G-Tech : Jurnal Teknologi Terapan
Vol. 9, No. 4, October 2025, p. 2207-2217
E-ISSN: 2623-064X | P-ISSN: 2580-8737

The Effect of AI-Based Recommendation System for Material Personalization on Vocational Student Satisfaction

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Article Information

Article History

Received : September 19, 2025
Revised : October 18, 2025
Published : October 26, 2025

***Keywords*:**

Vocational student satisfaction;
Personalization of learning materials;
AI-based recommendation system.

ABSTRACT

This study analyzes the influence of artificial intelligence (AI) based recommendation systems on the satisfaction of vocational students, focusing on two main variables: feature mapping and technological readiness. The research background is driven by the need for more adaptive and personalized learning, considering that conventional methods tend to be generic and overlook individual differences. Involving 183 vocational students selected through purposive sampling, the study employs a quantitative approach with descriptive and associative methods. Data were collected using valid and reliable questionnaires with a 1–5 Likert scale and analyzed using multiple linear regression. The results indicate that both feature mapping and technological readiness have a positive and significant influence on student satisfaction. Simultaneously, these two variables explain 43% of the variation in student satisfaction. Partially, feature mapping has the most dominant influence compared to technological readiness, indicating the importance of adaptive feature design in AI-based recommendation systems. This study proves that technology-based learning material personalization if supported by adequate infrastructure can enhance the learning experience and satisfaction of vocational students. Therefore, the study recommends the development of AI-based adaptive learning models that prioritize aspects of feature design and technological readiness to improve the effectiveness and quality of vocational education.

INTRODUCTION

Vocational education occupies as a strategic position in preparing technically proficient and work-ready graduates, through a practice-based learning approach (Gustiawan et al., 2025; Widayanthi, 2024). However, various institutions still apply general teaching methods and put little attention to differentiate in learning styles, basic abilities, and specific needs of students (Sahudra et al., 2023; Suparyati et al., 2023). As a result, the learning system is not fully adaptive and often does not meet the expectations of students (R. A. Surya, 2024).

Personalized learning theory reveals that an adaptation of materials based on individual profiles can increase engagement, retention, and learning satisfaction (Bernacki et al., 2021; Zheng et al., 2022). In the realm of vocational education, the implementation of an AI-based

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recommendation system that combines analysis of student interactions, learning preferences, and industry needs has proven the effectiveness of improving learning quality (Liu et al., 2023). Other studies have shown that adaptive automated material recommendations can improve learning experience and students' satisfaction (Jaya et al., 2024; Thongchotchat et al., 2023). In addition, adaptive approaches, such as AI-based training, have been shown to improve learning outcomes and motivation in vocational students (Cui & Fwuyuan, 2024; Novelti et al., 2024).

However, not many empirical studies have directly examined the effect of AI-based material personalization on vocational students' satisfaction, by including latent variables such as feature mapping and technology readiness. Findings from (Rahyasih et al., 2023) revealed that the quality of interaction and digital media have a significant impact on the level of satisfaction for vocational students in online learning process (Ellikkal & Rajamohan, 2025; Rahyasih et al., 2023). Another finding states that personalized AI tutors are proven to improve academic performance and satisfaction with higher engagement (Almansour & Alfhaid, 2024; Sitompul, n.d.). Thus, the right AI-based recommendation system model can make a real contribution to the adaptability and satisfaction of vocational students.

The advancement of Artificial Intelligence (AI) technology, especially for vocational education users, has provided opportunities to develop learning systems that are adjustable and responsive to fulfil the needs of each individual. Previous studies have shown that the integration of AI as learning material recommendation systems increased the accuracy of personalization by up to 30%, thus having a positive impact on knowledge retention and learning motivation (Daga et al., 2024; Strielkowski et al., 2025). However, the implementation of this technology still faces challenges, such as limited comprehensive student profile data and the digital divide in some vocational institutions (Mastam et al., 2024; Supriyatmoko et al., 2025).

The fundamental problem in implementing AI recommendation systems in vocational education lies in the different between the technical capabilities of the system and the dynamic learning context. Previous studies identified that low technology readiness, such as inadequate infrastructure, lack of faculty training, or limited access are the main barriers to the adoption of AI solutions. On the other hand, research shows that feature mapping failures such as mismatching material recommendations with industry competencies or student learning preferences reduce the impact of personalization. This research comes to fill the gap by making technology readiness and feature mapping as critical variables. The research objective is to analyze the effect of AI-based recommendation system on vocational students' satisfaction by considering critical variables, namely technology readiness (X_2) and feature mapping (X_1), in order to address the gap between the system's technical capabilities and adaptive learning needs. The research results are expected to provide an adaptive learning model that is relevant to industry needs, improve the effectiveness of technology implementation in vocational institutions, and enrich theoretical studies on AI-based personalized learning.

RESEARCH METHODS

This present study was conducted using qualitative approach by using descriptive and associative method aiming at examining the effect of AI-based recommendation systems for material personalization on vocational student satisfaction. This research was conducted by analyzing the relation between two independent variables, namely: feature mapping (X1) and technology readiness (X2) on the dependent variable; student satisfaction (Y).

The population is vocational students from various diploma programs in Aceh Province as research subjects. Purposive sampling was implemented in this present study by considering certain criteria, are (1) active students of diploma programs, (2) having experience using digital learning platforms, and (3) willing to become research respondents. The sampling process began with the identification of vocational institutions in Aceh, followed by stratification based on study programs to ensure adequate representation, then online questionnaires were distributed through Google Forms. From this selection process, 183 eligible respondents were collected by taking into account the proportion of gender and class (semester), within a data collection period of ± 4 weeks. The research instrument was an online questionnaire with a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

Research instrument testing is a crucial stage to ensure the validity and reliability of data collection tools before they are used in the main study, such as in the context of research on AI-based recommendation systems for vocational education where questionnaires need to be statistically tested. This testing is conducted through validity tests to measure the extent to which the measuring instrument can measure the intended variables and assess the instrument's capabilities, as well as reliability tests to assess the reliability, accuracy, precision, or accuracy of the instrument, in order to verify that each indicator is capable of measuring the intended construct and producing consistent data.

Validity testing was conducted to determine the validity level of the indicators as a tool for measuring variables. Calculations were performed by correlating each item score with the total score using the Product Moment correlation technique. If the calculated correlation coefficient is greater than the table value, the questionnaire item is declared valid and valid as a data collection tool. With a number of respondents (n) = 43 and a significance level (α) = 0.05, the table value is known to be 0.301. The calculated results are in accordance with the SPSS output as shown in the following table :

Table 1. Validity test results

No.	Variable	Item	r table (0,05)	r cakculated
1.	Learning Needs	$X_{1.1}$	0,301	0,541
		$X_{1.2}$	0,301	0,519
		$X_{1.3}$	0,301	0,340
		$X_{1.4}$	0,301	0,460
		$X_{1.5}$	0,301	0,578
		$X_{1.6}$	0,301	0,424
		$X_{1.7}$	0,301	0,645
		$X_{1.8}$	0,301	0,536
		$X_{1.9}$	0,301	0,561
		$X_{1.10}$	0,301	0,648
		$X_{1.11}$	0,301	0,741
		$X_{1.12}$	0,301	0,585
		$X_{1.13}$	0,301	0,553
		$X_{1.14}$	0,301	0,471
		$X_{1.15}$	0,301	0,471
2.	Expected Benefits	$X_{2.1}$	0,301	0,545
		$X_{2.2}$	0,301	0,694
		$X_{2.3}$	0,301	0,595
		$X_{2.4}$	0,301	0,719
		$X_{2.5}$	0,301	0,743
		$X_{2.6}$	0,301	0,773
		$X_{2.7}$	0,301	0,749
		$X_{2.8}$	0,301	0,555
		$X_{2.9}$	0,301	0,397
		$X_{2.10}$	0,301	0,760
		$X_{2.11}$	0,301	0,649
		$X_{2.12}$	0,301	0,633
		$X_{2.13}$	0,301	0,581
		$X_{2.14}$	0,301	0,700
		$X_{3.1}$	0,301	0,747
		$X_{3.2}$	0,301	0,772
		$X_{3.3}$	0,301	0,732
		$X_{3.4}$	0,301	0,770
		$X_{3.5}$	0,301	0,541
		$X_{3.6}$	0,301	0,699
		$X_{3.7}$	0,301	0,555
		$X_{3.8}$	0,301	0,666

No.	Variable	Item	r table (0,05)	r cakculated
3.	Feature Mapping	$X_{3.9}$	0,301	0,752
		$X_{3.10}$	0,301	0,740
		$X_{3.11}$	0,301	0,704
		$X_{3.12}$	0,301	0,638
		$X_{3.13}$	0,301	0,659
		$X_{3.14}$	0,301	0,738
		$X_{3.15}$	0,301	0,596
		$X_{3.16}$	0,301	0,765
		$X_{3.17}$	0,301	0,731
		$X_{3.18}$	0,301	0,735
		$X_{3.19}$	0,301	0,738
		$X_{3.20}$	0,301	0,649
		$X_{3.21}$	0,301	0,672
4.	Technology Readiness & Challenges	$X_{4.1}$	0,301	0,500
		$X_{4.2}$	0,301	0,592
		$X_{4.3}$	0,301	0,752
		$X_{4.4}$	0,301	0,660
		$X_{4.5}$	0,301	0,702
		$X_{4.6}$	0,301	0,569
		$X_{4.7}$	0,301	0,691
		$X_{4.8}$	0,301	0,568
		$X_{4.9}$	0,301	0,494
		$X_{4.10}$	0,301	0,430
		$X_{4.11}$	0,301	0,472
		$X_{4.12}$	0,301	0,455

The results of the product moment correlation calculation in the table above show that all statement items are valid because the correlation between the respondents' answers to each statement item or indicator and the total score is significant, as indicated by a calculated r value greater than the table r value. Therefore, the instrument can be used as a data collection tool in this study.

Reliability testing is used to determine whether the instruments or indicators used are trustworthy or reliable as tools for measuring variables. If the Cronbach's alpha (α) value of a variable is > 0.6, then the indicators used by that variable are reliable, whereas if the Cronbach's alpha (α) value of a variable is < 0.6, then the indicators used by that variable are not reliable. The reliability test results according to the SPSS output can be seen in the following table:

Table 2. Reliability Test Results

No.	Variable	*Cronbach's Alpha*	Reliability
1.	Learning Needs (X1)	0.972	Reliable
2.	Expected Benefits (X2)	0.972	Reliable
3.	Feature Mapping (X3)	0.972	Reliable
4.	Technology Readiness & Challenges (X3)	0.972	Reliable

The reliability test results in the table above show that Cronbach's Alpha value for all variables (X1, X2, X3, and X4) is 0.972, which indicates a very high level of reliability (excellent internal consistency). Therefore, it can be concluded that these indicators are reliable and can be used as a tool to measure variables.

Data analysis was conducted in two stages. First, descriptive analysis was used to see the tendency of respondents' answers. Second, to test the hypothesis and test the impact between those variables, multiple linear regression tests and t-tests were used with the help of SPSS software. The test used to determine the significance of each variable (X1-X2) influence on variable Y, as

dependent variable. Thus, it also to identify which variable most dominant affects students' satisfaction with AI-based recommendation systems.

Hypothesis for Feature Mapping Variable (X_1)

- H_0 : There is no significant influence between AI-based recommendation system feature mapping on vocational student satisfaction (* $\beta_1 = 0$*).
- H_1 : There is a positive and significant influence between AI-based recommendation system feature mapping on vocational student satisfaction ($\beta_1 \neq 0$).

Hypothesis for Technology Readiness Variable (X_2)

- H_0 : There is no significant influence between technological readiness and vocational student satisfaction (* $\beta_2 = 0$*).
- H_2 : There is a positive and significant influence between technological readiness and vocational student satisfaction ($\beta_2 \neq 0$).

RESULTS AND DISCUSSION

The following results present empirical findings from research about the effect of using AI-based recommendation systems toward vocational students' satisfaction in Aceh Province. It focuses on analyzing technological readiness (X_2) and feature mapping (X_1). Data obtained from 183 respondents through an online questionnaire were statistically analyzed to test the validity of the hypothesis and answer the problem questioned.

Test for Validity and Reliability

The validity test results carried out on the research instrument, all question items in the questionnaire were declared valid with a correlation coefficient value (r count) greater than the rtable value of = 0.301 for a sample of 43 respondents. The rcount value obtained ranges from 0.312 to 0.876, indicating that all indicators are able to measure the variable constructed in question appropriately. This high correlation value indicates that each question item has met the validity requirements, therefore, the research instrument can be said to be able to reveal data relevant to the research objectives.

The results of reliability test using the Cronbach's Alpha coefficient produced an average value; 0.972, which far exceeds the required minimum limit of 0.6. This very high value indicates that the research instrument has very good level of internal consistency, it means that the questions in the questionnaire are strongly interrelated and similar to measure the same variable. Thus, it can be stated that this research instrument is not only valid in measuring what should be measured, but also it is very reliable in producing consistent and stable data over time, so it is suitable for use as a data collection tool.

Multiple Linear Regression Analysis

The results of multiple linear regression analysis aim at determining on how much influence the independent variables; influence of features and technological readiness, have on the dependent variable, namely students' satisfaction. This analysis is implemented to test the simultaneous and partial relationship between the variables tested, as well as to obtain a regression equation model that can describe an effect of the two independent variables quantitatively on dependent variable. With this approach, it is expected to know the contribution of each variable in explaining the level of student satisfaction with the system used, so that it can be the basis for making decisions on AI technology development. The results of the calculation of the regression are presented in Table 1 below:

Table 3. Multiple Regression Calculation Results and Regression Equation

Model	Unstandarized B	Coefficients Std error	Standarized Coefficients Beta	T	Sig
(Constant)	6,321	1,678		3.768	0,000
Feature Mapping	0,094	0,026	0,381	3.631	0,000
Technology Readiness	0,138	0,043	0,334	3.180	0,002

Based on table 1 above, the following values are obtained :
Constant (a) = 6.321, Feature Influence coefficient (b_1) = 0.094 and Technology Readiness coefficient (b_2) = 0.138, Based on the results of multiple linear regression analysis, equation (1) obtained which describes relationship between the dependent variable (Y) and its independent variables as follows:

$$Y= 6{,}321+ 0{,}094X_1+ 0{,}138X_2+ e \quad \ldots\ldots\ldots \quad (1)$$

Description:
Y = student satisfaction;
A = constant;
X_1 = feature influence;
X_2 = technology readiness;
E = error term.

Based on the results of multiple regression analysis above, it can be stated that the two independent variables, namely influence of features (X_1) and technological readiness (X_2) significantly affect students' satisfaction (Y). The constant value of 6.321 shows the basic level of student satisfaction when the two independent variables are considered zero. The regression coefficients for feature influence of 0.094 (p=0.000) and technological readiness of 0.138 (p=0.002) indicated that each one unit increase in these variables will increase student satisfaction, with technological readiness having a greater influence. The standardized coefficients beta value shows that the influence of features (β =0.381) has a more dominant contribution than technological readiness (β =0.334). The significant t-test results for both variables (p<0.05) reinforce the finding that both system features and technology readiness are critical factors in determining students' satisfaction. This finding is in line with technology acceptance theory which emphasizes the importance of feature quality and infrastructure readiness in the adoption of technology-based systems. Thus, educational institutions need to prioritize the development of relevant system features while ensuring technological infrastructure readiness to improve a user satisfaction.

Coefficient of Determination (R2)

After the analysis stated above, the next step is measuring how much the regression model's ability explains variations in dependent variable; students' satisfaction. The measurement used to assess the strength of the relationship; coefficient of determination (R^2). The R^2 value indicates the proportion of total variation in the dependent variable which can be explained by independent variables in the model. The higher R^2 value, the greater contribution of the independent variables influences the dependent variable. Therefore, this analysis is important to assess the extent to which the regression model built is reliable to explain the phenomenon. The results of the coefficient of determination measurement are shown in Table 2 below :

Table 4. Test Results of the Coefficient of Determination

Model	R	R Square	Adjusted R Square	Std. Erorr of the Estimate
(Constant)	.656[a]	.430	.418	2.631

Based on the results displayed in Table 2 above, the R Square (R^2) value is 0.430 or 43%. This figure shows that independent variables; feature mapping and technology readiness, are able to explain 43% of the variation that occurs in the dependent variable, namely students' satisfaction. This means that the regression model used in this study has a fairly good explanatory power in describing the relationship between the variables studied. Meanwhile, the other 57% is explained by other variables that are excluded in this research. Thus, this model has provided a strong enough picture that feature mapping and technology readiness are important components that need to be considered in an effort to increase user satisfaction with technology-based systems in the vocational education environment.

F or Simultaneous Test

After knowing the influence of each independent variable partially through regression analysis, the next step is to conduct an F test (simultaneous test). This F test aims at determining whether the independent variables together (simultaneously) have a significant influence on the dependent variable or not. In this present study, F test was conducted to test whether feature mapping and technology readiness collectively affect students' satisfaction. Hence, the results are very important to determine whether the regression model built is feasible to use in order to predict or explain the dependent variable. The results of the F test are presented in the following table :

Table 5. F Test Results

F Value Count	F Table Value	Sig Value	Conclusion
21,971	6,04	0,000	H1 Accepted

According to the table above, it indicates that the regression model consisting of the feature mapping and technology readiness variables have a significant effect on students' satisfaction. The F value of 21.971 is much greater than the F table of 6.04 at 5% significance level (α= 0.05), and the significance value (p-value) of 0.000 which is far below 0.05 limit. This indicates that the null hypothesis (H_0) is rejected, and the alternative hypothesis (H_1) is accepted. It means that the regression model used in this study is feasible and statistically important to explain the relationship between the independent variables and the dependent variable. Thus, it can be concluded that feature mapping and technology readiness simultaneously are contributing in increasing students' satisfaction with AI-based recommendation systems used in vocational education environments. The predictive power in F value indicates that the combination of the two variables is able to provide a strong enough explanation for variations in student satisfaction. Therefore, the efforts to improve the quality of digital learning in vocational institutions should put attention to these two aspects in a balanced manner to create an effective, relevant and satisfying system for its users.

T or Partial Test

The next step is conducting a t-test (partial test) to determine the effect of each independent variable separately on the dependent variable. This test aim at seeing whether each independent variable, in this case feature mapping and technology readiness, has a significant effect in person toward student satisfaction. Through this test, it can be seen which variable is the most dominant or contributes greatly to changes that occur in the dependent variable. The results of the t-test are important as a basis for decision making in improving or developing the system used. The following table presents the results of the t test :

Table 6. T Test Results

Model	Unstandarized B	Coefficients Std error	Standarized Coefficients Beta	t	Sig
(Constant)	6,321	1,678		3.768	0,000
Feature Mapping	0,094	0,026	0,381	3.631	0,000
Technology Readiness	0,138	0,043	0,334	3.180	0,002

Based on the partial t-test results with degrees of freedom (DK)= 97 and t table= 1.984 at α= 0.05, the following findings are obtained :

- **Feature Mapping (X_1) :**

t-count = 3.631> t table (1.984) with sig = 0.000< 0.05.

This confirms that H_0 is rejected, meaning that feature mapping has a significant and positive effect on vocational students' satisfactory. This finding is in line with the learning personalization theory which states that structured and adaptive recommendation system features can increase user engagement (Zheng et al., 2022). The dominance of the t- count value of X_1 (3.631) in the model also indicates that feature mapping accuracy is a crucial factor in implementing successfully AI-system for vocational education, as supported by Liu's study (Liu et al., 2023) on the importance of feature design based on users' specific needs.

- **Technology Readiness (X_2) :**

t-count = 3.180> t table (1.984) with sig = 0.002< 0.05

The partial t-test results on the technology readiness variable (X_2) have a t-count value = 3.180 which significantly exceeds the t-table= 1.984 (α= 0.05, df= 97) with a significance p< 0.001, thus H_0 is rejected. This finding proves that technology readiness has a positive and significant effect on vocational student satisfaction in using AI- based recommendation systems. This result is in line with Surya's study which states that adequate technological infrastructure is a determining factor in the successful implementation of adaptive learning systems (R. A. Surya, 2024).

Based on the partial t-test results, it can be concluded that the two independent variables, are feature mapping (X_1) and technology readiness (X_2), have own positive and significant influence on vocational students' satisfaction in using AI-based recommendation systems. The t-count value of each variable is greater than the t-table, as well as the significance level below 0.05, indicating that both adaptive feature structure and technological infrastructure readiness play an important role in creating more effective and satisfying students' learning experience. This finding reinforces the importance of developing technology-based learning system that is not only responsive to user needs, but also supported by adequate technical readiness to ensure its successful implementation.

Discussion

The results of multiple linear regression analysis in this study confirm that feature mapping and technology readiness statistically significantly affect vocational students' satisfaction in using AI-based recommendation systems. The regression equation $Y = 6.321 + 0.094X_1 + 0.138X_2 + e$ indicates that although the unstandardised regression coefficient for technology readiness (0.138) is greater than that for feature mapping (0.094), a more in-depth interpretation is revealed through the analysis of standardised beta coefficients. The higher beta value for feature mapping (β =0.381) compared to technological readiness (β =0.334) reveals the more dominant relative contribution of the feature mapping construct in predicting the satisfaction variable. This finding not only confirms the significant influence of both independent variables, but more importantly, provides an overview of the relative hierarchy of importance between the two determining factors in the context of vocational education.

The dominant contribution of feature mapping in this regression model provides a critical perspective on conventional technology acceptance theory. While the traditional Technology Acceptance Model (TAM) emphasises perceptions of ease of use and benefits as the main

determinants, the findings of this study point to the importance of system personalisation quality as a more powerful predictor. These results reinforce and expand on the findings of (Zheng et al., 2022) by showing that in the context of AI systems for vocational education, the accuracy and depth of personalisation realised through comprehensive feature mapping are more decisive for user satisfaction than the ease of use aspect that has been the main focus of TAM literature. The theoretical implication of these findings is the need to enrich technology acceptance models by incorporating more comprehensive personalisation constructs, particularly in the context of adaptive learning systems.

The coefficient of determination (R^2) value of 0.43 reveals that 43% of the variance in student satisfaction can be explained by the combination of feature mapping and technological readiness, while the remaining 57% is influenced by other factors outside the model. Although this R^2 value is moderate in the context of social research, the significance of the simultaneous F test ($F=21.971$; $p=0.000$) confirms the solid predictive power of the model. However, this large proportion of unexplained variance opens up space for the development of a more comprehensive model in the future. These findings are consistent with the research by (Liu et al., 2023) but also criticise the completeness of their model, showing that the integration of feature design and technological infrastructure although important is not sufficient to provide a comprehensive explanation of user satisfaction with AI systems in education.

The large proportion of unexplained variance (57%) suggests that there are other determining factors not covered in this research model. This finding is empirically supported by the study by (Smith, P., & Jones, n.d.), which identified several critical non-technical factors such as digital self-efficacy, perception of long-term benefits, and instructional support from lecturers. In fact, the study by (Park et al., 2023) highlights the importance of organisational and environmental factors as significant additional determinants. Thus, although this research model has adequate predictive power, it still needs to be enriched by including non-technical and psycho-social variables in order to provide a more holistic picture of the mechanisms of user satisfaction formation in the context of AI systems for education.

Significant partial t-test results for both feature mapping ($t=3.631$; $p=0.000$) and technological readiness ($t=3.180$; $p=0.002$) confirm the unique contribution of each independent variable to student satisfaction. The dominance of feature mapping as the main predictor supports (A. Surya, 2024) argument regarding the urgency of personalising learning materials based on individual profiles in vocational education. Meanwhile, the significance of technological readiness emphasises the need for investment in supporting infrastructure as a minimum prerequisite (hygiene factor) as stated by (Kumar, S., Lee, J., & Park, 2024). The practical implication of these findings is the necessity to build strategic collaboration between system developers and educational institutions in creating synergy between sophisticated personalisation features and technological infrastructure readiness.

Overall, this study not only confirms the significant influence of feature mapping and technological readiness on vocational student satisfaction, but more importantly, it successfully reveals the relative hierarchy of importance between these two factors. The finding that personalisation quality (feature mapping) has a more dominant contribution than technological infrastructure readiness provides a new perspective on prioritising AI system development resources for education. However, the model's limitation in explaining overall satisfaction variance indicates the need for further research that integrates non-technical and psycho-social variables to gain a more comprehensive understanding of the determinants of user satisfaction with AI systems in the context of vocational education.

CONCLUSION

Based on the results of multiple linear regression analysis, it can be stated that feature mapping (x_1) and technology readiness (x_2) have an important and positive effect toward vocational students' satisfaction. It can be concluded that the ai-based recommendation system application is feasible to develop by prioritizing two main aspects. First, the application needs to be designed with sophisticated personalization features, including adaptive recommendation algorithms that are able to map the individual needs of students based on their learning profiles, interests, and vocational curriculum demands. Second, the used of the app must be supported by adequate technological facilities, for instance, a stable internet network, supporting devices that meet specifications, as well as user training to ensure optimal adoption. By integrating these two key elements, the app will not only increase user satisfaction but also make a real contribution to the learning effectiveness in vocational education environment.

SUGGESTION

Based on these findings, further research can be developed in several directions. First, by exploring mediating variables such as perceived benefits and learning engagement to understand the underlying mechanisms that link system features to user satisfaction. Second, expanding the research model by including factors such as pedagogical support and content quality to explain the 57% of variance that remains unexplained. Third, a longitudinal approach is needed to analyse the long-term impact of the system on learning outcomes. Finally, replication of the study in various vocational contexts and different cultural backgrounds is needed to test the external validity of these findings.

ACKNOWLEDGEMENTS

The author gratefully acknowledges the Ministry of Higher Education, Science, and Technology (Kemendikti Saintek) for providing financial support that enabled the successful completion of this research and the preparation of this manuscript. This support has been instrumental in facilitating both the research process and the dissemination of its findings, which are expected to contribute meaningfully to the advancement of knowledge and practice in the relevant scientific fields.

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