The following publication K. Wang, E. Y. Fu, G. Ngai and H. V. Leong, "Identifying Key Learning Factors in Service-Leaning Programs Using Machine Learning," 2022 IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC), Los Alamitos, CA, USA, 2022, pp. 1312-1317 is available at https://doi.org/10.1109/COMPSAC54236.2022.00207.

Identifying Key Learning Factors in Service-Leaning Programs Using Machine Learning

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***Abstract*—As an impactful experiential learning pedagogy in higher education, service-learning (SL) can enhance students' academic learning and their sense of community and social responsibility by involving them in comprehensive community services. Much extant literature has justified the positive impacts of SL. However, the lack of quantitative analysis on identifying significant learning and course factors that strongly impact students' SL outcomes limits SL's further enhancement and adaptive development. This paper proposes to use machine learning approaches for modeling and identifying key learning factors in SL. We collect and study a large-scale dataset, including students' feedback on learning factors related to the different student experiences, course elements, and self-perceived learning outcomes. Machine learning algorithms are applied to model the various learning factors, contributing to effective classification models that predict students' learning outcomes using their evaluation on the learning factors. The most predictive model is then selected to identify a key set of important variables most indicative to students' SL outcomes. Our experiment results show that learning factors related to study challenges and interactions have significant positive impacts on students' learning gains. We believe that this paper will benefit future studies in this field.**

Keywords—Service-learning, data analysis, learning factors, machine learning, classification

I. Introduction

For decades, the primary goal of modern higher education has been set to cultivate students with essential academic and social knowledge, which includes civic responsibilities, social identity, teamworking, social skills, etc., to prepare responsible citizens for the society [4, 6]. However, traditional classroom teaching in universities seldom provides adequate opportunities for students to interact and engage with their communities and apply professional knowledge to solve real-world problems. The problem of how to fulfil the academy's civic and social roles has sparked much discussion within the education research community. In this context, many researchers believe that service-learning (SL) is one feasible solution to the problem for its potential to effectively connect students' disciplinary study and social education with the increasingly salient commitment to public purposes[2, 5]. Some colleges have even implemented SL education into academic credit-bearing courses. As such, there is need for an essential understanding on how to facilitate effective teaching and maximize students' learning outcomes from these courses.

Some studies have provided practical suggestions on designing operative SL curricula. One prominent example is the advice from National SL Cooperative [10] for carrying out effective SL practices, such as using evaluation and reflection and setting clear educational goals. However, it still remains unclear on how different student and course factors (i.e., learning factors) impact students on achieving their SL outcomes [7], impeding further concrete suggestions to improve SL curricula or develop adaptive SL programs. Another problem is that the modeling of a wide range of learning factors that have complex inner-relations can be challenging to traditional statistic methods, limiting the investigation of the student learning process in SL. To address these challenges, this paper applies machine learning techniques to analyze and model the relationship between various learning factors and eventually identify key factors that significantly impact students' learning outcomes.

Much previous work is also limited by studying on small-scale datasets. To address that, we collect a large amount of data from over ten thousand students with different disciplinary backgrounds, who took the SL courses offered by a public university from 2014 to 2018. The collected data includes students' self-report ratings on various learning factors related to course elements, learning experiences, and their self-perceived learning outcomes after completing the courses. To our best knowledge, this is the first study in SL that conducts empirical analysis on such a large-scale dataset.

The contributions of this paper include: 1) we construct a large-scale dataset in SL with various diversity; 2) we conduct comprehensive statistical analysis to associate different learning factors with students' SL outcomes; 3) we develop and empirically evaluate machine learning models that predict students' learning outcomes using their evaluation on the learning factors; and 4) we identify a set of import learning factors based on the constructed prediction models.

II. Related Work

SL is a type of experiential pedagogy that combines rigorous academic study with valuable community activities and crucial

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reflection [3, 13, 14]. First proposed in 1967, SL is now widely acknowledged as an influential and effective instructional approach in higher education [16]. Students can enhance their classroom knowledge and social skills in SL programs by solving real-world problems in intensive community services. Various studies have demonstrated that SL can foster students' development in different aspects, including intellectual, social, civic, and personal development [5]. The quality of their learning experience in SL greatly influences how and what students learn [2, 8, 15]. Thus, it is necessary to identify key learning factors and understand their impact on students' learning outcomes.

Extant studies show that, in the context of SL and other experiential learning, students' subjective evaluation is perhaps the primary and appropriate approach to measuring students' learning experience and outcome. Student feedback is usually gathered using a combination of Likert-type items or scales and open-ended questions. Using this method, several researchers have conducted empirical studies to analyze the relations between learning experience features and students' learning outcomes in SL.

The research conducted by [9] analyzed a range of course experience features and learning outcomes in SL courses with statistical methods. Their results suggested the significance of increasing students' perceived value and willingness to engage in community service in the SL courses. In work conducted by Chan et al. [11], they examined the relationship between various learning factors and different learning outcomes. Their results suggested statistically significant correlations between learning factors (e.g., students' interest, challenging and meaningful tasks) and students' achievement on intellectual, social, and civic learning outcomes. These studies, however, are limited by mainly relying on statistical and regression analysis, which may be impractical for analyzing non-linear and complex relations between the learning factors and learning outcomes.

In our study, we propose to use machine learning methods to model the complex relationship between various learning factors and students' learning outcomes. Based on that, we can identify the most impactful factors. To our best knowledge, this is the first step toward that end.

III. Research Context

This research is carried out at a public university, whose undergraduates are required to complete at least one three-credit SL course before graduating. The details of the SL courses, our instruments, and data are presented as follows.

A. Service-Learning Courses

There are around 70 SL courses offered by all departments (e.g., computing, nursing, applied mathematics, etc.) in the university covering various academic disciplines. Although the educational contents may be different, all the SL courses have three standard teaching components:

1. Experiential component. Students are required to participate in one or more substantive projects to provide community services or look at current social issues.
2. Academic component. Students are provided with sufficient theoretical knowledge and skills for completing their projects.
3. Reflective component. Students are asked to write weekly reflective reports to monitor their progress.

Before course registration, students can find adequate information about all the SL courses (e.g., project introduction and course requirements, etc.) They can choose any course offered by any department that interests them.

TABLE I. Measures for Learning Outcomes from SPEQ

Constructs	Items
Intellectual Learning Outcome (ILO)	ILO_1: Deeper understanding of the linkage between SL and the academic content of the subject.
	ILO_2: Applying/integrating knowledge to deal with complex issues.
	ILO_3: Solving challenging real-life problems.
	ILO_4: Thinking critically.
Social Learning Outcome (SLO)	SLO_1: Working effectively in teams.
	SLO_2: Communicating effectively with peers, collaborators, and service recipients.
Civic Learning Outcome (CLO)	CLO_1: Better understanding of the problems facing underprivileged members of the community.
	CLO_2: Increased interest/commitment to serve people in need.
	CLO_3: Becoming a more responsible member of your community.
	CLO_4: Increased understanding and respect for people from different backgrounds.
	CLO_5: Becoming a more responsible global citizen.
Personal Learning Outcome (PLO)	PLO_1: Better understanding of my own strengths and weaknesses.

B. Instrument Design

At the end of the courses, students need to fill out and submit a Student Post-Experience Questionnaire (SPEQ), which collects their self-report ratings on different course elements and their learning experience (i.e., learning factors) and self-perceived learning outcomes in the courses. Specifically, there are twelve questions that ask students to rate, on a 7-point scale (1= 'very little'; 4= 'a fair amount'; 7= 'very much'), their learning outcomes after completing the courses. This includes their Intellectual (ILO), Social (SLO), Civic (CLO), and Personal Learning Outcome (PLO), as shown in Table I. In addition, there are eighteen questions that ask students to score their experience with the relevant course and pedagogical factors of the SL course on a 7-point scale (1 = 'strongly disagree'; 4 = 'neutral'; 7 = 'strongly agree'). The details are shown in Table II.

To better measure the learning factors and learning outcomes in SL courses, the SPEQ is designed by the research team with reference to an extensive literature review and the exclusive context in which the SL courses and projects were conducted. Furthermore, the instrument was assessed by a panel of expert

SL instructors and researchers to verify content and face validity. Exploratory and confirmatory factor analyses were used to assess the construct validity of the multiple-item scales. The results suggest that the instrument is reasonably valid, with all fit indices meeting the goodness of fit criterion (CFI = 0.973, TLI = 0.9564, NFI = 0.971, RMSEA = 0.073). Students are given the questionnaire as part of the university's quality assurance process. Students are well informed about the study's goal and are guaranteed that their replies will not be shared with the teachers or influence their grades. The authors have requested and got approval from the university ethics committee for this work and access to the data for analysis.

C. Participants and Survey Data

In this study, we collect data from undergraduate students who have completed SL courses between the academic year of 2014/15 and 2018/19 by the SPEQ. In total, we have 11,185 data instances from 11,100 students in our dataset (5494 females). Because 85 students took more than one SL course in the given period, they contributed to multiple data instances for the dataset.

Besides, some students may inattentively rate all questions with the same rating or leave some questions blank. To ensure the reliability of our data, we identify and remove all the instances that contain potential inattentive responses. Specifically, we removed 10 duplicated records; 451 records that provide the same ratings for all survey questions; 1340 records with incomplete feedback. Finally, we construct a dataset consisting of 9415 instances from 9365 students in this study.

IV. Statistical Analysis

We first conduct a statistical analysis to have an overall understanding of the data. The agreement distribution of each learning factor is illustrated in Fig. 1. For better visualization, based on the original description of survey questions, we categorize ratings from 1 to 3 as 'disagree', ratings with 4 as 'neutral', and ratings from 5 to 7 as 'agree' across each question regarding learning experience factors. As shown in Fig. 1, most students respond with higher ratings (5-7) on all learning experience factors, and only a few students express their dissatisfaction. In other words, most students 'Agree' that they have a 'good' experience in the SL courses.

Compared to other features, the ratio of 'Disagree' and 'Agree' is distinctively different for features "requirement for graduation" (CR_1), 'interest' (SI_1), and 'related discipline' (DC_1) (over 10% of students choose 'Disagree' and less than 70% of students choose 'Agree'). More specifically, CR_1 and SI_1 can be regarded as investigating the motivation for participating in SL courses. Noted that there is a moderate proportion of students with 'Disagree' and 'agree' on CR_1 and SI_1, which may indicate that SL courses have some features that attract students despite the compulsory credit requirement.

In addition, we also explore the relationship between learning experience factors and learning outcomes by carrying out a Spearman's Rank Correlation analysis. Since Spearman's Rank Correlation analysis is suitable for the ordinal data and non-linear relationship measurement, it can provide a more reliable correlation result than other correlation analysis methods (e.g., Pearson Correlation analysis). Specifically, we want to understand whether there exists any potential correlation between each learning experience factor and four learning outcomes, i.e., intellectual learning outcome (ILO), social learning outcome (SLO), civic learning outcome (CLO), and personal learning outcome (PLO).

TABLE II. Measures for Learning Experiences from SPEQ

Constructs	Items
Course Requirement	CR_1: The main reason for me to take this SL subject is to fulfill the SL Requirement for graduation.
Study Interest	SI_1: I was interested in the SL project.
Discipline Connection	DC_1: The service I performed was closely related to my major/discipline of study.
Study Effort	SE_1: I put a lot of effort into planning, preparing and delivering the service.
Program Value & Benefit	PVB_1: The service I did in the SL project has benefited the people I served. PVB_2: I felt that my service was appreciated by the NGOs/service recipients.
Help & Support	HS_1: My teachers/tutors prepared me well for performing the service. HS_2: My teachers/tutors were enthusiastic and passionate about the subject and the service. HS_3: I could get help and support from the teachers/tutors/NGOs when I needed it. HS_4: I benefited a lot from the interaction I had with the teachers, tutors, and other students.
Participation & Interaction	PI_1: My team in the SL project worked well together. PI_2: There were a lot of opportunities for me to meet and interact with the people I served. PI_3: I developed a good personal relationship with my teammates.
Study Challenge	SC_1: The SL project provided challenging and meaningful tasks for me to accomplish. SC_2: The SL project challenged me to try new things.
Study Autonomy	SA_1: In my SL project, I carried out tasks that were mainly designed by me/my team rather than simply follow instructions.
Study Reflection	SR_1: I was required to engage regularly in reflective activities (e.g., writing reflective journals or project logs, debriefing sessions, project reports) during and after the SL project. SR_2: The reflective activities had clear instructions and guidelines.

Here, we present the significant features that statistically correlate to the learning outcomes ($\rho \geq |0.5|$ and $p < 0.01$). The correlation analysis result is shown in Table III. We found out that Course Requirement (CR), Study Interest (SI), Discipline Connection (DC), and Study Autonomy (SA) have no strong correlation with any of the learning outcomes. Besides, ILO and CLO seem to be affected by the same learning experience factors. This may suggest that these factors have collective effects on them. SLO, on the other hand, has similar but fewer correlated experience features. It is worth mentioning that "team work well" (PI_1) has a distinctive correlation with SLO, which may indicate that effective grouping in SL projects facilitates students' social learning.

The correlation analysis allows us to gain an intuition about the relationship between learning factors and learning outcomes.

However, it is a simple statistical approach to investigate the potential connection between two variables and cannot provide insights into what learning experience features impact students' ratings on each learning outcome. Therefore, additional analysis is still necessary. In the next section, we experiment with different machine learning algorithms to model their relationship and identify the key factors that most impact students' learning outcomes.

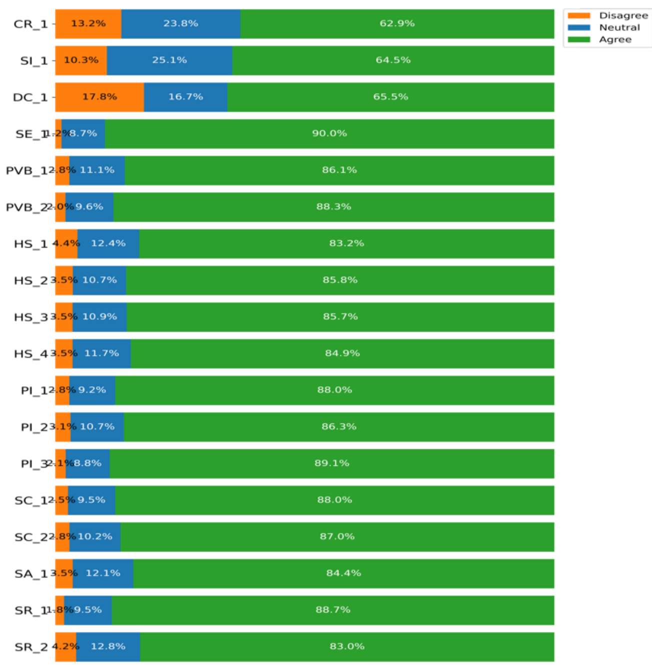

Fig. 1. Agreement distribution of learning experiences factors

V. Learning Outcome Prediction

In this study, we are more interested in identifying students who have higher ratings on learning outcomes that fall within the top 25% of all students, students who have lower ratings that fall within the bottom 25%, and the rest of the students with moderate learning gain (50%). Instead of using specific items, we only consider the four constructs of learning outcomes as appropriate measures in this classification task. One reason is that items of the same constructs may have a linear relationship, and it is more reasonable to consider them as one variable. Another reason is that we are only interested in these four learning outcomes related to the learning experience factors. The mean value and standard deviation of students' learning outcomes of three groups are shown in Table IV. The difference between each group is statistically significant and thus facilitates the following classification task.

The classification task aims to classify students into the three classes: 'Top25%', 'Middle50%' and 'Bottom25%' based on their self-report evaluation of the learning outcomes. The rationale behind this is that, by identifying students with different levels of each learning outcome, we can identify the potential learning experience factors that impact students learning outcomes. Therefore, we have built several classification models using various machine learning algorithms (e.g., KNN, SVM, Decision Tree, etc.). The models' performances are provided and discussed in Section 6.

VI. Experiment

We empirically evaluate the models and select the best classification model based on the model performances. Then, we can screen out the key learning experience factors by calculating the feature importance in the best classification model.

A. *Model Evaluation*

In this experiment, we employed several machine learning algorithms to build classification models for identifying students with different levels of learning outcomes. All classification models were trained using 10-fold cross-validation in this study. Besides, since there is a class imbalance problem as the ratio of the class 'middle 50%' to the rest two classes is 2:1:1, we adopt the resampling without replacement method to randomly select an equal example size with the other two classes.

TABLE III. Spearman's Rank Correlation Results

		ILO	SLO	CLO	PLO
Course Requirement	CR_1	-	-	-	-
Study Interest	SI_1	-	-	-	-
Discipline Connection	DC_1	-	-	-	-
Study Effort	SE_1	0.517	0.517	0.532	-
Program Value & Benefit	PVB_1	0.530	0.502	0.549	-
	PVB_2	0.546	0.540	0.576	-
Help & Support	HS_1	0.533	-	0.535	-
	HS_2	0.549	0.517	0.559	-
	HS_3	0.549	0.510	0.550	-
	HS_4	0.575	0.518	0.583	-
Participation & Interaction	PI_1	-	0.532	-	-
	PI_2	0.520	-	0.529	-
	PI_3	0.501	0.599	0.525	-
Study Challenge	SC_1	0.580	0.528	0.592	0.518
	SC_2	0.502	-	0.515	-
Study Autonomy	SA_1	-	-	-	-
Study Reflection	SR_1	0.502	-	0.522	-
	SR_2	0.542	-	0.549	-

TABLE IV. Mean Values and Standard Deviation of Learning Outcomes of Three Groups

	Top 25%	Middle 50%	Bottom 25%	Overall
ILO	6.38±0.36	5.47±0.34	4.31±0.67	5.41±0.87
SLO	6.08±0.68	5.70±0.36	4.48±0.68	5.64±0.91
CLO	6.45±0.35	5.53±0.35	4.36±0.66	5.46±0.87
PLO	6.66±0.47	5.65±0.48	4.39±0.80	5.59±0.99

Since there have been no similar studies before, we used Scikit-learn [12] to implement seven classic machine learning algorithms to build the classifiers in this study: Support Vector Machine (SVM), K-Nearest Neighbors (KNN), Decision Tree (DT), Multilayer Perception (MLP), Random Forest (RF), Logistic Regression, and Naïve Bayes. To achieve the best performance of each classification model, a cross-validated grid search method is used for fine-tuning the models and selecting the most optimal model parameters. More specifically, for SVM, the kernel we used is 'RBF', the trade-off parameter C=5; For KNN, the number of nearest neighbour K = 20; For MLP, we have implemented a three-fully connected layer with <128,128, 10> nodes; For RF, the number of base estimators is 50, and maximum depth of the tree is 10; For the rest of the algorithms, we applied the default parameters given by Python scikit-learn package.

B. Model Performance Analysis

The model performances are presented in Table V. For predicting students' ILO levels, SVM and Random Forest achieved the best performance with 64% accuracy. MLP and Random Forest performed well in classifying both SLO and CLO. Specifically, MLP performed slightly better than Random Forest, with 65% accuracy in identifying students' SLO. The performances of other classifiers are pretty similar except for Naïve Bayes. They achieve an accuracy of around 64% to 66%. Similar results are observed for PLO; the models attain about 55% to 57% accuracy. SVM and Random Forest are the most prominent models in this task.

TABLE V. PERFORMANCES OF DIFFERENT CLASSIFICATION MODELS

	ILO	SLO	CLO	PLO
SVM	**0.64± .03**	0.61±.02	0.65±.02	**0.57± .04**
KNN	0.59± .04	0.62±.02	0.64±.03	0.55± .04
Decision Tree	0.60±. 02	0.61±.02	0.64±.02	0.56± .05
MLP	0.62± .04	**0.65±.02**	**0.66±.02**	0.56± .04
Random Forest	**0.64± .03**	**0.64± .02**	**0.66±.02**	**0.57± .04**
Logistic Regression	0.60± .03	0.62±.03	0.61±.02	0.54± .04
Naïve Bayes	0.46± .02	0.45±.01	0.47±.03	0.42± .02

We note that non-linear classifiers like SVM and MLP outperformed the Logistic Regression in the individual classification task, which proved our hypothesis on the non-linear relationship between learning experience factors and learning outcomes. And machine learning models are more efficient in learning that. In general, Naïve Bayes performed poorly in each task compared to other algorithms. On the other hand, Random Forest yields the best performance across the board, which achieves the accuracy of 64%, 64%, 66%, and 57%, respectively. Thus, we consider Random Forest as the best model for predicting students' learning outcomes in this study.

C. Selection of Key Learning Factors

In this section, we aim to discover the most important factors that impact students' learning outcomes. To achieve this goal, we first derived the feature importance for each learning factor by training a Random Forest model using the whole dataset. After obtaining the model and feature importance, we employed the Sequential Forward Selection [1] (SFS) method to search for the most impactful learning factors for each learning outcome. We generate eighteen feature sets by adding one feature at a time based on the descending order of feature importance value. We then trained eighteen Random Forest models and compared their model performances to select the most optimal number of all features.

As shown in Fig. 2, there is a noticeable drop in models' performance with over the top 10 features in each learning outcome. Moreover, besides CLO, models trained with top 10 features nearly yielded the best performance in each learning outcome compared with other models. Therefore, it is reasonable to select the top 10 features as the most impactful on students' learning outcomes in SL study.

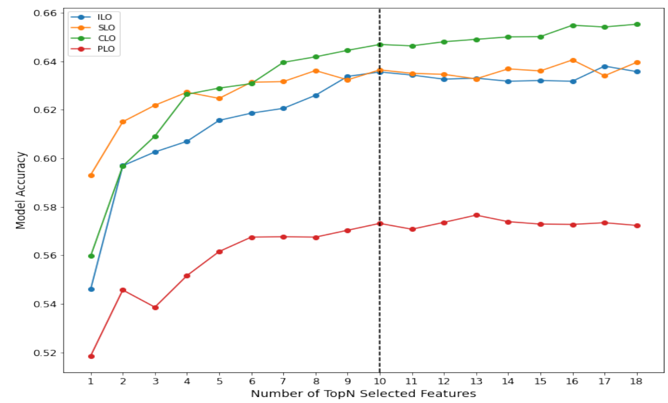

Fig. 2. Model performances with different feature sets

D. Key Learning Factors Analysis

The respective top-10 learning factors for students' intellectual, social, civic, and personal learning outcomes are summarized in Table VI. Overall, the results show that there exist multiple learning factors that have influences on some or even all the students' learning outcomes (e.g., SE_1, PVB_2, SC_1) and factors that have no substantial impact on any of these learning outcomes (e.g., CR_1, DC_1, SA_1). Besides, almost half of the top 10 impactful factors are subject to 'Study Effort', 'Pro-gram Value & Benefit', and 'Help & Support'. This may suggest that these are the core factors in SL courses that facilitate students' learning outcomes. Moreover, we note that the same learning factor can contribute unevenly to different learning outcomes. For example, HS_4 is the most important feature in predicting students' intellectual learning outcomes, while it is less helpful in students' social learning outcomes.

Some intriguing results can be found when it comes to the relationship between learning factors and each learning outcome. For ILO, "Help & Support" (HS_1-HS_4) and 'study challenge' are the most impactful factors, while 'study effort' (SE_1), as a traditionally necessary component in almost every discipline study, is the last one in the top 10 factors. However, it does make sense when considering that the knowledge transfer of SL courses mainly occurs in community services or other on-site services with teachers' supervision. In such a context, hands-on experience plays a vital role in students' intellectual learning. Thus, students who interact with teachers and students frequently can yield a better understanding on its academic content and yield better learning outcomes. For SLO, three learning factors from 'Participation & Interaction' are among the top 10 factors, and particularly, 'good relationship with teammates' (PI_3) and 'team works well together' (PI_3) are the top 2 impactful factors. This justifies that the interaction between students plays a dominant role in their social development. Besides, 'Help & Support' also provides a channel for students to forge a bond with others and thus contribute to their social learning outcome. As to CLO, the most impactful factors are almost the same with those of ILO. This result may suggest that ILO and CLO are closely related. In other words, students who yield better ILO results may also achieve good CLOs. For PLO, two learning factors from ‘study challenge’ are the top factors. This may be consistent with the universal understanding that one will only know the limits when dealing with complex and challenging problems, which in turn increase their self-perceptions.

TABLE VI. THE TOP 10 LEARNING EXPERIENCE FACTORS OF EACH LEARNING OUTCOME

		ILO	SLO	CLO	PLO
Course Requirement	CR_1	-	-	-	-
Study Interest	SI_1	9	-	8	-
Discipline Connection	DC_1	-	-	-	-
Study Effort	SE_1	10	8	9	6
Program Value & Benefit	PVB_1	8	10	6	4
	PVB_2	5	3	3	-
Help & Support	HS_1	7	-	-	-
	HS_2	3	4	4	5
	HS_3	4	7	5	8
	HS_4	1	5	2	3
Participation & Interaction	PI_1	-	2	-	-
	PI_2	-	9	10	-
	PI_3	-	1	-	9
Study Challenge	SC_1	2	6	1	1
	SC_2	-	-	-	2
Study Autonomy	SA_1	-	-	-	-
Study Reflection	SR_1	-	-	-	7
	SR_2	6	-	7	10

From the above observations and findings, we can further gain some insights on guiding effective SL instructions. First of all, SL courses need to involve more student-student and student-teacher interaction modules to encourage students to interact initiatively while dealing with real-world tasks. Particularly, SL teachers should always monitor students’ interaction levels throughout the course and ensure high-quality interactions through various actions such as encouraging question asking and experience sharing during and after the class. Secondly, since study challenge is another critical factor in study achievement, SL teachers should carefully design and adjust the task challenge level as the teaching progresses. This is an effective approach to drive students out of their comfort zones and stimulate their learning initiatives to maximize the learning outcomes. Last but not least, given that the perceived value of SL programs have significant impacts on students’ attitudes and commitments to their study, SL teachers should provide adequate background knowledge to help students recognize and identify with the cultural and social values of the SL programs.

VII. CONCLUSION

Investigating the complex relationship between learning factors and learning outcomes and identifying the key learning factors and their corresponding impact is quite challenging because too many variables are involved. This paper investigates the relationship between various learning factors and learning outcomes in SL courses by machine learning methods. Our experiment results suggest that the Random Forest classification model is the best model to predict students’ SL outcomes. Moreover, we conduct further analysis on quantitively describing the relationship between key learning factors and learning outcomes. We envision this study contributing to the future research of the SL process and facilitating the development of SL practices. In the future, this work will try to incorporate as many institutions as possible to enlarge our dataset and further generalize the analysis results.

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