



Examining Post-Pandemic Higher Education Systems: Predicting Students' Interests in Hybrid Learning Using Deep Neural Network

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Abstract. The advancement of technology has had a significant impact on the learning systems. That has resulted in the rise of hybrid learning, a learning system that combines face-to-face and online elements, following the decrease of the COVID-19 pandemic. In its implementation, hybrid learning requires effective technology integration to support the teaching and learning process. Successful implementation of hybrid learning depends on infrastructure, technology, and student acceptance. Therefore, this study uses the deep neural network (DNN) method and variable importance analysis to analyze students' interest in hybrid learning and identify significant predictors. Through the questionnaires, we evaluated a range of indicators encompassing social influence, perceived interactivity, perceived usefulness, ease of use, facility conditions, attitude, satisfaction, and user intention. The results of DNN analysis with various model variations showed that the highest accuracy achieved was 82.40%. Moreover, the results of variable importance analysis highlighted the role of satisfaction, which has a significant influence in shaping the variability of model output. This research provides insights to enhance the learning experience in industrial engineering through effective hybrid learning strategies.

Keywords: Higher Education, Hybrid Learning, Pandemic, Deep Neural Network, Variable Importance.

1 Introduction

Education has a pivotal role in the lives of students and other academics [1]. Technological developments significantly impact learning in educational institutions, intricately linked with the world of education. Technological advancements in the educational system that began to develop widely during the COVID-19 pandemic require academics to utilize technology effectively to support teaching and learning activities

[2]. One recent post-pandemic learning innovation was hybrid learning. Hybrid learning is a system that combines online and offline elements simultaneously and harmoniously to create a more effective and efficient learning experience [3][4].

However, the successful implementation of hybrid learning depends not only on the availability of infrastructure and technology but also on students' interest and acceptance of this learning system [4]. Therefore, understanding the factors influencing students' interests in hybrid learning becomes crucial. In this endeavor, the deep neural network (DNN) method has emerged as a powerful tool for predicting students' interests. DNN is a type of artificial neural network consisting of many layers of neurons and hidden layers that can recognize complex patterns in data and make accurate predictions [5].

Numerous studies have performed to predict students' interests in learning systems implemented using deep learning [6][7]. One study applied deep learning to predict students' interests in mobile learning during the pandemic [6]. Another study explored the potential of deep learning in predicting students' intentions to use the Metaverse in the learning process [7]. Several implemented studies have demonstrated deep learning's transformative ability to understand students' perceptions.

This research aims to apply the DNN method in predicting students' interests in hybrid learning. Through DNN analysis, this research provides deep insights into students' preferences for a hybrid learning system that combines face-to-face and online learning. Additionally, this research can enhance the effectiveness of hybrid learning by identifying students' behavioral patterns that influence their interest in this learning system. Armed with this valuable information, educational institutions can develop adaptive and responsive strategies to enhance the student learning experience.

We have organized this paper into several sections. Section 2 discusses the research method, which includes the variables affecting student interest, the questionnaire, and the research respondents. In Section 3, we have explored and analyzed the research results, followed by a thorough discussion of the findings and their implications in hybrid learning. Finally, Section 4 concludes this study by reflecting on the highlights of the research findings and providing valuable suggestions for further research.

2 Research Method

2.1 Research Design

The methodology for this research comprises several stages. Firstly, we conducted a comprehensive literature review on hybrid learning. Subsequently, we designed a questionnaire based on expert opinions and distributed it to the respondents. Finally, the collected data were processed and analyzed using the DNN method to identify the most significant predictors related to hybrid learning based on respondents' perceptions.

2.2 Questionnaire

The instrument used in this research was a 22-question questionnaire related to hybrid learning. The questionnaire represented several variables examined in this study, including social influence, perceived interactivity, perceived usefulness, perceived ease of use, facility conditions, attitude, satisfaction, and user intention as the target variable. Each variable has three indicators used as a basis for assessment. We rated each indicator using a scale of 1 to 5, reflecting a range of strongly disagree, disagree, neutral, agree, and strongly agree. In addition, we also categorized the assessment of the target variable into two categories reflecting the agreeing and disagreeing views towards hybrid learning. The indicators that were used in this study are shown in Table 1.

Table 1. Indicators used for the questionnaire

Variable	Item	Indicator	Possible values	References
Perceived ease of use	PEOU	I found it easy to attend lectures in a hybrid learning environment.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	[8][9]
		It was easy for me to navigate the lecture platform in a hybrid learning setup, which involved using tools like Zoom, Google Meet, and an LMS application.		
Perceived usefulness	PU	I feel that the material presented in the hybrid learning lectures is clear and easy to understand.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	[8][10]
		The availability of hybrid classes enables me to manage my daily activities more effectively and efficiently.		
Facility conditions	FC	The existence of hybrid classes helps me prioritize my activities effectively.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	[11]
		Hybrid learning can be accessed from anywhere, as long as there is an internet connection in the area.		
		I have the necessary equipment and facilities to participate in hybrid learning lectures.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	
		I possess the required knowledge to effectively utilize the course platform in a hybrid learning setting.		

Variable	Item	Indicator	Possible values	References
		My institution provides facilities that support hybrid learning in every classroom.		
Social influence	SI	I would be delighted to participate in hybrid classes if my institution implements it. My parents and family have provided the necessary equipment/facilities for me to attend lectures in a hybrid learning environment. My classmates can assist me if any issues arise while attending hybrid learning sessions.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	[12][10]
Perceived interactivity	PI	Generally, I find the atmosphere during hybrid learning classes to be quite interactive. I was able to engage in discussions with other students smoothly and without any issues during the hybrid class. During hybrid classes, the lecturer was able to address my questions without any problems.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	[13]
Satisfaction	SA	I am relatively satisfied with the hybrid learning platform I use. I had a relatively positive experience attending lectures in a hybrid learning environment. Opting for hybrid learning in the post-COVID-19 era seems like a wise decision.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	[14]
Attitude	AT	The availability of hybrid learning in the post-COVID-19 era has piqued my interest in trying or participating in it. I find the atmosphere of a class that utilizes hybrid learning quite pleasant. I still feel creatively stimulated when I participate in hybrid learning classes.	1: Strongly disagree 2: Disagree 3: Neutral 4: Agree 5: Strongly agree	[15]
User intention	UI	While participating in hybrid learning, I acquired new	1: Agree 2: Disagree	[11][12]

Variable	Item	Indicator	Possible values	References
(target variable)		knowledge related to technology. For instance, I learned how to use various features on Zoom, such as breakout rooms, reactions, whiteboard, and direct messaging.		

2.3 Deep Neural Network

The questionnaire results from respondents were processed using the deep neural network (DNN) method. DNN is a deep learning model designed to learn complex patterns and data relationships [16][17]. It consists of several layers of interconnected nodes that process input data and produce prediction results [5]. By employing the DNN method, we can process the questionnaire data comprehensively and deeply, enabling a profound exploration of how students assess hybrid learning.

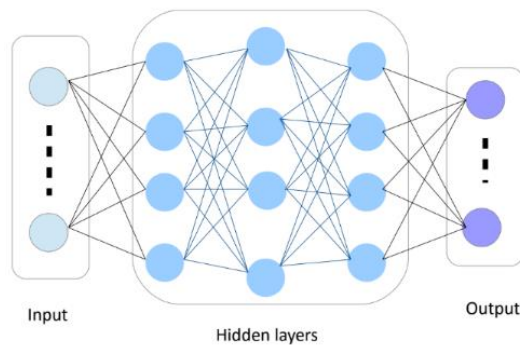


Fig. 1. DNN model architecture

Source: [18]

In utilizing a deep neural network (DNN), the input data is initially introduced to the first layer, describing the initial features. Afterward, the data passes through a series of concealed layers, each housing increasingly sophisticated neurons that extract abstract features more effectively. These layers interconnect via connection weights, which are adjusted during training by comparing predicted outcomes with actual values. Ultimately, the data culminates in the output layer, yielding the ultimate result or prediction. Each layer in the DNN plays a unique role in processing and transforming the data's representation, aiding in acquiring knowledge and comprehending intricate patterns.

3 Results and Analysis

3.1 Data summary

Respondents in this study were active students of the Industrial Engineering Study Program at the Kalimantan Institute of Technology (ITK) who participated in hybrid learning. ITK is a public institute in Balikpapan City, Indonesia, with a strong focus on technology to support the industrial world through various study programs. We distributed questionnaires related to hybrid learning to a total of 195 respondents. Among them, 69 students (35%) were in the 4th year or above, 56 students (29%) were in the 3rd year, and 70 students (36%) were in the 2nd year. Regarding gender, there were 94 male students (48%) and 101 female students (52%) as shown in Table 2.

Table 2. Demographic statistics

Criteria	Factor	Frequency	Percentage
Gender	Male	94	48%
	Female	101	52%
Year	4th and above	69	35%
	3rd	56	29%
	2nd	70	36%

3.2 Prediction results

The data collected via the distribution of questionnaires played a central role as input for the DNN method. Our approach included partitioning the data set employed for DNN input, allocating 70% for training and the remaining 30% for testing [16]. This split aimed to prevent overfitting of the training data [19]. Table 3 shows the results of applying the DNN method with user intention as the target variable.

Table 3. DNN results

Input	Hidden layer	Dropout layer	Node architecture	Accuracy
SI-related indicators: SI1, SI2, & SI3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
FC-related indicators: FC1, FC2, & FC3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
PI-related indicators: PI1, PI2, & PI3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321

Input	Hidden layer	Dropout layer	Node architecture	Accuracy
PEOU-related indicators: PEOU1, PEOU2, & PEOU3	3	0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
			10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
PU-related indicators: PU1, PU2, & PU3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
			10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
AT-related indicators: AT1, AT2, & AT3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
			10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
SA-related indicators: SA1, SA2, & SA3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
			10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
Attitude-related indicators: SII-3, PU1-3, & PII-3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
			10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
Satisfaction-related indicators: FC1-3 & PEOU1-3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
			10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
User intention-related indicators: AT1-3 & SA1-3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
			10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
Attitude and satisfaction-related indicators: SII-3, PU1-3, PII-3, PEOU1-3, & FC1-3	3	0,2	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
		0,5	10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
			10-10-5	0,7321
			20-10-5	0,7321
			15-10-5	0,7321
All variables	3	0,2	10-10-5	0,8235
			20-10-5	0,8235
			15-10-5	0,8235

Input	Hidden layer	Dropout layer	Node architecture	Accuracy
		0,5	10-10-5	0,8235
			20-10-5	0,8235
			15-10-5	0,8235

Table 3 shows the highest accuracy value, achieved by incorporating all variables as input, was 82.35%. Among the various DNN model settings employed, the majority exhibited an accuracy of 73.21%. This occurrence arises from the model’s constrained capacity to identify intricate patterns within the provided data variations, exacerbated by the absence of notable distinctions among the features across different inputs. Moreover, the size of the training data set and the chosen hyperparameter configurations might also influence the outcomes. Additionally, there’s the possibility that the model has converged to the same local minimum in most settings, underscoring the necessity for further exploration of architecture and hyperparameter variations to yield a more accurate representation of the underlying patterns within the data. Figure 2 presents an overview of one of the utilized DNN models.

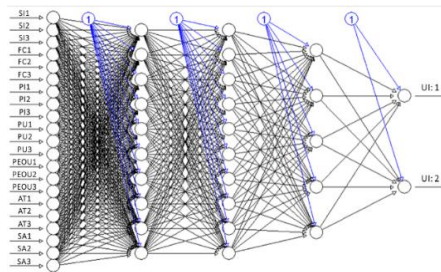


Fig. 2. DNN model with all indicators as inputs

Figure 2 illustrated the employed DNN model for predicting student interest in hybrid learning. The model indicates a dichotomy within the data categories. The first category reflects respondents’ agreement with hybrid learning implementation, while the second category represents respondents’ disagreement. The DNN prediction results align with this classification, indicating the majority of respondents expressed interest in hybrid learning, with an impressive 82.40% accuracy.

3.3 Variable importance analysis

In this study, we examined the importance of variables to uncover the fundamental factors that have the most significant influence in predicting model results by considering their importance values. The importance value is a measure that indicates the extent to which a variable affects the performance or outcome of an analysis or prediction model [20]. The importance value was obtained by analyzing how much small changes in input variables affect the output based on gradient calculations through backpropagation. The analysis of variable importance plays a vital role in comprehending the

intricacies of predictive modeling, offering a deeper insight into how each variable contributes proportionally to the overall model performance [21][22]. By analyzing the importance of the variables, the model can identify the most significant factors in predicting model results, as shown in Figure 3.

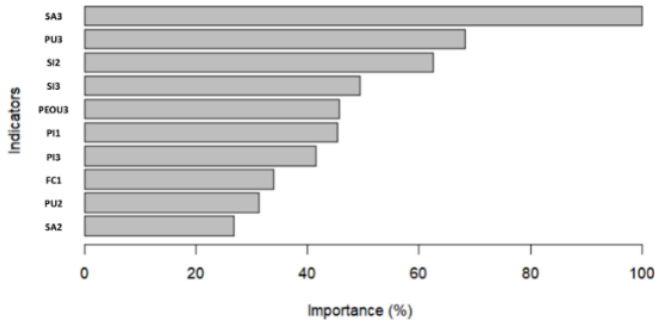


Fig. 3. Variable importance for top ten indicators

The results of the variable importance analysis reveal an intriguing finding concerning the model's most significant predictor. Variable satisfaction obtained a significantly higher importance score than the other variables. This study highlights the pivotal role of satisfaction level in shaping the model's output variability. Moreover, this variable strongly influenced the model's predictions, highlighting the importance of careful consideration when devising strategies or policies based on these predictions.

4 Conclusion

The results of this study indicate that the utilization of the DNN has assisted in predicting the interest level of industrial engineering students at ITK concerning the previously implemented hybrid learning approach. Among several employed DNN models, the highest accuracy rate reached 82.40%. Satisfaction variables have a significant effect on supporting students' preference for hybrid learning. This research offers valuable insights to develop more effective and relevant learning approaches in the future for industrial engineering students. Thus, hybrid learning might be an attractive option and enhance students' learning experience in industrial engineering.

However, we suggest integrating the DNN method with structural equation modeling (SEM) in future research. Through this integration, the study can delve deeper into significant factors. SEM's application can aid in identifying causal relationships among relevant variables and validating the employed model. Therefore, future research could offer a more comprehensive comprehension of the factors affecting students' interests in hybrid learning, thereby aiding the enhancement of more effective learning strategies and approaches.

5 Authors' contributions

Alvin Muhammad 'Ainul Yaqin: Conceptualization, Methodology, Validation, Investigation, Resources, Writing – original draft preparation, Writing – review and editing, Supervision, Project administration, Funding acquisition. **Ahmad Kamil Muqoffi:** Methodology, Software, Formal analysis, Investigation, Data curation, Writing – original draft preparation, Visualization. **Sigit Rahmat Rizalmi:** Validation, Writing – review and editing, Supervision, Project administration, Funding acquisition. **Faishal Arham Pratikno:** Validation, Project administration, Funding acquisition. **Alvin Muhammad 'Ainul Yaqin** and **Ahmad Kamil Muqoffi** are equal contributors to this work and designated as co-first authors.

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