Characterization Clustering of Educational Technologists Achievement in Higher Education Using Machine Learning Analysis

Pratya Nuankaew, Tipparat Sittiwong, and Wongpanya Sararat Nuankaew

***Abstract*—The research purpose was to develop a model for predicting cluster achievement of educational technologists. There are three research objectives: 1) to study the context of educational technologists' achievements in higher education, 2) to construct a model for predicting learning achievement of educational technologists in higher education, and 3) to evaluate a model for predicting learning achievement of educational technologists in higher education. The research scope was to study the success cluster of educational technologists in Thailand. The research data were 98 students from the Bachelor of Arts Program in Educational Technology and Communications during the academic year 2015 to 2017. Research tools consist of two main parts: statistical tools and machine learning analysis tools. The results showed that most of the students in the program had a high-grade point average with a grade point average of 3.11. In addition, the educational technologists' achievement cluster prediction model has an accuracy of 68.37%. The research results can be used to improve education programs to develop effective educational technologists where it is necessary to understand the context of the barriers and success factors of academic achievement.**

***Index Terms*—Academic achievement model, data science in education, disruptive technology, educational technologist achievements, lifelong learning.**

I. Introduction

The role of technology and innovation in education has made an impact on the way we learn and communicate in our daily lives, and will continue to evolve throughout our lives. As technology and innovation have become a compatible force in creating constant disruption in industries worldwide, the results have caused the educational institutions to be aware for academic technologists to adapt on the methods of teaching in order to keep updated and relevant with the issues occurring on technology. [1], [2]. Moreover, technology has made a widespread impact on all dimensions [3]-[5]. In order to survive and be able to adapt to technological changes, it is necessary to move with the current technological trends. However, disruptive technologies that have also an impact on improving the quality of education are evident in a wide variety of academic fields [6]-[10]. Therefore, the efficient and timely use of technology requires consideration and scrutiny. In which, promoting the use of educational technology and innovations to improve the quality of education results in a better understanding of the context of the learners. It can reasonably recommend appropriate education programs and learning styles to learners [11]. It is imperative to understand the context of the hindrances and the success factors of academic achievement [12]-[17]. Studies reviewed from the previous research of others provide an outline that their advantages and disadvantages occurring simultaneously with regards to the application of the idea. This issue has developed a great deal of interest on part of the researchers to make an in-depth exploration on the context of educational technologists with regards to academic achievement at the university level. From the immense importance, this research therefore aims to construct a model that recommends the expertise of educational technologists in accordance with the identity of the learners. It uses machine learning analytics to usher in a new era of educational technology. This research objectives consisted of three objectives: 1) to study the context of educational technologists' achievements in higher education, 2) to construct a model for predicting learning achievement of educational technologists in higher education, and 3) to evaluate a model for predicting learning achievement of educational technologists in higher education.

The research samples collected were selected from a purposive sampling. The data collection was 98 students from the Bachelor of Arts Program in Educational Technology and Communications during the academic year 2015 to 2017. The research tool was classified into two phases. The first phase was statistical analysis including average, standard deviation, frequency, and percentage. The second phase was a machine learning analysis consisting of k-means, k-determination, four classification tree techniques, cross-validation method, and confusion matrix performance.

The structural format of this research work is divided into six sections. The introduction section begins with the premises of the study that mentions about the inspiration and origin of the research problem to be examined. In the second section, a summary of the relevant research articles has been written out to point out the issues for formulating on the theoretical ideas for analysis. The third section provides the details on how the data is going to be collected and the procedure for analysis. In the fourth section, the results accumulated from the research method and design are

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showcased for the research findings. The fifth section discusses about the research objectives based on the findings from the authors' perception. In the final section, the study concludes with the findings in hopes that the viewpoint can help the practitioners of educational technologists improve the learning program.

II. Literature Reviews

This section of the literature reviews presents the issues related to the cognitive and research dimensions of the study. There are three key areas involved which are interconnected. It contains data science in education, disruptive technology, and educational technologist achievements.

A. Data Science in Education

Data Science in Education is also known as "Educational Data Science". It is to bring educational information such as learning behavior data of learners, learning achievement, learners' learning style, learning interests and motivation [6], [18], and so on. They were analyzed using a scientific and technological method known as "machine learning" [7], [19]-[21]. It is used for multidimensional analysis such as feature analysis [20], a selection of the most accurate forecasting tools [19], [20], and both teacher-student analysis [21].

The benefits obtained from such research have been shown to be important for improving the quality of education and developing learners' potential [15]. Learners receive institutional recommendations that are in line with their interests [10]. It is clear that applying data science to education is beneficial. Therefore, in order to broaden its effect, it is necessary to promote widespread learning and understanding of data science in education.

Researchers took the cognitive dimensions of educational technologists to study the impact of disruption in technology change, and the success of technologists by discussing related research in the next section.

B. Disruptive Technology

It is well known that technology is changing rapidly and drastically. It means that some occupations or disciplines are about to be replaced or on the verge of extinction. Some technologies do a better job than classroom such as Virtual Reality (VR), Augmented Reality (AR), Chat-Based Collaboration (CBC), AI-Guided Learning, and Online Learning [8], [9], [22]. A prime example is that AR and VR provide virtual experiences in different locations in a virtual world or historical moment rather than classroom storytelling. In safety training simulations, AR and VR can help worker experience emergencies without harm.

Moreover, adopting e-learning in an organization, it can support learners in many areas, including understanding student needs, determining success outcomes, creating learning strategies, and emphasizing learning direction [15], [23], [24]. In terms of artificial intelligence technology to support learners, researchers believe that students can learn in different ways at different rates and success. By combining artificial intelligence, the program can track learners' progress. Learners will not have to waste time on things that they already understand. But when the learner needs help, the program provides additional lessons until the learner can understand the concept. This principle is a competency-based approach whereby learners learn based on their subject matter expertise.

For these reasons, the researchers aimed to bring the machine learning tools to support and promote higher education as part of the disruptive technology concept.

C. Educational Technologist Achievements

The main driving factor in the adoption of technology to improve the quality of education is educational technologists. Research for the promotion and creation of educational technologists is in the spotlight of researchers worldwide [25]-[27]. The driving force that produces acceleration is the arrival of the disruptive technology transformation [27].

However, the foundation of human quality development is education. Therefore, the researchers attach importance to the success of learner development. Along with the development process in accordance with the era is extremely important. It is therefore why we need to study the process of developing educational technologists along with 21st century skills [28]-[30]. The 21st century skills in this research are limited to 6 comparative aspects according to the curriculum structure discussed in Table 1 as concluded in the data preparation section. The six skills of the 21st century include: citizenship, collaboration, communication, character (growth mindset), creativity (and innovation), and critical thinking. It is an education with 6 Cs, also known as 21st century competencies.

All six skills of the 21st century is contained in the Thai Qualifications Framework for Higher Education (TQF: HEd). It provides a framework for the outcomes and expectations of educational technologists in seven dimensions: systems approach in education, behavioral performance analytics, methods and techniques, educational communications, educational environment, administration and management of educational technology and communication, and assessment of educational technology and communication. It is clear that the creation of educational technologists has a framework and guidelines for development.

As a variety of importance and necessities, this research therefore aims to have significant implications for the education system to understand the context of educational technologists' achievement through the analysis of machine learning based on various priorities and necessities. It is highly expected to present the issues and perspectives of educational technologists' success through a different lens.

III. Research Methodology

The research methodology is based on the principles of machine learning analysis and data mining known as CRISP-DM. CRoss Industry Standard Process for Data Mining (CRISP-DM) is a process model that naturally describes the life cycle of data science, which consists of six major phases.

A. Business Understanding

Business Understanding (BU) is focused on understanding the issues that go into the research process. It is responsible for defining the direction of the research goals presented by the researchers in the research objectives to achieve the contextual search of educational technologists' achievement through the machine learning analytics.

B. Data Understanding

Data Understanding (DU) refers to understanding the data that needs to be gathered for research purposes. Usually, it is to define populations and samples to illustrate the significance and impact of research. Therefore, the research population and the data collected were bounded by selecting specific samples from the Bachelor of Arts Program in Educational Technology and Communications during the academic year 2015 to 2017, with a total of 98 samples.

The data collected not only consisted of the number of samples, but also data on the students' learning outcomes in each course. Moreover, researchers have strictly concealed the information to protect the right to access information according to the university regulations.

C. Data Preparation

Data Preparation is the process of data management. It includes cleaning the data, transforming the data into a state ready for analysis or developing a data science model. Therefore, the data preparation process is normally divided into 5 steps: select data, clean data, construct data, integrate data, and format data. The research was done as follows.

Selecting the data, the researchers considered the key elements in collecting the data with the aim of being consistent with the research objectives. Consequently, the data collected includes education program structure, and data on students enrolled in an education program and achieving academic achievement.

The goal of data cleaning is to eliminate any defective data. The cleaning procedure therefore screened for incomplete data, such as eliminating suspended students, eliminating students transferring education programs, and others that made the data different from the sample.

Data construction and data integration are homogeneous activities. This section therefore manages the courses that occur in the education program structure classified by the achievements of educational technologists in seven areas.

The last step is to format the data. The researchers grouped the sample data, categorized the analysis according to the technologists' achievement group, to separate the analysis between the course and the achievement group as detailed on website: https://bit.ly/3J4bnkV. Additionally, the structure of the education program is presented in Table I.

TABLE I: EDUCATION PROGRAM STRUCTURE

Program Structure	Credits
1. General Education Course	30
2. Specific Required Course	
2.1 Core Course	6
2.2 Major Required Course	81
2.3 Major Elective Course	15
3 Free Elective Course	6
Total	138

Please note that the data was collected through a process in accordance with the regulations of Naresuan University in order to access the data and obtain permission to use the data.

After the data has been prepared, the next step is to analyze and develop the model.

D. Modeling

Modeling phase is the process of finding important patterns nested within data. It basically consists of four sub-processes which the researchers perform as follows: select modeling technique, generate test design, built model, and assess model.

Please note that this research aims to develop a model that recommends the expertise of educational technologists in accordance with the identity of the learners.

The selection of techniques for model development is aimed at responding to research objectives. The researchers wanted to study the context of success by categorizing the educational technologists' achievement groups. Therefore, the two types of model development tools are well-known machine learning tools: supervised learning tools and unsupervised learning tools.

The supervised learning tool uses four techniques to predict a specialized learning group of educational technologists: decision tree technique, ID3 technique, random tree technique, and random forest technique. The main reason for adopting the classification tree principle is because it is easy to implement and can be applied in a practical work concretely.

The unsupervised learning tool uses k-means technique to define learning groups that are appropriate and consistent with educational technologists' success. In the generate test design phase, k-determination is used to determine the k-value as it provides an important basis for deciding the optimal number of clusters. When the appropriate k-value is obtained, the group that has modeled and tested the model is divided into two parts of the test data: the data to create the model and the data to test the model. In this section, decision tree techniques are used to forecast and recommend educational technologists' expertise groups that are aligned with the learner's identity. This assessment is presented in the evaluation sections.

The steps of model development to lead the testing process are presented in Fig. 1.

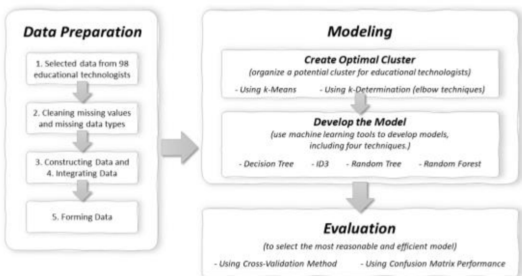

Fig. 1. Model development process.

E. Evaluation

The evaluation process aims to determine the effectiveness of the developed model. The tools used in this assessment therefore consisted of two parts: Cross-Validation method, and Confusion Matrix performance.

The Cross-Validation is used to divide the data in the model performance test. Usually, the divided data serves to build the model and test the model. Each part of the data that is divided is called a Fold. An example of a test method is to divide 10-Fold using 9-Fold for modeling and 1-Fold for testing. Each testing process requires Confusion Matrix performance to help determine the efficiency.

The Confusion Matrix is a tool for evaluating the components of a model's performance. It consists of three key components: accuracy, precision, and recall.

Accuracy is calculated by dividing all correct answer data by the total data. Precision is a calculation of predictive ability in each answer class, known as "Positive Predictive Value (PPV)". It calculates the accuracy resulting from the correct predictions in each answer class. Recall is the value that correctly predicted in each class, known as "True Positive Rate (TPR)". It is calculated as the correct number divided by the total number in class.

In order to diversify the development of the model, the researchers set development criteria by defining the types of tests as follows: 10-Fold Cross-Validation, 30-Fold Cross-Validation, and Leave-one-out Cross-Validation.

F. Deployment

The deployment process is the implementation of the selected efficient model. In the process of developing an education program, researchers are able to draw conclusions from this research and present them to the course development team. What the researchers did in this research corresponds to the data mining deployment process, which consists of four key components: develop deployment plans, plan monitoring and maintenance, produce final research report, and review the research to expand results.

IV. Research Findings

The research findings were separated into three areas: summarizing the context of educational technologists' achievements, presenting a model for predicting learning achievement of educational technologists, and assessments a model for predicting learning achievement of educational technologists. All three issues need to be summarized in accordance with the research objectives.

A. Context of Educational Technologists' Achievements

First of all, the researchers presented the course structure as shown in Table I. The course structure data can be correlated with the educational technologist achievement goals defined in the Thai Qualifications Framework for Higher Education (TQF: HEd) as summarized in Table II.

TABLE II: Summary of Course Credits and Technologists' Achievement Group

Program Structure	Credits	Technologists' Achievement Group						
		G1	G2	G3	G4	G5	G6	G7
1. General Education Course	30							
2. Specific Required Course								
2.1 Core Course	6	3		3				
2.2 Major Required Course	81	18	9	15	15	6	12	6
2.3 Major Elective Course	15							
3 Free Elective Course	6							
Total	138	21	9	18	15	6	12	6

*G1 = Systems Approach in Education, G2 = Behavioral Performance Analytics, G3 = Methods and Techniques, G4 = Educational Communications, G5 = Educational Environment, G6 = Administration and Management of Educational Technology and Communication, G7 = Assessment of Educational Technology and Communication.

Please note that the scope and structure of this education program precedes TQF: HEd. From the relationship that arises, it reflects that the curriculum developers have a broad vision for the development of educational technologists. The direction of education program design is distributed and encompasses all elements of the success of educational technologists in Thailand.

In the part of student analysis, the data that was collected and analyzed in this research was 98 students in the Bachelor of Arts Program in Educational Technology and Communications during the academic year 2015 to 2017.

The initial problem was the misunderstanding between the informants and the researchers. However, it succeeded in the end. The collected data as shown in Table III.

TABLE III: Summarize the Data Collection

Academic Year	Number of Students	Grade Point Average (G.P.A.)				
		Min	Max	Mean	Mode	Median
2015	27	2.23	3.61	3.12	3.19	3.13
2016	37	2.21	3.62	3.09	3.05	3.15
2017	34	2.47	3.67	3.14	2.86	3.14
Total:	98	2.21	3.67	3.11	2.86	3.15

Table III summarizes the students' grade point average. This collected student data was divided into eight grades: Grade A or 4.00 means Excellent, Grade B+ or 3.50 means Very Good, Grade B or 3.00 means Good, Grade C+ or 2.50 means Fairly Good, Grade C or 2.00 means Fair, Grade D+ or 1.50 means Poor, Grade D or 1.00 means Very Poor, and Grade F or 0.00 means Fail. Please note that students to graduate must have a grade point average of at least 2.00. These are the requirements of Naresuan University. From Table III, it can be seen that most of the students had a good grade point average, with an average of 3.11 for all students. However, the mode value showed that most of the students had grade point average at a fairly good level (2.86).

Therefore, the next section will analyze a group of highly successful educational technologists. By targeting learners from using machine learning tools to analyze and create predictive models for the success factors of educational technologists.

B. Model Construction

The modeling process consisted of finding reasonable groups of learners that could be used to determine those with high learning potential. The steps were illustrated in Figure 1.

This section therefore divides the workflow into three parts: assigning appropriate K values, defining learner potential clusters, and building a prediction model.

1) Assigning appropriate K values

The value K is used to determine the number of clusters. The appropriate k-value decision tool uses the k-determination technique to determine the dynamics of the graph pattern. As for the grouping tools, the k-means technique was used. The optimum k-value analysis results are shown in Fig. 2. A summary of the centroid distance values of each cluster is shown in Table IV. Finally, the number of members in each cluster is summarized in Table V.

Fig. 2 shows the k-value analysis that is suitable for determining the number of potential learners. The optimal k-value is 4, which can be summarized as the average within centroid distance in each cluster as shown in Table IV.

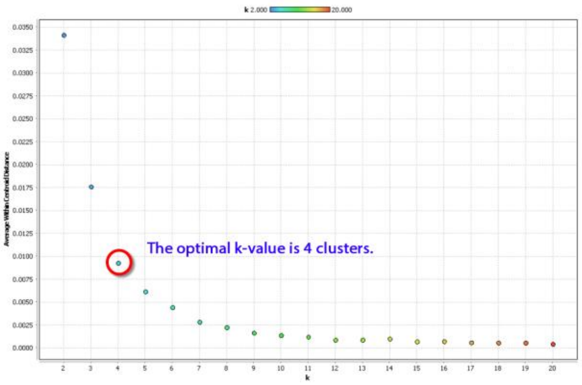

Fig. 2. Model development process.

TABLE IV: AVERAGE WITHIN CENTROID DISTANCE

NC	ACD	NC	ACD	NC	ACD	NC	ACD
2	0.0342	3	0.0176	4	0.0093	5	0.0062
6	0.0045	7	0.0029	8	0.0023	9	0.0017
10	0.0014	11	0.0012	12	0.0009	13	0.0009
14	0.0010	15	0.0007	16	0.0007	17	0.0006
18	0.0006	19	0.0006	20	0.0004		

*NC = Number of Cluster, ACD = Average within Centroid Distance

TABLE V: THE NUMBER OF MEMBERS IN EACH CLUSTER

	Cluster 1	Cluster 2	Cluster 3	Cluster 4
Number of Member	24	48	19	7
Centroid	3.467	3.149	2.823	2.423

Table IV and Table V show the acquisition of learners according to their potential. It is used to predict potential learner group modeling for future monitoring and planning.

2) Assigning potential clusters to learners

For labeling or assigning a potential cluster of students, researchers use the prepared data to add an attribute to assign an answer class to the dataset. The added data has been prepared and displayed on the source data at this link: https://bit.ly/3J4bnkV. It had a total of 65 attributes.

3) Modeling a potential learner cluster prediction

Model development uses four techniques including decision tree technique, ID3, random tree technique, and random forest technique. In addition, it performs preliminary testing to determine which model should be the most efficient model for deployment.

The composition of decision-making modeling defines four criteria: information_gain, gain_ratio, gini_index, and accuracy. This parameter selects the criterion on which attributes will be selected for splitting. In addition, this preliminary analysis uses a combination of two other tools: the consideration of Cross-Validation testing, and the use of Confusion Matrix criteria for decision making.

The results of the preliminary modeling analysis are enumerated in Table VI.

TABLE VI: DECISION TREE MODEL ANALYSIS

Techniques	Criterions	Cross-Validation Testing			
		10-Fold	30-Fold	50-Fold	Leave-one-out
Decision Tree	IG	43.88%	52.04%	59.18%	54.08%
	GR	51.02%	46.94%	48.98%	48.98%
	GI	43.88%	53.06%	57.14%	55.10%
	AC	51.02%	48.98%	51.02%	51.02%
ID3	IG	54.08%	48.98%	52.04%	57.14%
	GR	42.86%	44.90%	48.98%	44.90%
	GI	50.00%	48.98%	47.96%	46.94%
	AC	50.00%	37.76%	45.92%	44.90%
Random Tree	IG	52.04%	45.92%	53.06%	48.98%
	GR	52.04%	46.94%	53.06%	48.98%
	GI	51.02%	47.96%	48.98%	48.98%
	AC	54.08%	44.90%	52.04%	48.98%
Random Forest*	IG	65.31%	67.35%	65.31%	63.27%
	GR	63.27%	63.27%	65.31%	60.20%
	GI	65.31%	68.37%*	65.31%	64.29%
	AC	64.29%	64.29%	64.29%	63.27%

*IG = Information_gain, GR = Gain_ratio, GI = Gini_index, and AC = Accuracy

From Table VI, it was found that the model developed with the random forest technique using the Gini_index criterion and 30-Fold Cross-validation testing has the highest efficiency. It has a test value of 68.37%, with a detailed breakdown performance test being presented in Table VII.

C. Evaluation of Model Performance

From the preliminary model test as shown in Table VI. This section presents a detailed description of the selected models whose analysis elements include accuracy rate, precision rate, and recall rate as detailed in Table VII.

TABLE VII: MODEL PERFORMANCE

ACC = 68.37%	True Cluster 1	True Cluster 2	True Cluster 3	True Cluster 4	Class Precision
Pred. Cluster 1	17	1	0	0	94.44%
Pred. Cluster 2	7	47	16	0	67.14%
Pred. Cluster 3	0	0	3	7	30.00%
Pred. Cluster 4	0	0	0	0	0.00%
Class Recall	70.83%	97.92%	15.79%	0.00%	

* ACC = Accuracy

Table VII shows that predictions in cluster 2 have the highest accuracy in class. It is determined from the recall value. The 2^{nd} place with the 2^{nd} highest accuracy is the cluster 1. The problem presented in this table is that the model is unable to predict the cluster 4 at all. The cause is most likely due to the lowest number of members in the cluster 4, with the researchers discussing this issue in the discussion section.

V. RESEARCH DISCUSSION

This research achieved all three research objectives and goals. It is in line with numerous studies, with a number of researchers believing that studying learners' learning behavior can promote effective learning [1], [6], [19], [23]. Moreover, this research has discovered that the developers of this education program aim to develop educational technologists in Thailand with visions and attitudes that are consistent with the global context and society. It has designed a curriculum that aligns with the United Nations Sustainable Development Goals (UN: SDGs) with the intention of designing lifelong learning.

However, it is observed from the research data that there appears to be a small sample size and lagged. In fact, the data to be analyzed required information on student achievement throughout the four-year program of study. In addition, the Thai education system requires educational program updates every four or five years to improve education programs to keep up with the global situation. Therefore, this research has limited the sample boundaries to 98 students. But in fact, there are currently 228 students studying in the program.

A clear benefit from this research is that it can be used to create instructional strategies for students in the currently studying program. The strategy is to identify groups of learners who are expected to have low academic achievement and to design analyzes to help learners achieve higher academic achievement. Moreover, it can also help prevent student dropouts along the way.

From the development of educational technologists' achievement prediction models, researchers found that the model was unable to predict the fourth cluster. There are two points that could be the cause. The first point is the lowest number of members of the 4th cluster. It has seven members, or 7.14 percent of the total data. The small amount of data was the reason why it was not possible to create a model for prediction. The second point is that the average overall grade point average (GPA) for most of the students is high. Table III show that most of the students in the program had a high-grade point average, where the mean is equal to 3.11 and the median is equal to 3.15. Therefore, the collected data was biased towards a high GPA.

Based on the findings in the developed model, the researchers planned to compare it with current students in the program whose overall achievement level was moderate. It will be utilized to develop educational technologists to achieve higher academic achievement. Finally, it can be concluded that this research has achieved its intention and the conclusion of research is to be a guideline for developing learners and improving the educational quality of educational technologists in Thailand further.

VI. Conclusion

This research believes that the development of learners is necessary to develop the learners' composition in parallel. Creating strategies for understanding learner behavior will enable them to plan appropriate follow-up and assist learners in their potential. Consequently, this research is aimed to develop a predictive model for educational technologists' achievement. There are three research objectives: 1) to study the context of educational technologists' achievements in higher education, 2) to construct a model for predicting learning achievement of educational technologists in higher education, and 3) to evaluate a model for predicting learning achievement of educational technologists in higher education. The researchers achieved all three objectives.

For the first objective, the researchers summarized the issues of the education program context in relation to the vision of developing educational technologists into the 21st century as summarized in Tables II and Table III. Table III presents the competence of students in this education program with a high overall grade point average. For the second objective, the researchers developed a model to predict the success of educational technologists with a data mining process that applied two types of machine learning tools: unsupervised learning with k-means and k-determination, supervised learning with decision tree, ID3 random tree, and random forest. As a result of the potential clustering, technologists were able to analyze the number of clusters suitable for 4 clusters. The 4 clusters were used to develop a model as it was defined. For the third objective, the researchers tested the selected models. It has an efficiency value of 68.37%. It is generally considered moderate and should be improved in model development techniques to be more efficient. But when considering the reasons, it was found that the students had a high level of academic achievement as shown in Table III. In addition, the number of members of the 4th cluster is very small as summarized in Table V. The solution in the next research might be to split a cluster with overlapping cluster 2, cluster 3, and cluster 4.

However, the research has achieved the stated objectives and the researchers sincerely hope that the results of this research will be used to improve the educational program to develop the potential of educational technologists in Thailand.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

Pratya Nuankaew conducted the research by defining research frameworks, designing research methodology, analyzing, modeling, and writing the paper. Tipparat Sittiwong conducted the research by collecting data and preparing the data for modeling. Wongpanya Sararat Nuankaew conducted the research by editing the paper, reviewing models, and discussing the findings. All authors had approved the final version.

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REFERENCES

[1] M. G. Domingo and A. B. Garganté, "Exploring the use of educational technology in primary education: Teachers' perception of mobile technology learning impacts and applications' use in the classroom," *Comput. Hum. Behav.*, vol. 56, pp. 21-28, Mar. 2016, doi: 10.1016/j.chb.2015.11.023.

[2] J. Calvert and R. Abadia, "Impact of immersing university and high school students in educational linear narratives using virtual reality technology," *Comput. Educ.*, vol. 159, p. 104005, Dec. 2020, doi: 10.1016/j.compedu.2020.104005.

[3] A. Al Hadwer, M. Tavana, D. Gillis, and D. Rezania, "A systematic review of organizational factors impacting cloud-based technology adoption using technology-organization-environment framework," *Internet Things*, vol. 15, p. 100407, Sep. 2021, doi: 10.1016/j.iot.2021.100407.

[4] J. Li and A. Brar, "The use and impact of digital technologies for and on the mental health and wellbeing of Indigenous people: A systematic review of empirical studies," *Comput. Hum. Behav.*, vol. 126, p. 106988, Jan. 2022, doi: 10.1016/j.chb.2021.106988.

[5] A. L. Ahmad, J. Y. Chin, M. H. Z. Mohd Harun, and S. C. Low, "Environmental impacts and imperative technologies towards sustainable treatment of aquaculture wastewater: A review," *J. Water Process Eng.*, vol. 46, p. 102553, Apr. 2022, doi: 10.1016/j.jwpe.2021.102553.

[6] W. S. Nuankaew, P. Nuankaew, D. Teeraputon, K. Phanniphong, and S. Bussaman, "Perception and attitude toward self-regulated learning of Thailand's students in educational data mining perspective," *Int. J. Emerg. Technol. Learn. IJET*, vol. 14, no. 09, pp. 34-49, May 2019, doi: 10.3991/ijet.v14i09.10048.

[7] R. A. Estrellado, E. A. Freer, J. Mostipak, J. M. Rosenberg, and I. C. Velásquez, *Data Science in Education Using R*., London: Routledge, 2020. doi: 10.4324/9780367822842.

[8] M. Billinghurst, "Augmented reality in education," *New Horiz. Learn.*, vol. 12, no. 5, pp. 1-5, 2002.

[9] N. H. Gandedkar, M. T. Wong, and M. A. Darendeliler, "Role of virtual reality (VR), augmented reality (AR) and artificial intelligence (AI) in tertiary education and research of orthodontics: An insight," *Semin. Orthod.*, vol. 27, no. 2, pp. 69-77, Jun. 2021, doi: 10.1053/j.sodo.2021.05.003.

[10] 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.*, vol. 14, no. 21, pp. 205-226, Nov. 2019, doi: 10.3991/ijet.v14i21.11034.

[11] P. Nuankaew and P. Temdee, "Matching of compatible different attributes for compatibility of members and groups," *Int. J. Mob. Learn. Organ.*, vol. 13, no. 1, pp. 4-29, 2019, doi: 10.1504/IJMLO.2019.096469.

[12] J. S. Condo, E. S. M. Chan, and M. J. Kofler, "Examining the effects of ADHD symptoms and parental involvement on children's academic achievement," *Res. Dev. Disabil.*, vol. 122, p. 104156, Mar. 2022, doi: 10.1016/j.ridd.2021.104156.

[13] J. Smogorzewska, G. Szumski, S. Bosacki, P. Grygiel, and M. Karwowski, "School engagement, sensitivity to criticism and academic achievement in children: The predictive role of theory of mind," *Learn. Individ. Differ.*, vol. 93, p. 102111, Jan. 2022, doi: 10.1016/j.lindif.2021.102111.

[14] R. Laith and T. Vaillancourt, "The temporal sequence of bullying victimization, academic achievement, and school attendance: A review of the literature," *Aggress. Violent Behav.*, p. 101722, Jan. 2022, doi: 10.1016/j.avb.2022.101722.

[15] V. V. Busato, F. J. Prins, J. J. Elshout, and C. Hamaker, "Intellectual ability, learning style, personality, achievement motivation and academic success of psychology students in higher education," *Personal. Individ. Differ.*, vol. 29, no. 6, pp. 1057-1068, Dec. 2000, doi: 10.1016/S0191-8869(99)00253-6.

[16] A. E. Goldberg, N. McCormick, R. Frost, and A. Moyer, "Reconciling realities, adapting expectations, and reframing 'success': Adoptive parents respond to their children's academic interests, challenges, and achievement," *Child. Youth Serv. Rev.*, vol. 120, p. 105790, Jan. 2021, doi: 10.1016/j.childyouth.2020.105790.

[17] S. K. Kertechian, "Conscientiousness as a key to success for academic achievement among French university students enrolled in management studies," *Int. J. Manag. Educ.*, vol. 16, no. 2, pp. 154-165, Jul. 2018, doi: 10.1016/j.ijme.2018.02.003.

[18] 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, doi: 10.3991/ijet.v14i19.11177.

[19] C. Romero and S. Ventura, "Educational data mining and learning analytics: An updated survey," *Wiley Interdiscip. Rev. Data Min. Knowl. Discov.*, vol. 10, no. 3, p. e1355, 2020.

[20] A. M. Shahiri, W. Husain, and N. A. Rashid, "A review on predicting student's performance using data mining techniques," *Procedia Comput. Sci.*, vol. 72, pp. 414-422, Jan. 2015, doi: 10.1016/j.procs.2015.12.157.

[21] A. M. Ahmed, A. Rizaner, and A. H. Ulusoy, "Using data mining to predict instructor performance," *Procedia Comput. Sci.*, vol. 102, pp. 137-142, Jan. 2016, doi: 10.1016/j.procs.2016.09.380.

[22] B. Schiavi, V. Havard, K. Beddiar, and D. Baudry, "BIM data flow architecture with AR/VR technologies: Use cases in architecture, engineering and construction," *Autom. Constr.*, vol. 134, p. 104054, Feb. 2022, doi: 10.1016/j.autcon.2021.104054.

[23] W. Ang, A. Jedi, and N. Lohgheswary, "Factors affecting the acceptance of open learning as e-learning platform by technical course students," *J. Eng. Sci. Technol.*, vol. 16, no. 2, pp. 903-918, 2021.

[24] B. Collis and J. Moonen, "Flexible learning in a digital world," *Open Learn. J. Open Distance e-Learn.*, vol. 17, no. 3, pp. 217-230, 2002.

[25] J. L. F. Almeida and L. S. Machado, "Design requirements for educational serious games with focus on player enjoyment," *Entertain. Comput.*, vol. 38, p. 100413, May 2021, doi: 10.1016/j.entcom.2021.100413.

[26] H. C. P. Chun, S.-M. Skinner, and T. Rosewall, "The educational utility of blogging for MRI technologists," *J. Med. Imaging Radiat. Sci.*, vol. 50, no. 1, pp. 129-135, Mar. 2019, doi: 10.1016/j.jmir.2018.09.005.

[27] A. Gegenfurtner and C. Ebner, "Webinars in higher education and professional training: A meta-analysis and systematic review of randomized controlled trials," *Educ. Res. Rev.*, vol. 28, p. 100293, Nov. 2019, doi: 10.1016/j.edurev.2019.100293.

[28] E. Laar, A. J. A. M. Deursen, J. A. G. M. Dijk, and J. Haan, "Determinants of 21st-century digital skills: A large-scale survey among working professionals," *Comput. Hum. Behav.*, vol. 100, pp. 93-104, Nov. 2019, doi: 10.1016/j.chb.2019.06.017.

[29] T. Valtonen *et al.*, "How pre-service teachers perceive their 21st-century skills and dispositions: A longitudinal perspective," *Comput. Hum. Behav.*, vol. 116, p. 106643, Mar. 2021, doi: 10.1016/j.chb.2020.106643.

[30] R. Lavi, M. Tal, and Y. J. Dori, "Perceptions of STEM alumni and students on developing 21st century skills through methods of teaching and learning," *Stud. Educ. Eval.*, vol. 70, p. 101002, Sep. 2021, doi: 10.1016/j.stueduc.2021.101002.

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