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Student Readiness Scores a Rasch Model's for Facing E-Learning Using Decision Tree and Ensemble Methods

Ester Antika[1,*], Sri Nurdiati[1], Kasiyah Junus[2], & Mohamad Khoirun Najib[1]
[1]Department of Mathematics, IPB University, Indonesia
[2]Faculty of Computer Science, University of Indonesia, Indonesia

*Corresponding email: esterantika@apps.ipb.ac.id

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Abstract: Prediction of Rasch Model's Student Readiness Scores for Facing E-Learning Using Decision Tree and Ensemble Methods. Objective: This research aims to predict student readiness score in facing e-learning using Rasch models and machine learning. **Methods:** This research is a quantitative research using a non test instrument ini the form of a questionnaire using a Likert scale. The sample used were IPB University students. Analysis techniques use Rasch model, decision tree, and ensemble. **Finding:** Item reliability value is 0,93, person reliability value is 0,97, and cronbachalpha is 0,99. The standard deviation value is 2,34 and the average logit of respondents is 1,9. 34% of students have high readiness with a person measure value >2,34. 4% of students have moderate readiness with a score of 1,9 < person measure < 2,34. 62% of students have low readiness with a person measure value < 1,9. The accuracy of the decision tree model reached 75,97%. **Conclusion:** Based on person measure from the Rasch model, it can be concluded that the majority of respondents (62%) have low ability to carry out e-learning. Male students and those who have experience in dealing with e-learning have a higher percentage of having high ability in dealing with e-learning at the university level. Moreover, machine learning models are able to predict students' abilities in dealing with e-learning based on the measure score from the Rasch model. Furthermore, ensemble models are able to increase the accuracy of decision tree models. We found that the ensemble model with the LogitBoost (adaptive logistic regression) method provides best model in term of its accuracy (82.17%) and execution time.

Keywords: decision tree, e-learning, ensemble, machine learning, rasch model.

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INTRODUCTION

Technological developments in the 21st century have changed the world of education (Qureshi, et.al., 2021). According to the Central Statistics Agency, there has been an increase in the development of Information and Communication Technology (ICT) in Indonesia in the last five years. This is shown by the ICT development index in 2022 of 5.85 (scale 0-10) which previously was 5.07 in 2018. The Indonesian Internet Service Providers Association (APJII) also announced that the number of internet users in Indonesia in 2024 will reach 221,563,479 people. The increase in ICT development has also created a transformation in the world of education in that learning methods and systems that were initially conventional have become digital so that electronic-based learning (e-learning) is increasingly developing (Global Educator Monitoring Report Team, 2023).

IPB University is preparing itself to face the challenges of technological developments and changes that will occur in the future by designing the IPB 4.0 Millennial Education curriculum. There are five characters and dimensions that will be carried out, one of which is the learning dimension with place and time not as boundaries. This shows that IPB University has started to see the challenges ahead by developing e-learning which makes place and distance no longer a barrier to the learning process. One of the strategies and policies implemented by IPB University is changing or aligning the learning process with blended learning, Massive Open Online Courses (MOOCs), and Online Distance Learning (ODL) as well as preparing virtual teaching materials for learning activities. E-learning requires interactive communication between students and teachers by utilizing ICT. The requirements for e-learning are ICT literacy, independence, creativity, and critical thinking from students. Based on the conditions required for e-learning, it is necessary to know the readiness of students so that e-learning can run well.

Several studies related to e-learning readiness in Indonesia still mostly use descriptive methods (Fariani, 2013; Jamal, 2020; Kusnadi, 2015; Mardhiyana & Nasution, 2018). However, there has been research that uses analysis including Structural Equation Modeling (Hasanah et al., 2014), interval succession method (Setiaji & Dinata, 2020), and the ELR Chapnick model (Purwandani, 2017; Waryanto & Insani, 2013). The measurements from the research that have been used have not been able to analyze the respondents and the items given.

The Rasch model is used to analyze dichotomous data and rating scale data using a probability approach. The measurement process in the Rasch model is latent, which is an Item Response Theory (IRT) concept that combines subjects and items in one scale. The results of the Rasch study provide a clearer picture of what happened to respondents and the actions taken through instrument calibration with validity and reliability tests (Mardiyah & Puger, 2017). The Rasch model is widely used in research analysis in the social sciences, including educational assessment (Sumintono & Widhiarso, 2014), analyzing likert scale survey (Yamashita, 2022), bloom digital taxonomy application (Matore, 2021), learning media (Ramdani et al., 2018), motivation (Hartatiana, 2020), healty (Luthfa, 2016; Ekstrand, et. al. 2022), a comprehensive simulation study of estimation methods (Robitzsch,A, 2021), human behavior analysis (Asni et al., 2020), tourism experience (Hermanto & Miftahuddin, 2021), and e-learning readiness (Parkes et al., 2015).

In this study, e-learning readiness at IPB University will be examined using the Rasch model. E-learning readiness is important so that the implementation of e-learning gets optimal results. Universities must know the readiness of students so that e-learning can create graduates who can meet future challenges. The Rasch model is used to analyze student readiness factors and check the validity and reliability of the instruments used.

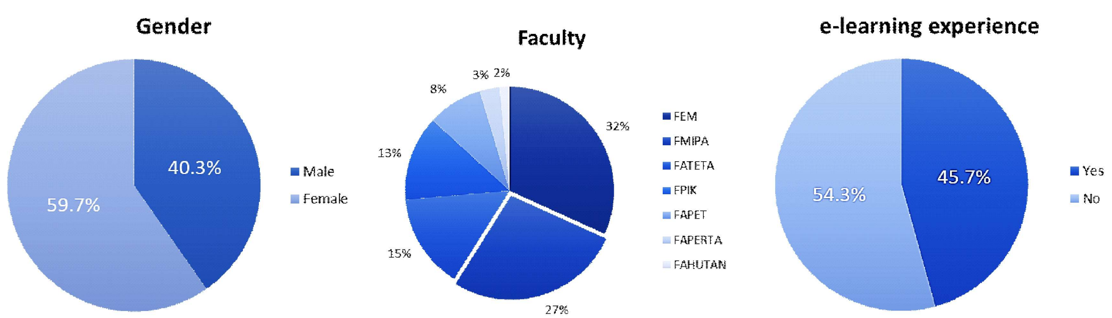
Because the readiness instrument requires many variables to measure students' level of readiness, this research uses machine learning methods, i.e., decision trees and ensembles, to predict students' readiness level scores based on the Rasch model using general information from each student. There are many points that are criteria in the Rasch model. In this research, three dimensions were used with a total of 58 questions. Using machine learning methods, this research tries to predict Rasch model scores with fewer predictors, without having to throw questionnaires at students. These predictors consist of gender, faculty, high school origin, domicile and experience participating in e-learning at the previous level. It is hoped that the results of this study will be able to help teachers predict the level of student readiness in facing e-learning by looking at the general information available to the students without having to ask them a questionnaire with lots of questions.

METHOD

Participants

The population of this study were first generation of IPB University students. The sample for this research were IPB University students from seven faculties at IPB University. The sample for this research were 129 students. Respondent characteristics data is respondent data collected to determine the respondent's profile. There are several aspects of the characteristics of respondents, i.e., gender, faculty, high school origin, domicile and experience following e-learning at previous levels.

In Figure 1.a., it is known that there are relatively more female respondents than male respondents. The number of female respondents was 77 (59.7%) and the number of male respondents was 52 (40.3%). In Figure 1.b., it is known that respondents came from 7 faculties at IPB University. These faculties are the Faculty of Economics and Management (FEM), the Faculty of Mathematics and Natural Sciences (FMIPA), the Faculty of Agricultural Technology (FATETA), the Faculty of Fisheries and Marine Sciences (FPIK), the Faculty of Animal Husbandry (FAPET), the Faculty of Agriculture (FAPERTA), and Faculty of Forestry (FAHUTAN). In Figure 1.c., it is known that there are more respondents who have never had e-learning learning experience at a previous level than respondents who already have e-learning learning experience. The number of respondents who did not have experience was 70 (54.3%) and the number of respondents who had experience was 59 (45.7%).



a. Gender b. Faculty c. Experience following e-learning

Figure 1. Chart of respondent characteristics

Research Design and Procedures

This research is included in quantitative research. The research implementation began with a literature study relating to student readiness in e-learning (Parkes, et.al., 2015). Then the researchers studied the instruments used by Parkes, et al and developed the instruments according to the conditions at IPB University. Before the questionnaire is distributed, validation of the instrument is carried out by checking that each item asked can be understood by the respondent. After that, questionnaires were distributed to students. The resulting data from the questionnaire was converted into rating scale data and processed using WINSTEP. Then an analysis of the data results is carried out. After obtaining the person measure value from the Rasch Model, the data is labeled to return and provide predictors of gender, domicile, high school origin, faculty, and e-learning experience at the previous

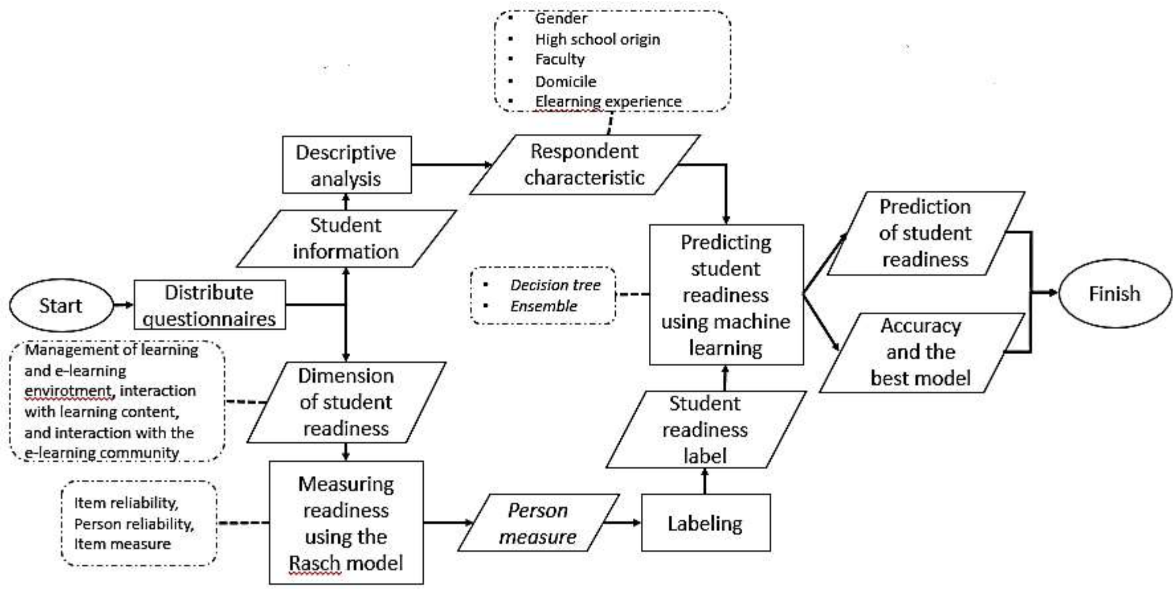


Figure 2. Flowchart of research

level to predict student readiness classification using the Decision Tree and Ensembe Methods to predict student readiness classification with the best accuracy and time. The following is a flowchart from the following research:

Instrument

The instrument used was a non test instrument by distributing questionnaire to IPB University students. The questionnaire consists of 58 e-learning competencies according to their level of student preparedness used a Likert scale and 3 essays related to factors that influence students' readiness to carry out e-learning. The Likert scale used is from 1-5. Number 1 states unprepared, 2 states not very prepared, 3 states some what prepared, 4 states prepared, and 5 states very prepared. The existence of a middle option in the five Likert scale items is an effort to facilitate respondents who have moderate characteristics so that respondents do not feel forced to choose alternatives that do not reflect their attitudes (Sumintono & Widhiarso, 2015). This is important because someone's compulsion to fill in will contribute to the large systematic error in measurement. The data from the questionnaire is in the form of ordinal data which will then be processed using the Rasch model. The questionnaire used was a questionnaire adapted from the questionnaire from (Parkes, et al., 2015) which assesses e-learning readiness into three dimensions, i.e.: management of learning and e-learning environment, interaction with the learning content, and interaction with the e-learning community.

Indicator of the dimensions management of learning and e-learning environment (24 question points) are how students carry out management: time management, use of the latest applications or software, use of technology that suits the student's learning style, skills in finding information that suits the student's needs and ability to adapt to existing technology. Indicator of the dimensions *of* interaction with e-learning content (13 question points) are how students can understand the knowledge or information they get from the teaching material provided and relate it to the knowledge they already have. Indicator of the dimensions of interaction with e-learning community (21 question points) are how students can search for information or ask other people, respond to others, use appropriate language styles in communicating with others both online and offline, collaborate with other people, and behave kindly and politely towards lecturers

Data Analysis

The data was analyzed by using the WINSTEP 3.73 and MATHLAB 9.10.0. 1602886 (R2021a). WINSTEP is used to process questionnaire results using the Rasch Model. Apart from that, the Rasch model can check the reliability of respondents and items from the questionnaire. MATHLAB is used to process the Decision Tree and Ensemble Methods. Apart from that, you can check the accuracy value of the classification obtained.

Model Rasch

Rasch modeling was introduced by a mathematician from Denmark named Dr. Georg Rasch in 1960. Rasch modeling makes measurements in the social sciences have the same units of measurement as units of measurement in physics. Rasch modeling estimates a true score which shows the level of individual ability and the level of item difficulty. Measurements using the Rasch model are objective and separate people's abilities and test characteristics. Rasch modeling has several advantages, such as accommodate a probability approach in looking at the attributes of an object being measured so that it is not deterministic (able to identify the measuring object more accurately), equalize measuring metrics (calibration) between items so that the resulting score is not a raw score but a pure score that is free from measurement error, and fulfill objective measurements (provide linear measurements, overcome missing data, carry out appropriate estimation processes, provide measurement instruments that are independent of the parameters studied).

Rasch modeling overcomes data interval problems by accommodating logit transformation (applying logarithms to the odds ratio function). This logit function will make the measurements into equal intervals. Mathematically it is expressed by an equation (Sumintono & Widhiarso, 2014).

$$\text{Odds Ratio} = \frac{p}{1-p}$$

$$\text{Logarithm odd unit (Logit)} = \ln\left(\frac{p}{1-p}\right)$$

Rasch modeling will create a hierarchical relationship between respondents and the items used. The scale formed is the basis for exploring participants' responses to various events. The application of an instrument whose data is converted into a logit scale creates responses that will measure a person's characteristics and abilities according to test output or behavioral responses in surveys completed by respondents.

Rasch modeling uses a scalogram matrix developed by Guttman. A scalogram is a measurement model that has the characteristic that each item has an order that can be systematically ranked from low to high. The aim is to make it easier to analyze, provide explanations and predict individual abilities as well as the level of difficulty of questions or items.

Based on Rasch modeling, the probability of success depends on the difference between a person's ability and the level of difficulty of the questions/items. For data in the form of a rating scale (rating scale model), Rasch modeling has the equation: (Sumintono & Widhiarso, 2015).

$$P_{ni1}(\text{x} = 1 / \beta_n, \delta_i, F_1) = \frac{e^{(\beta - [\delta + F])}}{1 + e^{(\beta - [\delta_i + F_1])}}$$

Where P_{ni1} is the probability respondent n choosing very less ready than very ready in one item (i), and F_1 is the threshold level of difficulty.

Rasch modeling looks at the reliability of the instruments developed with person reliability, item reliability, and Cronbach Alpha reliability. Person reliability measures the consistency of students' answers. Item reliability measures the quality of the questions based on the results of students' answers. Cronbach Alpha reliability calculates the overall reliability of the instrument developed.

Table 1. Category value of person reliability and item reliability of test items

Person Reliability and Item Reliability Values	Category
< 0.67	Poor
0.67-0.80	Moderate
0.80-0.90	Good
0.91-0.94	Very good
> 0.94	Excellent

Table 2. Cronbach alpha reliability value criteria for question items

Cronbach Alpha Reliability Value	Criteria
< 0.50	Very poor
0.50-0.60	Poor
0.60-0.70	Moderate
0.70-0.80	Good
>0.80	Very good

Apart from that, Rasch modeling can also see the sensitivity of response patterns in respondents through inlier-sensitive (Infit), the sensitivity of response patterns to items of certain levels of difficulty from respondents through outlier-sensitive fit (outfit), see the size of randomness or distortion in the measurement system through the mean -square fit statistics, and suitability of data to the model through standardized fit statistics. The criteria for checking non-conforming items (outliers or misfits) are accepted Outfit Mean Square (MNSQ) value: 0.5 < MNSQ < 1.5, Outfit Z-Standard (ZSTD) value accepted: -2.0 < ZSTD < 2.0, and Point Measure Correlation Value (Pt Mean Corr): 0.4 < Pt Measure Corr < 0.85. Thus, the Rasch model is a measurement that can be used to analyze e-learning readiness by paying attention to respondents and factors from the items provided properly.

Decision Tree

Decision tree refers to the use of a tree structure to represent a set of decisions or classification of data based on different data characteristics. Decision tree is an algorithm that is commonly used for decision making. Decision trees will look for solutions to problems by using criteria as nodes that are interconnected to form a tree-like structure (Babiè et al., 2000). In a decision tree there are three nodes, namely root, internal and leaf nodes. The root node is the top node. This node is determined by the best attribute. Furthermore, the root node has branches called internal nodes which can be divided into further branches if they still do not get an output value. Lastly is the leaf node. The output results of the classification are obtained from this node and will not be divided into branches again (Bukhari et al., 2023).

One method for dividing branches in a decision tree is the C4.5 algorithm. The C4.5 algorithm uses the divide and conquer method to build a suitable tree. The C4.5 algorithm uses training data to grow a tree. The value of the uncertainty measure (entropy) and the measure of the effectiveness of an attribute in classifying data (gain) are the main formulas in the C4.5 algorithm. The entropy value for the C4.5 algorithm can be calculated using the equation.

$$\text{Entropy}(S) = \sum_{i=1}^{n}(-p_i) \times log_2(p_i)$$

where S is a set of cases, n refers to the number of attribute partitions , and is the proportion of the -th partition in case . Meanwhile, the gain value is calculated using the equation

$$\text{Gain}\ (S, A) = \text{Entropy}\ (S) - \sum_{j=1}^{n}\frac{|A_j|}{|S|} \times \text{Entropy}\ (A_j)$$

where A_j is a partition of attribute A. The C4.5 algorithm is able to handle categorical and numerical data. For categorical data, the C4.5 algorithm selects one of the categories as the best attribute using the highest gain value, while the C4.5 algorithm changes numerical data into two categories first using a certain limit for numerical data (Quinlan, 1993). The stages of building a decision tree using the C4.5 algorithm is choose the attribute with the highest gain as the root. After that, create a branch on each value, then divide cases in branches, and repeat the process until all cases in each branch have the same class to determine the attribute as the root which is adjusted to the highest gain value of the existing attributes (Merawati & Rino, 2019).

Ensemble Method

Ensemble models are a technique in machine learning that utilizes multiple predictive models combined together to improve overall prediction performance. In other word, ensemble learning combines several individual models to obtain better generalization performance (Ganaie et al., 2022). With this model, the combination of decisions from several models can produce more accurate predictions than those produced by each model individually. There are several approaches to combining ensemble models. Classical methods in ensemble learning include bagging, boosting, and stacking. Bagging (Bootstrap Aggregating) is bagging involves training multiple models on a random subset of the training data and then combining the predictions from those models. Each model is generated by taking random samples from the training dataset with replacement (bootstrapping) and can use the same or different learning algorithms. Boosting: Boosting is a technique that uses "weak" models (usually relatively simple models) built sequentially. Each subsequent model focuses on examples that were difficult for the previous models to predict. The final predictions are generated by weighting the predictions from each model based on their relative performance. Stacking (Stacked Generalization): In stacking, predictions from base models are used as features for meta model training. This meta model then takes predictions from the base models as input and produces a final prediction. This allows the meta model to learn how to combine predictions from the base models to produce the best results.

Ensemble models can improve prediction performance in many cases, especially when used with different models, which have different weaknesses. This can help reduce overfitting and improve the generalization of the ensemble model. However, it should be noted that the use of ensemble models also increases computational complexity and cost. There are several ensemble methods used in this research as in Table 3 below.

Table 3. Ensemble methods used in this research

Method names	Description
Bag	Bootstrap aggregation (bagging, for example, random forest)
Subspace	Random subspace
AdaBoostM1	Adaptive boosting
GentleBoost	Gentle adaptive boosting
LogitBoost	Adaptive logistic regression

LPBoost	Linear programming boosting
RobustBoost	Robust boosting
RUSBoost	Random undersampling boosting
TotalBoost	Totally corrective boosting

Evaluation

Confusion matrix is a method for evaluating classification models using matrix tables. The matrix table used to find the confusion matrix is written as Table 4. The confusion matrix produces accuracy values from the implementation of the data classification method. Accuracy states the amount of data that is classified correctly after the testing process is carried out (Sokolova & Lapalme, 2009). The accuracy value is given by the following equation.

Table 4. Example of confusion matrix

Prediction Label	Actual Label 1	Actual Label 0
1	TP (*True Positive*)	FP (*False Positive*)
0	FN (*False Negative*)	TN (*True Negative*)

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \times 100\%$$

■ RESULT AND DISCUSSION

Rasch Model

From the three dimensions for assessing e-learning readiness which are divided into 58 questions in the questionnaire, the data is processed using the Rasch model to measure the level of student readiness in facing e-learning. From the results of data processing, Table 5 shows a statistical summary including the reliability of the instruments and other statistics.

Table 5. Statistical summary of Rasch model

	Reliability	Measure	Infit MNSQ	Outfit MNSQ	Infit ZSTD	Outfit ZSTD	Cronbach Alpha (KR-20)
Person	0.97	1.90	1.00	1.03	-0.60	-0.60	0.99
Item	0.93	0.00	1.00	1.03	-2.00	0.00	

In Table 5, the measure of 1.90 shows that the average respondent score in the instrument tends to answer more agrees on various items. The person reliability value of 0.97 shows that the consistency of the respondents' answers is excellent and the item reliability of 0.93 shows that the quality of the items in the instrument is very good. The Cronbach's alpha value of 0.99 is considered very good. This means that the instrument developed has a very good reliability coefficient. The application of the Rasch model in validity and reliability research instruments is valuable because the model able to define the constructs of valid items and provide a clear definition of the measurable constructs that are consistent with theoretical expectations (Mohamad, et.al., 2014)

Infit is inlier pattern sensitive fit statistic and outfit is outlier sensitive fit statistic (Linacre, J.M., 2020). Infit and outfit are used to check which item and responden match the model. The INFIT MNSQ and OUTFIT MNSQ values for respondents and instrument items have an average value of 1.00 and 1.03, respectively. This shows that it is good because it is close to 1.00. Meanwhile, the INFIT ZSTD and OUTFIT ZSTD values for the person are -0.6, indicating sufficient quality. Meanwhile, the INFIT ZSTD and OUTFIT ZSTD values for the instrument items are -0.2 and 0.00 respectively, indicating that the quality is getting better because it is approaching 0.00.

In Figure 3, the person measure shows students' ability to answer the questionnaire. The person measure shows the average score for all participants (Muslihin, et. al., 2022). The standard deviation value obtained was 2.34, while the average person logit value was 1.9. The main output of this Rasch model is to assess student capabilities regarding the student's readiness to face e-learning. Based on the results obtained, 34% of respondents had high ability (because they had a measure value > 2.34), which stated that students were very ready to carry out e-learning. Meanwhile, 4% (measure value between 1.9 and 2.34) have moderate ability, which states that students are ready to carry out e-learning. The remaining 62% have low ability (measure value < 1.9), which states that students are less ready to carry out e-learning.

ENTRY NUMBER	TOTAL SCORE	TOTAL COUNT	MEASURE	MODEL S.E.	INFIT MNSQ	INFIT ZSTD	OUTFIT MNSQ	OUTFIT ZSTD	PT-MEASURE CORR.	PT-MEASURE EXP.	EXACT MATCH OBS%	EXACT MATCH EXP%	Person
17	290	58	9.54	1.83		MAXIMUM	MEASURE		.00	.00	100.0	100.0	017LJC0
22	290	58	9.54	1.83		MAXIMUM	MEASURE		.00	.00	100.0	100.0	022PJC1
64	290	58	9.54	1.83		MAXIMUM	MEASURE		.00	.00	100.0	100.0	064LJG1
105	290	58	9.54	1.83		MAXIMUM	MEASURE		.00	.00	100.0	100.0	105PJH0
84	289	58	8.32	1.01	1.03	.4	1.98	1.0	-.09	.10	98.3	98.3	084LJG1
25	284	58	6.44	.43	2.12	2.4	2.66	2.6	.04	.22	94.8	89.9	025LJD0
96	284	58	6.44	.43	2.20	2.5	2.56	2.5	-.01	.22	94.8	89.9	096PJG1
10	281	58	5.98	.36	1.47	1.4	1.81	1.9	.12	.26	89.7	85.2	010LJG0
⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮	⋮
116	166	58	-.37	.27	.88	-.5	.86	-.5	.46	.32	75.9	74.3	116PJH1
124	165	58	-.45	.27	1.73	2.7	1.78	2.7	.68	.32	51.7	73.8	124PSG0
45	164	58	-.52	.27	.69	-1.5	.69	-1.4	.46	.32	79.3	73.1	045PJD1
58	159	58	-.86	.26	2.44	5.1	2.64	5.4	.59	.33	48.3	69.0	058LJF0
26	154	58	-1.18	.25	.82	-.9	.83	-.8	.33	.34	70.7	64.5	026LJC0
54	150	58	-1.42	.24	.84	-.9	.84	-.8	.48	.35	63.8	61.8	054PJA0
125	148	58	-1.54	.24	.84	-.9	.82	-1.0	.46	.35	67.2	60.5	125PJF0
20	146	58	-1.65	.24	.67	-2.2	.66	-2.2	.43	.36	62.1	59.4	020PJ 1
57	140	58	-1.98	.23	.68	-2.1	.68	-2.1	.34	.36	65.5	58.2	057PSE0
MEAN	203.5	58.0	1.90	.30	1.00	-.6	1.03	-.6			71.2	67.3	
S.D.	38.6	.0	2.34	.28	.65	3.2	.69	3.1			17.3	10.6	

Figure 3. Rasch model results showing the person measure of each student

Based on Figure 3, respondents' number 17, 22, 64, and 105 have the highest measure scores, i.e., 9.54, which shows that they have the highest ability in dealing with e-learning. Meanwhile, respondent 57 had the lowest measure score (i.e., -1.98) which made him the student with the lowest ability in dealing with e-learning. Moreover, the percentage of respondents' abilities based on gender and experience in dealing with e-learning is shown in Table 6 below.

Based on Table 6, male students and those who have experience in dealing with e-learning at the previous level have a higher percentage of having high ability in dealing with e-learning at the university level. On the other hand, female students and those who have no experience in dealing with e-learning at the previous level have

Table 6. Percentage of respondents' abilities based on gender and experience

Person measure	Male	Female	Inexperienced	Experienced
High ability	42.3%	28.6%	28.6%	40.7%
Moderate ability	7.7%	2.6%	7.1%	1.7%
Low ability	50%	68.8%	64.3%	57.6%

a high percentage of having low ability in dealing with e-learning at the university level. Thus, female and inexperienced students need special attention in facing e-learning so that their readiness can be increased. This is in accordance with other research which states that gender (male or female) influences in e-learning (Shahzad, et. al., 2020; Almasri, F., 2022)

Rasch Model Score Prediction Using Machine Learning

From the person measure for each student produced by the Rasch model in Figure 3, we grouped students who had low abilities (measure < 1.9) and labeled them with the number 1. Meanwhile, because the number of those who had moderate abilities was very small, we grouped students who had moderate abilities. moderate and high (measure $\geq$ 1.9) and label them with the number 2. From here, we obtain a Boolean classification problem to predict the class score measuring student readiness in facing e-learning from the Rasch model.

We use several predictors for this classification problem, including gender, faculty, high school origin, domicile and experience following e-learning at previous levels. Thus, if there are other students who want to predict their readiness, it is enough to ask for these five pieces of information and we can estimate their readiness based on data from previous respondents. In exiting research, decision tree was also used to e-learning readiness assessment with awareness, desire, knowledge, ability, and reinforcement (Zine, et.al., 2023)

Decision tree classification model

The first method used is the decision tree classifier. This method forms a tree-like structure to represent a classification of response data based on the characteristics of the predictor data. To predict a response, follow the decisions in the

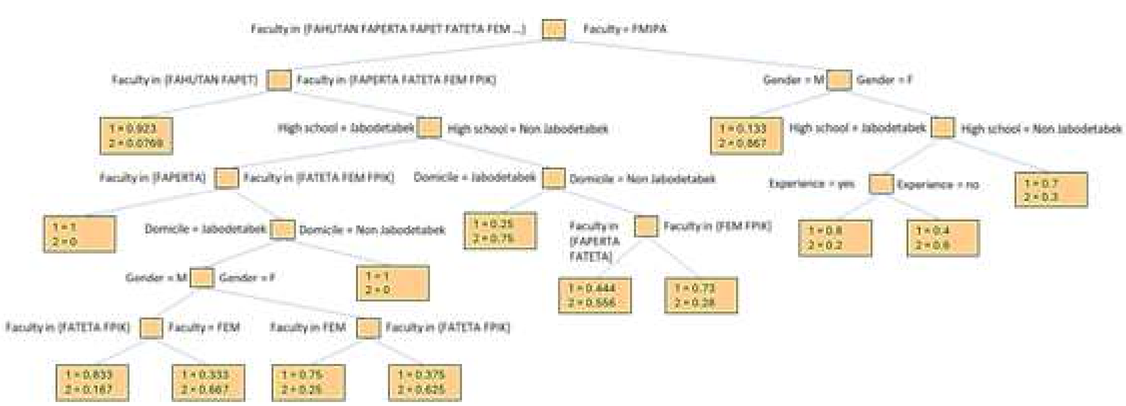


Figure 4. Decision tree classification for predicting students' abilities in dealing with e-learning based on the measure score from the Rasch model: 1 for low ability, and 2 for moderate to high ability

tree from the root (beginning) node down to a leaf node. There are several ways to determine the root node and other nodes depending on the algorithm used. In the C4.5 algorithm, the root node is selected based on the attribute that provides the greatest Information Gain. Furthermore, the leaf node contains the response. Classification trees give responses that are nominal, such as 1 or 2. Figure 4 shows the results of decision tree classification to predict students' abilities in dealing with e-learning based on the measure score from the Rasch model.

Reading predictions from a decision tree is quite easy, just trace the information obtained from the root node to a leaf. For example, if a student is from FMIPA and is male, then we can predict that he has an 86.7% probability of being in class 2 (moderate to high ability) and 13.3% being in class 1 (low ability). The predictions from the decision tree at the end of the leaf are the probabilities of each class, and the final predictions are taken from the class that has the highest probability. Thus, we can predict that the student will be in class 2 (moderate to high ability).

In figure 4, based on the classification of the decision tree model, it was found that students from the FMIPA faculty were better prepared to face e-learning than those from other faculties (FAHUTAN, FAPET, FAPERTA, FPIK, and FEM). Based on their characteristics, these faculties are more focused on practice in the field, so they are less prepared when facing e-learning. Students from Jabodetabek High School or domicile Jabodetabek tend to be better prepared than students from outside Jabodetabek

Table 7. Confusion matrix of decision tree model

Prediction Label	Actual Label 1	Actual Label 2
1	67	13
2	18	31

Table 7 shows the confusion matrix of predictions from the decision tree model obtained. A total of 67 respondents in class 1 and 31 respondents in class 2 were predicted correctly. In general, the accuracy of the decision tree model based on Eq. 6 is 75.97%.

Ensemble Model

In this section, we try to improve the accuracy of the decision tree model using ensemble models with various methods as listed in Table 3. In other research, ensemble model can outperform individual machine learning algorithms (Reddy, et.al., 2020). For similarity, we implemented ensemble models with 100 classification trees for all methods. Table 9 shows the accuracy of each method and the average execution (running) time of 10 runs.

Based on Table 8, several ensemble methods provide the highest accuracy with a value

Table 8. Results of ensemble model for predicting students' abilities in dealing with e-learning based on the measure score from the Rasch model

Method names	Accuracy	Execution time (s)
Bag	**0.8217**	1.5213
Subspace	0.5581	1.3272
AdaBoostM1	**0.8217**	1.3372
GentleBoost	**0.8217**	1.1220

LogitBoost	**0.8217**	**1.1115**
LPBoost	0.7054	1.9582
RobustBoost	**0.8217**	5.3708
RUSBoost	0.8140	1.6582
TotalBoost	0.7287	1.3080

of 82.17% and are better than the decision tree model, including Bag (*bagging* or *bootstrap aggregating*), AdaBoostM1 (*adaptive boosting*), GentleBoost (*gentle adaptive boosting*), LogitBoost (*adaptive logistic regression*), and RobustBoost (*robust boosting*) methods. However, based on execution time, the LogitBoost method outperforms the other four methods with the highest accuracy. Thus, we conclude that the LogitBoost method is the most appropriate ensemble model for predicting students' abilities in dealing with e-learning based on the measure score from the Rasch model. This is in line with the MATLAB program which makes the LogitBoost method the default choice for its syntax. Of course, the execution time depends on the device used and each experiment allows a different execution time.

■ CONCLUSION

The results of data processing using the Rasch model from data obtained from 129 IPB student respondents showed very good reliability values (more than 90%), including person reliability, item reliability, and Cronbach alpha reliability. Based on person measure from the Rasch model, it can be concluded that the majority of respondents (62%) have low ability to carry out e-learning. Moreover, male students and those who have experience in dealing with e-learning at the previous level have a higher percentage of having high ability in dealing with e-learning at the university level. Therefore, gender also influences stude readiness to face e-learning.

On the other hand, machine learning models are able to predict students' abilities in dealing with e-learning based on the measure score from the Rasch model. The accuracy of the decision tree model reached 75.97%. Based on the classification of the decision tree model, it was found that students from the FMIPA faculty were better prepared to face e-learning than those from other faculties (FAHUTAN, FAPET, FAPERTA, FPIK, and FEM). Furthermore, ensemble models are able to increase the accuracy of decision tree models. We found that the ensemble model with the LogitBoost (adaptive logistic regression) method is the best model in predicting students' abilities in dealing with e-learning based on the measure score from the Rasch model based on its accuracy and execution time. Apart from that, with machine learning we can predict students' readiness to face e-learning more easily

The results of this research reveal the level of e-learning readiness of IPB University students. Therefore, the importance of familiarizing students with e-learning needs to become a culture in order to adapt to technological developments. Apart from that, gender, faculty, domicile, high school origin, and experience at previous levels also influence student readiness. Therefore, universities need to hold socialization or coaching at the start to introduce and familiarize students with using e-learning. Faculties also need to prepare various learning resources to optimize student readiness. Apart from these findings, this research also has limitations, namely that this research was only carried out at IPB University so that other researchers can develop it to other universities to get more detailed results.

REFERENCES

Almasri. (2022). The impact of e-learning, gender-groupings and learning pendagogies in biology undergraduate female and male students' attiudes and achievement. Education and Information Technologies (2022) 27:8329–8380. https://doi.org/10.1007/s10639-022-10967-z

Asni, Fajri, N., Astuti, S., & Chairunnisa, D. (2020). *Pengembangan inventori perilaku asertif: analisis rasch model* [development of an assertive behavior inventory: rasch model analysis]. *Seminar Nasional Daring IIBKIN 2020*, 6–12.

Babiè, Š. H., Kokol, P., Podgorelec, V., Zorman, M., Šprogar, M., & Štiglic, M. M. (2000). The art of building decision trees. *Journal of Medical Systems*, *24*(1), 43–52. https://doi.org/10.1023/A:1005437213215

Badan Pusat Statitik. 2023. *Indeks pembangunan teknologi informasi dan komunikasi 2022* [information and communication technology development index 2022]. BPS RI.

Bukhari, F., Nurdiati, S., Najib, M. K., & Amalia, R. N. (2023). *Deteksi penyakit jantung menggunakan metode klasifikasi decision tree dan regresi logistik* [detection of heart disease using decision tree classification methods and logistic regression]. *Sains, Aplikasi, Komputasi Dan Teknologi Informasi*, *5*(1), 41–49. https://doi.org/10.30872/jsakti.v5i1.10780

Ekstrand, J., Westergren, A., Arestedt, K. Hellstrome, A., Hagel, P. 2022. Transformation of rasch model logits for enhanced interpretability. bmc medical research methodology. https://doi.org/10.1186/s12874-022-01816-1

Fariani, R. I. (2013). *Pengukuran tingkat kesiapan e-learning* [e-learning readiness]. *Seminar Nasional Aplikasi Teknologi Informasi (SNATI)*.

Ganaie, M. A., Hu, M., Malik, A. K., Tanveer, M., & Suganthan, P. N. (2022). Ensemble deep learning: A review. *Engineering Applications of Artificial Intelligence*, *115*, 105151. https://doi.org/https://doi.org/10.1016/j.engappai.2022.105151

Global Education Monitoring Report Team. (2023). Programme and meeting document. https://doi.org/10.54676/WJMY7427

Hartatiana. (2020). *Analisis rasch model pada motivasi mahasiswa melalui implementasi e-learning berbasis schoology* [rasch model analysis of student motivation through schoology-based e-learning implementation]. *Jurnal Pendidikan Matematika RAFA*, *6*(2), 162–169. https://doi.org/10.19109/jpmrafa.v6i2.4335

Hasanah, S., Nurdin, E. A., & Herbert. (2014). *Kajian implementasi e-learning berdasarkan tingkat kesiapan peserta e-learning* [study of e-learning implementation based on the level of readiness of e-learning participants]. *Prosiding Seminar Ilmiah Nasional Komputer Dan Sistem Intelijen*, *8*, 1–14.

Hermanto, B., & Miftahuddin, a. (2021). Tourism experience in indonesia: a new approach using the rasch model scale. GeoJournal of Tourism and Geosites, 38(4), 1051–1056. https://doi.org/10.30892/gtg.38409-743

Jamal, S. (2020). *Analisis kesiapan pembelajaran e-learning saat pandemi covid-19 di smk negeri 1 tambelangan* [analysis of e-learning readiness during the covid-19 pandemic at SMK Negeri 1 Tambelangan]. *Jurnal Nalar Pendidikan*, *8*(1), 16. https://doi.org/10.26858/

jnp.v8i1.13561

Kusnadi, A. (2015). *Analisis kesiapan mahasiswa tentang implementasi e-learning di departemen pendidikan teknik elektro fakultas pendidikan teknologi dan kejuruan universitas pendidikan Indonesia* [Undergraduate Thesis]. Universitas Pendidikan Indonesia.

Larose, D. T., & Larose, C. D. (2014). Discovering knowledge in data: an introduction to data mining: second edition. In *Discovering Knowledge in Data: An Introduction to Data Mining: Second Edition* (Vol. 9780470908). John Wiley & Sons, Inc. https://doi.org/10.1002/9781118874059

Linarcre, J.M. (2020). Fit diagnosis: infit outfit mean-square standardized, Winstep (R). https://www.winsteps.com/winman/misfitdiagnosis.htm

Luthfa, I. (2016). Family Support in Patients of type 2 diabetes mellitus bangetayu health center in semarang, rasch model analysis. *Nurscope Jurnal Keperawatan Dan Pemikiran Ilmiah*, *2*(2), 1–7. https://doi.org/10.30659/nurscope.2.1.12-23

Mardhiyana, D., & Nasution, N. B. (2018). *Kesiapan mahasiswa pendidikan matematika menggunakan e-learning dalam menghadapi era revolusi industri 4.0* [readiness of mathematics education students using e-learning in facing the era of industrial revolution 4.0]. *Seminar Nasional Pendidikan Matematika Ahmad Dahlan 2018*, 31–35.

Mardiyah, & Puger, I. G. N. (2017). *Kalibrasi Instrumen Kuesioner Penyesuaian Diri (Self Adjusment)*. *DAIWI WIDYA Jurnal Pendidikan*, *4*(2), 28–42. https://doi.org/10.37637/dw.v4i2.5

Matore, M. E. E. M. (2021). Rasch model assessment for blomm digital taxonomy applications. computers, materials & continua. https://doi.org/10.32604/cmc.2021.016143

Merawati, D., & Rino. (2019). *Penerapan data mining penentu minat dan bakat siswa smk dengan metode c4.5* [application of data mining to determine the interests and talents of vocational school students using the C4.5 Method]. *Jurnal Algor*, *1*(1), 28–37.

Mohamad, M.M., Sulaiman, N.L., Sern, L.C., Salleh, K.M. (2014). Measuring the validity and reliability of research instruments. Procedia Social and Behavioral Sciences. https://doi.org/10.1016/j.sbspro.2015.08.129

Muslihin, H.Y., Suryana, D., Ahman, Suherman, U., Dahlan, T.H. (2022). Analysis of the Reliability and Validity of the Self-Determination Questionnaire Using Rasch Model. International Journal of Instruction Vol.15 No.2. https://doi.org/10.29333/iji.2022.15212a.

Parkes, M., Stein, S., & Reading, C. (2015). Student preparedness for university e-learning environments. *The Internet and Higher Education*, *25*, 1–10. https://doi.org/10.1016/j.iheduc.2014.10.002

Purwandani, I. (2017). *Analisa tingkat kesiapan e-learning (e-learning readiness) studi kasus: amik bina sarana informatika jakarta*. *Jurnal Bianglala Informatika*, *5*(2), 102–107.

Quinlan, J. R. (1993). *C4.5 - Programs for machine learning*. Morgan Kaufmann Publisher, Inc.

Qureshi, M. I., Khan, N., Raza H., Ismail, A.I.F. (2021). Digital technologies in education 4.0. does it enhance the effectiveness of learning?. International Journal of Interactive Mobile Technologies (iJIM). https://www.researchgate.net/publication/349656472

Ramdani, Z., Widyastuti, T., & Ferdian, F. R.

(2018). Application of classical theory analysis, rasch model, & computer based test moodle: a pilot study. *Indonesian Journal of Educational Assessment*, *2*(1), 21–20.

Reddy, G.T., Bhattacharya S., Ramakrishnan, S. S., Chowdhary, C.L., Hakak, S., Kaluri, R., Reddy, M. P. K. 2020. An Ensemble based Machine Learning model for diabetic retinopathy classification. IEEE Xplore. https://ieeexplore.ieee.org/abstract/document/9077904/authors

Robitzsch, A. (2021). A comprehensive simulation study of estimation methods for the rasch model. Stats 2021. https://doi.org/10.3390/stats4040048

Setiaji, B., & Dinata, P. A. C. (2020). *Analisis kesiapan mahasiswa jurusan pendidikan fisika menggunakan e-learning dalam situasi pandemi Covid-19* [Analysis of the readiness of students majoring in physics education to use e-learning in the Covid-19 pandemic situation]. *Jurnal Inovasi Pendidikan IPA*, *6*(1), 59–70. https://doi.org/10.21831/jipi.v6i1.31562

Shahzad, A., Hassan, R., Aremu, A.Y., Hussain, A., Lodhi, R. N. (2020). Effect of COVID-19 in E-learning on higher education institution student: the group comparison between male and female. Quality & Quantity (2021) 55:805–826 https://doi.org/10.1007/s11135-020-01028-z

Sokolova, M., & Lapalme, G. (2009). A systematic analysis of performance measures for classification tasks. *Information Processing and Management*, *45*(4), 427–437. https://doi.org/10.1016/j.ipm.2009.03.002

Sumintono, B., & Widhiarso, W. (2014). *Aplikasi model rasch untuk penelitian ilmu-ilmu sosial*. Trim Komunikata Publishing House.

Sumintono, B., & Widhiarso, W. (2015). *Aplikasi pemodelan rasch pada assessment pendidikan*. Trim Komunikata Publishing House.

Waryanto, N. H., & Insani, N. (2013). *Tingkat kesiapan (readiness) implementasi e-learning di sekolah menengah atas kota yogyakarta* [level of readiness for implementing e-learning in yogyakarta city high schools]. *JPMS Jurnal Pendidikan Matematika Dan Sains*, *1*(2), 117–124. https://doi.org/10.21831/jpms.v2i2.2478

Yamashita, T. (2022). Analyzing Likert scale surveys with Rasch models. Research methods in applied linguistics Volume 1 Issue 3. https://doi.org/10.1016/j.rmal.2022.100022

Zine, M., Harrou, F., Terbeche, M., Bellahcene, M., Dairi, A., & Sun,Y. E-learning readiness assessment using machine learning methods. Sustainability 2023, 15, 8924. https://doi.org/10.3390/su15118924