ADVISORY RECOMMENDATION SYSTEM FOR DENTAL STUDENTS WITH A DECISION TREE MODEL

KATAYUT THAKAENG

MASTER OF SCIENCE
IN
INFORMATION TECHNOLOGY

SCHOOL OF APPLIED DIGITAL TECHNOLOGY
MAE FAH LUANG UNIVERSITY
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EXAMINATION COMMITTEE

Adisorn Leelasantitham ....CHAIRPERSON

(Assoc. Prof. Adisorn Leelasantitham, Ph. D.)

..........ADVISOR

(Asst. Prof. Santichai Wicha, Ph. D.)

P. Temdee ....EXAMINER

(Assoc. Prof. Punnarumol Temdee, Ph. D.)

..........EXAMINER

(Asst. Prof. Roungsan Chaisricharoen, Ph. D.)

..........EXAMINER

(Asst. Prof. Worasak Rueangsirarak, Ph. D.)

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Katayut Thakaeng

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Author	Katayut Thakaeng
Degree	Master of Science (Information Technology)
Advisor	Asst. Prof. Santichai Wicha, Ph. D.

ABSTRACT

Two main aspects are involved in becoming a dentist. The first is the academic dimension, which focuses on the acquisition of knowledge and the understanding of treatment methods for patients. The second is the practical aspect, which involves challenges related to direct interactions with patients. Subpar performance in this area can be caused by inadequate guidance from supervising professors, who may not be well-suited to students' needs.

The objective of this research is to develop a model that can assist in the identification of suitable advisors for dental students using Data Mining Classification Techniques. Questionnaires were utilized to examine the relationship between students' expectations of advisor behavior and assessments of advisor behavior based on three factors: the roles assumed by advisors, essential qualities for success, and other valuable behaviors and resources. Decision trees, neural networks, and k-nearest neighbors were applied to categorize the data, facilitating the efficient matching of dental students with advisors. This, in turn, improves decision-making and contributes to the educational success of dental students.

This study evaluates the predictive accuracy of different machine learning models in classifying advisor characteristics, advisor expectation attributes, and student satisfaction with educational outcomes from both expert and student perspectives. Using data from a survey of 105 dental students, three models Decision Tree, Neural Networks, and k-nearest neighbors (k-NN) were analyzed. Results indicate that from the expert's perspective, the Neural Networks model demonstrates the highest accuracy at 88.73% but exhibits lower precision. The Decision Tree model provides balanced performance with an accuracy of 86.00%, making it the most reliable. From the dental students' perspective, the Neural Networks model also shows strong performance with an accuracy of 79.36% and high precision and recall. These findings suggest that machine learning models can effectively predict advisor attributes, with Neural Networks and Decision Tree models offering the best performance in different contexts.

Keywords: Advisor Behavior, Data Minning, Machine Learning, Classification, Decision Trees, DISC Personality, Graph Search

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CHAPTER 1

INTRODUCTION

1.1 Background and Rational

In the present era, there is a high rate of dropout in dental education students. This is one of the critical issues in the education field, the prediction of a successful graduation rate has a crucial role for educational institutions [1]. One of the solutions for solving such problems in graduating the students [2] is the factor that the graduation of dental students is influenced by the guidance of the instructors or advisors in the right direction for achieving future careers [3]. Therefore, the advisor has a major role in encouraging, supporting, and guiding with the impactful method during the learning period.

Currently, when dental students begin their studies at the university, they are assigned one academic advisor throughout the courses of their learning education. The assignment used the method of using the last two digits of the student's ID number for grouping purposes. Some groups of advisors may already have designated students' groups as the advisees, resulting in a problem that the students and advisors may not screen each other' process and preference styles. Therefore, the student's needs and expectations may not align once they interact or follow the guidance of the academic advisor once they meet with their advisor. Accordingly, in other opportunities, students could refrain from seeking advice and guidance from their advisor because of the mismatches in communication, and behaviour compatibility. This problem could lead to unsatisfactory academic results from the inadequate guidance of the advisors. Which may lead to dropout from the education system of the dental students.

From studying the guidelines for addressing the mentioned problems of the dropout rate of dental students. There are various methods which utilize the technique of data correlation between academic advisors and students for selecting compatible relationships. Therefore, the objective of this research is to test a model for assisting in the suitable identification of academic advisors to dental students by applying the classification technique [2]. The data collection is conducted through questionnaires which have been used to examine the relations between dental students' expectations, advisor behaviour, and advisor behaviour evaluation based on three factors: the advisors' role, essential qualification for success, and other valuable behaviours and resources. Additionally, Decision trees, neural networks, and k-nearest neighbours models have been used to simulate the correction relationship of the data in effective pairing between dental students and advisors [4]. This will assist in the decision-making in the education for successful learning of dental students at both present and future times.

1.2 Objective

1.2.1 Developing a Positive Relationship Model between advisor/advisee selection Process.

1.2.2 Develop existing data to positive relationship the model between dental advisor/advisee to be more effective.

1.2.3 To study the opinions of students and advisors on the advisor attributes that students expect for achieving academic success.

1.3 Scope

1.3.1 Requirement analysis from stakeholder and existing data.

1.3.2 Model selection for advisor/advisee matching.

1.3.3 Build a positive correlation prediction model between Advisors/Advisee selection.

1.3.4 Evaluation process.

1.4 Expected Benefits from Research Project

1.4.1 Understanding the characteristics of advisors, students' expectations of advisors, and satisfaction with academic outcomes.

1.4.2 Exploring the feasibility of forming advisor groups that align with students' expectations to facilitate academic success.

1.4.3 Identifying students' needs and expectations regarding their advisors, impacting their academic performance across various advisor roles.

1.4.4 Findings from studying advisor characteristics, student expectations, and satisfaction can be used to enhance and develop advisors' roles for better outcomes.

1.4.5 Using the analyzed data to develop systems aligned with predictive forecasting models for student academic achievement, facilitating future data analysis.

CHAPTER 2

LITERATURE REVIEW

2.1 Related Works

The guidance on learning, teaching, and advising is a standard framework for studying at universities and educational institutions. This includes creating manuals and standardized methods to guide students during their time within the educational institutions. For example, the student handbook is a source of information that students must understand and follow to complete their chosen curriculum effectively.

Once students have entered their selected faculty, the faculty assigns an additional crucial role to assist them during their studies: the academic advisor.

What constitutes a good advisor? What essential qualities should a good advisor possess? First and foremost, when students need help in a specific academic discipline, the advisor should generally have more accurate knowledge than the students in that field. This considers the advisor’s role as a source of accurate information, which is fundamental yet critical. Advisors should also aim for broader goals, where students might seek help not only for straightforward queries but also for more complex or open-ended goals such as discovering new interests, receiving coaching by questioning established norms, or providing exemplary guidance in academic writing and discussions [5].

In this research, the researcher studied relevant documents and research and presented them according to the following related topics:

1. Analysis of the relationship and attributes of academic advisors.
2. Machine learning techniques.
3. Algorithm models used in machine learning techniques applied in the research.
4. Feature scaling.

5. Feature selection.
6. Hyper parameter tuning.
7. RapidMiner Process

2.2 Analysis of The Relationship and Attributes of Academic Advisors

The researcher divided the attributes of academic advisors into four main characteristics, and the attributes essential for student success include:

2.2.1 The Roles Assumed by Advisors

2.2.1.1 Mentor: The relationship in providing advice is beneficial to the advisor and the advisee. The mentor role involves building trust for both academic and professional pursuits in the future. Providing consulting and advice can improve the efficiency of dental students. Therefore, the mentor role can be considered as the role that can be an advisor, idea consultant, role model, and target for various aspects for developments to the dental students [6].

2.2.1.2 Teacher/educator: With the characteristic of sharing knowledge, educators promote critical thinking regarding decision-making and develop understanding and new skills relevant to learning for academic success. The educator or teacher has a crucial role as the consultant, advisor, conversationalist, and academic mentor for students. As a result, this helps the students in self-development and improves the learning efficiency in the university [7].

2.2.1.3 Motivator: The role of motivating, encouraging, and demonstrating beliefs in students' abilities, including setting goals and assisting in achieving educational success. Moreover, the advisor also has a major role in motivating students to learn by supporting basic psychological needs for independence, abilities, and relationships. These factors can lead to proper educational goals and success [8].

2.2.1.4 University policy/risk: An important role in assisting the students for courses selection and providing a suitable advice [9] with the target of enhancing experiences of the students [10]. In addition, this role also provides the education planning and recommendations in education for reducing the dropout rate or courses registration problems according to the specified curriculum.

2.2.2 Important Attributes for Success

2.2.2.1 Honesty: Honesty between students and advisors is crucial for effective advising [11]. Research indicates that suspicions about intentional bias lead to less severe recommendations compared to suspicions about unintentional errors [12]. Evaluating the advisor's credibility is important to mitigate misleading opinions due to dishonesty or subjective differences [13].

2.2.2.2 Autonomy: Autonomy with academic advisors plays a significant role in the development and success of students in various educational settings. Advisors, such as those in universities [14], benefit students by promoting self-directed learning. Through creating supportive environments, advisors help students enhance their potential for educational success.

2.2.2.3 Challenge and support: Academic advisor has a major role in both challenging and supporting students in various learning contexts and environments. For example, in the context of autistic students, advisors can help by discussing disclosure options, building confidence, and focusing on individuals' strengths through role-playing [15]. Overall, advisors must provide guidance that can challenge students and at the same time provide support to help them achieve educational success.

2.2.3 Other Valuable Behaviours and Resources

2.2.3.1 Communications: Advisors possess distinctive communication skills in analysing student interactions. For example, the communication behaviour that occurs within the relationship. The general type of communication that can be found the most is the face-to-face meeting. Additionally, effective communication behaviours by academic advisors, such as affirmation and creating a supportive atmosphere, are linked to positive outcomes for students, including intellectual and emotional learning outcomes and satisfaction [16]. Overall, clear communication is vital in supporting and enhancing students' counselling experiences and promoting their educational success.

2.2.3.2 Resources: In addition to being a source of information that students can access, advisors also act as facilitators in the development of learning both directly and indirectly. In addition, career counselling and guidance are important for students to acquire the right skills, abilities, and attitudes for relevant work, which ultimately increases the student's ability to succeed [17]. Thus, information sources and advisors have a major role in supporting students' academic success.

2.2.3.3 Academic interests: Academic advisors play a key role in shaping students' academic interests by facilitating connections with academics and helping to build academic networks [18]. Advisors provide guidance and relationships with academic peers and accelerate a student's socialization process [19]. Overall, academic advisors have a role in guiding students toward academic success by providing support and guidance as well as creating opportunities for networking and future employment.

These various roles collectively contribute to improving the educational path of dental students by providing guidance from advisors who support both the theoretical and practical aspects of their studies, helping them achieve academic success.

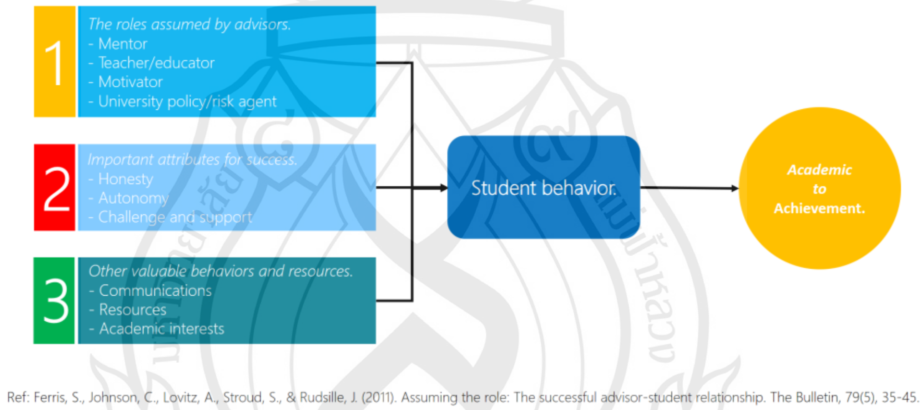

Figure 2.1 Three main factors which they affect the achievement of education of student which are; The roles assumed by advisors, Important attributes for success, and Other valuable behaviors and resource behaviours

2.3 Machine Learning Techniques

Machine Learning is a scientific study related to algorithms and statistical models used by computer systems to perform tasks. The main advantage of using machine learning is that once an algorithm learns how to handle data, it can process the data automatically. However, there is no single best algorithm since each algorithm uses different principles to predict or assist in decision-making based on the data [20], as shown in Figure 2.1 [21].

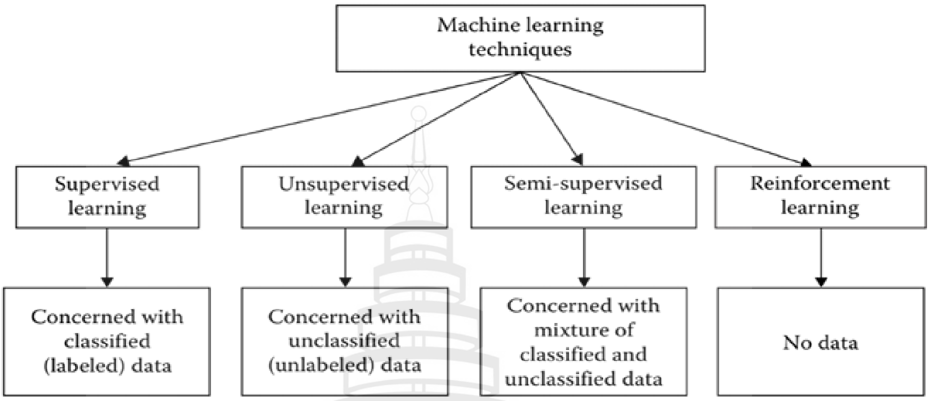

Figure 2.2 Diagram of different machine learning techniques

Machine Learning can be categorized into four types of learning.

1. Supervised Learning: Supervised learning is a type of machine learning where the algorithm learns to predict outcomes (targets) based on labeled data. It can be divided into two main types:

1) Classification is used to solve problems where the desired outcome is to produce results in the form of groups or categories of data. For example, predicting students' academic performance, forecasting the weather in different regions, and so on.

2) Regression analysis is used to solve problems where the desired outcome is to produce results as continuous numerical values. For example, predicting real estate prices, forecasting weather patterns, and so on.

2. Unsupervised learning is a machine learning technique where the algorithm learns from data that has not been labeled or classified. It can be categorized into two types of data:

1) Clustering is the process of organizing similar data points into a single group. Examples include grouping books, categorizing car models, and identifying similar DNA sequences or patterns.

2) Association is the process of discovering relationships between variables in a dataset. A common example is understanding consumer purchasing behavior.

3. Semi-supervised learning is a machine learning technique that utilizes both labeled and unlabeled data to build suitable models for data classification. The primary aim is to classify data, primarily using unlabeled data. Examples include image and audio analysis, categorization, and ranking search engine results.

4. Reinforcement Learning is a machine learning technique where learning takes place without data. It involves an agent making decisions to solve problems in various situations by observing and learning from the environment. Each action is rewarded, aiming to find the best outcome for solving the problem. Examples include robots finding their way out of mazes or organizing items in a large warehouse.

2.4 Algorithmic Models Used in Machine Learning Techniques Used in Research

The model used in the research employs Supervised Learning in Machine Learning (ML), utilizing data from questionnaire responses from dental students. Each attribute is imported, and the complete academic performance (GPA) is designated as the label. The machine is trained to search for relationships between the characteristics of advising professors and the academic success of dental students, aiming to predict the congruence of data in each attribute. Three models, Decision Trees, Neural Networks, and k-Nearest Neighbors, are utilized to test the occurring relationships. RapidMiner Studio software is used for data analysis with these three models and to verify their accuracy.

2.4.1 Decision Tree [22]

The technique used for classification operates by organizing the decision-making process into nodes, where decision conditions are displayed. These nodes are connected by straight lines, and the decision paths in each condition culminate at an activity. This method employs a tree diagram to illustrate processing by simulating branches of a tree as a framework, branching from the root on the left-hand side, further branching to the right, and continuously branching until all conditions are met. The final branches of all conditions represent the activities to be undertaken. When depicted according to these conditions, it can be illustrated as follows.

Figure 2.3 The concept of decision trees [22]

2.4.2 Neural networks [23]

Neural networks were developed to mimic the capabilities of biological nervous systems. The structure of neural network models encompasses various architectures, but they all share several common advantages. The most significant advantage of neural networks is their ability to approximate nonlinear continuous functions to the desired level of accuracy. With this characteristic, neural networks are employed to model nonlinear systems for subsequent control synthesis.

In this research, Neural Network methodology was employed due to its ability to effectively learn from input variables, regardless of whether they are interval variables, ordinal variables, or binary variables. Moreover, the input variables did not follow a normal distribution for interval variables, and the target variable did not exhibit a linear relationship with the characteristics of the data in this study.

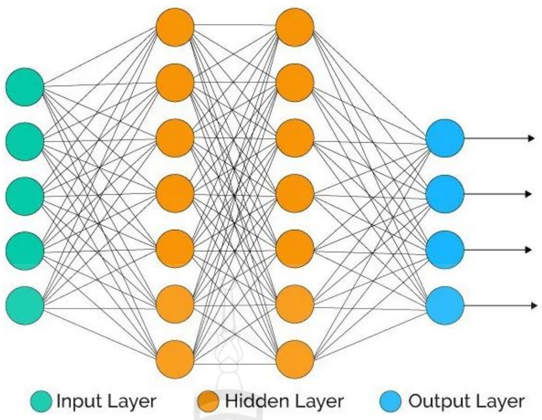

Figure 2.4 The concept of neural network [23]

The components of a Neural Network consist of three main parts:

1. Input Layer: This is the initial layer where the data is introduced to the network. Each neuron in this layer represents one feature or variable from the input data.

2. Hidden Layers: These are the intermediate layers between the input and output layers. They process the input data through a series of weighted connections and apply activation functions to produce outputs. Hidden layers enable the network to learn complex patterns and relationships within the data.

3. Output Layer: This is the final layer of the network that produces the desired output or prediction. The number of neurons in this layer depends on the type of problem being addressed (e.g., regression, classification). Each neuron typically corresponds to one class or target value, and the output is generated based on the activation of these neurons.

2.4.3 K-Nearest Neighbors (K-NN) [24]

The technique that classifies data relies on finding the nearest neighbors based on the most similar features with a value of K from the data in the sample dataset. It works by determining the shortest distance from the new input query instance or data to the trained dataset, calculating and finding the K nearest neighbors. After that, it collects the K nearest neighboring members, then selects the majority class among these neighbors, which is most frequently present in the K group, for the new input member. Data classification is achieved by using the K nearest neighboring data, which comprises multiple variable attributes X used for grouping Y. A positive integer value is assigned to K, indicating the number of cases to be searched for in predicting new instances. The K-Nearest Neighbors algorithm includes variations such as 1-NN, 2-NN, 3-NN, ... K-NN. When following these conditions, it can be demonstrated as such.

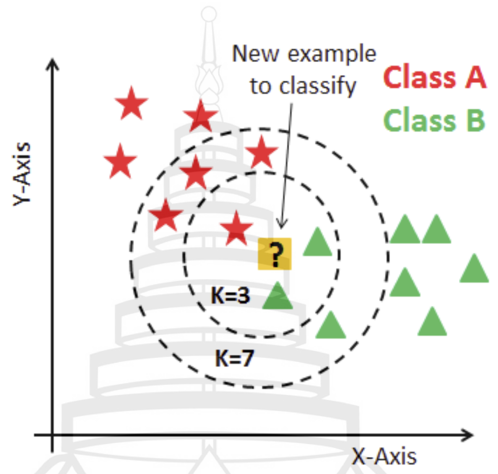

Figure 2.5 The concept of k-nearest neighbors (K-NN)

2.5 Feature Scaling

Adjusting the range or scale of data is one of the steps in preparing data to make it suitable for modeling or processing. It involves transforming numerical data with different ranges into numbers within the same range. The advantage of data range adjustment is that it reduces bias, which could lead to prediction errors in the generated models, and helps reduce the time required to build models because the dataset becomes smaller, enabling faster computation. This technique of adjusting data range has a [21] technique.

2.5.1 Min-Max Scaling

The technique used to adjust the range of data to a suitable group without significant outliers is called Min-Max Scaling. It utilizes the equation:

$$\bar{x} = \frac{x - \min(x)}{\max(x) - \min(x)}$$

2.5.2 Standardization or Variance Scaling

The technique used to adjust the range of data to have a mean of 0 and a standard deviation of 1, making the data easily comparable, is called Standardization or Z-score normalization. It is suitable for data with a normal distribution. where $\bar{x}$ is the mean of the data and σ is the standard deviation of the data.

$$Z = \frac{x - \mu}{\sigma}$$

2.6 Feature Selection

Feature selection is a method that helps reduce the number of variables used in predictive modeling. It may involve selecting the best individual features or choosing a group of features that are important for prediction. The feature selection process is crucial in preparing data for data mining to improve the efficiency of predictive modeling. By reducing the number of unnecessary features or features that introduce errors in predictions, feature selection can enhance the performance of predictive models.

There are two types of feature selection:

1. Univariate Feature Selection: This method involves evaluating each feature independently and selecting the best-performing features based on statistical tests or scoring methods. It focuses on selecting individual features that are most relevant to the target variable.

2. Feature Importance: In this approach, the importance of features is assessed collectively within the context of the entire feature set. Techniques such as

decision trees, random forests, or gradient boosting models are used to determine the importance of features based on how much they contribute to improving model performance. Features with higher importance scores are retained, while less important ones may be discarded.

2.7 Hyperparameter Tuning

The process of fine-tuning and improving a model to find the best parameters is known as model optimization. It aims to enhance the performance of the model by adjusting its parameters effectively. There are three main techniques commonly used in model optimization:

2.7.1 Manual Search is a method of tuning hyperparameters that relies on the expertise and experience of the model creator. It involves testing the model with predefined hyperparameter values and adjusting them until a satisfactory value is obtained.

2.7.2 Grid Search is a method of tuning hyperparameters by specifying a set of hyperparameter values in advance. It systematically searches for hyperparameter values according to the predefined grid and evaluates the model's performance with each combination. It selects the hyperparameter values that yield the best model performance, although it may take longer than Random Search.

2.7.3 Random Search is a method of tuning hyperparameters by randomly selecting values from a predefined range. These randomly chosen hyperparameters are tested with the model, and if they improve the model's performance compared to the current hyperparameters, they are adopted. The advantage of this method is its ability to quickly find good hyperparameters. However, the downside is that it may not find the optimal hyperparameters because the selection process is random.

2.8 RapidMiner Process

RapidMiner Studio is a program used for designing, analyzing, and processing data through a GUI (Graphical User Interface), which can easily manage data and create various prediction models.

2.8.1 Decision Tree

2.8.1.1 Import data (Data)

2.8.1.2 Select the label (Expert [1]) using Set Role.

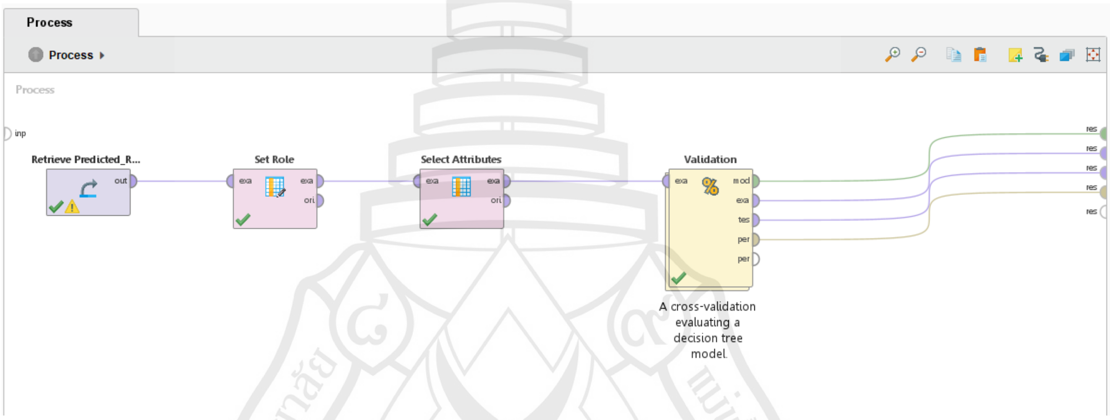

Figure 2.6 Select process decision tree

2.8.1.3 Select Cross-validation, set the number of folds, the number of data segmentations to be used as Training Data and Test Data, set the value at number of folds = 10.

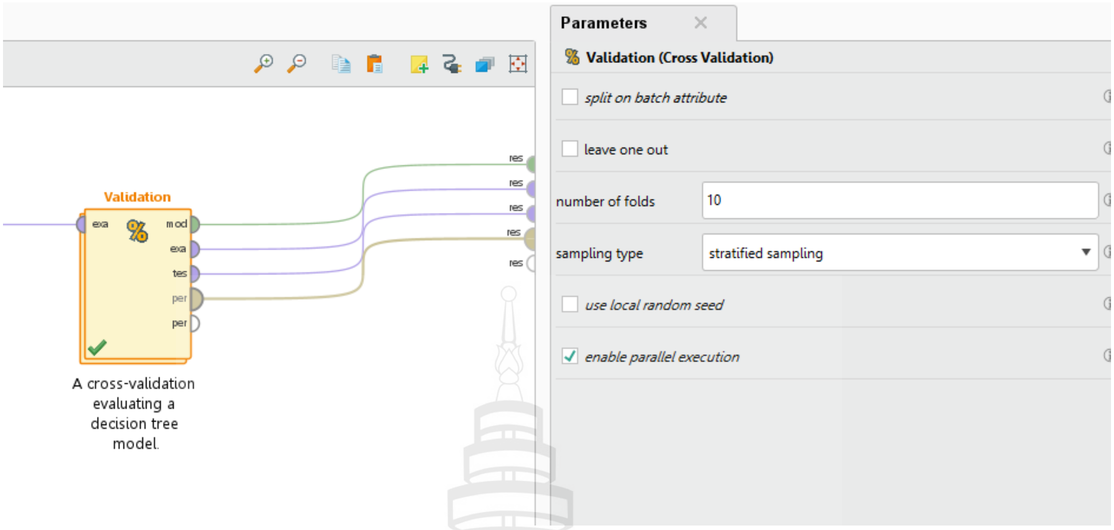

Figure 2.7 Set parameter for decision tree

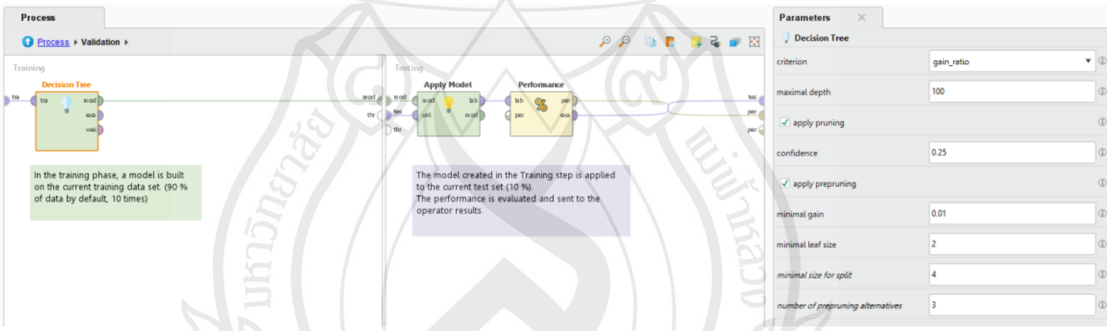

Figure 2.8 Add operation: Decision tree to the training side

2.8.2 Neural Network

2.8.2.1 Import data (Data)

2.8.2.2 Select the label (Expert [1]) using Set Role.

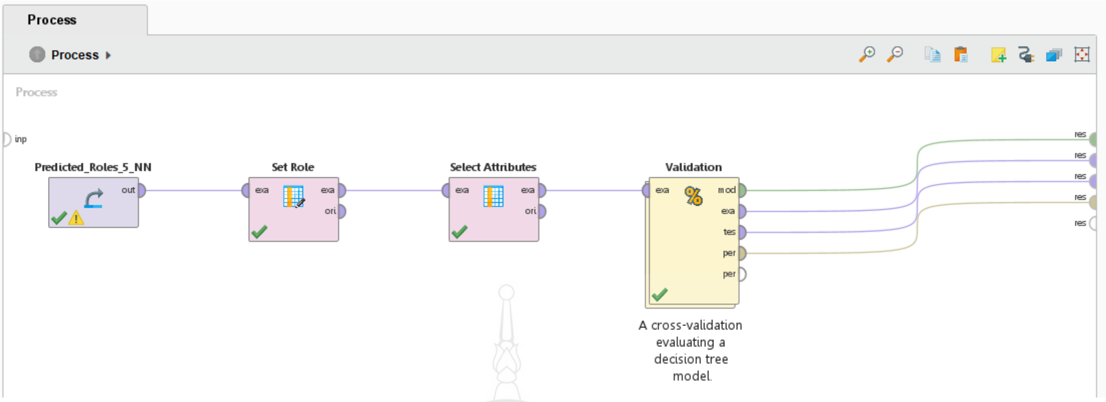

Figure 2.9 Select process neural network

2.8.2.3 Select Cross-validation, set the number of folds, the number of data segmentations to be used as Training Data and Test Data, set the value at number of folds = 10.

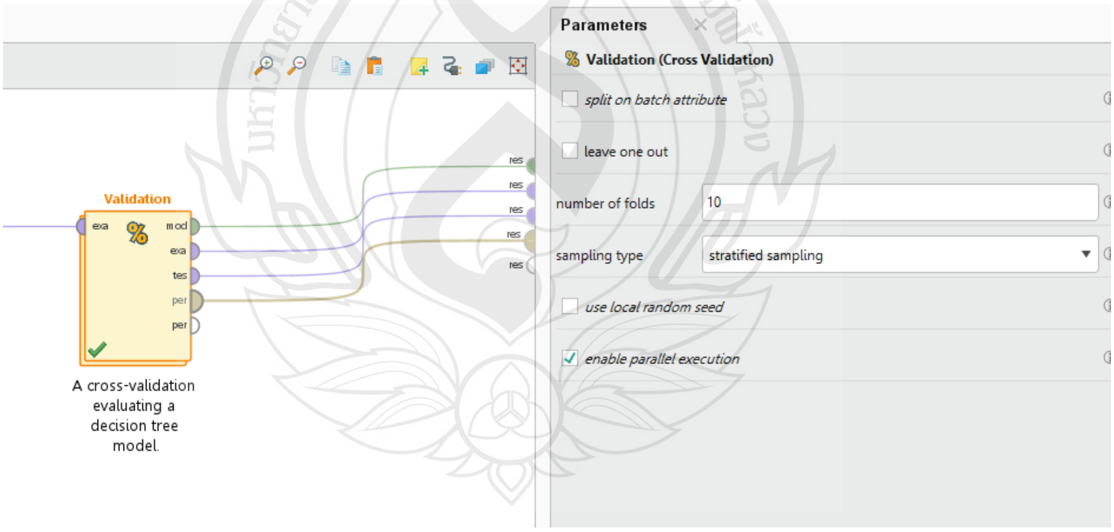

Figure 2.10 Set parameter for neural network

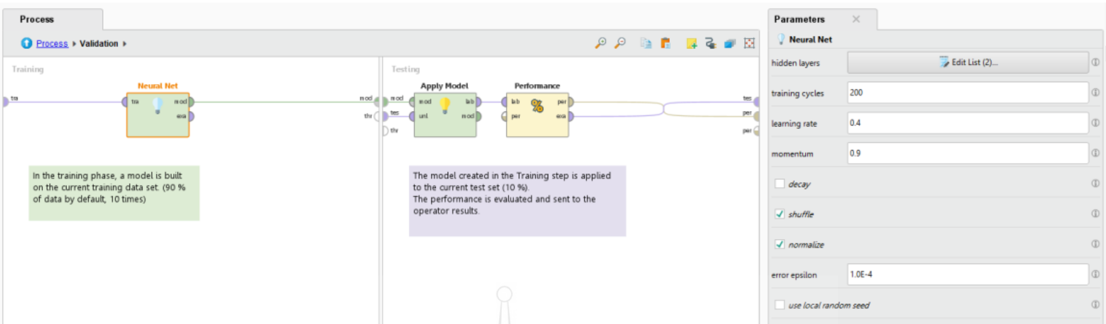

Figure 2.11 Add operation: Neural network to the training side

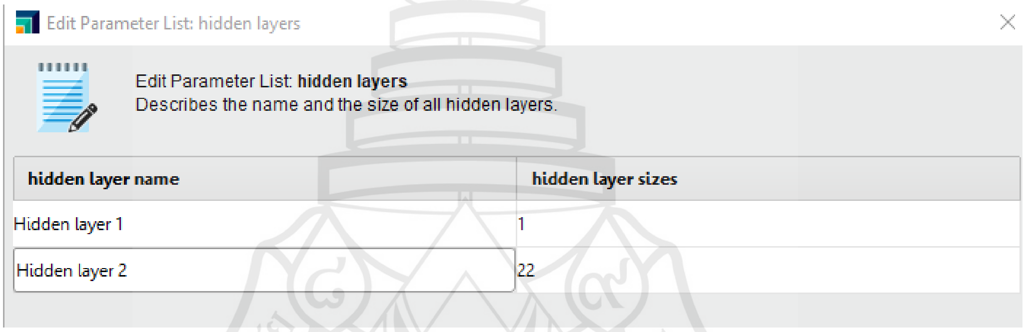

Figure 2.12 Add operation: Neural network to the configure hidden layer, add hidden layer 1= 1, hidden layer 2= 22

2.8.3 K-nearest Neighbors

2.8.3.1 Import data (Data)

2.8.3.2 Select the label (Expert [1]) using Set Role.

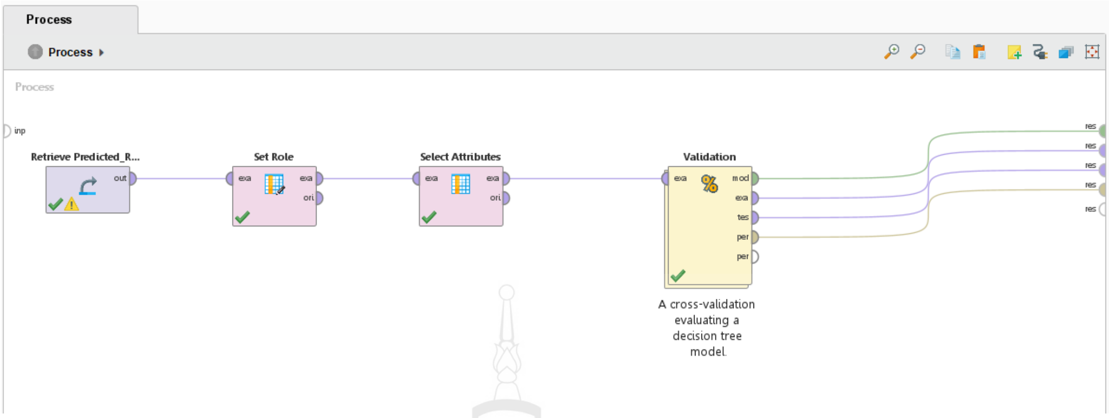

Figure 2.13 Select process k-nearest neighbors

2.8.3.3 Select Cross-validation, set the number of folds, the number of data segmentations to be used as Training Data and Test Data, set the value at number of folds = 10.

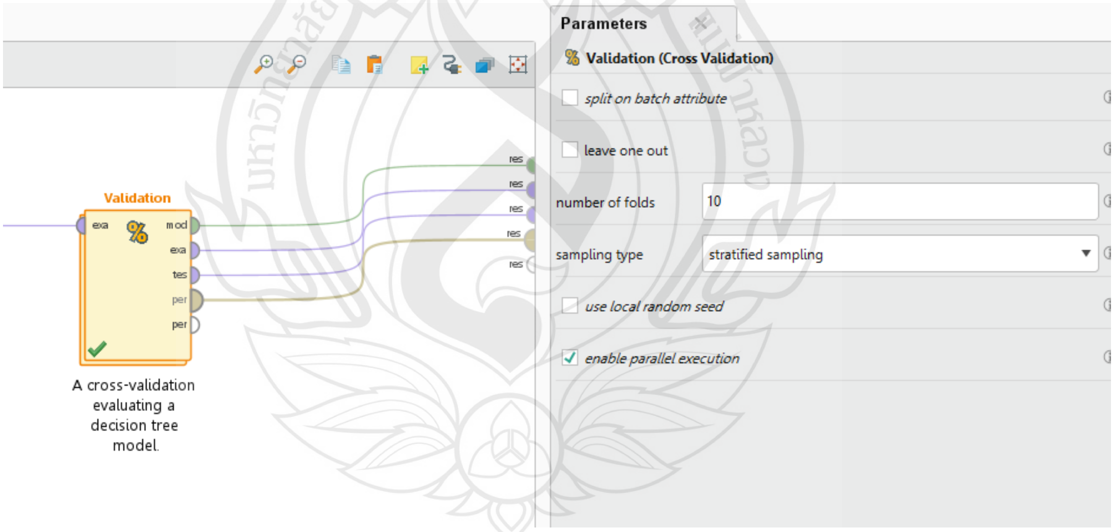

Figure 2.14 Set parameter for k-nearest neighbors

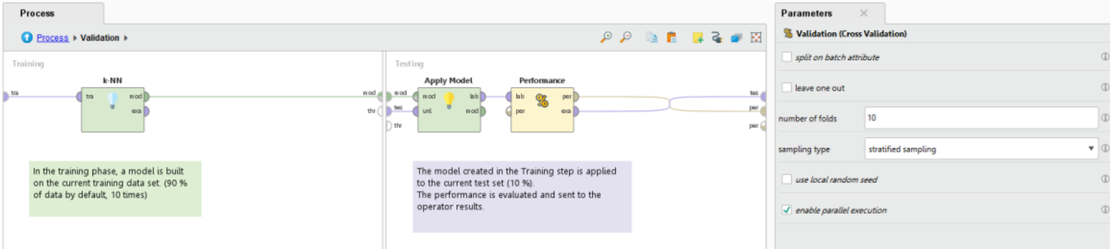

Figure 2.15 Add operation: k-nearest neighbors to the training side

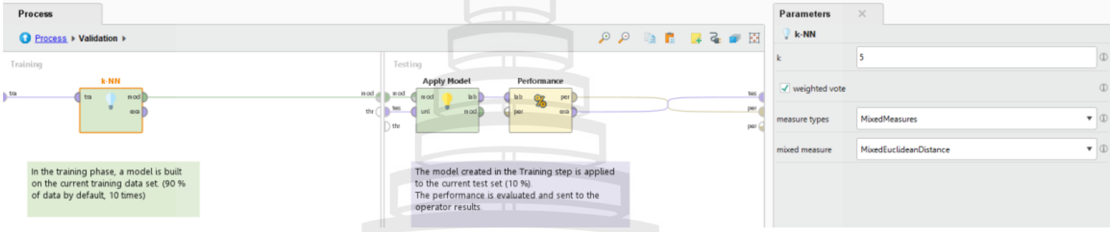

Figure 2.16 Add operation: k-NN model, set k=5

CHAPTER 3

METHODOLOGY

3.1 Process Design

This research utilized data collection techniques to screen the characteristics of advisors and the expectations that dental students have for their advisors. It aimed to identify closely related characteristics that contribute to academic success.

The participants consist of dental students from the School of Dentistry at Mae Fah Luang University. A total of 105 students voluntarily answered the questions, with data collected anonymously and without any personal information of the students were collected. The participants were the target group for studying the variables in a model used to predict the relationship between dental students and their advisors. The sample group consisted of 105 people, with females making up 80.95% and males 19.05%. The education levels included first-year students (26.67%), second-year students (29.52%), third-year students (15.24%), fourth-year students (9.52%), fifth-year students (9.52%), and sixth-year students (9.52%). The cumulative GPA levels were less than 2.00 (0.00%), between 2.00-2.50 (2.86%), between 2.51-3.00 (9.52%), between 3.01-3.50 (22.86%), and between 3.51-4.00 (64.76%).

Overall, the number of dental students who participated in the questionnaire had various levels of education, which can be used to test the prediction of the relationship between dental students and the characteristics of their advisors by taking the role of the advisors and characteristics that are important to advising of the advisors, and the expectations of the advisors' characteristics of the students to be used in the model for predicting the relationship as shown in Figure 3.1.

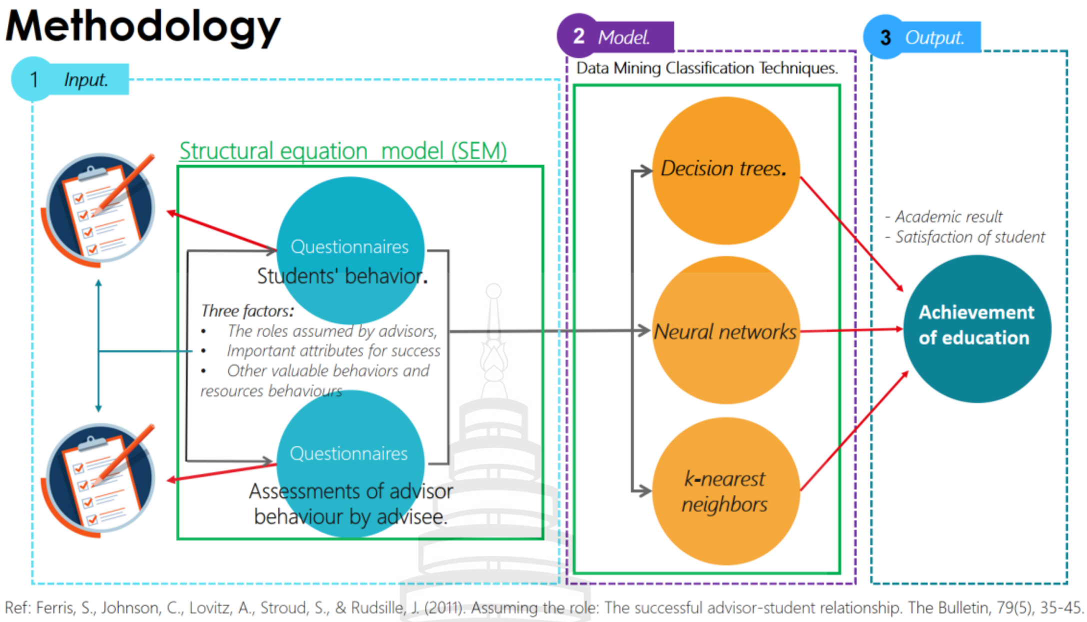

Figure 3.1 Structural equation model (SEM)

Flowchart of the analysis process for predicting the relationship between advisors and dental students' success.

To achieve the results of the research, the authors designed the experiment as shown in Figure 3.1 The authors conducted questionnaires to measure students' expectations of advisors and assessments of advisors' behaviour based on research on the successful advisor-student relationship.

The questionnaire focuses on studying three main factors which they affect the achievement of education of students which are the roles assumed by advisors, Important attributes for success, and other valuable behaviours and resource behaviours.

The result after collecting data will be statistically analysed using the Structural Equation Model (SEM) to check the impact level of each factor on the achievement of education. Also, checking the questionnaire's reliability to verify the truth of the data in each question "Is it enough to use for data mining analysis or not?". After statistical analysis, all data will be used to analyse using the Data Mining Classification

Techniques by applying three algorithms which are the Decision tree, neural network and K-nearest neighbour.

3.2 Data Collection

3.2.1 Questionnaires were distributed to dental students at the School of Dentistry, Mae Fah Luang University.

3.2.2 Participation was voluntary, with 105 students responding.

3.2.3 The data collection ensured anonymity and did not include any personal identifiers.

3.3 Data Understanding

The data obtained from survey responses regarding the relationship and characteristics of academic advisors consists of 105 individuals. It includes various attributes such as general information about the respondents, such as gender, education level, and GPA, as well as data on the characteristics of academic advisors and the expectations students have of their advisors.

Questionnaires were utilized to examine the relationship between students' behavior of advisor behavior and assessments of advisor behavior.

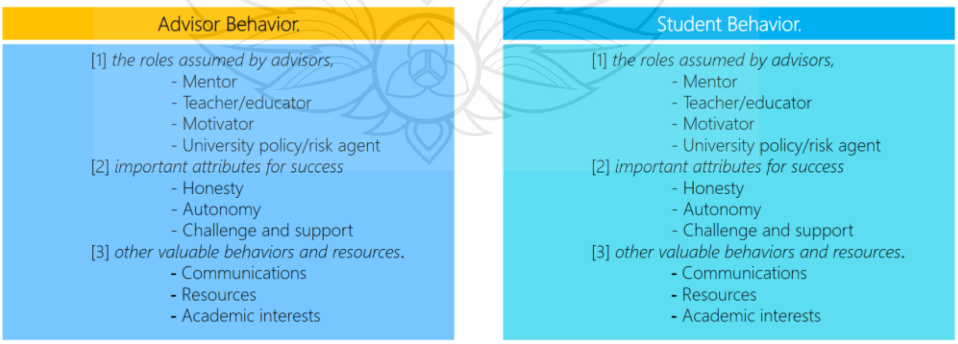

Figure 3.2 Designed questionnaire and sampling.

3.4 Data Description

The dataset used in this study was collected from 105 respondents through a survey about the relationship and characteristics of academic advisors. This dataset comprises various attributes, such as general information about the respondents, their academic performance, and detailed information about the characteristics and expectations of academic advisors. Below are the details of the dataset components:

3.4.1 General Information of Respondents:

Gender: Male, Female

Education Level: Year 1, Year 2, Year 3, Year 4, Year 5, Year 6

GPA: Categorical ranges (e.g., < 2.00, 2.00-2.50, 2.51-3.00, 3.01-3.50, 3.51-4.00)

3.4.2 Characteristics of Academic Advisors:

The assessment of the characteristics of academic advisors, the evaluation of students' expectations of their advisors, and the assessment of satisfaction with academic performance will utilize a 9-level Likert Scale as the primary tool in social science research [25]. The Likert Scale is a crucial instrument in social science research because it provides a good range of data for analysis. Researchers assigned numerical values to the scale, with 1 indicating "Strongly Disagree" and ranging up to 9, which indicates "Strongly Agree". This Likert Scale evaluation of advisor characteristics and student expectations will be utilized in analyzing the level of academic achievement attained by students. Using the Likert Scale allows for a clear understanding of respondents' opinions or feelings and provides accuracy in analyzing and summarizing survey data. This approach contributes to more efficient and accurate research compared to other measurement methods.

Questionnaires were utilized to examine the relationship between students' expectations of advisor behavior and assessments of advisor behavior based on three factors:

3.4.2.1 The roles assumed by advisors,

1. Mentor
2. Teacher/educator
3. Motivator

4. University policy/risk agent

3.4.2.2 Important attributes for success

1. Honesty
2. Autonomy
3. Challenge and support

3.4.2.3 Other valuable behaviors and resources.

1. Communications
2. Resources
3. Academic interests

3.5 Data Preparation

Data entering the analysis process, divided into 3 parts, (1) characteristics of the advisor, (2) expectations of the characteristics of the student advisor and (3) satisfaction with academic outcomes.

To test the model's predictive capabilities regarding the relationship between dental students and their advisors, the data will be used.

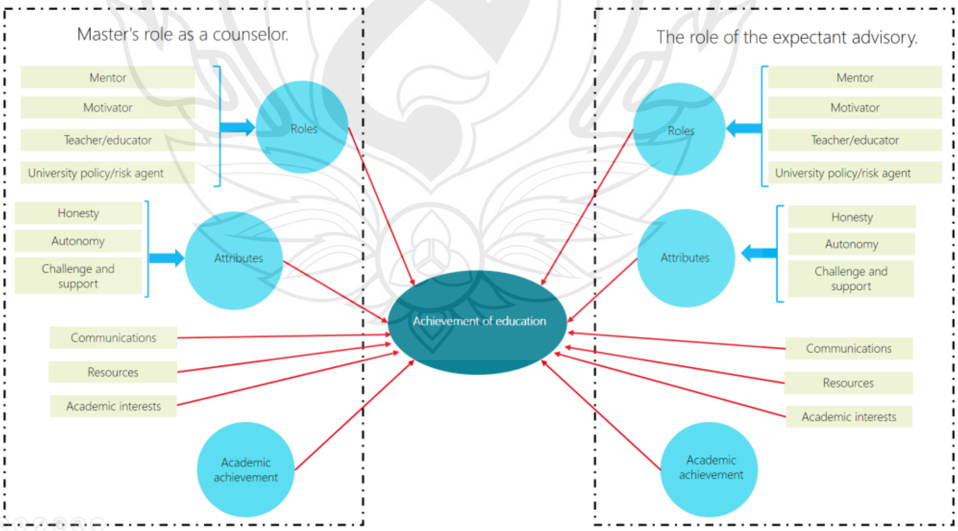

Figure 3.3 The features used to predict the relationship between dental students and their advisors can include attributes related to both students and advisors

Table 3.1 Characteristics of the advisor

STD Code	G Teacher	Mentor	Teacher and Educator	Motivator	University policy and Risk agent	Attribute			Commu nication	Resource	Academic interests
						Honesty	Autonomy	Challenge and support			
61xx08	T01	7	7	6	7	6	6	4	4	4	5
61xx09	T01	6	6	5	7	4	3	1	4	2	2
61xx10	T02	9	9	9	9	9	9	9	9	9	9
62xx08	T02	7	8	7	7	6	7	8	6	6	7
62xx10	T01	7	7	8	8	8	8	8	8	8	7

The expectations of dental students regarding the characteristics of their advisors include 4 attributes, comprising 4 questions:

1. The roles assumed by advisors:

1) Mentor: How do you perceive your advisor’s role as a mentor?

2) Teacher and Education: What are your expectations regarding your advisor’s teaching abilities and educational support?

3) Motivator: How do you expect your advisor to motivate you?

4) University Policy and Risk Agent: What role do you expect your advisor to play in terms of university policies and risk management?

2. Important attributes for success:

1) Honesty: How do you perceive the honesty of your advisor?

2) Autonomy: How much autonomy do you expect to have in your interactions with your advisor?

3) Challenge and Support: How do you expect your advisor to challenge and support you?

3. Other valuable behaviours and resources:

1) Communication: What are your expectations regarding communication with your advisor?

2) Resources: How much support and guidance do you expect from your advisor in terms of learning resources?

3) Academic Interests: How do you expect your advisor to support and engage with your academic interests?

Table 3.2 Expectations of the characteristics of the student advisor

STD Code	G Teacher	Mentor	Teacher and Educator	Motivator	University policy and Risk agent	Attribute			Commu nication	Resource	Academic interests
						Honesty	Autonomy	Challenge and support			
61xxxx08	T01	7	7	6	7	6	6	4	4	4	5
61xxxx09	T01	6	6	5	7	4	3	1	4	2	2
61xxxx10	T02	9	9	9	9	9	9	9	9	9	9
62xxxx08	T02	7	8	7	7	6	7	8	6	6	7
62xxxx10	T01	7	7	8	8	8	8	8	8	8	7

Table 3.3 Satisfaction with academic outcomes

STD Code	G Teacher	Question (1)	Question (2)	Question (3)
61xxxx08	T01	2	3	2
61xxxx09	T01	2	2	2
61xxxx10	T02	2	2	2
62xxxx08	T02	3	3	3
62xxxx09	T02	2	2	2
62xxxx10	T01	2	2	2

3.6 Feature Selection

Since the questions in each role have variance in each question, the analysis of each role requires the use of sociological research (Analysis of Variance) that uses a one-way analysis of variance. The analysis must follow the prerequisites first by dividing the advisors into groups according to the characteristics of the advisor and the expectations of the advisor characteristics from the students and satisfaction toward study results into groups by setting the main hypothesis of the one-way analysis of variance as follows:

Hypothesis

H0: The mean of each group is not different.

H1: The mean is different in at least one group.

H0: $\mu1= \mu2=\ldots= \mu3= \mu k$

H1: There is at least one pair that is not equal.

The test statistic calculated from the variance between groups from the data obtained from the questionnaire data divided by the characteristics of the advisor, the characteristics of the expectations of the advisor, and the satisfaction with the study results.

3.6.1 Advisor Characteristics

Figure 3.4 The format for dividing the characteristics of the advisor into 4 roles, 3 components, 3 approaches. Each section is divided into 3 evaluation questions, total of 29 questions. The sum of all 29 questions is the role of the advisor

3.6.2 Characteristics of Advisor Expectations

Figure 3.5 The format of the grouping of the characteristics of student advisor expectations, 4 roles, 3 components, 3 approaches, each section is separated into 3 evaluation questions, total of 29 questions. The sum of all 29 questions is the role of the advisor

3.6.3 Satisfaction Toward Educational Results

Figure 3.6 The format of the grouping of students’ satisfaction with the results of the study is divided into 3 assessment questions, total of 3 questions. The sum of all 3 questions is the satisfaction of the students toward educational results

3.7 Data Analysing Method

The testing of the model involves students selecting advisor characteristics that match their preferences based on survey scores. The characteristics of advisor expectations should align with the advisor group the students rated in the survey. The satisfaction with academic outcomes should also reflect the students’ survey responses. The details from the survey responses are randomly selected for dental faculty to review and provide their opinions on the roles and the weight given to each role by the dental students.

The dental faculty provided insights into the essential roles dental students should embody, considering their future careers in dental care. Their perspectives focus on professional practice and competency in the field, as well as training, guidance, and communication. They have prioritized the roles in dental education as follows:

Mentor: The role of a mentor is considered the most crucial. Having someone to guide and assist in practical training and patient care is paramount. The success of dental students hinges on their ability to treat and care for patients effectively and practice professionally. Dental education requires continuous guidance and training to ensure students acquire effective knowledge and skills.

Motivator: The role of a motivator is vital as dental education spans six years, covering both theoretical and practical aspects. During this time, students may experience discouragement and loss of motivation. The motivator's role is crucial in inspiring and supporting students emotionally and psychologically, helping them achieve academic success.

Teacher/Educator: With the wide availability of information today, students can self-study and gain knowledge independently. Many dental faculty members can access filtered, quality information from various sources. Thus, the educator's role is seen as less critical compared to mentoring and motivating.

Regulator: The role of a regulator is considered the least important as it mainly pertains to attendance rather than professional practice.

The data obtained from grouping based on these roles can be tested using models such as Decision Tree, Neural Networks, and k-nearest neighbors to predict the academic success of dental students. The faculty's input on the importance of these roles helps validate and refine the predictive models, ensuring they align with the practical needs and expectations in dental education.

STD Code	Men_Q1_1	Men_Q1_2	Men_Q1_3	Tea_Q1_4	Tea_Q1_5	Tea_Q1_6	Moti_Q1_7	Moti_Q1_8	Moti_Q1_9	Policy_Q1_10	Policy_Q1_11	Policy_Q1_12	A_Honesty_Q2_1	A_Honesty_Q2_2	A_Honesty_Q2_3	A_Autonomy_Q2_4	A_Autonomy_Q2_5	A_Autonomy_Q2_6	A_Support_Q2_7	A_Support_Q2_8	A_Support_Q2_9	Comnu_Q2_10	Comnu_Q2_11	Comnu_Q2_12	Resource_Q2_13	Resource_Q2_14	Academic_Q2_15	Academic_Q2_16	Academic_Q2_17
613xxxx008	8	5	8	5	5	9	6	4	4	6	8	9	4	3	8	9	9	9	7	5	2	9	9	9	9	7	7	4	5
613xxxx010	7	5	6	2	4	6	4	8	5	7	5	5	2	2	4	7	3	4	6	3	9	8	7	4	5	5	4	5	3
613xxxx011	9	4	6	4	1	8	1	1	1	7	7	7	5	5	7	9	6	6	3	5	4	9	7	5	5	5	5	4	5
613xxxx013	9	8	8	9	7	8	9	7	7	8	7	9	7	6	8	7	8	9	8	8	8	8	9	7	9	9	9	9	9
613xxxx015	7	5	7	6	7	6	6	7	6	6	6	6	7	6	6	6	6	6	6	8	6	6	6	7	6	6	6	6	6
613xxxx021	6	5	9	6	9	9	9	9	9	6	6	8	5	3	5	8	7	8	9	7	8	9	9	8	9	9	8	8	6
613xxxx025	7	4	8	5	4	8	4	4	7	5	5	8	7	5	7	7	7	6	5	6	4	9	9	6	7	4	8	7	7
613xxxx027	7	1	5	7	2	9	1	1	1	4	3	3	1	1	4	9	6	6	1	1	1	9	1	4	1	1	1	1	1
613xxxx031	3	1	3	3	3	5	2	1	3	2	2	3	3	2	2	5	5	5	2	2	3	5	3	1	2	3	2	2	2
613xxxx032	2	2	7	3	2	9	2	2	3	4	1	3	3	1	5	3	3	4	5	2	2	9	6	4	3	4	3	3	2
623xxxx001	7	7	7	8	6	9	7	6	7	9	7	6	7	3	8	8	7	4	3	6	3	5	3	5	3	5	5	5	5
623xxxx004	7	7	7	7	7	8	7	7	7	7	7	7	7	6	7	7	7	7	7	7	7	7	7	6	7	7	7	7	7
623xxxx005	7	7	7	7	5	9	4	5	6	8	6	5	9	8	9	7	6	6	6	7	5	9	9	8	8	6	5	6	6
623xxxx007	7	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5
623xxxx008	8	8	8	7	7	8	7	7	9	8	7	7	9	7	9	8	8	9	8	8	8	9	9	6	8	8	8	8	8
623xxxx017	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	6	9	9	9	9	9	9	9

STD Code	Men_Q3_1	Men_Q1_2.1	Men_Q3_3	Tea_Q3_4	Tea_Q3_5	Tea_Q3_6	Moti_Q3_7	Moti_Q3_8	Moti_Q3_9	Policy_Q3_10	Policy_Q3_11	Policy_3_12	A_Honesty_Q4_1	A_Honesty_Q4_2	A_Honesty_Q4_3	A_Autonomy_Q4_4	A_Autonomy_Q4_5	A_Autonomy_Q4_6	A_Support_Q4_7	A_Support_Q4_8	A_Support_Q4_9	Comnu_Q4_10	Comnu_Q4_11	Comnu_Q4_12	Resource_Q4_13	Resource_Q4_14	Academic_Q4_15	Academic_Q4_16	Academic_Q4_17	Achieve_Q5_1	Achieve_Q5_2	Achieve_Q5_3	Expert [1]
613xxxx008	8	8	7	8	8	8	7	8	8	7	8	8	8	8	7	7	7	8	7	8	7	8	7	8	7	7	8	7	7	4	6	5	Motivator
613xxxx010	5	5	5	5	5	5	5	6	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	6	5	5	5	5	5	5	5	5	Motivator
613xxxx011	5	5	8	7	6	6	7	9	6	7	7	7	6	6	4	7	6	5	7	4	5	6	8	9	7	6	6	6	7	7	4	7	Motivator
613xxxx013	9	9	8	8	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	6	8	9	Mentor
613xxxx015	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	Motivator
613xxxx021	9	9	9	8	7	7	7	7	8	8	8	8	5	5	6	5	5	7	7	7	7	7	8	8	7	7	7	7	7	5	4	7	Mentor
613xxxx025	8	8	8	9	9	9	9	8	9	9	9	9	7	6	7	8	8	8	7	6	6	9	8	7	9	7	9	9	7	7	7	7	Motivator
613xxxx027	8	8	8	8	8	8	8	8	8	8	8	8	8	8	9	9	9	8	9	9	9	9	9	9	9	9	9	9	9	9	9	8	Teacher/Educator
613xxxx031	9	9	9	9	9	9	9	9	9	9	9	9	9	8	9	9	9	9	9	9	9	9	8	9	9	9	9	9	9	9	9	9	Teacher/Educator
613xxxx032	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	7	9	9	Teacher/Educator
623xxxx001	9	9	6	8	9	9	9	9	9	9	9	9	5	4	8	9	9	9	9	7	8	5	1	9	9	9	9	9	9	7	9	7	Motivator
623xxxx004	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	Motivator
623xxxx005	6	9	9	6	6	9	9	9	9	9	9	9	9	6	7	8	8	8	9	8	8	9	9	7	9	8	8	9	7	5	8	7	Motivator
623xxxx007	8	7	7	7	8	7	8	8	8	7	8	7	7	7	7	7	8	8	7	8	8	7	8	8	7	7	7	8	7	7	8	8	Motivator
623xxxx008	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	Mentor
623xxxx017	9	5	8	6	8	8	7	8	7	7	9	8	6	6	8	9	9	8	8	5	7	8	7	6	7	7	8	9	8	6	7	6	Mentor

Figure 3.7 Data and roles from the opinions of dental faculty

After grouping the survey data from dental faculty members, we sought additional perspectives from dental students. Three dental students provided their views on the roles of advisors as follows:

1. Mentor (Most Important)

Role Description: A mentor offers guidance and assistance in practical training and patient care.

Reasoning: Students emphasized the importance of having someone who can support them through the hands-on aspects of their education, helping them navigate challenges and develop practical skills.

2. Teacher/Educator (Second Most Important)

Role Description: An educator provides knowledge and facilitates learning.

Reasoning: Students value the role of educators in providing foundational knowledge and supporting their academic growth, recognizing the importance of structured learning and access to expertise.

3. Regulator (Third Most Important)

Role Description: A regulator ensures compliance with rules and attendance.

Reasoning: While not directly linked to professional practice, students see the need for regulatory roles to maintain discipline and ensure that academic standards are met.

4. Motivator (Least Important)

Role Description: A motivator inspires and supports students emotionally and psychologically.

Reasoning: Although motivation is important, students ranked it lower compared to the other roles. They may feel that emotional and psychological support, while beneficial, is not as critical as practical guidance and academic instruction.

These opinions provide a balanced view of the roles from both faculty and students, highlighting the priorities and expectations in dental education.

STD Code	Men_Q1_1	Men_Q1_2	Men_Q1_3	Tea_Q1_4	Tea_Q1_5	Tea_Q1_6	Moti_Q1_7	Moti_Q1_8	Moti_Q1_9	Policy_Q1_10	Policy_Q1_11	Policy_Q1_12	A_Honesty_Q2_1	A_Honesty_Q2_2	A_Honesty_Q2_3	A_Autonomy_Q2_4	A_Autonomy_Q2_5	A_Autonomy_Q2_6	A_Support_Q2_7	A_Support_Q2_8	A_Support_Q2_9	Commu_Q2_10	Commu_Q2_11	Commu_Q2_12	Resource_Q2_13	Resource_Q2_14	Academic_Q2_15	Academic_Q2_16	Academic_Q2_17	Men_Q3_1	Men_Q1_2.1	Men_Q3_3	Tea_Q3_4	Tea_Q3_5	Tea_Q3_6	Moti_Q3_7	Moti_Q3_8	Moti_Q3_9	Policy_Q3_10	Policy_Q3_11	Policy_3_12	A_Honesty_Q4_1	A_Honesty_Q4_2	A_Honesty_Q4_3	A_Autonomy_Q4_4	A_Autonomy_Q4_5	A_Autonomy_Q4_6	A_Support_Q4_7	A_Support_Q4_8	A_Support_Q4_9	Commu_Q4_10	Commu_Q4_11	Commu_Q4_12	Resource_Q4_13	Resource_Q4_14	Academic_Q4_15	Academic_Q4_16	Academic_Q4_17	Achieve_Q5_1	Achieve_Q5_2	Achieve_Q5_3	Students
613xxxx008	8	5	8	5	5	9	6	4	4	6	8	9	4	3	8	9	9	9	7	5	2	9	9	9	9	7	7	4	5	8	8	7	8	8	8	7	8	8	7	8	8	8	8	7	7	7	8	7	8	7	8	7	8	7	7	8	7	7	4	6	5	Mentor
613xxxx010	7	5	6	2	4	6	4	8	5	7	5	5	2	2	4	7	3	4	6	3	9	8	7	4	5	5	4	5	3	5	5	5	5	5	5	5	6	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	6	5	5	5	5	5	5	5	5	Teacher/Educator
613xxxx011	9	4	6	4	1	8	1	1	1	7	7	7	5	5	7	9	6	6	3	5	4	9	7	5	5	5	5	4	5	5	5	8	7	6	6	7	9	6	7	7	7	6	6	4	7	6	5	7	4	5	6	8	9	7	6	6	6	7	7	4	7	Mentor
613xxxx013	9	8	8	9	7	8	9	7	7	8	7	9	7	6	8	7	8	9	8	8	8	8	9	7	9	9	9	9	9	9	9	8	8	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	6	8	9	Teacher/Educator
613xxxx015	7	5	7	6	7	6	6	7	6	6	6	6	7	6	6	6	6	6	6	8	6	6	6	7	6	6	6	6	6	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	Mentor
613xxxx021	6	5	9	6	9	9	9	9	9	6	6	8	5	3	5	8	7	8	9	7	8	9	9	8	9	9	8	8	6	9	9	9	8	7	7	7	7	8	8	8	8	5	5	6	5	5	7	7	7	7	7	8	8	7	7	7	7	7	5	4	7	Mentor
613xxxx025	7	4	8	5	4	8	4	4	7	5	5	8	7	5	7	7	7	6	5	6	4	9	9	6	7	4	8	7	7	8	8	8	9	9	9	9	8	9	9	9	9	7	6	7	8	8	8	7	6	6	9	8	7	9	7	9	9	7	7	7	7	Mentor
613xxxx027	7	1	5	7	2	9	1	1	1	4	3	3	1	1	4	9	6	6	1	1	1	9	1	4	1	1	1	1	1	8	8	8	8	8	8	8	8	8	8	8	8	8	8	9	9	9	8	9	9	9	9	9	9	9	9	9	9	9	9	9	8	Mentor
613xxxx031	3	1	3	3	3	5	2	1	3	2	2	3	3	2	2	5	5	5	2	2	3	5	3	1	2	3	2	2	2	9	9	9	9	9	9	9	9	9	9	9	9	9	8	9	9	9	9	9	9	9	9	8	9	9	9	9	9	9	9	9	9	Teacher/Educator
613xxxx032	2	2	7	3	2	9	2	2	3	4	1	3	3	1	5	3	3	4	5	2	2	9	6	4	3	4	3	3	2	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	7	9	9	Teacher/Educator
623xxxx001	7	7	7	8	6	9	7	6	7	9	7	6	7	3	8	8	7	4	3	6	3	5	3	5	3	5	5	5	5	9	9	6	8	9	9	9	9	9	9	9	9	5	4	8	9	9	9	9	7	8	5	1	9	9	9	9	9	9	7	9	7	Mentor
623xxxx004	7	7	7	7	7	8	7	7	7	7	7	7	7	6	7	7	7	7	7	7	7	7	7	6	7	7	7	7	7	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	6	6	6	6	6	6	6	6	6	6	6	6	6	6	6	Motivator
623xxxx005	7	7	7	7	5	9	4	5	6	8	6	5	9	8	9	7	6	6	6	7	5	9	9	8	8	6	5	6	6	6	9	9	6	6	9	9	9	9	9	9	9	9	6	7	8	8	8	9	8	8	9	9	7	9	8	8	9	7	5	8	7	Motivator
623xxxx007	7	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	5	8	7	7	7	8	7	8	8	8	7	8	7	7	7	7	7	8	8	7	8	8	7	8	8	7	7	7	8	7	7	8	8	Mentor
623xxxx008	8	8	8	7	7	8	7	7	9	8	7	7	9	7	9	8	8	9	8	8	8	9	9	6	8	8	8	8	8	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	7	Mentor
623xxxx017	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	6	9	9	9	9	9	9	9	9	5	8	6	8	8	7	8	7	7	9	8	6	6	8	9	9	8	8	5	7	8	7	6	7	7	8	9	8	6	7	6	Motivator
623xxxx018	9	9	9	9	9	9	9	9	7	9	9	9	9	7	9	9	9	9	8	9	9	3	5	7	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	Teacher/Educator
623xxxx021	7	6	9	7	6	9	7	6	9	7	9	8	7	6	9	9	9	9	8	9	9	9	8	9	9	8	9	9	9	7	7	7	7	7	7	7	7	7	7	7	8	8	8	8	8	8	8	8	8	8	8	7	7	7	7	7	7	7	7	7	7	Mentor
623xxxx027	5	5	6	5	5	7	5	4	5	5	6	5	5	1	7	8	6	6	5	5	5	8	7	7	5	7	5	4	5	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	9	Teacher/Educator
623xxxx030	8	8	8	7	8	9	7	7	8	8	7	7	8	8	8	9	8	8	8	8	8	8	8	9	7	8	8	8	8	9	9	9	9	9	9	9	9	8	9	9	9	9	9	9	9	9	9	9	9	9	9	8	9	9	9	9	9	9	7	9	9	Teacher/Educator
633xxxx006	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	8	7	8	8	8	8	8	8	7	7	7	9	8	8	7	8	9	9	8	8	8	8	8	8	7	7	7	8	Mentor

Figure 3.8 Data and roles from the opinions of dental students on advisor roles

To visualize the grouping of advisor characteristics, advisor expectation characteristics, and student satisfaction with academic outcomes, we can create separate bar charts for each set of characteristics. Below are the sample bar charts:

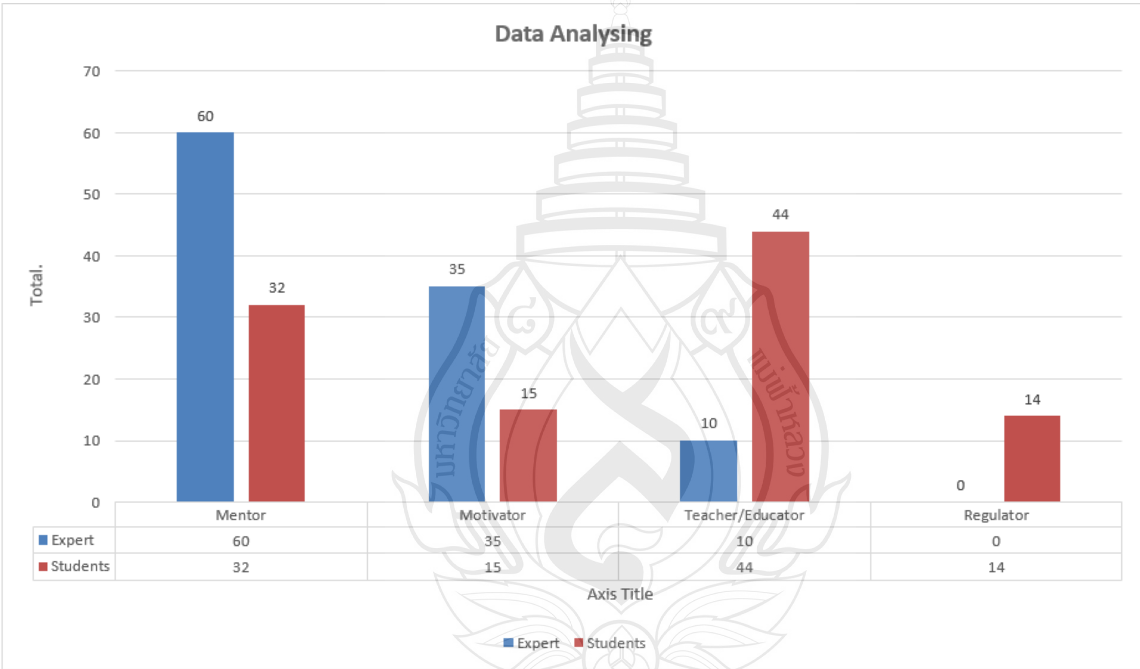

Figure 3.9 The grouping results for advisor characteristics, expectations of advisors, and satisfaction with academic outcomes indicate that most dental students are categorized into the Mentor group. Additionally, the role most valued by students is that of Teacher/Educator

3.8 Modelling and Evaluation of Model Performance

3.8.1 Modelling

There are three models used in this research: Decision tree, Neural Networks, and k-nearest neighbours. In modelling, Hyperparameter Tuning is used by applying the Grid Search technique to find Hyperparameter values from the pre-defined values and select the value that gives the highest model performance.

3.8.1.1 Decision Tree

For the Decision Tree model, the parameters (Hyperparameter Tuning) were adjusted by setting the following conditions:

1. Criterion: Gain ratio is a measure of the division of data into sub-data sets.

2. Maximal depth: is the depth of the tree. For the specified value, it is 2 to 10.

3. Confidence: is a parameter that is used to determine the level of confidence used to calculate the pruning error. For the specified value, it is 0.1.

4. Minimal gain: is a value that indicates how well the attribute that acts as the Root node can classify the data. For the specified value, it is 0.01.

5. Minimal leaf size: is the value of the number of Leaf nodes for the specified value, it is 2, 5, 10.

3.8.1.2 Neural Networks

The researchers created a prediction model using the neural network technique to predict the academic achievement of dental students by finding the probability of something that has never happened and testing the efficiency of the model using the Rapid Miner software by dividing the data using the Cross-validation command as 10 Fold Cross-validation is dividing the data into 10 parts, each part has the same amount of data. Then, some of the data will be used to test the efficiency of the model, repeating 10 rounds. Setting the Hidden Layer to be the most efficient is Hidden Layer, which means the layer between the Input and Output. The researcher adjusted the value to 1 Layer, while Hidden Layer size means the number of nodes in the Hidden Layer. The researcher adjusted the value to 10 Size and adjusted the model values for prediction with the parameters Training Cycles, Learning Rate and Momentum to be the most efficient as follows:

Training Cycles means the number of rounds in learning. The researchers adjusted the value to 100 Cycles.

Learning Rate means the amount of weight that must be changed in each step. The researchers adjusted the value to 0.3 for the appropriate training rate.

Momentum means increasing the proportion of weight in the previous round to update the current value to prevent the highest value in the area and the continuity of finding the best value. The researchers adjusted the value to 0.2 to avoid over-accelerating the training and learning.

This parameter adjustment is the adjustment that makes the model predicting the educational attainment outcome most efficient and causes overfitting.

3.8.1.3 K-nearest Neighbours

The researcher created a prediction model using the nearest neighbour technique to predict the educational achievement of dental students by finding the characteristics of the advisor, the characteristics of the advisor's expectations, and the satisfaction with the study results by finding the nearest neighbours. It is a grouping of data and measuring the distance between the data to be predicted and the neighbouring data as K. The Rapid Miner software, the K-Nearest neighbours operator, will analyse the data and then look at the value of "K" to see how much it is set and then create a prediction model. Set the value of k = 5 with a total of 105 dental students' data, 3 columns, which predict how close each item will be and which class it will be.

Based on the three models, the parameter settings for each predictive technique can be summarized as follows:

Table 3.4 Setting the parameters of each data prediction technique

Models	Parameter
Decision Tree	Criterion: Gain_ratio, used to measure the splitting of data into subsets. Maximal depth: The depth of the tree, set between 2 and 10. Confidence: A parameter used to determine the confidence level for calculating pruning errors, set at 0.1. Minimal gain: Indicates how well the attribute serving as the root node can classify the data, set at 0.01. Minimal leaf size: Specifies the number of leaf nodes, set at 2, 5, and 10.
Neural Networks	Training cycles: Number of learning cycles, set at 100. Learning rate: The rate at which weights are updated during training, set at 0.3. Momentum: Helps to prevent overshooting during training by incorporating a portion of the previous weight updates, set at 0.2. Hidden Layer: Number of hidden layers, set at 1. Hidden Layer size: Number of nodes in the hidden layer, set at 10. Cross-validation is performed using 10-Fold Cross Validation to test the model's effectiveness.
k-nearest neighbors	k: 5 weighted vote: true measure types: MixedMeasures mixed measure: MixedEuclideanDistance

By setting these parameters, each model is fine-tuned to enhance its predictive capability while reducing the likelihood of overfitting.

3.9 Model Performance Evaluation

To evaluate the performance of the predictive models, several key metrics and methods can be employed. Here are the common approaches and metrics used for evaluating the performance of Decision Trees, Neural Networks, and K- Nearest Neighbors (KNN).

3.9.1 Decision Tree

In this research, we used a technique to evaluate model performance using the Confusion Matrix table to solve Accuracy, Precision, Recall and F1 Score as shown in the figure.

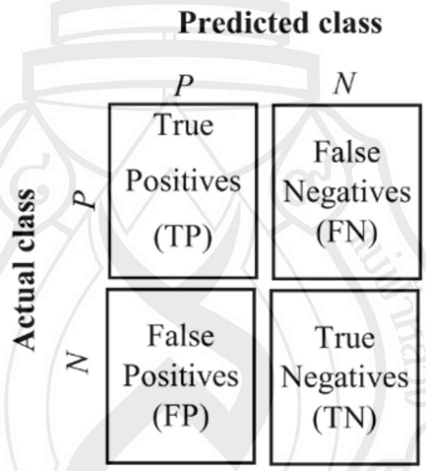

Figure 3.10 Provides a summary of prediction results on a classification problem

True Positive (TP) is a model that predicts that it is positive and that it is actually positive.

True Negative (TN) is the model predicts that it is negative and the reality is negative.

False Positive (FP) is when the model predicts it to be positive but is actually negative.

False Negative (FN) is the simulation predicts it to be negative but in reality it is positive.

Accuracy or precision: is the correct classification ratio. to the total amount of data used for classification

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

Precision: It is the ratio of correctly classified positive groups to the total number of classified positive groups.

$$Precision = \frac{True\ Positive\ (TP)}{True\ Positive(TP) + False\ Positive(FP)}$$

Recall (Sensitivity): The ratio of correctly predicted positive observations to all observations in the actual class.

$$Recall = \frac{TP}{TP + FN}$$

F1 Score: The weighted average of Precision and Recall.

$$F1\ Score = \frac{2\ x\ precision\ x\ recall}{precision + recall}$$

3.9.2 Neural Networks

Confusion Matrix: Same as Decision Tree.

Accuracy: Same as Decision Tree.

Precision, Recall, and F1 Score: Same as Decision Tree.

ROC Curve and AUC: Same as Decision Tree.

Cross-Entropy Loss: Measures the performance of a classification model whose output is a probability value between 0 and

Training and Validation Loss Curves: Plots the loss values during training and validation phases to monitor overfitting.

3.9.3 K-Nearest Neighbors (KNN)

Confusion Matrix: Same as Decision Tree.

Accuracy: Same as Decision Tree.

Precision, Recall, and F1 Score: Same as Decision Tree.

ROC Curve and AUC: Same as Decision Tree.

Mean Absolute Error (MAE): The average of the absolute errors between predicted values and actual values.

Root Mean Squared Error (RMSE): The square root of the average of squared differences between prediction and actual observation.

3.10 Evaluation Process

3.10.1 Data Splitting: Split the dataset into training and testing sets, often with a ratio of 70:30 or 80:20.

3.10.2 Cross-Validation: Use K-Fold Cross-Validation (e.g., 10-Fold) to ensure the model's performance is consistent across different subsets of data.

3.10.3 Model Training: Train each model using the training dataset and tune hyperparameters as needed.

3.10.4 Model Testing: Evaluate the model using the testing dataset and compute the performance metrics.

3.10.5 Comparative Analysis: Compare the performance metrics of all three models to determine the best performing model.

CHAPTER 4

RESULTS

4.1 Results

This research employs data mining techniques to create predictive models for the characteristics of advisors, the expectations of students regarding these characteristics, and student satisfaction with their academic outcomes. The objective is to identify attributes that contribute to effective advising and to compare the performance of these models based on the proportion of data for each role and significant characteristic. The techniques used include Decision Trees, Neural Networks, and K-Nearest Neighbors (KNN).

Table 4.1 The number of students who participated in the survey

Gender	Total	Percentage
Male	20	19.05
Female	85	80.95
	105	**100.00**

The participants were divided by gender as follows:

1. Male students: 20, accounting for 19.05%
2. Female students: 85, accounting for 80.95%

Table 4.2 The sample size for data collection, categorized by academic year

Grade level	Total	Percentage
First-year students	28	26.67
Second-year students	31	29.52
Third-year students	16	15.24
Fourth-year students	10	9.52
Fifth-year students	10	9.52
Sixth-year students	10	9.52
	105	**100.00**

Additionally, the participants were divided by academic year as follows:

1. First-year students: 28 (26.67%)
2. Second-year students: 31 (29.52%)
3. Third-year students: 16 (15.24%)
4. Fourth-year students: 10 (9.52%)
5. Fifth-year students: 10 (9.52%)
6. Sixth-year students: 10 (9.52%)

4.2 Results and Discussion

The results of the comparison of dental students' opinions on the characteristics of their advisors, the characteristics of their advisors' expectations, and their satisfaction with the results of their studies were analysed to achieve the results of the study using three techniques: Decision tree, Neural Networks, and k- nearest neighbours. The results are presented in a table of the Accuracy, Precision, Recall, and F1 Score values of each model.

Here's a comparison of the prediction results from the perspectives of both an expert and a dental student:

Table 4.3 Prediction results from the perspective of an expert

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	86.00	81.08	81.71	83.33
Neural Networks	88.73	75.56	97.14	85.00
k-nearest neighbours	78.18	80.00	57.14	66.67

Table 4.4 Prediction results from the perspective of a dental student

Algorithm	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Decision Tree	53.00	48.28	43.75	81.01
Neural Networks	79.36	88.57	96.88	85.53
k-nearest neighbours	66.64	85.71	56.25	67.92

Summary of Observations

Table 4.5 Accuracy comparison

Model	Expert Perspective	Student Perspective
Decision Tree	86.00%	53.00%
Neural Networks	88.73%	79.36%
k-nearest neighbours	78.18%	66.64%

Expert: Neural Networks has the highest accuracy (88.73%), followed by Decision Tree (86.00%) and k-nearest Neighbors (78.18%).

Dental Student: Neural Networks still shows the highest accuracy (79.36%), but Decision Tree accuracy drops significantly (53.00%), with k-nearest Neighbors performing better (66.64%).

Table 4.6 Precision comparison

Model	Expert Perspective	Student Perspective
Decision Tree	81.08%	48.28%
Neural Networks	75.56%	88.57%
k-nearest neighbours	80.00%	85.71%

Expert: k-nearest Neighbors shows the highest precision (80.00%), followed by Decision Tree (81.08%) and Neural Networks (75.56%).

Dental Student: Neural Networks has the highest precision (88.57%), while k-nearest Neighbors shows better precision (85.71%) compared to Decision Tree (48.28%).

Table 4.7 Recall comparison

Model	Expert Perspective	Student Perspective
Decision Tree	81.71%	43.75%
Neural Networks	97.14%	96.88%
k-nearest neighbours	57.14%	56.25%

Expert: Neural Networks has the highest recall (97.14%), followed by Decision Tree (81.71%) and k-nearest Neighbors (57.14%).

Dental Student: Neural Networks maintains the highest recall (96.88%), with k-nearest Neighbors and Decision Tree at 56.25% and 43.75%, respectively.

Table 4.8 F1-Score comparison

Model	Expert Perspective	Student Perspective
Decision Tree	83.33%	81.01%
Neural Networks	85.00%	85.53%
k-nearest neighbours	66.67%	67.92%

Expert: Neural Networks has the highest F1-Score (85.00%), followed by Decision Tree (83.33%) and k-nearest Neighbors (66.67%).

Dental Student: Neural Networks still shows the highest F1-Score (85.53%), with Decision Tree performing better in F1-Score (81.01%) than k-nearest Neighbors (67.92%).

This comparison highlights different perceptions of model performance between experts and dental students, possibly due to variations in evaluation criteria or understanding of metrics.

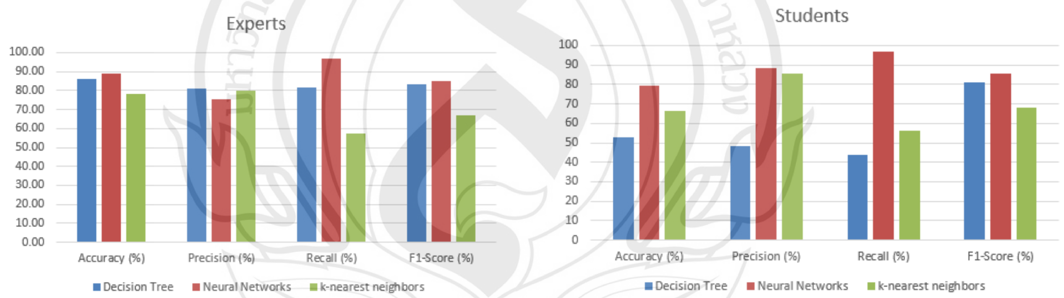

Figure 4.1 The accuracy, recall, and balance values of data classification comparing graphs

The results of the comparison of model efficiency from this research can be used as information for creating a model for grouping the characteristics of advisors according to student expectations for students to achieve academic results, as shown in Figure 14.

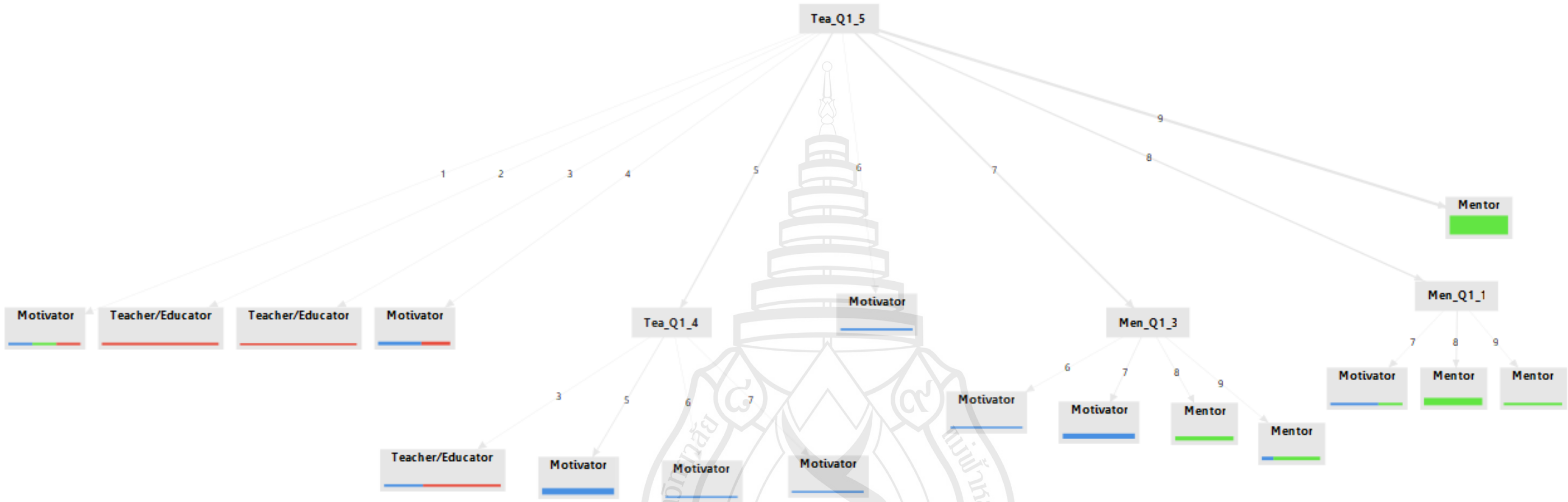

Figure 4.2 The decision tree shows the grouping of advisor characteristics according to student expectations

The data of the prediction of the grouping of advisor characteristics according to student expectations, it can be used to create a rule to predict the academic achievement of students. It is necessary to consider which advisor characteristics to consider when grouping students so that the average academic achievement of students will be at a good level, for example, students get a group of advisors who are enthusiastic about seeking knowledge, students get a group of advisors who provide information, and students get a group of advisors who have academic knowledge that focuses on teaching. When students have answered the questionnaire to create their own identity, they will be grouped with advisors, allowing them to achieve academic achievement. The prediction results can be used as a guideline to help in making decisions to group students in accordance with the context of the advisors.

4.3 Conclusion

The research on the creation of a model to predict the achievement in 3 aspects: characteristics of the advisor, characteristics of the advisor’s expectations, and satisfaction with the education results, using the results of the questionnaire from 105 dental students. From the comparison of the classification from 3 models: Decision trees, Neural network, k- nearest neighbours and designing a cross- validation experiment, the percentage of accuracy in classifying the characteristics of the advisor, characteristics of the advisor’s expectations, and satisfaction with the study results found that the use of predictive models using all 3 techniques.

This study aimed to evaluate the effectiveness of different machine learning models in predicting advisor attributes that align with dental students’ expectations and satisfaction. The models considered were Decision Tree, Neural Networks, and k-Nearest Neighbors (k-NN). Performance metrics such as Accuracy, Precision, Recall, and F1 - Score were used to assess each model from both expert and student perspectives.

The comparison of model prediction results from the perspectives of both an expert and a dental student reveals several key insights:

4.3.1 From Expert Perspective

4.3.1.1 Decision Tree Model: Shows a balanced performance with an accuracy of 86.00%, precision of 81.08%, recall of 81.71%, and an F1-Score of 83.33%.

4.3.1.2 Neural Networks Model: Exhibits the highest accuracy of 88.73% and an F1-Score of 85.00%, although it has lower precision (75.56%) compared to the Decision Tree.

4.3.1.3 k-nearest neighbors (k-NN) Model: Demonstrates the lowest performance with an accuracy of 78.18%, precision of 80.00%, recall of 57.14%, and an F1-Score of 66.67%.

4.3.2 From Dental Student Perspective

4.3.2.1 Decision Tree Model: Shows an accuracy of 53.00%, precision of 48.28%, recall of 43.75%, and an F1-Score of 81.01%.

4.3.2.2 Neural Networks Model: Exhibits strong performance with an accuracy of 79.36%, precision of 88.57%, recall of 96.88%, and an F1-Score of 85.53%.

4.3.2.3 k-nearest neighbors (k-NN) Model: Demonstrates an accuracy of 66.64%, precision of 85.71%, recall of 56.25%, and an F1-Score of 67.92%.

The results indicate that the Neural Networks model is highly effective from both expert and student perspectives, with the highest accuracy and strong precision and recall values. The Decision Tree model offers a balanced and reliable performance from the expert perspective but shows lower performance from the student perspective. The k-nearest neighbors model generally shows weaker performance across both perspectives. These findings highlight the potential of machine learning models in predicting advisor attributes, suggesting that Neural Networks and Decision Tree models can be particularly effective tools for educational outcome predictions.

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APPENDIX

APPENDIX

QUESTIONNAIRE

แบบสอบถามการจับคู่อาจารย์ที่ปรึกษา สำนักวิชาทันตแพทยศาสตร์ มหาวิทยาลัยแม่ฟ้าหลวง

<u>คำชี้แจง</u>

1. แบบสอบถามมีวัตถุประสงค์เพื่อศึกษาวิจัยแนวทางในการวิเคราะห์ เพื่อจับคู่อาจารย์ที่ปรึกษากับนักศึกษาทันตแพทยศาสตร์ เพื่อทำนายผลต่อความสำเร็จของนักศึกษา ขอความอนุเคราะห์ตอบตามความเป็นจริง ซึ่งการตอบแบบสอบถามครั้งนี้จะไม่มีการเผยแพร่ใดๆ ต่อผู้ที่เกี่ยวข้องกับตัวนักศึกษา ทั้งนี้ข้อมูลที่ได้จะเป็นประโยชน์อย่างยิ่งต่อการพัฒนาแนวทางการจัดกลุ่มอาจารย์ที่ปรึกษาให้เหมาะสมกับนักศึกษา เพื่อให้เป็นประโยชน์ต่อการให้คำแนะนำในการศึกษาถึงการสำเร็จการศึกษา โดยผลที่ได้จากการบันทึกจะมีการเก็บสถิติเพื่อการวิจัยเท่านั้น
2. แบบสอบถามมีทั้งหมด 2 ตอน ประกอบด้วย

   ตอนที่ 1 ข้อมูลทั่วไปของผู้ตอบแบบสอบถาม
   ตอนที่ 2 แนวทางการค้นหา/แบ่งกลุ่ม
3. กรุณาทำเครื่องหมาย ✓ ในข้อที่ตรงกับความเป็นจริงและในช่องที่ตรงกับความคิดเห็นของนักศึกษามากที่สุด

ตอนที่ 1 ข้อมูลทั่วไปของผู้ตอบแบบสอบถาม

1. **เพศ** ☐ ชาย ☐ หญิง
2. **นักศึกษาชั้นปีที่** ☐ ชั้นปีที่ 1 ☐ ชั้นปีที่ 2 ☐ ชั้นปีที่ 3 ☐ ชั้นปีที่ 4 ☐ ชั้นปีที่ 5 ☐ ชั้นปีที่ ☐ อื่นๆ
3. **ระดับผลการเฉลี่ยสะสม** (GPA) ☐ น้อยกว่า 2.00 ☐ 2.00 - 2.50 ☐ 2.51 - 3.00 ☐ 3.01 - 3.50 ☐ 3.51 - 4.00

ตอนที่ 2 แนวทางการค้นหา/แบ่งกลุ่ม

<u>คำชี้แจง</u> กรุณาทำเครื่องหมาย ✓ ในข้อที่ตรงกับความเป็นจริงและในช่องที่ตรงกับความคิดเห็นของนักศึกษามากที่สุด

เกณฑ์การให้คะแนนระดับ ความคิดเห็น

ระดับคะแนนหมายเลข 1 หมายถึง ท่านเห็นด้วยน้อยที่สุด เรียงลำดับถึง 9 หมายถึง ให้ท่านเห็นด้วยมากที่สุด

1. การประเมินลักษณะของอาจารย์ที่ปรึกษา

ข้อสอบถามความจริง/ความคิดเห็น	ระดับความคิดเห็น								
	1	2	3	4	5	6	7	8	9
1. บทบาทของการเป็นที่ปรึกษา (Role)									
1.1 อาจารย์ที่ปรึกษาของท่านเป็นพี่เลี้ยงที่ดีในการให้คำแนะนำในการวางตัวและการสื่อสารทางสังคมกับเพื่อนและอาจารย์เพื่อให้บรรลุผลในการเรียน									
1.2 อาจารย์ที่ปรึกษาของท่านเป็นพี่เลี้ยงที่สามารถให้คำปรึกษาเกี่ยวกับปัญหาส่วนตัวนักศึกษาได้ทุกเรื่อง									
1.3 อาจารย์ที่ปรึกษาของท่านเป็นพี่เลี้ยงที่เต็มใจที่จะแบ่งปันหรือมีนิสัยชอบดูแลให้คำแนะนำนักศึกษาในการวางตัวและการสื่อสาร									
1.4 อาจารย์ที่ปรึกษาของท่านมีการติดตามผลการเรียนของนักศึกษาและให้คำแนะนำในกรณีที่มีปัญหาในการเรียนวิชาใดวิชาหนึ่ง									
1.5 อาจารย์ที่ปรึกษาของท่านมีการให้คำปรึกษาและช่วยเหลือนักศึกษาเกี่ยวกับเทคนิคการเรียน การจดบันทึกการอ่าน การหาข้อมูลการเรียนและการทำวิจัย การเขียนตอบข้อสอบ และการจัดทำรายงาน ฯลฯ									
1.6 อาจารย์ที่ปรึกษาของท่านมีความรู้และความเชี่ยวชาญในทักษะการปฏิบัติงาน ที่สอน เป็นอย่างดีสามารถให้คำแนะนำได้อย่างถูกต้องและมีประสิทธิภาพ									
1.7 อาจารย์ที่ปรึกษาของท่านมีการติดตามแจ้งข้อมูล ข่าวสาร ความเคลื่อนไหวต่างๆ ในการเรียนให้นักศึกษาทราบทันต่อเหตุการณ์									
1.8 อาจารย์ที่ปรึกษาของท่านมีให้คำแนะนำเกี่ยวกับแหล่งทุนการศึกษาและโอกาสในการพัฒนาตนเองเพื่อให้ประสบผลสำเร็จในอาชีพที่ตนเองเรียนในอนาคต									

1. การประเมินลักษณะของอาจารย์ที่ปรึกษา (ต่อ)

ข้อสอบถามความจริง/ความคิดเห็น	ระดับความคิดเห็น								
	1	2	3	4	5	6	7	8	9
1.9 อาจารย์ที่ปรึกษาของท่านมีการสร้างแรงจูงใจ กำลังใจและกระตุ้นท่านให้มีความกระตือรือร้นในการเรียนรู้และพัฒนาตนเองอยู่เสมอ 1.10 อาจารย์ที่ปรึกษาของท่านมีความรู้และมีความเข้าใจเกี่ยวกับข้อบังคับ ประกาศและกฎระเบียบของมหาวิทยาลัย ตลอดจนสามารถนำมาใช้อ้างอิง ระหว่างการให้คำปรึกษาได้ในทันที 1.11 อาจารย์ที่ปรึกษาของท่านสามารถให้คำปรึกษาเกี่ยวกับปัญหาการลงทะเบียนเรียน และปัญหาอื่นๆ ที่เกี่ยวข้องกับการเรียน ดังเช่น การยื่นขอถอดถอนหรือเพิ่มรายวิชา 1.12 อาจารย์ที่ปรึกษาของท่านสามารถให้คำปรึกษาเกี่ยวกับวิธีจัดการปัญหาและความเสี่ยงที่จะเกิดขึ้นในการประกอบอาชีพในอนาคตเมื่อสำเร็จการศึกษา									
2. ลักษณะปรากฏความสัมพันธ์ของที่ปรึกษาและนักศึกษา (Attribute)									
2.1 ความซื่อสัตย์ (Honesty) 2.1.1 ท่านมีความไว้ใจในการที่จะขอคำปรึกษาจากอาจารย์ที่ปรึกษาของท่านในทุกเรื่อง 2.1.2 เมื่อท่านมีปัญหาในการเรียน คนแรกที่ท่านนึกถึงคืออาจารย์ที่ปรึกษาเพื่อที่จะขอคำปรึกษาในเรื่องที่มีปัญหา 2.1.3 ท่านมั่นใจว่าอาจารย์ที่ปรึกษาของท่านจะสามารถให้คำปรึกษาที่ดีและให้การช่วยเหลือได้อย่างมีประสิทธิภาพในปัญหาที่ท่านเจอ									
2.2 ความอิสระ (Autonomy) 2.2.1 อาจารย์ที่ปรึกษาของท่านได้ให้อิสระแก่ท่านในการตัดสินใจเกี่ยวกับการเรียนรู้และวางแผนที่จะพัฒนาตนเองเพื่อให้บรรลุผลในการเรียน 2.2.2 อาจารย์ที่ปรึกษาของท่านมีการสร้างความมั่นใจให้กับตัวท่านในการแสดงออกทางความคิดและในการตัดสินใจ เพื่อให้บรรลุเป้าหมายการเรียน 2.2.3 อาจารย์ที่ปรึกษาของท่านมีความเชื่อมั่นในตัวท่าน ว่าจะสามารถตัดสินใจในการทำงานได้อย่างถูกต้อง และสนับสนุนไม่ว่าท่านจะตัดสินใจอย่างไร									

1. การประเมินลักษณะของอาจารย์ที่ปรึกษา (ต่อ)

ข้อสอบถามความจริง/ความคิดเห็น	ระดับความคิดเห็น								
	1	2	3	4	5	6	7	8	9
2.3 การท้าทาย/การสนับสนุน (Challenge and support) 2.3.1 อาจารย์ที่ปรึกษาของท่านมักเล่าประสบการณ์ ความรู้และความสามารถ แนวทางแก้ไขที่เกี่ยวข้องกับการเรียน การสอนและการทำงาน เพื่อชี้แนะแนวทางการเรียนให้กับท่าน 2.3.2 อาจารย์ที่ปรึกษาของท่านมักท้าทายท่านด้วย การใช้คำพูดหรือการให้โอกาสในการมอบหมายงานที่เป็นความรับผิดชอบใหม่ๆ ให้ท่านได้ปฏิบัติ 2.3.3 อาจารย์ที่ปรึกษาของท่านสนับสนุนและส่งเสริมให้ท่านเข้าร่วมอบรมประชุม และสัมมนาวิชาการ/โครงการทางวิชาการต่างๆ									
3. Communications 3.1 ท่านสามารถติดต่ออาจารย์ที่ปรึกษาของท่านเพื่อขอคำปรึกษาได้โดยตรงผ่านช่องทาง social media ดังเช่น line หรือ face book นอกเหนือจากการติดต่อเข้าพบด้วยตนเองที่สำนักวิชา 3.2 ท่านสามารถติดต่อกับอาจารย์ที่ปรึกษาของท่านได้นอกเหนือจากเวลาทำงานปกติ (จันทร์-ศุกร์ เวลา 8.00-17.00น) 3.3 อาจารย์ที่ปรึกษาของท่านมีเวลาที่จะให้คำปรึกษาได้ตลอดเวลา									
4. Resources 4.1 อาจารย์ที่ปรึกษาของท่านมีการแบ่งปันประสบการณ์ที่ผ่านมา หรือมีการแนะนำให้รู้จักผู้ที่มีองค์ความรู้หรือผู้เชี่ยวชาญเฉพาะทางในการเรียนแต่ละสาขาวิชา 4.2 อาจารย์ที่ปรึกษาท่านมีการแนะนำแหล่งข้อมูลที่สนับสนุนการเรียนรู้และการทำงานวิจัย หรือมีการแบ่งปันเอกสารการเรียนและเอกสารอ้างอิงอื่นๆ ที่ใช้ในการเรียน									
5. Academic interests 5.1 อาจารย์ที่ปรึกษาของท่านมีการรับรู้และรับฟังในความสนใจ ในสาขาเฉพาะทางที่ท่านต้องการศึกษาในอนาคต 5.2 อาจารย์ที่ปรึกษาของท่านได้แนะนำโอกาสในการเรียนรู้และส่งเสริมความสนใจในหัวข้อที่เกี่ยวข้องกับการเรียนต่อเฉพาะทางในอนาคตของท่าน 5.3 การให้คำปรึกษา ของอาจารย์ที่ปรึกษาของท่านมีผลต่อความสนใจในการเรียนของท่านมากขึ้น									

2. การประเมินความคาดหวังคุณลักษณะอาจารย์ที่ปรึกษาของนักศึกษา

ข้อสอบถามความจริง/ความคิดเห็น	ระดับความคิดเห็น								
	1	2	3	4	5	6	7	8	9
1. บทบาทของการเป็นที่ปรึกษา (Role)									
1.1 ท่านต้องการอาจารย์ที่ปรึกษาที่สามารถให้คำแนะนำในการวางตัวและการสื่อสารทางสังคมกับเพื่อนและอาจารย์ผู้สอนเพื่อให้บรรลุผลในการเรียน									
1.2 ท่านต้องการอาจารย์ที่ปรึกษาที่สามารถให้คำปรึกษาเกี่ยวกับปัญหาส่วนตัวของนักศึกษาได้ทุกเรื่อง									
1.3 ท่านต้องการอาจารย์ที่ปรึกษา ที่เต็มใจที่จะแบ่งปันหรือมีนิสัยชอบดูแลให้คำแนะนำนักศึกษา									
1.4 ท่านต้องการอาจารย์ที่ปรึกษา ที่มีการติดตามผลการเรียนของนักศึกษาและให้คำแนะนำในกรณีมีปัญหาการเรียนวิชาใดวิชาหนึ่ง									
1.5 ท่านต้องการอาจารย์ที่ปรึกษา ที่มีให้การให้คำปรึกษาและช่วยเหลือนักศึกษาเกี่ยวกับเทคนิคการเรียน การจดบันทึก การอ่าน การหาข้อมูลการเรียนและการทำวิจัย การเขียนตอบข้อสอบ และการจัดทำรายงาน ฯลฯ									
1.6 ท่านต้องการอาจารย์ที่ปรึกษาที่มีความรู้และความเชี่ยวชาญในทักษะการปฏิบัติงาน งานที่สอนเป็นอย่างดี สามารถให้คำแนะนำได้อย่างถูกต้องและมีประสิทธิภาพ									
1.7 ท่านคิดว่าอาจารย์ที่ปรึกษาที่ดี ควรจะต้องมีการติดตามแจ้งข้อมูล ข่าวสารความเคลื่อนไหวต่างๆ ในการเรียนให้นักศึกษาทราบอย่างสม่ำเสมอ									
1.8 ท่านคิดว่าอาจารย์ที่ปรึกษาที่ดี ควรมีการให้คำแนะนำเกี่ยวกับแหล่งทุนการศึกษาและโอกาสในการพัฒนาตนเองเพื่อให้ประสบผลสำเร็จในอาชีพที่ตนเองเรียนในอนาคต									
1.9 ท่านคิดว่าอาจารย์ที่ปรึกษาที่ดี ต้องมีการสร้างแรงจูงใจกำลังใจและกระตุ้นท่านให้มีความกระตือรือร้นในการเรียนรู้และพัฒนาตนเองอยู่เสมอ									
1.10 ท่านคิดว่าอาจารย์ที่ปรึกษาที่ดี ต้องมีความรู้และเข้าใจเกี่ยวกับข้อบังคับ ประกาศและกฎระเบียบของมหาวิทยาลัย ตลอดจนสามารถนำมาใช้อ้างอิง ระหว่างการให้คำปรึกษาได้ในทันที									
1.11 ท่านต้องการอาจารย์ที่ปรึกษา ที่สามารถให้คำปรึกษาเกี่ยวกับ ปัญหาการลงทะเบียนเรียน และปัญหาอื่นๆที่เกี่ยวข้องกับการเรียนดังเช่น การยื่นขอถอดถอนหรือเพิ่มรายวิชา									

2. การประเมินความคาดหวังคุณลักษณะอาจารย์ที่ปรึกษาของนักศึกษา (ต่อ)

ข้อสอบถามความจริง/ความคิดเห็น	ระดับความคิดเห็น								
	1	2	3	4	5	6	7	8	9
1.12 ท่านคิดว่าอาจารย์ที่ปรึกษาที่ดี ต้องสามารถให้คำปรึกษาเกี่ยวกับวิธีจัดการปัญหาและความเสี่ยงที่จะเกิดขึ้นในการประกอบอาชีพทางทันตแพทย์ในอนาคตได้									
2. ลักษณะปรากฏความสัมพันธ์ของที่ปรึกษาและนักศึกษา (Attribute)									
2.1 ความซื่อสัตย์ (Honesty) 2.1.1 ท่านคิดว่าอาจารย์ปรึกษาที่สามารถปรึกษาปัญหาได้ในทุกเรื่องทั้งในเรื่องการเรียนและเรื่องส่วนตัวจะทำให้ท่านบรรลุผลสำเร็จในการเรียน 2.1.2 เมื่อท่านมีปัญหาในการเรียน อาจารย์ที่ปรึกษาจะเป็นคนแรกที่ท่านนึกถึงเพื่อขอคำปรึกษาและแก้ไขปัญหาดังกล่าว 2.1.3 ท่านมั่นใจว่าอาจารย์ที่ปรึกษาของท่านจะสามารถให้คำปรึกษาที่ดีและให้การช่วยเหลือได้อย่างมีประสิทธิภาพ									
2.2 ความอิสระ (Autonomy) 2.2.1 ท่านคิดว่าอาจารย์ที่ปรึกษาที่ดี ควรให้อิสระแก่ท่านในการตัดสินใจเกี่ยวกับการเรียนรู้และวางแผนที่จะพัฒนาตนเองเพื่อให้บรรลุผลในการเรียน 2.2.2 ท่านคิดว่าอาจารย์ที่ปรึกษาที่ดี ควรมีการสร้างความมั่นใจให้กับท่านในการแสดงออกทางความคิดและในการตัดสินใจ เพื่อให้บรรลุเป้าหมายในการเรียน 2.2.3 ท่านคิดว่าอาจารย์ที่ปรึกษาที่ดี ต้องมีความเชื่อมั่นในตัวท่านว่าจะสามารถตัดสินใจในการทำงานได้อย่างถูกต้องและสนับสนุนไม่ว่าท่านจะตัดสินใจอย่างไร									
2.3 การท้าทาย/การสนับสนุน (Challenge and support) 2.3.1 ท่านคิดว่าการได้เรียนรู้และรับฟังประสบการณ์จากอาจารย์ที่ปรึกษาทางด้านการเรียนและการสอน จะทำให้ท่านสามารถบรรลุผลทางการเรียนได้ 2.3.2 ท่านคิดว่าการท้าทายด้วยการใช้คำพูดหรือการให้โอกาสในการมอบหมายงานที่เป็นความรับผิดชอบใหม่ๆ ทำให้ท่านบรรลุสำเร็จการศึกษาได้ 2.3.3 ท่านต้องการ การสนับสนุนและส่งเสริมกิจกรรมที่เกี่ยวข้องกับการเรียน ดังเช่น การเข้าอบรมประชุม และสัมมนาวิชาการ/โครงการทางวิชาการต่างๆ จากอาจารย์ที่ปรึกษา									

2. การประเมินความคาดหวังคุณลักษณะอาจารย์ที่ปรึกษาของนักศึกษา (ต่อ)

ข้อสอบถามความจริง/ความคิดเห็น	ระดับความคิดเห็น								
	1	2	3	4	5	6	7	8	9
3. Communications 3.1 ท่านคิดว่าอาจารย์ที่ปรึกษา ควรต้องมีช่องทางการขอรับคำปรึกษาได้หลากหลายช่องทางดังเช่น line หรือ face book นอกเหนือจากการติดต่อเข้าพบด้วยตนเองที่สำนักวิชา 3.2 ท่านเห็นด้วยว่าอาจารย์ที่ปรึกษา ควรจะต้องสามารถติดต่อได้นอกเหนือจากช่วงเวลาทำงานปกติ (จันทร์-ศุกร์ เวลา 8.00-17.00น) 3.3 ท่านคิดว่าการให้คำปรึกษาของอาจารย์ที่ปรึกษาในลักษณะแบบตัวต่อตัวจะมีประสิทธิภาพ มากกว่าการให้คำแนะนำผ่านทางโทรศัพท์หรือ สื่อ social media									
4. Resources 4.1 ท่านคาดหวังว่าประสบการณ์และความรู้จากอาจารย์ที่ปรึกษาที่ผ่านมาจะช่วยให้ท่านบรรลุผลสำเร็จทางการศึกษาได้ 4.2 ท่านมีความต้องการคำแนะนำที่เกี่ยวข้องกับแหล่งข้อมูลที่สนับสนุนการเรียนรู้และการทำงานวิจัย หรือมีการแบ่งปันเอกสารการเรียนและเอกสารอ้างอิงอื่นๆ ที่ใช้ในการเรียนจากอาจารย์ที่ปรึกษา									
5. Academic interests 5.1 ท่านคิดว่าอาจารย์ที่ปรึกษาที่ดี ต้องมีการรับรู้และรับฟังความสนใจในด้านเฉพาะทางในแต่ละสาขาที่ท่านต้องการศึกษาในอนาคต 5.2 ท่านคิดว่าอาจารย์ที่ปรึกษาควรมีการแนะนำโอกาสในการเรียนรู้และส่งเสริมความสนใจในหัวข้อที่เกี่ยวข้องกับการเรียนต่อเฉพาะทางในอนาคตของท่าน 5.3 ท่านคิดว่าคำแนะนำของอาจารย์ที่ปรึกษา จะเป็นปัจจัยหนึ่งที่สามารถกระตุ้นให้มีความสนใจต่อการเรียนได้มากยิ่งขึ้น									

3. ประเมินความพึงพอใจในผลการศึกษา

ข้อสอบถามความจริง/ความคิดเห็น	ระดับความคิดเห็น								
	1	2	3	4	5	6	7	8	9
1. ผลกระทบทางการศึกษา									
1.1 ท่านมีความพึ่งพอใจต่อผลสัมฤทธิของการเรียนทั้งภาคทฤษฎีและภาคปฏิบัติของท่านมากน้อยขนาดไหน									
1.2 ท่านเห็นด้วยว่าการให้คำปรึกษาของอาจารย์ที่ปรึกษาจะมีผลการบรรลุผลต่อการเรียนของท่าน									
1.3 ผลจากการเรียนที่ผ่านมาทำให้ท่านมีความรู้ในแนวกว้าง ของสาขาวิชาทันตแพทย์ที่ท่านศึกษาอยู่เพื่อให้เล็งเห็นการเปลี่ยนแปลง และเข้าใจผลกระทบของเทคโนโลยีใหม่ๆ									

ขอขอบคุณในความรวมมือที่ท่านได้เสียสละเวลาให้ข้อมูลที่เป็นประโยชน์ในการทำงานวิจัยในครั้งนี้

CURRICULUM VITAE

CURRICULUM VITAE

NAME	Katayut Thakaeng

EDUCATIONAL BACKGROUND

2021	Bachelor of Science Computer Science Chiang Rai Rajabhat University

WORK EXPERIENCE

2018-Present	Systems Analyst School of Dentistry, Mae Fah Luang University