Intelligent Student Relationship Management Platform with Machine Learning for Student Empowerment

https://doi.org/10.3991/ijet.v18i04.32583

Sasitorn Issaro[1(✉)], Panita Wannapiroon[2]
[1]Nakhon Si Thammarat Rajabhat University, Tha Ngio, Thailand
[2]King Mongkut's University of Technology North Bangkok, Bangkok, Thailand
Sasitorn_Iss@nstru.ac.th

Abstract—Students' grades can affect their future studies at university. The COVID-19 situation has resulted in a greater amount of online teaching, in which teachers and learners rarely interact, causing additional problems with academic performance. This research aims to design and develop an intelligent student relationship management platform (an intelligent SRM platform) using machine learning prediction for student empowerment. This research begins with the synthesis of the factors, the machine learning prediction process, and the platform components. The results of the synthesis establish the design of the platform. Undergraduate students' grades are then predicted using the decision tree algorithm. Students are divided into two groups, empowerment and non-empowerment groups, using this algorithm. The results show that the learning outcome prediction model has an accuracy of 100.00% and an F-measure of 100%. The most important factor for improving grades is the grade point average, with a weight of 0.637. Therefore, student empowerment to provide students with better grades is essential. This paper presents two approaches to student empowerment: using artificial intelligence technology from the intelligent SRM platform and empowering teachers.

Keywords—intelligent student relationship management (SRM), student empowerment, machine learning, decision tree

1 Introduction

The COVID-19 pandemic has had an inevitable impact on today's lifestyles. COVID-19 has made teaching and learning in the classroom impossible to operate normally. Thus, a new approach to the teaching and learning process has emerged. Researchers studying COVID-19 in the context of education have addressed issues such as the relationship between the pandemic and quality of life, loneliness, happiness, and Internet addiction, assessed according to a relational survey model involving school administrators and teachers [1]. Investigate the relationships between COVID-19-related psychological distress, social media addiction, COVID-19-related burnout, and depression. Research data were collected through online surveys and then structural equation modeling (SEM) was used to test and analyze the proposed hypotheses. It was found that burnout associated with COVID-19 significantly and positively predicted depression. SEM results revealed that COVID-19-related psychological distress directly affected COVID-19-related burnout, depression, and social media addiction [2]. In addition, elements of the community-building curriculum and the promotion of learning through online courses have also been considered, with the finding that teaching and learning management were able to survive during the pandemic mainly due to online resources [1]. Moreover, the development needs of educators, faculty, and staff when participating in online instruction were also examined, with the conclusion that technology was a teaching challenge and that the future of faculty development should involve taking advantage of virtual and case-based learning, with online strategies for undergraduate students [3]. A survey evaluated the five elements of the discover, learn, practice, collaborate, and assess (DLPCA) blended learning strategy, finding that most students were satisfied with it, deeming it manageable and effective, and could adapt to the online tutoring that occurred in the post-COVID-19 period [4]. Finally, studies have identified depression in undergraduate students participating in online learning as an effect of students' educational behavior due to COVID-19, with the results showing that three in four university students had various symptoms, and half had moderate to severe depression [5].

Technology and teachers' attention can improve the effectiveness of student tracking and help in decision-making in the development of students' empowerment. The attention currently paid by teachers to university students may not be sufficient for student development. Therefore, the adoption of technology may improve the effectiveness of student tracking and help in decision-making in development or supplementation, as well as inducing students' empowerment to develop the potential for improvement. Machine learning (ML) is a computer algorithm that helps in every aspect. ML is accessible through both supervised and unsupervised learning, as well as reinforcement. ML algorithms include neural networks, decision trees, support vector machines, and genetic algorithms, etc. using multiple machine learning algorithms to determine model accuracy. The e-learning platform is designed to help students. This results in a more effective learning process. It helps students discover for themselves what environments they can learn best in and how machine learning techniques can efficiently extract, analyze and adapt data to the videos, games, etc., of the learning platform [6]. Student relationship management (SRM) is a multi-dimensional strategic approach and covers three important dimensions: technology, people, and processes. A state-of-the-art research framework for the benefit of SRM system development provides a guide to its effective implementation for decision-makers in educational systems [7]. It uses the Internet of Things to collect the digital footprints of students from higher education institutions and consists of five modules: identify, alert, tracking, SRM, and analytics [8]. Statistical methods and machine learning predict the course suitability of students participating in massive open online courses (MOOCs), using multiple machine learning algorithms to determine model accuracy [9].

According to the study, problems and gaps in online learning have emerged because teachers are unable to motivate and supervise students. Classroom behaviors during online teaching were diverse. Some people turned off the camera and did not pay attention to the teacher. Others did not engage in any interaction with classmates. A number failed to submit their assignments on time. These behaviors inevitably affect the level of academic performance. Therefore, this article presents a solution by empowering students to solve their academic performance problems, and through predicting students' learning outcomes by teaching using the learning management system (LMS). Behavioral, midterm, and final semester scores were collected from observations and cloud databases. The researcher found that students had dropped out, failed exams, or not completed their work. Classroom behaviors and exam scores were merely adequate, and students were frequently late or absent from school. These factors affected the level of academic performance for each course. The researcher proposed a method of using technology such as machine learning to predict student performance. These predictions are based on classroom behaviors, test scores, etc. A student with poor grades can be empowered by SRM approaches. The smart platform analyzes student performance levels with machine learning techniques to identify student behavior that affects grade improvement. Empowering students enables them to improve their university learning and lives after graduation.

This paper consists of seven sections: Section 1, the introduction, Section 2, the literature review, Section 3, which describes the methods, Section 4, which provides the results, Section 5, which covers student empowerment, Section 6, which provides a discussion of the findings, and Section 7, which concludes the study.

2 Literature review

SRM is a customer relationship management strategy for individual educational institutions [10]. SRM's aim is to create a good relationship between higher education institutions and students [11]. Intelligent technology to manage student relationships involves presenting various learning materials and providing services according to the characteristics and behavior of each student. Automated recommendations are provided to help students gain satisfaction and develop loyalty to the university [12]. Intelligent SRM is the application of intelligent technology to manage student relationships, provide services, and optimize and maintain relationships between students and educational institutions.

The Intelligent SRM platform comprises four main dimensions and 12 elements. The first dimension, strategic SRM, consists of five components: SRM vision, SRM strategy, student life cycle, SRM metrics, and student retention. The second dimension, operational SRM, has one component, student services. The third dimension, analytical SRM, consists of four components: student identification, differentiation, student portfolio analysis, and valued student experience. The fourth dimension, collaborative SRM, consists of two components: value proposition development and network development [13]. Intelligent SRM consists of seven components: recruitment, counseling, student life, housing, student support services such as tutoring, etc., alumni/development, and career/employment services [14]. The components of intelligent SRM platform consist of four components: knowledge management, employee/student involvement, student orientation, and SRM technology [15]. The components of the Intelligent SRM platform include student relationship retention, identification, mentoring, and using SRM technology to help manage intelligent student relationships.

Researchers analyze and determine the impact of digital marketing on relationship management with university students during the COVID-19 pandemic. The results developed using a data structure and scheduling model with SmartPLS3 and Content Marketing showed a significant influence on the operational management of customer relationships, as well as on analytics and collaboration. Customer Relationship Management for Social Media Marketing has been found to have a strong influence on customer relationship management in operations as well as analytical and collaborative customer relationship management because digital media used by Continental University is attractive to parents and families [16]. Researchers propose a conceptual framework that reinforces cutting-edge research to benefit the successful development of SRM systems. It could also be a guide for higher education decision-makers on how to implement effective SRMs, and may complement research on institutional sustainability, which is gaining increasing interest in educational institutions [15]. Researchers offers the driving force of student-centered learning and how colleges of education can empower students as clients with true responsibility to drive their own learning, highlighting the role of administrative staff in implementing student relationships [17].

Machine learning is the study of algorithms and statistical patterns by computer systems to perform specific tasks according to the nature of the work. Machine learning is a form of data analysis that automates model analysis. It is a branch of artificial intelligence technology, based on the idea that systems can learn and interact with different datasets and can identify patterns that occur, leading to self-determination and thus no reliance on humans. This allows software applications to be more accurate in predicting outcomes without programming. Thus, machine learning is used as the brain of artificial intelligence to enable learning and to improve user experiences, automatically learning what to do with the data [18]. Machine learning can be divided into two types based on behavior type: supervised learning, involving prediction and classification wherein each algorithm learns a certain pattern from training data and applies it to datasets (algorithms including those such as decision tree, Naïve Bayes, and support vector machine); and unattended learning (unsupervised learning), wherein algorithms identify and present interesting structures in the data and use previously learned attributes to remember classes of data. The latter is mainly used for grouping and reducing properties, and includes principal component analysis, neural networks, and k-nearest neighbors [18].

A neural network algorithm was used to predict the bachelor's average. A neural network algorithm was used to predict the bachelor's average, and to address school guidance issues in the Guelmim Oued Noun region and its impact on students' lives school guidance issues in the Guelmim Oued Noun region and its impact on students' lives. Predictive outcomes should include academic and professional orientation for best academic performance [19]. Neural networks predicted student performance based on student behavior in an online learning environment, using the e-learning environment as an input variable to predict student performance. The results showed an accuracy rate of more than 80%; therefore, it is recommended to use the model in learning management [20]. An e-learning performance-based classification behavior prediction framework (BCEP) was proposed. The e-learning behavior property uses a combination of attributes with behavior data based on a behavior classification model to obtain the categorical property values of each behavior type. BCEP has good predictive results.

The model's performance in predicting learning efficiency was better than that of conventional classification methods [21].

Decision tree learning is one of the most widely used and useful methods for inductive inference on account of various features. The decision tree represents the steps in which the data are categorized, and, in addition, it is used for processing large amounts of data [22]. A decision tree is a technique that results in a tree-like structure consisting of nodes, each node having test properties to make decisions. The most class-related attribute is selected as the root node by searching for the relevance of the attribute (information gain), which is calculated as follows:

$$\begin{aligned} IG(parent, child) = entropy(parent) - [\,p(c1) \times entropy(c1) \\ + p(c2) \times entropy(c2) + \ldots] \end{aligned} \tag{1}$$

When *entropy* $(c1) = -p(c1) \log p(c1)$ *and* $p(c1)$ *is a probability of* $c1$

Measuring the Performance of the Machine learning Model. The accuracy of the prediction model involves extracting the predicted grades obtained from the training dataset and determining the precision, recall, accuracy, and F-measure values, as follows:

$$\text{Precision} = \frac{TP}{TP + FP} \tag{2}$$

$$\text{Recall} = \frac{TP}{TP + FN} \tag{3}$$

$$\text{Accuracy} = \frac{TP + TN}{TP + FP + FN + TN} \tag{4}$$

$$\text{F-Measure} = \frac{2 \times Precision \times Recall}{Precision + Recall} \tag{5}$$

where TP is the number of extracted correct data

FP is the number of extracted incorrect data

TN is the number of correct unextracted data

FN is the number of incorrect unextracted data

The evidence emerging from recent studies has ignited the need to have a serious conversation about student empowerment and the importance of flexibility and course completion rates [23]. Student empowerment must occur through the digital and online teaching and learning model in higher education that has been exponentially increasing as a result of the COVID-19 pandemic [24] [25]. Empowerment, in this context, means empowering students with work and life skills involving information media, technology, and innovation. These skills aid students in the learning process [26]. An empowerment-through-reasoning program was completed for the development of a shorter attitude and belief survey which may be easier for teachers to implement and interpret [27]. The main goal of empowerment is to produce graduates with the understanding and skills to work [28]. Therefore, the empowerment of students involves the development of knowledge, skills, and abilities to control and develop self-learning, allowing students to realize their worth by using strategies that promote academic success.

3 Methodology

3.1 Synthesis of documents and related research

The synthesis of relevant documents and research to design the architecture and develop the Intelligent SRM platform was achieved via content analysis of issues that affect the process of developing a platform with machine learning for student empowerment, as shown in Tables 1–3.

Table 1. Factors of machine learning prediction to enhance the learning power of undergraduate students

Factors	[9]	[29]	[30]	[31]	[32]	[33]	[34]	[35]	Synthesis
frequency of access to the system	✓	✓	✓	✓	✓		✓	✓	✓
number of activities	✓	✓		✓	✓	✓	✓		✓
lessons, quizzes, and assignments		✓		✓	✓		✓	✓	✓
frequency of access to discussion boards	✓		✓		✓	✓			✓
number of new threads added to the discussion forums	✓		✓		✓	✓			✓
grade point average	✓	✓		✓			✓	✓	✓

There were six factors related to machine learning prediction to empower undergraduate students: frequency of access to the system; number of activities; lessons quizzes and assignments; frequency of access to discussion boards; number of new threads added to the discussion forums; and grade point average (GPA).

Table 2. Machine learning prediction process for student empowerment

Process of Machine Learning	[36]	[37]	[38]	[39]	[40]	[41]	[42]	Synthesis
Data collection		✓	✓	✓	✓	✓	✓	✓
Data cleansing	✓		✓	✓	✓	✓	✓	✓
Feature extraction	✓		✓	✓	✓	✓	✓	✓
Feature classification				✓	✓	✓	✓	✓
Predictive model	✓	✓	✓	✓			✓	✓
Experimental		✓	✓	✓			✓	✓
Evaluation			✓	✓	✓		✓	✓
Data visualization		✓	✓	✓			✓	✓

Exploring the influence of various factors on the machine learning prediction process revealed that the process consists of eight steps: data collection, data cleansing, feature extraction, feature classification, predictive model, experimental, evaluation, and data visualization.

Table 3. The components of an Intelligent SRM platform

Components of Intelligent Student Relationship Management Platform	[11]	[13]	[15]	[43]	[44]	[29]	[17]	Synthesis
Identify module	✓	✓		✓	✓	✓	✓	✓
Alert module	✓	✓	✓	✓		✓		✓
SRM module	✓	✓	✓	✓	✓		✓	✓
Analytic module	✓	✓	✓	✓	✓	✓		✓
Content management module			✓	✓	✓	✓	✓	✓
Comment module				✓	✓		✓	✓
Assessment module			✓	✓		✓	✓	✓
Scaffolding module			✓		✓	✓	✓	✓

Studying the components of an Intelligent SRM platform revealed that it consists of eight modules: identify module, alert module, SRM module, analytic module, content management module, comment module, assessment module and scaffolding module.

3.2 Designing an intelligent SRM platform

The workflow of intelligent SRM platform, using information from document synthesis and related research as per Tables 1, 2, and 3, to create an Intelligent SRM platform with predictive machine learning for student empowerment is shown in Figure 1.

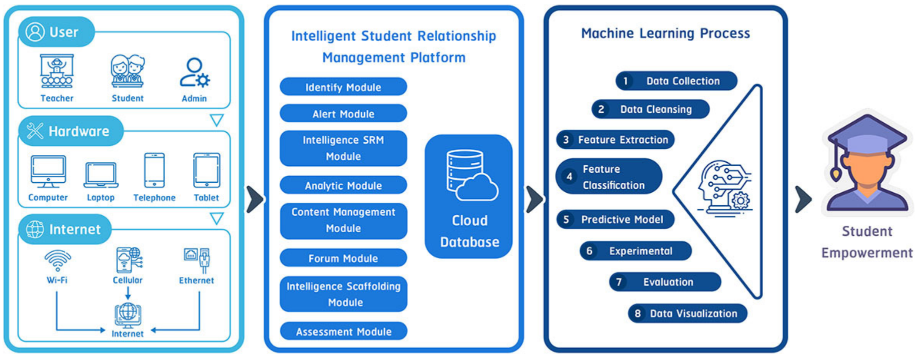

Fig. 1. The workflow of an intelligent SRM platform with machine learning for student empowerment

As per Figure 1, the intelligent SRM platform with machine learning for student empowerment consists of the user (teacher, student, and admin), hardware (computer, laptop, telephone, and tablet) and Internet (wi-fi, cellular, and ethernet). System users access hardware devices via an Internet connection to open the intelligent SRM platform. The platform consists of eight modules: identify module, alert module, intelligence SRM module, analytic module, content management module, forum module, intelligence scaffolding module, and assessment module.

The evaluation of the intelligent SRM platform with machine learning for student empowerment involved 10 experts in computer technology and eight main questions concerning 1) hardware, 2) software, 3) peopleware, 4) the database system, 5) network system, 6) prediction process, 7) appropriateness of platform architecture implementation, and 8) the overall feasibility of an intelligent SRM platform using machine learning prediction to empower learners. The overall evaluation of the system architecture by experts was at an appropriately high level. The next step involved collecting data on student usage generated on the intelligent SRM platform and storing it in a cloud database.

3.3 Machine learning prediction process

The data were used to predict learning performance (Table 2) using an eight-step machine learning prediction algorithm. The details are shown in Figure 2.

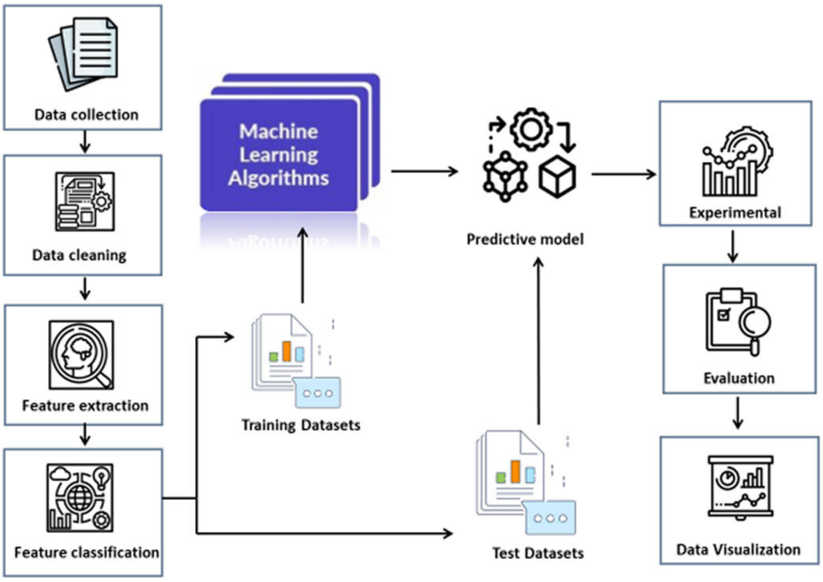

Fig. 2. The process of prediction with machine learning for student empowerment

Figure 2 shows the process of prediction with machine learning for student empowerment. The steps were as follows:

Step 1. Data collection: collect data from the system (LMS).

Step 2. Data cleansing: prepare the data.

Step 3. Feature extraction: extract the specific data attributes used for prediction.

Step 4. Feature classification: classify the data attributes used to predict academic performance (80% training datasets and 20% test datasets).

Step 5. Create a model for prediction: create a model to calculate the level of academic performance using a machine learning algorithm.

Step 6. Experimental: practical use of the predictive model.

Step 7. Evaluation: evaluate the level of prediction of the model.

Step 8. Data visualization: presentation of the data and the accuracy of the predictions.

These steps are illustrated by a flowchart (Figure 3).

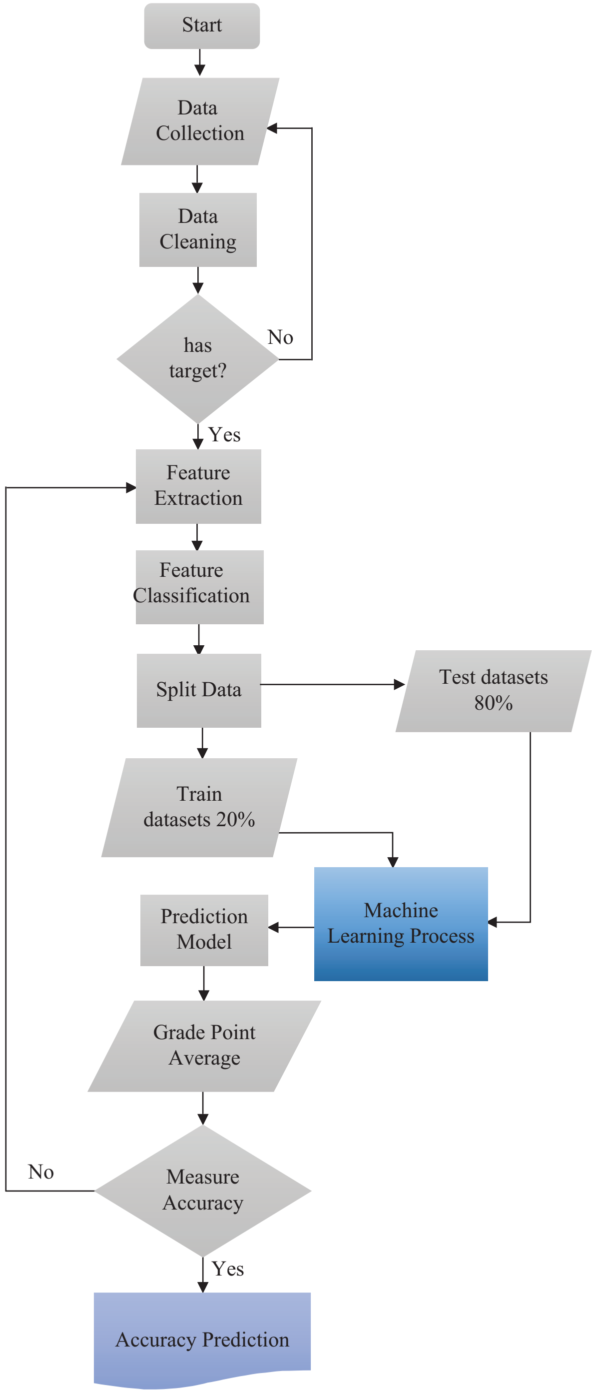

Fig. 3. Flowchart of prediction with machine learning for student empowerment

The evaluation of the process of machine learning for student empowerment involved 10 experts and 10 items: 1) data collection, 2) data cleansing, 3) feature extraction, 4) feature classification, 5) predictive model, 6) experimentation, 7) evaluation, 8) data visualization, and 9) appropriateness for implementing the algorithm. It was found that the predictive process with machine learning for empowering learners had the highest level of suitability.

3.4 Machine learning prediction model experiments

Students' grades are predicted based on an eight-step machine learning process as follows:

Step 1. Data collection: data were collected on the teaching and learning management of 30 students taking a system analysis and design course during the first semester of the 2021 academic year at the Department of Computer Innovation and Digital Industry, Faculty of Industrial Technology, Nakhon Si Thammarat Rajabhat University, Thailand.

Step 2. Data cleansing: collected data may can contain errors and outliers, or be incomplete or inconsistent. The information should be checked for correctness and the data formatted to remove irrelevant information, to support the next step in the process.

Step 3. Feature extraction: the extraction of attributes was deemed suitable for predicting students' grades and related to observations of learners' behavior and recorded scores during the instruction.

Step 4. Feature classification: the attributes, which were collected through feature extraction and document synthesis, could be grouped into six sets: the frequency of access to the system, number of activities, lessons quizzes and assignments, frequency of access to discussion boards, number of new threads added to the discussion forums, and GPA.

Step 5. predictive model: A grade prediction model was devised with the Iterative Dichotomizer 3 (ID3) decision tree algorithm.

Step 6. Experimental: an experimental predictive model for learning outcomes was created with a decision tree algorithm for data analysis, using data mining with 10-fold cross-validation. The model for the prediction of learning outcomes established students' grade as A, B+, B, C+, C, D+, D, or E, as shown in Figure 4.

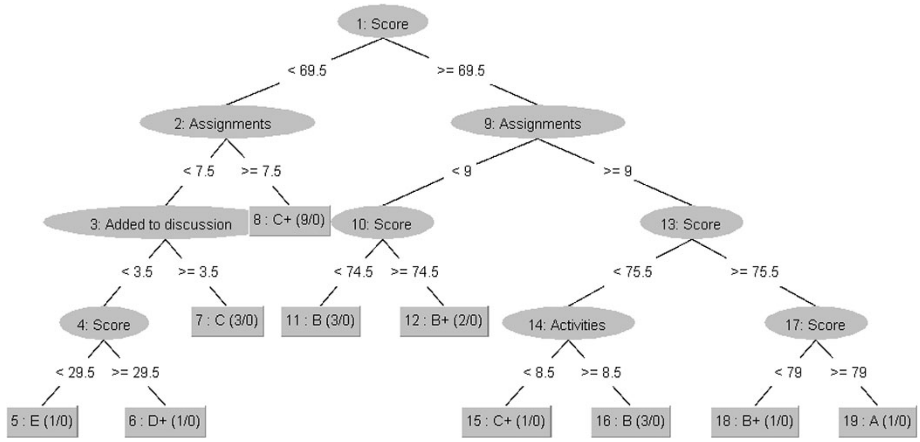

Fig. 4. Decision tree prediction model

As per Figure 4, the decision tree prediction model is based on the learning outcomes for all student grades, namely A, B+, B, C+, C, D+, D, and E. Regarding the rules for the number of predictions, 25 are estimated.

The predictive model divides the students into two groups: Group 1: empowerment and Group 2: no empowerment, as shown in Figure 5.

Fig. 5. Empowerment model

As per Figure 5, Group 1 students do not need to be empowered to achieve better grades, i.e., a grade greater than 65.5 or C+. Group 2 students need to be empowered to achieve better grades, i.e., a grade less than or equal to 65.5 or less than C+.

Step 7. Evaluation: the accuracy of the model was assessed in terms of accuracy, precision, recall, F-measure, and information gain of the attributes used for prediction.

Step 8. Data visualization: the values of the experimental results are presented in the results section.

3.5 Developing an intelligent SRM platform

The intelligent SRM platform with predictive machine learning to empower students was developed using a software development life cycle with five phases: analysis, design, implementation, testing, and evaluation [3].

Phase 1. Analysis: identifies problems and the needs of system development, then draws both a context and data flow diagram as a model for system development.

Phase 2. Design: designs the system architecture and machine learning prediction process, which has been evaluated by an expert to optimize the adjustment.

Phase 3. Implementation: comprises the installation and use of the system by the sample group.

Phase 4. Testing: black-box testing consisting of eight platform modules: identify, alert, SRM, analytics, content management, forum, scaffolding, and assessment, with three users: a teacher, student, and administrator.

Phase 5. Evaluation: assesses the use of the platform to maintain and perform system improvements.

4 Results

The results of experiments intelligent SRM platform and implementing machine learning predictions are shown in Tables 4 and 5.

Table 4. Accuracy, precision, recall, and F-measure of the decision tree prediction model

Model	Precision%	Recall%	Accuracy%	F-Measure%
Decision tree	100.00	100.00	100.00	100.00

As per Table 4, for the decision tree prediction model for all student grades, the accuracy was 100.00%, precision 100.00%, recall 100.00%, and F-measure 100.00%. The results of the empowerment model reveal an accuracy of 93.55%. The precision, recall, and F-measure values are shown in Table 5.

Table 5. Empowerment model

Class	Precision (%)	Recall (%)	F-Measure
No empowerment	96.15	96.15	96.15
Empowerment	80.00	80.00	80.00

As per Table 5, the empowerment model values for the empowered and non-empowered groups are as follows. The non-empowered group had a precision rate of 96.15%, a recall rate of 96.15%, and an F-measure of 96.15%. For the empowerment group, precision was 80.00%, recall was 80.00%, and the F-measure was 80.00%. The information gain of the attributes used for prediction are shown in Table 6.

Table 6. Information gain of the attributes used for prediction

Order	Attribute	Weight
1	Grade point average (GPA)	0.637
3	Frequency in accessing discussion boards	0.442
4	Lessons, quizzes, and assignments	0.350
5	Frequency access to system	0.201
6	Number of new threads added to discussion forum	0.193
7	Number of activities	0.089

Table 6 presents the information gained from the attributes used for prediction and reveals that of the factors influencing academic performance, GPA had the most influence (weight = 0.637), followed by the frequency of accessing discussion boards (weight = 0.442), and lessons, quizzes, and assignments (weight = 0.350). This is illustrated in a graph (Figure 6).

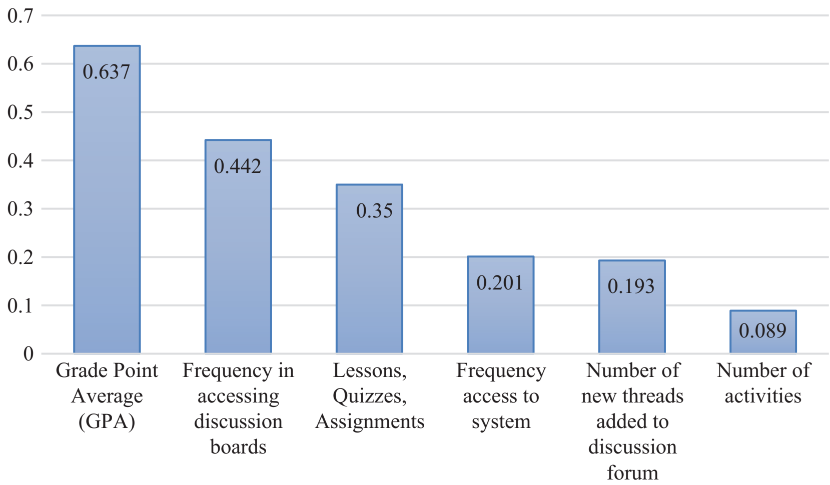

Fig. 6. Information gain of the attributes used for prediction

5 Student empowerment

For the grade level prediction, students are divided according to their grades: A, B+, B, C+, C, D+, D and E. Students with a grade C, D+, D or E are of concern. In this research, techniques for student empowerment are used to help students achieve better learning outcomes and are divided into two parts: artificial intelligence empowerment and teacher empowerment.

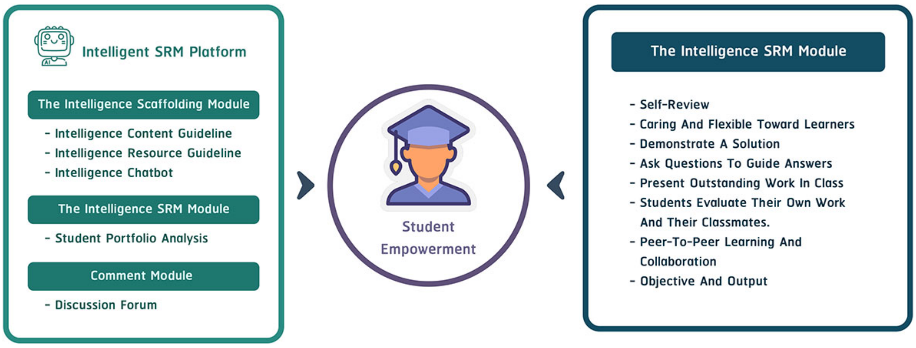

Fig. 7. Student empowerment

As per Figure 7, student empowerment has two elements: empowerment using artificial intelligence technology and empowerment from teachers.

Part 1: Regarding empowerment using artificial intelligence technology from an intelligent SRM platform, the details are as follows:

The intelligence scaffolding module includes a student support module consisting of three sub-modules: an intelligence content guideline, for content guidance; an intelligence resource guideline, recommending necessary resources; and an intelligence chatbot, for automated responses to student questions.

The intelligence SRM module involves an analysis of individual student portfolios stored in a database, using the student portfolio analysis module to identify and isolate students.

The forum module allows students to participate in discussions through the discussion forum. The forum offers a basis for future work, for establishing and addressing discussion questions for upcoming papers or presentation topics, as well as for building a model of engagement determining what is right and wrong.

Part 2: Regarding empowering teachers, the details are as follows:

Self-review: students are asked to write a self-review about their learning and progress during the course after the midterm.

Teachers should:

Be caring and flexible toward learners.
Demonstrate a solution.
Ask questions to guide answers.
Present outstanding work in class to raise morale for creators and inspire classmates.
Ask students to evaluate both their own work and their classmates.
Create peer-to-peer learning and collaboration: opportunities for students to complete group activities using Wikis or Google Docs.
Establish the objective and output: explain the goals and desired results of the course.

6 Discussion

This research aimed to develop an intelligent SRM platform using machine learning prediction for student empowerment. This process consists of an SRM platform composed of eight modules: identify module, alert module, SRM module, analytics module, content management module, forum module, scaffolding module, and assessment module. The six factors related to student behavior prevalent during teaching and learning on the SRM platform are as follows: frequency of access to the system, number of activities, lessons quizzes and assignments, frequency of access to discussion boards, number of new threads added to the discussion forums, and GPA. These factors are predicted using an eight-step process, involving data collection, data cleansing, feature extraction, feature classification, predictive model, experimentation, evaluation, and data visualization.

Machine learning predictions were conducted with 30 students from the system analysis and design course at the Department of Computer Innovation and Digital Industry, Faculty of Industrial Technology, Nakhon Si Thammarat Rajabhat University, Thailand. The research aimed to predict grade level with an ID3 decision tree algorithm. A 25-rule grade prediction model was assessed using a 10-fold cross-validation, with an accuracy of 100.00%, a recall rate of 100.00%, and an F-measure of 100.00%.

The students were divided into two groups: non-empowerment and empowerment. The information gained from the attributes used in the prediction found that of the factors influencing the grade of academic performance, GPA had the most weight, at 0.637, followed by the frequency of accessing discussion boards, with a weight of 0.442, and lessons, quizzes, and assignments, with a weight of 0.350.

Machine learning helped predict the grades and was then able to classify students into A, B+, B, C+, C, D+, D, and E grades, where students with a grade C, D+, D, or E were of concern. This empowered students to improve their learning outcomes and can be divided into two parts. Part 1 concerns the artificial intelligence empowerment: the intelligence scaffolding module, intelligence SRM module, and forum module. Part 2 involves teachers' empowerment: students should self-review while teachers should be caring and flexible toward students, demonstrating solutions, asking questions to guide answers, and presenting outstanding work in class to raise morale for the creators and inspire their classmates. Students evaluate both their own work and their classmates' and create opportunities for peer-to-peer learning and collaboration, as well as acknowledge the desired goals for activities and the course overall.

The experimental results of this study (Table 6) show the information gain of the attributes used for prediction. It was found that the factor affecting the student's grade the most was GPA, with a weight of 0.637. Consistent with [7] [9] and [6], the results reveal that if a student has good grades, whether midterm or final scores, the level of academic performance is affected and developed. As a result, the dropout, expulsion, and low GPA rates are reduced. Student empowerment to achieve higher GPAs is extremely important [9].

7 Conclusion

This research employed an intelligent SRM platform with machine learning for student empowerment, especially during the COVID-19 pandemic. The student empowerment approach has not been applied to students who are at a level of concern. For future research, the researcher intends to apply the student empowerment approach to enable students to achieve better learning outcomes. Experts have offered suggestions for this research, including adding a sample group to training datasets to make more accurate predictions and considering balanced data for both training and testing sets to make the model more efficient. These can be used as guidelines for subsequent studies.

8 Acknowledgment

The researchers would like to thank, Nakhon Si Thammarat Rajabhat University and King Mongkut's University of Technology North Bangkok, which supported this research. Special thanks to the Innovation and Technology Management Research Center, King Mongkut's University of Technology North Bangkok, which supported the tools for the research.

9 References

[1] R. Hesen, A. E. J. Wals, and R. L. Tauritz, "Creating a sense of community and space for subjectification in an online course on sustainability education during times of physical distancing," *International Journal of Sustainability in Higher Education*, vol. 23, no. 8, pp. 85–104, Dec. 2022, https://doi.org/10.1108/IJSHE-07-2021-0270

[2] T. Karakose, R. Yirci, and S. Papadakis, "Examining the associations between COVID-19-related psychological distress, social media addiction, COVID-19-related burnout, and depression among school principals and teachers through structural equation modeling," *Int J Environ Res Public Health*, vol. 19, no. 4, Feb. 2022, https://doi.org/10.3390/ijerph19041951

[3] A. M. Yorke *et al.*, "Interprofessional education faculty development survey: Perspectives on IPE and collaborative practice and COVID-19," *J Interprof Educ Pract*, vol. 29, Dec. 2022, https://doi.org/10.1016/j.xjep.2022.100529

[4] L. D. Lapitan, C. E. Tiangco, D. A. G. Sumalinog, N. S. Sabarillo, and J. M. Diaz, "An effective blended online teaching and learning strategy during the COVID-19 pandemic," *Education for Chemical Engineers*, vol. 35, pp. 116–131, Apr. 2021, https://doi.org/10.1016/j.ece.2021.01.012

[5] F. M. Azmi, H. N. Khan, and A. M. Azmi, "The impact of virtual learning on students' educational behavior and pervasiveness of depression among university students due to the COVID-19 pandemic," *Global Health*, vol. 18, no. 1, Dec. 2022, https://doi.org/10.1186/s12992-022-00863-z

[6] I. Katsaris and N. Vidakis, "Adaptive e-learning systems through learning styles: A review of the literature," *Advances in Mobile Learning Educational Research*, vol. 1, no. 2, pp. 124–145, 2021, https://doi.org/10.25082/AMLER.2021.02.007

[7] S. H. Kirk, C. Newstead, R. Gann, and C. Rounsaville, "Empowerment and ownership in effective internationalisation of the higher education curriculum," *High Educ (Dordr)*, vol. 76, no. 6, pp. 989–1005, Dec. 2018, https://doi.org/10.1007/s10734-018-0246-1
[8] M. Farhan Nasir, M. Jasim, U. Qureshi, P. Mitra, and T. Islam, *INTRODUCING A NEW SDLC TRIGON MODEL FOR SOFTWARE DEVELOPMENT Smart Medicine Reminder System for Elderly People View project IoT based Agriculture Plant Monitoring System View project INTRODUCING A NEW SDLC TRIGON MODEL FOR SOFTWARE DEVELOPMENT*. 2021. [Online]. Available: https://www.researchgate.net/publication/353688914
[9] R. Al-Shabandar, A. Hussain, A. Laws, R. Keight, J. Lunn, and N. Radi, "Machine learning approaches to predict learning outcomes in massive open online courses," in *Proceedings of the International Joint Conference on Neural Networks*, 2017, pp. 713–720. https://doi.org/10.1109/IJCNN.2017.7965922
[10] P. Srisakonsub, N. Jeerungsuwan, and P. Piriyasurawong, "Student relation management on cloud technology for academic and internship counseling model in Rajabhat University," *Higher Education Studies*, vol. 9, no. 4, p. 148, 2019, https://doi.org/10.5539/hes.v9n4p148
[11] N. Songsom, P. Nilsook, and P. Wannapiroon, "The synthesis of the student relationship management system using the internet of things to collect the digital footprint for higher education institutions," *International journal of online and biomedical engineering*, vol. 15, no. 6, pp. 99–112, 2019, https://doi.org/10.3991/ijoe.v15i06.10173
[12] V. J. Nutthapat Kaewrattanapat, and Jarumon Nookhong, "The System Development of Digital Library By Using Conversational Agent for Enhancing Intelligent Student," *The 2019 International Academic Research Conference in Zurich*, no. Dm, pp. 83–88, 2019.
[13] N. Kaewrattanapat and P. Wannapiroon, "Intelligent student relationship management model," *Journal of Industrial Education*, vol. 15, no. 1, pp. 222–230, 2018.
[14] H. De Juan-Jordán, M. Guijarro-García, and J. Hernandez Gadea, "Feature analysis of the 'customer relationship management' systems for higher education institutions," *Multidisciplinary Journal for Education, Social and Technological Sciences*, vol. 5, no. 1, p. 30, 2018, https://doi.org/10.4995/muse.2018.9232
[15] H. Gholami, M. Z. M. Saman, A. Mardani, D. Streimikiene, S. Sharif, and N. Zakuan, "Proposed analytic framework for student relationship management based on a systematic review of CRM systems literature," *Sustainability (Switzerland)*, vol. 10, no. 4, Apr. 2018, https://doi.org/10.3390/su10041237
[16] W. Vicente-Ramos and L. M. Cano-Torres, "The effect of digital marketing on the management of relationships with university students in times of covid-19," *International Journal of Data and Network Science*, vol. 6, no. 1, pp. 59–66, Dec. 2022, https://doi.org/10.5267/j.ijdns.2021.10.004
[17] J. N. L. Lamptey, I. M. Umude, and E. Atteh, "The role of administrative staff in student relationship management (SRM): A tool for quality teacher education," *Asian Journal of Advanced Research and Reports*, pp. 5–15, Aug. 2020, https://doi.org/10.9734/ajarr/2020/v13i230303
[18] M. Batta, "Machine learning algorithms – A review," *International Journal of Science and Research*, vol. 9, no. 1, pp. 381–386, 2020, https://doi.org/10.21275/ART20203995
[19] T. Ahajjam, M. Moutaib, H. Aissa, M. Azrour, Y. Farhaoui, and M. Fattah, "Predicting students' final performance using artificial neural networks," *Big Data Mining and Analytics*, vol. 5, no. 4, pp. 294–301, Dec. 2022, https://doi.org/10.26599/BDMA.2021.9020030
[20] Ş. Aydoğdu, "Predicting student final performance using artificial neural networks in online learning environments," *Educ Inf Technol (Dordr)*, vol. 25, no. 3, pp. 1913–1927, May 2020, https://doi.org/10.1007/s10639-019-10053-x
[21] F. Qiu *et al.*, "Predicting students' performance in e-learning using learning process and behaviour data," *Sci Rep*, vol. 12, no. 1, Dec. 2022, https://doi.org/10.1038/s41598-021-03867-8

[22] A. Arora, B. Gupta, P. Uttarakhand, and I. A. Rawat, "Analysis of Various Decision Tree Algorithms for Classification in Data Mining," *Int J Comput Appl*, vol. 163, no. 8, pp. 15–19, 2017. https://doi.org/10.5120/ijca2017913660

[23] J. H. Santos Aguiar and A. C. Ribeiro da Silva, "Aprendizado autorregulado em contabilidade: uma análise comparativa entre discentes de modalidade presencial e a distância," *Revista Catarinense da Ciência Contábil*, vol. 16, no. 48, Aug. 2017, https://doi.org/10.16930/2237-7662/rccc.v16n48.2374

[24] B. Dube, "Rural online learning in the context of COVID-19 in South Africa: Evoking an inclusive education approach," *Multidiscip J Educ Research*, vol. 10, no. 2, pp. 135–157, Jun. 2020, https://doi.org/10.17583/remie.2020.5607

[25] M. Mapuya and A. M. Rambuda, "Teaching approaches compatible with first-year accounting student teachers' learning styles: Theoretical and phenomenological perspectives," *International Journal of Higher Education*, vol. 11, no. 2, p. 120, Oct. 2021, https://doi.org/10.5430/ijhe.v11n2p120

[26] T. Djudin, "Exploring the 21st century skills and science teaching pedagogy: Profiles, readiness, and barriers," 2020. https://doi.org/10.26737/jetl.v5i2.1738

[27] J. S. Martins and W. E. Lindsay, "Evaluation of high school student responses to the colorado learning attitudes about science survey," *Phys Rev Phys Educ Res*, vol. 18, no. 1, Jun. 2022, https://doi.org/10.1103/PhysRevPhysEducRes.18.010132

[28] I. R. W. Atmojo, R. Ardiansyah, and D. Y. Saputri, "Empowering science-based entrepreneurship (SciPreneur) skills through CEL-BaDiS up learning model on food biotechnology materials," *International Journal of Instruction*, vol. 15, no. 3, pp. 83–102, Jul. 2022, https://doi.org/10.29333/iji.2022.1535a

[29] S. Islam and H. Mahmud, "Integration of learning analytics into learner management system using machine learning," *ACM International Conference Proceeding Series*, pp. 1–4, 2020, https://doi.org/10.1145/3401861.3401862

[30] Y. Park and I. H. Jo, "Factors that affect the success of learning analytics dashboards," *Educational Technology Research and Development*, vol. 67, no. 6, pp. 1547–1571, 2019, https://doi.org/10.1007/s11423-019-09693-0

[31] Y. Safsouf, K. Mansouri, and F. Poirier, "Experimental design of learning analysis dashboards for teachers and learners," *L@S 2021 – Proceedings of the 8th ACM Conference on Learning @ Scale*, pp. 347–350, 2021, https://doi.org/10.1145/3430895.3460990

[32] N. R. Aljohani, A. Daud, R. A. Abbasi, J. S. Alowibdi, M. Basheri, and M. A. Aslam, "An integrated framework for course adapted student learning analytics dashboard," *Comput Human Behav*, vol. 92, pp. 679–690, 2019, https://doi.org/10.1016/j.chb.2018.03.035

[33] J. Han, K. H. Kim, W. Rhee, and Y. H. Cho, "Learning analytics dashboards for adaptive support in face-to-face collaborative argumentation," *Comput Educ*, vol. 163, p. 104041, 2021, https://doi.org/10.1016/j.compedu.2020.104041

[34] F. S. Kia, S. D. Teasley, M. Hatala, S. A. Karabenick, and M. Kay, "How patterns of students dashboard use are related to their achievement and self-regulatory engagement," *ACM International Conference Proceeding Series*, pp. 340–349, 2020, https://doi.org/10.1145/3375462.3375472

[35] Y. Fan, J. Saint, S. Singh, J. Jovanovic, and D. Gašević, "A learning analytic approach to unveiling self-regulatory processes in learning tactics," *ACM International Conference Proceeding Series*, pp. 184–195, 2021, https://doi.org/10.1145/3448139.3448211

[36] I. M. Schwartz, P. York, E. Nowakowski-Sims, and A. Ramos-Hernandez, "Predictive and prescriptive analytics, machine learning and child welfare risk assessment: The Broward County experience," *Child Youth Serv Rev*, vol. 81, pp. 309–320, 2017, https://doi.org/10.1016/j.childyouth.2017.08.020
[37] D. Buenaño-Fernández, D. Gil, and S. Luján-Mora, "Application of machine learning in predicting performance for computer engineering students: A case study," *Sustainability (Switzerland)*, vol. 11, no. 10, pp. 1–18, 2019, https://doi.org/10.3390/su11102833
[38] A. Polyzou and G. Karypis, "Grade prediction with models specific to students and courses," *Int J Data Sci Anal*, vol. 2, no. 3–4, pp. 159–171, 2016, https://doi.org/10.1007/s41060-016-0024-z
[39] S. Sun, Z. Cao, H. Zhu, and J. Zhao, "A survey of optimization methods from a machine learning perspective," *IEEE Trans Cybern*, vol. 50, no. 8, pp. 3668–3681, 2020, https://doi.org/10.1109/TCYB.2019.2950779
[40] T. Hamim, F. Benabbou, and N. Sael, "Student profile modeling using boosting algorithms," *International Journal of Web-Based Learning and Teaching Technologies*, vol. 17, no. 5, pp. 1–13, 2022, https://doi.org/10.4018/IJWLTT.20220901.oa4
[41] D. Sobnath, T. Kaduk, I. U. Rehman, and O. Isiaq, "Feature selection for UK disabled students' engagement post higher education: A machine learning approach for a predictive employment model," *IEEE Access*, vol. 8, pp. 159530–159541, 2020, https://doi.org/10.1109/ACCESS.2020.3018663
[42] G. Sambasivam, J. Amudhavel, and G. Sathya, "A predictive performance analysis of vitamin D deficiency severity using machine learning methods," *IEEE Access*, vol. 8, pp. 109492–109507, 2020, https://doi.org/10.1109/ACCESS.2020.3002191
[43] M. T. Munir, S. Baroutian, B. R. Young, and S. Carter, "Flipped classroom with cooperative learning as a cornerstone," *Education for Chemical Engineers*, vol. 23, pp. 25–33, 2018, https://doi.org/10.1016/j.ece.2018.05.001
[44] Y. Xiaokun, "Design and implementation of student status management system based on SSH2 framework technology," *Proceedings – 2016 International Conference on Smart City and Systems Engineering, ICSCSE 2016*, pp. 222–225, 2017, https://doi.org/10.1109/ICSCSE.2016.0067

10 Authors

Sasitorn Issaro is an assistant professor at the Division of Computer Innovation and Digital Industry, Faculty of Industrial Technology, Nakhon Si Thammarat Rajabhat University, Thailand.

Panita Wannapiroon is an associate professor in the Division of Information and Communication Technology for Education, the Faculty of Technical Education at King Mongkut's University of Technology North Bangkok (KMUTNB), Bangkok, Thailand. She has experience in many positions such as the director at Innovation and Technology Management Research Center, assistant director of Online Learning Research Center, assistant director of Vocational Education Technology Research Center, and assistant director of Information and Communication Technology in Education Research Center. She also received the Burapha University Thesis Award 2002. And she is a membership of professional societies in Association for Educational Technology of Thailand.

Article submitted 2022-05-20. Resubmitted 2022-11-28. Final acceptance 2022-11-28. Final version published as submitted by the authors.