

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

Rahayu Abdul Rahman¹, Suraya Masrom², Nor Hafiza Abd Samad³, Rulfah M. Daud⁴, Evi Meutia⁴

¹Faculty of Accountancy, Universiti Teknologi MARA, Tapah, Malaysia

²Computing Sciences Studies, College of Computing, Informatics and Media, Universiti Teknologi MARA, Tapah, Malaysia

³Faculty of Computing and Multimedia, Kolej Universiti Poly-Tech MARA, Kuala Lumpur, Malaysia

⁴Department of Accounting, Faculty of Economic and Business, Syiah Kuala University, Banda Aceh, Indonesia

Article Info

Article history:

Received Jul x, 2022

Revised Oct x, 2022

Accepted Nov x, 2022

Keywords:

COVID-19 pandemic

Online learning

Technology acceptance model

Video content

Video-based learning

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.

This is an open access article under the [CC BY-SA](#) license.



Corresponding Author:

Suraya Masrom

Computing Sciences Studies, College of Computing, Informatics and Media, Universiti Teknologi MARA Perak Branch, 34500 Tapah, Perak, Malaysia

Email: suray078@uitm.edu.my

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 wider use of 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 learning 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_depths*. 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 ² (+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^2) 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.

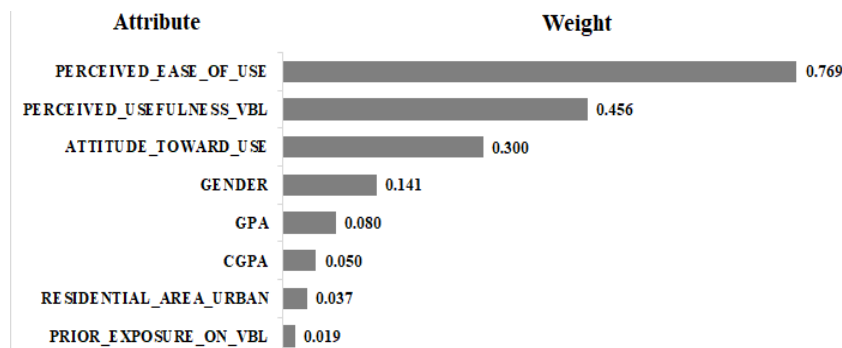


Figure 1. Weight of attributes in generalized linear model

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.

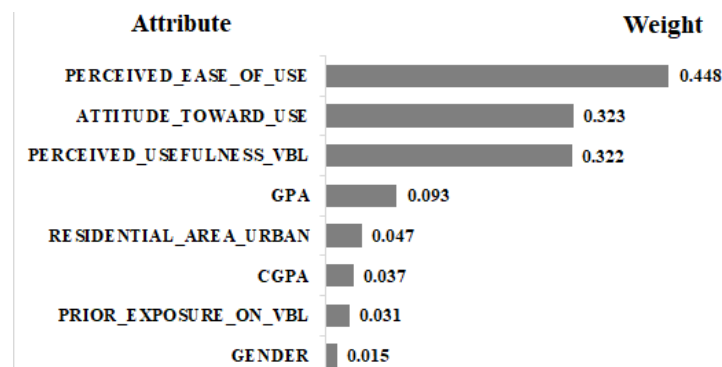


Figure 2. Weight of attributes in random forest

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.

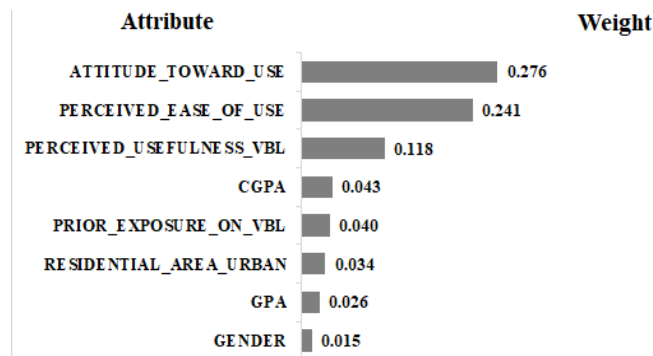


Figure 3. Weight of attributes in decision tree

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.

ACKNOWLEDGEMENTS

We acknowledge the Ministry of Higher Education Malaysia and the Kolej Universiti Poly-Tech MARA for the full support to this research under KUPTM University Research Grant (URG).





REFERENCES

- [1] R. H. Kay, "Exploring the use of video podcasts in education: A comprehensive review of the literature," *Computers in Human Behavior*, vol. 28, no. 3, pp. 820–831, May 2012, doi: 10.1016/j.chb.2012.01.011.
- [2] M. Dalal, "Impact of multi-media tutorials in a computer science laboratory course an empirical study," *Electronic Journal of e-Learning*, vol. 12, no. 4, pp. 366–374, 2014.
- [3] I. O. Pappas, M. N. Giannakos, and P. Mikalef, "Investigating students' use and adoption of with-video assignments: lessons learnt for video-based open educational resources," *Journal of Computing in Higher Education*, vol. 29, no. 1, pp. 160–177, Apr. 2017, doi: 10.1007/s12528-017-9132-6.
- [4] Z. Turan and H. B. Cetintas, "Investigating university students' adoption of video lessons," *Open Learning*, vol. 35, no. 2, pp. 122–139, May 2020, doi: 10.1080/02680513.2019.1691518.
- [5] M. Sablić, A. Miroslavljević, and A. Škugor, "Video-based learning (VBL)-past, present and future: an overview of the research published from 2008 to 2019," *Technology, Knowledge and Learning*, vol. 26, no. 4, pp. 1061–1077, Dec. 2021, doi: 10.1007/s10758-020-09455-5.
- [6] D. Surgenor *et al.*, "The impact of video technology on learning: A cooking skills experiment," *Appetite*, vol. 114, pp. 306–312, Jul. 2017, doi: 10.1016/j.appet.2017.03.037.
- [7] B. K. Weeks and S. A. Horan, "A video-based learning activity is effective for preparing physiotherapy students for practical examinations," *Physiotherapy (United Kingdom)*, vol. 99, no. 4, pp. 292–297, Dec. 2013, doi: 10.1016/j.physio.2013.02.002.
- [8] D. Zhang, L. Zhou, R. O. Briggs, and J. F. Nunamaker, "Instructional video in e-learning: Assessing the impact of interactive video on learning effectiveness," *Information and Management*, vol. 43, no. 1, pp. 15–27, Jan. 2006, doi: 10.1016/j.im.2005.01.004.
- [9] R. M. Bartlett and J. Strough, "Multimedia versus traditional course instruction in introductory social psychology," *Teaching of Psychology*, vol. 30, no. 4, pp. 335–338, Oct. 2003, doi: 10.1207/S15328023TOP3004_07.
- [10] D. A. Johnson and J. Christensen, "A comparison of simplified-visually rich and traditional presentation styles," *Teaching of Psychology*, vol. 38, no. 4, pp. 293–297, Oct. 2011, doi: 10.1177/0098628311421333.
- [11] P. S. Kissi, M. Nat, and R. B. Armah, "The effects of learning-family conflict, perceived control over time and task-fit technology factors on urban-rural high school students' acceptance of video-based instruction in flipped learning approach," *Educational Technology Research and Development*, vol. 66, no. 6, pp. 1547–1569, Dec. 2018, doi: 10.1007/s11423-018-9623-9.
- [12] A. Priyadarshini, S. Mishra, D. P. Mishra, S. R. Salkuti, and R. Mohanty, "Fraudulent credit card transaction detection using soft computing techniques," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 23, no. 3, pp. 1634–1642, Sep. 2021, doi: 10.11591/ijeecs.v23.i3.pp1634-1642.





- [13] N. Z. Salih and W. Khalaf, "Prediction of student's performance through educational data mining techniques," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 22, no. 3, p. 1708, Jun. 2021, doi: 10.11591/ijeecs.v22.i3.pp1708-1715.
- [14] O. Chamorro-Atalaya *et al.*, "Supervised learning using support vector machine applied to sentiment analysis of teacher performance satisfaction," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 28, no. 1, pp. 516–524, Oct. 2022, doi: 10.11591/ijeecs.v28.i1.pp516-524.
- [15] P. H. D. A. Samad, S. Mutalib, and S. Abdul-Rahman, "Analytics of stock market prices based on machine learning algorithms," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 16, no. 2, p. 1050, Nov. 2019, doi: 10.11591/ijeecs.v16.i2.pp1050-1058.
- [16] H. Suparwito, A. M. Polina, and M. Budiraharjo, "Student Perceptions Analysis of Online Learning: A Machine Learning Approach," *Indonesian Journal of Information Systems*, vol. 4, no. 1, pp. 64–75, Aug. 2021, doi: 10.24002/ijis.v4i1.4594.
- [17] A. Adeleke, N. Samsudin, A. Mustapha, and S. A. Khalid, "Automating quranic verses labeling using machine learning approach," *Indonesian Journal of Electrical Engineering and Computer Science (IJECS)*, vol. 16, no. 2, pp. 925–931, Nov. 2019, doi: 10.11591/ijeecs.v16.i2.pp925-931.
- [18] I. Akour, M. Alshurideh, B. Al Kurdi, A. Al Ali, and S. Salloum, "Using machine learning algorithms to predict people's intention to use mobile learning platforms during the COVID-19 pandemic: Machine learning approach," *JMIR Medical Education*, vol. 7, no. 1, p. e24032, Feb. 2021, doi: 10.2196/24032.
- [19] A. Q. M. Alhamad, I. Akour, M. Alshurideh, A. Q. Al-Hamad, B. Al Kurdi, and H. Alzoubi, "Predicting the intention to use google glass: A comparative approach using machine learning models and PLS-SEM," *International Journal of Data and Network Science*, vol. 5, no. 3, pp. 311–320, 2021, doi: 10.5267/j.ijdns.2021.6.002.
- [20] M. A. Almaiah, O. Almomani, A. Al-Khasawneh, and A. Althunibat, "Predicting the acceptance of mobile learning applications during COVID-19 using machine learning prediction algorithms," in *Studies in Systems, Decision and Control*, vol. 348, 2021, pp. 319–332.
- [21] M. Alshurideh, B. Al Kurdi, S. A. Salloum, I. Arpac, and M. Al-Emran, "Predicting the actual use of m-learning systems: a comparative approach using PLS-SEM and machine learning algorithms," *Interactive Learning Environments*, pp. 1–15, Oct. 2020, doi: 10.1080/10494820.2020.1826982.
- [22] I. Arpac, M. Al-Emran, M. A. Al-Sharafi, and K. Shaalan, "A novel approach for predicting the adoption of smartwatches using machine learning algorithms," in *Studies in Systems, Decision and Control*, vol. 295, 2021, pp. 185–195.
- [23] N. Marangunić and A. Granić, "Technology acceptance model: a literature review from 1986 to 2013," *Universal Access in the Information Society*, vol. 14, no. 1, pp. 81–95, Mar. 2015, doi: 10.1007/s10209-014-0348-1.
- [24] D. Pal and S. Patra, "University students' perception of video-based learning in times of COVID-19: A TAM/TTF perspective," *International Journal of Human-Computer Interaction*, vol. 37, no. 10, pp. 903–921, Jun. 2021, doi: 10.1080/10447318.2020.1848164.
- [25] F. D. Davis, "Perceived usefulness, perceived ease of use, and user acceptance of information technology," *MIS Quarterly: Management Information Systems*, vol. 13, no. 3, pp. 319–339, Sep. 1989, doi: 10.2307/249008.
- [26] H. H. Chang, "Task-technology fit and user acceptance of online auction," *International Journal of Human Computer Studies*, vol. 68, no. 1–2, pp. 69–89, Jan. 2010, doi: 10.1016/j.ijhcs.2009.09.010.
- [27] B. Wu and X. Chen, "Continuance intention to use MOOCs: Integrating the technology acceptance model (TAM) and task technology fit (TTF) model," *Computers in Human Behavior*, vol. 67, pp. 221–232, Feb. 2017, doi: 10.1016/j.chb.2016.10.028.
- [28] M. T. Dishaw and D. M. Strong, "Extending the technology acceptance model with task-technology fit constructs," *Information and Management*, vol. 36, no. 1, pp. 9–21, Jul. 1999, doi: 10.1016/S0378-7206(98)00101-3.

BIOGRAPHIES OF AUTHORS






Dr. Rahayu Abdul Rahman     is an Associate Professor at the Faculty of Accountancy, UiTM. She received her Ph.D in Accounting from Massey University, Auckland, New Zealand in 2012. Her research interest surrounds areas, like financial reporting quality such as earnings management and accounting conservatism as well as financial leakages including financial reporting frauds and tax aggressiveness. She has published many research papers on machine learning and its application to corporate tax avoidance. She is currently one of the research members of Machine Learning and Interactive Visualization Research Group at UiTM Perak Branch. She can be contacted through email at rahay916@uitm.edu.my.






Associate Professor Ts. Dr Suraya Masrom     is the head of Machine Learning and Interactive Visualization (MaLIV) Research Group at Universiti Teknologi MARA (UiTM) Perak Branch. She received her Ph.D. in Information Technology and Quantitative Science from UiTM in 2015. She started her career in the information technology industry as an Associate Network Engineer at Ramgate Systems Sdn. Bhd (a subsidiary of DRB-HICOM) in June 1996 after receiving her bachelor's degree in computer science from Universiti Teknologi Malaysia (UTM) in Mac 1996. She started her career as a lecturer at UTM after receiving her master's degree in computer science from Universiti Putra Malaysia in 2001. She transferred to the Universiti Teknologi MARA (UiTM), Seri Iskandar, Perak, Malaysia, in 2004. She is an active researcher in the meta-heuristics search approach, machine learning, and educational technology. She can be contacted through email at suray078@uitm.edu.my.






Nor Hafiza Abd Samad    is Senior Lecturer at the Faculty of Computing and Multimedia, Kolej Universiti Poly-Tech MARA. She received her master's degree in Computer Networking from UiTM in 2014. Her research interest surrounds areas, like computer security, computer architecture and data communication and network. She also actively involves in publications, research and innovation projects activities in other related computer science and information technology. She can be contacted through email at hafiza@kuptm.edu.my.



Rulfah M. Daud    is a lecturer of Department of Accounting, Economics and Business Faculty of Syiah Kuala University since March 1, 1992. My field major are Cost Accounting, Managerial Accounting, Cost Management and Financial Accounting. She is a teacher some other subjects related to financial accounting such as introduction to accounting and intermediate accounting and cost accounting. She is a Head of Accounting Laboratories. She has a completed a post-graduate program in 2002 in Padjajaran University majoring in Accounting. She is a Pembina (IV A) and my functional position is Head Lector. She have earned Satya Lencana Award for a 20-year working period on August 17, 2015. She can be contacted through email at ruflahmdaudfe@unsyiah.ac.id.



Evi Meutia    is a senior lecturer in the Accounting Department at Universitas Syiah Kuala, USK. She received the Master of science in Accounting Department from Syiah Kuala University, Indonesia, in 2009. Currently, she is taking a doctoral program at USK. Her research projects cover topics about Sharia Accounting, Islamic Economics and Finance, NonProfit Organisations and Waqf and accounting behavior. Currently, she is interested in research about Sustainability Issues. Evi Mutia published a number of papers in preferred Journals and chapters in books and participated in a range of forums on Islamic economics and finance. She can be contacted through email at evimutiafe@unsyiah.ac.id.

[< Back to results](#) | 1 of 1
[Download](#)
[Print](#)
[Save to PDF](#)
[Add to List](#)
[Create bibliography](#)

Indonesian Journal of Electrical Engineering and Computer Science • [Open Access](#) • Volume 29, Issue 3, Pages 1560 - 1566 • March 2023

Document typeArticle • [Gold Open Access](#) • [Green Open Access](#)**Source type**

Journal

ISSN

25024752

DOI

10.11591/ijeecs.v29.i3.pp1560-1566

[View more](#)

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

[Rahman, Rahayu Abdul^a](#) ; [Masrom, Suraya^b](#) ; [Samad, Nor Hafiza Abd^c](#) ;

[Daud, Rulfah M.^d](#) ; [Mutia, Evi^d](#)
[Save all to author list](#)^a Faculty of Accountancy, Universiti Teknologi MARA, Tapah, Malaysia^b Computing Sciences Studies, College of Computing, Informatics and Media, Universiti Teknologi MARA, Tapah, Malaysia^c Faculty of Computing and Multimedia, Kolej Universiti Poly-Tech MARA, Kuala Lumpur, Malaysia^d Department of Accounting, Faculty of Economic and Business, Syiah Kuala University, Banda Aceh, Indonesia

1 66th percentile
Citation in Scopus

0.59
FWCI

5
Views count

[View all metrics](#)
[View PDF](#)
[Full text options](#)
[Export](#)
[Abstract](#)[Author keywords](#)[SciVal Topics](#)[Metrics](#)[Funding details](#)**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-

Cited by 1 document

Quality of service management in telecommunication network using machine learning technique

Ayan, Z. , Alimzhan, B. , Olga, M. (2023) *Indonesian Journal of Electrical Engineering and Computer Science*

[View details of this citation](#)

Inform me when this document is cited in Scopus:

[Set citation alert >](#)**Related documents**

Machine learning with task-technology fit theory factors for predicting students' adoption in video-based learning

Masrom, S. , Rahman, R.A. , Baharun, N. (2023) *Bulletin of Electrical Engineering and Informatics*

University Students' Perception of Video-Based Learning in Times of COVID-19: A TAM/TTF Perspective

Pal, D. , Patra, S. (2021) *International Journal of Human-Computer Interaction*

Comparisons of automated machine learning (AutoML) in predicting whistleblowing of academic dishonesty with demographic and theory of planned behavior

Rahman, R.A. , Masrom, S. , Mohamad, M. (2023) *MethodsX*

[View all related documents based on references](#)

Find more related documents in Scopus based on:

[Authors >](#) [Keywords >](#)

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. © 2023 Institute of Advanced Engineering and Science. All rights reserved.

Author keywords

COVID-19 pandemic; Online learning; Technology acceptance model; Video content; Video-based learning

SciVal Topics 



Metrics



Funding details




References (28)


[View in search results format >](#)

☐ All

[Export](#)

 [Print](#)

 [E-mail](#)

 [Save to PDF](#)

[Create bibliography](#)

☐ 1

Kay, R.H.

Exploring the use of video podcasts in education: A comprehensive review of the literature

(2012) *Computers in Human Behavior*, 28 (3), pp. 820-831. Cited 327 times.
doi: 10.1016/j.chb.2012.01.011

[View at Publisher](#)

☐ 2

Dalal, M.

Impact of multi-media tutorials in a computer science laboratory course - An empirical study

(2014) *Electronic Journal of e-Learning*, 12 (4), pp. 366-374. Cited 17 times.
<http://www.ejel.org/issue/download.html?idArticle=305>

☐ 3

Pappas, I.O., Giannakos, M.N., Mikalef, P.

Investigating students' use and adoption of with-video assignments: lessons learnt for video-based open educational resources

(2017) *Journal of Computing in Higher Education*, 29 (1), pp. 160-177. Cited 30 times.
<https://www.springer.com/journal/12528>
doi: 10.1007/s12528-017-9132-6

[View at Publisher](#)
