education specifically designed for industry needs. • Project-based curriculum and partnerships with companies.
9	Problem-Based Learning Curriculum (PBLC) [74, 75].	• Based on learning through real problems in the industry. • Students work collaboratively to solve problems, such as real-world work simulations.
10	Industrial Placement Curriculum (IPC) [76, 77].	• Providing hands-on experience in the industry through internships and apprenticeships. • Internship programs are a mandatory part of the university curriculum.

Based on feedback data from respondents, the MABAC method was applied to determine the division of matrix areas for each curriculum object. The assessment results are collected, as shown in Figure 2.

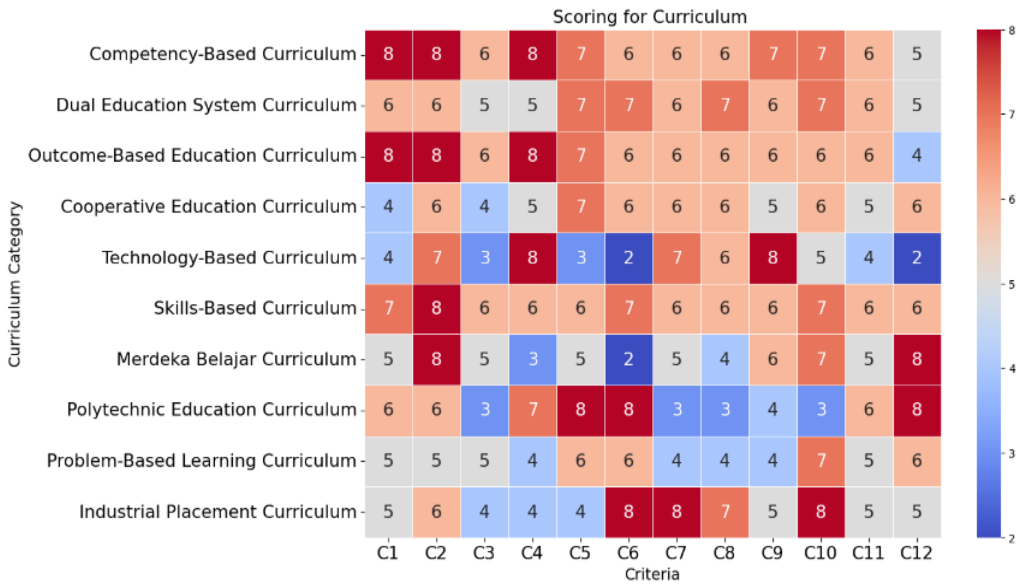


Fig. 2. Scoring of the curriculum based on criteria

Based on the input data presented in the heatmap graph, the Weighted Matrix Elements (V) values are calculated for each curriculum. The results are displayed in Table 7 below.

Table 7. Results of calculation of the weighted matrix elements (V)

Curriculum	Criteria											
	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
CBC	0.029	0.265	0.464	0.986	1.078	0.956	0.843	0.644	0.499	0.282	0.107	0.018
DESC	0.022	0.199	0.387	0.616	1.078	1.115	0.843	0.751	0.427	0.282	0.107	0.018
OBEC	0.029	0.265	0.464	0.986	1.078	0.956	0.843	0.644	0.427	0.242	0.107	0.014
CEC	0.015	0.199	0.309	0.616	1.078	0.956	0.843	0.644	0.356	0.242	0.089	0.021
TBC	0.015	0.232	0.232	0.986	0.462	0.319	0.983	0.644	0.570	0.202	0.072	0.007
SBC	0.025	0.265	0.464	0.740	0.924	1.115	0.843	0.644	0.427	0.282	0.107	0.021
MBC	0.018	0.265	0.387	0.370	0.770	0.319	0.702	0.429	0.427	0.282	0.089	0.028
PEC	0.022	0.199	0.232	0.863	1.232	1.274	0.421	0.322	0.285	0.121	0.107	0.028
PBLC	0.018	0.166	0.387	0.493	0.924	0.956	0.562	0.429	0.285	0.282	0.089	0.021
IPC	0.018	0.199	0.309	0.493	0.616	1.274	1.124	0.751	0.356	0.323	0.089	0.018

The formation of the matrix element values involves weight values derived using the Lq-ROFNs method. The next step is to calculate the G Matrix, which evaluates the relative distance of each alternative to the border area based on the specified criteria and their corresponding weights. The results are presented in Table 8 below.

Table 8. The result of the calculation of the value of the G matrix

G	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
	0.459	0.740	0.812	0.926	0.977	0.965	0.950	0.894	0.831	0.756	0.625	0.450

Based on the values of the G Matrix, the Estimated Border Area (Q) values are calculated to evaluate and rank the alternatives according to their distance from the estimated border. Each resulting value offers direct insight into the quality of curriculum performance relative to the border reference for each criterion. The results are illustrated in Figure 3 below.

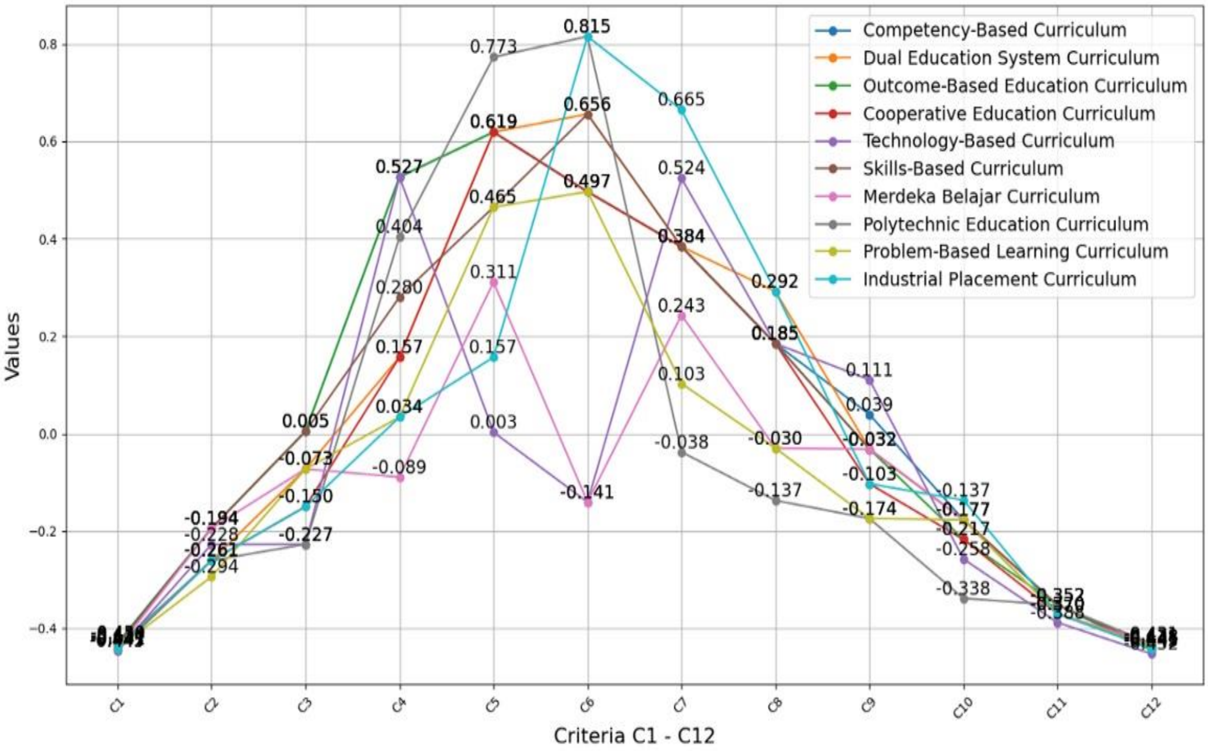


Fig. 3. Illustration value of distance matrix elements - approximate border (Q)

Based on the illustration in Figure 3, the analysis reveals that most curriculum perform strongly in criteria C5 and C6, with the polytechnic education curriculum achieving the highest score (0.815) in C6, indicating a strong emphasis on practical and hands-on learning components. In contrast, C1 and C12 consistently exhibit negative values across all curriculum, underscoring the need for targeted improvement in these areas.

Notably, Competency-Based and Outcome-Based Education curriculum display nearly identical performance patterns, suggesting a shared design philosophy. Conversely, Technology-Based and Merdeka Belajar curriculum show significant deviations in C5 through C8, reflecting differing priorities or implementation challenges in these dimensions. The sharp increases observed in C5 to C7 for Polytechnic Education and Industrial Placement curriculum further highlight their focus on practical experience and industrial relevance.

Based on the resulting scores shown in Table 9, it is known that the curriculum is clustered into three groups:

1) Highly Recommended (A): Curriculum in this group exhibit strong readiness for implementation and high relevance to both educational objectives and labour market demands.
2) Potentially Viable (B): Curriculum in this group show promising potential but may require certain adjustments or improvements to enhance their effectiveness.
3) Requires Significant Revision (C): Curriculum in this group need substantial revision to improve their relevance and feasibility for implementation.

Table 9. Group of the curriculum based on the level of readiness and effectiveness

No	Curriculum	Score	Level of Readiness
1	CBC	0.0550	A
2	DESC	0.0279	B
3	OBEC	0.0454	A
4	CEC	-0.0119	C
5	TBC	-0.0657	C
6	SBC	0.0289	A
7	MBC	-0.1186	C
8	PEC	-0.0337	C
9	PBLC	-0.0749	C
10	IPC	0.0050	B

The result shows that the curriculum grouping is dynamic and adjusted to the assessment results of each department. Through this process, each department can understand the level of curriculum readiness more comprehensively, thereby supporting strategic decision making in the implementation process following educational needs and goals.

Although the SWARA method offers a systematic approach to eliciting stakeholder priorities, it remains inherently vulnerable to subjectivity stemming from individual judgment, institutional perspectives, or variability in professional expertise [78]. To mitigate these limitations, this study incorporates Lq-ROFNs into the weighting process. This fuzzy extension allows for representing uncertainty, hesitation, and partial truth in linguistic evaluations, thereby enhancing the reliability and resilience of the derived criterion weights in the presence of ambiguous or inconsistent expert input. While this hybridization improves robustness and reduces the influence of any single evaluator, it is acknowledged that subjective bias cannot be eliminated.

In parallel, this study examines ten curriculum types to ensure that the evaluation model is applicable across different curriculum structures, as detailed in Table 9. While CBC, SBC, and OBEC are emphasized in later sections for their alignment with national reform priorities, the selection also includes diverse instructional models such as the CEC, TBC, PEC, MBC, and PBLC. This diversity strengthens the framework's adaptability and supports the generalizability of findings across various educational and institutional contexts.

3.2. Sensitivity Analysis

Applying MCDM, which incorporates many options and criteria, necessitates a performance analysis measurement found in data collection [79]. The sensitivity test to the results in the MCDM process was carried out by adding a value of 0.02 to each criterion weight, as shown in Table 10-12.

Table 10. Result of the sensitivity analysis for criterion C1

No	Curriculum	Sensitivity Score - C1	Level of Readiness
1	CBC	0.0058	A
2	DESC	-0.0217	A
3	OBEC	-0.0038	A
4	CEC	-0.0618	A
5	TBC	-0.1157	B
6	SBC	-0.0204	A
7	MBC	-0.1684	C
8	PEC	-0.0832	B
9	PBLC	-0.1246	C
10	IPC	-0.0448	A

Table 11. Result of the sensitivity analysis for criteria C2, C4, C5, C6, C9, C11, and C12

No	Curriculum	Sensitivity Score							Level of Readiness
		C2	C4	C5	C6	C9	C11	C12	
1	CBC	0.0225	0.0225	0.0204	0.0204	0.0183	0.0183	0.0163	A
2	DESC	-0.0112	-0.0092	-0.0092	-0.0071	-0.00709	-0.0092	-0.0113	A
3	OBEC	0.0129	0.0129	0.0087	0.0108	0.00875	0.0087	0.0046	A
4	CEC	-0.0514	-0.0493	-0.0514	-0.0473	-0.04935	-0.0514	-0.0493	A
5	TBC	-0.0990	-0.1011	-0.0990	-0.1094	-0.11151	-0.1073	-0.1115	B
6	SBC	-0.0079	-0.0037	-0.0079	-0.0079	-0.00583	-0.0079	-0.0079	A
7	MBC	-0.1621	-0.1517	-0.1559	-0.1580	-0.16423	-0.1580	-0.1517	C
8	PEC	-0.0686	-0.0707	-0.0749	-0.0666	-0.06655	-0.0707	-0.0666	A
9	PBLC	-0.1163	-0.1142	-0.1163	-0.1121	-0.11213	-0.1142	-0.1121	B
10	IPC	-0.0364	-0.0323	-0.0344	-0.0365	-0.02812	-0.0344	-0.0344	A

Table 12. Result of the sensitivity analysis for criteria C3, C7, C8, and C10

No	Curriculum	Sensitivity Score				Level of Readiness
		C3	C7	C8	C10	
1	CBC	0.0183	0.0183	0.0183	0.0204	A
2	DESC	-0.0092	-0.0113	-0.0071	-0.0071	A
3	OBEC	0.0087	0.0087	0.0087	0.0087	A
4	CEC	-0.0493	-0.0535	-0.0493	-0.0493	A
5	TBC	-0.1011	-0.1094	-0.1032	-0.1053	B
6	SBC	-0.0079	-0.0079	-0.0079	-0.0058	A
7	MBC	-0.1580	-0.1580	-0.1601	-0.1538	C
8	PEC	-0.0770	-0.0770	-0.0770	-0.0770	B
9	PBLC	-0.1163	-0.1142	-0.1163	-0.1100	B
10	IPC	-0.0281	-0.0365	-0.0302	-0.0281	A

Based on the calculation results displayed in Table 10-12, it can be known to what extent the decision results on the curriculum readiness level are affected by changes in the weight of the criteria, thus ensuring that the decisions taken are reliable even if there are small changes. It is illustrated in Figure 4 below.

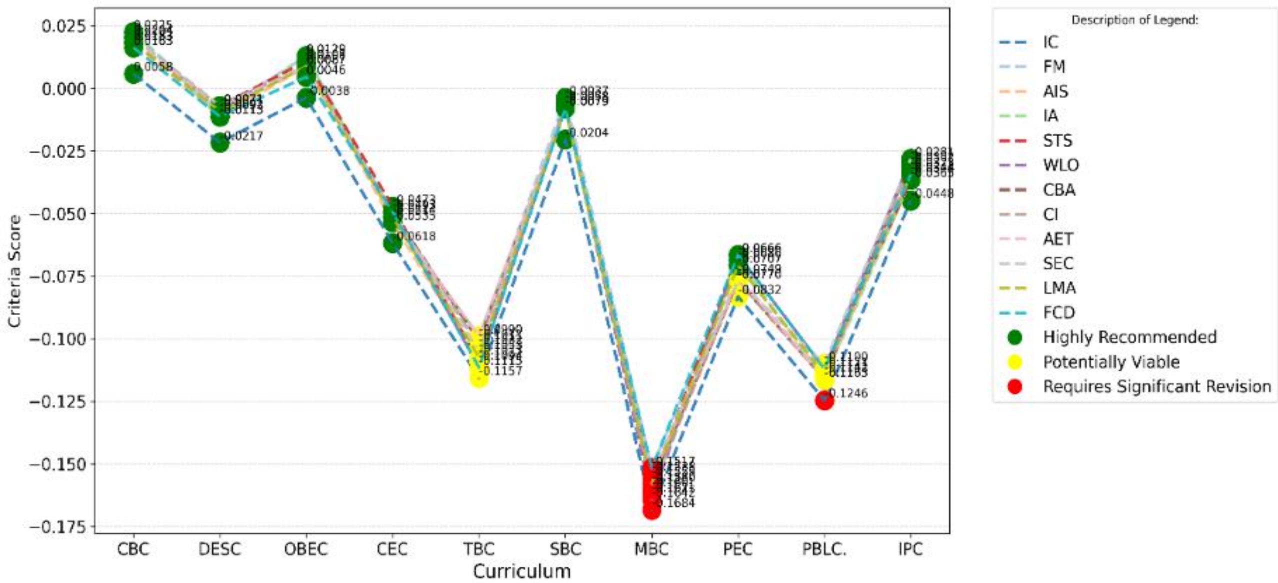


Fig. 4. Results of sensitivity analysis of the level of readiness for curriculum implementation

Based on the sensitivity analysis of criterion weight variations, the readiness levels of various curriculum were systematically assessed. Curriculum such as CBC, DESC, OBEC, SBC, and IPC demonstrated strong resilience to criterion-weight changes and are thus classified as Highly Recommended. In contrast, TBC and PEC, which showed moderate sensitivity to weight adjustments, are categorized as Potentially Viable. Meanwhile, MBC and PBL exhibited high sensitivity to changes in weighting, indicating structural weaknesses and are therefore placed in the Requires Significant Revision category. These findings suggest that curriculum positioned near the threshold of readiness categories are particularly susceptible to fluctuations in evaluation parameters, highlighting the critical role of weight stability in curriculum robustness.

3.3. Machine Learning for Evaluation of Curriculum

The integration of SSO and SVM within the curriculum evaluation framework represents a notable advancement in methodological rigour. By leveraging SSO, the framework adaptively determines the weights of evaluation indicators using empirical data, thereby addressing the limitations of manual weighting approaches, such as subjectivity and expert bias. Concurrently, the use of SVM enhances the framework's predictive capabilities by accurately classifying curriculum and capturing complex, non-linear interdependencies among indicators. This synergy improves classification performance and enables the reliable evaluation of newly proposed curriculum, offering valuable foresight in curriculum planning and reform. The results highlight the potential of data-driven, machine learning-enhanced methods to support more objective and responsive educational decision-making.

In this study, the industry needs is operationalized through seven evaluation indicators, including Relevance of Curriculum (RCI), Relevance of Graduate Competencies (RGCI), Entrepreneurship Opportunities (EOI), Certification to Industrial Standards (CISI), Technological Innovation and Adoption (TIAI), Industrial Adaptation (IAI), and Industrial Feedback (IFI). These indicators were derived through extensive consultation with industry representatives across sectors (Table 1) and are intended to capture a holistic view of employability, innovation readiness, and industrial adaptability. These indicators collectively assess curriculum effectiveness at both individual and holistic levels.

The proposed framework consists of two interdependent components: curriculum evaluation and implementation assessment. Each component is supported by a hybrid methodology that integrates MCDM techniques with optimization strategies, thereby enhancing analytical precision and reducing subjectivity. This integrative design enables a comprehensive analysis of curriculum effectiveness while facilitating systematic alignment between academic program structures and evolving industry requirements. By addressing this alignment gap, the framework supports the development of more adaptive and industry-relevant curriculum. Furthermore, it provides a structured roadmap for academic departments to improve curriculum relevance and monitor implementation outcomes over time, as illustrated in Figure 5.

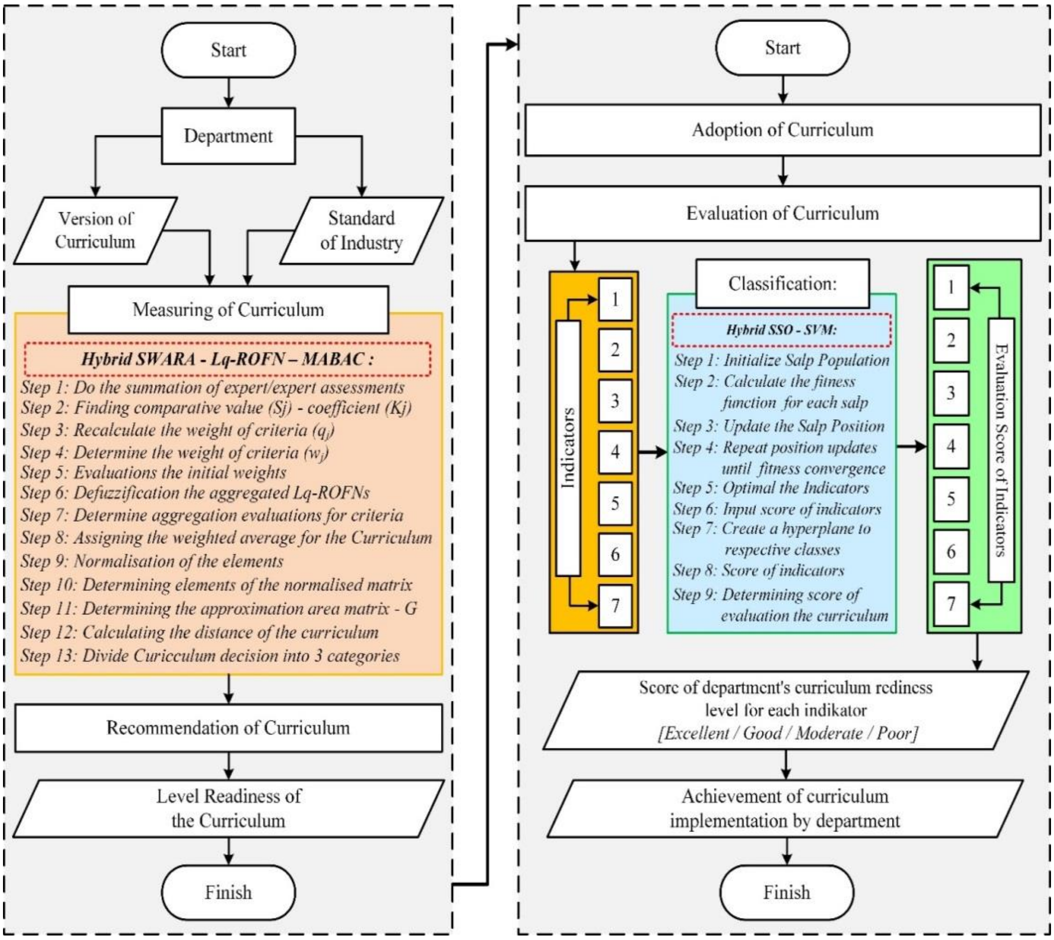


Fig. 5. Illustration of how machine learning works in curriculum evaluation

3.4. Classification Using Hybrid SSO - SVM

The Salp Swarm Optimization (SSO) algorithm is employed to optimise the Support Vector Machine (SVM) classifier by precisely tuning its critical hyperparameters, including the penalty parameter "C" and the kernel coefficient "γ", thereby improving its effectiveness in curriculum evaluation tasks. Each salp within the swarm represents a

```
SSO-Optimized SVM for Curriculum Classification

Input:
    - Dataset D with features X and labels Y
    - Parameter search space for SVM: C_range, gamma_range
    - SSO parameters: N (number of salps), max_iter (maximum iterations)
Output:
    - Best SVM model with optimal (C*, γ*) producing highest classification accuracy

Begin:
1. Initialize a salp population with N individuals:
       For each salp i:
           Randomly initialize position[i] = (C_i, γ_i) ∈ [C_range, gamma_range]
2. Evaluate fitness of each salp:
       For each salp i:
           Train an SVM using (C_i, γ_i)
           Perform k-fold cross-validation
           Compute accuracy[i] as fitness
3. Identify the best salp leader:
       leader ← salp with highest accuracy
4. For iter = 1 to max_iter:
       For each salp i in the population:
           If i == 1 (leader):
               Update leader's position using exploration formula:
                   position[i] ← leader + c1 × (ub - lb) × r + lb
           Else:
               Update follower salp using chain dynamics:
                   position[i] ← (position[i] + position[i-1]) / 2
       Enforce boundary constraints on each salp's position
       Re-evaluate fitness of each salp:
           For each salp i:
               Train SVM with updated (C_i, γ_i)
               Compute accuracy[i] with cross-validation
       Update leader if a better salp is found
5. Return final SVM trained with best (C*, γ*) = position[leader]
End.
```

Fig. 6. Algorithm of Hybrid SSO - SVM for Curriculum Classification

candidate solution (C, γ), and the fitness of each solution is assessed using the SVM's cross-validation accuracy. The leader salp updates its position through stochastic exploration, while the follower salps adjust their positions based on the preceding salp, collectively guiding the swarm toward the optimal hyperparameter configuration. Once identified, the optimal parameter pair is used to train the SVM, significantly improving its generalisation capability and classification accuracy in curriculum evaluation tasks. The overall optimisation procedure is illustrated in Figure 6.

Based on the algorithm, it is known that each salp represents a potential hyperparameter pair (C, γ), The leader salp performs stochastic exploration of the search space, while follower salps update their positions relative to the leader, enabling the swarm to converge on an optimal solution. The resulting parameters are used to train the SVM, leading to enhanced predictive accuracy for curriculum evaluation.

Curriculum evaluation is critical in ensuring educational programs' relevance, effectiveness, and appropriateness, particularly when adopting recommended models. In this study, the OBEC is selected as the focus of evaluation. The initial phase involved a comprehensive assessment with 189 respondents, including graduates (50), students (100), faculty members (22), and industry representatives (17). The scoring data obtained from these stakeholders is summarised in Table 13.

Table 13. Record the scoring data by respondents

Group	Stakeholder	RCI	RGCI	EOI	CISI	TIAI	IAI	IFI
Graduate	Graduate - 1	5	5	2	4	3	2	3
	Graduate - 2	4	2	4	2	2	3	4
	...	...	...	...	...	...	...	...
	Graduate - 50	4	4	4	5	4	4	2
Student	Student - 1	4	5	2	2	4	4	4
	Student - 2	2	2	2	4	2	2	3
	...	...	...	...	...	...	...	...
	Student - 100	4	2	3	5	2	2	2
Lecturer	Lecturer - 1	3	4	4	5	4	2	2
	Lecturer - 2	4	2	4	4	4	4	5
	...	...	...	...	...	...	...	...
	Lecturer - 22	3	5	4	5	5	3	2
Industry	Industry - 1	3	3	5	4	4	4	2
	Industry - 2	4	5	4	5	3	2	4
	...	...	...	...	...	...	...	...
	Industriy- 17	2	4	2	3	2	5	5

To ensure that all features contribute equally to the model's learning process, we apply normalisation by scaling the data to the [0, 1] range. This step is critical for improving model performance, enhancing accuracy, promoting numerical stability, and increasing computational efficiency, as illustrated in Table 14 below.

Table 14. Result of input data normalisation

Group	Stakeholder	RCI	RGCI	EOI	CISI	TIAI	IAI	IFI
Graduate	Graduate - 1	0.6667	0.3333	0.0000	0.0000	1.0000	0.3333	1.0000
	Graduate - 2	0.0000	1.0000	0.6667	0.3333	1.0000	0.3333	0.0000
	...	...	...	...	...	...	...	...
	Graduate - 50	1.0000	0.0000	0.6667	1.0000	0.0000	0.3333	0.6667
Student	Student - 1	0.3333	0.0000	0.3333	0.6667	0.0000	1.0000	0.0000
	Student - 2	0.3333	0.3333	0.6667	0.0000	0.5000	0.6667	0.0000
	...	...	...	...	...	...	...	...
	Student - 100	0.0000	0.0000	0.3333	0.0000	0.5000	0.6667	0.0000
Lecturer	Lecturer - 1	0.3333	0.0000	1.0000	1.0000	1.0000	0.6667	0.3333
	Lecturer - 2	0.0000	1.0000	0.3333	0.0000	1.0000	0.6667	0.3333
	...	...	...	...	...	...	...	...
	Lecturer - 22	0.3333	1.0000	0.6667	0.6667	1.0000	0.0000	0.0000
Industry	Industry - 1	0.3333	0.0000	1.0000	0.6667	0.0000	0.6667	0.6667
	Industry - 2	0.3333	0.0000	1.0000	0.6667	0.5000	0.6667	1.0000
	...	0.6667	0.3333	0.0000	0.0000	1.0000	0.3333	1.0000
	Industry - 17	0.6667	0.3333	0.0000	0.0000	1.0000	0.3333	1.0000

Next, calculate the normalisation value using the simple average as expressed using:

$$\text{AvN} = \frac{x'A + x'B}{2} \tag{23}$$

The calculation results are shown in Table 15 below.

Table 15. Result of the simple average of the normalization value

Group	RCI	RGCI	EOI	CISI	TIAI	IAI	IFI
Graduate	0.47	0.50	0.55	0.47	0.49	0.59	0.51
Student	0.47	0.56	0.54	0.47	0.49	0.52	0.56
Lecturer	0.48	0.47	0.51	0.43	0.43	0.59	0.51
Industry	0.56	0.51	0.57	0.50	0.47	0.53	0.48

Based on the normalisation data in Table 15, the criteria weight optimisation was carried out using SSO, wherein the initial stage for the initial population of the salp is created (n) with random positions represented through the weight of the criteria, among others, RCI=0.3, RGCI=0.2, EOI=0.15, CISI=0.1, TIAI=0.15, IAI=0.05, IFI=0.05, and Crossover Rate (CR)=0.5.

In the first iteration, it is explained that the change in weight to RCI ($RCI_{initial}$) = 0.3 as the first individual Xi of the population. In the mutation process, Vektor_Donor (Vi) is calculated based on three random individuals from the population using:

$$V_i = X_{ri} + \mathrm{F} * (X_{r2} - X_{r3}) \qquad (24)$$

Set, $X_{r1}^{RCI} = 0.28$, $X_{r2}^{RCI} = 0.35$, $X_{r3}^{RCI} = 0.32$, and Scale factor (F = 0.8).

Substitute for the mutation function: V_i^{RCI}= 0.28 + 0.8 * (0.35 − 0.32) = 0.28 + 0.8 * 0.03 = 0.28 + 0.024 = 0.304.

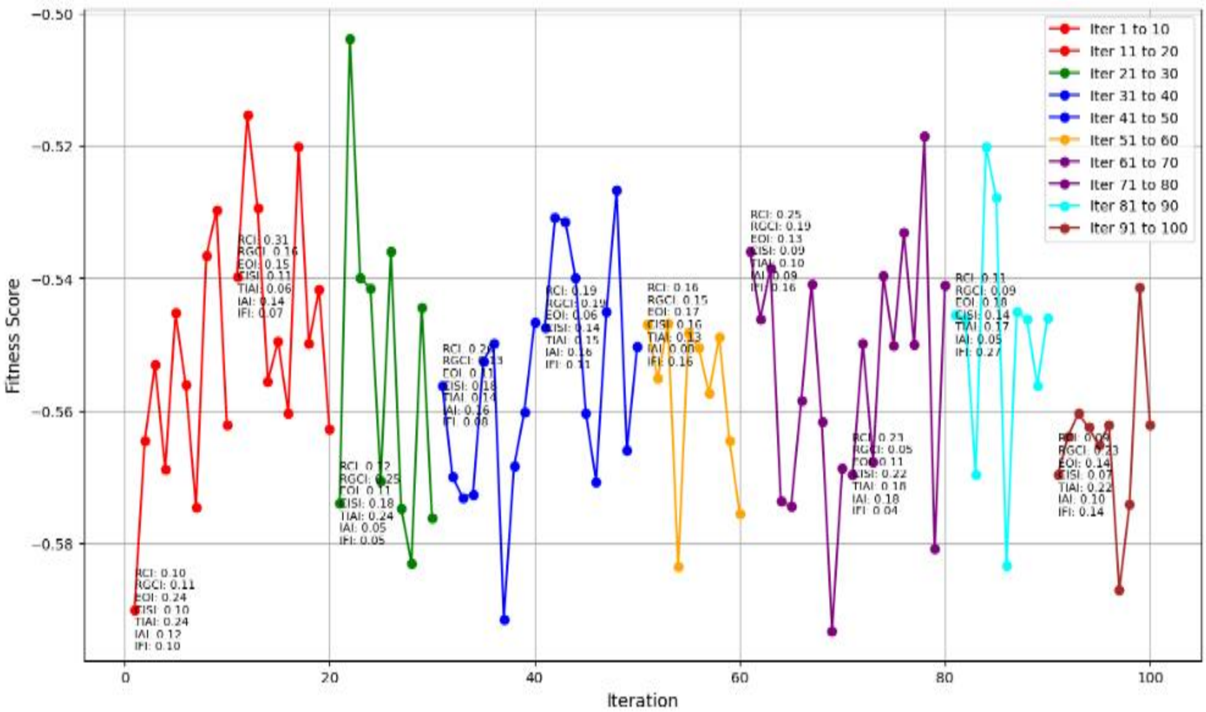
Next, a recombination process was carried out to obtain the test vector value (*Ui*) based on the *CR* value and random value (R1) = 0.4, where it is stated: U_i^{RCI}= V_i^{RCI}, if R1 ≤ CR = 0.304.

Furthermore, the fitness value obtained from the normalisation process is determined as a negative value, and the average score is Test Individual (Ui) = -0.54 and Original Individual (Xi) = -0.56. As is stated:

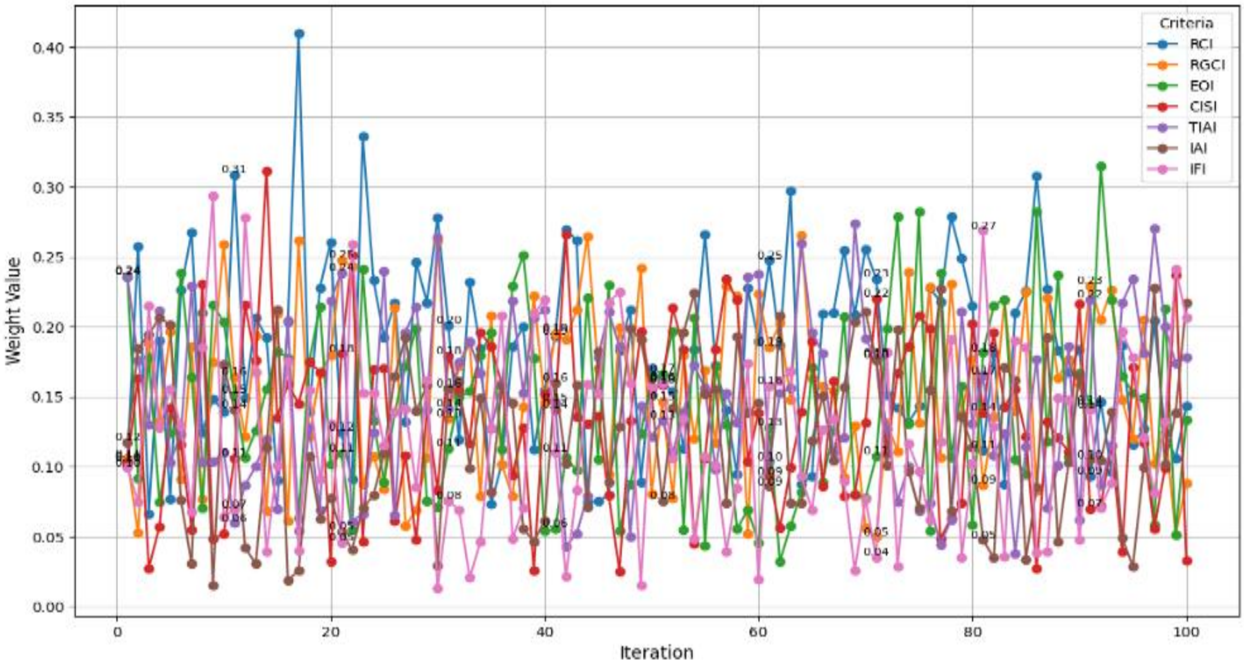
U_i^{next} = U_i , if $f(U_i) < f(X_i)$ = 0.304. Finally, normalisation is carried out on the weight of RCI:

$$W_{Normalized}{}^{RCI} = \frac{V_i^{RCI}}{0.304 + 0.2 + 0.15 + 0.1 + 0.15 + 0.05 + 0.05} = \frac{0.304}{1.004} = 0.303.$$

The same process is repeated for the next iteration, with the final result set on a selection based on fitness scores. After reaching the iteration limit of 100, the RCI weight gradually decreases until it reaches an optimal value of 0.015. Overall, the weight optimisation process is illustrated in Figure 7 below.



(a). Result of illustration for every 10 iterations



(b). Result of illustration for all iterations

Fig. 7. Illustration of changing the weight of criteria using SSO

Based on the illustration in Figure 7, the increase in fitness scores indicates that the SSO algorithm successfully identified better combinations of weights. The significant rise in fitness values throughout the iterations demonstrates that the algorithm effectively explored the search space to fine-tune the weight distribution and converge toward an optimal solution.

The optimised weight represents the redistribution based on the significance of each criterion in achieving the target goal. As seen in Figure 8, the TIAI criterion emerges as the dominant criterion, highlighting the importance of decision-making for curriculum evaluation.

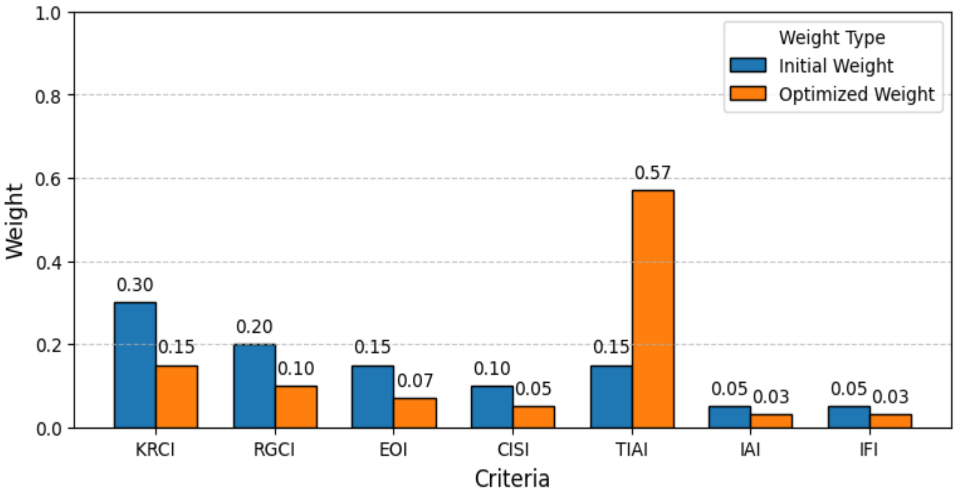


Fig. 8. Results of criterion weight optimisation using SSO

The evaluation scores are calculated to determine the status of achievement in the implementation of the curriculum by the department, where the division of status groups is determined based on Table 16 below.

Table 16. Class of the curriculum implementation achievement status

No	Code	Status	Value	Description
1	E	Effective	0.75 – 1.0	The curriculum is implemented optimally.
2	S	Satisfactory	0.50 – 0.74	The curriculum is implemented well and according to standards, although it needs improvement.
3	N	Needs Improvement	0.10 – 0.49	The curriculum is not yet effective and needs a lot of improvement.

The evaluation calculation results are presented in Table 17, providing a clear and structured overview of the findings.

Table 17. Evaluation results based on grades stakeholder-score

Stakeholder	RCI	RGCI	EOI	CISI	TIAI	IAI	IFI	Indicator Value
Graduate	*0.0690*	0.0500	0.0378	0.0235	0.2793	0.0174	0.0150	*0.4920*
Student	0.0690	0.0560	0.0378	0.0235	0.2793	0.0156	0.0168	0.4980
Lecturer	0.0720	0.0470	0.0350	0.0215	0.2451	0.0177	0.0153	0.4536
Industry	0.0840	0.0500	0.0399	0.0250	0.2622	0.0156	0.0144	0.4911
Evaluation Value	*0.4837*							
Status	Needs Improvement							

The values on each indicator are obtained using SVM by involving the optimised weight (OW) data and normalisation value in Table 17, explained as follows:

Graduate_RCI= 0.47 * 0.15 = 0.0690
Graduate_Indicator-Score= (OWRCI * RCI) + (OWRGCI * RGCI) +... + (OWIFI * IFI)
= 0.0690 + 0.0500 + ... + 0.4920 = 0.4920

$$\text{Evaluation\_Value} = \frac{0.4920 + 0.4980 + 0.4536 + 0.4911}{4} = 0.4873.$$

The calculation results show that the evaluation value of 0.4837 is included in the "***Needs Improvement***" status group, which means that the implementation of the evaluated curriculum is below the expected standard. Furthermore, the evaluation results can motivate the department to encourage the implementation of a flexible and innovative approach through training, incentives, and the development of a culture of creativity involving stakeholders.

Beyond its technical contribution, this classification framework provides pedagogical value by identifying curriculum models that need targeted instructional redesign. For instance, curriculum categorised as "***Needs Improvement***" offer direct cues for departments to revisit not only their content structure but also their teaching methods, assessment models, and industry engagement strategies. This makes the framework not only a decision-making tool but also a formative guide for educators to adapt teaching practices in alignment with evolving job market expectations.

3.5. Comparative Analysis

This study uses a comparative analysis approach to evaluate and compare various classification methods to identify their advantages, weaknesses, and potential applications and determine the classification method that best predicts the achievement status of curriculum implementation. The five machine learning methods analysed include Logistic Regression, Decision Trees, KNN, SVM, and hybrid SVM-SSO. The testing data collected against 40 departments that conducted the curriculum evaluation are shown in Table 18 below.

Table 18. Data testing is used to evaluate the curriculum in departments

No	Department	Curriculum	RCI	RGCI	EOI	CISI	TIAI	IAI	IFI	Method for Predicted Status				
										Logistic Regression	Decision Trees	KNN	SVM	SVM - SSO
1	International Relations and Diplomacy	CBC	0.046	0.009	0.013	0.016	0.196	0.290	0.099	S	S	S	S	S
2	Mechanical Engineering	OBEC	0.088	0.014	0.024	0.019	0.322	0.229	0.013	N	S	S	S	S
3	Communication Science Engineering	OBEC	0.022	0.006	0.023	0.039	0.28	0.385	0.064	N	N	S	S	S
4	Electrical and Computer Engineering	OBEC	0.085	0.012	0.011	0.039	0.056	0.298	0.098	N	N	N	N	N
5	Civil and Environmental Engineering	OBEC	0.043	0.014	0.014	0.036	0.056	0.252	0.062	N	N	N	N	N
6	Public Administration Engineering	CBC	0.043	0.01	0.015	0.038	0.056	0.321	0.006	S	S	S	N	S
7	Software Engineering	OBEC	0.043	0.017	0.023	0.032	0.056	0.321	0.015	S	E	S	N	S
8	Digital Business	OBEC	0.043	0.007	0.01	0.02	0.056	0.321	0.062	N	E	S	S	S
9	Business Administration	DESC	0.043	0.006	0.012	0.024	0.056	0.252	0.017	N	E	S	N	N

10	Nursing and Health Professions	DESC	0.043	0.016	0.026	0.017	0.486	0.252	0.062	E	E	S	E	E
11	Education and Human Sciences	DESC	0.043	0.012	0.014	0.046	0.411	0.252	0.04	E	S	S	S	S
12	Information System	OBEC	0.043	0.015	0.023	0.033	0.114	0.252	0.062	S	S	S	S	S
13	International Business	OBEC	0.043	0.015	0.023	0.033	0.114	0.252	0.062	S	S	S	S	S
14	Economics	OBEC	0.043	0.015	0.023	0.033	0.114	0.252	0.014	S	S	S	S	S
15	Marketing	OBEC	0.043	0.015	0.023	0.033	0.114	0.252	0.062	N	S	S	N	S
16	Environmenta l and Sustainability	OBEC	0.043	0.015	0.023	0.033	0.114	0.252	0.023	E	S	E	E	E
17	Architecture	MBC	0.012	0.036	0.056	0.016	0.196	0.290	0.099	N	S	S	S	S
18	Law	PEC	0.024	0.056	0.024	0.019	0.322	0.229	0.013	N	N	N	S	S
19	Psychology	PBLC	0.252	0.006	0.023	0.039	0.28	0.385	0.064	N	N	N	S	S
20	Computer Science	IPC	0.085	0.012	0.011	0.039	0.056	0.298	0.098	N	S	N	S	S
21	Accounting	TBC	0.252	0.056	0.012	0.014	0.046	0.252	0.017	N	S	N	N	S
22	Tourism and Hospitality Management	SBC	0.015	0.023	0.033	0.043	0.012	0.014	0.046	S	S	S	N	E
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
40	Informatics	CBC	0.038	0.012	0.014	0.05	0.186	0.215	0.042	S	S	E	E	S

The performance evaluation process of each method is carried out using Precision metrics, Recall, F1–Score, and Accuracy, where the validation results calculated through the confusion matrix for each method are presented in Figure 9 below.

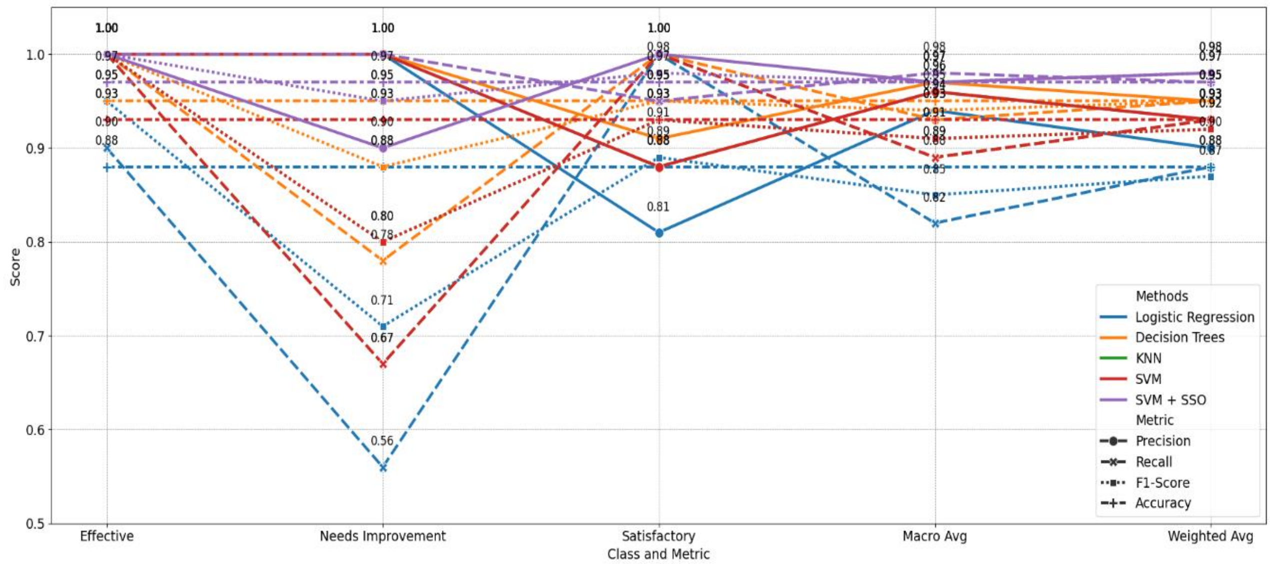


Fig. 9. Comparison of the confusion matrix for evaluating the department curriculum

The hybrid SVM-SSO model significantly outperforms other methods, underlining the effectiveness of optimisation techniques in improving classification performance. These findings confirm that hybrid SVM-SSO are worthy of being recommended as the most suitable model to be applied to datasets with similar characteristics.

3.5.1. Performance Metrics Overview

Each model was evaluated using standard classification metrics: Accuracy, Precision, Recall, and F1-Score. These metrics were computed for each class (Effective, Satisfactory, Needs Improvement) along with macro and weighted averages. Results demonstrate that SVM-SSO consistently achieves the highest performance across nearly all categories, with overall accuracy reaching 97% and F1-Score exceeding 0.95 for each class.

Models such as Logistic Regression and KNN performed adequately but exhibited weaknesses in classifying "***Needs Improvement***" programs. While all models correctly identified “Effective” departments, as F1-Score (1.00) in most cases, the ability to detect underperforming departments varied significantly.

3.5.2. Error and Misclassification Analysis

This study analysed the nature of misclassifications across all models to provide a deeper insight into model behaviour. Special focus was placed on the "Needs Improvement" category due to its practical importance in educational policy.

- The Logistic Regression method displayed a recall of only 0.56 for the class of ***Needs Improvement***, indicating that many underperforming programs were wrongly classified as ***Satisfactory***. While precision remained high, the imbalance between precision and recall resulted in a lower F1-Score (0.71).
- Decision Trees and KNN methods achieved moderate improvements but still exhibited misclassifications near score thresholds. For instance, KNN had a recall of 0.67 for the class of ***Needs Improvement,*** suggesting its difficulty in distinguishing borderline cases.
- The SVM method, though capable of separating the class of ***Effective*** cleanly, struggled similarly with the class of ***Needs Improvement***, with a recall of 0.67.
- Hybrid SVM-SSO showed substantial improvements. It achieved perfect recall (1.00) for the class of ***Needs Improvement*** with an F1-score of 0.95, demonstrating its ability to capture non-linear boundaries and identify all underperforming programs without false negatives.

These findings highlight the critical limitations of traditional classifiers in handling class overlaps and the importance of hyperparameter optimisation. Hybrid SVM-SSO's superiority stems from its ability to learn complex margins using the adaptive search capabilities of the SSO algorithm.

3.6. Justification of the Hybrid Approach

Integrating SWARA, Lq-ROFNs, MABAC, SVM, and SSO in the proposed framework is strategically designed to address the multifaceted challenges in evaluating curriculum relevance concerning evolving industry requirements. SWARA is employed for its procedural simplicity and effectiveness in capturing stakeholder preferences and generating initial criterion weights. Recognising that human assessments often involve ambiguity and hesitation, Lq-ROFNs are incorporated to enhance SWARA's capacity by modeling the inherent uncertainty in linguistic evaluations.

Following the derivation of fuzzy-weighted criteria, the MABAC method is utilised to rank curriculum alternatives. MABAC is chosen for its ability to compute the relative closeness of each alternative to ideal and anti-ideal solutions, while maintaining interpretability and computational efficiency. For classification tasks, SVM is selected due to its robustness and strong generalisation capabilities, particularly in structured, high-dimensional spaces. However, the classification performance of SVM is highly dependent on the selection of its hyperparameters namely, the penalty parameter "C" and kernel function parameter "γ". To address this, the SSO algorithm is integrated to perform adaptive optimisation of these parameters, thereby enhancing predictive accuracy while minimising manual tuning and model bias.

This hybrid integration leverages the complementary strengths of MCDM and machine learning. It enables a comprehensive, interpretable, and data-driven decision support system that facilitates the alignment of higher education curriculum with the dynamic and multi-dimensional expectations of the industrial sector.

4. Conclusion

This study demonstrates the transformative potential of integrating machine learning methodologies within higher education to systematically align academic curriculum with the evolving demands of contemporary industries. The proposed framework incorporates a combination of advanced MCDM techniques, including SWARA, Lq-ROFNs, and the MABAC method alongside a hybrid classification model that employs SVM optimized via the SSO algorithm. This integrated approach facilitates a comprehensive evaluation of curriculum against industry-relevant criteria while enabling the development of personalized, data-driven educational pathways. Empirical results confirm the framework's effectiveness in classifying curriculum based on readiness and relevance, thereby supporting the advancement of adaptive, future-oriented educational programs. In light of these findings and constraints, the study emphasizes the need for sustained collaboration among academic institutions, industry stakeholders, and policymakers. Such engagement is critical for designing and implementing curriculum that reflect current industry standards and are resilient to future shifts. The framework proposed herein represents a significant step toward establishing a sustainable, innovative, and industry-responsive educational model that can enhance graduate employability and strengthen the strategic relevance of higher education institutions.

In addition to offering a robust evaluation mechanism, the proposed framework contributes to pedagogy by fostering data-informed curriculum improvement. It supports academic leaders and educators in identifying instructional weaknesses, enhancing industry relevance, and adopting adaptive teaching models. These findings underscore the importance of integrating machine learning-based decision systems not only for institutional planning, but also for enriching the learning experience and increasing graduate employability through better pedagogical alignment.

Despite these contributions, the study is subject to several limitations. First, potential bias in the input data may affect the accuracy with which industry needs are represented, particularly given the variability of competency standards across different sectors. Second, the inherently dynamic nature of educational systems and industrial demands poses a temporal mismatch; while industry requirements evolve rapidly, curriculumr reform processes tend to be slow and institutionally constrained. Third, resistance to change among key stakeholders such as faculty, academic administrators, and institutional bodies may impede the practical implementation of the proposed framework. Additionally, the stakeholder feedback utilized in this study was limited to students, graduates, lecturers, and industry professionals. Although these groups are directly involved in curriculum design and outcomes, future work should incorporate broader stakeholder perspectives, including policymakers, accreditation bodies, and alums employers, to enhance the comprehensiveness and generalizability of the evaluation process. Lastly, while the framework enables systematic curriculum evaluation and alignment with industry needs, this study did not extend to the empirical measurement of long-term outcomes such as graduate success or employer satisfaction.

Future work is encouraged to build upon this foundation by integrating longitudinal data and real-world performance indicators to validate the downstream impact of alignment decisions. Furthermore, regional variations in industry structures and educational systems may constrain the direct applicability of the framework, underscoring the importance of contextual customization in diverse implementation settings.

References

[1] A. Strzelecki, "Students' Acceptance of ChatGPT in Higher Education: An Extended Unified Theory of Acceptance and Use of Technology," *Innov. High. Educ.*, vol. 49, no. 2, pp. 223–245, Apr. 2024, doi: 10.1007/s10755-023-09686-1.

[2] E. W. Ziemba, E. W. Maruszewska, D. Grabara, and K. Renik, "Acceptance and Use of ChatGPT Among Accounting and Finance Higher Education Students," in *Lecture Notes in Networks and Systems*, vol. 1079 LNNS, 2024, pp. 185–202.

[3] H. P. A. Tjahyaningtijas *et al.*, "Machine learning on academic education: Bibliometric studies," *E3S Web Conf.*, vol. 450, p. 02010, Nov. 2023, doi: 10.1051/e3sconf/202345002010.

[4] C. Yang, F.-K. Chiang, Q. Cheng, and J. Ji, "Machine Learning-Based Student Modeling Methodology for Intelligent Tutoring Systems," *J. Educ. Comput. Res.*, vol. 59, no. 6, pp. 1015–1035, Oct. 2021, doi: 10.1177/0735633120986256.

[5] V. Nelyub, A. Glinscaya, V. Kukartsev, A. Borodulin, and D. Evsyukov, "Machine learning to identify key success indicators," *E3S Web Conf.*, vol. 431, 2023, doi: 10.1051/e3sconf/202343105014.

[6] M. Nauman, N. Akhtar, A. Alhudhaif, and A. Alothaim, "Guaranteeing Correctness of Machine Learning Based Decision Making at Higher Educational Institutions," *IEEE Access*, vol. 9, pp. 92864–92880, 2021, doi: 10.1109/ACCESS.2021.3088901.

[7] E. M. Onyema *et al.*, "Prospects and Challenges of Using Machine Learning for Academic Forecasting," *Comput. Intell. Neurosci.*, vol. 2022, pp. 1–7, Jun. 2022, doi: 10.1155/2022/5624475.

[8] B. Yang, "An Empirical Study on the Application of Machine Learning for Higher Education and Social Service," *J. Glob. Inf. Manag.*, vol. 30, no. 7, pp. 1–16, Feb. 2022, doi: 10.4018/JGIM.296723.

[9] A. R. Riyadi, T. Syaripudin, Kurniasih, A. Hendriani, C. Sutinah, and M. A. Sirojudin, "ChatGPT and Education: A Scopus Bibliometric Analysis," 2024, pp. 264–272.

[10] R. A. Navarro, E. Barbarasa, and A. Thakkar, "Addressing workforce needs by disrupting traditional industry–higher education relations: The case of El Salvador," *Ind. High. Educ.*, vol. 33, no. 6, pp. 391–402, Dec. 2019, doi: 10.1177/0950422219875886.

[11] W. Holmes *et al.*, "Ethics of AI in Education: Towards a Community-Wide Framework," *Int. J. Artif. Intell. Educ.*, vol. 32, no. 3, pp. 504–526, Sep. 2022, doi: 10.1007/s40593-021-00239-1.

[12] A. Tsamados *et al.*, "The Ethics of Algorithms: Key Problems and Solutions," in *Philosophical Studies Series*, vol. 144, 2021, pp. 97–123.

[13] S. Masrom, R. A. Rahman, N. Baharun, S. R. S. Rohani, and A. S. A. Rahman, "Machine learning with task-technology fit theory factors for predicting students' adoption in video-based learning," *Bull. Electr. Eng. Informatics*, vol. 12, no. 3, pp. 1666–1673, Jun. 2023, doi: 10.11591/eei.v12i3.5037.

[14] L. Chen, P. Chen, and Z. Lin, "Artificial Intelligence in Education: A Review," *IEEE Access*, vol. 8, pp. 75264–75278, 2020, doi: 10.1109/ACCESS.2020.2988510.

[15] H. Cui, H. Zhang, L. Zhou, C. Yang, B. Li, and X. Zhao, "Fuzzy analytic hierarchy process with ordered pair of normalized real numbers," *Soft Comput.*, vol. 27, no. 17, pp. 12267–12288, Sep. 2023, doi: 10.1007/s00500-023-08232-7.

[16] H. Taherdoost, "Navigating the Ethical and Privacy Concerns of Big Data and Machine Learning in Decision Making," *Intell. Converg. Networks*, vol. 4, no. 4, pp. 280–295, Dec. 2023, doi: 10.23919/ICN.2023.0023.

[17] A. Ahmed and D. Tolera, "Multi-Category Prediction of Students' Academic Performance Using Machine Learning: For Students Joining Higher Educational Institutions in Ethiopia." p. 6, Sep. 18, 2023, doi: 10.21203/rs.3.rs-3342736/v1.

[18] D.-C. Chang and S. Lin, "Using Azure Machine Learning to Detection of At-Risk Students," *IIAI Lett. Institutional Res.*, vol. 3, p. 89, 2023, doi: 10.52731/lir.v003.089.

[19] J. Daley and B. Baruah, "Leadership skills development among engineering students in Higher Education – an analysis of the Russell Group universities in the UK," *Eur. J. Eng. Educ.*, vol. 46, no. 4, pp. 528–556, Jul. 2021, doi: 10.1080/03043797.2020.1832049.

[20] J. Li and R. Wang, "Machine Learning Adoption in Educational Institutions: Role of Internet of Things and Digital Educational Platforms," *Sustainability*, vol. 15, no. 5, p. 4000, Feb. 2023, doi: 10.3390/su15054000.

[21] B. S. Abunasser, M. R. J. AL-Hiealy, A. M. Barhoom, A. R. Almasri, and S. S. Abu-Naser, "Prediction of Instructor Performance using Machine and Deep Learning Techniques," *Int. J. Adv. Comput. Sci. Appl.*, vol. 13, no. 7, pp. 78–83, 2022, doi: 10.14569/IJACSA.2022.0130711.

[22] A. S. AL-Malaise AL-Ghamdi, M. Ragab, and M. Farouk S. Sabir, "Enhanced Artificial Intelligence-based Cybersecurity Intrusion Detection for Higher Education Institutions," *Comput. Mater. Contin.*, vol. 72, no. 2, pp. 2895–2907, 2022, doi: 10.32604/cmc.2022.026405.
[23] M. U. Hassan, S. Alaliyat, R. Sarwar, R. Nawaz, and I. A. Hameed, "Leveraging deep learning and big data to enhance computing curriculum for industry-relevant skills: A Norwegian case study," *Heliyon*, vol. 9, no. 4, p. e15407, Apr. 2023, doi: 10.1016/j.heliyon.2023.e15407.
[24] Weifeng Wang, "Research on the Direction Optimization of Professional Cluster in Higher Education Institutions Based on Industrial Demand," *Int. J. New Dev. Educ.*, vol. 6, no. 1, 2024, doi: 10.25236/IJNDE.2024.060130.
[25] V. Garousi, G. Giray, E. Tuzun, C. Catal, and M. Felderer, "Closing the Gap Between Software Engineering Education and Industrial Needs," *IEEE Softw.*, vol. 37, no. 2, pp. 68–77, Mar. 2020, doi: 10.1109/MS.2018.2880823.
[26] V. Sukackė *et al.*, "Towards Active Evidence-Based Learning in Engineering Education: A Systematic Literature Review of PBL, PjBL, and CBL," *Sustain.*, vol. 14, no. 21, p. 13955, Oct. 2022, doi: 10.3390/su142113955.
[27] A. Radchenko, G. Dyukareva, T. Afanasyeva, A. Kornitskaya, S. Yakubyan, and S. Karapandzha, "COMPETENCY-BASED APPROACH IN HIGHER EDUCATION: COMPETENCY-BASED MODEL OF THE ENGINEER FOR THE FOOD INDUSTRY," *ScienceRise*, vol. 3, pp. 58–65, Jun. 2020, doi: 10.21303/2313-8416.2020.001344.
[28] M. Favaretto, E. De Clercq, A. Caplan, and B. S. Elger, "United in Big Data? Exploring scholars' opinions on academic-industry partnership and the use of corporate data in digital behavioral research," *PLoS One*, vol. 18, no. 1, p. e0280542, Jan. 2023, doi: 10.1371/journal.pone.0280542.
[29] B. Heriyadi, H. Yustisia, L. Asnur, V. Efrianova, and Y. Darma, "Analysis of Educational Curriculum Reconstruction Mining Vocational in Preparation of MBKM in Industry," *paperASIA*, vol. 39, no. 6(b), pp. 116–123, Dec. 2023, doi: 10.59953/paperasia.v39i6(b).62.
[30] M. A. V Bermejo, M. Eynian, L. Malmsköld, and A. Scotti, "University–industry Collaboration in Curriculum Design and Delivery: A Model and Its Application in Manufacturing Engineering Courses," *Ind. High. Educ.*, vol. 36, no. 5, pp. 615–622, 2021, doi: 10.1177/09504222211064204.
[31] A. Oke and F. A. P. Fernandes, "Innovations in Teaching and Learning: Exploring the Perceptions of the Education Sector on the 4th Industrial Revolution (4IR)," *J. Open Innov. Technol. Mark. Complex.*, vol. 6, no. 2, p. 31, 2020, doi: 10.3390/joitmc6020031.
[32] E. Pereira, "Constructive Alignment in a Graduate-Level Project Management Course: An Innovative Framework Using Large Language Models," *Int. J. Educ. Technol. High. Educ.*, vol. 21, no. 1, 2024, doi: 10.1186/s41239-024-00457-2.
[33] S. Marsudi, "Development of a Shipping Higher Education Curriculum That Is Responsive to the Challenges of Industry 4.0," *Marit. Park J. Marit. Technol. Soc.*, pp. 99–105, 2023, doi: 10.62012/mp.v2i3.28267.
[34] S. K. Soam *et al.*, "Academia-Industry Linkages for Sustainable Innovation in Agriculture Higher Education in India," *Sustainability*, vol. 15, no. 23, p. 16450, Nov. 2023, doi: 10.3390/su152316450.
[35] F. Tuğrul and M. Çitil, "A New Perspective on Evaluation System in Education With Intuitionistic Fuzzy Logic and Promethee Algorithm," *J. Univers. Math.*, 2021, doi: 10.33773/jum.796173.
[36] F. Ş. YÜKSEL, A. N. KAYADELEN, and F. ANTMEN, "A Systematic Literature Review on Multi-Criteria Decision Making in Higher Education," *Int. J. Assess. Tools Educ.*, vol. 10, no. 1, pp. 12–28, 2023, doi: 10.21449/ijate.1104005.
[37] M. Aziz and S. Surono, "Integration Model Of Occupational Certification Scheme Into Instructional Design To Close The Gap Of Learning Outcomes And Industry Needs," *J. Transnatl. Univers. Stud.*, vol. 3, no. 6, pp. 285–300, Jun. 2024, doi: 10.58631/jtus.v3i6.97.
[38] M. Faisal *et al.*, "A Hybrid MOO, MCGDM, and Sentiment Analysis Methodologies for Enhancing Regional Expansion Planning: A Case Study Luwu - Indonesia," *Int. J. Math. Eng. Manag. Sci.*, vol. 10, no. 1, pp. 163–188, Feb. 2025, doi: 10.33889/IJMEMS.2025.10.1.010.
[39] E. Pereira, M. Vilas-Boas, and C. Rebelo, "University Curriculum and Employability: The Stakeholders' Views for a Future Agenda," *Ind. High. Educ.*, vol. 34, no. 5, pp. 321–329, 2020, doi: 10.1177/0950422220901676.
[40] P. Chikasha, K. Ramdass, N. Ndou, R. Maladzhi, and K. Mokgohloa, "Industrial Engineers of the Future – A Concept for a Profession That Is Evolving," *Adv. Sci. Technol. Eng. Syst. J.*, vol. 6, no. 4, pp. 72–79, 2021, doi: 10.25046/aj060409.
[41] M. N. Roma, "Redefining Assessment in Tourism and Hospitality Education," *Int. J. High. Educ.*, vol. 10, no. 4, p. 113, 2021, doi: 10.5430/ijhe.v10n4p113.
[42] Y. Chang and H.-L. Lien, "Mapping Course Sustainability by Embedding the SDGs Inventory Into the University Curriculum: A Case Study From National University of Kaohsiung in Taiwan," *Sustainability*, vol. 12, no. 10, p. 4274, 2020, doi: 10.3390/su12104274.
[43] N. A. Appiah, "Higher Fashion Education in Perspective: The Effects of Work-Based Learning on Industry Requirements," *Br. J. Multidiscip. Adv. Stud.*, vol. 4, no. 3, pp. 137–150, 2023, doi: 10.37745/bjmas.2022.00206.
[44] H. Daniel, F. J. Nicholas, K. Chavali, and R. R. Gundala, "The Perceived Effects of Graduate Business Education on Personal and Professional Development: An Empirical Study," *Tem J.*, pp. 341–350, 2023, doi: 10.18421/tem121-43.
[45] S. Salehi, "A Fuzzy Multicriteria Decision Making Approach in Higher Education," *Int. J. Comput. Digit. Syst.*, vol. 14, no. 1, pp. 10159–10168, 2023, doi: 10.12785/ijcds/140189.
[46] A. Guryeva, "The Use of Virtual Reality Technology in Training Transport Industry Specialists," *SHS Web Conf.*, vol. 164, p. 46, 2023, doi: 10.1051/shsconf/202316400046.
[47] J. Williamson, K. Wardle, and H. Hasmi, "Developing WIL curriculum which enhances hospitality students capabilities," *High. Educ. Ski. Work. Learn.*, vol. 11, no. 3, pp. 635–648, Jun. 2021, doi: 10.1108/HESWBL-04-2020-0055.
[48] T. Sekiyama, "The Impact of the Fourth Industrial Revolution on Student Mobility From the Perspective of Education Economics," *Creat. Educ.*, vol. 11, no. 04, pp. 435–446, 2020, doi: 10.4236/ce.2020.114031.
[49] M. Faisal, T. K. A. Rahman, I. Mulyadi, K. Aryasa, Irmawati, and M. Thamrin, "A Novelty Decision-Making Based on Hybrid Indexing, Clustering, and Classification Methodologies: An Application to Map the Relevant Experts Against the Rural Problem," *Decis. Mak. Appl. Manag. Eng.*, vol. 7, no. 2, pp. 132–171, Feb. 2024, doi: 10.31181/dmame7220241023.
[50] E. Soltani and M. Mirzaei Aliabadi, "Risk assessment of firefighting job using hybrid SWARA-ARAS methods in fuzzy environment," *Heliyon*, vol. 9, no. 11, p. e22230, Nov. 2023, doi: 10.1016/j.heliyon.2023.e22230.

[51] J. Wang, G. Wei, C. Wei, and Y. Wei, “MABAC method for multiple attribute group decision making under q-rung orthopair fuzzy environment,” *Def. Technol.*, vol. 16, no. 1, pp. 208–216, Feb. 2020, doi: 10.1016/j.dt.2019.06.019.
[52] X. Dai, H. Li, L. Zhou, and Q. Wu, “The SMAA-MABAC approach for healthcare supplier selection in belief distribution environment with uncertainties,” *Eng. Appl. Artif. Intell.*, vol. 129, p. 107654, Mar. 2024, doi: 10.1016/j.engappai.2023.107654.
[53] H. Zhang, Y. Feng, W. Huang, J. Zhang, and J. Zhang, “A novel mutual aid Salp Swarm Algorithm for global optimization,” *Concurr. Comput. Pract. Exp.*, vol. 35, no. 17, Aug. 2023, doi: 10.1002/cpe.6556.
[54] A. R. Yildiz and M. U. Erdaş, “A new Hybrid Taguchi-salp swarm optimization algorithm for the robust design of real-world engineering problems,” *Mater. Test.*, vol. 63, no. 2, pp. 157–162, Feb. 2021, doi: 10.1515/mt-2020-0022.
[55] S. I. Mohammed, N. K. Hussein, O. Haddani, M. Aljohani, M. A. Alkahya, and M. Qaraad, “Fine-Tuned Cardiovascular Risk Assessment: Locally Weighted Salp Swarm Algorithm in Global Optimization,” *Mathematics*, vol. 12, no. 2, p. 243, Jan. 2024, doi: 10.3390/math12020243.
[56] Y. Zhao, S. Bi, F. Li, H. Zhang, and Z. Chen, “Dynamic weight and mapping mutation operation-based salp swarm algorithm for global optimization.” p. 6, Nov. 29, 2022, doi: 10.21203/rs.3.rs-2276369/v1.
[57]Z. Lai, G. Liang, J. Zhou, H. Kong, and Y. Lu, “A joint learning framework for optimal feature extraction and multi-class SVM,” *Inf. Sci. (Ny).*, vol. 671, p. 120656, Jun. 2024, doi: 10.1016/j.ins.2024.120656.
[58] H. Yatim, J. Jamilah, N. Sahnir, and A. Abduh, “Analysis of Habituation in Implementing the Merdeka Belajar Curriculum in Art Education in Schools,” *J. Ad'ministrare*, vol. 10, no. 1, p. 111, Apr. 2023, doi: 10.26858/ja.v10i1.45310.
[59] W. H. Ndimbo and H. Kessy, “Primary School Teachers' Instructional Competences in the Implementation of Competence-based Curriculum: A Case Study of Mpwapwa District Council,” *J. Educ. Soc. Behav. Sci.*, vol. 36, no. 5, pp. 24–43, Mar. 2023, doi: 10.9734/jesbs/2023/v36i51222.
[60] J. Mpofu and M. M. Sefotho, “Challenges of competency-based curriculum in teaching learners with learning disabilities,” *African J. Disabil.*, vol. 13, Feb. 2024, doi: 10.4102/ajod.v13i0.1268.
[61]A. Halim, “Dual System Curriculum in Chemical Engineering Education,” *IJCER (International J. Chem. Educ. Res.*, pp. 75–82, Oct. 2022, doi: 10.20885/ijcer.vol6.iss2.art3.
[62] A. Aizhan and G. A. Virginia, “A Comparative Study of Stakeholder Engagement in the Dual Education System: A Case of Germany, the United States and Kazakhstan,” *J. Tech. Educ. Train.*, vol. 15, no. 3, pp. 154–168, Sep. 2023, doi: 10.30880/jtet.2023.15.03.014.
[63] F. Ali, M. Minaz, S. Shehzad, G. N. Baig, and W. Ahmad, “An Analysis of Outcome-based Education into Educational Practices at University Level,” *Qlantic J. Soc. Sci. Humanit.*, vol. 5, no. 1, pp. 89–98, 2024, doi: 10.55737/qjss.510267290.
[64] Et. al., Muhammad Rozahi Istambul, “Strategy for Implementing Elearning to Achieve Outcome-Based Education,” *Turkish J. Comput. Math. Educ.*, vol. 12, no. 4, pp. 847–851, Apr. 2021, doi: 10.17762/turcomat.v12i4.572.
[65] S. Mendo-Lázaro, B. León-del-Barco, M.-I. Polo-del-Río, and V. M. López-Ramos, “The Impact of Cooperative Learning on University Students' Academic Goals,” *Front. Psychol.*, vol. 12, Jan. 2022, doi: 10.3389/fpsyg.2021.787210.
[66] S. Y. Mei, S. Y. Ju, and A. B. Mohd, “Cooperative Learning Strategy in teaching Arabic for Non Native Speakers,” *Humanit. Today Proc.*, vol. 1, no. 2, pp. 112–120, Oct. 2022, doi: 10.26417/ejser.v11i2.p261-266.
[67] Ilknur Istifci and Nil Goksel, “The Relationship between Digital Literacy Skills and Self-Regulated Learning Skills of Open Education Faculty Students,” *English as a Foreign Lang. Int. J.*, vol. 2, no. 1, pp. 59–81, 2022, doi: 10.56498/164212022.
[68] R. Nthenya Wambua, “Digital Learning Strategies Within Universities In Developing Countries: A Systematic Literature Review,” *Int. J. Res. Publ.*, vol. 117, no. 1, Jan. 2023, doi: 10.47119/IJRP1001171120234446.
[69] K. Z. Naufel, S. M. Spencer, J. F. Van Kirk, and A. S. Richmond, “Method matters: The importance of understanding the creation of the skillful psychology student.,” *Scholarsh. Teach. Learn. Psychol.*, May 2023, doi: 10.1037/stl0000357.
[70] C. Mountain and R. Hill, “Academic Electronic Health Record in Mental Health Clinical,” *CIN Comput. Informatics, Nurs.*, vol. 42, no. 7, pp. 490–494, Mar. 2024, doi: 10.1097/CIN.0000000000001118.
[71]K. A. Aji, “Literature Review: The Relationship between Merdeka Curriculum and Student Learning Achievement,” *J. Pendidik. Jasm.*, vol. 4, no. 1, pp. 17–30, Jun. 2023, doi: 10.55081/jpj.v4i1.732.
[72] E. Idris, D. Choy, and B. L. Chua, “Polytechnic Students' Perspectives of a Blended Problem-Based Learning Approach in Singapore,” *ASCILITE Publ.*, pp. 440–444, Nov. 2023, doi: 10.14742/apubs.2023.612.
[73] I. K. Sugiarta, C. Ardina, I. K. Parnata, and I. M. Bagiada, “Work Readiness of Accounting Vocational Education Students in Facing the Era of the Industry 4.0 and Society 5.0,” *Int. J. Educ. Learn. Dev.*, vol. 11, no. 9, pp. 1–8, Aug. 2023, doi: 10.37745/ijeld.2013/vol11n918.
[74] Shofiyatul Masruro, Elok Sudibyo, and Tarzan Purnomo, “Profile of Problem Based Learning to Improve Students' Critical Thinking Skills,” *IJORER Int. J. Recent Educ. Res.*, vol. 2, no. 6, pp. 682–699, 2021, doi: 10.46245/ijorer.v2i6.171.
[75] Y. Wu *et al.*, “Effects of a grouping intervention using the Felder-Silverman learning style model on problem-based learning among nursing students: A randomized controlled trial,” *Nurse Educ. Today*, vol. 145, p. 106489, Feb. 2025, doi: 10.1016/j.nedt.2024.106489.
[76] M. Ismail *et al.*, “Cybersecurity activities for education and curriculum design: A survey,” *Comput. Hum. Behav. Reports*, vol. 16, p. 100501, Dec. 2024, doi: 10.1016/j.chbr.2024.100501.
[77] A. Pfluger *et al.*, “Framework for analyzing placement of and identifying opportunities for improving technical communication in a chemical engineering curriculum,” *Educ. Chem. Eng.*, vol. 31, pp. 11–20, Apr. 2020, doi: 10.1016/j.ece.2020.02.001.
[78] M. Faisal and T. K. A. Rahman, “Optimally Enhancement Rural Development Support Using Hybrid Multy Object Optimization (MOO) and Clustering Methodologies: A Case South Sulawesi - Indonesia,” *Int. J. Sustain. Dev. Plan.*, vol. 18, no. 6, pp. 1659–1669, Jun. 2023, doi: 10.18280/ijsdp.180602.
[79] S. H. Mian, E. Abouel Nasr, K. Moiduddin, M. Saleh, M. H. Abidi, and H. Alkhalefah, “Assessment of consolidative multi-criteria decision making (C-MCDM) algorithms for optimal mapping of polymer materials in additive manufacturing: A case study of orthotic application,” *Heliyon*, vol. 10, no. 10, p. e30867, May 2024, doi: 10.1016/j.heliyon.2024.e30867.

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