Learning Management Impacted with COVID-19 at Higher Education in Thailand

Learning Strategies for Lifelong Learning

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Pratya Nuankaew (✉)
University of Phayao, Phayao, Thailand
pratya.nu@up.ac.th

Patchara Nasa-Ngium
Rajabhat Maha Sarakham University, Maha Sarakham, Thailand

Kanakarn Phanniphong
Rajamangala University of Technology Tawan-Ok,
Bangkok, Thailand

Oranan Chaopanich
Kalasin Technical College, Kalasin, Thailand

Sittichai Bussaman, Wongpanya Sararat Nuankaew
Rajabhat Maha Sarakham University, Maha Sarkam, Thailand

Abstract—The COVID-19 situation has a serious global impact on the education system. Thus, the research purpose is aimed to construct the models of online learning strategies for Thailand students on learning management in the coronavirus 2019 scenario. The research methodology was conducted according to the process of the cross-industry standard process for data mining, known as the CRISP-DM model for developing the best research. The data collected 487 students from the University of Phayao (UP), and Rajabhat Maha Sarakham University (RMU) from the 1st semester in academic year 2020. The collected data has been agreed upon in accordance with research ethics. The results of the study revealed that the factors influencing the model consisted of 8 out of 38 attributes, with a high predictive accuracy (85.14%). Finally, the researchers can plan for the management of teaching and learning for students at the University of Phayao to solve the Coronavirus 2019 Scenario in the academic year 2021 and the future.

Keywords—Online learning strategies, covid-19 impact, educational data mining, learning analytics modeling

1 Introduction

The impacts of the coronavirus disease (COVID-19) situation have been described by a range of authors [1]–[8]. Thailand has been seriously affected in all spheres such as public health, economic, local livelihoods in the urban and regional setting, and social functioning which have disrupted the normal ways of communicating with one another [9]. In the dimension of the education system in Thailand, they are all affected by the situation of COVID-19. An important example is the teaching and learning style that had to be altered from the original method [10]. Students are required to use the new online learning system through digital technology. The consequence is that the digital technology cannot catch up with the people, due to the expenses hindering the needs to find the proper learning tools and materials for students to perform effectively. In addition, the important problem is the internet network system that is not covered in many rural areas.

However, education cannot wait. It is necessary to study to design and plan the educational process for Thai students in the COVID 19 situation. As an educator, we aim to develop an online learning system by using the basic statistical tools and modern knowledge in this study. The main objective of this research is to study the students' attitude and perspective on online learning from the impact of coronavirus disease (COVID-19) at higher education.

The purpose of this research is to study the model of learning management impacted with COVID-19 at the higher education in Thailand. There are four sub-objectives: (1) to study the attitudes and perceptions of the coronavirus 2019 scenario at Thailand universities. (2) to cluster the attitudes and perceptions of remote learning. (3) to select the attributes of the online learning strategies model for Thai students on learning management in the coronavirus 2019 scenario. (4) to evaluate the online learning strategies model of Thai students on learning management in the coronavirus 2019 scenario.

The research process was designed as two components. The first process aims to collect data using online questionnaires as a data collection tool and to use statistical tools for initial analysis. The second process is to use machine learning tools and data mining techniques for research: k-Means Clustering [11], Decision Tree Classification, Feature Selection Methods, Cross-Validation Methods, Confusion Matrix in classification methods, Accuracy, Precision, and Recall Metrics Performance [12]–[14]. The details of research approaches are followed in Figure 1.

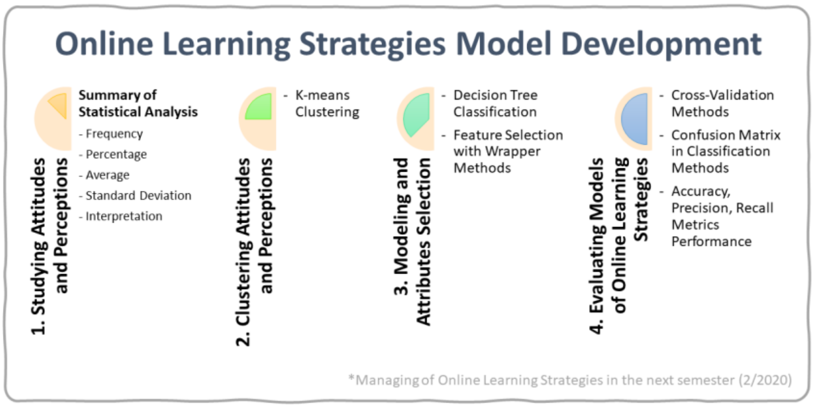

Fig. 1. The Conceptual Framework

The conceptual framework (Figure 1.) shows the process of online learning strategies development consisting of four significant phases: The 1st phase is studying attitudes and perceptions towards online learning management on the coronavirus 2019 scenario in Thai universities. The 2nd phase is clustering attitudes and perceptions towards online learning management on the coronavirus 2019 scenario in Thai universities. The 3rd phase is modeling and selecting attributes of the online learning strategies model for Thai students on learning management in the coronavirus 2019 scenario. The 4th phase is evaluating the online learning strategies model of Thai students on learning management in the coronavirus 2019 scenario.

2 Materials and Methods

This research was performed following the cross-industry standard process for data mining, known as the CRISP-DM model [14]–[17] as shown in Figure 2.

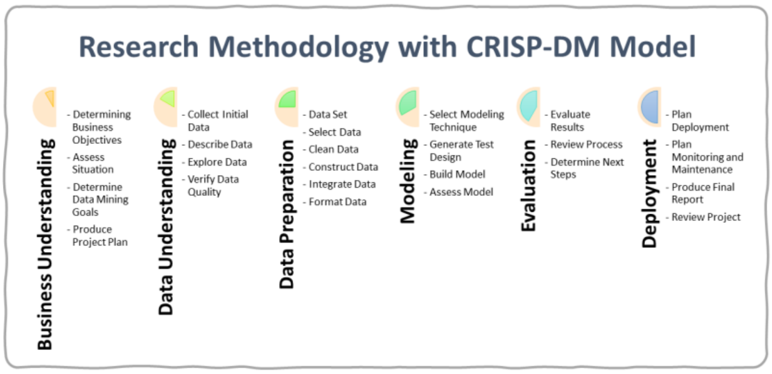

Fig. 2. Research Methodology with CRISP-DM model

2.1 Business understanding

The first process starts at business understanding. It has important goals in formulating research problems. The steps in this section are therefore made up of four elements: determine the business objectives, assess the situation, determine the data mining goals, and produce a project plan.

In this research, the business understanding is the process of understanding the situations and educational implications of the Coronavirus 2019 (COVID-19) scenario. The most obvious impact is the change in learning management and learning styles of the learner. Traditionally, teaching and learning management was the classroom management (face-to-face approach), but the impact of COVID-19 had led to online teaching and online learning.

Therefore, the key goal of this phase is to understand the sudden changes in the educational process. The researchers found that the impact has an effect on learners in a variety of dimensions, including economic aspect (the learners must invest in tools and technology), social aspect (the learners must leave the real world to enter the virtual world), and health aspect (the learners must pay a high cost for treatment and prevention). Therefore, the government and the university have decided to use the online education system to primarily address issues during the COVID-19 situation. The important question for learners is asking "how does this rapid change affect learner adaptation?" This question is brought for research and to search for a concrete answer.

2.2 Data understanding

The second process is data understanding phase. It aims to explore the consistency of the data and the goals of the research, so the importance of this section is closely related to the previous (business understanding) and next steps (data preparation). Therefore, the key component of the data understanding phase is the initiation of the data collection, describing the data, exploring the data, and verifying the data quality.

In this research, the data understanding phase is the process of collecting data through validated instruments, reliable tools, quality data, and functional instruments. The instruments used for collecting data in this research was an online questionnaire, which was reviewed and approved by three educational experts, as shown in the following website: https://n9.cl/rbv5. The contents of the questionnaire consisted of three parts:

1. The first part is to query respondents' general information.
2. The second part is the satisfaction with the online learning management on the impact of COVID-19 scenario.
3. The third part is feedback from respondents. Questionnaire issues are presented in Table 1, and the collected data are presented in the following sections.

Table 1. Questionnaire issues with online learning management on the impact of COVID-19

Stages	Questionnaire Issues
Stage 1: Institutional Readiness Dimension for COVID 19 Scenario	
Stage 1.1	The online learning management policy of universities is appropriate for the situation and epidemic prevention of 2019 coronavirus.
Stage 1.2	The online learning approach of universities is appropriate for the situation and epidemic prevention of 2019 coronavirus.
Stage 1.3	Learners and instructors are clarified by the university for their support and preparation for the online learning management.
Stage 1.4	The university provides grievance and coordination channels for solving problems related to online learning management.
Stage 1.5	The satisfaction with the university's preparation for online learning management policy of educational institutions.
Stage 2: Dimensions of Timing, Environment, and Communication for COVID 19 Scenario	
Stage 2.1	The duration of the online instructional course is appropriate to the situation of the 2019 coronavirus.
Stage 2.2	The environment of the online instructional course is appropriate to the situation of the 2019 coronavirus.
Stage 2.3	The communication of the online instructional course is appropriate to the situation of the 2019 coronavirus.
Stage 3: Instructor Readiness Dimension for COVID 19 Scenario	
Stage 3.1	Instructors are ready to use online teaching materials.
Stage 3.2	Instructors have the ability to solve various problems during online learning to ensure continuity of learning.
Stage 3.3	Instructors have planned an online teaching preparation in advance.
Stage 3.4	Instructors have the ability to pass on knowledge, enabling learning in the subject matter.
Stage 3.5	The instructors are knowledgeable in the subject they teach as well.
Stage 3.6	The instructors are very cognizant of the changing science and technology.
Stage 3.7	The instructors are friendly, give advice and listen to opinions.
State 4: Learning Management and Activities Readiness Dimension for COVID 19 Scenario	
Stage 4.1	The teaching and learning process has created knowledge and understanding in line with the objectives and goals of educational management.
Stage 4.2	The teaching and learning process emphasized the participation of learners in line with the objectives and goals of educational management.
Stage 4.3	The teaching and learning process used materials and innovative technology to enhance learners in line with the objectives and goals of educational management.
Stage 4.4	The teaching and learning process invited experts and communities to participate in learning activities to promote learner experiences.
Stage 4.5	The teaching and learning process used a variety of teaching methods suitable for the subject matter learned.
Stage 4.6	The teaching and learning process has activities that encourage learners to develop thinking processes, discussion, questioning, and expressing opinions.
Stage 4.7	The teaching and learning process has organized activities to encourage students to learn on their own.
Stage 4.8	The teaching and learning process has activities to promote research and knowledge continuously.
Stage 4.9	The teaching and learning process has activities to promote the use of English language and retrieval of knowledge.
Stage 4.10	The teaching and learning process has activities that are linked and integrated with the academic services for society, research, art and culture.

Stages	Questionnaire Issues
Stage 5: Assessment and Evaluation Readiness Dimension for COVID 19 Scenario	
Stage 5.1	Instructional management uses a variety of techniques, measurement, and evaluation methods.
Stage 5.2	Instructional management uses effective techniques, measurement, and evaluation methods.
Stage 5.3	Instructional management has an assessment of teaching and learning results in accordance with the learning activities provided to the learner and is based on the learner's development.
Stage 5.4	Instructional management has been answered and guidance of the answer knows the learning outcome
Stage 5.5	Instructional management has disclosed the scores obtained from the assessment.
Stage 5.6	Instructional management provides feedback leading to personal development.
Stage 5.7	Instructional management are measured and evaluated with clarity and fairness.
Stage 6: Instructional Support Factors Readiness Dimension for COVID 19 Scenario	
Stage 6.1	Educational institutions have provided classrooms, libraries, and learning spaces to facilitate learning in an appropriate and sufficient.
Stage 6.2	Educational institutions have provided online materials to facilitate learning in an appropriate and sufficient.
Stage 6.3	Educational institutions have provided physical materials to facilitate learning in an appropriate and sufficient.
Stage 6.4	Educational institutions provide research publications and dissertations to facilitate learning in an appropriate and sufficient.
Stage 6.5	Educational institutions have provided computer and printer materials to facilitate learning in an appropriate and sufficient.
Stage 6.6	Educational institutions have provided communication network materials to facilitate learning in an appropriate and sufficient.

2.3 Data preparation

The data preparation phase is the process of preparing all activities for creating the final dataset. Data preparation needs to be comprehensive and accurate to be fed into the modelling tools. Preparing data process is to take raw data for preparation by considering the tendency to be performed in each order. The components of the data preparation phase consist of five parts: select data, clean data, construct data, integrate data, and format data.

The data prepared in this section is collected from an online questionnaire. It contains a data set of 487 students from two academic institutions: University of Phayao, and Rajabhat Mahasarakham University.

2.4 Modelling

In the modelling phase, there were many different machine learning techniques. In order to construct a reasonable model, it was necessary to select the appropriate machine learning techniques for the research purpose and the collected data. In addition, the various modelling techniques were selected and applied according to the parameters that were calibrated to the optimal value. Basically, there are several techniques for the same data mining type problem. Some techniques require specific data formats. There is a close link between data preparation and modelling. The modelling process is comprised of five steps: select modelling technique, generate test design, build model, and assess model.

In the c section, k-Means clustering was selected to extract the collected data from the online questionnaires based on similar and different characteristics. k-Means clustering is a vector quantitative method which aims to divide n observations into k-clustering where each observation belongs to the cluster with the nearest mean, known as cluster centres or cluster centroid. This results in a partitioning of the data space into cells. It is popular for cluster analysis in data mining.

In the modelling segment, the Decision Tree Technique was selected to construct the prediction model. The Decision Tree Technique is a supervised machine learning technique that encourages decision-making structures from training data. In addition, the Decision Tree is also called a classification tree or reduction tree. It is a predictive model, which is mapping from an observation about an item to a conclusion about its target value.

To improve the accuracy of the prediction model, this research applied the Wrapper Feature Selection Methods [18] to select the significant features derived from the model development. Moreover, the wrapper methods are used to reduce the size of the Decision Tree produced and to increase the understanding of prediction models. The procedure for applying wrapper methods is shown in Figure 3.

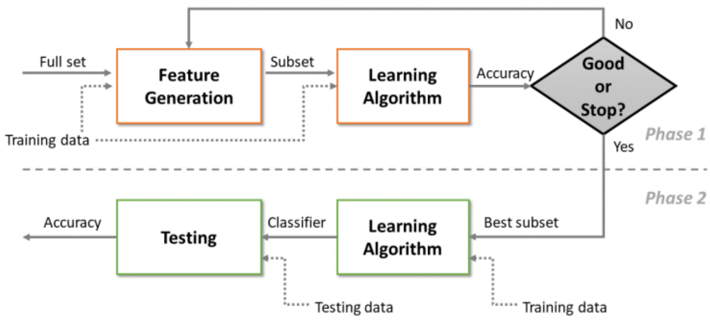

Fig. 3. Applying Wrapper Methods for Feature Selection

This research uses machine learning tools based on their purpose and their properties as described.

2.5 Evaluation

The evaluation phase is the process of testing a model by comparing one or more of the established models to determine the performance of the model. It is used to analyze data from the overall of the data gathered. Before proceeding with the final model deployment, it is important to evaluate the model more thoroughly and review the steps taken to construct the model. It is important to ensure that the model is properly meeting the business objectives. Its primary objective is to determine whether certain critical business issues are being considered sufficient. At the end of this step, a decision should be made regarding the use of the data mining results. Therefore, the essential elements of the evaluation phase consist of three parts: evaluation of the results, review process, and determining next steps (list of possible actions decision).

In this research, the evaluation phase was defined for the purpose of finding the most effective and reasonable model. Therefore, the tools selected for use must be diverse, which consist of five types as follows: cross-validation methods, confusion matrix in classification methods, accuracy measurement, precision measurement, and recall measurement [12], [14], [17] as presented in Figure 4.

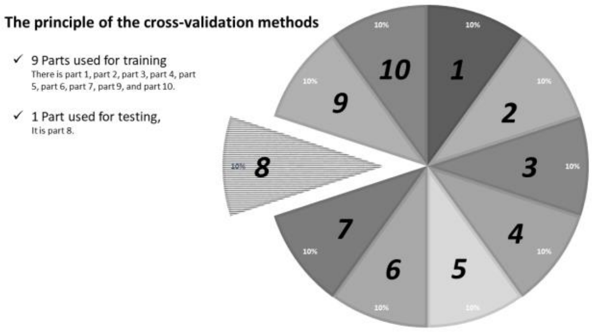

Fig. 4. The principle of the cross-validation methods

Figure 4 shows the principle of the cross-validation methods. It consists of two major parts. The first part serves to create a model (training) using nine pieces of data. There is part 1, part 2, part 3, part 4, part 5, part 6, part 7, part 9, and part 10. On the other hand, the second part is to test the model using the rest of the data. This is part 8. This principle is used to find the most efficient and reasonable model.

However, there is another part that needs to be done to measure the performance of the model. This is the use of a tool called confusion matrix in classification methods, which has three sub-components: accuracy, precision, and recall. It is presented as the equation and calculation method in the Figure 5.

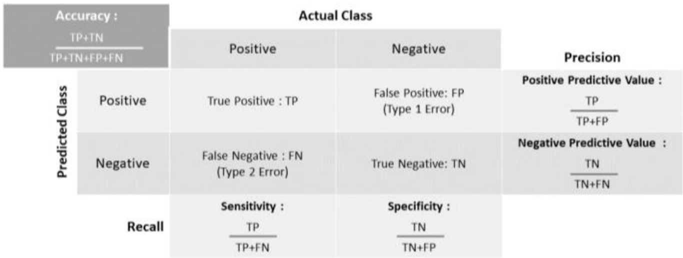

Fig. 5. The confusion matrix in classification methods

2.6 Deployment

Typically, models gained will be organized and presented in a format that can be put to practical use. It may depend on the requirements and the implementation process, which can be easy to implement by simply generating reports or processes to find reproducible data. Occasionally, users are not data analysts, who will have difficulty completing the deployment process. In any case, it is important to understand in advance what action must be taken to utilize the model being built. Thus, the essential components of the deployment phase are in four parts: plan deployment, plan monitoring and maintenance, produce final report, and review project.

In this research, the deployment is planned to be implemented in the 1st semester of the academic year 2021. The researchers plan to apply the strategy derived from the model development in the course 221110 Fundamental Information Technology in Business at University of Phayao, Thailand.

3 Research Results

The research results were reported according to the four objectives:

3.1 Attitudes and perceptions

The data collection contains a data set of 487 students from two academic institutions: University of Phayao (UP), and Rajabhat Maha Sarakham University (RMU). The data gathered from online questionnaires as consists of three parts: The first part is the inquiry of the general information of the respondents. The second part is the satisfaction survey on the management of online instruction on the impact of the coronavirus 2019 (COVID-19) situation. The third part is the feedback from the respondents. The data collected were analyzed and classified according to the research issue as shown in Tables 1-6.

Table 2. Data collected classify by gender and education level.

Data Collected	Bachelor's degree	Master's degree	Doctorate's degree	Total
Male	178 (36.55%)	2 (0.41%)	13 (2.67%)	193 (39.63%)
Female	278 (57.08%)	8 (1.64%)	8 (1.64%)	294 (60.37%)
Total	456 (93.63%)	10 (2.05%)	21 (4.31%)	487 (100%)

Table 2 shows the data collected classified by gender and education level, with a total of 487 respondents. The data showed that respondents were more female than male. The proportion of respondents was 294 females per 193 males, or equivalent to 60.37% per 39.63%.

Table 3. Data collected classify by career and related academic disciplines.

Data Collected	Instructor	Staff	Student	Total
Social Science	11 (2.26%)	4 (0.82%)	176 (36.14%)	191 (39.22%)
Science and Technology	10 (2.05%)	2 (0.41%)	278 (57.08%)	290 (59.55%)
Health Science	2 (0.41%)	1 (0.21%)	3 (0.62%)	6 (1.23%)
Total	23 (4.72%)	6 (1.44%)	457 (93.84%)	487 (100%)

Table 3 shows the data collected classified by status and related academic disciplines. The data showed that most respondents were student with 457 respondents, or equivalent to 93.84%. Most of the respondents were majoring in science and technology, with 290 respondents or equivalent to 59.55%.

Table 4. Data collected classify by university and academic year

Data Collected	1st year	2nd year	3rd year	4th year	5th year	Grad	Total
UP	129 (26.49%)	86 (17.66%)	25 (5.13%)	10 (2.05%)	1 (0.21%)	14 (2.87%)	265 (54.41%)
RMU	86 (17.66%)	28 (5.75%)	83 (17.04%)	8 (1.64%)	1 (0.21%)	16 (3.29%)	222 (45.59%)
Total	215 (44.15%)	114 (26.41%)	108 (22.18%)	18 (3.70%)	2 (0.41%)	30 (6.16%)	487 (100%)

UP: University of Phayao, RMU: Rajabhat Mahasarakham University

Table 4 shows the data collected classified by university and academic year, with a total of 487 respondents. The data showed that most respondents were students from the University of Phayao with 265 respondents (54.41%). Most of the respondents were in their 1st academic year, with 215 respondents or equivalent to 44.15%.

After summarizing the initial data, the second part is an analysis of the satisfaction survey on the impact of the COVID-19 situation as summarized in Table 6. Where criteria and interpretation were performed with the Likert scale as detailed in Table 5.

Table 5. Scoring criteria for satisfaction assessment and interpretation

Ranking Level	Definition	Scoring Criteria	Interpretation
5	Highest level of satisfaction	4.21 - 5.00	Strongly agree
4	High level of satisfaction	3.41 - 4.20	Agree
3	Moderate level of satisfaction	2.61 - 3.40	Neither agree nor disagree
2	Low level of satisfaction	1.81 - 2.60	Disagree
1	Lowest level of satisfaction	1.00 - 1.80	Strongly disagree

Table 5 shown the scoring criteria for satisfaction assessment and interpretation. It is divided into two parts: the first part is the level of satisfaction score and the definition of the level of satisfaction. The second part is the scoring criteria of satisfaction levels and their interpretation.

Table 6. Satisfaction with online learning management on the impact of COVID-19

Stage / Issue	Ranking Level					Mean	S.D.	Interpretation
	5	4	3	2	1			
Stage 1:								
Stage 1.1	5.13%	7.40%	5.73%	1.13%	0.60%	3.767	0.994	Agree
Stage 1.2	5.13%	7.64%	5.61%	1.31%	0.30%	3.800	0.947	Agree
Stage 1.3	4.90%	7.04%	6.09%	1.67%	0.30%	3.728	0.973	Agree
Stage 1.4	4.00%	7.16%	5.79%	2.51%	0.54%	3.579	1.029	Agree
Stage 1.5	4.30%	7.58%	5.79%	1.61%	0.72%	3.657	1.017	Agree
Average	*23.46%*	*36.84%*	*29.01%*	*8.24%*	*2.45%*	*3.706*	*0.994*	*Agree*
Stage 2:								
Stage 2.1	7.16%	13.63%	10.25%	1.89%	0.40%	3.758	0.895	Agree
Stage 2.2	6.67%	12.44%	11.34%	2.49%	0.40%	3.675	0.918	Agree
Stage 2.3	7.96%	11.04%	10.75%	2.79%	0.80%	3.678	1.005	Agree
Average	*21.79%*	*37.11%*	*32.34%*	*7.16%*	*1.59%*	*3.703*	*0.940*	*Agree*
Stage 3:								
Stage 3.1	4.14%	5.93%	3.24%	0.85%	0.13%	3.916	0.912	Agree
Stage 3.2	3.33%	6.18%	3.92%	0.77%	0.09%	3.833	0.866	Agree
Stage 3.3	5.07%	5.63%	2.81%	0.64%	0.13%	4.042	0.901	Agree
Stage 3.4	4.39%	5.93%	3.45%	0.43%	0.09%	3.988	0.851	Agree
Stage 3.5	5.37%	6.01%	2.56%	0.30%	0.04%	4.146	0.804	Agree
Stage 3.6	4.31%	6.44%	2.99%	0.55%	0.0%	4.015	0.817	Agree
Stage 3.7	4.61%	6.18%	3.16%	0.30%	0.04%	4.051	0.808	Agree
Average	*31.22%*	*42.30%*	*22.13%*	*3.84%*	*0.51%*	*3.998*	*0.856*	*Agree*
State 4:								
Stage 4.1	2.45%	4.45%	2.81%	0.24%	0.06%	3.899	0.816	Agree
Stage 4.2	2.48%	3.64%	3.43%	0.33%	0.12%	3.803	0.891	Agree
Stage 4.3	2.57%	3.97%	3.13%	0.27%	0.06%	3.872	0.847	Agree
Stage 4.4	2.33%	3.58%	3.43%	0.51%	0.15%	3.743	0.922	Agree
Stage 4.5	2.48%	3.67%	3.13%	0.63%	0.09%	3.782	0.921	Agree
Stage 4.6	2.48%	4.00%	2.72%	0.78%	0.03%	3.812	0.908	Agree
Stage 4.7	2.57%	3.58%	3.40%	0.42%	0.03%	3.824	0.873	Agree

Stage / Issue	Ranking Level					Mean	S.D.	Interpretation
	5	4	3	2	1			
Stage 4.8	2.66%	3.55%	2.99%	0.75%	0.06%	3.800	0.938	Agree
Stage 4.9	2.12%	3.49%	3.61%	0.63%	0.15%	3.681	0.927	Agree
Stage 4.10	2.09%	3.67%	3.49%	0.48%	0.27%	3.684	0.945	Agree
Average	*24.21%*	*37.61%*	*32.15%*	*5.01%*	*1.01%*	*3.789*	*0.901*	*Agree*
Stage 5:								
Stage 5.1	3.75%	5.12%	4.31%	1.02%	0.09%	3.800	0.931	Agree
Stage 5.2	3.62%	5.46%	4.18%	0.85%	0.17%	3.806	0.926	Agree
Stage 5.3	3.33%	5.80%	4.22%	0.90%	0.04%	3.803	0.877	Agree
Stage 5.4	3.24%	5.63%	4.65%	0.60%	0.17%	3.782	0.884	Agree
Stage 5.5	4.18%	5.12%	4.22%	0.68%	0.09%	3.884	0.906	Agree
Stage 5.6	3.50%	5.12%	5.03%	0.55%	0.09%	3.797	0.876	Agree
Stage 5.7	3.88%	5.71%	4.09%	0.60%	0.00%	3.901	0.847	Agree
Average	*25.50%*	*37.95%*	*30.70%*	*5.20%*	*0.64%*	*3.824*	*0.893*	*Agree*
Stage 6:								
Stage 6.1	4.78%	7.06%	4.23%	0.55%	0.05%	3.958	0.836	Agree
Stage 6.2	3.93%	6.67%	5.32%	0.65%	0.10%	3.821	0.857	Agree
Stage 6.3	4.28%	6.22%	5.37%	0.60%	0.20%	3.827	0.896	Agree
Stage 6.4	3.93%	5.97%	5.82%	0.80%	0.15%	3.764	0.896	Agree
Stage 6.5	4.18%	5.07%	6.22%	0.90%	0.30%	3.716	0.960	Agree
Stage 6.6	4.23%	6.27%	5.12%	0.85%	0.20%	3.809	0.915	Agree
Average	*25.32%*	*37.26%*	*32.09%*	*4.33%*	*1.00%*	*3.816*	*0.896*	*Agree*
Summary						3.821	0.912	Agree

Table 6 shows the data analysis compiled according to statistical principles: frequency, percentage, mean, standard deviation (S.D.), and interpretation.

The results of the analysis showed that the respondents had a highest satisfied level with Stage 3: Instructor Readiness Dimension for COVID 19 Scenario, with average of 3.998 (Strongly agree). While the second most favored dimension was Stage 5: Assessment and Evaluation Readiness Dimension for COVID 19 Scenario, with average of 3.824 (Strongly agree). The third satisfied dimension was Stage 6: Instructional Support Factors Readiness Dimension for COVID 19 Scenario, with average of 3.816 (Strongly agree). The fourth satisfied dimension was Stage 4: Learning Management and Activities Readiness Dimension for COVID 19 Scenario, with average of 3.789 (Strongly agree). The fifth satisfied dimension was Stage 1: Institutional Readiness Dimension for COVID 19 Scenario, with average of 3.706 (Strongly agree). The last satisfied dimension was Stage 2: Dimensions of Timing, Environment, and Communication for COVID 19 Scenario, with average of 3.703 (Strongly agree). Finally, the overall satisfaction from the questionnaire was the highly average (3.821: Strongly agree) out of 487 respondents.

3.2 Appropriate clustering

The objective of clustering is to study the patterns and characteristics of respondents to be used for analysis to develop the models of online learning strategies for Thai students on learning management in the Coronavirus 2019 scenario. The steps for k-Means clustering are composed of four stages[11]: (1) The first stage is determining the number of groups to cluster the data by replacing the value with k. (2) The second stage is the algorithm that calculates the centre value of each cluster, known as the centroid. (3) The third stage is to calculate the distance from the various data points (data sets) to the centre. The data is clustered with the nearest centre point. Calculating distance from a data point with Centroid using a formula (1), known as the Euclidean Distance. (4) The last stage is to find the mean of each cluster to redefine the centre, then the third stage is repeated until the mean or centre does not change.

To determine the consistency of k-Value, several methods can be considered. In this research, the k-Determination was chosen. The principle of k-determination operation is known as the elbow principle, using graphs in consideration by choosing the point where the graph is shifting strongly from vertical to horizontal or horizontal to vertical.

The research results in this section are reported in two parts: the first part is reporting the appropriate k-Value for the research, and the second part is reporting the centroid in each cluster according to k-Value.

Appropriate k-value: The report of the appropriate k-Value for research was divided into two parts: the first part is the appropriate k-Value analysis as shown in Figure 6. The second part is the k-Value analysis results as shown in Table 7.

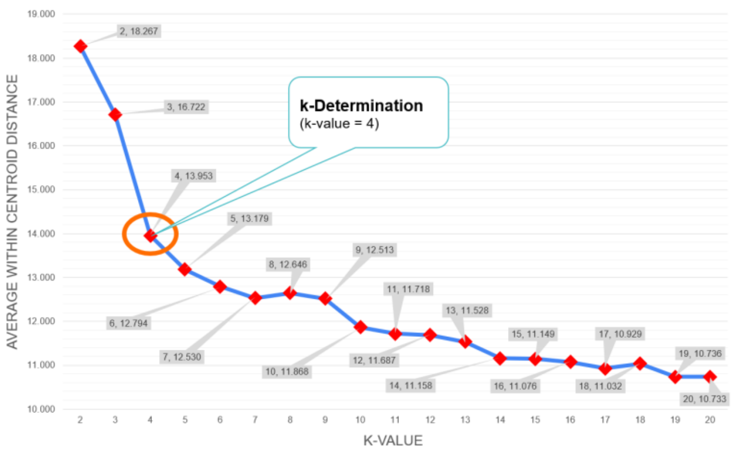

Fig. 6. The Appropriate k-Value

Figure 6 shows the appropriate k-Value. It found that the k-Value should be developed in the models of online learning strategies for Thai students on learning management in the coronavirus 2019 scenario: k-Value is equal to 4. The reasons for the selection of k-Value equal to 4 are shown in Figure 7 and Table 7.

Table 7. Average within Centroid Distance

k-Value	ACD	k-Value	ACD	k-Value	ACD
k-Value = 2	18.267	k-Value = 3	16.722	k-Value = 4	13.953
k-Value = 5	13.179	k-Value = 6	12.794	k-Value = 7	12.530
k-Value = 8	12.646	k-Value = 9	12.513	k-Value = 10	11.868
k-Value = 11	11.718	k-Value = 12	11.687	k-Value = 13	11.528
k-Value = 14	11.158	k-Value = 15	11.149	k-Value = 16	11.076

ACD: Average within Centroid Distance

It was concluded that the data from the respondents should be categorized for the satisfaction with the teaching and learning of five groups. The researchers summarized the centroid value in Table 8.

Centroid of clusters: The centroid reports for each cluster by k-Value are summarized and displayed as shown in Table 8.

Table 8. Summary of centroid values in each cluster

Attributes / Clusters / Centroid Values	Cluster_0	Cluster_1	Cluster_2	Cluster_3
Stage 1:				
Stage 1.1	3.967	3.136	2.471	4.684
Stage 1.2	3.992	3.169	2.529	4.722
Stage 1.3	3.967	3.068	2.294	4.658
Stage 1.4	3.620	2.949	2.588	4.671
Stage 1.5	3.818	3.025	2.059	4.696
Stage 2:				
Stage 2.1	3.909	3.178	2.412	4.684
Stage 2.2	3.835	3.000	2.765	4.633
Stage 2.3	3.917	3.008	2.294	4.608
Stage 3:				
Stage 3.1	4.140	3.398	2.118	4.734
Stage 3.2	4.041	3.297	2.118	4.684
Stage 3.3	4.198	3.593	2.294	4.848
Stage 3.4	4.157	3.525	2.176	4.810
Stage 3.5	4.231	3.797	2.765	4.835
Stage 3.6	4.140	3.517	2.588	4.873
Stage 3.7	4.215	3.576	2.647	4.810
State 4:				
Stage 4.1	4.091	3.331	2.412	4.772
Stage 4.2	3.983	3.161	2.176	4.835
Stage 4.3	3.967	3.331	2.412	4.848
Stage 4.4	3.876	3.076	2.588	4.785
Stage 4.5	3.893	3.195	2.000	4.873
Stage 4.6	3.950	3.229	2.235	4.810
Stage 4.7	4.025	3.178	2.412	4.785
Stage 4.8	4.041	3.102	2.176	4.823

Attributes / Clusters / Centroid Values	Cluster_0	Cluster_1	Cluster_2	Cluster_3
Stage 4.9	3.736	3.076	2.353	4.785
Stage 4.10	3.777	3.034	2.294	4.810
Stage 5:				
Stage 5.1	3.992	3.127	2.235	4.848
Stage 5.2	4.008	3.136	2.235	4.835
Stage 5.3	4.025	3.186	2.118	4.747
Stage 5.4	3.959	3.203	2.353	4.684
Stage 5.5	4.074	3.263	2.765	4.759
Stage 5.6	4.041	3.127	2.647	4.671
Stage 5.7	4.074	3.297	2.706	4.797
Stage 6:				
Stage 6.1	4.058	3.50	2.882	4.722
Stage 6.2	3.950	3.288	2.353	4.734
Stage 6.3	3.967	3.212	2.529	4.810
Stage 6.4	3.934	3.136	2.412	4.734
Stage 6.5	3.802	3.136	2.529	4.709
Stage 6.6	3.893	3.263	2.471	4.785

Table 8 shows a summary of centroid values in each cluster. It shows the distribution of each cluster in detail. The next part is to develop the model and select significant features for predicting the clustering of respondents based on their attitude and satisfaction.

3.3 Modelling

This section provides an appropriate model development and feature selection. It consists of three significant parts as follows: The first part is the presentation of the validity analysis results obtained from developing a clustered model with a Decision Tree Algorithm as shown in Table 9. The second part is the presentation of the validity analysis results obtained from developing a clustered model with the Forward Selection Scheme as shown in Table 10. Finally, the third part is the presentation of the validity analysis results obtained from developing a clustered model with the Backward Elimination Scheme as shown in Table 11.

Table 9. Modeling Results from k-Means Clustering

Depth of Decision Tree	Cross Validation Methods: Number of Folds			
	10-folds	***30-folds***	***50-folds***	***Leave-one-out***
Level 4	71.32%	69.32%	70.52%	65.97%
Level 5	75.48%	75.25%	74.57%	70.45%
Level 6	77.27%	77.68%	74.57%	72.24%
Level 7*	79.37%	79.47%*	77.38%	79.10%
Level 8	79.36%	79.39%	76.86%	78.21%

Table 9 shows the validity analysis results obtained from developing a clustered model with a Decision Tree Algorithm. It can be seen that the optimum model from the analysis with a Decision Tree Algorithm is a model with 7 depth levels of the Decision Tree model. The 30-folds cross-validation was used to determine the most efficient model with an accuracy of 79.47%.

Table 10. Improve Modeling Results with the Forward Selection Scheme

Number of Attributes	Stopping Behavior			
	Without Increase	***Without Significant Increase***		
		0.1	***0.05***	***0.01***
3 Attributes	82.10%	75.78%	75.78%	75.78%
4 Attributes	82.40%	75.78%	75.78%	75.78%
5 Attributes	82.70%	75.78%	75.78%	75.78%
6 Attributes	82.70%	75.78%	75.78%	75.78%
7 Attributes	82.80%	75.78%	75.78%	75.78%
8 Attributes*	85.14%*	75.78%	75.78%	75.78%
9 Attributes	85.14%	75.78%	75.78%	75.78%
10 Attributes	85.14%	75.78%	75.78%	75.78%
11 Attributes	85.14%	75.78%	75.78%	75.78%
12 Attributes	85.14%	75.78%	75.78%	75.78%

Table 10 shows the validity analysis results obtained from developing a clustered model with the Forward Selection Scheme. It can be seen that the optimum model from the analysis with the Forward Selection Scheme is a model with 8 attributes. The speculative rounds and stopping behavior techniques were used to determine the most efficient model with an accuracy of 85.14%.

Table 11. Improve Modeling Results with the Backward Elimination Scheme

Number of Attributes	Stopping Behavior			
	Without Increase	***Without Significant Increase***		
		0.1	***0.05***	***0.01***
3 Attributes	83.61%	82.25%	82.25%	82.25%
4 Attributes	83.84%	83.84%	83.84%	83.84%
5 Attributes	83.84%	83.03%	83.03%	83.03%
6 Attributes	83.84%	83.38%	83.38%	83.38%
7 Attributes	83.84%	83.59%	83.59%	83.59%
8 Attributes	83.84%	83.03%	83.03%	83.03%
9 Attributes	83.84%	83.21%	83.21%	83.21%
10 Attributes	83.84%	84.55%	84.55%	84.55%
11 Attributes*	83.84%	84.75%*	84.75%*	84.75%*
12 Attributes	83.84%	84.44%	84.44%	84.44%

Table 11 shows the validity analysis results obtained from developing a clustered model with the Backward Elimination Scheme. It can be seen that the optimum model from the analysis with the Backward Elimination Scheme is a model with 11 attributes. The speculative rounds and stopping behaviour techniques were used to determine the most efficient model with an accuracy of 84.75%.

The research has developed three models, all of which are interrelated to the process in order to select the best model that will be used in the next step of the process.

3.4 Appropriate model

This section is a presentation of the appropriate model from previous section. It consists of three performance models from three techniques: The 1st model is the evaluation of model performance based on a clustered model with a Decision Tree Algorithm as the highest accuracy of 79.47%. The 2nd model is the evaluation of model performance based on a clustered model with the Forward Selection Scheme as the highest accuracy of 85.14%. Finally, the last model is the evaluation of model performance based on a clustered model with the Backward Elimination Scheme as the highest accuracy of 84.75%. It has been shown that the most appropriate model is the second model with the highest accuracy as detailed in Table 12.

Table 12. Model Performance with the Forward Selection Scheme

Accuracy: 85.14%	**True Condition**				**Class Precision**
Prediction Condition	***True Cluster_0***	***True Cluster_1***	***True Cluster_2***	***True Cluster_3***	
Pred. Cluster_0	19	4	0	0	86.67%
Pred. Cluster_1	11	145	22	0	81.82%
Pred. Cluster_2	0	20	145	12	81.82%
Pred. Cluster_3	0	0	11	98	91.03%
Class Recall	65.00%	86.09%	81.82%	89.87%	

Table 13 shows the performance testing of the models from k-Means clustering with the Forward Selection Scheme. It found that the model had an accuracy of 85.14%, which is a high level of accuracy.

4 Research Discussion

4.1 Optimal model

According to the analysis and the development of the models, the researchers can conclude that the model has a development process with reasonable selection of the model as following. In Figure 6, it shows the selection of the appropriate k-Value for the appropriate clustering of learners in the teaching and learning management that is consistent with the Covid-19 situation. In addition, Table 7 shows the distribution of each cluster, which is appropriate for considering it as the elbow principle, and k-Determination as shown with an average within the centroid distance in Table 8.

After having the appropriate clusters and members were obtained in each cluster, the researchers developed a prediction model for use in developing a model for appropriate clustering of learners. As a result of the analysis, it was found that the model with the highest accuracy was the Decision Tree model with 7 depth of levels using a

30-folds cross-validation with 79.47% accuracy as shown in Table 9. However, the Decision Tree models in Table 9 needed to be improved for greater validity and to be more effective in selecting the predictive attributes. Therefore, the researchers decided to use two types of wrapper methods for feature selection processes [19]. It includes Forward Selection Scheme and Backward Elimination Scheme to qualify and optimize the model.

The results of qualifying and optimizing the model with the Forward Selection Scheme in Table 10 found that the Decision Tree model improved its validity. The resulting model had an accuracy of 85.14% with 8 significant attributes. At the same time, the results of qualifying and optimizing the model with the Backward Elimination Scheme in Table 11 found that the Decision Tree model improved its validity. The resulting model had an accuracy of 84.75% with 11 significant attributes. Finally, it can be concluded that the model that deserves to be selected is the Decision Tree model using the Forward Selection Scheme for feature selection, which has the highest accuracy (85.14%) and consists of 8 significant attributes.

4.2 Deployment of the model

After the researchers developed an appropriate model, the researchers applied it by testing the model's performance with the collected data as shown in Table 13.

Table 13. Model Deployment

Rule	Condition (if)	Prediction (then)
1	If Stage 4.1 more than 3.50 and Stage 4.1 more than 4.50 and Stage 3.1 more than 4.50 and Stage 1.2 more than 4.50	Then, suitable for cluster_2 = 2.22%, cluster_3 = 97.78%
2	If Stage 4.1 more than 3.50 and Stage 4.1 more than 4.50 and Stage 3.1 more than 4.50 and Stage 1.2 less than 4.50 and Stage 2.2 more than 4.50	Then, suitable for cluster_3 = 100%
3	If Stage 4.1 more than 3.50 and Stage 4.1 more than 4.50 and Stage 3.1 more than 4.50 and Stage 1.2 less than 4.50 and Stage 2.2 less than 4.50	Then, suitable for cluster_2 = 71.43%, cluster_3 = 28.57%
4	If Stage 4.1 more than 3.50 and Stage 4.1 more than 4.50 and Stage 3.1 less than 4.50 and Stage 2.2 more than 3.50 and Stage 5.6 more than 4.50 and Stage 1.1 more than 4.50	Then, suitable for cluster_3 = 100%
5	If Stage 4.1 more than 3.50 and Stage 4.1 more than 4.50 and Stage 3.1 less than 4.50 and Stage 2.2 more than 3.50 and Stage 5.6 more than 4.50 and Stage 1.1 less than 4.50	Then, suitable for cluster_2 = 50.00%, cluster_3 = 50.00%
6	If Stage 4.1 more than 3.50 and Stage 4.1 more than 4.50 and Stage 3.1 less than 4.50 and Stage 2.2 more than 3.50 and Stage 5.6 less than 4.50 and Stage 2.3 more than 3.50	Then, suitable for cluster_2 = 87.50%, cluster_3 = 12.50%
7	If Stage 4.1 more than 3.50 and Stage 4.1 more than 4.50 and Stage 3.1 less than 4.50 and Stage 2.2 more than 3.50 and Stage 5.6 less than 4.50 and Stage 2.3 less than 3.50	Then, suitable for cluster_3 = 100%
8	If Stage 4.1 more than 3.50 and Stage 4.1 more than 4.50 and Stage 3.1 less than 4.50 and Stage 2.2 less than 3.50	Then, suitable for cluster_2 = 100%
9	If Stage 4.1 more than 3.50 and Stage 4.1 less than 4.50 and Stage 5.6 more than 3.50 and Stage 1.1 more than 2.50 and Stage 5.6 more than 4.50 and Stage 3.2 more than 4.50	Then, suitable for cluster_3 = 100%

Rule	Condition (if)	Prediction (then)
10	If Stage 4.1 more than 3.50 and Stage 4.1 less than 4.50 and Stage 5.6 more than 3.50 and Stage 1.1 more than 2.50 and Stage 5.6 more than 4.50 and Stage 3.2 less than 4.50	Then, suitable for cluster_2 = 75.00%, cluster_3 = 25.00%
11	If Stage 4.1 more than 3.50 and Stage 4.1 less than 4.50 and Stage 5.6 more than 3.50 and Stage 1.1 more than 2.50 and Stage 5.6 less than 4.50	Then, suitable for cluster_1 = 5.41%, cluster_2 = 87.83%, cluster_3 = 6.76%
12	If Stage 4.1 more than 3.50 and Stage 4.1 less than 4.50 and Stage 5.6 more than 3.50 and Stage 1.1 less than 2.50	Then, suitable for cluster_1 = 100%
13	If Stage 4.1 more than 3.50 and Stage 4.1 less than 4.50 and Stage 5.6 less than 3.50 and Stage 3.2 more than 3.50 and Stage 2.2 more than 3.50 and Stage 1.2 more than 3.50	Then, suitable for cluster_1 = 12.50%, cluster_2 = 87.50%
14	If Stage 4.1 more than 3.50 and Stage 4.1 less than 4.50 and Stage 5.6 less than 3.50 and Stage 3.2 more than 3.50 and Stage 2.2 more than 3.50 and Stage 1.2 less than 3.50	Then, suitable for cluster_1 = 75.00%, cluster_2 = 25.00%
15	If Stage 4.1 more than 3.50 and Stage 4.1 less than 4.50 and Stage 5.6 less than 3.50 and Stage 3.2 more than 3.50 and Stage 2.2 less than 3.50 and Stage 3.1 more than 4.50	Then, suitable for cluster_1 = 25.00%, cluster_2 = 50.00%, cluster_3 = 25.00%
16	If Stage 4.1 more than 3.50 and Stage 4.1 less than 4.50 and Stage 5.6 less than 3.50 and Stage 3.2 more than 3.50 and Stage 2.2 less than 3.50 and Stage 3.1 less than 4.50	Then, suitable for cluster_1 = 100%
17	If Stage 4.1 more than 3.50 and Stage 4.1 less than 4.50 and Stage 5.6 less than 3.50 and Stage 3.2 less than 3.50	Then, suitable for cluster_1 = 100%
18	If Stage 4.1 less than 3.50 and Stage 3.2 more than 2.50 and Stage 3.1 more than 3.50 and Stage 3.2 more than 4.50	Then, suitable for cluster_2 = 100%
19	If Stage 4.1 less than 3.50 and Stage 3.2 more than 2.50 and Stage 3.1 more than 3.50 and Stage 3.2 less than 4.50 and Stage 1.1 more than 4.50	Then, suitable for cluster_2 = 100%
20	If Stage 4.1 less than 3.50 and Stage 3.2 more than 2.50 and Stage 3.1 more than 3.50 and Stage 3.2 less than 4.50 and Stage 1.1 less than 4.50	Then, suitable for cluster_1 = 86.21%, cluster_2 = 13.79%
21	If Stage 4.1 less than 3.50 and Stage 3.2 more than 2.50 and Stage 3.1 less than 3.50 and Stage 2.3 more than 2.50 and Stage 2.2 more than 3.50 and Stage 1.1 more than 4.50	Then, suitable for cluster_1 = 100%
22	If Stage 4.1 less than 3.50 and Stage 3.2 more than 2.50 and Stage 3.1 less than 3.50 and Stage 2.3 more than 2.50 and Stage 2.2 more than 3.50 and Stage 1.1 less than 4.50	Then, suitable for cluster_0 = 66.67%, cluster_1 = 33.33%
23	If Stage 4.1 less than 3.50 and Stage 3.2 more than 2.50 and Stage 3.1 less than 3.50 and Stage 2.3 more than 2.50 and Stage 2.2 less than 3.50	Then, suitable for cluster_1 = 100%
24	If Stage 4.1 less than 3.50 and Stage 3.2 more than 2.50 and Stage 3.1 less than 3.50 and Stage 2.3 less than 2.50 and Stage 3.1 more than 2.50 and Stage 2.2 more than 3.50	Then, suitable for cluster_1 = 100%
25	If Stage 4.1 less than 3.50 and Stage 3.2 more than 2.50 and Stage 3.1 less than 3.50 and Stage 2.3 less than 2.50 and Stage 3.1 more than 2.50 and Stage 2.2 less than 3.50	Then, suitable for cluster_0 = 66.67%, cluster_1 = 33.33%
26	If Stage 4.1 less than 3.50 and Stage 3.2 more than 2.50 and Stage 3.1 less than 3.50 and Stage 2.3 less than 2.50 and Stage 3.1 less than 2.50	Then, suitable for cluster_1 = 100%
27	If Stage 4.1 less than 3.50 and Stage 3.2 less than 2.50	Then, suitable for cluster_0 = 100%
Correct: 305 out of 335 training examples (91.04%).		

Table 13 shows the tests for determining the performance of the decision tree model with the collected data. It was found that the model was 91.04% of accuracy.

5 Conclusion

The necessity and importance of research to solve problems in Thailand's Covid-19 epidemic situation on the Thai education system needs to be urgently promoted. Thus, this research is aimed to discover the models of online learning strategies for Thai students on learning management in the coronavirus 2019 scenario. There are four sub-objectives: (1) to study the attitudes and perceptions of Thai students on the coronavirus 2019 scenario in Thai universities as shown in Table 2 to Table 6, (2) to cluster the attitudes and perceptions of Thai students on learning management in the coronavirus 2019 scenario with machine learning as shown the result in Figure 6, Table 7 to Table 12, (3) to select the attributes of the online learning strategies model for Thai students on learning management in the coronavirus 2019 scenario as shown in Table 11, and (4) to evaluate the online learning strategies model of Thai students on learning management in the coronavirus 2019 scenario as shown in Table 12. The research approaches are separated into two stages as follows: The 1st stage is to study and gather data for basic statistical analysis which consists of frequency, percentage, average, standard deviation, and interpretation as shown in Table 2 to Table 6. The 2nd stage is the study and analysis with data mining and machine learning techniques which consist of k-Means, Decision Tree, Feature Selection, Cross-Validation, Confusion Matrix, Accuracy, Precision, and Recall as shown in Figure 6, and Table 7 to Table 12.

Finally, the researchers found that the model being studied had the highest level of accuracy (85.15%), and that the attributes obtained from the study were 8 significant attributes. It covers all dimensions of the study. Therefore, the researchers can conclude that this study is successful and should be expanded for further distribution.

6 Future Works

Overall, the researchers found that during the COVID-19 situation the instructional management was severely impacted from obtaining its aims and objectives. Many learners are directly and indirectly affected. The data from the feedback obtained from the survey questionnaire found that students wanted both online and normal learning management, which is the root cause and problem of this research.

As a result of this research, the researchers are committed to be implemented in the 1st semester of the academic year 2021. The researchers plan to apply the strategy derived from the model development in the course 221110 Fundamental Information Technology in Business at University of Phayao, Thailand. It is aimed at providing appropriate teaching and learning for enabling undergraduates to learn happily and successfully in their further study.

7 Conflict of Interest and Research Ethics

The authors declare no conflict of interest. Research ethics, this research is allowed to conduct research according to the announcement of the University of Phayao: No. 2/020/63 on April 22, 2020.

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9 References

[1] O. Grechukhina *et al.*, "Coronavirus Disease 2019 Pregnancy Outcomes in a Racially and Ethnically Diverse Population," *Am. J. Obstet. Gynecol. MFM*, vol. 2, no. 4, Supplement, p. 100246, Nov. 2020, https://doi.org/10.1016/j.ajogmf.2020.100246.

[2] N. H. Greene, S. J. Kilpatrick, M. S. Wong, J. A. Ozimek, and M. Naqvi, "Impact of labour and delivery unit policy modifications on maternal and neonatal outcomes during the coronavirus disease 2019 pandemic," *Am. J. Obstet. Gynecol. MFM*, vol. 2, no. 4, Supplement, p. 100234, Nov. 2020, doi: https://doi.org/10.1016/j.ajogmf.2020.100234

[3] R. N. Keswani, A. Sethi, A. Repici, H. Messmann, and P. W. Chiu, "How to Maximize Trainee Education During the Coronavirus Disease-2019 Pandemic: Perspectives from Around the World," *Gastroenterology*, vol. 159, no. 1, pp. 26–29, Jul. 2020, https://doi.org/10.1053/j.gastro.2020.05.012.

[4] S. Jacques, A. Ouahabi, and T. Lequeu, "Remote Knowledge Acquisition and Assessment During the COVID-19 Pandemic," *Int. J. Eng. Pedagogy IJEP*, vol. 10, no. 6, Art. no. 6, Dec. 2020, https://doi.org/10.3991/ijep.v10i6.16205.

[5] D. Idnani, A. Kubadia, Y. Jain, and P. P. Churi, "Experience of Conducting Online Test During COVID-19 Lockdown: A Case Study of NMIMS University," *Int. J. Eng. Pedagogy IJEP*, vol. 11, no. 1, Art. no. 1, Jan. 2021, https://doi.org/10.3991/ijep.v11i1.15215.

[6] L. N. Fewella, L. M. Khodeir, and A. H. Swidan, "Impact of Integrated E-learning: Traditional Approach to Teaching Engineering Perspective Courses," *Int. J. Eng. Pedagogy IJEP*, vol. 11, no. 2, Art. no. 2, Mar. 2021, https://doi.org/10.3991/ijep.v11i2.17777.

[7] A. P. Sasmito, D. Kustono, P. Purnomo, H. Elmunsyah, D. Nurhadi, and P. Sekarsari, "Development of Android-Based Teaching Material in Software Engineering Subjects for Informatics Engineering Students," *Int. J. Eng. Pedagogy IJEP*, vol. 11, no. 2, Art. no. 2, Mar. 2021, https://doi.org/10.3991/ijep.v11i2.16299.

[8] N. Zhiyenbayeva, E. Belyanova, I. Petunina, S. Dmitrichenkova, and E. Dolzhich, "Personalized Computer Support of Performance Rates and Education Process in High School: Case Study of Engineering Students," *Int. J. Eng. Pedagogy IJEP*, vol. 11, no. 2, Art. no. 2, Mar. 2021, https://doi.org/10.3991/ijep.v11i2.19451.

[9] K. Intawong, D. Olson, and S. Chariyalertsak, "Application technology to fight the COVID-19 pandemic: Lessons learned in Thailand," *Biochem. Biophys. Res. Commun.*, vol. 534, pp. 830–836, Jan. 2021, https://doi.org/10.1016/j.bbrc.2020.10.097.

[10] E. J. Sintema, "Effect of COVID-19 on the Performance of Grade 12 Students: Implications for STEM Education," *Eurasia J. Math. Sci. Technol. Educ.*, vol. 16, no. 7, p. em1851, Apr. 2020, https://doi.org/10.29333/ejmste/7893.
[11] G. Hamerly and J. Drake, "Accelerating Lloyd's algorithm for k-means clustering," in *Partitional clustering algorithms*, Springer, 2015, pp. 41–78. https://doi.org/10.1007/978-3-319-09259-1_2
[12] X. Deng, Q. Liu, Y. Deng, and S. Mahadevan, "An Improved Method to Construct Basic Probability Assignment based on the Confusion Matrix for Classification Problem," *Inf. Sci.*, vol. 340–341, pp. 250–261, May 2016, https://doi.org/10.1016/j.ins.2016.01.033.
[13] P. Nuankaew, "Clustering of Mindset towards Self-Regulated Learning of Undergraduate Students at the University of Phayao," *Adv. Sci. Technol. Eng. Syst.*, vol. 5, no. 4, pp. 676–685, 2020, https://doi.org/10.25046/aj050481.
[14] P. Nuankaew, "Dropout Situation of Business Computer Students, University of Phayao," *Int. J. Emerg. Technol. Learn. IJET*, vol. 14, no. 19, Art. no. 19, Oct. 2019, https://doi.org/10.3991/ijet.v14i19.11177.
[15] P. Chapman *et al.*, "CRISP-DM 1.0: Step-by-step data mining guide," *SPSS Inc*, vol. 9, p. 13, 2000.
[16] R. Wirth and J. Hipp, "CRISP-DM: Towards a Standard Process Model for Data Mining," in *Proceedings of the 4th international conference on the practical applications of knowledge discovery and data mining*, 2000, pp. 29–39.
[17] W. Nuankaew and P. Nuankaew, "The Study of the Factors and Development of Educational Model: The Relationship between the Learner Context and the Curriculum Context in Higher Education," *Int. J. Emerg. Technol. Learn. IJET*, vol. 14, no. 21, pp. 205–226, Nov. 2019, https://doi.org/10.3991/ijet.v14i21.11034.
[18] G. Chen and J. Chen, "A Novel Wrapper Method for Feature Selection and its Applications," *Neurocomputing*, vol. 159, pp. 219–226, Jul. 2015, https://doi.org/10.1016/j.neucom.2015.01.070.
[19] J. Chen, H. Huang, S. Tian, and Y. Qu, "Feature Selection for Text Classification with Naïve Bayes," *Expert Syst. Appl.*, vol. 36, no. 3, Part 1, pp. 5432–5435, Apr. 2009, https://doi.org/10.1016/j.eswa.2008.06.054.

10 Authors

Pratya Nuankaew received a B.Ed. Degree in Educational Technology in 2001, M.Sc. degree in Information Technology in 2008 from Naresuan University, and a Ph.D. degree in Computer Engineering in 2018 from Mae Fah Luang University. He is currently a lecturer at the School of Information and Communication Technology, University of Phayao, Phayao, Thailand.

Patchara Nasa-Ngium received the B.S. degree in computer science from Rajabhat Maha Sarakham University, the M.S. degree and Ph.D. degree in computer science from Khon Kaen University, Thailand. He is also a Lecturer with the Department of Computer Science, Rajabhat Maha Sarakham University. His research interests include artificial intelligence, machine learning, evolutionary computing, and data mining.

Kanakarn Phanniphong received his B.B.A. degree in Information System in 2005 from Rajamangala University of Technology Thanyaburi, Pathum Thani, Thailand, M.B.A. degree Business Administration in 2008 and D.B.A. degree in Business

in 2018 from Pathumthani University, Pathum Thani, Thailand. He is currently a lecturer at the Faculty of Business Administration and Information Technology, Rajamangala University of Technology Tawan-Ok, Bangkok, Thailand.

Oranan Chaopanich is currently an instructor at the Department of Business Computer, Kalasin Technical College, Kalasin, 46000, Thailand. Her research interests are in knowledge management, local public transport, Thailand local communities, and learning analytics.

Sittichai Bussaman received his B.Sc. in Statistic in 1990 from Srinakharinwirot University, M.Sc. in Computer Science and Information Technology in 1997 from King Mongkut's Institute of Technology Ladkrabang and Ph.D. in Educational Technology and Communications in 2013 from Mahasarakham University. He is currently an Associate Professor at the Faculty of Science and Technology, Rajabhat Maha Sarakham University, Maha Sarakham, Thailand.

Wongpanya Nuankaew received a B.Sc. degree in Computer Science in 2004, and M.Sc. degree in Information Technology in 2007 from Naresuan University. She is currently a lecturer at the Faculty of Information Technology, Rajabhat Maha Sarakham University, Maha Sarakham, Thailand.

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