

AI-Based Personalised Learning Systems for Students with Special Educational Needs: A Machine Learning Approach

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HOW TO CITE:

Kandala Kalyana Srinivas, Ashwini S R, Shubhashri Waghmare, Swati Choudhary, Arijit Dutta, G. Kharmega Sundararaj, Ranjan Banerjee (2026). AI-Based Personalised Learning Systems for Students with Special Educational Needs: A Machine Learning Approach. International Journal of Special Education, 41(8s), 1225-1245

ABSTRACT:

AI-based personalised learning systems offer new opportunities to support students with Special Educational Needs by adapting content, pace, feedback, accessibility features, and learning pathways according to individual learner requirements. The present research examined teachers' readiness to adopt AI-based personalised learning systems in SEN education using a quantitative survey and machine-learning approach. Data were collected from 150 teachers, special educators, SEN coordinators, counsellors, and educational technology professionals. The questionnaire measured AI awareness, perceived usefulness, digital competence, perceived accessibility benefits, ethical concerns, institutional support, and teacher readiness. Descriptive statistics, reliability analysis, correlation analysis, and machine-learning classification models were applied. The findings showed a high overall level of teacher readiness, with perceived usefulness, accessibility benefits, and digital competence showing the strongest positive relationships with readiness. Ethical concerns showed a negative relationship, indicating the importance of privacy, transparency, and

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responsible AI use. Among the machine-learning models, Random Forest achieved the best predictive performance, with perceived usefulness and accessibility benefits emerging as the strongest predictors. The findings suggest that AI-based personalised learning can support inclusive SEN education when implemented with teacher training, institutional support, accessibility-focused design, and ethical safeguards..

Keywords: Artificial Intelligence; Personalised Learning; Special Educational Needs; Machine Learning; Teacher Readiness; Inclusive Education

1. Introduction

Students with Special Educational Needs (SEN) may have varying educational needs in terms of learning style, learning speed, social interaction, attention, sensory processing and communication, and they may need learning support that is flexible, individualised and accessible. This may not always be differentiated in the traditional classroom setting, especially when teachers are expected to work with students with a variety of disabilities, learning challenges, behaviour and development needs. The development of inclusive education is accompanied by a need for an instructional system that can meet the needs of individual learners and assist teachers in planning, monitoring and adapting instruction.

In the field of education, AI has gained significance due to its capacity to assist with adaptive learning content, automated assessment feedback, student profiling, tracking student progress, and creating personalised learning paths. AI-powered personalised learning systems can process learner-related data and offer customised recommendations, including content leveling, learning format adjustments, assistive resources, and even detecting students that might need extra assistance. In SEN education, these skills are particularly important, as learners may need to access the content in a multimodal way, have simpler materials, receive verbal support, visual cues and prompts, be given more time to practice and learn, and have materials repeated. Recent research indicates that adaptive systems

based on AI can enhance learning access by tailoring learning to students' abilities, needs, and learning styles (Farhah et al., 2025).

A large number of AI-powered personalised learning systems are based on machine learning. Classification, prediction, clustering and recommendation methods can be used with machine-learning models to identify learning patterns and to facilitate data-informed decision-making. Machine learning has been applied in adaptive e-learning systems for predicting learner performance, recommending learning content, identifying learner's learning styles, and adapting instructional pathways (Murtaza et al., 2022). These functions are important in SEN education as teachers need information about student progress, engagement and support needs in a timely manner. There are, however, potential issues of bias in the data, inaccurate predictions, and failure to account for individual and contextual differences that can impact SEN learners when using machine learning in special education.

AI-based assistive technologies also have potential to enhance the learning access for students with neurodevelopmental disorders and other disabilities. Intelligent tutoring systems, speech recognition, text-to-speech, emotion-aware systems, and adaptive learning environments are among the technologies that can be used. Barua et al. (2022) highlighted the importance of AI tools that offer personalised assistive support for children with neurodevelopmental disorders, improving

learning accessibility and personalised support. Likewise, AI-driven systems can support teachers in adapting their teaching methods to be more responsive, such as by offering suggestions for alternative representations or extra practice opportunities for students.

Despite these opportunities, it is still a complex process to implement AI-based personalised learning systems in SEN education. The success and effectiveness of such systems is a key decision made by teachers as to whether they are useful, ethical, practical, and appropriate for learners with special needs. The readiness may be influenced by various factors, such as awareness of AI, perceived usefulness, digital competence, perceived accessibility benefits, institutional support, and ethical concerns. Research on adaptive learning systems using AI has emphasized the need for an understanding of the conditions of implementation, the characteristics of the learners, and the pedagogical integration, in addition to technological performance (Kabudi et al., 2021). Thus, teacher readiness is a crucial area of study as even the most powerful AI tools can be unsuccessful without teacher confidence, preparation, or trust in the technology.

Another key issue with using AI in SEN education is ethics, as well as accessibility. Data on disability is a sensitive issue and must be handled with care. The following concerns should be taken into account by teachers and institutions: informed consent, data privacy, algorithmic bias, transparency, and potential overreliance on algorithmic recommendations. While AI has the potential to enhance personalized and inclusive learning for students with disabilities, its implementation should be rooted in ethical, inclusive, and human-centered principles, as highlighted by Ahmed et al. (2025). This is especially crucial as AI should not be used as a substitute for teacher professional judgment – it should complement teacher-led decisions and inclusive practice.

While the use of AI in personalised learning and special education has been explored in previous

studies, empirical research is still required to explore teachers' readiness to implement AI-based personalised learning systems with SEN students. Specifically, there has been little focus on the prediction of readiness to adopt through machine-learning approaches, taking into account teacher-related, institutional, accessibility and ethical factors. In special needs education, the significance of teacher preparation, responsible implementation, and inclusive design have been highlighted in the research on AI (Alkan, 2024). This study focuses on the perception of teachers on the use of AI-based personalised learning systems for students with SEN, and uses machine-learning models to identify the most important factors that predict teachers' readiness. The research provides a contribution to the special education field by connecting the use of AI, teacher preparedness, accessibility, ethics, and predictive capabilities using machine learning in SEN education.

2. Literature Review

Personalised learning using AI has emerged as a key focus in educational technology, enabling the customisation of learning experiences to meet the needs, performance, preferences, and progress of the learner. Personalised learning is especially important when teaching students with Special Educational Needs as they might need different methods for delivering content, providing assistive support, communicating, pacing, feedback and assessment. Adaptive learning platforms are becoming a topic of conversation as a tool that can enhance the learning outcomes of students with special needs by creating user-centred and customised digital learning environments. According to Ayeni et al. (2024), AI-powered adaptive learning platforms can aid students with special needs by providing personalized digital tools tailored to individual student needs. This shows the potential of AI in the field of inclusive and special education as well as its broader use as an educational technology.

AI has enhanced the scope of assistive technologies in special education, allowing for more responsive and intelligent support for

learners. AI has opened up new avenues for assistive technology in special education, making it more responsive and intelligent in providing support to learners. Assistive technologies that can be leveraged with AI include speech recognition, text-to-speech, automated feedback, intelligent tutoring, adaptive assessment and personalised content recommendation. Sureshkumar et al. (2026) emphasized the importance of assistive technologies in inclusive learning contexts, and explained how AI-based technologies can help to facilitate access and participation for learners with disabilities. This is applicable to SEN education as students may have difficulties in reading, writing, attention, communication, sensory processing or accessing physically. When accessibility and supervision are designed into the system, AI-supported systems can help mitigate these barriers.

AI-based personalised learning is achieved through various methods, one of which is machine learning. It can help systems to use learner data to detect patterns that can be used for informing instruction. To identify learning styles and make learning experiences adaptable, personalised adaptive learning technologies based on machine-learning techniques have been applied (Essa et al., 2023). While the prediction of learning style is still a topic of discussion in educational research, the main usefulness of machine learning is its ability to categorize the needs of the learner, predict his/her performance, identify problems and suggest appropriate support materials. In SEN contexts, these functions can help teachers to identify students who require further support or alternative learning formats.

There has been more recent research into the use of AI supported learning management systems for particular groups of SEN. Gadzhimusieva et al. (2026) investigated the development and a pilot testing of an AI based learning management system for personalised education of autistic students. This is significant because autistic learners might need to learn in a structured way, have predictable interfaces, visual supports,

communication support, and individual progress monitoring. If designed in the learner's profile, rather than using a generic model for all students, AI-based systems can help with these requirements.

Personalised learning pathways are a key aspect of AI in education. As AI technologies evolve, they have the potential to enhance personalised learning pathways by tailoring learning experiences to individual needs and progress, as discussed by Tapalova and Zhiyenbayeva (2022). In special education, these can be beneficial as SEN students can learn at different rates or to different learning outcomes. Based on the learner's performance and interaction pattern, the AI system can suggest more exercises, easier content, video explanations, or other activities.

The wider research on use of AI to support personalised learning reveals that personalisation is not restricted to content recommendation. It also includes assessment, feedback, monitoring of engagement, modelling and adaptation. Farhood et al. (2025) conducted a review of artificial intelligence (AI) in the context of personalised learning and found that AI can facilitate personalised learning by analysing data and making decisions. However, the implementation of such systems must be done with care as personalisation in education must not only be algorithmic prediction, but also be carefully designed and implemented. For learners with SEN, teacher judgement is still very important as the emotional, behavioural and social needs of learners may not be fully captured in digital data.

Bibliometric studies also indicate that the field of personalised learning has received increasing research interests from the academia. Li and Wong (2023) reported that the studies on AI for personalised learning have grown in the educational technology, learning analytics, and adaptive learning fields. This growth is a testament to the growing interest in the role that AI can play in supporting learner-centred education. The SEN context is still a niche area that needs more targeted empirical research,

particularly regarding teacher preparedness, ethical appropriation, accessibility and implementation.

The potential application of AI in special education has also been explored as a niche area where AI systems can assist students with special needs. Kumar et al. (2023) highlighted the importance of AI-powered tools for students who need special assistance. These can be used to plan personalised learning activities, track learner progress and offer different ways of engaging learners. However, its effective use will rely on teacher readiness to use such systems in practice.

Identification of learning styles and modification of content are other common aspects of AI personalisation. Kanchon et al. (2024) also noted that AI can be used to identify learning styles and modify the content to better suit them, which could help to deliver educational content more effectively. Content modification is particularly relevant in SEN education as learners may need to have the information made simpler, presented through audio materials, visual cues, alternative assessments, and/or repetition. But there are challenges beyond technical design when it comes to inclusive education and AI. While AI has the potential to assist individuals with special needs and language barriers, there is a need for inclusive implementation, which entails considerations of equity, access, and ethical protections, according to Fitas (2025). This is consistent with the requirement to create accessible, transparent and supportive personalised learning systems based on AI.

AI has also been suggested as a means of understanding how learning disabilities relate to

the learning strategies used and academic achievement. Bressane et al. (2024) demonstrated how AI could be utilized to analyse educational factors associated with student achievement and learning difficulties. There is support for the use of data-based strategies to identify learning barriers and inform intervention strategies. Last but not least, the prediction of learning styles in online learning using AI has shown the potential of machine learning models in educational data for prediction and adaptation. Pardamean et al. (2022) applied the AI-based prediction in online learning in primary education, highlighting the importance of machine learning in the classification of learner characteristics. While it is not restricted to SEN learners, it is a component of the methodological approach of the present study, where machine-learning models are employed to predict teachers' preparedness to use AI-based personalised learning systems with students who have SEN.

3. Conceptual Framework

3.1 Conceptual Basis and Study Variables

The conceptual framework elucidates the influence of selected factors on teachers' readiness to use AI-based personalised learning systems with students with SENs. Teacher readiness is the dependent variable in this study, whereas independent variables are the awareness of AI, perceived usefulness, digital competence, perceived accessibility benefits, ethical concerns, and institutional support. Table 1 shows study variables, operational definitions and expected relationships.

Table 1. Study Variables and Operational Definitions

Variable Type	Variable	Operational Definition	Expected Relationship
Independent variable	AI awareness	Teachers' knowledge of AI-based educational tools and adaptive learning systems.	Positive

Independent variable	Perceived usefulness	Teachers' belief that AI-based personalised learning supports SEN instruction.	Positive
Independent variable	Digital competence	Teachers' confidence and ability to use digital technologies.	Positive
Independent variable	Perceived accessibility benefits	Teachers' belief that AI improves access through adaptive and assistive features.	Positive
Independent variable	Ethical concerns	Teachers' concerns about privacy, bias, transparency, and overdependence on AI.	Negative
Independent variable	Institutional support	Availability of training, infrastructure, technical support, and policy guidance.	Positive
Dependent variable	Teacher readiness	Teachers' willingness and preparedness to adopt AI-based personalised learning systems.	Outcome variable

The readiness of teachers is expected to increase as a result of the awareness of AI, perceived usefulness, digital competence, perceived accessibility benefits, and institutional support. Ethical issues are likely to impact readiness as teachers may be concerned about privacy, bias, inaccurate recommendations, and misuse of SEN related data.

3.2 Conceptual Model and Hypotheses

According to the conceptual model, there are six predictors that affect teachers' readiness. It is expected that 5 predictors will be positively correlated and ethical concerns will be negatively correlated. The conceptual model of the study is shown in Figure 1.

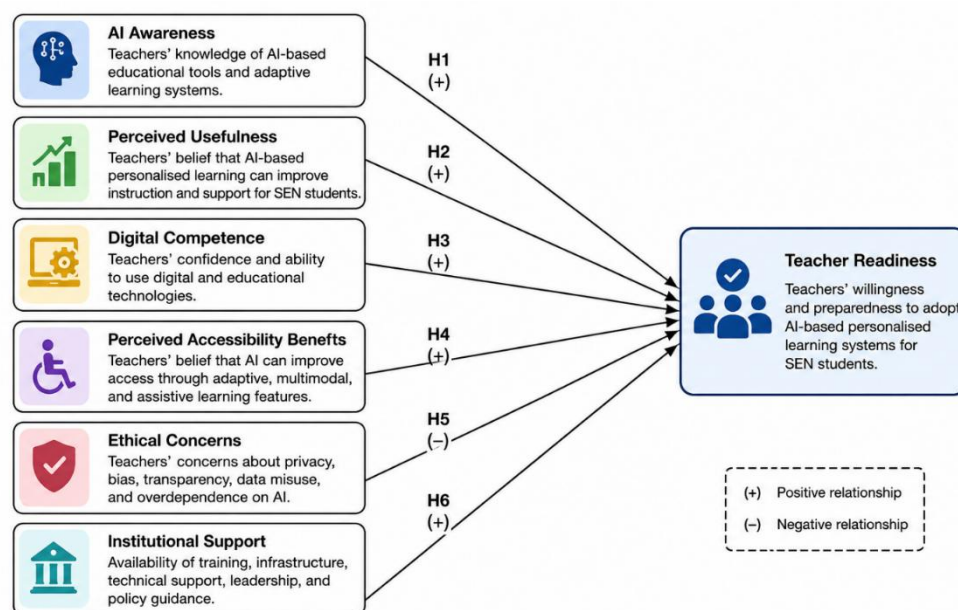


Figure 1. Conceptual Model of Factors Influencing Teacher Readiness for AI-Based Personalised Learning

The model represents the following relationship:

AI Awareness + Perceived Usefulness + Digital Competence + Perceived Accessibility Benefits

+ Ethical Concerns + Institutional Support → Teacher Readiness

Table 2 presents the hypothesised relationships among the study variables.

Table 2. Hypothesised Relationships Among Study Variables

Hypothesis	Relationship	Expected Direction
H1	AI awareness influences teacher readiness.	Positive
H2	Perceived usefulness influences teacher readiness.	Positive
H3	Digital competence influences teacher readiness.	Positive
H4	Perceived accessibility benefits influence teacher readiness.	Positive
H5	Ethical concerns influence teacher readiness.	Negative
H6	Institutional support influences teacher readiness.	Positive

These hypotheses guide the statistical and machine-learning analyses by defining the expected relationships between the predictor variables and teacher readiness.

3.3 Machine-Learning Prediction Framework

The machine-learning part takes the independent variables as input features and the independent

variable teacher readiness as the target variable. Teacher readiness is determined by the responses to the items on the questionnaire and categorized as low, moderate, or high readiness. Table 3 shows the criteria used to classify teacher readiness.

Table 3. Classification of Teacher Readiness

Mean Score Range	Readiness Category	Interpretation
1.00–2.33	Low readiness	Limited willingness to adopt AI-based personalised learning systems.
2.34–3.66	Moderate readiness	Partial readiness, requiring further training, support, or ethical assurance.
3.67–5.00	High readiness	Strong willingness to adopt AI-based personalised learning systems.

The data collected from the questionnaires are cleaned, coded, and split into training and test sets. The models selected are then trained to classify teacher readiness. The accuracy, precision, recall, F1 score and confusion matrix

are used to evaluate model performance. The best predictors are identified using feature importance. The process of prediction using machine learning is shown in Figure 2.

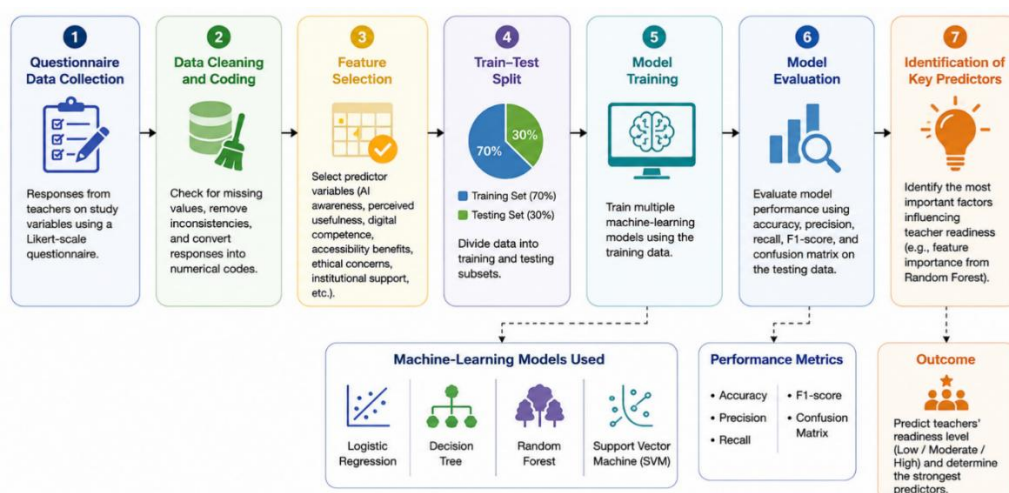


Figure 2. Machine-Learning Process for Predicting Teacher Readiness in SEN Education

The process follows this sequence:

Questionnaire Data → Data Cleaning and Coding → Feature Selection → Train-Test Split

→ Model Training → Model Evaluation → Identification of Key Predictors

Table 4 presents the proposed machine-learning models and their roles in the study.

Table 4. Proposed Machine-Learning Models

Model	Role in the Study	Reason for Use
Logistic Regression	Predicts teacher readiness category.	Baseline and interpretable model.
Decision Tree	Classifies readiness using decision rules.	Simple and explainable.
Random Forest	Predicts readiness and identifies key predictors.	Handles variable interactions and provides feature importance.
Support Vector Machine	Classifies readiness categories.	Useful for performance comparison.

This framework connects the educational aspects of the study to the machine-learning analysis by outlining the factors that affect teachers' preparedness to implement AI-based personalised learning systems in SEN education.

4. Methodology

4.1 Research Design

The study used a quantitative survey research design and a predictive analysis approach using machine learning. The quantitative survey design allowed for gathering numerical data from teachers, special educators, SEN coordinators and inclusive education professionals on their perceptions of AI-based personalised learning systems for students with Special Educational

Needs. The machine-learning method was used to predict the readiness of teachers to use such systems based on selected predictor variables. The study focused on six independent variables: AI awareness, perceived usefulness, digital competence, perceived accessibility benefits, ethical concerns, and institutional support. The dependent variable was the teachers' preparedness to use AI-based personalised learning systems in SEN students. This design was suitable because it enabled the study to look

at the relationship between the variables and also classify the level of readiness of the teachers based on the predictive models.

4.2 Population and Sample

The respondents for the study were teachers and education professionals who were directly or indirectly engaged in the education of students with Special Educational Needs. This included special education teachers, inclusive classroom teachers, SEN coordinators, school counsellors,

and educational technology professionals. A total of 100–200 respondents were targeted for the study. Purposive sampling was used to select the respondents as the study required participants who had relevant experience in teaching, supporting or managing SEN students. In addition, where necessary, snowball sampling was employed to help achieve additional respondents via professional networks. The population and sample characteristics of the study are presented in Table 5.

Table 5. Population and Sample Characteristics

Category	Description
Target population	Teachers and education professionals involved in SEN or inclusive education
Respondent groups	Special education teachers, inclusive classroom teachers, SEN coordinators, counsellors, and educational technology professionals
Sampling technique	Purposive sampling and snowball sampling
Sample size	100–200 respondents
Inclusion criterion	Professional experience in teaching or supporting students with Special Educational Needs
Exclusion criterion	No teaching, SEN, or inclusive education-related experience

4.3 Research Instrument

Structured questionnaire was used for data collection. The questionnaire assessed teachers' perceptions of AI-based personalised learning systems and their willingness to use AI-based personalised learning systems with students with Special Educational Needs. The questionnaire had two sections. The first section gathered demographic data, such as gender, age, academic qualifications, years of teaching experience, school type, experience with SEN students, and prior training in educational technology or artificial intelligence. The second part consisted

of Likert scale questions on the key study variables.

A five-point Likert scale was used:

1 = Strongly Disagree

2 = Disagree

3 = Neutral

4 = Agree

5 = Strongly Agree

Table 6 presents the structure of the research instrument.

Table 6. Structure of the Questionnaire

Section	Construct Measured	Focus
A	Demographic information	Age, qualification, teaching experience, school type, SEN experience
B	AI awareness	Knowledge of AI tools, adaptive learning, and personalised systems

C	Perceived usefulness	Belief that AI supports instruction, feedback, and progress monitoring
D	Digital competence	Confidence in using digital and educational technologies
E	Perceived accessibility benefits	Belief that AI supports accessible and multimodal learning
F	Ethical concerns	Concerns about privacy, bias, transparency, and overdependence
G	Institutional support	Availability of training, infrastructure, technical support, and policy guidance
H	Teacher readiness	Willingness and preparedness to adopt AI-based personalised learning systems

The questionnaire items were developed based on the conceptual framework of the study. Each construct included multiple items to support reliable measurement.

4.4 Validity and Reliability

Content validity was used to determine the validity of the questionnaire. The draft questionnaire was discussed with experts from the fields of special education, educational

technology, and research methodology. They were used to help clarify, make relevant and make suitable items. Cronbach's alpha was used to test reliability. An acceptable Cronbach's alpha value was accepted to be 0.70 or higher for each construct. Items with low reliability scores were examined and items with problems were eliminated prior to final analysis. The reliability criteria used in this study are shown in Table 7.

Table 7. Reliability Criteria

Cronbach's Alpha Value	Interpretation
Below 0.60	Poor reliability
0.60–0.69	Questionable reliability
0.70–0.79	Acceptable reliability
0.80–0.89	Good reliability
0.90 and above	Excellent reliability

4.5 Data Collection Procedure

The data was gathered by using an online or printed questionnaire. Participants were informed of the study's purpose, voluntary participation, and confidentiality of their responses. All respondents gave informed consent to participate in the study. Teachers and education professionals were targeted for the questionnaire in schools, professional organisations, via email and online. No personally identifiable information or sensitive student records were collected. The gathered

responses were coded and ready for statistical and machine learning analysis.

4.6 Data Analysis Procedure

Data analysis was done in two phases. The descriptive and inferential statistical analysis was the first step. The second stage was the predictive analysis using machine learning. Demographic data and answers to the study variables were summarised using descriptive statistics. The level of AI awareness, perceived usefulness, digital competence, accessibility benefits, ethical concerns, institutional support, and teacher

readiness were interpreted using the mean and standard deviation. To find the relationships between the independent variables and teacher readiness, correlation analysis was employed. The data was cleaned, coded and prepared for training the machine-learning model. The teacher readiness was divided into three categories: low, moderate, and high readiness.

The teacher readiness was categorized as low, moderate, and high readiness according to the mean score of the readiness items. The data set was then split into a training set and a testing set. Various classification models were trained and evaluated. The data analysis techniques in the study are presented in Table 8.

Table 8. Data Analysis Techniques

Analysis Type	Technique	Purpose
Descriptive analysis	Frequency and percentage	To describe demographic characteristics
Descriptive analysis	Mean and standard deviation	To examine the level of each study variable
Reliability analysis	Cronbach's alpha	To test internal consistency of questionnaire items
Inferential analysis	Correlation analysis	To examine relationships among variables
Machine-learning analysis	Classification models	To predict teacher readiness level
Model evaluation	Accuracy, precision, recall, F1-score, confusion matrix	To assess model performance
Feature analysis	Feature importance	To identify strongest predictors of teacher readiness

The machine learning models employed in the study were Logistic Regression, Decision Tree, Random Forest and Support Vector Machine. The models chosen were suitable for classification tasks and can be compared with

baseline, interpretable and more advanced predictive approaches. Table 9 shows the machine-learning models and evaluation metrics employed in the study.

Table 9. Machine-Learning Models and Evaluation Metrics

Component	Description
Input features	AI awareness, perceived usefulness, digital competence, accessibility benefits, ethical concerns, institutional support
Target variable	Teacher readiness
Readiness categories	Low, moderate, high
Machine-learning models	Logistic Regression, Decision Tree, Random Forest, Support Vector Machine
Evaluation metrics	Accuracy, precision, recall, F1-score, confusion matrix
Feature-importance method	Random Forest feature importance

4.7 Ethical Considerations

This study followed ethical principles for educational research. The respondents gave informed consent and participation was voluntary. The participants were told that they could opt out of the study at any time without repercussion. The confidentiality and anonymity of the research process were preserved. No names, student records, disability diagnoses or personally identifiable student information were gathered. Only teachers' perceptions and readiness were studied. Data was kept securely and only used for academic purposes. Special care was taken in the interpretation of the machine-learning results, which were done responsibly. The models were not employed to

evaluate specific teachers, schools or students. The study acknowledged that special education professionals' professional judgment should not be replaced by AI-based personalised learning systems, but rather supported.

5. Results

5.1 Demographic Profile of Respondents

The study included 150 respondents consisting of teachers, special educators, SEN coordinators, counsellors, and educational technology professionals. Demographic profile was analysed by using the frequency and percentage distribution. The demographic profile of the respondents is presented in Table 10.

Table 10. Demographic Profile of Respondents

Demographic Variable	Category	Frequency	Percentage
Gender	Male	56	37.3
	Female	91	60.7
	Prefer not to say	3	2.0
Age	Below 25 years	18	12.0
	25–34 years	52	34.7
	35–44 years	49	32.7
	45 years and above	31	20.6
Academic qualification	Diploma/Certificate	21	14.0
	Bachelor's degree	67	44.7
	Master's degree	54	36.0
	Doctorate	8	5.3
Teaching experience	Less than 5 years	34	22.7
	5–10 years	48	32.0
	11–15 years	39	26.0
	More than 15 years	29	19.3
Type of institution	Special education school	41	27.3
	Inclusive school	63	42.0
	Mainstream school	38	25.4
	Other	8	5.3

Experience with SEN students	Yes	132	88.0
	No	18	12.0
Previous AI/EdTech training	Yes	61	40.7
	No	89	59.3

The demographic results indicate that the sample consisted of respondents from various educational settings and teaching experience levels. The majority of respondents had first-hand experience of working with students with Special Educational Needs, further enhancing the relevance of the responses to the focus of this study.

5.2 Descriptive Statistics of Study Variables

To explore the level of each study variable, descriptive statistics were used. The mean and standard deviation were computed for awareness of AI, perceived usefulness, digital competence, perceived accessibility benefits, ethical concerns, institutional support, and teacher readiness. The descriptive statistics of the study variables are shown in Table 11.

Table 11. Descriptive Statistics of Study Variables

Variable	Number of Items	Mean	Standard Deviation	Interpretation
AI awareness	4	3.42	0.74	Moderate
Perceived usefulness	5	4.08	0.63	High
Digital competence	4	3.67	0.71	High
Perceived accessibility benefits	5	4.15	0.58	High
Ethical concerns	5	3.89	0.69	High
Institutional support	4	3.31	0.77	Moderate
Teacher readiness	5	3.76	0.66	High

The highest mean score was found for perceived accessibility benefits, meaning that respondents were highly confident that the use of AI-based personalised learning systems would enhance accessibility to learning for SEN students. The mean score for perceived usefulness was also high, indicating that respondents believed AI-based systems to be useful for differentiated instruction, progress monitoring, and personalised support. The lowest mean score was for institutional support where respondents rated the training, infrastructure, and implementation support in school as being only

moderate. The average score for teacher readiness was 3.76, showing a high level of readiness to implement AI based personalised learning systems. This indicates a positive attitude toward the use of AI-powered personalized learning tools, as long as proper training, ethical measures, and institutional support are provided.

5.3 Reliability Analysis

The internal consistency of the questionnaire constructs was checked using Cronbach's alpha. Any value of 0.70 or higher was deemed

acceptable. The results of the reliability of the study constructs are shown in Table 12.

Table 12. Reliability Analysis of Study Constructs

Construct	Number of Items	Cronbach's Alpha	Interpretation
AI awareness	4	0.81	Good
Perceived usefulness	5	0.87	Good
Digital competence	4	0.79	Acceptable
Perceived accessibility benefits	5	0.88	Good
Ethical concerns	5	0.84	Good
Institutional support	4	0.76	Acceptable
Teacher readiness	5	0.86	Good

Cronbach's alpha values were between 0.76 and 0.88, which is higher than the minimum value of 0.70. This indicates that the questionnaire constructs had acceptable to good internal consistency and were suitable for further statistical and machine-learning analysis.

5.4 Classification of Teacher Readiness

The teacher readiness items were used to determine a teacher's mean score, which was then used to categorize teacher readiness as low, moderate, and high. The distribution of the respondents by readiness level is shown in Table 13.

Table 13. Distribution of Teacher Readiness Categories

Readiness Category	Mean Score Range	Frequency	Percentage
Low readiness	1.00–2.33	14	9.3
Moderate readiness	2.34–3.66	52	34.7
High readiness	3.67–5.00	84	56.0
Total		150	100.0

The results indicate that 56.0% of the respondents were highly ready to use AI-based personalised learning systems, 34.7% moderately ready, and 9.3% were lowly ready. This suggests that while a high proportion of respondents were willing to implement personalised learning

systems with AI support for SEN students, there was still a significant number who needed more training, institutional support, and ethical assurance. The distribution of respondents by teacher readiness category is shown in figure 3.

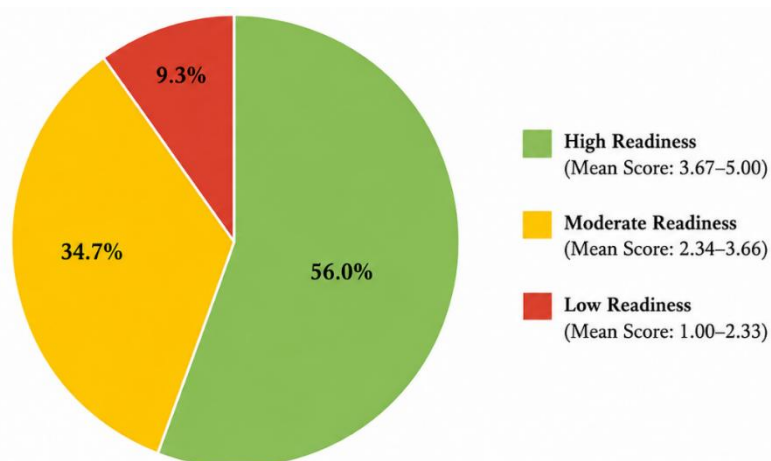


Figure 3. Distribution of Teachers' Readiness to Adopt AI-Based Personalised Learning Systems

5.5 Correlation Analysis

Pearson correlation analysis was used to explore the correlation between each predictor variable

and teachers' readiness to use AI-based personalised learning systems. The correlation results are shown in Table 14.

Table 14. Correlation Between Predictor Variables and Teacher Readiness

Predictor Variable	Correlation with Teacher Readiness (r)	Significance Level	Relationship
AI awareness	0.54	$p < .01$	Moderate positive
Perceived usefulness	0.68	$p < .01$	Strong positive
Digital competence	0.61	$p < .01$	Strong positive
Perceived accessibility benefits	0.64	$p < .01$	Strong positive
Ethical concerns	-0.32	$p < .01$	Weak negative
Institutional support	0.59	$p < .01$	Moderate positive

The findings reveal that perceived usefulness was correlated with teacher readiness the highest, followed by perceived accessibility benefits and digital competence. The awareness of AI and institutional support were also moderately positively correlated. Ethical concerns were related weakly and negatively with readiness, with greater concern about privacy, bias, and transparency being correlated with less readiness.

5.6 Machine-Learning Model Performance

Teachers' readiness to use AI-based personalised learning systems was predicted using machine-learning classification models. The input features were AI awareness, perceived usefulness, digital competence, perceived accessibility benefits, ethical concerns, and institutional support. The dependent variable was teacher readiness, which was measured as low, moderate, and high. The data set was split into two sets: 80% for training and 20% for testing. Logistic Regression, Decision Tree, Random Forest and Support

Vector Machine were trained and tested. The accuracy, precision, recall and F1-score were used to evaluate model performance. The

performance of the machine-learning models is compared in table 15.

Table 15. Performance Comparison of Machine-Learning Models

Model	Accuracy	Precision	Recall	F1-Score
Logistic Regression	0.80	0.79	0.80	0.79
Decision Tree	0.77	0.76	0.77	0.76
Random Forest	0.87	0.86	0.87	0.86
Support Vector Machine	0.83	0.82	0.83	0.82

The highest performance was obtained by the Random Forest model, which had an accuracy of 0.87, a precision of 0.86, a recall of 0.87 and an F1 score of 0.86. This means that the Random Forest model was the best model for the classification of teachers' readiness levels. The other two models, Support Vector Machine and Decision Tree, had good performance, and the

lowest performance was seen in Decision Tree. The results indicate that the teacher readiness was affected by several interacting factors and that ensemble-based modelling is more effective than a single decision-tree structure. The performance comparison of the machine-learning models is shown in figure 4.

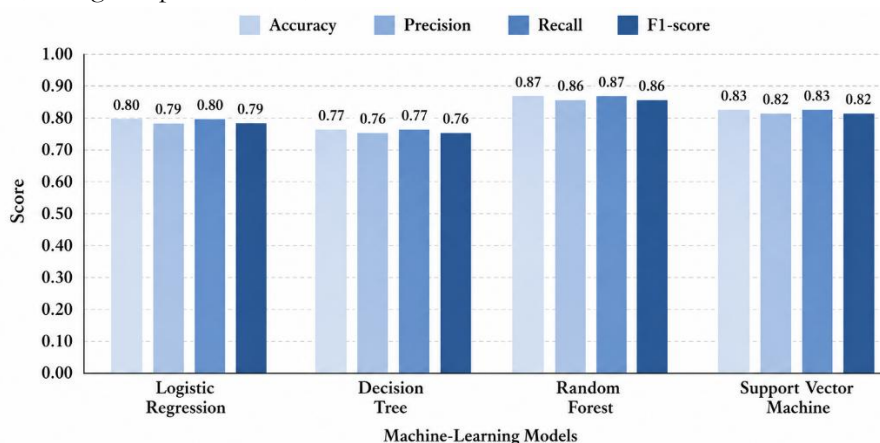


Figure 4. Performance Comparison of Machine-Learning Models Used to Predict Teacher Readiness

5.7 Confusion Matrix of the Best-Performing Model

Random Forest had the best overall performance and its confusion matrix was analyzed to evaluate

the accuracy of classification for the three readiness categories. The confusion matrix of the Random Forest model is shown in Table 16.

Table 16. Confusion Matrix of the Random Forest Model

Actual / Predicted	Low Readiness	Moderate Readiness	High Readiness
Low readiness	2	1	0
Moderate readiness	0	8	2
High readiness	0	1	16

The Random Forest model correctly classified most of the respondents in the moderate and high readiness categories. The most common misclassifications were between moderate and high readiness, indicating that these two readiness groups had comparable response patterns. This is fair as teachers with moderate readiness might have positive attitudes towards the use of AI-based personalised learning but still need more training, institutional support or

ethical assurance to fully implement the technology.

5.8 Feature Importance Analysis

The Random Forest model was used for feature importance analysis to determine the strongest predictors of teacher readiness. The feature importance scores for the predictor variables are shown in Table 17.

Table 17. Feature Importance of Predictors Influencing Teacher Readiness

Predictor Variable	Feature Importance Score	Rank
Perceived usefulness	0.24	1
Perceived accessibility benefits	0.21	2
Digital competence	0.18	3
Institutional support	0.15	4
AI awareness	0.13	5
Ethical concerns	0.09	6

The feature importance results indicate that the perceived usefulness was the most important feature for teacher readiness, followed by the perceived accessibility benefits and digital competence. This suggests that teachers were more likely to be ready when they felt that the use of AI-based personalised learning systems would enhance the delivery of SEN instruction, that they would be able to access learning support through AI, and that they would be able to use it confidently in their classroom practice.

Institutional support also played a significant role in prediction, indicating that training, infrastructure, technical assistance and policy guidance continue to be important for adoption. The feature importance score for AI awareness was moderate, with ethical concerns having the lowest score. Ethical issues, however, were still relevant as readiness was shown to be negatively correlated. The feature importance of predictors contributing to teacher readiness is shown in Figure 5.

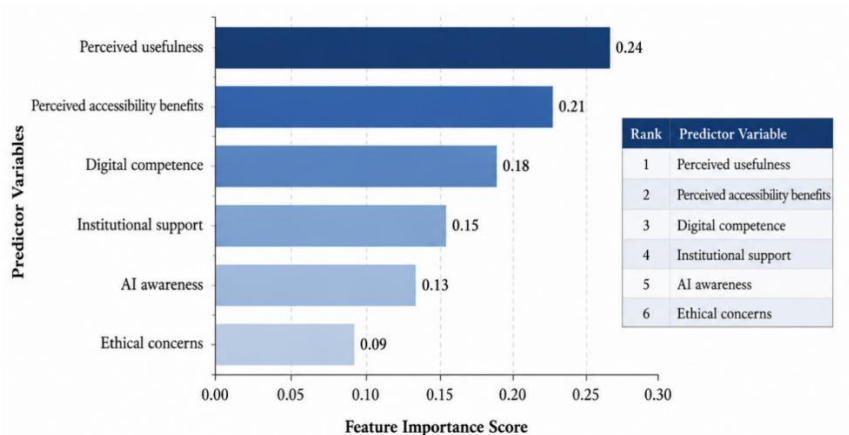


Figure 5. Feature Importance of Predictors Influencing Teachers' Readiness to Adopt AI-Based Personalised Learning Systems

5.9 Hypothesis Testing

The hypotheses were evaluated using the direction and significance of the correlation

results. Table 18 presents the hypothesis testing results.

Table 18. Hypothesis Testing Results

Hypothesis	Statement	Result
H1	AI awareness positively influences teacher readiness.	Supported
H2	Perceived usefulness positively influences teacher readiness.	Supported
H3	Digital competence positively influences teacher readiness.	Supported
H4	Perceived accessibility benefits positively influence teacher readiness.	Supported
H5	Ethical concerns negatively influence teacher readiness.	Supported
H6	Institutional support positively influences teacher readiness.	Supported

The results of the hypothesis testing show that all the hypotheses were accepted. Teacher readiness was positively correlated with awareness of the benefits of using AI, perceived usefulness, digital competence, perceived accessibility benefits, and institutional support, and negatively correlated with ethical concerns. The results indicate that the use of AI-based personalised learning systems in SEN education is influenced by teachers' perceptions of the educational value of AI, its accessibility, digital competence, institutional factors, and ethical confidence.

6. Discussion

The results suggest that teachers were generally prepared to implement AI based personalised learning systems with students with SEN. A majority (more than half) of the respondents were considered high readiness, with a smaller proportion being moderate or low readiness. This indicates that teachers are aware of the potential of AI-powered systems in enhancing differentiated teaching, accessibility, and personalised learning support. But the fact that there are moderate and low readiness groups also demonstrates that adoption is not automatic. For teachers to fully embrace the use of AI-powered personalised learning in SEN classrooms, additional training, institutional support, and ethical approval are needed.

The descriptive results indicated that the highest mean score was obtained in the perceived accessibility benefits. This indicates that respondents were strongly convinced that AI has the potential to assist SEN students in various ways, such as adaptive formats, multimodal materials, assistive features, and flexible pacing. This is in line with the findings of Sayed et al. (2023) that adaptive systems can enhance e-learning through customization of content presentation and exercise navigation using artificial intelligence. In the field of SEN education, this reinforces the idea that AI can be beneficial by adapting teaching methods to meet the needs of students, rather than simply providing digital content.

Perceived usefulness also was a significant factor. Teachers were more prepared to implement AI-based personalised learning systems when they thought that such systems could enhance teaching, feedback, monitoring, and learner support. This discovery corresponds with Murtaza et al. (2022) who discussed the role of AI-based personalized e-learning systems in adaptive learning, learner modelling, and better teaching, and highlighted the issues of implementation, privacy, and system design. The present results indicate that perceived usefulness is a key component of teacher readiness, however, it is not sufficient; systems should be

practical, accessible and at the same time ethically sound.

The correlation results indicated that there were positive relationships between teacher readiness and perceived usefulness, perceived accessibility benefits, and digital competence, with the highest positive relationships between perceived usefulness and teacher readiness, and between perceived accessibility benefits and teacher readiness. This indicates that teachers will be more inclined to implement AI based systems if they feel there is educational value in the use of such technology, if they think that such systems will help SEN learners and if they are confident in using digital technologies. The significance of digital competence is in line with Pardamean et al. (2022), who showed that the use of learner data and digital learning environments is a key factor in predicting learning in online learning using artificial intelligence. In SEN education, teachers need to be not only knowledgeable of the educational role of AI but also feel confident in interpreting and implementing AI-supported recommendations.

There was a weak negative correlation between teacher readiness and ethical concerns. This suggests that privacy concerns, bias, lack of transparency, inaccurate recommendations, and overreliance on AI could make teachers hesitant to use such systems. While less strong than the positive predictors, it is still significant since data related to SEN is sensitive. The finding corroborates Murtaza et al. (2022), who found that privacy, trust, data quality and implementation challenges are significant problems for AI-based personalised e-learning systems. In reality, teachers might only accept AI tools when they are sure that student information is secure and that AI suggestions are monitored by people.

The results obtained from the machine learning indicated that Random Forest gave the best prediction followed by Support Vector Machine, Logistic Regression and Decision Tree. That means that teacher readiness is a function of multiple factors that interact with each other

instead of being determined by one. This is because Random Forest is better able to deal with the nonlinear relationship and interactions between variables, which is why it may have performed better. This aligns with the broader adoption of machine-learning models in educational prediction, where algorithms are utilized to categorize learners, predict their performance, and guide adaptive decision-making (Pardamean et al., 2022). The discovery is also in line with the applicability of machine-learning techniques in educational technologies research as highlighted by Reddy et al. (2026) in their discussion of learning assistants based on machine-learning techniques in educational contexts.

The results of the feature importance analysis revealed that perceived usefulness was the most significant factor influencing teacher readiness, followed by perceived accessibility benefits, digital competence, institutional support, AI awareness, and ethical concerns. This means that teachers' attitudes towards the use of AI-based personalised learning systems are most shaped by their perception of the systems as meaningful and useful in terms of instruction for SEN students. Sayed et al. (2023) also highlighted the effectiveness of adaptive systems when they enhance the content presentation and learner engagement. Thus, the systems for SEN education based on AI should be developed based on practical needs in the classroom, accessibility and ease of use for teachers.

There are some limitations of the study. First, the data was collected from self-reported questionnaires, and this could be a reflection of the teachers' perceptions rather than actual classroom behaviour. Secondly, this study did not measure the learning outcomes of the SEN students directly. Third, the machine-learning models were constructed from survey data, not from real-time data of classroom interactions. Fourth, the sample size is adequate for exploratory analysis but may not allow for generalisation of the results.

The results have implications for schools, teachers, policy makers and developers of AI. AI literacy training, infrastructure, and technical assistance should be available in schools. There is a need for guidelines to be established by policymakers for ethical use of AI in SEN education, particularly with respect to data privacy, transparency, and teacher oversight. As AI developers, it is important to create systems that are explainable, accessible, and flexible to various SEN profiles. Future studies should directly evaluate the personalised learning systems using AI with SEN students, involve larger datasets, incorporate longitudinal designs, and explore the views of parents, therapists, and learners themselves.

Conclusion

The present study explored AI-based personalised learning systems for students with Special Educational Needs by adopting a machine-learning approach that considers teachers' readiness for the adoption. The results suggest that overall, teachers expressed a positive attitude towards the integration of AI into personalised learning, especially if they believe the technology can be beneficial and easily accessible, and if it aligns with their teaching methods and supports differentiated instruction. The strongest factors related to teacher readiness

were perceived usefulness, accessibility benefits and digital competence, whereas the ethical concerns had a negative relationship. The machine-learning analysis also showed that a prediction of the teacher readiness can be done by certain pedagogical, technological, ethical and institutional variables. Random Forest performed best of the models tested indicating that readiness is dependent on a number of interacting factors. The results of the feature importance showed that the perceived usefulness benefits and accessibility benefits were the most important. The study underscores the potential of AI-driven personalised learning systems to facilitate SEN education through features such as adaptive content, flexible pacing, assistive functions, progress monitoring, and personalised feedback. However, for successful implementation, teachers need to be trained, institutional support is needed, ethical safeguards, data privacy, transparency and human oversight are required. AI should be considered as a tool to assist teachers, not replace them, in making decisions. Overall, the study makes a significant contribution to special education research by demonstrating the potential of machine-learning methods to gain insights into and predict teachers' willingness to implement AI-driven personalised learning systems in SEN settings.

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