Jurnal Inovasi Teknologi Pendidikan
Volume 12, No. 1, March 2025 (92-103)
Online: http://journal.uny.ac.id/index.php/jitp

Measuring interest and talent in determining learning using the quadrant model in the learning process in a smart classroom

Irfan Santiko [1,2]*, **Tri Retnaningsih Soeprobowati** [1], **Bayu Surarso** [1], **Imam Tahyudin** [2]
[1] Universitas Diponegoro, Indonesia.
[2] Universitas Amikom Purwokerto, Indonesia.
* Corresponding Author. E-mail: irfan.santiko@amikompurwokerto.ac.id

ARTICLE INFO

Article History
Received:
24 May 2024;
Revised:
26 February 2025;
Accepted:
27 February 2025;
Available online:
31 March 2025.

Keywords
Educational technology; Learning evaluation; Smart classroom; Prediction achievement

ABSTRACT
Naturally, the learning process in smart classrooms is greatly impacted by the trend of individual learning, now known as personalized learning. Several studies have demonstrated that, because of the problem of technological advances, the effectiveness of the anticipated results has not been fully achieved. While there are technology benefits, some scholars link them to issues. This study aims to demonstrate it by evaluating learning interests and talents. A sample of at least 1000 students from 419 universities participated in the questionnaire experiment. Each of the three questionnaire domains, affective, cognitive, and psychomotor, was examined using ANOVA. The coefficient test uses two variables: interest and talent. With an ANOVA P-value of 0.021 for psychomotor and 0.031 for affective and cognitive, the three domains demonstrated a statistically significant connection. The coefficients of interest and talent, which average between 1 and 0.05 for P emotional and cognitive interest (0.054) and P talent (0.023) and between 0.027 and 0.055 for P psychomotor interest and P talent, demonstrate the significant values of both factors. The developed interest and talent measuring model can be used to forecast learning outcomes based on these findings. In addition to information technology, the results of this interest and talent-measuring design can be utilized to define and evaluate the learning process, including its appropriateness. Further research recommendations include a framework to measure interests and talents early, aiding admissions, curriculum, resources, methods, and learning media development.

How to cite:
Santiko, Irfan., et al., (2025). Measuring interest and talent in determining learning using the quadrant model in the learning process in a smart classroom. *Jurnal Inovasi Teknologi Pendidikan*, *12*(1), 92-103. https://doi.org/10.21831/jitp.v12i1.73585

INTRODUCTION

Learning is a dynamic process between students and teachers, and each program must have a clear purpose (Ekantiningsih & Sukirman, 2023). Learning involves three main areas: affective, cognitive, and psychomotor aspects, and various factors must be considered when evaluating educational programs (Reis et al., 2021). Techniques, methods, and materials in the learning process are very important because they guide education and predict effective outcomes (Harefa et al., 2023). There are mixed claims about the effectiveness of smart classes, and ongoing research continues to explore this area (Mahler et al., 2018).

Interest and talent are two very important internal factors in the learning process. Interest provides motivation and encouragement for students to learn, while talent provides the potential and ability to achieve optimal results (Georgiou & Kyza, 2018). When students learn according to their interests and talents, they tend to be more enthusiastic, passionate, and focused. This can increase the effectiveness of learning and produce better learning outcomes (Akbari & Sahibzada, 2020). The ideal curriculum and education system should be able to accommodate the diversity of students' interests and talents (Gao et al., 2020). However, in practice, the curriculum is often too dense and uniform, so it does not provide enough space for students to develop their interests and talents optimally (Yu & Singh, 2018). An evaluation system that focuses too much on academic test results can also ignore students' potential in other areas, such as art, sports, or practical skills (Sutarto et al., 2020).

Recent developments point to the idea of society 5.0, where personalized learning based on established methodologies becomes more common (Santiko et al., 2025). Knowing whether interest in talent affects learning achievement, especially in the context of digital systems, remains an open question (Santiko et al., 2024). Although smart classrooms show promising results in improving learning outcomes, consistent evidence of their effectiveness is still limited (Santiko et al., 2022). Several factors influence outcome measurement and implementation variability, and each classroom situation may produce different results based on the specifics of teacher training and technology accessibility (Achmad & Mulyati, 2023).

According to a related study, a learning's efficacy is also determined by how appropriate it is for both the teacher and the students (Chen et al., 2021). Dimensional modeling of learning style classification is thought to be appropriate for assessing efficacy from the standpoint of the teacher's and students' respective learning type compatibility (Santiko et al., 2025; Lo & Hew, 2020).

Many students choose majors or fields of study that do not match their interests and talents due to pressure from parents, friends, or the surrounding environment (Désiron et al., 2024). This can lead to a lack of motivation to learn, difficulty in understanding the material, and suboptimal learning outcomes (Murillo-Zamorano et al., 2021). Many schools lack the facilities and support to develop students' interests and talents, such as laboratories, art studios, sports fields, or competent teachers (El-Sabagh, 2021). This can hinder students from developing their potential to the fullest. When students do not study according to their interests and talents, they tend to feel bored, fed up, and unmotivated (Lo & Hew, 2020). This can lead to decreased academic achievement, negative behavior, and even dropping out of school. An education system that focuses too much on academic test results can ignore students' potential in other areas, such as art, sports, or practical skills. This can lead to a loss of opportunities for students to develop their potential holistically (Shen & Ho, 2020).

This study will evaluate the influence of personal interests and talents on learning achievement in smart classes. This study will use an experimental method, collecting data from students in Central Java, Indonesia. The questionnaire will assess learning outcomes based on affective, cognitive, and psychomotor dimensions. This analysis will explore the correlation between students' interests, talents, and academic achievement using regression analysis (Jiao et al., 2022). The influence of interests and talents on learning outcomes is very significant. Therefore, it is important for all parties involved, namely the government, schools, teachers, parents, and students, to work together in creating an educational environment that is conducive to the development of students' interests and talents.

METHOD

To answer the problems that arise, this study will use an experimental methodology (Putri & Meilana, 2023). Several examples of the use of experiments are considered quite reliable in cases of measurement and assessment of a person (Tussa et al., 2024). Based on the experimental design, respondents who contributed around 1000 students in 419 Universities located in the Central Java Province Region have provided data for two semesters of learning. Universities that have used smart class services in their teaching and learning processes received questionnaires. As shown in Figure 2, the sample used is an evaluation of learning outcomes based on three elements, namely affective, cognitive, and psychomotor. Next, as you will see in the next step, identify the independent and dependent variables for regression analysis. Then, to get the value of the variable, the researcher uses a question instrument that will be tested for validity and reliability first. After getting the value, a multiple linear regression analysis will be carried out to determine the prediction of whether the interest and talent variables have a strong influence or not on learning achievement according to Bloom's aspects.

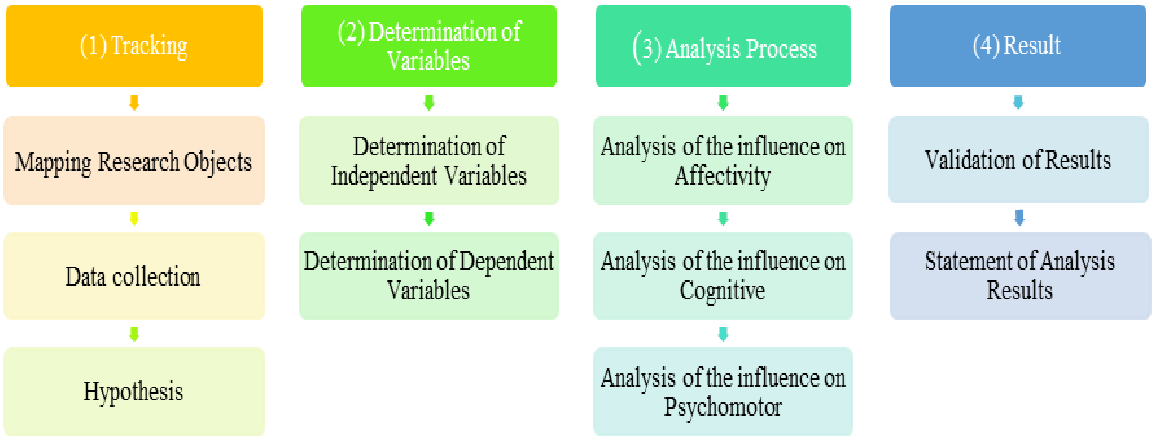

Figure 1. Stages of Research Implementation

The researchers developed an assessment tool in the form of questionnaire score findings to make the data in this study easily comprehensible. To gather and categorize variables, researchers separate them into independent and dependent categories using a variety of instruments. These categories serve as resources for the hypothesis that will be tested. Multiple linear regression analysis will be performed using the two derived categories. Table 1 below displays the variable distribution model:

Table 1. Pattern of Preparation and Determination of Variable Instruments

	Dependent Variable (Y)			**Independent Variable (X)**	
Aspect	Affective	Cognitive	Psychomotor	Interest (Motivation)	Aptitude (Learning Style)
Indicator	Attitude	Understand	Imitate	Happiness	Personality
	Responsibility	Analyze	Manipulate	Interest	Habit
	Obedient	Apply	Operate	Attention	Skills
	Organize	Evaluation	Create	Involvement	Achievement

Statistics are used in this research's data analysis procedure. The first test that is conducted is a validity and reliability test for every variable. This is required since qualitative data is used in the data linked to the evaluation of the variables' findings. To give the qualitative data a numerical value, it is transformed into quantitative data. The researcher then performed multiple regression analyses to examine the link between the independent and dependent variables once each variable was deemed legitimate and realistic. This experiment will demonstrate the extent to which the independent variable affects the dependent variable.

RESULTS AND DISCUSSION

Results

Tracking the sample was the researcher's initial action. Several campuses or colleges that have an intelligent class system and use this approach will serve as samples for the researchers. The Central Java Province of Indonesia's university population provided samples. Table 2 presents the distribution of sample data obtained.

Table 2. Sample of Universities that Use a Smart Classroom System

No.	Campus Name	Learning System	Learning Methods	Resource Material	Media Platform	Use of Technology
1	Campus 1	Hybrid Class	Discussions, Forums, Assignments, Practice	Book, Article, Video, Portfolio	Website, Webex, Zoom, Face Recognition Presence	Internet, IoT, AI, AR, VR
2	Campus 2	Online Class	Discussions, Forums, Assignments, Practice, Games, Sociodrama	Book, Article, Video, Library	Website, Mobile Apps, Zoom	Internet, IoT, AI, VR
	…	…	…	...	…	…
419	Campus 419	Offline Class	Discussions, Forums, Assignments, Practice, Drill	Book, Article, Video	Website	Internet

In the province of Central Java, 419 universities have adopted the smart class system; 76% still use the traditional method. The two factors that make up this thorough data are the learning system and the system's usage of technology.

Results for the learning system showed that 293 campuses out of 419 used hybrid technology, or 70% of all campuses; 326 campuses out of 419 used online technology, or 78% of all campuses; and 117 campuses out of 419 still used offline technology, or 28% of all campuses. The Central Java campus is dominated by the online system. It is also possible to conclude that, while technology use has temporarily advanced, the smart classroom system itself is still in the process of transitioning to dynamic learning, based on the hybrid usage statistics, which combine online and offline systems.

Using the data collected, tracking will be done once more using the 3M elements Methods, Materials, and Media as shown in Figure 2. Ten randomly chosen current students from each university served as the sample of students from which the tracking data was gathered. The following outcomes were attained:

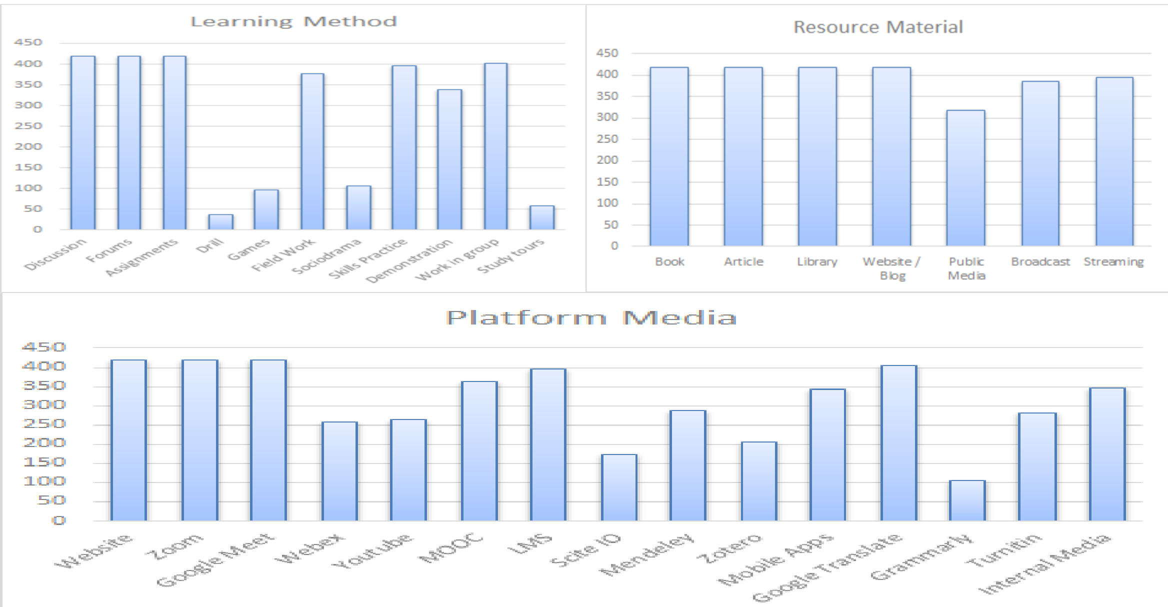

Figure 2. Tracking Diagram for the Use of the Intelligent Classroom System based on 3M Aspects

Figure 2 illustrates how campuses in the province of Central Java have, on average, integrated technology into their teaching and learning processes based on the 3M elements of methods, materials, and media. When it comes to methods, the most popular ones are the assignment, forum, and discussion approaches, all of which are comparatively frequent. When it comes to the material side, the majority of acquisitions originate from books, journals, and libraries, all of which are thought to be widely utilized on campuses. On the other hand, when it comes to the media that is utilized, colleges typically use websites that are associated with the commonly employed approaches, as well as teleconference tools like Zoom and Google Meet. This indicates that the learning services that take place still use patterns in general; they have just been replaced by the idea of teleconferences, which merely relocate the classroom setting and add flexibility to the schedule.

To determine the variables, the author first tracked student interactions in using technology in the learning process. The data taken is the result of student interactions in the use of technology regarding bloom aspects. The list of questions provided is measured based on previously determined Bloom aspects. Table 3 is an example of questions asked through a questionnaire from the affective aspect.

Table 3. List of Questionnaires

No.	Question List of Affective Aspects
Attitude	
1	I am Always Online on Time, According to the Lesson Schedule.
2	When Meeting Online, I Always Activate the Camera.
3	I Always turn off the Microphone when the Teacher is Explaining.
4	I Always Ask Permission when I want to leave an Online Forum.
Responsibility	
5	I Always Ensure the Network Connection is Secure before Learning Begins.
6	I Immediately Switched to Chat Media when the Connection was Interrupted.
7	I Always Upload Assignments on Time.
8	I Always Signal when I want to Interact.
Obedient	
9	I Accept the Results of the Learning Scores given Under any Conditions.
10	I Accept the Forms of Reward and Punishment given by the Teacher.
11	I Always Follow the Contract and Learning Plan that have been given.
12	I Follow the Rules Enforced by the Online System.
Organize	
13	I will Form a Team in a Separate Chat Group if You want to Discuss it.
14	I Always Pay Attention to the Duration given.
15	I Utilize the Mobile App Platform to Provide Instructions.
16	I Always make Decisions based on the Votes of the Members of the Group.

The list of questions, each of which will be assessed based on point values, is divided into 3 criteria, namely, Always (A) with a weight value of 3, Sometimes (S) with a weight value of 2, and Never (N) with a weight value of 1. The explanatory assessment model is presented in Table 4.

Table 4. Questionnaire Assessment Model

Taxonomy Bloom Aspect			
Questions	**Always (A) - Point 3**	**Sometimes (S) - Point 2**	**Never (N) - Point 1**
		Dimension	
Q1	Value	Value	Value
Q2	Value	Value	Value
Q3	Value	Value	Value
Q4	Value	Value	Value

According to each criterion, they will be totaled in this value model. Next, an average value is derived from the total number of values for each criterion. The value will be combined to create a description value once the average value has been determined. The overall maximum value of all questions for each criterion, that is, the maximum value for criterion A is 12 points, the maximum value for criterion S is 8, and the maximum value for criterion N is 4, is what yields the information value. The following are the average values for each criterion presented in Table 5.

Table 5. Description of the Average Value for Each Bloom Aspect Criterion

No.	Average Value	Rank	Description
1	8 – 12	High Level	Students have High Effectiveness Scores in this Aspect.
2	4 – 8	Medium Level	Students have Medium Effectiveness Scores in this Aspect.
3	0 – 4	Low Level	Students have Low Effectiveness Scores in this Aspect.

Create the same thing for the interest and talent elements after establishing an assessment model for the bloom aspect. Distinct in how interest and talent variables are scored. The author uses a quadrant matrix to organize value categories. The students' place in a certain quadrant will be ascertained by answering questions on their talent interests in the questionnaire. The correlation between the resultant quadrant value and the bloom aspect value will be examined. It will be evident from this value whether or not it had an impact. The question is now a statement with two values in this talent interest area, with positive statements having a value of 1 and negative statements having a value of -1. Table 6 shows examples of statements included in the student questionnaire.

Table 6. Examples of Statements in a Questionnaire to Determine Interest and Talent Values

Interest Aspect			
Statement		**Score**	**Rule**
When I Decided to Choose the Campus where I Studied			
a.	I'll Find out as I see Fit.	1	Positive
b.	I will Follow what Others Think is Good for Me.	-1	Negative
Talent Aspect			
Statement		**Score**	**Rule**
When I Decided to Choose the Campus where I Studied			
a.	I will Take the Initiative to Find out from Various Sources	1	Positive
b.	I will Wait for Good Information for Me	-1	Negative

This value applies to both aspects, therefore, the statements given to each aspect of talent interest must be balanced between positive and negative statements. The total score will determine the position of the student's interests and talents in the quadrant matrix. A description of the designed talent interest quadrant matrix is presented in Figure 3.

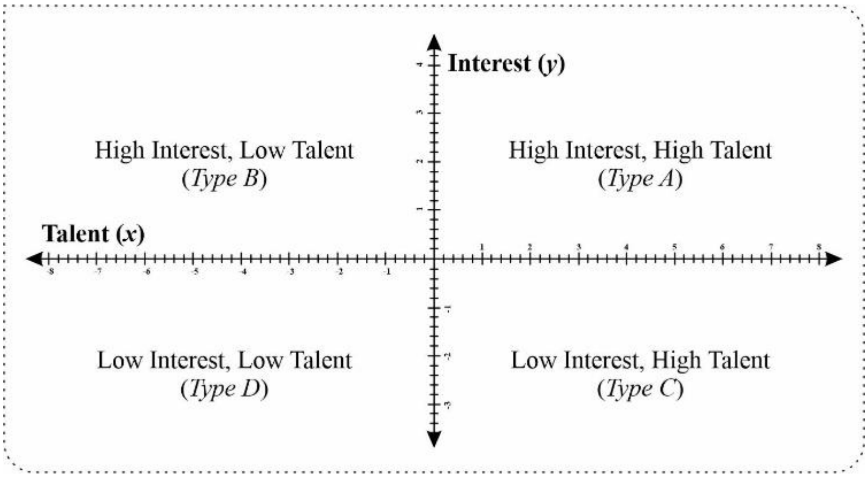

Figure 3. Interest and Talent Quadrant Matrix

The questionnaire is then given to several samples once an assessment model has been obtained to identify variables. Every university student in the province of Central Java made up the sample. Out of the 419 campuses, 1000 respondents in total completed the survey at random. The data will be tested by the author using a sample of twenty responders. The following are the results of distributing the questionnaire, which are presented in Tables 7 and 8.

Table 7. The Results of the Questionnaire Values are in the Form of Independent Variables

No.	Participant	Average value (Y)		
		Affective	Cognitive	Psychomotor
1	Student 1	8	4	5
2	Student 2	5	10	10
3	Student 3	4	8	9
…	…	…	…	…
1000	Student 1000	3	9	7

Table 8. The Results of the Questionnaire, Values are in the Form of a Dependent Variable

No.	Participant	Average value (X)	
		Interest	Talent
1	Student 1	3	3
2	Student 2	-2	3
3	Student 3	-1	4
…	…	…	…
1000	Student 1000	-1	6

After variables are created and specified value attributes are produced, data analysis is the next step. The analysis's findings are as follows:

Multiple Regression Analysis on Affective Aspects

The results of the multiple regression analysis for the affective aspect can be seen in Table 9.

Table 9. ANOVA Test and Coefficient Formula Between Affective and Interest Variables

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	9.237	2	4.618	1.113	0.031
	Residual	70.513	17	4.148		
	Total	79.750	19			

Note. The intercept model is omitted as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	8.250	0.458		18.009	< .001
H_1	(Intercept)	8.620	1.682		5.124	< .001
	Interest	-0.276	0.186	-0.346	-1.490	0.054
	Talent	-0.150	0.416	-0.084	-0.360	0.023

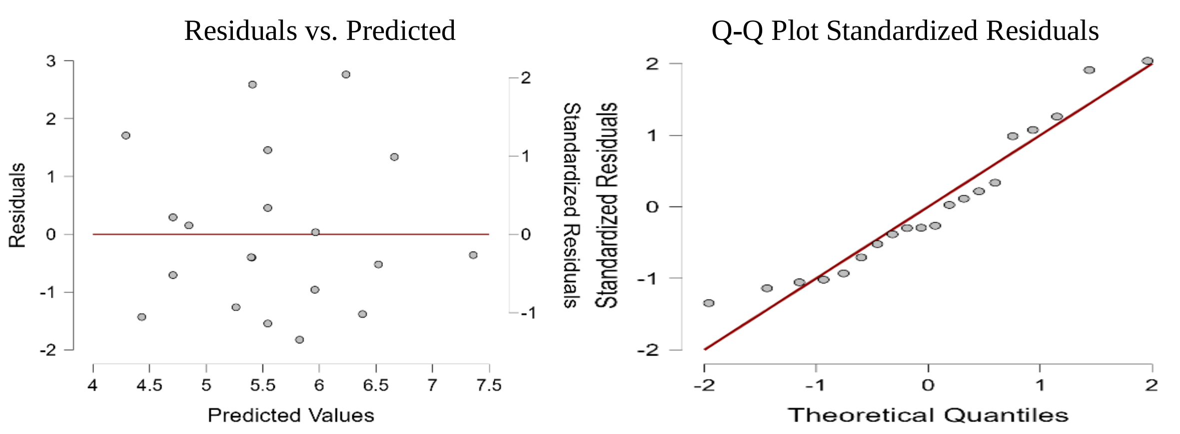

Figure 4. Results of Analysis of Residuals and Affective Quantiles

The ANOVA figure in the affective aspect was 0.023, which is less than the 0.05 principle, and the coefficient value was less than 0.001. Figure 4 illustrates how the residuals appear to be around the conventional quantile line and how the data distribution appears to be even. This investigation establishes a relationship between talent interest and effective achievement results, and the model can be applied as a predictive tool.

Multiple Regression Analysis on Cognitive Aspects

The results of the multiple regression analysis for the cognitive aspect can be seen in Table 10.

Table 10. ANOVA Test and Coefficient Formula Between Cognitive and Interest Variables

Model		Sum of Squares	df	Mean Square	F	p
H_1	Regression	9.237	2	4.618	1.113	0.031
	Residual	70.513	17	4.148		
	Total	79.750	19			

Note. The intercept model is omitted as no meaningful information can be shown.

Coefficients

Model		Unstandardized	Standard Error	Standardized	t	p
H_0	(Intercept)	8.250	0.458		18.009	< .001
H_1	(Intercept)	8.620	1.682		5.124	< .001
	Interest	-0.276	0.186	-0.346	-1.490	0.054
	Talent	-0.150	0.416	-0.084	-0.360	0.023

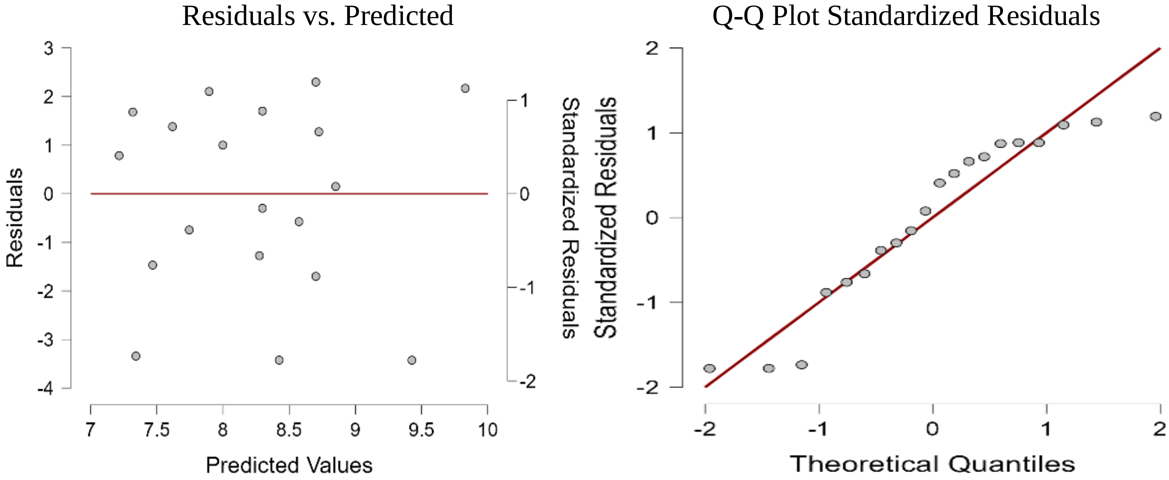

Figure 5. Cognitive Residual and Quantiles Analysis Results

The ANOVA number for the cognitive component was 0.031, which is less than the 0.05 principle, and the coefficient value was less than 0.001. Figure 5 illustrates how the residuals appear to be around the conventional quantile line and how the data distribution appears to be even. This investigation establishes a relationship between talent interest and effective achievement results, and the model can be applied as a predictive tool.

Multiple Regression Analysis on Psychomotor Aspects

The results of the multiple regression analysis for the psychomotor aspect can be seen in Table 11.

Table 11. ANOVA Test and Coefficient Formula Between Psychomotor and Interest Variables

Model		**Sum of Squares**	**df**	**Mean Square**	**F**	**p**
H_1	Regression	12.108	2	6.054	1.690	0.021
	Residual	60.892	17	3.582		
	Total	73.000	19			

Note. The intercept model is omitted as no meaningful information can be shown.

Coefficients

Model		**Unstandardized**	**Standard Error**	**Standardized**	**t**	**p**
H_0	(Intercept)	8.500	0.438		19.393	< .001
H_1	(Intercept)	7.406	1.563		4.738	< .001
	Interest	-0.276	0.172	-0.362	-1.604	0.027
	Talent	0.221	0.386	0.129	0.572	0.055

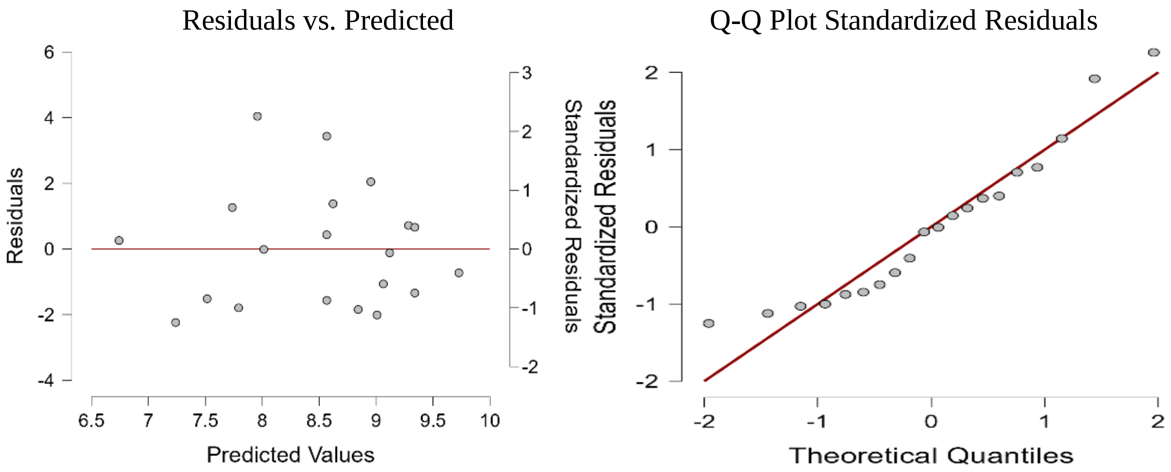

Figure 6. Results of Analysis of Psychomotor Residuals and Quantiles

The psychomotor component yielded an ANOVA number of 0.021, which was less than the 0.05 principle, and a coefficient value of less than 0.001. Figure 6 illustrates how the residuals appear to be around the conventional quantile line and how the data distribution appears to be even. This investigation establishes a relationship between talent interest and psychomotor achievement results, and the model can be applied as a predictive tool.

Discussion

In this discussion, we review the problems that have occurred previously, including educational inconsistencies, uniform curriculum, evaluations that only focus on academics, limited educational facilities, and lack of involvement and understanding. Some variables are considered very important but have not been implemented optimally, namely the variables of personal interests and talents (Hell et al., 2021). These variables are needed, considering that currently, it is a learning model where personalization is starting to run in the era of society 5.0. This paper also reveals how to initiate solutions to problems found in the variables of interest and talent in line with various research on learning motivation (Oubibi et al., 2022). After what was stated in the research results, that interests and talents can also predict affective, cognitive, and psychomotor abilities, the prediction results make it possible to provide recommendations for the development of future learning systems (Hsu, 2022).

The next solution is to develop a curriculum that is more flexible and adaptive to the needs of each student, implement a comprehensive and sustainable talent and interest identification method, and provide various extracurricular activities that are by the talents and interests of students, this will go hand in hand with the previously known interest and talent measurement indicators using this talent and interest quadrant (Yesilyurt et al., 2016). By the concept carried out in measuring self-assessment of talent interests, the talent demand measurement design model discussed in this paper is by interests where before determining the learning we want, we first measure potential through interests and talent abilities that are by learning objectives in Education (Nguyen, 2022).

Theories such as Knowledge Tracing (KT) and Item Response Theory (IRT) provide dynamic and static models for assessing learning. These models help identify skill mastery and inform personalized interventions, improving educational strategies (Li, 2024). Meanwhile, the quadrant model built in this study can be said to be more in-depth in terms of personalization because it is immediately recognized when appropriate decisions are needed in choosing learning and does not look at past elements like the Knowledge Tracing model. Measuring and influencing students' interests and talents are vital for enhancing their learning experiences and outcomes. By leveraging frameworks, technologies, and personalized strategies, educators can foster engagement, creativity, and employability, ultimately addressing broader educational and societal challenges (Durmuşçelebi, 2018). The integration of these elements ensures that education systems adapt to individual needs, preparing students for future demands.

CONCLUSION

Based on the preceding discussion, the following deductions can be made: (1) The affective, cognitive, and psychomotor categories of Bloom's taxonomy can be used to assess learning outcomes in an intelligent classroom system. (2) Technology-focused services Technology services based on the Bloom aspect in the smart class system solely assist cognitive and psychomotor parts, with little to no impact on affective aspects, according to the analysis and mapping results. Technology currently merely modifies the process of assessing emotionally charged achievements. (3) The model illustrates how the two variables, the Talent Interest and the Bloom Aspect, affect learning accomplishment inside the smart classroom system and offers criteria for assessing learning achievement based on the Bloom Aspect. (4) Smart classes with all technology-based services must be able to adapt the learning process based on various factors, namely affective, cognitive, and psychomotor, to achieve learning outcomes that are considered effective and efficient. For technology services in smart classes to support learning holistically, there must be at least three technologies, namely artificial intelligence, the Internet of Things, and the cloud (big data). These three technologies will be able to provide services to interests and talents and facilitate the implementation of the processes, resources, and media needed to ensure that each student achieves the expected learning outcomes. The following recommendation, which includes a framework for measuring interests and talents at the start of the learning process, can be used as starting capital to create an educational system at the time of admission. It can also be taken into account when developing the curriculum, teaching resources, methods, and learning media.

ACKNOWLEDGEMENT

The author would like to thank the respondents who have been willing to provide information to complete this research, including teachers and experts who have provided suggestions for the author in compiling the research. Finally, the author would also like to thank the Institute for Research and Community Service (LPPM) of Amikom University Purwokerto for providing the opportunity to participate in the internal research program.

REFERENCES

Achmad, R. K., & Mulyati, Y. (2023). The perceptions of high school teachers and students towards digital interest and literacy. *Jurnal Inovasi Teknologi Pendidikan*, *10*(3), 283–297. https://doi.org/10.21831/jitp.v10i3.58804

Akbari, O., & Sahibzada, J. (2020). Students' self-confidence and its impacts on their learning process. *American International Journal of Social Science Research*, *5*(1), 1–15. https://doi.org/10.46281/aijssr.v5i1.462

Chen, X., Zou, D., Xie, H., & Wang, F. L. (2021). Past, present, and future of smart learning: A topic-based bibliometric analysis. *International Journal of Educational Technology in Higher Education*, *18*(2), 1–29. https://doi.org/10.1186/s41239-020-00239-6

Désiron, J. C., Schmitz, M.-L., & Petko, D. (2024). Teachers as creators of digital multimedia learning materials: Are they aligned with multimedia learning principles. *Technology, Knowledge, and Learning*, *29*(4), 1–17. https://doi.org/10.1007/s10758-024-09770-1

Durmuşçelebi, M. (2018). Examination of students' academic motivation, research concerns and research competency levels during the education period. *Universal Journal of Educational Research*, *6*(10), 2115–2124. https://doi.org/10.13189/ujer.2018.061008

Ekantiningsih, P. D., & Sukirman, D. (2023). Trends of education and training teacher competency in information and communication technology. *Jurnal Inovasi Teknologi Pendidikan*, *10*(1), 87–105. https://doi.org/10.21831/jitp.v10i1.52630

El-Sabagh, H. A. (2021). Adaptive e-learning environment based on learning styles and its impact on development students' engagement. *International Journal of Educational Technology in Higher Education*, *18*(53), 1–24. https://doi.org/10.1186/s41239-021-00289-4

Gao, X., Li, P., Shen, J., & Sun, H. (2020). Reviewing assessment of student learning in interdisciplinary STEM education. *International Journal of STEM Education*, *7*(24), 1–14. https://doi.org/10.1186/s40594-020-00225-4

Georgiou, Y., & Kyza, E. A. (2018). Relations between student motivation, immersion and learning outcomes in location-based augmented reality settings. *Computers in Human Behavior*, *89*, 173–181. https://doi.org/10.1016/j.chb.2018.08.011

Harefa, D., Sarumaha, M., Telaumbanua, K., Telaumbanua, T., Laia, B., & Hulu, F. (2023). Relationship student learning interest to the learning outcomes of natural sciences. *International Journal of Educational Research & Amp*, *4*(2), 240–246. https://doi.org/10.51601/ijersc.v4i2.614

Hell, M., Knežević, A., & Babić, Z. (2021). Multicriteria analysis of the quality of teaching process in higher education: How to evaluate implementation of critical thinking. *Croatian Operational Research Review*, *12*(1), 15–26. https://doi.org/10.17535/crorr.2021.0002

Hsu, C. L. (2022). Applying cognitive evaluation theory to analyze the impact of gamification mechanics on user engagement in resource recycling. *Information & Management*, *59*(2), 1–11. https://doi.org/10.1016/J.IM.2022.103602

Jiao, Y. P., Liu, P., & Qi, P. Q. (2022). Quality evaluation method for settlement data matching based on grey correlation analysis. *Journal of Physics*, *2181*, 1–7. https://doi.org/10.1088/1742-6596/2181/1/012034

Li, M. (2024). Integrating models in education: Evaluating strategies and enhancing student learning through advanced analytical methods. *Lecture Notes in Education Psychology and Public Media*, *51*(1), 29–35. https://doi.org/10.54254/2753-7048/51/20240560

Lo, C. K., & Hew, K. F. (2020). A comparison of flipped learning with gamification, traditional learning, and online independent study: The effects on students' mathematics achievement and cognitive engagement. *Interactive Learning Environments*, *28*(4), 464–481. https://doi.org/10.1080/10494820.2018.1541910

Mahler, D., Großschedl, J., & Harms, U. (2018). Does motivation matter? The relationship between teachers' self-efficacy and enthusiasm and students' performance. *PloS One*, *13*(11), 145–156. https://doi.org/10.1371/journal.pone.0207252

Murillo-Zamorano, L. R., López Sánchez, J. Á., Godoy-Caballero, A. L., & Bueno Muñoz, C. (2021). Gamification and active learning in higher education: Is it possible to match digital society, academia and students' interests? *International Journal of Educational Technology in Higher Education*, *18*(15), 1–27. https://doi.org/10.1186/s41239-021-00249-y

Nguyen, V. A. (2022). A model to detect student's learning styles in the blended learning course. *ICFET '22: Proceedings of the 8th International Conference on Frontiers of Educational Technologies*, 46–51. https://doi.org/10.1145/3545862.3545870

Oubibi, M., Zhao, W., Wang, Y., Zhou, Y., Jiang, Q., Li, Y., Xu, X., & Qiao, L. (2022). Advances in research on technological, pedagogical, didactical, and social competencies of preservice TCFL teachers. *Sustainability*, *14*(4), 1–20. https://doi.org/10.3390/su14042045

Putri, N. R. S., & Meilana, S. F. (2023). Effect of experimental learning methods on students' cognitive abilities in science learning. *Jurnal Penelitian Pendidikan IPA*, *9*(9), 7539–7546. https://doi.org/10.29303/jppipa.v9i9.4602

Reis, S. M., Renzulli, S. J., & Renzulli, J. S. (2021). Enrichment and gifted education pedagogy to develop talents, gifts, and creative productivity. *Education Sciences*, *11*(10), 615–625. https://doi.org/10.3390/educsci11100615

Santiko, I., Soeprobowati, T. R., & Surarso, B. (2024). Experiments to review literature on topic trends in technology development in educational information systems. *2023 IEEE 7th International Conference on Information Technology, Information Systems and Electrical Engineering (ICITISEE)*, 94–99. https://doi.org/10.1109/icitisee58992.2023.10404276

Santiko, I., Soeprobowati, T. R., Surarso, B., & Tahyudin, I. (2025). Traditional-enhance-mobile-ubiquitous-smart: Model innovation in higher education learning style classification using multidimensional and machine learning methods. *Journal of Applied Data Sciences*, *6*(1), 753–772. https://doi.org/10.47738/jads.v6i1.598

Santiko, I., Wijaya, A. B., & Hamdi, A. (2022). Smart campus evaluation monitoring model using rainbow framework evaluation and higher education quality assurance approach. *Journal of Information Systems and Informatics*, *4*(2), 336–348. https://doi.org/10.51519/journalisi.v4i2.258

Shen, C., & Ho, J. (2020). Technology-enhanced learning in higher education: A bibliometric analysis with latent semantic approach. *Computers in Human Behavior*, *104*(6), 106–117. https://doi.org/10.1016/j.chb.2019.106177

Sutarto, S., Sari, D. P., & Fathurrochman, I. (2020). Teacher strategies in online learning to increase students' interest in learning during COVID-19 pandemic. *Jurnal Konseling dan Pendidikan*, *8*(3), 129–137. https://doi.org/10.29210/147800

Tussa, H., Yana, I. N., Satria, S., Pendit, D., & Kunci, K. (2024). Implementing experimental learning methods on student learning motivation. *Journal of Psychology and Instruction*, *8*(2), 75–82. https://doi.org/10.23887/jpai.v8i2.79404

Yeşilyurt, E., Ulaş, A. H., & Akan, D. (2016). Teacher self-efficacy, academic self-efficacy, and computer self-efficacy as predictors of attitude toward applying computer-supported education. *Computers in Human Behavior*, *64*(11), 591–601. https://doi.org/10.1016/j.chb.2016.07.038

Yu, R., & Singh, K. (2018). Teacher support, instructional practices, student motivation, and mathematics achievement in high school. *The Journal of Educational Research*, *111*(1), 81–94. https://doi.org/10.1080/00220671.2016.1204260