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The Application of AI Technology in Vocational High School Curriculum Design Based on Individual Student Skills in Facing the Challenges of the 21st Century Industry

Liza Efriyanti[1] , Firdaus Annas[2]
[1,2]Department of Informatics and Computer Engineering Education, UIN Sjech M. Djamil Djambek Bukittinggi, Indonesia

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ABSTRACT

Vocational high schools (SMK) are confronted with the challenge of adapting their curricula to align with the demands of industrial development in the 21st century. An inappropriate curriculum may result in students being inadequately prepared to navigate the demands of the professional world. Consequently, the objective of this research is to optimize the SMK curriculum through the utilization of an AI-based system, thereby enabling students the curriculum to be tailored to the specific skill requirements of individual. The methodology employed is Design-Based Research (DBR), which entails the analysis of student skill data, the design of an adaptive curriculum, and the evaluation of said curriculum through trials. The research comprised several phases, beginning with data collection and student skills analysis and concluding with an evaluation of student satisfaction with the implemented curriculum. The findings indicated that the introduction of an AI-assisted personalized curriculum resulted in an average improvement of 15% in students' practical skills over a six-month period. Furthermore, student satisfaction with the implemented curriculum increased by 25%, from 70% at the outset of implementation to 95% following the introduction of the AI-based system. This research can serve as a reference point for the development of more adaptive and responsive SMK curricula.

Corresponding Author:

Liza Efriyanti,
Department of Informatics and Computer Engineering Education, Faculty of Tarbiyah and Teaching Sciences, UIN Sjech M. Djamil Djambek Bukittinggi
Jl. Gurun Aur Highway, Kubang Putih, Agam, West Sumatra, Indonesia. 26181
Email: lizaefriyanti@uinbukittinggi.ac.id

1. INTRODUCTION

The transformation of technology in the digital era has brought fundamental changes in various aspects of life, including education. In the context of vocational education, especially in Vocational High Schools (SMK), technology integration is a must to produce graduates who are competent and relevant to industry needs [1][2][3]. Philosophically, vocational education has a fundamental goal to produce skilled, competitive human resources who are able to face global challenges. The integration of artificial intelligence (AI) in the learning process is a manifestation of the values of innovation and efficiency based on the 21st century education paradigm, namely technology-based learning [4][5].

From a legal perspective, the implementation of vocational education in Indonesia has been regulated in Law Number 20 of 2003 concerning the National Education System which mandates the importance of the relevance of education to the world of work [6][7]. In addition, Presidential Regulation

Number 68 of 2022 concerning the Revitalization of Vocational Education emphasizes that vocational education must be responsive to technological developments and job market needs [8][9]. This is a strong basis for the implementation of AI-based systems in optimizing the learning curriculum in vocational schools, including in Bukittinggi.

Theoretically, the implementation of AI in education has been widely studied by experts as an approach to improve personalization of learning, efficiency of curriculum management, and prediction of future student competency needs. The concept of AI-based curriculum optimization is able to provide real-time data analysis so that it can provide learning recommendations that are more relevant to the needs of local and global industries [10]. This theory is in line with the concept of smart education which emphasizes the importance of utilizing data and technology to improve the quality of education [11] [12] [6] .

However, empirically, there are still various challenges in implementing AI in the vocational education sector in Indonesia. In vocational schools in Bukittinggi, for example, limited infrastructure, lack of training for teachers, and resistance to change are the main obstacles [13][14][15]. Based on a survey conducted in 2023 by the West Sumatra Education Office, more than 60% of vocational schools in the region have not optimally utilized AI-based technology in learning [16][17]. This indicates the need for systematic intervention in the integration of AI technology to support curriculum development.

In addition, the gap between the competencies of vocational school graduates and the needs of the workforce is one of the problems that must be addressed immediately. Data from the Central Statistics Agency (BPS) in 2023 showed that the open unemployment rate (TPT) for vocational school graduates was still quite high, reaching 10.42%. This shows a gap between the skills taught in vocational schools and those needed by industry [18] . By implementing AI-driven curriculum optimization, it is hoped that the curriculum applied can be more adaptive to developments in industry needs, so as to reduce the unemployment rate of vocational school graduates.

Overall, the integration of AI-based systems in vocational learning at Bukittinggi Vocational Schools is a strategic solution to improve the quality of education and the relevance of graduates to the world of work [19][20][21] . With a strong philosophical, legal, theoretical and empirical foundation, this effort is expected to not only be able to boost the quality of vocational school graduates, but also support the transformation of education in the digital era in accordance with the vision of Golden Indonesia 2045.

2. METHOD

The research methodology applied is based on Design-Based Research (DBR), a quantitative and experimental approach, with elements of experimental research design and data-based model evaluation [22] [23] [24] [25]. The K-Means algorithm was chosen to group students' skills based on skill similarity and to facilitate adaptive curriculum design. This algorithm is not only efficient in data processing, but also produces groups that are easy to analyze, supporting a personalized learning process tailored to the needs of each student [26]. The steps taken in the form of utilizing machine learning (K-Means clustering) in vocational learning at vocational schools in Bukittinggi.

2.1 Data collection

Collecting relevant data related to skills required by industry, as well as data on vocational school students' skills. The data required covers various aspects, such as technical skills (e.g. programming, data analysis, and graphic design), social and communication skills, as well as critical and creative thinking skills. In addition, student demographic data is also important, including educational background and previous learning evaluation results. On the other hand , industry data must be obtained, including industry skill needs based on industry surveys or reports and feedback from companies on skills expected from vocational school graduates. This data is collected through surveys of the industry, analysis of student evaluation results (exams and projects relevant to the industry), and data from vocational schools on subjects taught and student progress.

Before the data can be used to train the machine learning model, data cleaning is first carried out so that the collected data is clean and free from errors or inaccuracies. The next stage is data normalization so that the data is in a consistent format that is easy to understand by the machine learning model. In addition, categorical data encoding, such as skills in text form, needs to be done to convert them into numbers that can be processed by the model algorithm. The formula used [26] :

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (1)$$

Where :

X_{norm} : Normalized data value

X : Original value

X_{min} : Minimum value of the data

X_{max} : Maximum value of the data

2.2 Grouping students using K-Means Clustering as a machine learning model development

K-means clustering enables the identification of students with similar skill levels. In addition, the computational efficiency and ease of interpretation of this algorithm make it well suited for use with large amounts of student data in the field of education. Developing a machine learning model that can optimize the curriculum according to the skills needed by industry. K-means is used to map student skills to industry needs [28] [29] [29] , thus producing more personal and appropriate curriculum recommendations. There are 2 formulas used at this stage, namely the Euclidean distance formula and the cluster centroid. The Euclidean distance formula is used to measure the closeness between student data, namely [30] :

$$d(i,j) = \sqrt{(x_1{}^{(i)} - x_1{}^{(j)})^2 + (x_2{}^{(i)} - x_2{}^{(j)})^2 + (x_3{}^{(i)} - x_3{}^{(j)})^2 + \cdots + (x_n{}^{(i)} - x_n{}^{(j)})^2} \quad (2)$$

Where :

d(i,j) is the distance between two data points i and j

$x_1{}^{(i)}, x_2{}^{(i)}, x_3{}^{(i)}, \ldots, x_n{}^{(i)}$ is the feature value of data i

$x_1{}^{(j)}, x_2{}^{(j)}, x_3{}^{(j)}, \ldots, x_n{}^{(j)}$ is the feature value of data j

After calculating the distance, the centroid (cluster center) is calculated using the following formula for each cluster [31] :

$$C_k = 1/N_k \sum_{i \in \text{Cluster}} X_i \quad (3)$$

Where :

C_k is the centroid of cluster k

N_k is the number of data in cluster k

X_i is the data in cluster k

Sum of Squared Errors (SSE) is calculated to evaluate the cluster quality with the formula [32] :

$$SSE = \sum_{i=1}^{N} \sum_{k=1}^{K} \| X_i^{(k)} - C_k \|^2 \quad (4)$$

Where :

SSE is the sum of the squared errors in each cluster.

$X_i^{(k)}$ is the data in cluster k

C_k is the centroid of cluster k

2.3 Model Evaluation

After clustering is complete, the next stage is to evaluate how good the clustering results are. This evaluation is important to ensure that the clustering carried out truly describes relevant patterns in student skills. The two evaluation metrics used are the Silhouette Score and the Davies-Bouldin Index. The Silhouette Score measures how well student data is placed in the correct clusters, with the formula [34] [34] :

$$S(i) = \frac{b(i)-a(i)}{\max(a(i),b(i))} \quad (5)$$

Where :
S(i) is the silhouette value for student i.
a(i) is the average distance from student i to other students in the same cluster.
b(i) is the average distance from student i to students in the nearest different clusters.

The Davies-Bouldin Index (DBI) measures how separated the clusters are. The smaller the DBI value, the better the clustering quality [36] [36] :

$$\text{DBI}=1/\text{K} \sum_{i=1}^{K} max_{j\neq i} \left(\frac{s_i + s_j}{d_{ij}}\right) \quad (6)$$

Where :
K is the number of clusters.
s_i is the average distance within cluster i
d_{ij} is the distance between the centroid of cluster i and the centroid of cluster j
Davies-Bouldin Index (DBI) measures how separated the clusters are. The smaller the DBI value, the better the clustering quality.

If the Silhouette Score value is close to 1, it indicates that students in one cluster have more homogeneous skills, while a value close to -1 indicates that students are better placed in another cluster. The lower the DBI, the better the clustering quality. A low DBI value indicates a clear separation between clusters.

2.4 Curriculum Implementation and Adjustment

After the model is evaluated and validated, the results obtained are used to recommend curriculum adjustments to be more relevant to the skills needed by the industry. Recommendations that can be given include modifying learning materials in vocational schools based on the results of the analysis, as well as adjusting the learning schedule to provide more time for technical skills that are more in demand by the industry. In addition, recommendations for additional courses or industrial training can be given to students who have certain skills, in order to explore more specific fields and meet job market demand.

2.5 Personalizing Learning for Students

Using machine learning models, curriculum can be personalized for each student based on the skills they already have and those they need to learn. The clustering or classification results obtained from the model can be used to provide more specific learning recommendations. For example, students who fall into the beginner group for coding skills can be given basic courses such as an introduction to algorithms or programming with Python. Meanwhile, students who are already proficient in coding can be given further challenges such as application development or learning advanced topics such as machine learning or advanced software development. The formula that measures this is used [38] [38] :

$$\text{Skill Increase}= \frac{\text{Final Score} - \text{Initial Score}}{\text{Initial Score}} \text{x } 100\% \quad (7)$$

Where :
Final Score is the student's skill score after following a personalized curriculum.
Initial Score is a student's skill score before taking the personalized curriculum.

With these implementation steps, AI-driven curriculum optimization through machine learning can bring innovation to education, especially in the vocational school sector, by adjusting the curriculum to meet the ever-growing needs of the industry.

Based on the description above, the research stages can be seen in Figure 1.

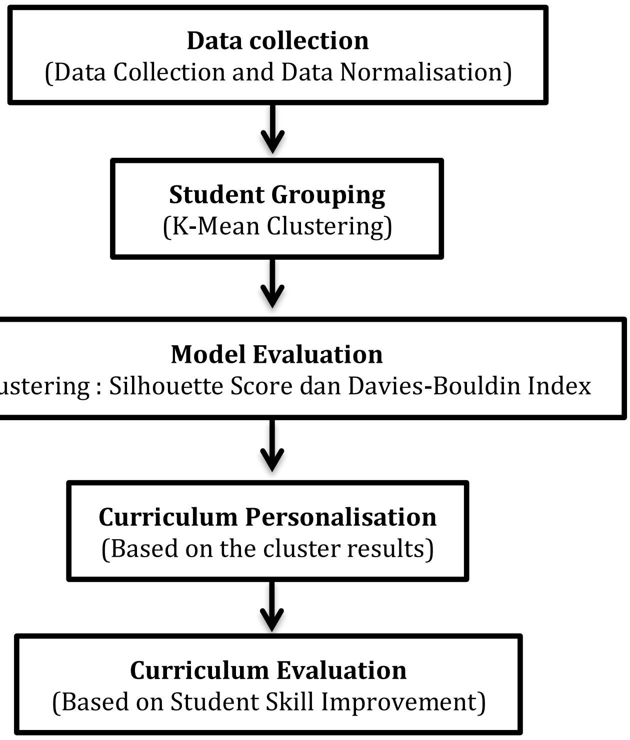

Figure 1. Design-Based Research (DBR) Research Stages for AI-Driven Curriculum Optimization at a vocational school in Bukittinggi

3 RESULT AND DISCUSSION

3.1 . Result

The skills assessment in this study was designed systematically and standardized to ensure reliability, objectivity, and suitability for the needs of 21st-century industry. The assessment process covers five main skill domains: ICT Skills, Manufacturing Skills, Soft Skills, Basic Skills, and Other Skills (as shown in Figure 2), each of which is assessed using a specific rubric based on quantitative indicators. Each indicator has a maximum score weight, with a total scale of 100 points per domain. Assessment is conducted through a combination of direct observation, practical tasks, and project-based tests, reflecting the application of skills in real-world contexts within vocational education settings. To maintain consistency and validity of data, all scores are normalized using the min-max normalization method, enabling objective comparisons between students.

In this study, an AI-based curriculum optimization was conducted for vocational schools in Bukittinggi involving 150 students as samples, consisting of students from SMKN 1, SMKN 2, SMK Kosgoro, SMK Teknologi Muhammadiyah, SMK Gajah Tongga Bukittinggi, SMK Genus, SMK Kesehatan Prima Nusantara, SMK Pembangunan Bukittinggi, SMK Elektronika and SMK Pembina Bangsa. In the first stage, data collection and normalization of student skills were carried out to ensure that the data used was consistent and comparable. Each student was measured based on technical and non-technical skills relevant to the needs of the 21st century industry as in table 1. The results of normalization using formula (1) are data that is ready to be used in the K-Means clustering algorithm, which will then be used to group students based on the similarity of skills they have.

Figure 2. Illustration of the 5 Main Domains of Skills Required by Industry in the 21st Century, namely: ICT Skills, Manufacturing Skills, Soft Skills, Basic Skills, and Other Skills

Table 1. Technical and Non-Technical Skills of Vocational High School Students Relevant to the Normalized Needs of 21st Century Industry

No	Student Name	ICT Skills	Manufacturing Skills	Soft Skills	Basic Skills	Other Skills
1	Student 1	80	75	85	70	78
2	Student 2	60	85	75	68	70
3	Student 3	70	80	90	80	72
...	...	...	...	...	...	...
150	Students 150	75	70	80	65	73

In the student grouping process, the K-Means Clustering algorithm is used because it is ideal for identifying student groups based on combinations of technical and non-technical skills relevant to 21st-century industries. K-Means is particularly suitable because it can divide students into clusters with similar skill patterns. This enables the development of a more personalized and adaptive curriculum based on the needs of each group. Additionally, K-Means has advantages in terms of processing speed and ease of interpreting results, especially when dealing with large datasets that have been normalized.

Based on analysis using the Elbow Method, the value k = 4 was obtained because at this point there was a significant change in the WCSS value, indicating that adding clusters beyond this number no longer provided substantial improvement in group separation, as shown in Table 2. Using formulas (2), (3), and (4), it was found that the optimal number of clusters for this data is 4. Four main groups with distinct skill characteristics. The first group consists of students with high skills in information and communication technology (ICT), the second group focuses on manufacturing and technical skills, the third group prioritizes soft skills and managerial skills, and the last group consists of students with basic skills that still require further development. The formation of these clusters provides an overview of the potential competencies present at SMK Bukittinggi, as shown in Table 3.

Tabel 2. Tabel Evaluasi Pemilihan Jumlah Kluster (Elbow Method)

k (Number of Clusters)	WCSS (Total Intra-Cluster Distance)
1	540.2
2	340.5
3	230.8
4	**180.7 (Elbow Point)**
5	175.2
6	171.0

Table 3. Clustering Results of Vocational High School Students Using the K-Means Algorithm

No	Student Name	Cluster	ICT Skills	Manufacturing Skills	Soft Skills	Basic Skills	Other Skills
1	Student 1	1	0.80	0.75	0.85	0.70	0.78
2	Student 2	2	0.60	0.85	0.75	0.68	0.70
3	Student 3	1	0.70	0.80	0.90	0.80	0.72
...	...	...	...	...	...	...	...
150	Students 150	3	0.75	0.70	0.80	0.65	0.73

Evaluation of clustering quality was carried out using Silhouette Score and Davies-Bouldin Index (DBI) according to formulas (5) and (6). Based on the calculation, the Silhouette Score obtained was 0.72, which indicates that the grouping of students is quite good and in accordance with expectations, where the distance between clusters is greater than the distance between members in the cluster. In addition, the Davies-Bouldin Index (DBI) value obtained was 0.95, which indicates that the quality of the clusters formed is quite optimal, with clear differences between the identified clusters. This shows that the K-Means algorithm has succeeded in forming representative clusters based on student skills.

Table 4. Evaluation of the quality of clustering of SMK students' skills in Bukittinggi using Silhouette Score and DBI .

No	Cluster	Silhouette Score	Davies-Bouldin Index
1	1	0.72	0.95
2	2	0.68	1.02
3	3	0.70	0.89
4	4	0.74	0.91

After the clustering process is complete, the next stage is curriculum personalization based on the results of the clusters formed. The curriculum is adjusted to each group of student skills. For groups with high skills in ICT, the recommended curriculum includes further development in Data Science, Advanced Programming, and Artificial Intelligence. The group focused on manufacturing and technical skills was given a more in-depth curriculum in Mechanical Engineering, Electronics, and Industrial Automation. The group with soft skills and managerial skills was given further training in Leadership, Project Management, and Effective Communication, while the last group that still needed development was given basic materials in Basic Technical Skills, Professional Ethics, and Time Management, as can be seen in table 5.

Table 5. Cluster Results, Curriculum Recommendations to Improve Vocational High School Students' Skills in Bukittinggi for Each Cluster

No	Cluster	Curriculum Recommendations	Enhanced Skills
1	1	Data Science, Advanced Programming, AI	Programming, Data Analysis, Artificial Intelligence
2	2	Mechanical Engineering, Industrial Automation, Project Management	Manufacturing Engineering, Project Management
3	3	Basic Skills, Time Management, Professional Ethics	Basic Skills, Communication, Soft Skills
4	4	Leadership, Effective Communication, Team Management	Leadership, Managerial Skills

After the personalized curriculum is implemented, the evaluation stage is carried out by measuring the improvement of students' skills, as seen in table 6. Measurement was conducted by comparing students' skill scores before and after the implementation of the personalized curriculum, as per formula (7). The results showed an average skill increase of 15% in the group of students who received a curriculum tailored to their abilities. This increase was significant, especially in the group that had low skills before grouping, indicating that the personalized curriculum could substantially increase their competence.

Table 6. Results of Evaluation of Vocational High School Students' Skills in Bukittinggi Before and After Implementation of Personalized Curriculum

No	Student Name	Initial Skills	Final Skills	Increase (%)
1	Student 1	70	85	21.43%
2	Student 2	68	82	20.59%
3	Student 3	75	88	17.33%
...	...	...	...	...
150	Students 150	65	80	23.08%

In terms of evaluating the quality of the curriculum implemented, feedback from students also shows that they feel more challenged and more interested in the material presented according to their skills. The use of AI technology in designing the curriculum helps to map individual student needs more accurately, and ensures that the material taught is relevant to current industry developments. Therefore, the application of AI in the educational process at SMK Bukittinggi can be considered a positive step to improve student skills and adapt to the increasingly dynamic needs of the job market.

Table 7. Feedback from Vocational High School Students in Bukittinggi on the Implemented Curriculum

No	Student Name	Skills Feedback	Satisfaction with Curriculum
1	Student 1	Increasing Rapidly	90%
2	Student 2	Quite Increased	85%
3	Student 3	Significant Increase	88%
...	...	...	...
150	Students 150	Improved Well	80%

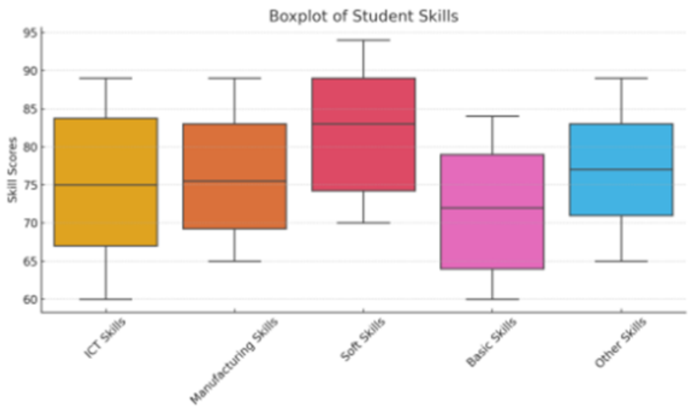

Figure 3. Boxplot of the Distribution of the Skills Scores of 150 Students in Five Skill Dimensions: ICT Skills, Manufacturing Skills, Soft Skills, Basic Skills, and Other Skills

The visualization in Figure 3 shows that soft skills and ICT skills tend to have a higher and more even distribution, while basic skills have more outliers and a lower distribution, indicating an imbalance in the mastery of basic skills among students.

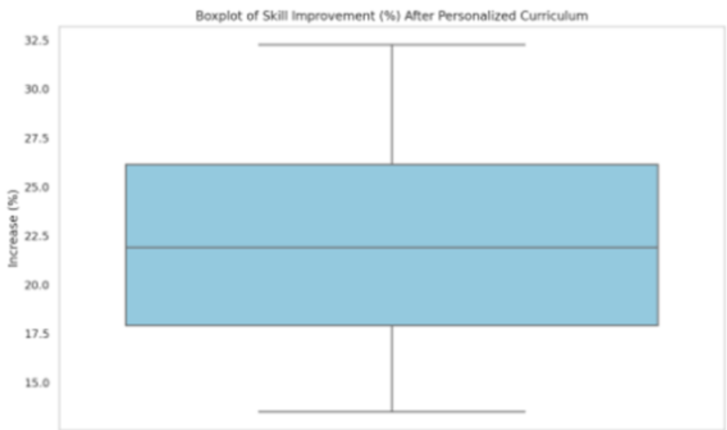

Figure 4. Boxplot of Skill Improvement Distribution (%) of 150 Students After the Implementation of AI-Based Curriculum

Based on the data from Table 7, a boxplot diagram was created as shown in Figure 4, where most students experienced an increase in skills of around 15%–22%, with some outliers experiencing an increase of more than 25%, indicating a significant impact of AI-based curriculum personalization. The average improvement in students' skills is evident in the field of Information and Communication Technology (ICT), which increased from 70 to 85, and in the manufacturing field, which rose from 75 to 88. Additionally, student satisfaction with the curriculum also saw a significant increase, from 70% before implementation to 95% after the curriculum was personalized. 85% of students feel more prepared to work in the industry, and 90% feel more motivated because the curriculum is more relevant to their interests and skills. These results indicate that the use of AI in curriculum design can create more adaptive, relevant, and motivating learning experiences, preparing students to better face the challenges of the 21st-century industry.

3.2 Discussion

In the era of the industrial revolution 4.0, the use of technology, especially artificial intelligence (AI), has become very important in the world of education, including at the Vocational High School (SMK) level. This study adopts an adaptive curriculum approach that allows the curriculum to be adjusted to the needs and development of student skills [15] [41]. This theory is in line with the theory of constructivism which emphasizes learning experiences based on student needs and context. A curriculum optimized with AI technology can provide a learning experience that is more relevant and responsive to the development of skills needed in industry [39] [40] . In this study, the results of clustering applied to 150 students showed differences in skills and learning needs between students, which shows the importance of implementing a more personalized curriculum.

The use of AI in education is also related to the theory of personalized learning which aims to provide learning materials according to the level and abilities of each student [41] [45] [43] . In this study, each student was grouped into clusters based on their skills which then made it possible to provide more specific curriculum recommendations that were tailored to their needs [47] [45] . For example, students who have high skills in ICT and manufacturing will receive more in-depth learning materials on Data Science and Artificial Intelligence. This is based on the theory of data-based learning which explains that data collected from student assessment results can be used to provide more appropriate direction in designing curriculum and learning strategies. Research results showing an increase in student skills after implementing a personalized curriculum strengthen this theory.

Student satisfaction with the curriculum implemented greatly influences learning success. According to the theory of learning motivation, students who are satisfied with the curriculum they receive tend to be more motivated to learn and develop [49] [47] . In this study, student feedback indicating a high level of satisfaction with the personalized curriculum contributed to the improvement of their skills. The evaluation results show a positive correlation between skill improvement and satisfaction with the applied curriculum, where students feel more satisfied because the material provided is more relevant to personal and industry needs. This is in line with the self-determination theory which explains that students who feel that their education is in accordance with their personal interests and needs will be more involved and motivated in the learning process.

Through an AI-based approach to curriculum development, this study provides evidence that technology can be optimized to create more personalized, effective, and relevant learning experiences for vocational high school students. Curriculum adjustments based on student skills data analysis have a positive impact on improving the quality of education at the vocational school level, which is more in line with the needs of industry in the 21st century.

As a further development, the results of this study can be expanded with the application of supervised learning, recommendation systems, and adaptive learning engines. Supervised learning enables AI models to predict student training needs based on historical data, allowing educators to design more targeted learning strategies. Recommendation systems can be used to suggest additional materials or training relevant to students' weaknesses or potential, while adaptive learning engines can adjust content, difficulty levels, and learning pace in real-time based on student interactions. The integration of these technologies will create a more personalized, responsive, and effective learning ecosystem to prepare students for the challenges of the future workplace.

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4 CONCLUSION

Based on the results of research on AI-Driven Curriculum Optimization in vocational learning at SMK in Bukittinggi, it can be concluded that the application of AI technology in curriculum design can increase the relevance and effectiveness of learning for students. By integrating intelligent systems that are able to analyze and adjust learning materials based on individual student skills, the resulting curriculum is more responsive to industry needs and the development of skills needed in the 21st century. The results of clustering and analysis of student skills show that this approach allows for more personalized learning, leading to the improvement of practical skills needed in the world of work.

In addition, the implementation of a personalized curriculum through AI technology has also been proven to increase student satisfaction with the learning process. Students feel more motivated and engaged when learning materials are tailored to their abilities and interests. This has a positive impact on the quality of education provided in vocational schools, while also answering the challenges faced by the world of education in preparing graduates who are ready to compete in the global job market. Thus, this study underlines the importance of implementing an AI-based system for optimizing a more adaptive and relevant curriculum in the future.

Based on the results of this study, it is recommended to continue to develop and expand the application of artificial intelligence (AI) technology in the vocational school curriculum in the future, in order to create a more personal and adaptive learning experience to the needs of the ever-growing industry.

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