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Machine learning prediction of video-based learning with technology acceptance model

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ABSTRACT

COVID-19 outbreak has significant impacts on education system as almost all countries shift to new way of teaching and learning; online learning. In this new environment, various innovative teaching methods have been created to deliver educational material in ensuring the learning outcomes such as video content. Thus, this research aims to implement machine learning prediction models for video-based learning in higher education institutions. Using survey data from 103 final year accounting students at Malaysian public university, this paper presents the fundamental frameworks of evaluating three machine learning models namely generalized linear model, random forest and decision tree. Besides demography attributes, the performance of each machine learning algorithm on the video-based learning usage has been observed based on the attributes of technology acceptance model namely perceived ease of use, perceived usefulness and attitude. The findings revealed that the perceived ease of use has given the highest weight of contributions to the generalized linear model and random forest while the major effects in decision tree has been given by the attitude variable. However, generalized linear model outperformed the two algorithms in term of the prediction accuracy.

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1. INTRODUCTION

COVID-19 has been announced as a global pandemic by World Health Organization on 11 March 2020. In response, almost all countries including Malaysia have announced and implemented national lockdown as an effective way to curb the spread of the virus. In Malaysia, the first lockdown, also known as movement control order (MCO) has been enforced by the government on 18th March 2020. The MCO is a strict social confinement enforcement led to the suspension of all education activities. During the MCO, all universities are required to cancel the campus activities such as classroom lectures, conferences, and workshops. Due to that, in response to the abrupt transition to distance online education, most of educators introduce various innovative teaching and learning tools in continuing the learning process. One of them is video contents.

Video-based learning widely uses by the educators around the world to increase students' understanding, improve their study habits, and compensate for any missed lessons [1]. Besides traditional textbooks, video lectures will give additional advantages to students that offer more flexible learning and proved to increase their rate of learning [2]-[4]. In fact, some educators have implemented video lectures to deliver knowledges related laboratory experiment [5] or giving some practical demonstrations [6].

Due to huge benefits offered by the video educational tools, some scholars explore students' perceptions on intention and adoption of video contents for their study before COVID-19 pandemic. The research however produces mixed and inconclusive results. While some studies [7], [8] find positive student perceptions on video-based learning, [9], [10] fail to find significant differences between the traditional and video teaching tools. In addition, researcher in [11] successfully identified that video-based learning might have adverse impact on students learning outcome and in-class performance as some of them tend to skip video lessons.

Given the inconclusive results, this study aims to expand prior works by examining student's perceptions on video-based learning using unique academic setting, forced online learning during COVID-19 outbreak. Unlike prior studies [7]-[10] that employed traditional statistical method, this study attempts to construct video-based learning usage based on students' perception and attitudes to be analyzed with machine learning prediction technique. Previous research that used machine learning for prediction, classification and detection problems in financial, accounting and education domains highlighted the effectiveness and accuracy of such methods to that of traditional statistical methods in problems such as in detection of financial fraud [12], students and teachers' performance [13], [14], firm performance [15] and education technologies adoption [16]-[23]. Despite the wiser used machine learning in accounting and education areas, yet study on machine learning prediction and classification on accounting education is inadequate. Additionally, this study provides a new contribution on the inclusion of technology acceptance model (TAM) in modelling the machine learning prediction model for video-based learning.

This study has two main contributions. First, it attempts to extend prior works [16]-[23] in constructing online education and technologies adoption prediction model using machine learning algorithms in order to deepen current understanding on the acceptance of video-based learning as one of the educational technologies learning tools in online learning environment especially during Covid-19 pandemic. Second, it provides another design and implementation of machine learning prediction in video-based learning by using three constructs of TAM.

The following section provides a brief description on the research methodology from the dataset to the experimental design. Section 3 presents the empirical results for the representative compared algorithms. Finally, section 4 elaborates the conclusions and suggests the potential future research directions.

2. METHOD

2.1. Sample of data

The research gathered data by using questionnaires survey. The questionnaire consists of two sections; demographic and TAM constructs. In particular, the first section collected demographic attributes of the respondents including gender, academic performance, residential area and monthly family income. Additionally, information on students' exposure of video-based learning prior covid-19 outbreak was also included in this section. The second section is to measure students' actual usage of video content in learning process. Three attributes from TAM were used in measuring actual usage of video content. The attributes are perceived usefulness (PU), perceived ease of use (PEOU) and attitude as the relevant factors in classifying the students' perceptions to adopt video-based leaning in remote learning environment during COVID-19 pandemic. Following [24], the specific indicators applied to measure each of the TAM constructs in accordance to the works highlighted by researchers in [25]-[28]. The questionnaires were personally administered to undergraduate accounting students from the one public university in Malaysia during the 2021/2022 academic year. Due to the COVID-19 pandemic, the university still implement remote teaching for the whole semester and most of the subjects use live or prerecorded video in learning process. All the students who participated in this survey had at least for one full semester experienced or exposure to video-based learning. From the total of 280 questionnaires, 103 valid responses (36.78% response rate) have been used for the analysis.

2.2. Correlations of variables in the model

Table 1 lists the demography and TAM attributes as well as the student's video-learning exposure that used as the independent variables (IVs) in predicting the dependent variable (DV). The average of video-learning usages spent by the students is selected as the DV or target label for the machine learning prediction. Based on Pearson correlation test, the TAM attributes present positive strong correlations (above 0.7 correlation coefficient) to the video-learning usages.

Table 1. Pearson correlation of independent variables

Independent variables	Correlation coefficient
Perceived_ease_of_use	0.78
Attitude_toward_use	0.75
Perceived_usefulness_vbl	0.71
Cgpa	0.31
Gpa	0.23
Residential_area_urban	0.15
Prior_exposure_on_vbl	0.07
Monthly_household_income	0.06
Gender	0.02

2.3. Machine learning

Generalized linear model, random forest and decision tree are the machine learning algorithms to be compared that have been executed in the RapidMiner platform with a 16 GB computer RAM. Observing the hyper-parameters setting in accordance with the results of error rate is essential before final performances comparison can be accomplished for each of the selected machine learning algorithms. Table 2 and Table 3 show the different error rate generated by decision tree and random forest respectively during the preliminary machine learning hyper-parameters tuning.

As listed in Table 2, the lowest error rate is 7.8 generated when the *maximal_depth* of the decision tree was set to 7. The highest error rate is 8.9 with *maximal_depth* 8 and consistent error rate 8 is occurred from *maximal_depth* 7,10, 15 and 25. Different with Decision Tree, Random Forest has *number_of_trees* as an additional parameter to *maximal_depth.*

Table 2. Optimal hyper-parameter of decision tree

maximal_depth	Error rate
8	8.9
4	7.8
7	8
10	8
15	8
25	8

Table 3. optimal hyper-parameter of random forest

Number_of_trees	maximal_depth	Error rate
20	2	7.1
60	2	7.3
100	2	7.6
140	2	7.7
20	4	6.1
60	4	6.3
100	4	6.0
140	4	6.2
20	7	6.3
60	7	6.2
100	7	6.3
140	7	6.2

From the preliminary study, random forest has shown the lowest error rate with 100 *number_of_trees* and 4 *maximal_depth.* For separating the training and testing datasets, the research split training approach with ratio of 60:40 percentages. Therefore, from the 103 data, 62 of them were training dataset while the rest 41 were evaluated as the hold out testing dataset.

3. RESULTS AND DISCUSSION

Firstly, the performances results of the machine learning in the video-learning usage prediction model are given in Table 4. Secondly, how the TAM attributes and the students' demography effecting the prediction models with the different algorithms are presented. Both results are important for getting specifics insights of the machine learning prediction to be used in future research extensions or experimental replications in other cases of study.

Table 4. The performance results

Algorithm	R^ (+-std.dev)	RMSE (+-std.dev)	TCT (ms)
Generalized linear model	0.72 (0.21)	0.33(0.13)	990
Random forest	0.70(0.15)	0.35(0.10)	703
Decision tree	0.66(0.16)	0.39(0.10)	176

R square (R^) presenting the proportion of the variance in the prediction model that is explained by the IVs. The highest R squared was generated in the generalized linear model. Besides, the lowest error presented by root mean square error (RMSE) is 0.33 that was generated by generalized linear model. The relative error, which is not listed in Table 4 for this machine learning algorithm is 6.5% compared to 7.6% by decision tree and random forest. Therefore, the most outperforming algorithm for the machine learning prediction of video-learning usage is generalized linear model. Furthermore, it is interesting to understand how the TAM attributes effect on the machine learning prediction model with regards to the different algorithms. Figure 1 presents the weight of the contributions from each TAM attributes together with the demography elements in the generalized linear model.

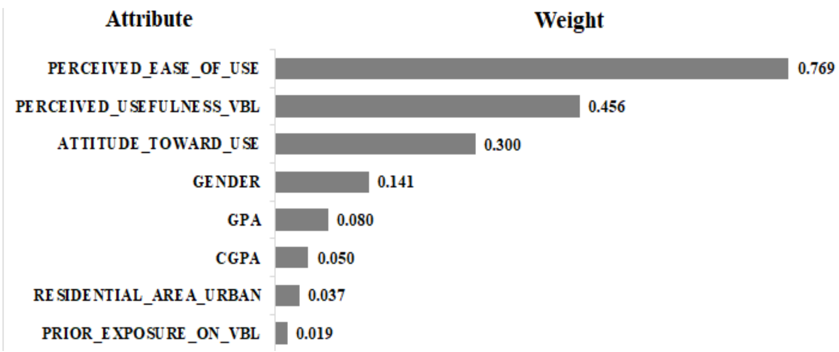

Figure 1. Weight of attributes in generalized linear model

The most significant TAM attribute in generalized linear model is *Perceived Ease of Use* with 0.77 correlation coefficient. Otherwise, moderate effect has been presented by the *Perceived Usefulness* and *Attitude*. Similarly, *Perceived Ease of Use* in random forest is the most influence attribute but the correlation coefficient value (0.45) is extremely lower than in the generalized linear model. In random forest, the three TAM attributes worked at the moderate effects between 0.3 to 0.45 correlation coefficient values. Figure 2 presents the weight of attributes in random forest.

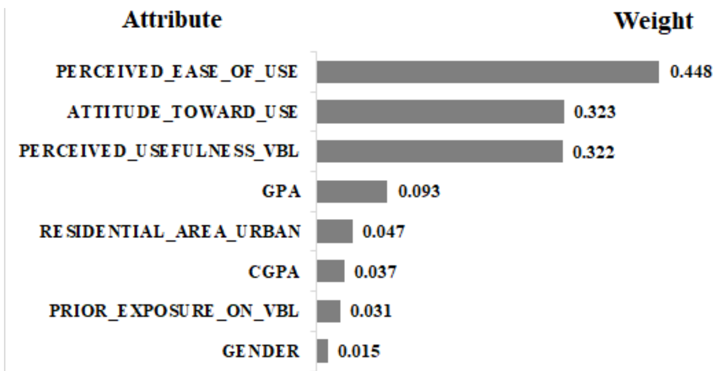

Figure 2. Weight of attributes in random forest

Lastly, Figure 3 depicts the weight of attributes in decision tree. All the TAM attributes have very low contributions (less than 0.5) to the machine learning model with decision tree algorithm. The first attribute in the range of weight is students' attitude followed by *Perceived Ease of Use* and *Perceived Usefulness*. All the demography elements performed very low contributions in all the machine learning models.

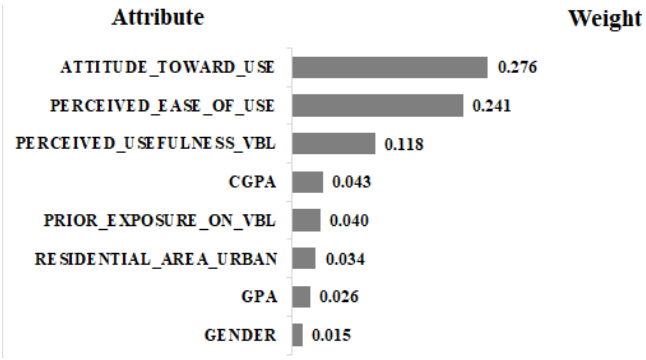

Figure 3. Weight of attributes in decision tree

4. CONCLUSION

This paper presents significant findings of research concerned with educational technology in a higher education setting with a video-learning approach. By using machine learning analytical approach, the findings provide new insights into the effect of TAM attributes on the video-learning utilization by higher education students. This research will be a great of interest to researchers in education technology and machine learning to expand the findings with different approaches of machine learning educational technology models.

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