

Supplementary materials

S.1. Likert's five-point spectrum, codes, and definitions

Table S1. Likert's five-point spectrum, codes, and definitions

Numeric value	Response spectrum	Code	Definition
5	Strongly Agree	SA	Very Agree/Very High
4	Agree	A	Agree/High
3	Neutral	N	No Opinion/Abstain
2	Disagree	D	Disagree/Low
1	Strongly Disagree	SD	Very Disagree/Very Low

S.2. Boruta method

Boruta is a variable selection model that aims to find all relevant variables in a dataset. It is based on the idea of comparing the importance of original variables with randomly generated shadow variables [1]. The shadow variables are copies of the original variables with shuffled values. Boruta uses any classifier such as decision trees or support vector machines [2]. In our study, we use a DT classifier to assign an importance score to each variable and then compare the scores of original and shadow variables. If an original variable has a higher score than the maximum score of any shadow variable, it is considered relevant and confirmed. If an original variable has a lower score than the minimum score of any shadow variable, it is considered irrelevant and rejected. Calculating the accuracy of the model preserves the questions that improve the model and candidates to discard the questions those do not improve the model with a confidence point of 0.95 [1]. If an original variable has a score between the minimum and maximum scores of any shadow variables, it is considered tentative and needs more iterations to decide [1], [2]. In Table S2, questions that were removed by the Boruta method from the decision tree model are indicated.

Table S2. Confirmed questions based on the Boruta method using the DT model with a ratio of 30% test to 70% learning for train data.

Students			Instructors		
DT (Test: 30%; Train=70%)					
3-point Likert					
Theoretical I2	Practical I4	Theoretical-Practical I6	Theoretical H2	Practical H4	Theoretical-Practical H6
A1	C8	A1	B5	B5	B1
A2	E3	B1	B6	D2	B6
B1	E4	B3	D3	G2	C1
B4	E6	B4			E1
E2	G7	C2			E5
E4		C6			G4
E5		C7			
E6		C8			
E7		D2			
F2		E2			
F4		E4			
G8		E5			
		E6			
		E7			
		G1			
		G5			
		G6			
		G7			
		G8			
5-point Likert					
Theoretical I2	Practical I4	Theoretical-Practical I6	Theoretical H2	Practical H4	Theoretical-Practical H6
A1	B3	A1	B5	B5	A1
A2	C7	A4	B6	E4	B1
A4	E4	B1	D3		B6
C5	E6	B3	E13		C1
D4		B4			E5
E2		C2			G4
E4		C6			
E5		C7			
E6		C8			
E7		D1			
F4		E2			
G1		E4			
		E5			
		E6			
		E7			
		G1			
		G5			
		G6			
		G7			
		G8			

S.3. Mutual Information method (Maximum Relevance Minimum Redundancy)

In the realm of variable selection, mutual information plays a pivotal role by quantifying the relationship between two variables – the dataset's variables and the target variable for prediction. MI measures the amount of information a variable provides about the target variable, aiding in identifying influential variables. The goal in variable selection is to maximize MI by selecting informative variables while minimizing redundancy. This process enhances model performance and reduces complexity. The optimization hinges on both elevating mutual information among chosen variables and ensuring their uniqueness. Achieving this balance involves strategic selection and optimization under constraints, ultimately bolstering the predictive power and effectiveness of the chosen variables.

Mutual information $I(X;Y)$ (in Eq S1) is defined as the difference between the joint entropy of the two variables (X and Y) and the conditional entropy of one variable given the other. The entropy terms, $H(X)$ and $H(Y)$ (in Eq S2), represent the amount of uncertainty in variables X and Y , respectively. The MI formula, $I(X;Y) = H(X) - H(Y|X)$, captures the shared information between X and Y . It can be computed through the summation of probabilities of their joint distribution and conditional probabilities.

$$I(X;Y) = H(X) - H(X|Y) = H(X) - H(Y|X) = \sum_{x,y} p(x,y) \log \frac{p(x,y)}{p(x)p(y)} \quad (\text{Eq S1. Mutual information})$$

Where the $H(X;Y)$ is the entropy and the function $I(X;Y)$ computes the extent of required information.

$$H(X;Y) = - \sum_{x \in X} \sum_{y \in Y} p(x,y) \log p(X;Y)$$

$$H(Y|X) = - \sum_{x \in X} \sum_{y \in Y} p(x, y) \log p(y|x)$$

(Eq S2. Commands pertaining to mutual information)

Mathematically, mutual information is calculated as the difference between the joint entropy of variables X and Y , representing variables and the target variable respectively, and the conditional entropy of one variable given the other. This captures shared information between the variables and guides variable ranking. Higher mutual information values indicate more relevant variables with greater predictive potential.

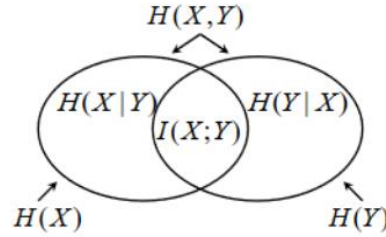


Figure S1. How the $I(X; Y)$ obtain the information by mutual information method [3].

In Figure S1, utilizing the computation of $I(X; Y)$, while considering the set S as the set of variables, the maximal correlation (Eq S3) and minimal redundancy (Eq S4) are derived. This entails optimizing for the utmost correlation. The MRMR (Maximum Relevance Minimum Redundancy) as a part of mutual information method is a variable selection technique that aims to choose variables that have high relevance to the target variable while minimizing redundancy among selected variables [3]. The Maximum Relevance Minimum Redundancy model aims to identify a subset of variables that have high relevance to the target variable while minimizing redundancy among the selected variables. The values of $H(x)$ and $I(x)$ respectively represent the relevance of a variable to the target variable, and redundancy between variables which was calculated with a significance point of $\alpha=0.05$. The negative scores of MRMR are the candidate

for removing from the model (highlighted in yellow). Results are presented in Table S3. In this method, most of non-Likert type multi-choice questions, pertain to pedagogical methods such as the flipped class and the name of the learning management system, focusing on the educational management environment and classroom monitoring selected [3].

Maximization of correlation (V):

$$\max V_I;$$

$$V_i = \frac{1}{|S|} \sum_{i \in S} I(h, i)$$

(Eq S3. Maximization of correlation)

Minimal redundancy (W):

$$\max W_I;$$

$$W_i = \frac{1}{|S|^2} \sum_{i, j \in S} I(h, i)$$

(Eq S4. Minimal redundancy)

Table S3. Score of questions by MRMR method.

Students						Instructors					
3-point Likert											
Theoretical I2		Practical I4		Theoretical- Practical I6		Theoretical H2		Practical H4		Theoretical- Practical H6	
code	Score	code	Score	code	Score	code	Score	code	Score	code	Score
A1	0.08	B4	0.09	A1	0.12	B5	0.13	E5	0.09	C1	0.09
F4	0.06	G4	0.03	C6	0.06	E6	0.03	E6	0.02	D1	0.03
A2	0.03	C7	0.04	G1	0.07	D2	0.03	B5	0.02	E1	0.04
E5	0.05	D2	0.03	E6	0.03	E12	0.02	B7	0.02	E12	0.03
C2	0.02	C6	0.03	C2	0.02	B6	0.02	G2	0.02	E5	0.03
C7	0.02	C1	0.02	C7	0.03	E1	0.02	E12	0.02	B6	0.03
G6	0.01	E3	0.02	E4	0.03	C11	0.02	G4	0.02	B7	0.02
E1	0.01	C8	0.02	B4	0.02	E5	0.02	D2	0.02	C2	0.02
B1	0.01	C3	0.01	A2	0.01	E8	0.02	E4	0.01	B1	0.02
A4	0.00	E4	0.02	E7	0.02	D3	0.02	C1	0.01	A1	0.02
E3	0.00	G7	0.02	A4	0.01	B4	0.02	E11	0.01	E10	0.01
G7	0.00	D1	0.01	E2	0.02	E14	0.02	A1	0.01	B5	0.01
C5	0.00	B3	0.01	C8	0.01	C1	0.02	E8	0.01	D2	0.00
B4	0.00	D3	0.01	G6	0.01	G6	0.01	C11	0.00	B2	0.00

G4	0.00	F5	0.00	G5	0.01	B1	0.01	B3	0.00	F1	0.00
C6	0.00	C12	0.00	E5	0.01	F1	0.00	C2	0.00	G1	0.00
E4	0.00	E5	0.00	G3	0.01	E10	0.00	D1	0.00	D3	0.00
C1	0.00	A4	0.00	D2	0.01	E3	0.00	B2	0.00	B4	0.00
D4	-0.01	E6	0.00	C12	0.01	B2	0.00	E1	0.00	C11	0.00
E2	0.00	D4	0.00	G8	0.01	C2	0.00	B6	0.00	E4	0.00
C3	-0.01	E1	0.00	B3	0.00	E11	0.00	B4	0.00	E9	0.00
G5	0.00	B2	0.00	G2	0.00	A1	0.00	E2	0.00	G4	0.00
F2	-0.01	C5	-0.01	D1	0.00	D1	0.00	E9	-0.01	E6	0.00
E6	-0.01	G8	0.00	E3	0.00	G2	0.00	G1	-0.01	G2	0.00
D1	-0.01	A1	-0.01	C3	0.00	G1	0.00	F1	-0.01	E13	0.00
B2	-0.01	G2	-0.01	B1	0.00	B3	-0.01	D3	-0.01	E7	-0.01
G2	-0.01	C2	-0.01	E1	0.00	G4	-0.01	B1	-0.01	E8	-0.01
D2	-0.01	F2	-0.01	D3	0.00	E13	-0.01	E7	-0.01	E2	-0.01
D3	-0.01	B1	-0.01	C1	0.00	E7	-0.01	E13	-0.01	B3	-0.01
G8	-0.01	E2	-0.01	B2	-0.01	E2	-0.01	E14	-0.02	E3	-0.01
E7	-0.01	A2	-0.02	G7	-0.01	E9	-0.01	E3	-0.02	E14	-0.02
C12	-0.01	G3	-0.02	F4	-0.01	E4	-0.01	E10	-0.02	E11	-0.02
G3	-0.01	G6	-0.02	C5	-0.01	B7	-0.02	G6	-0.03	G6	-0.03
C8	-0.02	F4	-0.02	G4	-0.01	F2	-0.04	F2	-0.04	F2	-0.04
F5	-0.02	G5	-0.03	D4	-0.01						
G1	-0.02	G1	-0.03	F5	-0.01						
B3	-0.02	F3	-0.04	F2	-0.02						
F3	-0.03	E7	-0.04	F3	-0.04						
5-point Likert											
Students						Instructors					
Theoretical I2		Practical I4		Theoretical- Practical I6		Theoretical H2		Practical H4		Theoretical- Practical H6	
code	Score	code	Score	code	Score	code	Score	code	Score	code	Score
A1	0.16	B4	0.21	C6	0.21	B6	0.23	B5	0.13	B6	0.15
G6	0.03	D3	0.04	E4	0.08	G4	0.03	E9	0.05	E12	0.04
A4	0.04	C7	0.09	A1	0.06	E6	0.05	E4	0.05	E1	0.05
A2	0.04	G5	0.04	C7	0.04	B1	0.05	E5	0.05	C1	0.06
E5	0.03	C8	0.04	C2	0.05	C1	0.06	D1	0.03	E6	0.04
D4	0.01	E5	0.03	E6	0.06	D2	0.05	C1	0.03	B1	0.04
B2	0.01	B3	0.02	G1	0.04	C11	0.03	C2	0.01	C11	0.04
F4	0.01	C2	0.03	G8	0.04	E3	0.03	E14	0.01	E5	0.04
C1	0.01	E3	0.03	C8	0.02	E10	0.03	B7	0.01	A1	0.04
E2	0.01	C6	0.03	E2	0.02	B5	0.03	G4	0.00	C2	0.02
C6	0.01	D2	0.02	F5	0.02	D3	0.03	C11	0.01	E3	0.01
B1	0.00	E6	0.02	A4	0.02	E2	0.02	E6	0.01	G2	0.00
D2	0.00	C12	0.02	E5	0.02	E8	0.01	G1	0.00	E7	0.00
C5	-0.01	C1	0.01	C3	0.01	C2	0.00	G2	0.01	B7	0.01
E4	-0.01	F5	0.01	B3	0.02	E7	0.00	A1	0.01	D1	0.00
C2	-0.01	B1	0.01	G5	0.02	F1	0.00	D2	0.01	E10	0.00
G7	-0.01	G4	0.01	D2	0.02	E12	0.00	E7	0.00	E14	0.00
C3	-0.01	D1	0.01	E7	0.02	A1	0.00	E11	0.00	G4	0.00

E1	-0.01	G7	0.01	B4	0.02	B4	0.00	E12	-0.01	B5	0.00
B4	-0.01	E4	0.01	A2	0.01	E5	0.00	E1	-0.01	D3	0.00
F3	-0.01	A1	0.01	B1	0.01	E1	0.00	B6	-0.01	D2	-0.01
C7	-0.01	A4	0.01	D1	0.01	B3	0.00	E8	-0.02	B2	-0.01
D3	-0.01	C3	0.00	G6	0.01	E14	-0.01	F1	-0.02	F1	-0.01
G3	-0.01	G1	-0.01	C1	0.01	E13	-0.01	B2	-0.02	E4	-0.01
G1	-0.01	C5	-0.01	G7	0.01	G6	-0.02	E2	-0.02	G1	-0.01
D1	-0.01	B2	-0.01	E3	0.00	B2	-0.02	G6	-0.02	B4	-0.01
E3	-0.02	A2	-0.01	C12	0.00	D1	-0.02	B1	-0.02	E13	-0.01
G8	-0.02	D4	-0.01	B2	0.00	E11	-0.02	E13	-0.03	G6	-0.01
C12	-0.03	F4	-0.01	C5	0.00	B7	-0.02	B3	-0.03	E9	-0.02
E6	-0.03	G8	-0.02	G3	0.00	G1	-0.03	E3	-0.04	E2	-0.02
G4	-0.03	G2	-0.02	D4	0.00	G2	-0.03	B4	-0.04	B3	-0.03
G5	-0.03	F3	-0.02	F4	-0.01	E4	-0.04	E10	-0.05	E8	-0.03
C8	-0.03	E2	-0.02	G2	-0.01	E9	-0.04	D3	-0.06	E11	-0.04
G2	-0.04	E1	-0.03	E1	-0.01	F2	-0.05	F2	-0.08	F2	-0.04
E7	-0.04	G6	-0.03	F3	-0.02						
B3	-0.04	E7	-0.04	D3	-0.02						
F5	-0.04	G3	-0.04	G4	-0.03						
F2	-0.05	F2	-0.06	F2	-0.04						

S.4. Recursive Feature Elimination

The Recursive Feature Elimination (RFE) process involved initially considering all variables and subsequently removing variables one by one until the last variable was eliminated, while assessing the changes in accuracy. Recursive Feature Elimination and Boruta are two commonly utilized wrapper methods [4]. Recursive Feature Elimination is an iterative variable selection technique that begins with all variables and progressively eliminates the least significant ones. It achieves this by training the model with the full set of variables, ranking them based on their importance, and subsequently removing the least important variables [4]. Given a dataset with n instances and p variables, the goal of RFE is to iteratively select a subset of variables S of size k that minimizes a chosen performance metric J while reducing k from p to a predefined stopping criterion:

$$S^* = \arg \min_S \{J(S)\} \quad (\text{Eq 5. } S^* \text{ as the selected subset of variable } S)$$

Where $S \subset \{1, 2, \dots, p\}$ and $|S| = k$. At each iteration, the least important variable according to a certain criterion is removed, and the process is repeated recursively until the

stopping criterion is met. The choice of performance metric J and the method for ranking variable importance may vary based on the specific problem and model being used. RFE procedure resulted in a list of variables, ranging from the first output to the final output variable, at a significance point of $\alpha=0.05$. The RFE will be on train data and with $k=10$ for students (I2, I4, I6) and $k=5$ for instructors (H2, H4, H6) and random forest with 500 trees (test 30%, train 70%).

Table S4 indicates the results of the RFE method of variable selection for different values of k (number of variables to select) on a dataset. The table indicates the accuracy, kappa, accuracy standard deviation, kappa standard deviation, and whether the variable was selected for each value of k . The optimal number of variables is indicated by the star (*) in the last row and this number of items is the best first number of items to be added and do not meaningfully decrease the accuracy. However, sometimes item number 4 or 7 are the items that indicate the drop-down of accuracy but because we have to reject most of the items, we will jump to the next item that drop happening there. The accuracy and kappa values are measures of the performance of the model with the selected variables. The accuracy is the proportion of correctly classified instances, while the kappa is a measure of agreement between the predicted and actual classes that takes into account the possibility of agreement by chance. The accuracy and kappa standard deviations indicate the variability of the performance estimates across different cross-validation folds. The RFE method of variable selection works by recursively eliminating the least important variables until the desired number of variables is reached. The variables are ranked by their importance based on the model's coefficients or variable importance, and the least important variables are eliminated in each iteration. The optimal number of variables is determined by running cross-validation on the top of the RFE class. As the data inaccuracy in some of the response variables

get the variables with less than 10 questions and the accuracy didn't change more than 0.1 and again the accuracy recovered itself, so we consider the further number of variables for subsets.

Table S4. Ranking of number of best subsets with k=5 (students) and k=10 (instructors) of RF for RFE method as variable selection

Students									Instructors								
3-point Likert (RF, 500 trees, test 30%, train 70%)																	
Theoretical I2			Practical I4			Theoretical-Practical I6			Theoretical H2			Practical H4			Theoretical-Practical H6		
Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa
The number of candidates of removing																	
Num: 31			Num: 23			Num: 25			Num: 22			Num: 20			Num: 20		
1.00	0.62	0.00	1.00	0.45	0.08	1.00	0.62	0.03	1.00	0.69	0.31	1.00	0.48	0.14	1.00	0.57	0.26
2.00	0.62	0.00	2.00	0.48	0.12	2.00	0.66	0.31	2.00	0.69	0.32	2.00	0.54	0.23	2.00	0.62	0.34
3.00	0.66	0.25	3.00	0.51	0.15	3.00	0.70	0.39	3.00	0.69	0.24	3.00	0.58	0.30	3.00	0.59	0.28
4.00	0.64	0.29	4.00	0.47	0.11	4.00	0.70	0.41	4.00	0.68	0.27	4.00	0.56	0.28	4.00	0.46	0.12
5.00	0.66	0.31	5.00	0.44	0.06	5.00	0.70	0.38	5.00	0.69	0.29	5.00	0.56	0.29	5.00	0.52	0.19
6.00	0.64	0.29	6.00	0.49	0.16	6.00	0.71	0.40	6.00	0.64	0.20	6.00	0.57	0.30	6.00	0.50	0.19
7.00	0.67	0.33	7.00	0.53	0.20	7.00	0.72	0.42	7.00	0.65	0.19	7.00	0.58	0.31	7.00	0.50	0.17
8.00	0.65	0.28	8.00	0.53	0.20	8.00	0.72	0.42	8.00	0.68	0.22	8.00	0.55	0.27	8.00	0.49	0.15
9.00	0.64	0.28	9.00	0.54	0.24	9.00	0.73	0.46	9.00	0.64	0.20	9.00	0.52	0.21	9.00	0.48	0.13
10.00	0.66	0.31	10.00	0.55	0.25	10.00	0.73	0.44	10.00	0.68	0.24	10.00	0.51	0.20	10.00	0.50	0.16
11.00	0.67	0.31	11.00	0.54	0.21	11.00	0.73	0.44	11.00	0.68	0.24	11.00	0.53	0.23	11.00	0.51	0.17
12.00	0.67	0.30	12.00	0.54	0.23	12.00	0.72	0.41	12.00	0.67	0.23	12.00	0.52	0.21	12.00	0.48	0.11
13.00	0.67	0.32	13.00	0.54	0.23	13.00	0.73	0.45	13.00	0.67	0.21	13.00	0.53	0.22	13.00	0.49	0.12
14.00	0.69	0.35	14.00	0.55	0.22	14.00	0.71	0.42	14.00	0.69	0.26	14.00	0.53	0.22	14.00	0.51	0.16
15.00	0.70	0.35	15.00	0.55	0.24	15.00	0.73	0.44	15.00	0.69	0.24	15.00	0.53	0.23	15.00	0.52	0.17
16.00	0.68	0.31	16.00	0.55	0.23	16.00	0.73	0.44	16.00	0.68	0.24	16.00	0.54	0.25	16.00	0.51	0.16
17.00	0.69	0.34	17.00	0.57	0.27	17.00	0.73	0.43	17.00	0.69	0.24	17.00	0.50	0.17	17.00	0.52	0.17
18.00	0.68	0.32	18.00	0.55	0.25	18.00	0.73	0.44	18.00	0.67	0.20	18.00	0.53	0.22	18.00	0.53	0.19
19.00	0.67	0.28	19.00	0.54	0.22	19.00	0.73	0.45	19.00	0.68	0.22	19.00	0.54	0.24	19.00	0.53	0.20
20.00	0.68	0.31	20.00	0.53	0.21	20.00	0.73	0.44	20.00	0.69	0.23	20.00	0.54	0.24	20.00	0.51	0.16
21.00	0.68	0.29	21.00	0.54	0.22	21.00	0.73	0.44	21.00	0.70	0.24	21.00	0.49	0.15	21.00	0.54	0.21
22.00	0.70	0.33	22.00	0.53	0.21	22.00	0.73	0.45	22.00	0.70	0.23	22.00	0.50	0.17	22.00	0.52	0.18
23.00	0.70	0.32	23.00	0.56	0.25	23.00	0.73	0.43	23.00	0.68	0.16	23.00	0.54	0.23	23.00	0.58	0.28
24.00	0.69	0.33	24.00	0.54	0.23	24.00	0.73	0.43	24.00	0.66	0.11	24.00	0.51	0.18	24.00	0.54	0.22
25.00	0.67	0.28	25.00	0.53	0.20	25.00	0.74	0.46	25.00	0.67	0.16	25.00	0.54	0.23	25.00	0.55	0.24
26.00	0.70	0.35	26.00	0.53	0.20	26.00	0.73	0.44	26.00	0.65	0.12	26.00	0.55	0.25	26.00	0.53	0.21
27.00	0.69	0.31	27.00	0.53	0.19	27.00	0.73	0.44	27.00	0.69	0.19	27.00	0.56	0.27	27.00	0.52	0.19
28.00	0.69	0.32	28.00	0.50	0.14	28.00	0.73	0.44	28.00	0.66	0.11	28.00	0.54	0.24	28.00	0.53	0.20
29.00	0.69	0.31	29.00	0.54	0.22	29.00	0.73	0.44	29.00	0.67	0.13	29.00	0.56	0.27	29.00	0.54	0.21
30.00	0.69	0.32	30.00	0.54	0.22	30.00	0.73	0.44	30.00	0.68	0.15	30.00	0.55	0.25	30.00	0.58	0.27
31.00	0.71	0.36	31.00	0.54	0.23	31.00	0.74	0.45	31.00	0.67	0.15	31.00	0.50	0.17	31.00	0.57	0.25
32.00	0.70	0.33	32.00	0.55	0.23	32.00	0.73	0.44	32.00	0.68	0.17	32.00	0.53	0.21	32.00	0.57	0.26
33.00	0.69	0.31	33.00	0.56	0.25	33.00	0.74	0.45	33.00	0.69	0.17	33.00	0.56	0.26	33.00	0.55	0.22
34.00	0.70	0.32	34.00	0.58	0.28	34.00	0.73	0.44	34.00	0.69	0.19	34.00	0.56	0.27	34.00	0.56	0.23
35.00	0.70	0.32	35.00	0.56	0.25	35.00	0.73	0.43									
36.00	0.70	0.32	36.00	0.57	0.26	36.00	0.73	0.43									
37.00	0.70	0.32	37.00	0.56	0.25	37.00	0.71	0.40									
38.00	0.70	0.32	38.00	0.53	0.19	38.00	0.73	0.42									
5-point Likert (RF, 500 trees)																	
students									Instructors								
Theoretical I2			Practical I4			Theoretical-Practical I6			Theoretical H2			Practical H4			Theoretical-Practical H6		
Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa	Number of questions	Accuracy	Kappa
The number of candidates of removing																	
Num: 30			Num: 26			Num: 23			Num: 17			Num: 18			Num: 23		
1.00	0.31	0.01	1.00	0.35	0.10	1.00	0.39	0.08	1.00	0.47	0.06	1.00	0.35	0.10	1.00	0.34	0.02
2.00	0.33	0.08	2.00	0.35	0.10	2.00	0.36	0.11	2.00	0.47	0.05	2.00	0.36	0.07	2.00	0.34	0.05

3.00	0.36	0.12	3.00	0.33	0.07	3.00	0.39	0.16	3.00	0.46	0.03	3.00	0.35	0.07	3.00	0.42	0.16
4.00	0.37	0.14	4.00	0.33	0.08	4.00	0.38	0.16	4.00	0.44	0.06	4.00	0.28	0.13	4.00	0.42	0.16
5.00	0.35	0.11	5.00	0.33	0.09	5.00	0.39	0.17	5.00	0.46	0.11	5.00	0.31	0.11	5.00	0.43	0.19
6.00	0.35	0.11	6.00	0.33	0.08	6.00	0.41	0.20	6.00	0.47	0.13	6.00	0.30	0.07	6.00	0.45	0.20
7.00	0.40	0.17	7.00	0.35	0.11	7.00	0.45	0.25	7.00	0.48	0.16	7.00	0.32	0.05	7.00	0.48	0.23
8.00	0.38	0.14	8.00	0.42	0.19	8.00	0.45	0.25	8.00	0.45	0.08	8.00	0.35	0.09	8.00	0.45	0.19
9.00	0.38	0.16	9.00	0.35	0.11	9.00	0.45	0.24	9.00	0.45	0.08	9.00	0.36	0.07	9.00	0.40	0.15
10.00	0.37	0.14	10.00	0.37	0.14	10.00	0.47	0.26	10.00	0.47	0.11	10.00	0.36	0.13	10.00	0.38	0.10
11.00	0.39	0.15	11.00	0.36	0.12	11.00	0.48	0.28	11.00	0.53	0.21	11.00	0.38	0.11	11.00	0.37	0.10
12.00	0.39	0.16	12.00	0.36	0.12	12.00	0.47	0.27	12.00	0.50	0.15	12.00	0.36	0.13	12.00	0.39	0.13
13.00	0.40	0.17	13.00	0.38	0.15	13.00	0.48	0.29	13.00	0.51	0.16	13.00	0.35	0.09	13.00	0.39	0.11
14.00	0.43	0.20	14.00	0.40	0.17	14.00	0.49	0.29	14.00	0.50	0.14	14.00	0.35	0.07	14.00	0.43	0.17
15.00	0.41	0.17	15.00	0.38	0.15	15.00	0.52	0.33	15.00	0.49	0.11	15.00	0.38	0.07	15.00	0.43	0.17
16.00	0.38	0.13	16.00	0.40	0.16	16.00	0.50	0.30	16.00	0.48	0.10	16.00	0.40	0.04	16.00	0.45	0.19
17.00	0.39	0.15	17.00	0.39	0.16	17.00	0.52	0.33	17.00	0.53	0.18	17.00	0.38	0.06	17.00	0.44	0.18
18.00	0.39	0.15	18.00	0.40	0.16	18.00	0.49	0.28	18.00	0.50	0.13	18.00	0.44	0.03	18.00	0.40	0.13
19.00	0.41	0.17	19.00	0.41	0.18	19.00	0.52	0.33	19.00	0.53	0.17	19.00	0.44	0.07	19.00	0.41	0.12
20.00	0.39	0.14	20.00	0.42	0.20	20.00	0.50	0.30	20.00	0.49	0.10	20.00	0.42	0.03	20.00	0.42	0.15
21.00	0.40	0.15	21.00	0.42	0.20	21.00	0.52	0.32	21.00	0.49	0.08	21.00	0.42	0.07	21.00	0.41	0.13
22.00	0.40	0.16	22.00	0.40	0.16	22.00	0.51	0.30	22.00	0.50	0.09	22.00	0.41	0.05	22.00	0.41	0.13
23.00	0.38	0.13	23.00	0.43	0.21	23.00	0.51	0.31	23.00	0.50	0.08	23.00	0.40	0.06	23.00	0.44	0.17
24.00	0.39	0.14	24.00	0.43	0.21	24.00	0.51	0.31	24.00	0.50	0.09	24.00	0.39	0.10	24.00	0.40	0.11
25.00	0.39	0.15	25.00	0.42	0.19	25.00	0.50	0.29	25.00	0.50	0.09	25.00	0.40	0.05	25.00	0.40	0.10
26.00	0.37	0.11	26.00	0.46	0.25	26.00	0.51	0.30	26.00	0.49	0.08	26.00	0.40	0.06	26.00	0.42	0.14
27.00	0.39	0.15	27.00	0.45	0.23	27.00	0.50	0.29	27.00	0.50	0.09	27.00	0.38	0.06	27.00	0.40	0.11
28.00	0.38	0.13	28.00	0.43	0.19	28.00	0.51	0.30	28.00	0.49	0.06	28.00	0.41	0.05	28.00	0.40	0.11
29.00	0.38	0.14	29.00	0.43	0.21	29.00	0.52	0.32	29.00	0.50	0.08	29.00	0.38	0.03	29.00	0.41	0.12
30.00	0.41	0.17	30.00	0.45	0.23	30.00	0.51	0.30	30.00	0.48	0.02	30.00	0.42	0.03	30.00	0.40	0.10
31.00	0.40	0.16	31.00	0.45	0.24	31.00	0.50	0.29	31.00	0.48	0.04	31.00	0.41	0.05	31.00	0.40	0.10
32.00	0.36	0.10	32.00	0.44	0.22	32.00	0.52	0.30	32.00	0.48	0.05	32.00	0.41	0.05	32.00	0.43	0.14
33.00	0.39	0.14	33.00	0.45	0.23	33.00	0.53	0.32	33.00	0.49	0.05	33.00	0.42	0.05	33.00	0.44	0.16
34.00	0.41	0.17	34.00	0.43	0.20	34.00	0.51	0.30	34.00	0.48	0.03	34.00	0.42	0.02	34.00	0.43	0.14
35.00	0.39	0.15	35.00	0.40	0.16	35.00	0.50	0.29									
36.00	0.39	0.14	36.00	0.43	0.21	36.00	0.51	0.30									
37.00	0.42	0.18	37.00	0.42	0.18	37.00	0.52	0.31									
38.00	0.41	0.17	38.00	0.48	0.27	38.00	0.52	0.31									

Note: Other number of items that automatically removed because of miss fit

S.5. chi-square test for variable selection

The chi-square test has been employed in the variable selection section, essentially examining the interdependence between each pair of variables and between each predictor variable and the response variable. Moreover, the mutual information tool leverages the measurement of the proximity or resemblance of the joint distribution function of two variables or their marginal functions [5], [6]. The following delineates the methodology of this approach, assuming that X and Y are multivariate random variables, and $p(x; y)$ represents the joint probability density function:

$$I(X; Y) = \int_X \int_Y p(x, y) \cdot \log \frac{p(x, y)}{p(x) \cdot p(y)} dx dy \quad (\text{Eq S6. Joint probability density function})$$

A value of zero in the mutual information measure $I(X; Y)$ signifies that the two variables are completely unrelated or independent. Conversely, leveraging principles of linear algebra and

operational research, it is feasible to obtain a suitable ranking of k variables using the following objective function:

$$\begin{aligned}\tilde{S} &= \arg \max_S I(X_S; y), \\ s. t. |S| &= k,\end{aligned}$$

(Eq S7. Joint probability density function)

To use the chi-square test for variable selection, we need to compute the chi-square statistic for each variable with respect to the target question and compare it with a critical value or a p-value based on a significance point. We can then select only those variables that have chi-square statistics above the critical value or p-value below the significance point [5], [6]. It should be noted that solving this problem, in the context of operational research models and methods, is approached progressively, recursively, and incrementally. Each approach encompasses distinct characteristics; for instance, in the forward-looking solution, this objective function is employed by assuming the maximization of the divergence between frequencies and the relevance function $I(X; Y)$ [5–6]. For variable selection using the chi-square test, the chi-square statistic is computed for each variable in relation to the target question and compared to a critical value or p-value determined by the chosen significance point. Variables with chi-square statistics exceeding the critical value or p-values below the significance point are selected [7]. As the chi-square test as the filter method do not have the direct method for selecting threshold, we had to use the k-fold of cross validation of wrapper method specifically the REF method. As the RFE clear the best number of variables by cross validation, we will use that number as the threshold of chi-square test.

Table S5. Results of Chi-squared ranking by considering the order of question from k fold of cross validation by RFE method.

3-point Likert	
students	students

Theoretical I2		Practical I4		Theoretical-Practical I6		Theoretical H2		Practical H4		Theoretical-Practical H6	
code	Chi-square	code	Chi-square	code	Chi-square	code	Chi-square	code	Chi-square	code	Chi-square
The number of candidates of removing											
Num: 31		Num: 23		Num: 25		Num: 22		Num: 20		Num: 20	
E5	0.28	E4	0.30	E2	0.33	B5	0.31	B5	0.32	C1	0.30
F4	0.26	G7	0.30	A1	0.33	B6	0.28	G2	0.29	E5	0.27
A1	0.25	E6	0.29	E4	0.33	E6	0.28	E6	0.28	E1	0.27
G7	0.22	C8	0.28	G1	0.33	D3	0.28	D2	0.27	B1	0.27
E7	0.22	B4	0.28	C6	0.33	B4	0.28	E5	0.27	F2	0.25
A2	0.22	C7	0.26	E7	0.31	E12	0.27	C1	0.25	B5	0.25
E4	0.21	C6	0.26	E6	0.30	E5	0.25	E7	0.24	G4	0.25
B1	0.21	G8	0.26	G8	0.30	D2	0.25	E1	0.21	B6	0.24
G6	0.21	E5	0.24	E5	0.29	F1	0.24	D3	0.21	D2	0.22
E6	0.21	B1	0.24	G6	0.29	E10	0.23	E10	0.20	E10	0.22
E3	0.20	E3	0.24	B4	0.27	F2	0.22	B7	0.19	B7	0.21
G8	0.20	C12	0.22	C7	0.27	C11	0.22	B6	0.19	D1	0.21
G1	0.20	D2	0.22	G5	0.26	E7	0.22	E8	0.19	B4	0.20
C6	0.19	F5	0.21	C8	0.25	B1	0.22	D1	0.19	G1	0.18
E1	0.19	G6	0.21	B1	0.25	G6	0.22	E4	0.18	G2	0.18
E2	0.19	E2	0.20	D2	0.24	C1	0.21	E9	0.18	A1	0.18
G2	0.19	B3	0.19	G7	0.23	E11	0.21	A1	0.17	E12	0.17
G5	0.19	F3	0.19	C2	0.21	G2	0.21	C11	0.17	E3	0.17
B4	0.17	E7	0.19	B3	0.21	G4	0.21	E11	0.16	C2	0.17
C7	0.17	A1	0.19	G2	0.21	E14	0.20	G4	0.16	E13	0.17
C2	0.17	D1	0.18	G3	0.20	E1	0.20	G1	0.16	E9	0.15
F2	0.16	B2	0.18	A4	0.17	A1	0.19	B3	0.16	F1	0.15
D2	0.15	C3	0.18	E1	0.17	E13	0.19	B2	0.15	G6	0.15
A4	0.15	G1	0.18	F4	0.17	E8	0.19	G6	0.15	D3	0.14
C8	0.15	C5	0.17	A2	0.16	E3	0.18	C2	0.14	B2	0.14
F3	0.14	F2	0.17	E3	0.16	B3	0.18	E2	0.14	C11	0.13
C1	0.12	C2	0.16	C12	0.16	E4	0.17	E12	0.13	E7	0.12
B3	0.12	C1	0.16	F5	0.15	E2	0.17	E14	0.12	E8	0.12
C5	0.12	G5	0.15	B2	0.13	D1	0.17	B4	0.12	E6	0.11
D1	0.12	D3	0.15	D1	0.13	G1	0.17	B1	0.11	B3	0.11
C12	0.11	G2	0.15	F2	0.13	E9	0.15	F2	0.11	E2	0.11
G4	0.11	E1	0.15	C1	0.11	C2	0.15	F1	0.11	E11	0.11

F5	0.10	F4	0.14	G4	0.11	B2	0.15	E13	0.07	E4	0.10
D3	0.10	D4	0.14	F3	0.09	B7	0.15	E3	0.06	E14	0.09
D4	0.10	G4	0.14	D3	0.09						
G3	0.09	A4	0.13	C5	0.09						
B2	0.08	A2	0.12	C3	0.09						
C3	0.05	G3	0.09	D4	0.07						
5-point Likert											
students						Instructors					
Theoretical I2		Practical I4		Theoretical-Practical I6		Theoretical H2		Practical H4		Theoretical-Practical H6	
code	Chi-square	code	Chi-square	code	Chi-square	code	Chi-square	code	Chi-square	code	Chi-square
Num: 30		Num: 26		Num: 23		Num: 17		Num: 18		Num: 23	
A1	0.27	C7	0.36	E6	0.39	B5	0.39	E9	0.29	C1	0.34
A4	0.26	C6	0.35	C6	0.34	B6	0.38	B5	0.28	C11	0.29
E5	0.24	B4	0.34	G8	0.33	D3	0.36	C1	0.28	B1	0.29
F4	0.22	B3	0.34	E4	0.33	D2	0.34	E4	0.27	B6	0.29
E4	0.22	C2	0.33	E5	0.32	E6	0.33	G1	0.27	G4	0.28
B1	0.22	C8	0.33	B1	0.32	C11	0.33	D2	0.26	E1	0.27
G7	0.21	B1	0.31	C7	0.32	B3	0.33	E14	0.26	E5	0.27
C7	0.21	E5	0.31	C8	0.30	B1	0.31	G2	0.26	A1	0.27
C6	0.20	C12	0.30	E7	0.30	A1	0.28	E5	0.25	G2	0.25
G8	0.20	G1	0.29	E2	0.29	E13	0.27	D1	0.25	D2	0.25
E6	0.20	E6	0.29	G7	0.29	E10	0.27	E13	0.24	C2	0.24
B4	0.20	E4	0.29	A1	0.28	E5	0.27	E6	0.24	D3	0.24
C5	0.20	F5	0.28	G1	0.28	B4	0.26	C11	0.24	B5	0.24
E2	0.20	G7	0.28	B4	0.28	G4	0.25	E7	0.24	E12	0.23
E7	0.20	A1	0.27	G6	0.28	C1	0.25	E10	0.23	E14	0.23
G2	0.19	G8	0.27	G5	0.27	E12	0.25	B6	0.23	E13	0.23
G1	0.19	C1	0.27	C2	0.26	E11	0.25	G6	0.23	E3	0.23
G6	0.19	G2	0.26	F5	0.26	E14	0.24	B2	0.22	B3	0.23
C8	0.19	E7	0.26	B3	0.26	E1	0.24	D3	0.22	B2	0.22
B3	0.19	A4	0.25	D2	0.24	E7	0.23	E1	0.22	G6	0.22
C1	0.18	C5	0.25	A4	0.24	F2	0.23	E8	0.22	E6	0.22
E3	0.18	D2	0.24	C1	0.23	E2	0.23	G4	0.21	F2	0.21
D4	0.18	D3	0.24	G2	0.22	G6	0.23	E11	0.21	E4	0.21
C2	0.18	G5	0.23	B2	0.22	D1	0.23	A1	0.20	E10	0.21
G5	0.17	F4	0.23	C12	0.22	G2	0.23	C2	0.20	B7	0.21

A2	0.17	F3	0.23	E3	0.21	F1	0.22	B1	0.20	E2	0.20
F5	0.17	G4	0.23	F4	0.21	B7	0.22	E2	0.20	D1	0.20
G4	0.17	G6	0.22	C5	0.20	E3	0.21	B7	0.20	G1	0.20
B2	0.16	B2	0.22	D1	0.19	C2	0.20	B4	0.18	E7	0.20
G3	0.16	E3	0.21	C3	0.18	G1	0.19	E12	0.18	B4	0.19
F3	0.16	D4	0.20	F3	0.17	E8	0.18	B3	0.17	E9	0.17
C12	0.15	A2	0.20	F2	0.17	E4	0.17	F1	0.15	E11	0.17
D2	0.15	E2	0.20	A2	0.17	B2	0.14	E3	0.14	F1	0.16
E1	0.15	G3	0.20	G3	0.17	E9	0.13	F2	0.11	E8	0.15
F2	0.15	D1	0.19	D4	0.16						
D3	0.14	F2	0.19	G4	0.15						
D1	0.13	E1	0.18	E1	0.15						
C3	0.11	C3	0.17	D3	0.14						

S.6. Majority Voting in variable selection

Table S6 indicates the variables that each of the chi-square, MRMR, Boruta, and RFE methods selected (sections A.2 to A.6; Tables A2 to A5) and describes the situation of each variable and the reason for its selection. These variables were used for ML models as input. As the REF considers the population of first best variables that enter to the ML and Chi-square consider the variables that have less relation to the response variable and do not have a general rule to exclude the items based on P-value, we just used the first best variables of Chi-square as one result in Table S6.

Table S6. Rejected and confirmed questions based on the variable selection methods and by the data frame that involved.

#	code	Chi-square & RFE	MRMR	Boruta	>2: reject <2: confirm	#	code	Chi-square & RFE	MRMR	Boruta	>2: reject <2: confirm
I2, 3-points students						I2 5-points students					
1	A1			0	0	1	A1			0	0
2	A2			0	0	2	A2			0	0
3	A4			1	1	3	A4			0	0
4	B1			0	0	4	B1		1	1	2
5	B2	1	1	1	3	5	B2			1	1

6	B3		1	1	2	6	B3		1	1	2
7	B4			0	0	7	B4		1	1	2
8	C1		1	1	2	8	C1			1	1
9	C2			1	1	9	C2		1	1	2
10	C3	1	1	1	3	10	C3	1	1	1	3
11	C5			1	1	11	C5		1	0	1
12	C6		1	1	2	12	C6			1	1
13	C7			1	1	13	C7		1	1	2
14	C8		1	1	2	14	C8		1	1	2
15	C12	1	1	1	3	15	C12	1	1	1	3
16	D1		1	1	2	16	D1	1	1	1	3
17	D2		1		1	17	D2	1	1	1	3
18	D3	1	1	1	3	18	D3	1	1	1	3
19	D4	1	1	1	3	19	D4			0	0
20	E1			1	1	20	E1	1	1	1	3
21	E2		1	0	1	21	E2			0	0
22	E3			1	1	22	E3		1	1	2
23	E4		1	0	1	23	E4		1	0	1
24	E5			0	0	24	E5			0	0
25	E6		1	0	1	25	E6		1	0	1
26	E7		1	0	1	26	E7		1	0	1
27	F2		1	0	1	27	F2	1	1	1	3
28	F3		1	1	2	28	F3	1	1	1	3
29	F4			0	0	29	F4			0	0
30	F5	1	1	1	3	30	F5		1	1	2
31	G1		1	1	2	31	G1		1	0	1
32	G2		1	1	2	32	G2		1	1	2
33	G3	1	1	1	3	33	G3	1	1	1	3
34	G4	1	1	1	3	34	G4		1	1	2
35	G5		1	1	2	35	G5		1	1	2
36	G6			1	1	36	G6			1	1
37	G7			1	1	37	G7		1	1	2
38	G8		1	0	1	38	G8		1	1	2
I4 3-points						I4 5-points students					
1	A1		1		1	1	A1			1	1
2	A2	1	1	1	3	2	A2	1	1	1	3
3	A4	1		1	2	3	A4	1		1	2
4	B1			1	1	4	B1		1	1	2
5	B2		1	1	2	5	B2	1		1	2

6	B3			1	1	6	B3			0	0
7	B4			1	1	7	B4			1	1
8	C1	1		1	2	8	C1			1	1
9	C2	1	1	1	3	9	C2			1	1
10	C3	1		1	2	10	C3	1		1	2
11	C5	1	1	1	3	11	C5	1	1	1	3
12	C6			1	1	12	C6			1	1
13	C7			1	1	13	C7			0	0
14	C8			0	0	14	C8			1	1
15	C12			1	1	15	C12			1	1
16	D1			1	1	16	D1	1		1	2
17	D2			1	1	17	D2	1		1	2
18	D3	1		1	2	18	D3	1		1	2
19	D4	1	1	1	3	19	D4	1			1
20	E1	1	1	1	3	20	E1	1	1	1	3
21	E2		1	1	2	21	E2	1	1	1	3
22	E3			0	0	22	E3	1		1	2
23	E4			0	0	23	E4			0	0
24	E5			1	1	24	E5			1	1
25	E6		1	0	1	25	E6			0	0
26	E7			1	1	26	E7			1	1
27	F2	1	1	1	3	27	F2	1	1	1	3
28	F3		1	1	2	28	F3	1	1	1	3
29	F4	1	1	1	3	29	F4	1	1	1	3
30	F5			1	1	30	F5			1	1
31	G1	1	1	1	3	31	G1		1	1	2
32	G2	1	1	1	3	32	G2		1	1	2
33	G3	1	1	1	3	33	G3	1	1	1	3
34	G4	1		1	2	34	G4	1		1	2
35	G5	1	1	1	3	35	G5	1		1	2
36	G6		1	1	2	36	G6	1	1	1	3
37	G7			0	0	37	G7			1	1
38	G8		1	1	2	38	G8		1	1	2
I6 3-points						I6 5-points students					
1	A1			0	0	1	A1			0	0
2	A2	1		1	2	2	A2	1		1	2
3	A4			1	1	3	A4			0	0
4	B1		1	0	1	4	B1			0	0
5	B2	1	1	1	3	5	B2	1		1	2

6	B3			0	0	6	B3			0	0
7	B4			0	0	7	B4			0	0
8	C1	1	1	1	3	8	C1			1	1
9	C2			0	0	9	C2			0	0
10	C3	1	1	1	3	10	C3	1		1	2
11	C5	1	1	1	3	11	C5	1		1	2
12	C6			0	0	12	C6			0	0
13	C7			0	0	13	C7			0	0
14	C8			0	0	14	C8			0	0
15	C12	1		1	2	15	C12	1		1	2
16	D1	1	1	1	3	16	D1	1		0	1
17	D2			0	0	17	D2			1	1
18	D3	1	1	1	3	18	D3	1	1	1	3
19	D4	1	1	1	3	19	D4	1	1	1	3
20	E1		1	1	2	20	E1	1	1	1	3
21	E2			0	0	21	E2			0	0
22	E3	1	1	1	3	22	E3	1		1	2
23	E4			0	0	23	E4			0	0
24	E5			0	0	24	E5			0	0
25	E6			0	0	25	E6			0	0
26	E7			0	0	26	E7			0	0
27	F2	1	1	1	3	27	F2	1	1	1	3
28	F3	1	1	1	3	28	F3	1	1	1	3
29	F4		1	1	2	29	F4	1	1	1	3
30	F5	1	1	1	3	30	F5			1	1
31	G1			0	0	31	G1			0	0
32	G2			1	1	32	G2	1	1	1	3
33	G3			1	1	33	G3	1	1	1	3
34	G4	1	1	1	3	34	G4	1	1	1	3
35	G5			0	0	35	G5		1	0	1
36	G6			0	0	36	G6			0	0
37	G7		1	0	1	37	G7			0	0
38	G8			0	0	38	G8			0	0
H2 3-points instructors						H2 5-points instructors					
1	A1	1	1	1	3	1	A1			1	1
2	B1			1	1	2	B1			1	1
3	B2			1	1	3	B2	1	1	1	3
4	B3	1	1	1	3	4	B3		1	1	2
5	B4	1		1	2	5	B4			1	1

6	B5			1	1	6	B5			0	0
7	B6			0	0	7	B6			0	0
8	B7		1	0	1	8	B7	1	1	1	3
9	C1	1		1	2	9	C1			1	1
10	C2			1	1	10	C2	1		1	2
11	C11	1		1	2	11	C11			1	1
12	D1		1	1	2	12	D1	1	1	1	3
13	D2			1	1	13	D2			1	1
14	D3	1		1	2	14	D3			0	0
15	E1			1	1	15	E1	1		1	2
16	E2		1	0	1	16	E2	1		1	2
17	E3			1	1	17	E3	1		1	2
18	E4	1	1	1	3	18	E4	1	1	1	3
19	E5	1		1	2	19	E5			1	1
20	E6	1		1	2	20	E6			1	1
21	E7		1	1	2	21	E7	1		1	2
22	E8			1	1	22	E8	1		1	2
23	E9		1	1	2	23	E9	1	1	1	3
24	E10	1		1	2	24	E10			1	1
25	E11	1	1	1	3	25	E11	1	1	1	3
26	E12			1	1	26	E12			1	1
27	E13		1	1	2	27	E13		1	0	1
28	E14			1	1	28	E14	1	1	1	3
29	F1	1			1	29	F1			1	1
30	F2		1	1	2	30	F2	1	1	1	3
31	G1		1	1	2	31	G1	1	1	1	3
32	G2		1	1	2	32	G2	1	1	1	3
33	G4	1	1	1	3	33	G4			1	1
34	G6			1	1	34	G6	1	1	1	3
H4 3-points instructors						H4 5-points instructors					
1	A1			1	1	1	A1			1	1
2	B1	1	1	1	3	2	B1	1	1	1	3
3	B2	1	1	1	3	3	B2	1	1	1	3
4	B3	1	1	1	3	4	B3	1	1	1	3
5	B4	1	1	1	3	5	B4	1	1	1	3
6	B5			0	0	6	B5			0	0
7	B6		1	1	2	7	B6		1		1
8	B7			1	1	8	B7	1		1	2
9	C1			1	1	9	C1			1	1

10	C2			1	1	10	C2	1		1	2
11	C11			1	1	11	C11			1	1
12	D1			1	1	12	D1			1	1
13	D2			0	0	13	D2			1	1
14	D3		1	1	2	14	D3	1	1	1	3
15	E1		1	1	2	15	E1	1	1	1	3
16	E2	1	1	1	3	16	E2	1	1	1	3
17	E3	1	1	1	3	17	E3	1	1	1	3
18	E4			1	1	18	E4			0	0
19	E5			1	1	19	E5			1	1
20	E6			1	1	20	E6			1	1
21	E7		1	1	2	21	E7		1	1	2
22	E8		1	1	2	22	E8	1	1	1	3
23	E9			1	1	23	E9			1	1
24	E10		1	1	2	24	E10		1	1	2
25	E11		1	1	2	25	E11	1	1	1	3
26	E12	1	1	1	3	26	E12	1	1	1	3
27	E13	1	1	1	3	27	E13		1	1	2
28	E14	1		1	2	28	E14			1	1
29	F1	1	1	1	3	29	F1	1	1	1	3
30	F2	1	1	1	3	30	F2	1	1	1	3
31	G1	1			1	31	G1			1	1
32	G2			0	0	32	G2			1	1
33	G4	1		1	2	33	G4	1		1	2
34	G6	1	1	1	3	34	G6		1	1	2
H6 3-points						H6 5-points					
1	A1			1	1	1	A1			0	0
2	B1			0	0	2	B1			0	0
3	B2	1		1	2	3	B2		1	1	2
4	B3	1	1	1	3	4	B3		1	1	2
5	B4		1	1	2	5	B4	1	1	1	3
6	B5			1	1	6	B5		1	1	2
7	B6			0	0	7	B6			0	0
8	B7			1	1	8	B7	1		1	2
9	C1			0	0	9	C1			0	0
10	C2			1	1	10	C2			1	1
11	C11		1	1	2	11	C11			1	1
12	D1			1	1	12	D1	1			1
13	D2			1	1	13	D2		1	1	2

14	D3	1		1	2	14	D3		1	1	2
15	E1			0	0	15	E1			1	1
16	E2	1	1	1	3	16	E2	1	1	1	3
17	E3		1	1	2	17	E3			1	1
18	E4	1	1	1	3	18	E4	1	1	1	3
19	E5			0	0	19	E5			0	0
20	E6	1	1	1	3	20	E6			1	1
21	E7	1	1	1	3	21	E7	1		1	2
22	E8	1	1	1	3	22	E8	1	1	1	3
23	E9	1		1	2	23	E9	1	1	1	3
24	E10			1	1	24	E10	1		1	2
25	E11	1	1	1	3	25	E11	1	1	1	3
26	E12			1	1	26	E12			1	1
27	E13	1	1	1	3	27	E13		1	1	2
28	E14	1	1	1	3	28	E14			1	1
29	F1	1			1	29	F1	1	1	1	3
30	F2		1	1	2	30	F2		1	1	2
31	G1			1	1	31	G1	1	1	1	3
32	G2		1	1	2	32	G2		1	1	2
33	G4		1	0	1	33	G4			0	0
34	G6	1	1	1	3	34	G6			1	1

Table S7. Remaining questions in the problem (Question codes: Table S21.)

5-point Likert	items	5-point Likert	items
Theoretical-Practical H6	A1, B2, B3, B4, B5, B7, D2, D3, E2, E4, E7, E8, E9, E10, E11, E13, F2, G1, G2	Theoretical-Practical H6	A1, A2, B1, B3, B4, B5, B7, C11, D3, E2, E3, E4, E6, E7, E8, E9, E11, E13, E14, F2, G2, G6
Practical H4	A1, B2, B3, B4, B7, C1, C11, D1, D3, E1, E3, E7, E8, E10, E11, E12, E13, F2, G6	Practical H4	A1, A2, B1, B2, B3, B4, B7, C1, C11, D1, D3, E1, E2, E3, E7, E8, E10, E11, E12, E13, E14, F2, G6
Theoretical H2	A1, B2, B3, B4, B7, C1, C11, D1, D3, E4, E5, E6, E7, E9, E10, E11, E13, F2, G1, G2	Theoretical H2	A2, B1, B5, B6, C2, D2, D3, E1, E2, E3, E8, E12, E14, F1, G4, G6
Theoretical-Practical I6	A1, A4, B1, B3, B4, B5, B6, B7, C1, C2, C6, C7, C8, C9, C11, D1, D2, E2, E4, E6, E7, E8, E9, E10, E11, E12, E13, E14, F1, G1, G2, G3, G5	Theoretical-Practical I6	A1, A2, B1, B3, B4, C2, C3, C5, C12, D1, D3, D4, E1, E3, F2, F3, F4, F5, G4
Practical I4	A1, B3, B4, B5, B6, B7, C6, C7, C8, C9, C11, C12, D1, D2, E3, E4, E5, E6, E8, E9, E10, E11, E12, E13, E14, F5, G3, G5	Practical I4	A1, A2, B1, B2, C2, C3, C5, D1, D2, D3, E1, E2, E3, F2, F3, F4, G1, G2, G3, G4, G5, G6, G8
Theoretical I2	A1, A2, A4, B2, B5, B6, B7, C1, C5, C6, C9, C11, D1, D4, E2, E4, E5, E6, E8, E9, E10, E11, E12, E13, E14, F1, F4, G1, G6	Theoretical I2	A1, A2, A4, B1, B3, B4, C2, C3, C7, C8, C12, D1, D2, D3, E1, E3, E7, F2, F3, F5, G2, G3, G4, G5, G7, G8

S.7. Chronic correlation

This approach has been employed to compute correlation in the "4-3-2- Correlation" section. In summary, consider Z1 and Z2 as two ordinal questions with categories 1m and m2, respectively. Their distribution in the sample is presented through a provided probability table.

n11	...	n1m2
n21	...	n2m2
•	...	•
•	...	•
nm1	...	nm1m2

The variables Z_1^* and Z_2^* can be regarded as those for which their combined distribution follows a bivariate normal distribution exhibiting correlated behavior. Multivariate correlation arises from the various states of the bivariate (or multivariate) normal distribution $N(0,0,1,1,\rho)$

$$P[X = i, Y = j] = p_{ij} = \int_{a_{i-1}}^{a_i} \int_{b_{j-1}}^{b_j} \frac{1}{2\pi\sqrt{1-\rho^2}} \exp^{-\frac{1}{2(1-\rho^2)}(x^2 - 2xy\rho + y^2)} dx dy$$

(Eq S8. Chronic correlation)

Whereby an objective function can be defined as follows:

$$\ln L = \sum_{i=1}^{m_1} \sum_{j=1}^{m_2} n_{ij} \log p_{ij}$$

(Eq S9. Objective function of Chronic correlation)

However, in this method, it is necessary to assume the normality of the two variables prior to calculating the tested correlation, and given such a presumption violation, this correlation holds relatively robustly. This approach is employed for continuous values, yet it should be noted that it can also encompass discrete values.

S.8. Heterotrait-Monotrait

The Heterotrait-Monotrait (HTMT) correlation ratio is an approach to examine the extent to which latent constructs are independent of each other, as per the formula provided in equation 6 of Henseler, Ringle, and Sarstedt [8]. Tables A6 and A7 indicate the HTMT values for all subscales of both surveys. The highest HTMT value observed for instructors is 0.6 and for students

0.532. By ensuring that the HTMT values remained below the threshold of 0.9 for both instructors and students, we confirmed sufficient distinction between the any two subscales in both surveys. The results confirm the appropriateness of correlations between attributes of different subscales and indicate the extent the subscales differ from each other assessed [9].

Table S8. Heterotrait-Monotrait ratio output for instructors (points of significance)

$\alpha=0.005$, N=140	Theory and practice	Motivation	Pedagogy	Knowledge, Insight, and Skill	Working-Life orientation	Quality of Assessment and ICT
Theory and practice						
Motivation	0.427					
Pedagogy	0.425	0.423				
Knowledge, Insight, and Skills	0.612	0.518	0.510			
Working-Life orientation	0.512	0.418	0.319	0.455		
Quality of Assessment and ICT	0.415	0.402	0.326	0.517	0.316	

Table S9. Heterotrait-Monotrait ratio output for students (points of significance)

$\alpha=0.005$, N=379	Theory and practice	Motivation	Pedagogy	Knowledge, Insight, and Skill	Working-Life orientation	Quality of Assessment and ICT
Theory and practice						
Motivation	0.413					
Pedagogy	0.446	0.53				
Knowledge, Insight, and Skills	0.532	0.518	0.538			
Working-Life orientation	0.472	0.401	0.419	0.385		
Quality of Assessment and ICT	0.365	0.302	0.416	0.451	0.326	

S.9. Shorter survey

The study aimed to identify the most important questions for predicting preferences among the 55 questions included in the surveys. Table S8 highlighted the instructors' and students' surveys as the most crucial. These surveys encompassed all the subscales and were applicable to both students and instructors. The study further extracted 12 and 11 specific questions from these surveys for instructors and students by the MDI more than 0.86. This shortened survey allows for the collection of more extensive data in future research endeavors. Additionally, the selection of

questions in this shortened survey ensures a balanced distribution across the six subscales. The accuracy of the shortened survey was evaluated in Table S10, which reports the change in accuracy when considering the results from the five-point and 3-point Likert scales. The preference prediction was initially conducted using the 12 selected questions, employing classification methods as outlined in section A.4 – A.7. The Table S10 also presents the difference between the accuracy obtained from the shortened survey and the accuracy values derived from the original survey. The accuracy reductions were lowest for the random forest method, indicating that utilizing the shortened survey with its 12 main questions, despite some reduction in prediction accuracy, enables the gathering of more extensive statistical data.

Table S10. Best 12 questions of instructors and 11 questions of students.

Question	Instructors	Students
Usability and perception of alternative laboratory tools	F4	F5
Motivation in TEL environment is higher than traditional environment	B2	B4
Capability of TEL tools in transferring hard and soft skills	C4	C2
Comparison of active learning methods in TEL environment with traditional teaching methods	E4	E2
Evaluation in TEL environment and its quality compared to traditional method	G1	G3
Ability to teach real-world problem solving	B4	B2
Classroom management strategy for adaptation in TEL	E2	E5
Flexibility in teaching and learning in TEL compared to face-to-face teaching	D2	D1
The extent to which course delivery becomes practical in TEL compared to face-to-face teaching	A1	A4
Willingness to change role and become an active actor in TEL	B1	B3
Monitoring educational progress and understanding learning from people during class time in TEL	E5	-
The ability to create research and interactive communication outside the classroom in TEL	F3	F7

S.10. ML in detail

Table S11. Changes in the accuracy of the results from 5-point to 3-point Likert scale

ML model	Change in accuracy						Mean
	Students-Theoretical	Instructors-Theoretical	Students-Practical	Instructors-Practical	Students-Theoretical-Practical	Instructors-Theoretical-Practical	
RF	0.3356	0.259	0.2303	0.3155	0.415	0.266	0.29
DT	0.3224	0.1291	0.2698	0.1786	0.1212	0.1071	0.17
SVM	0.2468	0.0684	0.1908	0.2679	0.1214	0.2206	0.16

S.11. Response variables

Table S12. Response variables according to the surveys

Students			Instructors		
I2	I4	I6	H2	H4	H6
Theoretical	Practical	Theoretical-Practical	Theoretical	Practical	Theoretical-Practical
I feel satisfied using technology-enhanced learning in Theoretical courses.	I feel satisfied using technology-enhanced learning in practical courses.	I feel satisfied using technology-enhanced learning in Theoretical-practical courses.	I feel satisfied using technology-enhanced learning in Theoretical courses.	I feel satisfied using technology-enhanced learning in practical courses.	I feel satisfied using technology-enhanced learning in Theoretical-practical courses.

S.12. Random Forest results

Table S13. Random Forest within the 5-point Likert spectrum on test data (in percentage) of train and test.

Response variable	Accuracy	SA	A	N	D	SD		Response variable	Accuracy	SA	A	N	D	SD	
test								train							
I2	Accuracy: 0.4539 95% CI : (0.3731, 0.5366) No Information Rate: 0.3289 P-Value [Acc > NIR] : 0.0008929 Kappa: 0.2305	0	0	0	0	1	SD	I2	Accuracy: 0.9956 95% CI : (0.9757, 0.9999) No Information Rate: 0.3568 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 0.9941	0	0	0	0	14	SD
		3	2	3	9	3	D			0	0	1	38	0	D
		1	2	3	1	1	N			0	0	33	0	0	N
		3	14	3	2	0	A			0	60	0	0	0	A
		42	32	7	14	6	SA			81	0	0	0	0	SA
I4	Accuracy: 0.4219 95% CI : (0.2994, 0.5518) No Information Rate: 0.375 P-Value [Acc > NIR] : 0.2574 Kappa: 0.2269	0	0	0	0	3	SD	I4	Accuracy: 1 95% CI : (0.9623, 1) No Information Rate: 0.3125 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1	0	0	0	0	13	SD
		1	6	2	10	2	D			0	0	0	30	0	D
		0	1	3	10	1	N			0	0	21	0	0	N
		4	9	3	4	3	A			0	28	0	0	0	A
		2	0	0	0	0	SA			4	0	0	0	0	SA
I6		0	0	0	5	14	SD	I6	Accuracy: 1	0	0	0	0	48	SD

	Accuracy: 0.5855 95% CI : (0.5029, 0.6648) No Information Rate: 0.375 P-Value [Acc > NIR] : 1.156e-07 Kappa: 0.4148	1	11	7	47	24	D	95% CI : (0.9839, 1) No Information Rate: 0.4009 P-Value [Acc > NIR] : < 2.2e-16	0	0	0	91	0	D
		0	2	9	1	0	N		0	0	35	0	0	N
		3	11	1	4	1	A		0	41	0	0	0	A
		8	2	1	0	0	SA		12	0	0	0	0	SA
H2	Accuracy: 0.625 95% CI : (0.4855, 0.7508) No Information Rate: 0.5893 P-Value [Acc > NIR] : 0.3445 Kappa: 0.2543	0	0	0	0	0	SD	Accuracy: 1 95% CI : (0.957, 1) No Information Rate: 0.5595 P-Value [Acc > NIR] : < 2.2e-16 Kappa : 1	0	0	0	0	2	SD
		0	1	0	0	0	D		0	0	0	8	0	D
		0	1	4	2	0	N		0	0	17	0	0	N
		6	29	6	3	0	A		0	47	0	0	0	A
H4	Accuracy: 0.375 95% CI : (0.2492, 0.5145) No Information Rate: 0.375 P-Value [Acc > NIR] : 0.5503 Kappa: 0.0581	0	0	0	0	0	SD	Accuracy: 1 95% CI : (0.957, 1) No Information Rate: 0.4524 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1	0	0	0	0	2	SD
		0	2	1	3	1	D		0	0	0	15	0	D
		0	2	2	1	0	N		0	0	21	0	0	N
		4	16	18	6	0	A		0	38	0	0	0	A
H6	Accuracy: 0.4107 95% CI : (0.281, 0.5502) No Information Rate: 0.3571 P-Value [Acc > NIR] : 0.2408 Kappa: 0.0923	0	0	0	0	0	SD	Accuracy: 1 95% CI : (0.957, 1) No Information Rate: 0.4524 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1	0	0	0	0	2	SD
		0	1	0	1	0	D		0	0	0	14	0	D
		0	0	3	2	1	N		0	0	26	0	0	N
		5	19	17	7	0	A		0	35	0	0	0	A
H6	Accuracy: 0.4107 95% CI : (0.281, 0.5502) No Information Rate: 0.3571 P-Value [Acc > NIR] : 0.2408 Kappa: 0.0923	0	0	0	0	0	SD	Accuracy: 1 95% CI : (0.957, 1) No Information Rate: 0.4524 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1	0	0	0	0	2	SD
		0	1	0	1	0	D		0	0	0	14	0	D
		0	0	3	2	1	N		0	0	26	0	0	N
		5	19	17	7	0	A		0	35	0	0	0	A

Table S14. Random Forest within the 3-point Likert spectrum on test data (in percentage) of train and test

Response variable	Accuracy	A	N	D		Response variable	Accuracy	A	N	D	
test						train					
I2	Accuracy: 0.7895 95% CI : (0.716, 0.8513) No Information Rate: 0.6513 P-Value [Acc > NIR] : 0.0001469 Kappa: 0.5064 McNemar's Test P-Value: 9.048e-05	2	0	23	D	I2	Accuracy: 0.9427 95% CI : (0.9041, 0.9692) No Information Rate: 0.6211 P-Value [Acc > NIR] : < 2e-16 Kappa: 0.8904 McNemar's Test P-Value: 0.01857	1	3	49	D
		1	1	1	N			0	25	0	N
		96	15	13	A			140	6	3	A
I4	Accuracy: 0.6945 95% CI : (0.4326, 0.6901) No Information Rate: 0.4194 P-Value [Acc > NIR] : 0.014895 Kappa: 0.2934 McNemar's Test P-Value: 0.008497	7	8	20	D	I4	Accuracy: 0.9785 95% CI : (0.9245, 0.9974) No Information Rate: 0.5269 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 0.963 McNemar's Test P-Value: NA	0	0	48	D
		0	3	1	N			0	10	0	N
		15	4	4	A			33	1	1	A

I6	Accuracy: 0.8158 95% CI : (0.7449, 0.874) No Information Rate: 0.6316 P-Value [Acc > NIR] : 5.89e-07 Kappa: 0.6222 McNemar's Test P-Value: 0.05147	11	7	90	D	I6	Accuracy: 1 95% CI : (0.9839, 1) No Information Rate: 0.6123 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1	0	0	139	D
		1	8	1	N			0	35	0	N
		26	3	5	A			53	0	0	A
H2	Accuracy: 0.9405 95% CI : (0.8665, 0.9804) No Information Rate: 0.6786 P-Value [Acc > NIR] : 6.033e-09 Kappa: 0.8692	0	0	9	D	H2	Accuracy: 0.7321 95% CI : (0.597, 0.8417) No Information Rate: 0.7321 P-Value [Acc > NIR] : 0.5689 Kappa: 0.2453	1	2	2	D
		0	13	0	N			2	1	0	N
		57	4	1	A			38	7	3	A
H4	Accuracy: 0.79 95% CI : (0.6634, 0.8366) No Information Rate: 0.5357 P-Value [Acc > NIR] : 0.7489 Kappa: 0.4642 McNemar's Test P-Value: 0.6022	1	2	2	D	H4	Accuracy: 0.9762 95% CI : (0.9166, 0.9971) No Information Rate: 0.5476 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 0.9595	0	0	15	D
		2	1	0	N			0	21	0	N
		38	7	3	A			46	0	2	A
H6	Accuracy: 0.6767 95% CI : (0.3974, 0.6701) No Information Rate: 0.5536 P-Value [Acc > NIR] : 0.6579 Kappa: 0.15 McNemar's Test P-Value: 0.3085	2	2	2	D	H6	Accuracy: 0.9881 95% CI : (0.9354, 0.9997) No Information Rate: 0.5714 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 0.9794	0	0	16	D
		4	6	3	N			0	25	0	N
		25	5	7	A			42	1	0	A

S.13. Decision Tree results:

Table S15. Decision Tree (DT) within the 5-point Likert on test data (in percentage) of train and test

Response variable	Accuracy	SA	A	N	D	SD		Response variable	Accuracy	SA	A	N	D	SD	
								train							
I2	Accuracy: 0.3947 95% CI : (0.5636, 0.6929) No Information Rate: 0.3436 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 0.5059	3	1	0	2	6	SD	I2	Accuracy: 0.63 95% CI : (0.5636, 0.6929) No Information Rate: 0.3436 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 0.5059	3	1	0	2	6	SD
		5	3	2	27	4	D			5	3	2	27	4	D
		5	10	22	3	0	N			5	10	22	3	0	N
		7	30	2	1	0	A			7	30	2	1	0	A
		58	16	8	8	4	SA			58	16	8	8	4	SA
I4	Accuracy: 0.4032	1	0	3	4	8	SD	I4	Accuracy: 0.5806	1	0	5	4	6	SD
		4	10	4	11	1	D			0	11	6	32	4	D
		0	0	0	0	0	N			0	0	0	0	0	N
		0	5	1	1	2	A			0	12	4	1	0	A

	95% CI : (0.2805, 0.5355) No Information Rate: 0.3065 P-Value [Acc > NIR] : 0.0672743 Kappa: 0.2289 McNemar's Test P-Value: 0.0008054	1	4	2	0	0	SA		95% CI : (0.4738, 0.6822) No Informati on Rate: 0.3978 P-Value [Acc > NIR] : 0.000279 1 Kappa: 0.4024	4	1	1	0	1	SA
I6	Accuracy: 0.4539 95% CI : (0.3731, 0.5366) No Information Rate: 0.4211 P-Value [Acc > NIR] : 0.22933 Kappa: 0.2582 McNemar's Test P-Value: 0.04701	1	2	0	20	16	SD	I6	Accuracy: 0.6784 95% CI : (0.6134, 0.7387) No Informati on Rate: 0.37 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 0.5593	0	4	2	10	37	SD
		1	8	4	33	9	D			2	7	8	67	16	D
		1	5	7	0	1	N			0	1	16	1	2	N
		5	12	10	8	4	A			5	26	5	6	1	A
H2	Accuracy: 0.5357 95% CI : (0.3974, 0.6701) No Information Rate: 0.625 P-Value [Acc > NIR] : 0.9341 Kappa: 0.144	1	0	1	3	0	SA	H2	Accuracy: 0.6548 95% CI : (0.5431, 0.7552) No Informati on Rate: 0.5357 P-Value [Acc > NIR] : 0.01811 Kappa: 0.4172	8	2	0	0	1	SA
		0	0	0	0	0	SD			0	0	0	0	0	SD
		0	0	1	0	1	D			0	1	3	3	0	D
		0	9	3	0	0	N			1	3	9	2	1	N
H4	Accuracy: 0.3286 95% CI : (0.2971, 0.4478) No Information Rate: 0.3571 P-Value [Acc > NIR] : 0.1643 Kappa: 0.1571	7	24	3	3	0	A	H4	Accuracy: 0.5595 95% CI : (0.447, 0.6678) No Informati on Rate: 0.4286 P-Value [Acc > NIR] : 0.01066 Kappa: 0.3268	3	39	8	4	0	A
		3	2	0	0	0	SA			4	2	0	1	0	SA
		0	0	0	0	0	SD			0	0	0	0	0	SD
		0	2	4	1	0	D			0	2	4	6	3	D
H6	Accuracy: 0.4286	0	5	4	2	1	N	H6	Accuracy: 0.5595	2	7	14	4	0	N
		4	13	13	7	0	A			2	27	8	5	0	A
H6	Accuracy: 0.4286	0	0	0	0	0	SA	H6	Accuracy: 0.5595	0	0	0	0	0	SA
		0	2	6	3	0	D			0	3	6	6	1	D

	95% CI : (0.2971, 0.5678) No Information Rate: 0.3571 P-Value [Acc > NIR] : 0.1643 Kappa: 0.1571	2	2	5	2	1	N		95% CI : (0.447, 0.6678) No Informati on Rate: 0.4881 P-Value [Acc > NIR] : 0.1149 Kappa: 0.3268	3	3	6	3	1	N
		3	16	9	5	0	A			4	35	7	6	0	A
		0	0	0	0	0	SA			0	0	0	0	0	SA

Table S16. Decision Tree (DT) within the 3-point Likert on test data (in percentage) of train and test

Response variable	Accuracy	A	N	D		Response variable	Accuracy	A	N	D	
test						train					
I2	Accuracy: 0.7171 95% CI : (0.6384, 0.7871) No Information Rate: 0.6711 P-Value [Acc > NIR] : 0.1303 Kappa: 0.3927 McNemar's Test P-Value: 0.3837	7	3	15	D	I2	Accuracy: 0.7797 95% CI : (0.7201, 0.8319) No Information Rate: 0.6079 P-Value [Acc > NIR] : 2.725e-08 Kappa: 0.562 McNemar's Test P-Value: 0.0009105	7	3	35	D
		7	6	4	N			2	13	4	N
		88	7	15	A			129	18	16	A
I4	Accuracy: 0.5323 95% CI : (0.4012, 0.6602) No Information Rate: 0.4194 P-Value [Acc > NIR] : 0.04799 Kappa: 0.2189 McNemar's Test P-Value: 6.092e-05	12	12	24	D	I4	Accuracy: 0.6667 95% CI : (0.5613, 0.7611) No Information Rate: 0.5161 P-Value [Acc > NIR] : 0.0023491 Kappa: 0.3788 McNemar's Test P-Value: 0.0002408	11	14	44	D
		0	0	0	N			0	0	0	N
		9	3	2	A			18	2	4	A
I6	Accuracy: 0.7237 95% CI : (0.6454, 0.793) No Information Rate: 0.6184 P-Value [Acc > NIR] : 0.004185 Kappa: 0.4331 McNemar's Test P-Value: 0.001477	18	7	87	D	I6	Accuracy: 0.7974 95% CI : (0.7391, 0.8477) No Information Rate: 0.6211 P-Value [Acc > NIR] : 8.198e-09 Kappa: 0.5784 McNemar's Test P-Value: 3.422e-05	23	12	136	D
		2	7	0	N			2	15	1	N
		16	8	7	A			30	4	4	A
H2	Accuracy: 0.7143 95% CI : (0.5779, 0.827) No Information Rate: 0.8036 P-Value [Acc > NIR] : 0.96292 Kappa: 0.0448 McNemar's Test P-Value: 0.07905	5	0	1	D	H2	Accuracy: 0.7024 95% CI : (0.5927, 0.7973) No Information Rate: 0.631 P-Value [Acc > NIR] : 0.105638 Kappa: 0.3631 McNemar's Test P-Value: 0.009036	1	5	5	D
		1	0	1	N			2	4	1	N
		39	7	2	A			50	11	5	A

H4	Accuracy: 0.4807 95% CI : (0.281, 0.5502) No Information Rate: 0.5357 P-Value [Acc > NIR] : 0.977730 Kappa: 0.109 McNemar's Test P-Value: 0.001647	2	1	2	D	H4	Accuracy: 0.5833 95% CI : (0.4706, 0.69) No Information Rate: 0.4762 P-Value [Acc > NIR] : 0.031640 Kappa: 0.3561 McNemar's Test P-Value: 0.000333	2	1	6	D
		19	12	6	N			18	23	7	N
		9	3	2	A			20	2	5	A
H6	Accuracy: 0.5357 95% CI : (0.3974, 0.6701) No Information Rate: 0.4464 P-Value [Acc > NIR] : 0.113472 Kappa: 0.2247 McNemar's Test P-Value: 0.004766	1	2	5	D	H6	Accuracy: 0.6905 95% CI : (0.5802, 0.7869) No Information Rate: 0.5714 P-Value [Acc > NIR] : 0.01698 Kappa: 0.4563 McNemar's Test P-Value: 0.76465	6	2	10	D
		2	3	1	N			4	10	1	N
		22	15	5	A			38	7	6	A

S.14. Support Vector Machine

Table S17. Support Vector Machine (SVM) within the 5-point Likert on test data (in percentage) of train and test

Response variable	Accuracy	SA	A	N	D	SD		Response variable	Accuracy	SA	A	N	D	SD	
test								train							
I2	Accuracy: 0.4671 95% CI : (0.3858, 0.5497) No Information Rate: 0.3421 P-Value [Acc > NIR] : 0.0009645 Kappa: 0.2744 McNemar's Test P-Value: NAv	0	0	0	0	4	SD	I2	Accuracy: 1 95% CI : (0.9839, 1) No Information Rate: 0.3436 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1 McNemar's Test P-Value: NA	0	0	0	0	14	S D
		5	6	3	15	3	D			0	0	0	41	0	D
		5	5	1	2	3	N			0	0	34	0	0	N
		15	24	10	1	0	A			0	60	0	0	0	A
		27	15	2	5	1	SA			78	0	0	0	0	S A
I4	Accuracy: 0.4516 95% CI : (0.3248, 0.5832) No Information Rate: 0.3065 P-Value [Acc > NIR] : 0.01126 Kappa: 0.2624	0	0	0	0	4	SD	I4	Accuracy: 1 95% CI : (0.9611, 1) No Information Rate: 0.3978 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1	0	0	0	0	11	S D
		2	8	4	12	5	D			0	0	0	37	0	D
		0	1	2	2	1	N			0	0	16	0	0	N
		4	10	3	2	1	A			0	24	0	0	0	A
		0	0	1	0	0	SA			5	0	0	0	0	S A
I6	Accuracy: 0.5658 95% CI : (0.4831, 0.6459) No Information Rate: 0.4211	0	0	0	9	16	SD	I6	Accuracy: 1 95% CI : (0.9839, 1)	0	0	0	0	57	S D
		3	12	11	46	12	D			0	0	0	84	0	D
		0	1	8	2	1	N			0	0	31	0	0	N
		4	14	3	7	1	A			0	40	0	0	0	A

	P-Value [Acc > NIR] : 0.0002282 Kappa: 0.3696	2	0	0	0	0	SA		No Information Rate: 0.37 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1	15	0	0	0	0	SA
H2	Accuracy: 0.5357 95% CI : (0.3974, 0.6701) No Information Rate: 0.625 P-Value [Acc > NIR] : 0.9341 Kappa: 0.0732 McNemar's Test P-Value: NA	0	0	0	0	0	SD	H2	Accuracy: 1 95% CI : (0.957, 1) No Information Rate: 0.5357 P-Value [Acc > NIR] : < 2.2e-16	0	0	0	0	1	SD
		0	2	0	0	1	D			0	0	0	10	0	D
		0	6	2	0	0	N			0	0	20	0	0	N
		8	26	5	3	0	A			0	45	0	0	0	A
		2	1	0	0	0	SA			8	0	0	0	0	SA
H4	Accuracy: 0.4286 95% CI : (0.2971, 0.5678) No Information Rate: 0.3929 P-Value [Acc > NIR] : 0.3379 Kappa: 0.1665	0	0	0	0	0	SD	H4	Accuracy: 1 95% CI : (0.957, 1) No Information Rate: 0.4286 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1	0	0	0	0	3	SD
		1	1	1	2	0	D			0	0	0	15	0	D
		3	11	12	5	0	N			0	0	26	0	0	N
		4	10	3	3	0	A			0	36	0	0	0	A
		0	0	0	0	0	SA			4	0	0	0	0	SA
H6	Accuracy: 0.4464 95% CI : (0.3134, 0.5853) No Information Rate: 0.3571 P-Value [Acc > NIR] : 0.1058 Kappa: 0.1638	0	0	0	0	0	SD	H6	Accuracy: 1 95% CI : (0.957, 1) No Information Rate: 0.4881 P-Value [Acc > NIR] : < 2.2e-16 Kappa: 1	0	0	0	0	2	SD
		1	1	1	2	1	D			0	0	0	15	0	D
		0	0	4	2	0	N			0	0	19	0	0	N
		4	19	15	6	0	A			0	41	0	0	0	A
		0	0	0	0	0	SA			7	0	0	0	0	SA

Table S18. Support Vector Machine (SVM) within the 3-point Likert on test data (in percentage) of train and test

Response variable	Accuracy	A	N	D		Response variable	Accuracy	A	N	D	
test						train					
I2	Accuracy: 0.7039 95% CI : (0.6246, 0.7752) No Information Rate: 0.6711 P-Value [Acc > NIR] : 0.2198 Kappa: 0.3874 McNemar's Test P-Value: 0.8847	10	3	23	D	I2	Accuracy: 1 95% CI: (0.9839, 1) No Information Rate: 0.6079 P-Value [Acc > NIR]: < 2.2e-16 Kappa: 1	0	0	55	D
		9	1	3	N			0	34	0	N
		83	12	8	A			138	0	0	A
I4	Accuracy: 0.5 95% CI : (0.3702, 0.6298) No Information Rate: 0.4355 P-Value [Acc > NIR] : 0.1848 Kappa: 0.1859 McNemar's Test P-Value: 0.1589	11	4	19	D	I4	Accuracy: 1 95% CI: (0.9611, 1) No Information Rate: 0.5161 P-Value [Acc > NIR]: < 2.2e-16 Kappa: 1	0	0	48	D
		3	1	5	N			0	16	0	N
		11	5	3	A			29	0	0	A

I6	Accuracy: 0.7566 95% CI : (0.6804, 0.8225) No Information Rate: 0.6184 P-Value [Acc > NIR] : 0.0002139 Kappa: 0.533 McNemar's Test P-Value: 0.2838861	11	8	81	D	I6	Accuracy: 1 95% CI: (0.9839, 1) No Information Rate: 0.6211 P-Value [Acc > NIR]: < 2.2e-16 Kappa: 1	0	0	141	D
		2	11	2	N			0	31	0	N
		23	3	11	A			55	0	0	A
H2	Accuracy: 0.8036 95% CI : (0.6757, 0.8977) No Information Rate: 0.8036 P-Value [Acc > NIR] : 0.5797 Kappa: 0.201	0	0	1	D	H2	Accuracy: 0.9405 95% CI: (0.8665, 0.9804) No Information Rate: 0.631 P-Value [Acc > NIR]: 3.737e-11 Kappa: 0.8815	0	0	9	D
		2	1	0	N			0	17	0	N
		43	6	3	A			53	3	2	A
H4	Accuracy: 0.55 95% CI : (0.3634, 0.6366) No Information Rate: 0.5357 P-Value [Acc > NIR] : 0.7489 Kappa: 0.1773 McNemar's Test P-Value: 0.2273	2	1	2	D	H4	Accuracy: 0.9643 95% CI: (0.8992, 0.9926) No Information Rate: 0.4762 P-Value [Acc > NIR]: < 2.2e-16 Kappa: 0.9428	0	0	15	D
		11	9	5	N			0	26	1	N
		17	6	3	A			40	0	2	A
H6	Accuracy: 0.667 95% CI : (0.3634, 0.7366) No Information Rate: 0.4464 P-Value [Acc > NIR] : 0.25012 Kappa: 0.2037 McNemar's Test P-Value: 0.03116	6	3	3	D	H6	Accuracy: 1 95% CI: (0.957, 1) No Information Rate: 0.5714 P-Value [Acc > NIR]: < 2.2e-16 Kappa: 1	0	0	17	D
		1	7	5	N			0	19	0	N
		18	10	3	A			48	0	0	A

S.15. Mean Decrease in Impurity

The Mean Decrease in Impurity (MDI) is a methodology used in decision tree-based models, such as Random Forest, to assess the importance of individual variables in making accurate predictions. It quantifies the contribution of each variable to the overall reduction in impurity, typically measured by Gini impurity or entropy, achieved through the splitting of nodes in the decision tree. The MDI is computed by averaging the impurity decrease across all decision tree nodes where a specific variable is utilized for splitting. Mathematically, for a given variable j , the MDI can be expressed as:

$$MDI(j) = \frac{1}{N_{nodes}} \sum_{nodes \text{ using feature } j} (Impurity \text{ before split} - Impurity \text{ after split})$$

(Eq S10. MDI formulation [10], [11])

Where N_{nodes} is the total number of nodes that utilize variable j for splitting, and the impurity decrease is calculated as the difference between the impurity of the node before the split

and the weighted sum of impurities of resulting child nodes after the split. In our data set, Specifically, for each variable j , the MDI is calculated by averaging the impurity decrease across all nodes where variable j is used for splitting. Once the MDI values are computed for all variables (questions), they can be used to rank the importance of each variable in predicting the target variable. Higher MDI values indicate that a variable contributes more to reducing impurity, which signifies its importance in classification. To determine the importance of each subscale, aggregate the MDI values of the questions belonging to each subscale. Summing or averaging the MDI values of questions within a subscale provides an estimate of the subscale's overall importance in the classification task. Subscales with higher aggregated MDI values are considered more influential in making accurate predictions [10], [11]. We designed the Table S9 by analyzing the Figures A2 to A10.

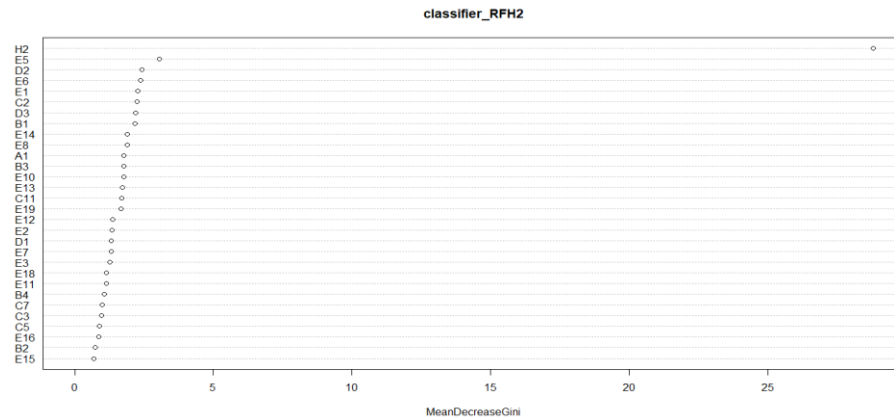


Figure S2. Variable Importance in Random Forest for H2 (Instructors) within the five-level Likert spectrum

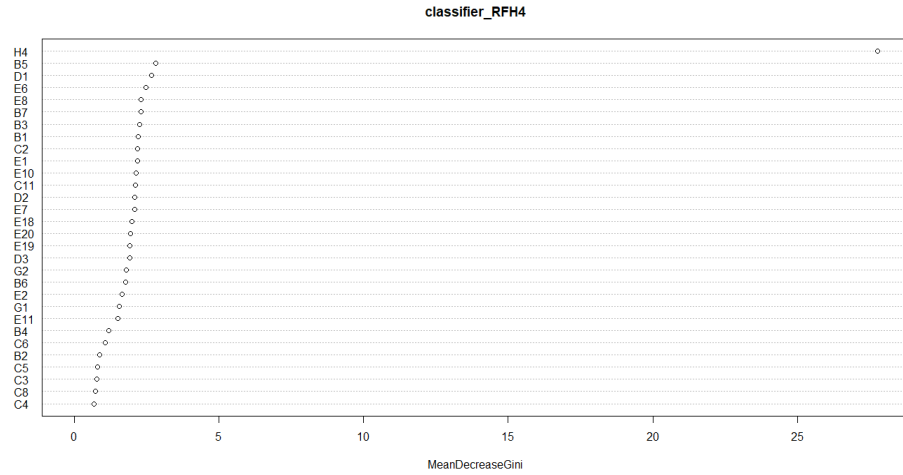


Figure S3. Variable Importance in Random Forest for H4 (Instructors) within the five-level Likert spectrum

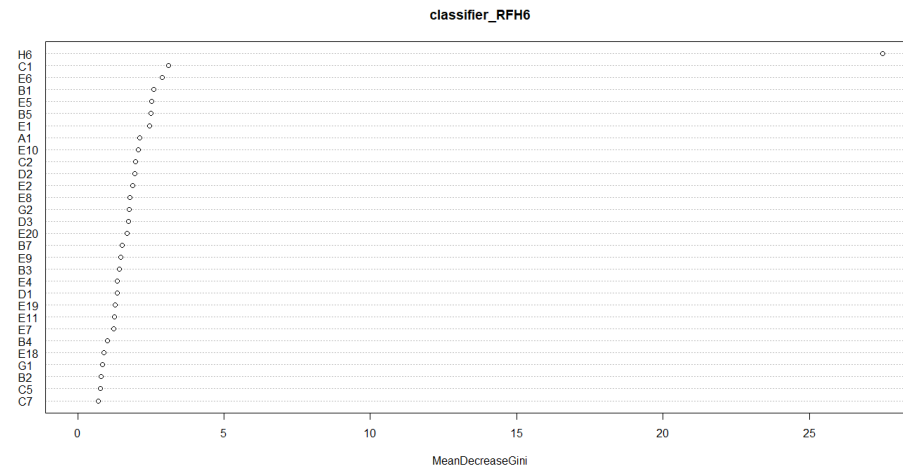


Figure S4. Variable Importance in Random Forest for H6 (Instructors) within the five-level Likert spectrum

Utilizing Tables A18 to A20, within the 5-point Likert spectrum, the Random Forest method was employed on the test data for survey response variables of Students, resulting in the accuracy of the models. These tables have been succinctly summarized in Tables A19.

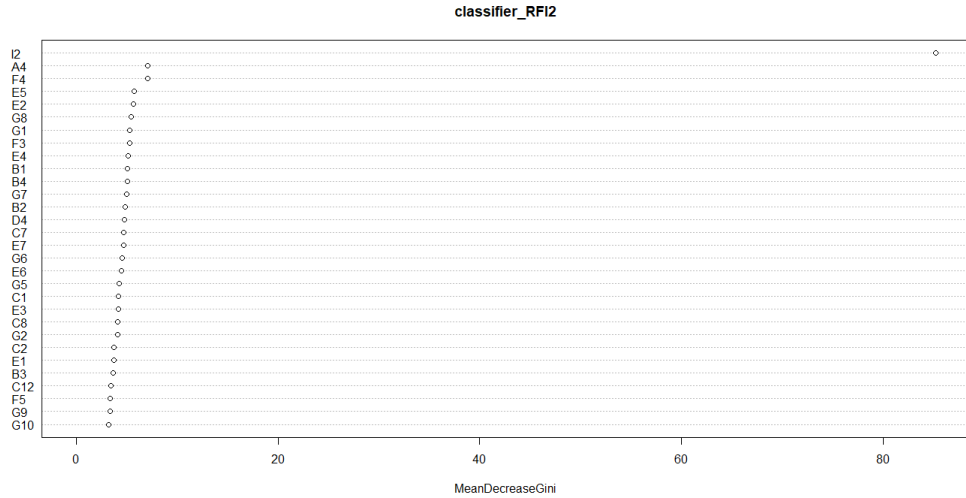


Figure S5. Variable Importance in Random Forest for I2 (Students) within the five-level Likert spectrum

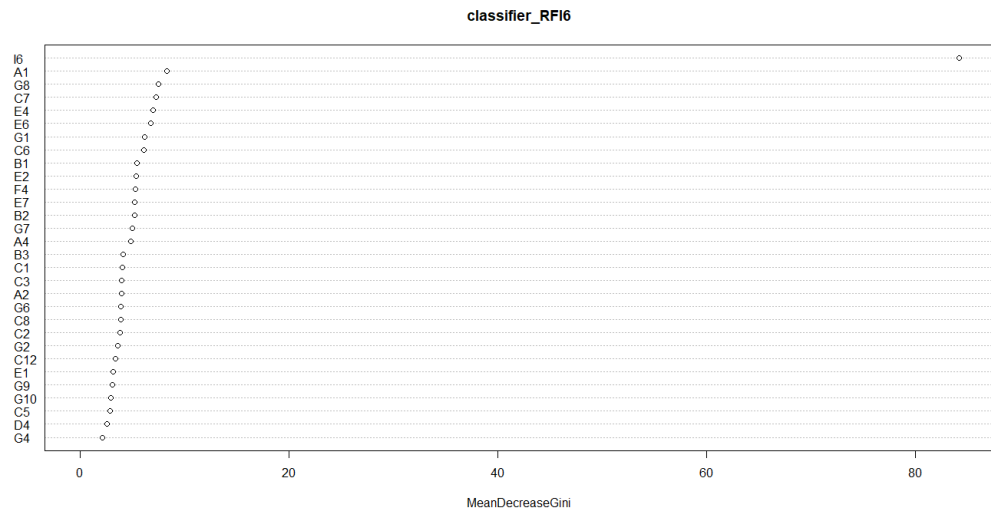


Figure S6. Variable Importance in Random Forest for I2 (Students) within the five-level Likert spectrum

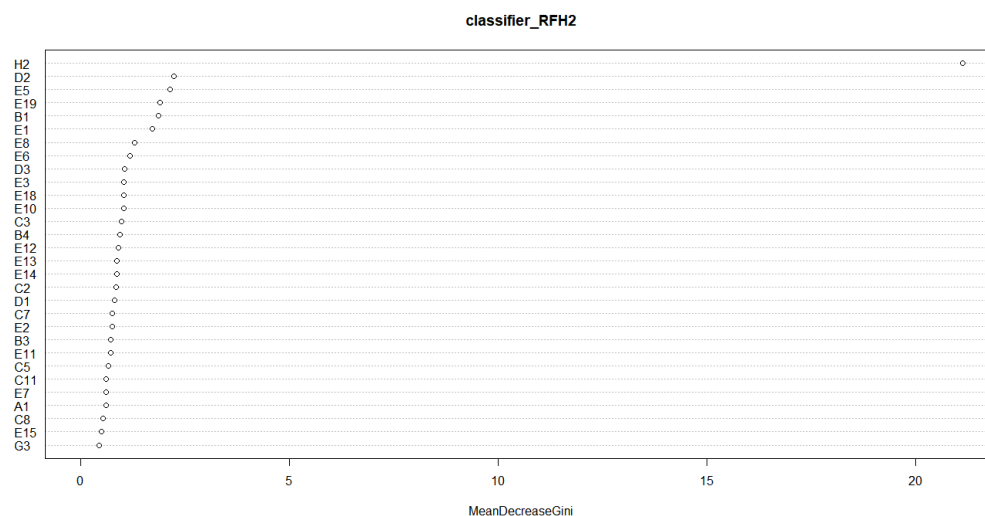


Figure S7. Variable Importance in Random Forest within the 3-point Likert spectrum for H2

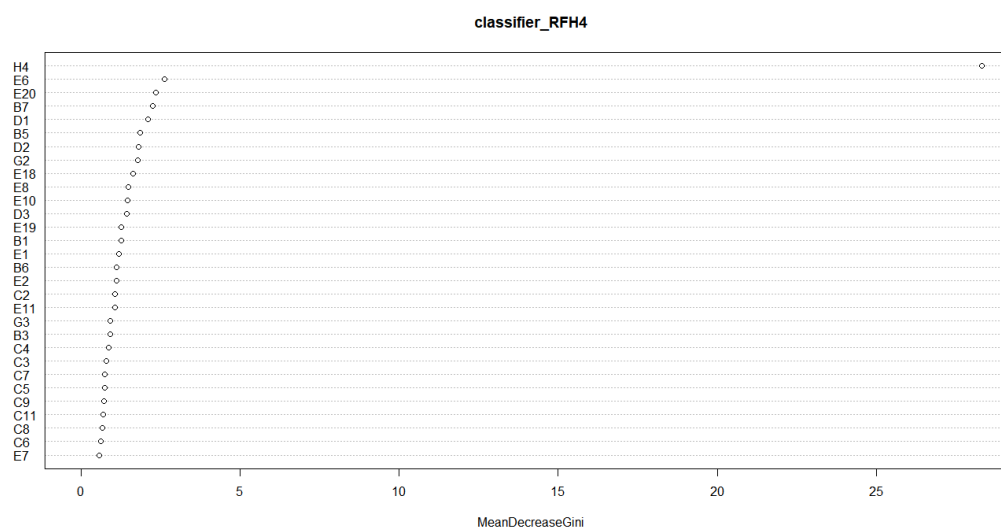


Figure S8. Variable Importance in Random Forest within the 3-point Likert spectrum for H4

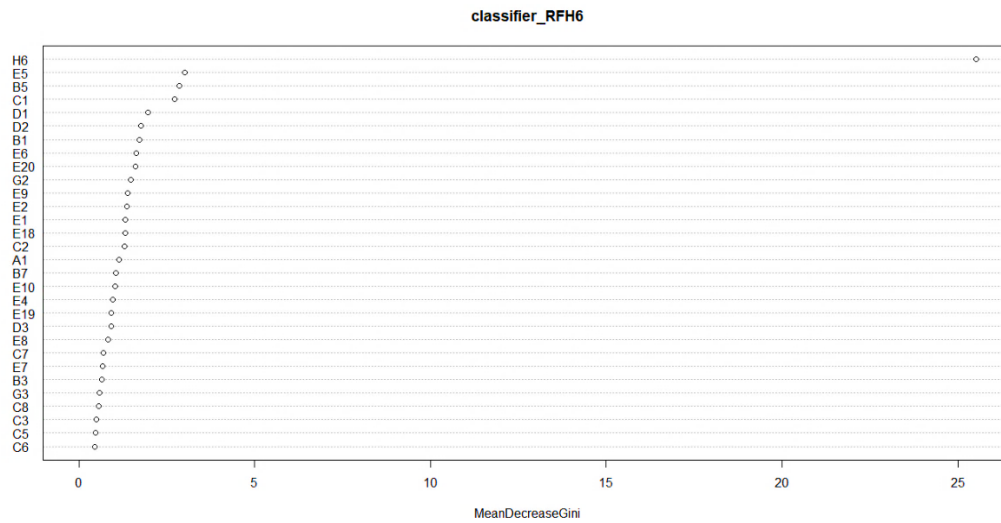


Figure S9. Variable Importance in Random Forest within the 3-point Likert spectrum for H6

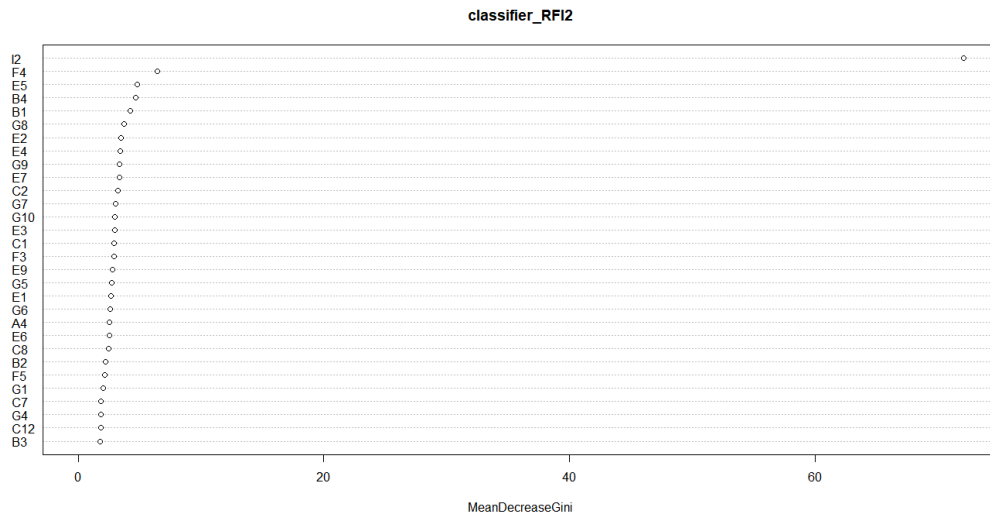


Figure S10. Variable Importance in Random Forest within the 3-point Likert spectrum for I2

Table S19. Most important variables of the RF and DT method within the 3-point Likert spectrum

Instructors			Students		
I6	I4	I2	H6	H4	H2
RF					
E5	B5	B1	E6	D4	E7
D2	B1	E5	D2	C1	D2
E2	E11	E6	D1	E7	B2
E10	E12	E10	E2	B4	E4

C11	D2	D2	E7	B2	B4
B2	E5	A4	B2	B1	B1
B1	D1	F4	E5	E6	E5
B5	B1	B4	B1	B5	B2
E2	B2	E4	E6	D2	E5
B4	E2			E8	E6
E7	B4			B1	E10
	E7				E12
DT					
C1	G8	B5	B1	E10	E10
E7	E10	E12	E8	B4	E4
C11	D2	D2	E7	B2	B4
E13	C11	C2	B4	E7	B1
B4	E7	C1	C1	E8	C1

S.16. Software and code

R is an open-source programming language that, following installation and incorporation of various libraries and packages, can execute a diverse range of pre-written and customized commands. An appended list of these libraries is provided herein. It is noteworthy that the version of R Studio in use is the latest available version 4.1.3, which is freely accessible to the public [8].

Table S20. R packages and their citations

Name	Library or function with citation	Name	Library or function with citation	
MRMR	The mRMRe package is commonly used for Minimum Redundancy Maximum Relevance (MRMR) variable selection [3].	leaps	CRAN Link	Regression subset selection.
Boruta	The Boruta package provides the Boruta model for variable selection [12].	varrank	hCRAN Link	An R package for variable ranking based on mutual information.
RFE	The caret package, particularly its rfe() function, can be used for Recursive Feature Elimination [13].	CRANsearcher	\hCRAN Link	Search CRAN R Packages using the 'crandb' API.

Chi-square as variable selection	The caret package can also be used for chi-squared (Chi-square) variable selection with its chisqFilter() function [14].		praznik	\hCRAN Link	Collection of tests and tools for feature selection.
RF	The randomForest package provides the Random Forest model for classification and regression tasks [15], [16].		devtools	S" \hCRAN Link	Tools to make developing R packages easier.
SVM	The e1071 package offers Support Vector Machine implementation in R [17].		Biocomb	mb" \hCRAN Link	Bi-objective combinatorial optimization.
DT	The rpart package provides decision tree functionality using the rpart() function [18].		mitools	ols" \hCRAN Link	Tools for multiple imputation in R.
Mean Decrease in Impurity	The "randomForest" package provides a method to calculate the Mean Decrease in Impurity (MDI) for assessing variable importance in Random Forest models [16].		infotheo	theo" \hCRAN Link	Information-theoretic measures of entropy, mutual information, etc.
ggplot2	relaimpo		Boruta	ruta" \hCRAN Link	Feature selection with the Boruta algorithm.
ggcorrplot	InformationValue		ltm	=ltm" \hCRAN Link	Latent trait models under IRT (Item Response Theory).
xlsx	xlsx" \hCRAN Link	MXM	car	=car" \hCRAN Link	Companion to Applied Regression: extends regression diagnostics.
moments	ents" \hCRAN Link	projpred	polycor	ycor" \hCRAN Link	Polychoric and polyserial correlations.
corr	orrr" \hCRAN Link	ExhaustiveSearch	correlation	tion" \hCRAN Link	Explore correlations, partial correlations, and more.
dplyr	plyr" \hCRAN Link	mRMRe	corrplot	plot" \hCRAN Link	Visualize a correlation matrix using 'ggplot2'.
matrixStats	tats" \hCRAN Link	Bios2cor	ggstatsplot	plot" \hCRAN Link	Enhanced data visualization using 'ggplot2'.
mlbench	ench" \hCRAN Link	DescTools	lares	ares" \hCRAN Link	Analytics and machine learning workflow toolbox.
caret	aret" \hCRAN Link	Classification and Regression Training: tools for data splitting and pre-processing.	ForwardSearch	arch" \hCRAN Link	Forward search method for robust data analysis.

randomForest	rest" \hCRAN Link	Random Forest implementation for classification and regression.	party	arty" \hCRAN Link	Recursive partitioning for linear models, survival models, and more.
Hmisc	misc" \hCRAN Link	Contains functions for data analysis, high-level graphics, utility operations, and many more.	Boruta	ruta" \hCRAN Link	Feature selection with the Boruta algorithm.
MASS	MASS" \hCRAN Link	Modern Applied Statistics with S: functions and datasets to support Venables and Ripley's book.	ltm	=ltm" \hCRAN Link	Latent trait models under IRT (Item Response Theory).
rpart.plot	plot" \hCRAN Link	Plot 'rpart' models. An enhanced version of 'plot.rpart'.	car	=car" \hCRAN Link	Companion to Applied Regression: extends regression diagnostics.
faux	faux" \hCRAN Link	Simulated datasets for teaching and learning data analysis.	polycor	ycor" \hCRAN Link	Polychoric and polyserial correlations.
DataExplorer	orer" \hCRAN Link	Fast data exploration functions for understanding data.	correlation	tion" \hCRAN Link	Explore correlations, partial correlations, and more.
mlr	=mlr" \hCRAN Link	Machine Learning in R: Provides a unified interface for ML tasks like classification, regression, etc.	corrplot	plot" \hCRAN Link	Visualize a correlation matrix using 'ggplot2'.
glmnet	mnet" \hCRAN Link	Lasso and elastic-net regularized generalized linear models.	ggstatsplot	plot" \hCRAN Link	Enhanced data visualization using 'ggplot2'.
klaR	klaR" \hCRAN Link	Classification and visualization using R.	lares	ares" \hCRAN Link	Analytics and machine learning workflow toolbox.
e1071	1071" \hCRAN Link	Functions for latent class analysis, short time Fourier transform, and more.	ForwardSearch	arch" \hCRAN Link	Forward search method for robust data analysis.
dynwrap	wrap" \hCRAN Link	Wrap dynamical systems in R.	party	arty" \hCRAN Link	Recursive partitioning for linear models, survival models, and more.
FSelector	ctor" \hCRAN Link	Provides functions for feature selection with visualizations.	psych	sych" \hCRAN Link	Procedures for psychological, psychometric, and personality research.

rpart	part" \hCRAN Link	Recursive Partitioning for classification, regression, and survival trees.	cluster.datasets	sets" \hCRAN Link	Standard and simulated clustering datasets for cluster analysis and visualization.
FSinR	SinR" \hCRAN Link	Feature selection in R.	gbm	=gbm" \hCRAN Link	Generalized Boosted Regression Models.
MRMR	The mRMRe package is commonly used for Minimum Redundancy Maximum Relevance (MRMR) variable selection [3].		leaps	CRAN Link	Regression subset selection.
Boruta	The Boruta package provides the Boruta model for variable selection [12].		varrank	CRAN Link	An R package for variable ranking based on mutual information.
RFE	The caret package, particularly its rfe() function, can be used for Recursive Feature Elimination [13].		CRANsearcher	CRAN Link	Search CRAN R Packages using the 'crandb' API.
Chi-square as variable selection	The caret package can also be used for chi-squared (Chi-square) variable selection with its chisqFilter() function [14].		praznik	CRAN Link	Collection of tests and tools for feature selection.
RF	The randomForest package provides the Random Forest model for classification and regression tasks [15], [16].		devtools	CRAN Link	Tools to make developing R packages easier.
SVM	The e1071 package offers Support Vector Machine implementation in R [17].		Biocomb	CRAN Link	Bi-objective combinatorial optimization.
DT	The rpart package provides decision tree functionality using the rpart() function [18].		mitools	CRAN Link	Tools for multiple imputation in R.
Mean Decrease in Impurity	The "randomForest" package provides a method to calculate the Mean Decrease in Impurity (MDI) for assessing variable importance in Random Forest models [16].		infotheo	CRAN Link	Information-theoretic measures of entropy, mutual information, etc.
ggplot2	relaimpo		Boruta	CRAN Link	Feature selection with the Boruta algorithm.
ggcorrplot	InformationValue		ltm	CRAN Link	Latent trait models under IRT (Item Response Theory).
xlsx	CRAN Link	MXM	car	CRAN Link	Companion to Applied Regression: extends regression diagnostics.

moments	CRAN Link	projpred	polycor	CRAN Link	Polychoric and polyserial correlations.
corrr	CRAN Link	ExhaustiveSearch	correlation	CRAN Link	Explore correlations, partial correlations, and more.
dplyr	CRAN Link	mRMRe	corrplot	CRAN Link	Visualize a correlation matrix using 'ggplot2'.
matrixStats	CRAN Link	Bios2cor	ggstatsplot	CRAN Link	Enhanced data visualization using 'ggplot2'.
mlbench	CRAN Link	DescTools	lares	CRAN Link	Analytics and machine learning workflow toolbox.
caret	CRAN Link	Classification and Regression Training: tools for data splitting and pre-processing.	ForwardSearch	CRAN Link	Forward search method for robust data analysis.
randomForest	CRAN Link	Random Forest implementation for classification and regression.	party	CRAN Link	Recursive partitioning for linear models, survival models, and more.
Hmisc	CRAN Link	Contains functions for data analysis, high-level graphics, utility operations, and many more.	Boruta	CRAN Link	Feature selection with the Boruta algorithm.
MASS	CRAN Link	Modern Applied Statistics with S: functions and datasets to support Venables and Ripley's book.	ltm	CRAN Link	Latent trait models under IRT (Item Response Theory).
rpart.plot	CRAN Link	Plot 'rpart' models. An enhanced version of 'plot.rpart'.	car	CRAN Link	Companion to Applied Regression: extends regression diagnostics.
faux	CRAN Link	Simulated datasets for teaching and learning data analysis.	polycor	CRAN Link	Polychoric and polyserial correlations.
DataExplorer	CRAN Link	Fast data exploration functions for understanding data.	correlation	CRAN Link	Explore correlations, partial correlations, and more.
mlr	CRAN Link	Machine Learning in R: Provides a unified interface for ML tasks like classification, regression, etc.	corrplot	CRAN Link	Visualize a correlation matrix using 'ggplot2'.

glmnet	CRAN Link	Lasso and elastic-net regularized generalized linear models.	ggstatsplot	CRAN Link	Enhanced data visualization using 'ggplot2'.
klaR	CRAN Link	Classification and visualization using R.	lares	CRAN Link	Analytics and machine learning workflow toolbox.
e1071	CRAN Link	Functions for latent class analysis, short time Fourier transform, and more.	ForwardSearch	CRAN Link	Forward search method for robust data analysis.
dynwrap	CRAN Link	Wrap dynamical systems in R.	party	CRAN Link	Recursive partitioning for linear models, survival models, and more.
FSelector	CRAN Link	Provides functions for feature selection with visualizations.	psych	CRAN Link	Procedures for psychological, psychometric, and personality research.
rpart	CRAN Link	Recursive Partitioning for classification, regression, and survival trees.	cluster.datasets	CRAN Link	Standard and simulated clustering datasets for cluster analysis and visualization.
FSinR	CRAN Link	Feature selection in R.	gbm	CRAN Link	Generalized Boosted Regression Models.
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Boruta	The Boruta package provides the Boruta model for variable selection [12].		varrank	hCRAN Link	An R package for variable ranking based on mutual information.
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Chi-square as variable selection	The caret package can also be used for chi-squared (Chi-square) variable selection with its chisqFilter() function [14].		praznik	\hCRAN Link	Collection of tests and tools for feature selection.
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SVM	The e1071 package offers Support Vector Machine implementation in R [17].		Biocomb	mb" \hCRAN Link	Bi-objective combinatorial optimization.

DT	The rpart package provides decision tree functionality using the rpart() function [18].		mitools	ols" \hCRAN Link	Tools for multiple imputation in R.	
Mean Decrease in Impurity	The "randomForest" package provides a method to calculate the Mean Decrease in Impurity (MDI) for assessing variable importance in Random Forest models [16].		infotheo	theo" \hCRAN Link	Information-theoretic measures of entropy, mutual information, etc.	
ggplot2	relaimpo		Boruta	ruta" \hCRAN Link	Feature selection with the Boruta algorithm.	
ggcorrplot	InformationValue		ltm	=ltm" \hCRAN Link	Latent trait models under IRT (Item Response Theory).	
xlsx	MRMR	The mRMRe package is commonly used for Minimum Redundancy Maximum Relevance (MRMR) variable selection [3].	leaps		CRAN Link	Regression subset selection.
Boruta	The Boruta package provides the Boruta model for variable selection [12].		varrank	hCRAN Link	An R package for variable ranking based on mutual information.	
RFE	The caret package, particularly its rfe() function, can be used for Recursive Feature Elimination [13].		CRANsearcher	\hCRAN Link	Search CRAN R Packages using the 'crandb' API.	
Chi-square as variable selection	The caret package can also be used for chi-squared (Chi-square) variable selection with its chisqFilter() function [14].		praznik	\hCRAN Link	Collection of tests and tools for feature selection.	
RF	The randomForest package provides the Random Forest model for classification and regression tasks [15], [16].		devtools	S" \hCRAN Link	Tools to make developing R packages easier.	
SVM	The e1071 package offers Support Vector Machine implementation in R [17].		Biocomb	mb" \hCRAN Link	Bi-objective combinatorial optimization.	
DT	The rpart package provides decision tree functionality using the rpart() function [18].		mitools	ols" \hCRAN Link	Tools for multiple imputation in R.	
Mean Decrease in Impurity	The "randomForest" package provides a method to calculate the Mean Decrease in Impurity (MDI) for assessing variable importance in Random Forest models [16].		infotheo	theo" \hCRAN Link	Information-theoretic measures of entropy, mutual information, etc.	
ggplot2	relaimpo		Boruta	ruta" \hCRAN Link	Feature selection with the Boruta algorithm.	

FSinR	SinR \hCRAN Link	Feature selection in R.	gbm	=gbm \hCRAN Link	Generalized Boosted Regression Models.
MRMR	The mRMRe package is commonly used for Minimum Redundancy Maximum Relevance (MRMR) variable selection [3].		leaps	CRAN Link	Regression subset selection.
Boruta	The Boruta package provides the Boruta model for variable selection [12].		varrank	hCRAN Link	An R package for variable ranking based on mutual information.
RFE	The caret package, particularly its rfe() function, can be used for Recursive Feature Elimination [13].		CRANsearcher	\hCRAN Link	Search CRAN R Packages using the 'crandb' API.
Chi-square as variable selection	The caret package can also be used for chi-squared (Chi-square) variable selection with its chisqFilter() function [14].		praznik	\hCRAN Link	Collection of tests and tools for feature selection.
RF	The randomForest package provides the Random Forest model for classification and regression tasks [15], [16].		devtools	S \hCRAN Link	Tools to make developing R packages easier.
SVM	The e1071 package offers Support Vector Machine implementation in R [17].		Biocomb	mb \hCRAN Link	Bi-objective combinatorial optimization.
DT	The rpart package provides decision tree functionality using the rpart() function [18].		mitools	ols \hCRAN Link	Tools for multiple imputation in R.
Mean Decrease in Impurity	The "randomForest" package provides a method to calculate the Mean Decrease in Impurity (MDI) for assessing variable importance in Random Forest models [16].		infotheo	theo \hCRAN Link	Information-theoretic measures of entropy, mutual information, etc.
ggplot2	relaimpo		Boruta	ruta \hCRAN Link	Feature selection with the Boruta algorithm.
ggcorrplot	InformationValue		ltm	=ltm \hCRAN Link	Latent trait models under IRT (Item Response Theory).

S.17. Files and survey

File of For4.csv is just cleaned version of Students6.csv while we deleted the records which didn't responded to the I4 response.

- Multiple correlations of students: [Link](#)
- Multiple correlations of instructors: [Link](#)
- Correlations for both instructor and student groups: [Link](#)
- Instructors' data file for R (CSV format): [Link](#)
- Students' data file for R (CSV format): [Link](#)
- Students' data file for R for I4 response variable (CSV format): [Link](#)
- R codes with ML: [Link](#)
- R codes for Variable selection [Link](#)
- Excel of full ML results [Link](#)

Table S21. Survey of students and instructors (translated from Farsi (Persian) to English)

	Code	Question of students	Subscale
1	A1	Implementing important actions and practical experiments for engineers is possible in an online learning environment.	Theory and practice
2	A2	The university should shift its focus from theory to dedicated practical applications.	
3	A3	Online learning assists me in connecting theory and application effectively.	
4	A4	Instructional videos of experiments, research articles, and empirical data provided for analysis and interpretation can be a good substitute for practical actions in the online learning environment.	
5	B1	Online learning has transformed my role as a student in class, making me more engaged and active rather than just a passive receiver of knowledge.	Motivation
6	B2	My motivation for education/studying/participating in online learning environments is lower compared to traditional in-person classes.	
7	B3	Online education increases my independence and flexibility in learning, allowing me greater control over my learning process.	
8	B4	In an online learning environment, a student can track their progress effectively.	
9	C1	I believe technology-based learning is effective in providing practical skills.	Knowledge, Insight, and Skill
10	C2	I believe technology-based learning is effective in providing soft skills.	
11	C3	I prefer working independently and focusing on individual activities in the online learning environment.	
12	C4	Online learning is suitable for learning any type of skill, whether practical or Theoretical.	
13	C5	In the online learning environment, emphasis should be placed on teaching problem-solving skills relevant to real-life situations.	
14	C6	In my opinion, students acquire knowledge, insight, and skills better in their field through collaborative online learning.	
15	C7	Engaging in group activities and projects in the online learning environment is easier than in traditional in-person classes.	
16	C8	The online learning environment helps students acquire problem-solving skills transferable to various contexts and platforms.	
17	C9	I understand the difference between a virtual lab and a remote lab.	
18	C10	I think using online methods based on virtual labs for learning hard skills is suitable.	
19	C11	I think using online methods based on remote labs for learning hard skills is suitable.	
20	C12	I think using online methods based on virtual labs for learning soft skills is suitable.	
21	C13	I believe the essential skills for successful participation in online courses, such as time management and effective communication (individual and content-based), are necessary.	
22	D1	I believe universities should provide more opportunities for students to engage in projects in industrial environments.	Working-life orientation
23	D2	I am satisfied with the university's support (technical, mental, attitudinal, etc.) in preparing students for the job market.	
24	D3	I believe tasks and activities in technology-based courses should, to the extent possible, be based on real workplace issues.	
25	D4	I believe technology-based learning should focus more on teaching problem-solving skills relevant to real-life situations.	
26	E1	The average level of proficiency of our professors in using technology-based learning is appropriate.	Pedagogy

27	E2	The teaching methods and strategies used by professors in online classes lead to better and deeper learning.	
28	E3	Professors in online classes clearly communicate learning objectives, expectations, participation rules, teaching methods, activities, and assessment methods from the beginning of the course.	
29	E4	Assessment in the online learning environment is reliable.	
30	E5	Active learning methods are more effectively implemented in the online learning environment.	
31	E6	The content and resources in online courses are of high quality and contribute to better and deeper learning.	
32	E7	Professors provide timely and comprehensive feedback in the online learning environment.	
33	E8	Which of the following activities do your professors use more in the online learning environment?	
34	E9	In your opinion, which of the following activities is more effective for implementation in the online learning environment?	
35	F1	Have you experienced using a Learning Management System (LMS)?	Quality of assessment and ICT
36	F2	I regularly follow the course through the Learning Management System (LMS).	
37	F3	I regularly attend live sessions of the course through the Learning Management System (LMS).	
38	F4	The audio and visual quality of live (synchronous) online learning sessions is at a high level (independent of internet speed and bandwidth).	
39	F5	Overall, working with the Learning Management System is easy and user-friendly.	
40	G1	Professors are knowledgeable about appropriate student assessment methods in the online learning environment.	
41	G2	Professors use various innovative methods (projects, oral questions, peer assessment, e-portfolios, etc.) for assessment in the online learning environment.	
42	G3	In my opinion, when professors conduct assessments periodically throughout the term, not just once at the end, learning is enhanced.	
43	G4	In my opinion, providing timely feedback on the learning process, activities, assignments, and exams by professors improves learning.	
44	G5	Professors use modern technologies like simulations in the online environment.	
45	G6	The use of modern elements and technologies in the online learning environment has increased my motivation and excitement for learning.	Response variables
46	G7	Assigned activities by professors in the online environment, compared to traditional classes, are more effective in enhancing the depth of learning.	
47	G8	Online learning boosts my motivation to actively participate in class.	
48	I2	I feel satisfied using technology-based learning in Theoretical classes.	
49	I4	I am satisfied using technology-based learning in practical classes (labs, workshops).	Subscale
50	I6	I feel satisfied using technology-based learning in Theoretical-practical classes.	
	Question Code	Question of instructors	
1	A1	I emphasize Theoretical training more than practical application in teaching.	Theory and practice
2	A2	In my opinion, technology-enhanced learning is more successful in integrating Theoretical and practical education compared to traditional classes.	
3	A3	I feel comfortable with practical teaching in an online environment.	
4	A4	Please state your reason for this choice.	
5	A5	I believe having support from instructional assistants in the online environment is beneficial.	
6	B1	Online learning changes the role of an instructor. I am no longer just a knowledge transmitter but also guide and facilitate the learning process for students.	Motivation
7	B2	My aim is to encourage students to have a more active role in the learning process.	
8	B3	At the beginning of an online course, I assess students' short-term and long-term goals and expectations.	
9	B4	I use various elements of the ARCS model to motivate students for better learning in the online environment.	
10	B5	I think students can manage their learning process better when using technology-enhanced learning.	
11	B6	I am interested in using technology-enhanced learning more in my teaching.	
12	B7	University administrators encourage instructors to use online teaching methods.	

13	C1	I believe technology-based learning is effective in providing efficient training in complex skills.	Knowledge, Insight, and Skills
14	C2	I believe technology-based learning is effective in providing efficient training in soft skills.	
15	C12	Online learning is suitable for teaching any type of skill, whether practical or Theoretical.	
16	C13	I believe instructional videos, simulation tools, and virtual or remote labs can assist engineering students in learning essential skills.	
17	D1	Tailoring online education to individual students' interests and abilities is challenging.	Working-life orientation
18	D2	Technology-enhanced learning brings more flexibility to my teaching.	
19	D3	I think our university curriculum needs revision to align more with online learning.	
20	E1	Technology-enhanced learning has increased my motivation to focus teaching on student-centered approaches.	Pedagogy
21	E2	Technology-enhanced learning has led me to use a variety of assessment methods.	
22	E3	In the online learning environment, there is no need to strictly adhere to pedagogical principles in teaching.	
23	E5	I am satisfied with the technical support provided by the university in online education.	
24	E6	Active learning is more effectively implemented in the online learning environment.	
25	E7	Providing timely feedback to students in online education is challenging.	
26	E8	I am more familiar with traditional teaching methods and struggle to adapt to online teaching methods.	
27	E9	I believe technology-enhanced learning does not require specific content and can utilize traditional class content for online teaching.	
28	E10	The university has specific programs to support instructors in enhancing their competencies through new teaching and assessment methods in the online environment.	
29	E11	The university organizes short-term workshops or training sessions to enhance instructors' skills in designing technology-based courses.	
30	E12	More preparation is needed for conducting online classes at the university.	
31	E13	I share my opinions with my colleagues regarding research activities.	
32	E14	I share my opinions with my colleagues regarding teaching activities.	
33	E15	I think evaluation processes need to be reviewed to be compatible with online learning.	
34	E16	In your opinion, which traditional assessment tool(s) can be used in online education?	
35	E17	What support tools and methods have you referred to while implementing technology-enhanced teaching? (Yes/No)	
36	E18	What approach have you used in conducting your online classes?	
37	E19	In your opinion, which approach is more effective for online learning?	
38	E20	Which Learning Management System (LMS) do you actively use and support?	Quality of assessment and ICT
39	G1	All instructors should receive training in using online learning management systems.	
40	G2	Online learning management systems are user-friendly.	
41	G3	Have you experienced using virtual labs in your teaching?	
42	G4	I believe virtual labs provide a similar interactive experience to practical classes in engineering and STEM courses.	
43	G5	Have you experienced using remote labs in your teaching?	
44	F10	Overall, I am satisfied with working with LMS.	
45	F5	In my opinion, assessing students periodically during the term, not just at the end, leads to better learning.	Response variables
46	F11	I know how to monitor students' activities using the LMS automated reporting tool.	
47	H2	I feel satisfied using technology-enhanced learning in Theoretical courses.	
48	H4	I feel satisfied using technology-enhanced learning in practical courses.	
49	H6	I feel satisfied using technology-enhanced learning in Theoretical-practical courses.	

S.18. Reliability

Table S22. Alpha Cronbach of instructors and students

Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items	Cronbach's Alpha	Cronbach's Alpha Based on Standardized Items	N of Items
.767	.766	29	.598	.596	25

S.19. F1, Recall, Precision

Table S22. F1, recall, precision for 5-scale Likert

		Class	F1-Score	Precision	Recall
RF	I2	SD	0.533333	0.363636	1
		D	0.545455	0.652174	0.46875
		N	0.0625	0.0625	0.0625
		A	0.48	0.48	0.48
		SA	0.529412	0.519231	0.54
	I4	SD	0.451613	0.516129	0.4
		D	0.705882	0.764706	0.65517
		N	0.098039	0.1	0.09677
		A	0.527273	0.529412	0.525
		SA	0	0	0
	I6	SD	0.5	0.307692	1
		D	0.586207	0.666667	0.52564
		N	0.152542	0.130435	0.18421
		A	0.25	0.2	0.33333
		SA	0	0	0
	H2	SD	0	0	0
		D	0	0	0
		N	0.333333	0.333333	0.33333
		A	0.46875	0.464286	0.47368
		SA	0.5	0.5	0.5
	H4	SD	0	0	0
		D	0.210526	0.166667	0.28571
		N	0.521739	0.611111	0.45455
		A	0.47619	0.464286	0.48889
		SA	0	0	0
	H6	SD	0	0	0
		D	0.380952	0.357143	0.40741
		N	0.6	0.6	0.6
		A	0.666667	0.6	0.75
		SA	0	0	0
DT	I2	SD	0.571429	0.363636	1
		D	0.457143	0.647059	0.35

		N	0.137931	0.15	0.12821
		A	0.434783	0.423077	0.44737
		SA	0.576923	0.525	0.64
	I4	SD	0.315789	0.333333	0.3
		D	0.692308	0.692308	0.69231
		N	0.133333	0.142857	0.125
		A	0.543478	0.52381	0.56522
		SA	0.444444	0.444444	0.44444
	I6	SD	0.576471	0.486486	0.7
		D	0.5625	0.578947	0.54717
		N	0.18	0.166667	0.19608
		A	0.392857	0.35	0.45
		SA	0.117647	0.090909	0.16667
	H2	SD	0	0	0
		D	0	0	0
		N	0.222222	0.2	0.25
		A	0.547619	0.518519	0.57955
		SA	0.4	0.571429	0.30769
	H4	SD	0	0	0
		D	0.133333	0.111111	0.16667
		N	0.47619	0.454545	0.5
		A	0.409091	0.4	0.4186
		SA	0	0	0
	H6	SD	0	0	0
		D	0.272727	0.25	0.3
		N	0.333333	0.375	0.3
		A	0.47619	0.47619	0.47619
		SA	0	0	0
SVM	I2	SD	0.5	0.25	1
		D	0.410256	0.615385	0.30769
		N	0.2	0.230769	0.18182
		A	0.459459	0.533333	0.4
		SA	0.653061	0.551724	0.8
	I4	SD	0.5	0.25	1
		D	0.564103	0.578947	0.55
		N	0.285714	0.25	0.33333
		A	0.514286	0.5	0.52941
		SA	0.277778	0.25	0.3125
	I6	SD	0.565217	0.52	0.62069
		D	0.588235	0.606061	0.571429
		N	0.235294	0.2	0.285714

		A	0.409091	0.372549	0.45
		SA	0.117647	0.090909	0.166667
	H2	SD	0	0	0
		D	0.285714	0.222222	0.4
		N	0.266667	0.285714	0.25
		A	0.609756	0.628571	0.59259
		SA	0.25	0.25	0.25
	H4	SD	0	0	0
		D	0.307692	0.230769	0.45455
		N	0.2	0.3	0.15
		A	0.477273	0.5	0.45652
		SA	0	0	0
	H6	SD	0	0	0
		D	0.307692	0.285714	0.33333
		N	0.275862	0.333333	0.23529
		A	0.52381	0.5	0.55
		SA	0	0	0

Table S23. F1, recall, precision for 3-scale Likert

ML model	Groups	Class	F1-Score	Precision	Recall
RF	I2	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	I4	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	I6	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	H2	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	H4	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	H6	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
DT	I2	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825

	I4	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	I6	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	H2	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	H4	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	H6	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
SVM	I2	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	I4	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	I6	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	H2	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	H4	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825
	H6	D	0.657143	0.676471	0.638889
		N	0.068966	0.0625	0.076923
		A	0.809756	0.813725	0.805825

Table S24. F1, recall, precision for 5-scale Likert sampling by ROSE

Model	Target	Class	Precision	Recall	F1-Score
Random Forest	I2	SD	0.67	0.25	0.36
	I2	D	0.57	0.36	0.44

	I2	N	0	0	0
	I2	A	0.5	0.03	0.06
	I2	SA	0.31	0.95	0.47
Decision Tree	I2	SD	0.3	0.38	0.33
	I2	D	0.28	0.45	0.34
	I2	N	0.25	0.33	0.29
	I2	A	0.8	0.27	0.4
	I2	SA	0.37	0.52	0.43
	I2	SD	1	0.25	0.4
SVM	I2	D	0.3	0.27	0.29
	I2	N	0	0	0
	I2	A	0.5	0.07	0.12
	I2	SA	0.32	0.9	0.47
	I2	SD	0	0	0
Random Forest	I4	SD	0.75	0.98	0.85
	I4	D	0.28	0.45	0.34
	I4	A	0.25	0.33	0.29
	I4	SA	0.8	0.27	0.4
	I4	SD	0.37	0.52	0.43
Decision Tree	I4	D	0.79	0.79	0.79
	I4	N	0	0	0
	I4	A	0.12	0.2	0.15
	I4	SA	0.33	0.5	0.4
	I4	SD	0	0	0
SVM	I4	D	0.74	0.88	0.8
	I4	N	0.8	0.33	0.47
	I4	A	0.5	0.5	0.5
	I4	SA	0.38	0.44	0.41
	I4	SD	1	0.17	0.29
Random Forest	I6	D	0.53	1	0.69
	I6	N	0.75	0.27	0.4
	I6	A	0.8	0.33	0.47
	I6	SA	0.5	0.5	0.5
Decision Tree	I6	SD	0.38	0.44	0.41
	I6	D	0.48	0.45	0.47
	I6	N	0.45	0.45	0.45
	I6	A	0.4	0.17	0.24
	I6	SA	0.12	0.5	0.2
SVM	I6	SD	0.67	0.11	0.19
	I6	D	0.46	0.97	0.62
	I6	N	0	0	0

	I6	A	0.67	0.17	0.27
	I6	SA	0.48	0.45	0.47
Random Forest	H2	SD	0.45	0.45	0.45
	H2	D	0.4	0.17	0.24
	H2	N	0.67	0.95	0.78
	H2	A	0.18	0.24	0.21
	H2	SA	0.18	0.15	0.17
	H2	SD	0.25	0.25	0.25
Decision Tree	H2	D	0.4	0.17	0.24
	H2	N	0.7	0.84	0.76
	H2	A	0.5	0.33	0.4
	H2	SA	0.48	0.45	0.47
	H2	SD	0.45	0.45	0.45
SVM	H2	D	0.4	0.17	0.24
	H2	N	0.67	0.95	0.78
	H2	A	0	0	0
	H2	SA	0	0	0
	H2	SD	0.45	0.45	0.45
Random Forest	H4	SD	0	0	0
	H4	D	0	0	0
	H4	N	0.42	0.77	0.54
	H4	A	0	0	0
	H4	SA	0	0	0
Decision Tree	H4	SD	0	0	0
	H4	D	0.14	0.12	0.13
	H4	N	0.36	0.38	0.37
	H4	A	0	0	0
	H4	SA	0.28	0.45	0.34
SVM	H4	SD	0.25	0.33	0.29
	H4	D	0	0	0
	H4	N	0.46	1	0.63
	H4	A	0	0	0
	H4	SA	0	0	0
Random Forest	H6	SD	0	0	0
	H6	D	0	0	0
	H6	N	0.48	0.8	0.6
	H6	A	0	0	0
	H6	SA	0	0	0
Decision Tree	H6	SD	0	0	0
	H6	D	0	0	0
	H6	N	0.44	0.53	0.48
	H6	A	0.25	0.5	0.33

	H6	SA	0	0	0
SVM	H6	SD	0	0	0
	H6	D	0	0	0
	H6	N	0.54	1	0.7
	H6	A	0	0	0
	H6	SA	0	0	0

S.20. References

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