Determining the Students' Preferable Learning Mode for both Traditional Classrooms Teaching Under Normal Situations and Forced Virtual Teaching in Quarantine Period

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Abstract*—The Research to Practice Full Paper aims to determine the students' preferable learning mode for traditional classroom teaching under typical situations and forced virtual teaching in quarantine. Although many academic institutions have promoted online and distance education, face-to-face traditional classroom teaching has always been the dominant approach in the US. However, the sudden outbreak of the COVID-19 disease forced the academic institutions to convert the entire curriculum into a virtual method of teaching and learning. This drastic change in the educational system has dramatically impacted educators and students, and very little is known about the students' preferred teaching and learning mode. In this regard, the present study collected data from the civil engineering department at the University based on a questionnaire survey. A total of 337 students participated and responded to 18 multiple-choice questions. The questionnaire was divided into four parts: admission information, activity information, Fundamentals of Engineering Examination (FE exam) planning, and preferred teaching mode. The preferred teaching mode is further divided into 'Synchronous' that represents scheduled and live virtual engagements with students such as zoom meetings and 'Asynchronous', representing pre-recorded lectures such as watching YouTube videos. This study performed two analyses to obtain precise results regarding: (1) online vs. traditional classroom learning, (2) synchronous vs. asynchronous learning. For this purpose, distinct tree-based methods, including bagging, boosting, and random forest were employed to investigate the significant factors that affect the students' choice of learning modes under different circumstances. The findings reveal that the activities such as participation in clubs or organizations, internships, or jobs, are the statistically significant factors that play a vital in the students' choice of teaching and learning mode under different situations. This study is expected to provide crucial insights for the academic professionals in adopting the teaching and learning modes that would substantially improve and enhance the quality of education.

***Keywords*—Online Teaching, COVID-19, Machine Learning, Tree-based Methods, Pedagogical Strategies**

I. Introduction

The current teaching system has evolved alongside the advent of technology and its availability [1]. Online learning has been available since the mid-1990s, and at the time, many have already noticed that it is a "potential course delivery platform" [2]. Over time, online learning became more efficient and popular as schools and universities began to incorporate online courses into their curricula [3,4]. Online courses [5] were more beneficial to those students and professors who cannot attend conventional classrooms since they only required a computer and an internet connection [6,7]. It was discovered that although students taught traditionally in classrooms scored marginally higher than their online counterparts, there was no statistically significant difference in either groups' abilities to comprehend the material in the course [8].

In times of crisis, caused by disastrous local events to national pandemics, mass gatherings are likely to be discouraged to outright banned [9]. This includes all forms of social gatherings such as concerts, public events, sports matches, academic institutions, and many more. Recently, the rapid spread of coronavirus, COVID-19, has forced educational institutions to switch traditional in-classroom teachings with digital teaching methods [10,11]. These digital methods include both synchronous and asynchronous online courses. This alone presents some issues as these different online teaching methods have their advantages and disadvantages in how students can comprehend information [12,13]. The issue revolves around the fact that up until this point, the only people using online learning were those who either wanted to use it and those who needed to use it, while the option of traditional education was still available to other students and professors [14,15]. Currently, all academic institutions are closed, and any learning is now only being offered online, forcing those who preferred traditional classroom classes to convert into online education [16].

To this end, due to the current pandemic period caused by COVID-19, teaching, and learning at different academic levels is now completely converted into online education. However, students and academic instructors have some concerns regarding the conversion to online learning [17-19]. The main issue is the utilization of technology in a short time that some students and instructors were not familiar with [20,21], such as individual's experience with the internet, workloads, as well as computer experience [22]. In addition to the unfamiliarity with technology, there also lies the issue of the limitations that technology already has [23]. Some courses require more than only videos and real-time "conferences" with their professors and require additional software such as language recognition software to understand or learn the foreign language. Despite the advancements of language recognition software, it is still imperfect, affecting students' ability to practice a foreign language in pronunciation of vocabulary [24]. Finally, the conversion of traditional classroom teaching to online teaching procedures might create some hurdles for students and instructors, most notably those who are not familiar with newer technology and have difficulty comprehending newer methods [25].

A plethora of studies in the field of higher education have employed various methods to evaluate the data such as ordered logit or ordered probit models, multinomial logit model, latent class clustering model, support vector machines, decision trees and so on. The various decision trees like single tree, bagging, boosting, and random forest have been used in recent studies because of their benefits like the outputs are easy to read and interpret, take less effort for data preparation, less data cleaning required, etc. Therefore, to obtain more precise and accurate inferences, the current study employed the popular decision tree techniques which involve bagging, boosting, and random forest.

Given this context, determining the students' preferred learning patterns and adjusting the teaching plans accordingly for traditional classroom learning under typical situations and the forced virtual teaching in the quarantine period could enhance the quality of education. In this regard, the main objective of this study is to evaluate the influential factors of students' preferred teaching mode under normal situations and the forced virtual teaching circumstances. The data used in this study were based on a questionnaire survey gathered from the civil engineering department of California State Polytechnic University, Pomona. This paper adopted three distinct tree-based methods to analyze the data: bagging, boosting, and random forest. It is expected that this study will provide crucial insights regarding the pedagogical strategies on the possible adjustment of learning mode.

II. Data Description

To conduct the analysis, this study performed the survey based on students' preferred study mode in the department of civil engineering of California State Polytechnic University, Pomona (CPP) in 2020. The impacts of COVID-19 forced the entire curriculum to be converted into online learning. The civil engineering department of CPP is committed to providing quality education, so they invited students to provide feedback regarding the forced online environment for better virtual instruction. A total of 337 students participated in providing their opinions based on the given 18 multiple choice questions, as shown in Table 1. The questionnaire was divided into four parts: admission information, activity information, FE exam (Fundamentals of Engineering Examination) planning, and preferred teaching mode. Each question was treated as a variable in the model development. Furthermore, the variable 'Preferred online teaching mode' is further divided into 'Synchronous' that represents scheduled and live virtual engagements with students such as zoom meetings and 'Asynchronous', representing pre-recorded lectures such as watching YouTube videos. The details of the 18 questions and their responses are shown in Table 1.

This study conducted a correlation analysis using Principal Component Analysis (PCA) to obtain more precise and accurate results. In this study, PCA helps to reduce the dimensionality of the dataset to two dimensions (Dim 1 and Dim 2) to show the variation in the data. As shown in Fig. 1, the x-axis (Dim 1, 9.5%) and y-axis (Dim 2, 6.1%) in the plot represent the proportion of variation. The distance from the origin can interpret the contribution (or influence) of the variables. The small distance from the origin represents low contribution and vice versa. It can be seen in Fig.1 that the variables are not overlapping or closely grouped. This demonstrates that the covariates used in the analysis do not correlate with each other.

III. Methodology

This study used machine learning techniques to develop various tree-based models to analyze influential factors regarding students' preferred teaching mode and online teaching mode. Recently, a large number of studies have employed such techniques in the field of higher education due to its enormous benefits, which include the identification of trends and pattern with ease, less time consumption, capable of handling multi-dimensional and multi-variety data. To get the most accurate results, methods including bagging, boosting, and random forest were employed as alternatives to determine the optimal technique. The details of each method are provided as follows.

A. Bagging

Bagging, also known as bootstrap aggregation, an ensemble learning used to reduce the variance of a single tree and enhance the model performance and stability [26,27]. Bagging can randomly produce bootstrap samples from the training set with replacement. It develops independent models for each sample and averages the resulting predictions to decrease the variance of results and improve model performance. Given the data used in this study, the number of bootstrap samples was set to 500. The model randomly generated 500 samples from the training set to develop 500 simple trees with 16 distinct predictors (variable a~p from Table 1). This model can produce B samples from the training set, then develop a single decision tree for the bth sample to get the resulting prediction f^(*b) (x), and finally average all the predictions of B samples to reduce the variance, given by Equation 1 [28]:

$$\hat{f}_{bag}(x) = \frac{1}{B}\sum_{b=1}^{B} \hat{f}^{*b}(x) \qquad (1)$$

Where $\hat{f}_{bag}(x)$ refers to the predicted outcome of the model, B is the total number of training sets the model produced, and f*b is the outcome of each training set.

Table I. Descriptive Statistics for Variables

Variable	Description	Details of categories (frequency, percentage)
Academic	Academic level	1-Freshman (24, 7.12%); 2-Sophomore (36, 10.68%); 3-Junior (88, 26.11%); 4-Senior (170, 50.46%); 5-Graduate (19, 5.6%)
Clubs	Clubs or organizations attendance.	1-Held one or more offices (81, 24.04%); 2- Actively involved neve r held and office (56, 16.62%); 3- Regularly attended meetings not a ctive (34, 10.09%); 4-Occasionally attended meetings (71, 21.07%); 5- Little or none (95, 28.19%)
ASCE_Conf	Pacific Southwest Regional ASCE Student Conferences attendance.	1-Yes (63, 18.69%); 2-No (274, 81.31%)
Stu_Conf	Student-led professional conferences or seminars attendance.	1-Yes (86 ,25.52%); 2-No (251, 74.48%)
Meeting_Atte	Professional society chapter meetings in the local area attendance.	1-Yes (64, 18.99%); 2-No (273, 81.31%)
Non-Stu_Conf	Non-student led professional conferences or seminars attendance.	1-Yes (86, 25.52%); 2-No (251, 74.48%)
Posters_Conf	Papers or posters at a non-student led professional conferences or seminars attendance.	1-Yes (31, 9.20%); 2-No (306, 90.80%)
Job_Summer	Full-time summer engineering job or internship.	1-Yes (100, 29.67%); 2-No (237, 70.33%)
Job_Engg	Part-time engineering job or internship.	1-Yes (106, 31.45%); 2-No (231, 68.55%)
Job_Non-Engg	Part-time non-engineering job.	1-Yes (76, 22.55%); 2-No (261, 77.45%)
Research_CPP	The student research program at Cal Poly Pomona.	1-Yes (27, 8.01%); 2-No (310, 91.99%)
Research_Uni	The student research program at another university.	1-Yes (6, 1.78%); 2-No (331, 98.22%)
Empoly_W	Weekly employed hours.	1- 10 hours or less (132,39.17%); 2- 11 to 20 hours (116, 34.42%); 3 - 21 to 30 hours (52,15.43%); 4- 30 or more hours (37, 10.98%)
EIT_Plan	EIT exam planning.	1- 2 or 3 semesters before graduate (131, 38.87%); 2- More than 3 semesters before graduate (15, 4.45%); 3- The semester of graduate (115, 34.12%); 4- After graduate (55, 16.32%); 5- Do plan to take (21, 6.23%)
EIT_Exp	Expected times of taking EIT exam.	1- None (123, 36.99%); 2- Once (162, 48.07%); 3- Twice (48, 14.24%); 4-Three or more (4, 1.19%)
EIT_After	Exam after EIT.	1- Another exam (2, 0.59%); 2- Not applicable (259, 76.85%); 3- Civil engineering exam (69,20.47%); 4- The general exam (7, 2.08%)
Class_Mode	Preferred classroom teaching mode.	1- Online (49, 14.54%); 2- Typical classroom instruction (288, 58.46%)
Online_Mode	Preferred online teaching mode.	1- Synchronous (207, 61.42%); 2- Asynchronous (130, 38.58%)

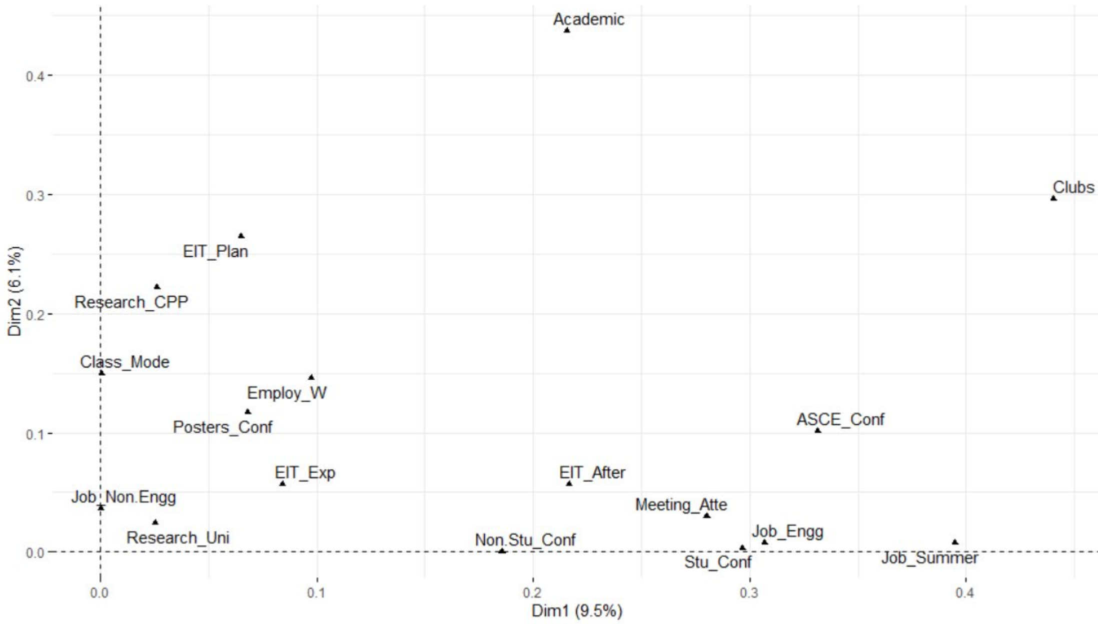

Fig. 1 Correlation Plot of Variables in terms of Principal Component Analysis

B. *Boosting*

Boosting is an ensemble learning method for reducing bias [29]. Compared with bagging, boosting turns to improve the model performance by training a series of weak models, each of which makes up the deficiency of its predecessor. The boosting algorithm for making predictions can be expressed by the following equation [30]:

$$\hat{f}(x) = \sum_{b=1}^{B} \lambda \hat{f}^{b}(x) \qquad (2)$$

Where B represents the number of single trees, which is determined by a cross-validation process to ensure overfitting issues, for this study, B was set to be 5000. The shrinkage factor (λ) controls the rate at which boosting learns. To fit a more accurate resulting prediction, the number of trees (B) needs to be larger, corresponding to a smaller λ. Finally, b represents the ordinal number of the current boosting tree.

C. *Random Forest*

Random forest [31] is a special case of bagging in ensemble learning [32]. The key difference between random forest and bagging is through the decorrelation of trees in which random forest chooses only a part of the predictor (variable a~p from Table 1) for each sample. Therefore, instead of generating the total number of trees, random forest generates trees by being forced to use other predictors. Thus, decorrelating each tree and making its predictions more accurate. The number of predictors for the random forest decision models applied equation 2 [30]:

$$m = \sqrt{p} \qquad (3)$$

Where P represents the number of total predictors from the original data, which is variable a top. Considering the data used in this study, m is the predictor of each random sample applied in the random forest method. The major difference between the bagging method and the random forest is applying the number of predictors m, which leads to a reduction in test error and better model performance over bagging.

Under the random forest method, mean decrease Gini (MDG) is a significant criterion to measure the relative importance among all variables. The Gini index is defined by:

$$G = \sum_{k=1}^{K} \hat{p}_{mk}(1 - \hat{p}_{mk}) \qquad (4)$$

Which is a measure of total variance across the K classes. Where p^_mk represents the proportion of training observations in the mth region that are from the kth class [30]. The mean decrease in the Gini index illustrates how much the Gini index will decrease if the current variable is removed.

IV. Results

As previously mentioned, the primary goal of this study is to investigate the influential factors affecting the students' choice of study mode in typical situations where traditional classroom education is involved and in quarantine periods where classroom learning is forcibly converted to online classes. The present study conducted two different analyses to obtain precise results: (1) online vs. traditional classroom learning, (2) synchronous vs. asynchronous learning. Three distinct techniques, including bagging, boosting, and random forest, were employed to analyze the data and get detailed inferences from different aspects using the statistical software 'R.' A detailed description of the results is provided in the below sections.

A. Online vs. Traditional Classroom learning

The first analysis was performed to determine the students' preferred study mode for traditional classroom teaching in normal situations and online instruction in quarantine periods. According to the survey, out of 337 students, only 49 students chose online education, and the remaining students (288) preferred typical classroom instruction. This indicates that a large number of students prefer to attend traditional classroom lectures than online learning. However, it is crucial to investigate the significant variables that play a pivotal role in selecting preferred learning mode. Determining the significant variables will help the academic professionals and researchers to focus on such important issues, which will enhance the students' learning. In this regard, variable importance ranking was performed by employing the random forest metric.

A.1. Ranking of Variable Importance

Fig. 2 illustrates the ranking of variable importance of MDA and MDG, which affects the students' choice of learning mode. The horizontal dot chart shown in Fig. 2 represents the importance of the variable, where the longer the horizontal dot illustrates, the higher importance and vice-versa. As shown in the figure below, the variable 'Clubs' (clubs or organizations attendance) was observed to have the highest statistically significant impact on the students' preferred learning mode for MDG. The variable 'EIT_After' (EIT after exam) appeared to be the most influential variable to affect the students' choice of learning mode for MDA. Other variables such as 'Employ_W' (weekly employed hours), 'Academic' (academic level), and 'EIT_Exp' (expected timed of taking EIT exam) impact the students' selection of learning mode. Interestingly, the variables 'Stu_Conf' (the student attendance in Conference) was observed to have the lowest effect on student's preferred learning styles for both MDA and MDG.

For comparison, both the Mean Decrease Accuracy (MDA) and MDG are shown in Figure 2. The vertical scale represents the different variables outlined in Table I while horizontal scale determines the value being represented on both graphs presented. Upon closer inspection, several interesting points of interest appear. For starters, several variables including "Stu_Conf", "ASCE_Conf", "EIT_Exp", "Non-Stu_Conf", "Employ_W", "Job_Summer", and "Posters_Conf" are considered unimportant in the model's prediction capabilities. Inversely, variable "Research_Uni" is regarded as the most important predicting variable according to the Mean Decrease Accuracy, followed by "EIT_Plan". MDG shows some similar results. The variable "EIT_Plan" is considered the most significant variable, which agrees with the MDA, and the variable "Clubs" is highly significant.

A.2. Model Accuracy Comparison

Boosting shows the highest accuracy with 84.61%, slightly larger than random forest 84.02%. Bagging trees with a model accuracy of 79.29% illustrates the lowest accuracy.

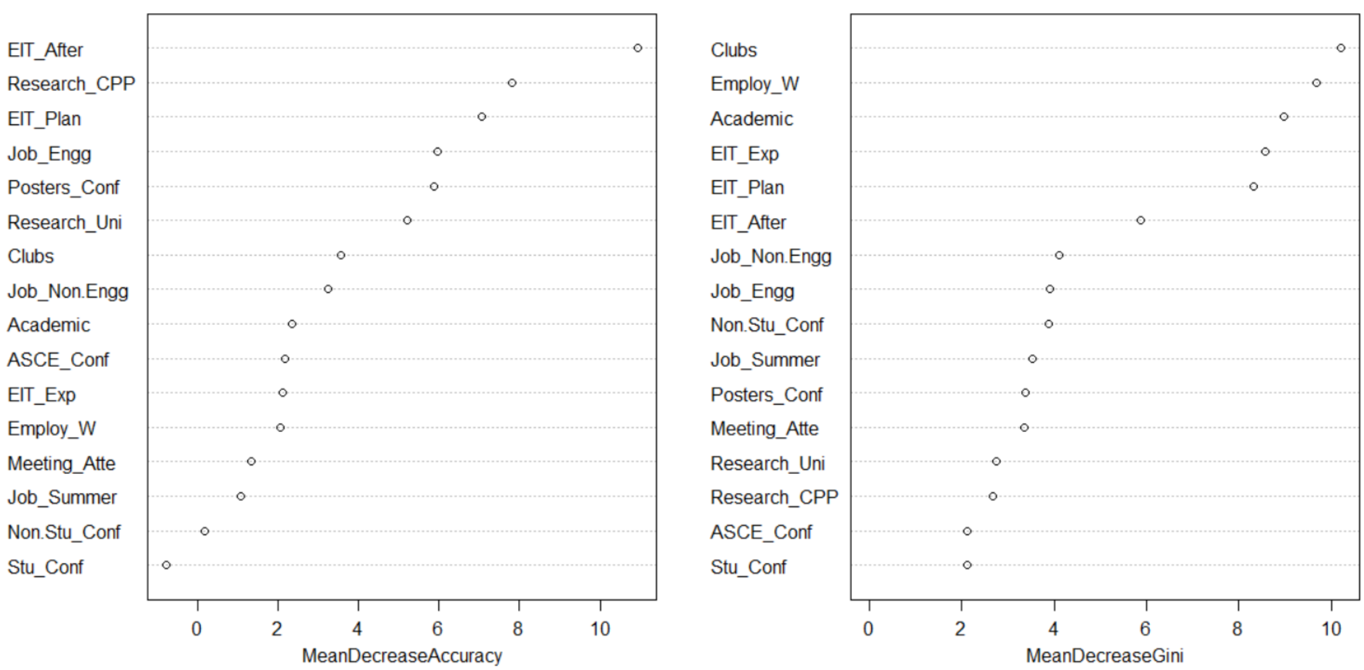

Fig. 2 Plot of (a) Mean Decrease Accuracy (MDA) (b) Mean Decrease Gini (MDG) for variable importance ranking of Traditional vs. Online learning mode

B. Synchronous vs. Asynchronous learning mode

The second analysis was conducted to determine the students' preferred study mode between asynchronous and synchronous learning modes. The synchronous online teaching is scheduled, live virtual engagements with students, zoom meetings with professors, and asynchronous online instruction is pre-recorded lectures, such as watching YouTube videos. The survey conducted by the civil engineering department of Cal Poly Pomona reveals that out of 49 students that preferred online classes, 37 students selected synchronous courses and the remaining 12 students choose asynchronous learning mode. This shows that the majority of students prefer asynchronous learning style to asynchronous instruction. This study investigates the influential variables impacting the selection of preferred learning mode. With that said, random forest was used to perform the variable importance ranking.

A.1. Ranking of Variable Importance

As shown in Fig. 3, the variable importance ranking for synchronous vs. asynchronous learning style was performed using random forest (MDA and MDG). Interestingly, the first five variable importance ranking for synchronous vs. asynchronous learning style was the same as the variable importance ranking for traditional vs. online instruction. The variable 'Clubs' (clubs or organization attendance) appeared to have the highest impact on students' selection of learning mode, and 'Research_Uni' (the student research program at another university) was observed to be the lowest influential variable that affected the students' choice of instruction for MDG.

Fig. 3 shows both the MDA and MDG for comparison purposes. Looking at Fig. 3, it is apparent that several variables are unimportant according to the MDA, including: "Clubs", "Job_Engg", "Academic", "Non-Stu_Conf", "Meeting_Atte", "Posters_Conf", "ASCE_Conf", "Research_Uni", "Job_Summer", and "Stu_Conf". Inversely, the variables "Employ_W" and "EIT_Exp" are considered the most important predicting variables. The MDG shows some similar results in which the variable "Employ_W" is regarded as the most significant variable, which agrees with the MDA, and the variables "EIT_Plan" and "Clubs" are highly significant, which concurs with Fig. 3.

When comparing the results of the variable importance ranking of Fig. 2 and Fig. 3, the top 5 most important variables: "Clubs", "EIT_Plan", "Employ_W", "Academic", and "EIT_Plan" are the same. The same can be said about the bottom four variables: "Research_Uni", "Research_CPP", "Posters_Conf" and "Meeting_Atte". These variables should be looked at in finer details to find more potentially critical relations with online teaching and its forms.

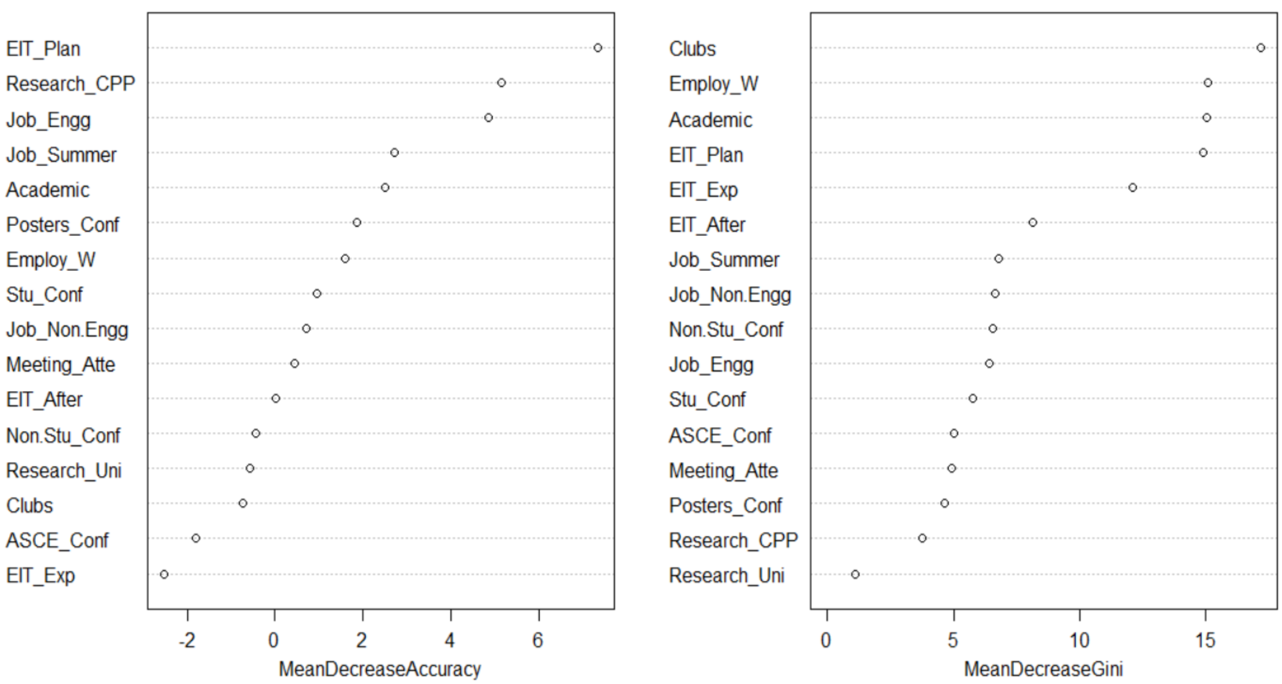

Fig. 3 Plot of (a) Mean Decrease Accuracy (MDA) (b) Mean Decrease Gini (MDG) for variable importance ranking of Synchronous vs Asynchronous learning mode.

A.2. Model Accuracy Comparison

In the second analysis, the random forest shows the highest model accuracy (59.17 %). The bagging model accuracy (56.80 %) is moderately higher than boosting (54.43 %) by 2.37 %. Overall, the accuracy of all the techniques are higher with slightly different among each other.

V. Conclusions

The main objective of this study was to explore influential factors of student's preferred study mode in a different situation. The data used in this study were collected from the civil engineering department of CPP. Three hundred thirty-seven effective observations were used to carry out modeling analysis. Three distinct metrics were employed in this study, which includes bagging, boosting, and random forest. Two different analyses were performed to determine the influential variables of students' preferred learning mode: (1) traditional classroom teaching in typical situations and online teaching in quarantine periods, (2) Synchronous vs. Asynchronous instruction. Building upon the results, the following conclusions were drawn as follows:

- The variable importance ranking for traditional vs. online classes and synchronous vs. asynchronous instruction illustrates the clubs or organization attendance is one of the most influential variables regarding students' preferred teaching mode. This finding demonstrates that participating in clubs or organizations more frequently leads the students to be more willing to take typical classroom instruction.
- Based on the second analysis, the variable 'clubs and organization attendance' is the most influential variable regarding students' preference of online teaching mode, as displayed in Fig. 3. It suggests that the participation of students in clubs and organizations influence the students to interact with instructors or classmates, that makes them to choose synchronous online teaching.
- The boosting shows a higher level of accuracy (84.61%) than random forest and bagging in the first analysis. The random forest illustrates the highest accuracy, 59.17%, compared to other metrics in the second analysis.

It is expected that the above findings will be helpful to academic professionals in designing online and classroom teaching. However, this paper needs some caveats. The results may not hold true when data from other sources or countries were used. Second, the present study employed tree-based techniques to perform the analysis. Future studies are recommended to utilized alternative metrics that might lead to different results. Third, random forest metric was used to perform the variable importance ranking. The implementation of other variable selection methods like backward or forward selection, principal component analysis, recursive partitioning, or auto-encoder could provide different response variables for model development.

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REFERENCES

[1] Kim, K. J., & Bonk, C. (2006), "The future of online teaching and learning in higher education: The survey says…", Educause Quarterly, Vol. 29 No. 4, pp. 22-30.

[2] Volery, T., & Lord, D. (2000), "Critical success factors in online education. The International journal of educational management", Vol. 14 No. 5, pp. 216-223.

[3] Allen, I. E., & Seaman, J. (2007), "Online nation: Five years of growth in online learning", The Sloan Consortium, PO Box 1238, Newburyport, MA 01950.

[4] Little, M. and Cordero, E. (2014), "Modeling the relationship between transportation-related carbon dioxide emissions and hybrid-online courses at a large urban university", International Journal of Sustainability in Higher Education, Vol. 15 No. 3, pp. 270-279.

[5] Posey, L. & Pintz, C. (2006), "Online teaching strategies to improve collaboration among nursing students," Nurse Education Today Vol. 26 No. 8, December 2006, pp. 680-687.

[6] Wang, A. Y., & Newlin, M. H. (2001), "Online lectures: Benefits for the virtual classroom", The Journal, Vol. 29 No. 1, pp. 17-18.

[7] Tallent-Runnels, M. K., Thomas, J. A., Lan, W. Y., Cooper, S., Ahern, T. C., Shaw, S. M. & Liu, X. (2016), "Teaching Courses Online: A Review of the Researc", Review of educational research, 2016, Vol. 76 No. 1, pp.93-135.

[8] Klecker, B. M. (2007), "The impact of formative feedback on student learning in an Online Classroom". Journal of Instructional Psychology, Vol. 34 No. 3, pp. 161-165.

[9] Anderson, R. M., "Heesterbeek, H., Klinkenberg, D., & Hollingsworth, T. D. (2020), How will country-based mitigation measures influence the course of the COVID-19 epidemic?", The Lancet, Vol. 395 No. 10228, pp. 931-934.

[10] Wang, G., Zhang, Y., Zhao, J., Zhang, J., & Jiang, F. (2020), "Mitigate the effects of home confinement on children during the COVID-19 outbreak", The Lancet, Vol. 395 No. 10228, pp. 945-947.

[11] Anholon, R., Rampasso, I.S., Silva, D.A.L., Leal Filho, W. and Quelhas, O.L.G. (2020), "The COVID-19 pandemic and the growing need to train engineers aligned to the sustainable development goals", International Journal of Sustainability in Higher Education, Vol. 21 No. 6, pp. 1269-1275.

[12] Koutsoupidou, T. (2014), "Online distance learning and music training: benefits, drawbacks and challenges", Open Learning, Vol. 29 No. 3, pp. 243-255.

[13] Pretorius, R.W., Anderson, R., Khotoo, A. and Pienaar, R. (2019), "Creating a context for campus sustainability through teaching and learning: The case of open, distance and e-learning", International Journal of Sustainability in Higher Education, Vol. 20 No. 3, pp. 530-547.

[14] Dunlap, J. C. & Lowenthal, P. R. (2018), "Online educators' recommendations for teaching online: Crowdsourcing in action", Open praxis, 2018, Vol. 10 No. 1, pp.79-89.

[15] Savelyeva, T. and McKenna, J.R. (2011), "Campus sustainability: emerging curricula models in higher education", International Journal of Sustainability in Higher Education, Vol. 12 No. 1, pp. 55-66.

[16] Basilaia, G. & Kvavadze, D. (2020), "Transition to Online Education in Schools during a SARS-CoV-2 Coronavirus (COVID-19) Pandemic in Georgia", Pedagogical Research, 2020, Vol. 5 No. 4, em0060, e-ISSN:2468-4929.

[17] Moorhouse, B. L. (2020), "Adaptations to a face-to-face initial teacher education course 'forced' online due to the COVID-19 pandemic", Journal of Education for Teaching, 1-3(2020). available at: https://www.tandfonline.com/doi/full/10.1080/02607476.2020.1755205 (Accessed 09 April 2020)

[18] Scull, J. & Michael, P. (2020), "Innovations in teacher education at the time of COVID19: an Australian perspective", Journal of Education for Teaching, available at: https://www.tandfonline.com/doi/full/10.1080/02607476.2020.1802701 (Accessed 31 July, 2020).

[19] Koenig, J., Jager-Biela, D. J. & Glutsch, N. (2020), "Adapting to online teaching during COVID-19 school closure: teacher education and teacher competence effects among early career teachers in Germany", European Journal of Teacher Education, available at: https://www.tandfonline.com/doi/full/10.1080/02619768.2020.1809650 (Accessed 18 August, 2020).

[20] Papadima-Sophocleous, S., & Loizides, F. (2016), "Exploring the benefits and disadvantages of introducing synchronous to asynchronous online technologies to facilitate flexibility in learning", CALL communities and culture–short papers from EUROCALL 2016 Edited by Salomi Papadima-Sophocleous, Linda Bradley, and Sylvie Thouësny, p. 363.

[21] Adedoyin, O. B., Soykan, E. (2020), "Covid-19 pandemic and online learning: the challenges and opportunities", Interactive Learning

Environments, available at: https://www.tandfonline.com/doi/full/10.1080/10494820.2020.1813180 (Accessed 02 September, 2020).

[22] Arkorful, V., & Abaidoo, N. (2015), "The role of e-learning, advantages and disadvantages of its adoption in higher education", International Journal of Instructional Technology and Distance Learning, Vol. 12 No. 1, pp. 29-42.

[23] Cole, L.B., Quinn, J., Akturk, A. and Johnson, B. (2019), "Promoting green building literacy through online laboratory experiences", International Journal of Sustainability in Higher Education, Vol. 20 No. 2, pp. 264-287.

[24] Bueno Alastuey, M. C. (2011), "Perceived benefits and drawbacks of synchronous voice-based computer-mediated communication in the foreign language classroom," Computer Assisted Language Learning, Vol. 24 No. 5, pp. 419-432.

[25] Bao, W. (2020), ″COVID ‐ 19 and online teaching in higher education: A case study of Peking University″, Human Behavior and Emerging Technologies, available at: https://onlinelibrary.wiley.com/doi/full/10.1002/hbe2.191 (Accessed 07 April, 2020).

[26] Strobl, C., Malley, J., & Tutz, G.(2009), "An Introduction to Recursive Partitioning: Rationale, Application, and Characteristics of Classification and Regression Trees, Bagging, and Random Forests", Psychological Methods, 2009-12, Vol. 14 No. 4, pp. 323-348.

[27] Montgomery, J. M. & Olivella, S. (2018), "Tree-Based Models for Political Science Data", American Journal of Political Science, Vol. 62, No. 3, pp. 729-744.

[28] Alotaibi, N.& Sasi, S. (2016), "Tree-based ensemble models for predicting the ICU transfer of stroke in-patients", 2016 International Conference on Data Science and Engineering (ICDSE), Cochin, pp. 1-6.

[29] Biau, G., Cadre, B., & Rouviere, L. (2019). "Accelerated gradient boosting", Machine learning, 2019, Vol. 108 No. 6, pp.971-992.

[30] James, G., Witten, D., Hastie, T., & Tibshirani, R. (2013), "An introduction to statistical learning", New York: springer, Vol. 112, p. 18.

[31] Breiman, L. (2001), "Radom forests", Mach. Leain., 45(2001), pp. 5-32.