MODELING AND ANALYSIS IN THE RISK LEVEL OF NOMOPHOBIA FROM SMARTPHONE USAGE BEHAVIOR USING DATA MINING TECHNIQUES

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ABSTRACT

Currently, smartphone is one of the most important tools for communication purposes. A large number of people encountered mobile phone addiction since spending much time on mobile phone. Nomophobia is a new mental health disorder or disease, which is classified as a psychiatric disorder, when people do not have mobile phone activities. This research was conducted to create a model for analyzing the risk level of nomophobia with regard to smartphone behavior. The data mining techniques i.e. decision tree and Naive Bayes theorem were used to determine the model accuracy. The data used were 2,040 sets of sample data. The results showed that the model developed using the decision tree technique was the most effective approach that could be used to evaluate the risk of nomophobia concerning smartphone behavior. The accuracy was equal to 95.4% for K = 20. As the results, 126 rules of prediction are obtained. Thus, this efficient model can be used for further system development.

Keywords: Nomophobia, decision tree, Naïve Bayes, data mining.

1. INTRODUCTION

In most people's daily lives technology is indispensable [1] [2]. This is because, besides being used as a primary tool for communication purposes, it can also help in many other activities [3]. Such as using social media, playing games, watching movies for entertainment Contacting the media, making appointments through various applications, etc. [4] with the ability of the smartphone due to increase. The results of the "Global Digital 2019" [5] survey that gathers information from around the world, indicated the updated digital usage scenarios, and that of the internet for the year 2019. It appears that more than 50% of the world's population uses the internet and social media. In the case of Thailand, a survey found that 90% of Thai people use the internet every day, with google being still the number 1 website which most people access. In addition, from a survey of household use of information and communications technology for 2018 from the National Statistics Office of Thailand, it was found that of the population aged 6 years and over, that is around 63.3 million people, there were 17.9 million computer users (28.3 %), 36.0 million internet users (56.8 %) and 56.7 million mobile phone users (89.6 %). This is a number which is likely to increase steadily, especially with regard to the use of smart phones on the part of teenagers and working people. Due to user behavior with regard to using the said smartphone, there may be an increase in smartphone addiction. A lack of mobile phone access [6] [7] is the source of the Nomophobia disease.

Nomophobia, or mobile phone addiction, comes from the term "no mobile phone phobia" which is a term coined by large market research agencies [8]. It is a term used to refer to the symptoms caused by fear and anxiety when an individual lacks a mobile phone or is unable to use a mobile phone for a long period of time[8] [9]. The symptoms are classified as a type of psychiatric disorder in the anxiety group. The survey found that people in the 18-24 age group are 77% more likely to have nomophobia, followed by those of 25-34 years of age (68%), while the third group is those of 55 years of age [10] [11]. The effects of using a smartphone too much can adversely affect the body and cause various conditions [13] which adversely affect the user's health, such as dry eyes, poor eyesight, finger fatigue, locking stress, neck and wrist pain, insomnia and depression. In addition to physical effects, it also affects relationships with those around one and one's family, causing relationships to deteriorate. One effect of smartphone addiction, results in reduced conversation with people around the individual and making that person turn his/her attention to internet conversations instead [12].

From the said problem the researcher has the idea of creating a model to analyze the risk level of nomophobia arising from smartphone behavior by using data mining techniques. This is a process used for data analysis and processing in the form of models. The approach applies prediction rules that have been used in various fields [13]. The data used are 2,040 sample sets of data from a collection of sample data about smartphone usage behavior. The models will be built using decision tree techniques and Naïve Bayes to compare the efficiency of the models.

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2. LITERATURE REVIEW

This paper, consist of six basic concepts that relates to the prototype: modeling to analyze the risk level of nomophobia due to behavior of using a smartphone by using data mining techniques Each concept will be described in this section.

2.1 Nomophobia

Nomophobia is derived from the term "no mobile phone phobia", which is a term used by YouGov in 2008 to describe the cause of fear and worry when lacking a mobile phone to communicate. This symptom is classified as a type of psychiatric disorder in the anxiety group. The highest risk groups are the 18-24 age group, the next is 25-34 years and the 55 years' age group respectively [10] [11].

Characteristics of people with nomophobia[12]

1. The phone is always in their possession and they have concerns when they don't have their phone.
2. They pick up the phone to look at it often, even when there are no urgent matters. They are often obsessed with checking messages from social media including applications such as Facebook or Instagram, or are frequently updating information on the phone.
3. If there is any notification signal from the phone, they will pay attention to it immediately. If they can't check quickly, they will be disturbed.
4. They get up early and the first thing they do is to play on the phone. They also use the phone just before bed, or play games
5. The usually play on the phone while doing other activities such as eating, going to the bathroom, driving, or while waiting for a bus or to catch a sky train.
6. When the phone cannot be found they will feel more alarmed than if they had lost any other item.
7. They are scared of losing their phone, even if placing it in a safe place.
8. They never turn off their mobile phone.
9. They spend a great deal of time talking to people.

The effects of nomophobia [12]

1. Not enough sleep, leading to exhaustion.
2. Aches in various parts of the body such as the neck and shoulder as a result of using a smartphone while sitting in the same position for long periods.
3. The symptoms of dry eye and retinal degenerative eye fatigue.
4. Trigger finger can occur.
5. There is a danger of obesity and gastric obstruction when using the phone for a long time. The body does not burn calories causing fat to accumulate which may cause obesity. It can affect the stomach and intestines, leading to less bowel movement, indigestion, flatulence and a weak bowel.
6. Depressive disorder occurs when using media or reading messages from too many social media sources. Such actions make you think a lot and compare one's own life with that of others. This can lead to early symptoms of depression
7. Smartphone face disease or premature aging can be caused by bending over the screen for a long time. This causes the neck muscles to contract and increases pressure on the cheeks. This in turn causes the elastic fibers on the face to stretch the cheek tissue. This in turn causes the face to become wrinkled, or to may look different from how it had been.

2.2 Nomophobia Questionnaires (NMP-Q)

The questions in the research questionnaire were adapted from the study of Yildirim and Correia [9] to create a tool to assess the severity of nomophobia disease. It is consisted of 20 questions dividing scored on a 7-point Likert scale. Using evaluation results of the severity of the symptoms to divide into 4 risk levels of nomophobia: a score less than or equal to 20 is not at all nomophobia, a score of 21-59 indicates being mildly nomophobia, a score of 60-99 indicates moderate nomophobia while a score of between 100 and 140 indicates severe nomophobia. The Yildirim and Correia's questionnaire was analyzed the content validity and Cronbach Alpha Coefficient at 0.945. The 20 questions in the NMP-Q as the follows:

1. I would feel uncomfortable without constant access to information through my smartphone.
2. I would be annoyed if I could not look information up on my smartphone when I wanted to do so.
3. Being unable to get the news (e.g., happenings, weather, etc.) on my smartphone would make me nervous.
4. I would be annoyed if I could not use my smartphone and/or its capabilities when I wanted to do so.
5. Running out of battery in my smartphone would scare me.
6. If I were to run out of credits or hit my monthly data limit, I would panic.
7. If I did not have a data signal or could not connect. to Wi-Fi, then I would constantly check to see if I had a signal or could find a Wi-Fi network.
8. If I could not use my smartphone, I would be afraid of getting stranded somewhere.
9. If I could not check my smartphone for a while, I would feel a desire to check it.

If I did not have my smartphone with me, ….

10. I would feel anxious because I could not instantly communicate with my family and/or friends.
11. I would be worried because my family and/or friends could not reach me.
12. I would feel nervous because I would not be able to receive text messages and calls.
13. I would be anxious because I could not keep in touch with my family and/or friends.
14. I would be nervous because I could not know if someone had tried to get a hold of me.
15. I would feel anxious because my constant connection to my family and friends would be broken.
16. I would be nervous because I would be disconnected from my online identity.

17. I would be uncomfortable because I could not stay up-to-date with social media and online networks.

18. I would feel awkward because I could not check my notifications for updates from my connections and online networks.

19.I would feel anxious because I could not check my email messages.

20.I would feel weird because I would not know what to do.

2.3 Data Mining

Data mining is a process used to analyze large amounts of data. This is done through various techniques or methods which can be divided into 3 main categories is Association Rules Clustering and Classification[13]. The characteristics of the data used in the analysis are that they are data in various file formats, both structured and unstructured types, such as databases, transactions, text, pictures, spatial databases etc. To get the results of the data analysis in the form of various forms[14].The characteristics of the model in each technique can be divided into 2 forms - supervised and unsupervised [15]. Data mining can be applied to various fields such as education, banking, diagnosis, etc.

2.4 Decision tree

This is a method for creating models using data classification techniques in forecasting by creating a supervised model that relies on past information to predict future events. The data is divided into 2 types: data for creating models, and data for model testing. A decision tree is a flow-chart-like tree structure, where each node denotes a test of an attribute value, each branch represents an outcome of the test, and the tree leaves represent classes or class distributions. Decision trees can easily be converted to classification rules in the form (IF-DENT) to further develop the system or application [13].

2.5 Naïve Bayes

This is a data mining technique which operates by using mathematical principles in statistics, namely calculating the probability of an event from the total number of events based on Bayesian theory [16].

$$\frac{P(A|B) = P(A)\,P(B|A)}{P(B)} \quad (1)$$

P(A|B) is the probability of the occurrence of event A when event B occurs,
P(A) is the probability of the occurrence of A,
P(B|A) is the probability of the occurrence of event B when event A occurs,
P(B) is the probability of the occurrence of B

2.6 Crisp-DM Methodology

This is a process for creating models using various data mining techniques. consists of 6 steps which are [17] [18]

1. Business Understanding is the first step in problem analysis. This relates to the cause of a particular problem to determine the guidelines or methods to be used to solve the problem and to specify the desired answer characteristics.

2. Data Understanding is a process of collecting relevant information, creating a model that can be used to identify credible data sources and to consider the scope of the information to be used

3. Data Preparation is the process of preparing the chosen information. Various techniques are used to make the information complete and ready in order to create the models being used. This is considered to be the most time-consuming step in that it consists of 3 sub-steps in the form of data selection, data cleaning and data transformation.

4. Modeling is the process of creating a model by using the information obtained from data preparation. In this paper we will create a model using 3 techniques from the association rules clustering and classification.

5. Evaluation is the process of measuring the performance of the model in order to determine the model's accuracy before it is put into general use.

6. Deployment is the process of publishing the model for use in various fields suitable for the institution or business.

2.7 Cross Validation

This is a method for classifying data to measure the effectiveness of that is commonly used in research due to its high degree of accuracy. This is because the data is divided into K groups for use in model building and model testing. For example, if K=5 groups, the model can be divided into 4 groups and 1 group for testing the model. We continue the same process until we have achieved 5 cycles of the specified k value. This causes all sample data sets to be used in model creation and also in model testing. Therefore, the resulting model has a higher degree of accuracy than is the case with the Spilt test method which divides the data set into 2 parts percentage[18] [19] .

3. BASIC CONCEPT

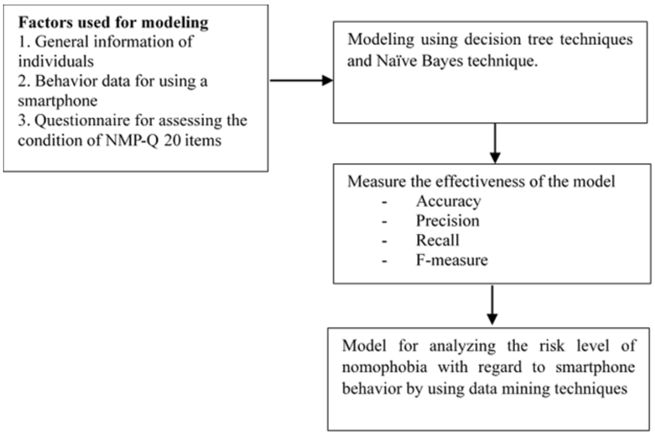

Figure 1. Research Freamwork

4. METHODOLOGY

The researcher has implemented the following 6 steps of Crisp-DM data mining process as follows:

4.1 Business Understanding

Nomophobia or mobile-associated disease. It is a condition that affects interaction with people having a smartphone less often from than those around them. It negatively affects the health of the individual, such as Trigger Finger , crazy eyes, blurred vision, dry eyes, aching neck, shoulders and headaches. All of this is caused by using smartphones for too long [12]. It is most common in youths aged 18-24 with up to 70% of cases, followed by working people aged between 24 and 34 years, and retired individuals aged 55 years or over [7]. Due to these problems, the researcher had the idea of using data mining techniques as part of data analysis to create a model to predict the chances of contracting nomophobia due to smartphone behavior. In order to predict the risk of nomophobia Let those who are using their smartphones know whether they are at risk of developing nomophobia or not.

4.2 Data Understanding

4.2.1 Data with regarding to behavior were collected from 2,040 smartphone users using questionnaires incorporating closed-ended questions. There were 2 types of data collection: offline with the use of questionnaires distributed at various locations, and online via Google in order to collect data from groups of people of all ages so that a variety of data could be analyzed and modeled.

4.2.2 The data used in creating this model consists of 2,040 sample data sets from respondents about smartphone usage behavior. The questions are divided into 3 parts in the form of, firstly, general information with regare do the respondents such as gender, age, income, education level, and occupation. Secondly, there is telephone usage behavior data such as duration of smartphone ownership, average time spent daily use of the smartphone, frequency of checking the phone, number of phone calls made/received per day, number of text messages sent/received per day, number of applications on the smartphone, purposes for which the smartphone is used, and contexts in which the smartphone[9]. Thirdly, there is questionnaire information about mobile addiction. The nomophobia questionnaire section included 20 items in the NMP-Q The researcher translated and developed the severity assessment form with regard to nomophobia from the study by [9]. In terms of the accuracy of the questionnaire, Cronbach's alpha was found to be 0.945 [20].In addiiton a questionnaire used in research into the prevalence of nomophobia among Thai undergraduate students using smartphones in public university was used[21]. This questionnaire also passed the validity checking process. It used a 7-point Likert scale incorporating Strongly Disagree, Slightly Disagree, Disagree, Neither Agree nor Disagree, Slightly Agree, Agree, Strongly Agree[22].

Table 1. The attributes that effect the answers

No.	Attributes
1	Age
2	Sex
3	college
4	Career
5	Income
6	Duration of smartphone ownership
7	average time spent daily using the smartphone
8	frequency of checking, number of phone calls made/received per day
9	number of text messages sent/received per day
10	number of applications on the smartphone
11	purposes for which the smartphone is used
The 20 items in the NMP-Q	
1	Q1= I would feel uncomfortable without constant access to information through my smartphone
2	Q2=I would be annoyed if I could not look information up on my smartphone when I wanted to do so
3	Q3= Being unable to get the news (e.g., happenings, weather, etc.) on my smartphone would make me nervous
4	Q4=I would be annoyed if I could not use my smartphone and/or its capabilities when I wanted to do so
5	Q5=Running out of battery in my smartphone would scare me
6	Q6=If I were to run out of credits or hit my monthly data limit, I would panic
7	Q7=If I did not have a data signal or could not connect to Wi-Fi, then I would constantly check to see if I had a signal or could find a Wi-Fi network

No.	Attributes
8	Q8=If I could not use my smartphone, I would be afraid of getting stranded somewhere
9	Q9=If I could not check my smartphone for a while, I would feel a desire to check it
If I did not have my smartphone with me,	
10	Q10=I would feel anxious because I could not instantly communicate with my family and/or friends
11	Q11=I would be worried because my family and/or friends could not reach me
12	Q12=I would feel nervous because I would not be able to receive text messages and calls
13	Q13=I would be anxious because I could not keep in touch with my family and/or friends
14	Q14=I would be nervous because I could not know if someone had tried to get a hold of me
15	Q15=I would feel anxious because my constant connection to my family and friends would be broken
16	Q16=I would be nervous because I would be disconnected from my online identity
17	Q17=I would be uncomfortable because I could not stay up-to-date with social media and online networks
18	Q18=I would feel awkward because I could not check my notifications for updates from my connections and online networks
19	Q19=I would feel anxious because I could not check my email messages
20	Q20=I would feel weird because I would not know what to do

4.3 Data Preparation

4.3.1 Selecting attributes that affect the answer by using the Wrapper approach is a feature of the selection by creating a model (a classification model) [18] . Using the decision tree technique, the model will show only the node or the factor that affects the word, answer value, and the total of 26 attribute including Sex, Age, Education level, occupation, and income, and 20 nomophobia questions (NMP-Q) [9] [21] was also rated using a 7-point Likert scale incorporating Strongly Disagree, Slightly Disagree, Disagree, Neither Agree nor Disagree, Slightly Agree, Agree, Strongly Agree [22]. The results of the analysis of the risk of nomophobia consists of 4 levels. According to the sum of the scores from all assessments as follows: [9] [21]

1. The score is less than or equal to 20 indicates not at all nomophobia.
2. The score is 21-59 indicates mildly nomophobia.
3.The score is 60-99 indicates moderately nomophobia.
4. The score is 100-140 indicates severely nomophobia.

4.3.2 Data cleaning converts information that is different from a given attribute with an answer other than that specified. It converts such information to suit the answer values such as career attributes, answer values, sewing converted into trading/personal business, temporary employees, converted to private employee/company employees, teachers converted to civil servant/state enterprise.

4.3.3 Data transformation transforms data values with regard to each attribute to the form of a data value range in order to suit the decision tree techniques:

1. Age data can be converted into data ranges as follows

- Under 18 years old = <18
- 19-34 years = 19-34
- 35 years and older => 35

2. Educational information (Education) can be converted to the following data range:

- Education level High school / vocational certificate = High school
- Bachelor Degree = Bachelor Degrees
- Education Level Postgrad / Graduate = Master’s Degrees

3. Occupation information

- Student = Student = Student
- Agriculture = Agriculture
- Trading / personal business = Trade / Personal business
- Private employee / Company employees = Employees
- Civil servant / State enterprise = Official / State enterprise

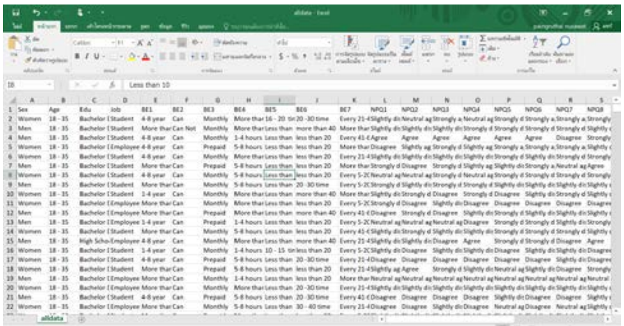

Figure 2. Sample data set

4.4 Modeling

Creating a model to analyze the risk level of nomophobia due to smartphone behavior. This is done with the use of the decision tree technique and Naïve Bayes technique by using the data segmentation method to measure the cross validation efficiency. Set the number of groups (K) to K = 5, K = 10, K = 15 through rapid miner program 9.3 version.

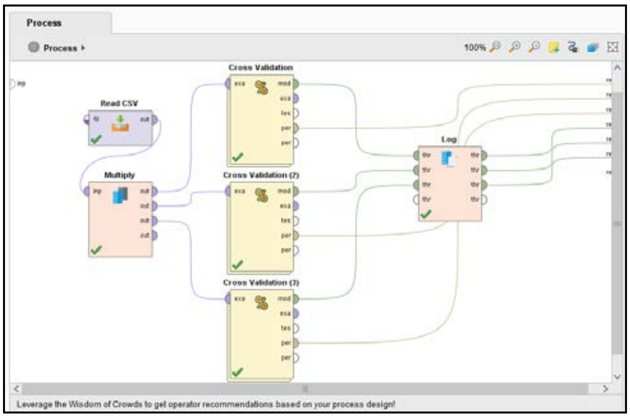

Figure 3. Modeling process

Figure 4 illustrates to modeling process. This involves taking the complete data file from the data preparation process through the operator used for segmenting data for cross validation performance testing, divided into K = 10,

K = 15 and K = 20, under the process of decision tree techniques and Naïve Bayes techniques.

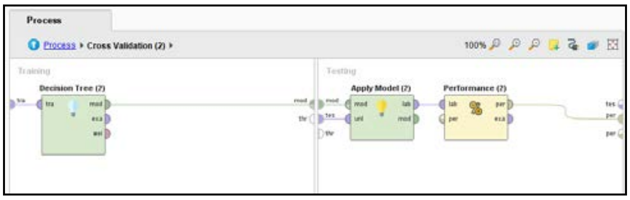

Figure 4. Example of decision tree techniques

Figure 5 illustrates decision tree process modeling techniques by dividing the work into two parts in terms of the model. The performance testing section is used to find the accuracy of the model. The amount of data used to model and test the model will vary according to the specified K value. For example, if K = 10 groups, we will divide the data for training into 9 groups and divide the data for testing into 1 group.

4.5 Evaluation

The researcher measured the performance of the model by comparing the accuracy from 2 techniques, namely the decision tree technique and the naïve Bayes technique using cross validation data segmentation, and setting K = 10, 15 and 20 to compare them in order to determine the greatest accuracy.

4.6 Deployment

The predictive rules model can be used from the nomophobia a risk analysis model based on smartphone usage behavior by using data mining techniques to further develop a system or application to predict the risk level of disease from the behavior associated with using a smartphone. This will enable individuals to be aware of their mobile phone addiction levels, and suggest ways of conducting further research.

5. RESULT

5.1 Sample characteristics

From collecting the respondent's information Demonstrate the demographic characteristics of the respondents as Table 2.

Table 2. Baseline demographic characteristics of the Respondents

Characteristics	Number (N=2,040)	Percentage
Gender		
Male	978	47.9
Female	1,062	52.1
Age (year)		
Less than 18 year	655	32.1
18 - 25	1,032	50.6
26 - 35 ปี	76	3.7
36 - 45 ปี	205	10.1
45 year and above	72	3.5
Educational		
Lower Junior High School	69	3.4
Junior High School	396	19.4
High school/ Vocational certificate	374	18.3
High Vocational Certificate	108	5.3
B.A. (Bachelor of Arts)	978	47.9
High B.A. (Bachelor of Arts)	115	5.6
Career		
Agriculture	36	1.8
Civil servant / state enterprise	131	6.4
Trading / personal business	181	8.9
Student	1,599	78.4
employees	93	4.6
Salary (Baht)		
>=10,000	1,500	73.5
10,001 – 20,000	274	13.4
20,001 – 30,000	212	10.4
30,001 – 40,000	28	1.4
< 40,000	26	1.3

5.2 The creation of a model for predicting the possibility of nomophobia as a result of smartphone behavior. This is done by using decision tree techniques. Show is figure 6.

5.3 The creation of a model for predicting the possibility of nomophobia as a result of smartphone behavior. This is done by using Naive Bayes techniques. Show is figure 7.

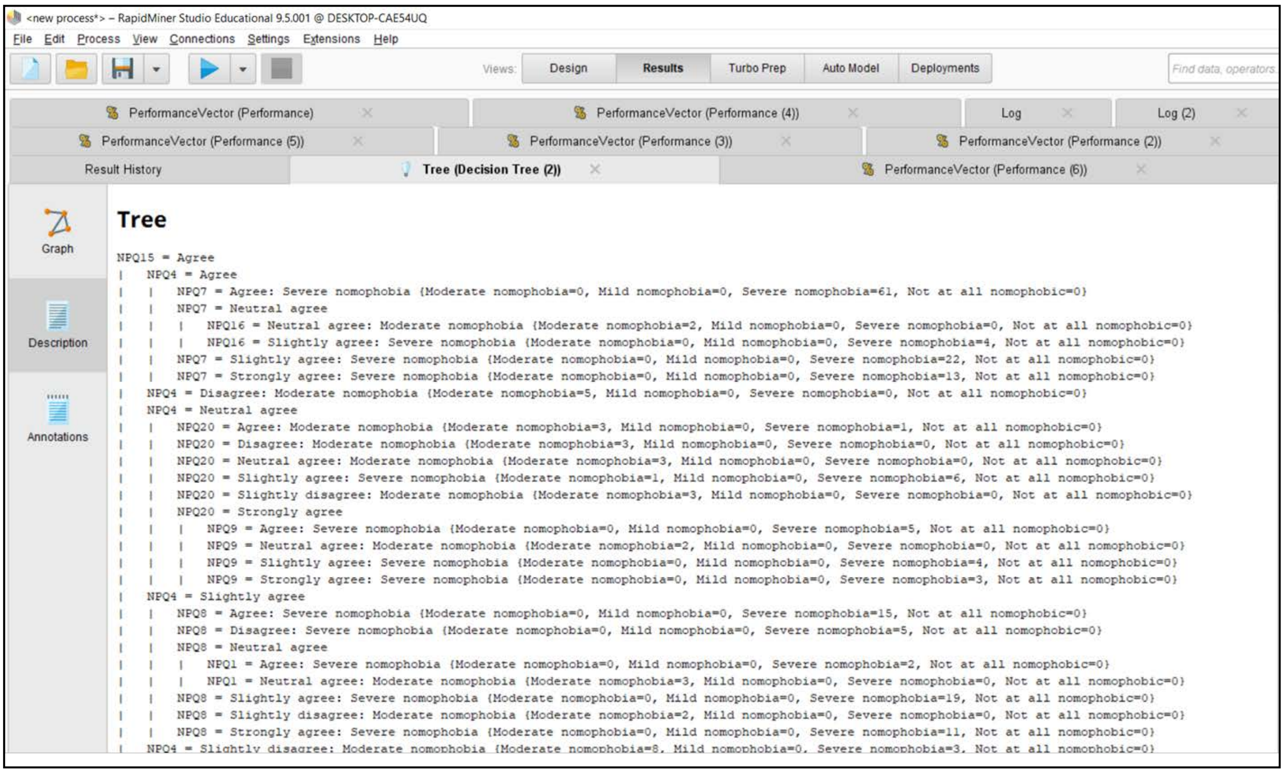

Figure 5. Sample predictive rules from decision tree techniques

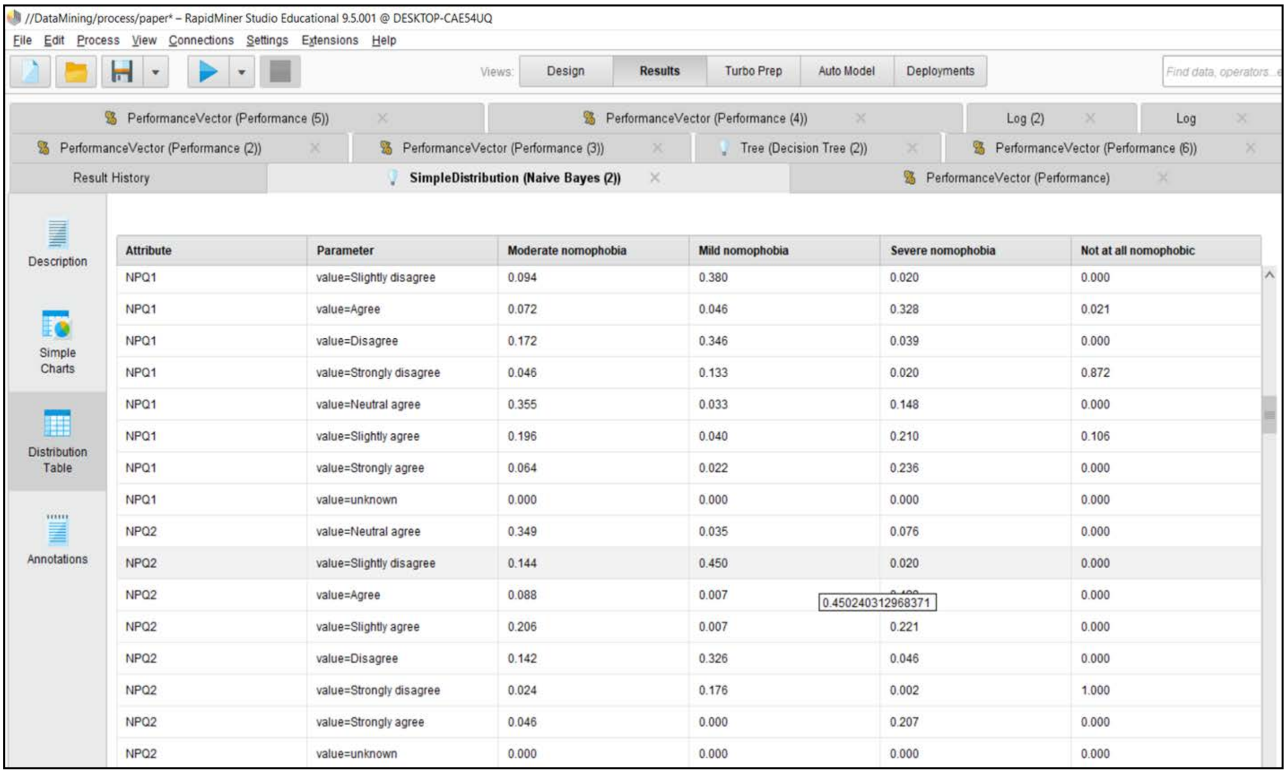

Figure 6. Modeling Naïve Bayes

5.4 Comparison of model performance

Illustrates the results with regard to measuring the efficiency of the model.

Log (2) (1 rows, 3 columns)

Decision tree (K=15)	Decision tree(K=20)	Decision tree (K=25)
0.952	0.954	0.953

Figure 7. The accuracy of decision tree technique

As shown in figure 7, it shows the model's accuracy from the decision tree technique. By grouping the data for cross validation performance testing, the model has the highest accuracy of 95.4% with K = 20.

Log (1 rows, 3 columns)

Naive bayes (K=15)	Naive bayes (K=20)	Naive bayes (K=25)
0.919	0.908	0.906

Figure 8. The accuracy of Naïve Bayes technique

As shown in figure 8, it shows the model's accuracy from the Naïve Bayes technique. By grouping the data for cross validation performance testing, the model has the highest accuracy of 91.9% with K = 15.

Table 3. The accuracy of Model

Classification method	K-flod Cross validation		
	K=15	K=20	K=15
Decision tree	95.2%	95.4%	95.3%
Naïve Bayes	91.9%	90.8%	95.3%

As shown in figure 10, It shows the accuracy of the model from decision tree technique and naive Bayes technique by segmenting data for cross validation testing. It is found that the model constructed by decision tree technique has the highest accuracy equal to 95.4% with K = 20.

6. DISSCUSSION

The researcher, using the data provided by 2,040 sets of respondents in terms of smartphone behavior, allowed the creation of a model for analyzing the risk level associated with nomophobia as a result of smartphone behavior. This was done using a decision tree technique and the naïve Bayes technique. The segmentation method was used to measure the effectiveness of the Cross Validation model with the most accurate model. It is a model with an accuracy equal to 95.4% which was constructed using decision tree techniques. which is in the acceptable criteria from the k = 20 assignment and 1 2 6 prediction rules are formatted. This corresponds to a research of Rahman, et al. [23] In the case of modeling prediction of heart disease by using data mining techniques to compare the performance of various models, it was found that the model constructed using the judging tree technique had the highest predictive value with an accuracy of 99%. This was consistent with the research of Nematzadeh et al. [24]. They found that comparative studies of breast cancer classifications with k-fold cross validation and a determination of the set of groups could be used to create a model for comparing the accuracy of the model.

Table 4. Example of 10 rules for prediction rules

No	Rule
1	if Q15 = Agree and Q4 = Agree and Q7 = Agree then Severe nomophobia
2	if Q15 = Agree and Q4 = Agree and Q7 = Neutral agree and Q16 = Neutral agree then Moderate nomophobia
3	if Q15 = Agree and Q4 = Agree and Q7 = Neutral agree and Q16 = Slightly agree then Severe nomophobia
4	if Q15 = Agree and Q4 = Agree and Q7 = Slightly agree then Severe nomophobia
5	if Q15 = Agree and Q4 = Agree and Q7 = Strongly agree then Severe nomophobia
6	if Q15 = Agree and Q4 = Disagree then Moderate nomophobia
7	if Q15 = Agree and Q4 = Neutral agree and Q20 = Agree then Moderate nomophobia
8	if Q15 = Agree and Q4 = Neutral agree and Q20 = Disagree then Moderate nomophobia
9	if Q15 = Agree and Q4 = Neutral agree and Q20 = Neutral agree then Moderate nomophobia
10	if Q15 = Agree and Q4 = Neutral agree and Q20 = Slightly agree then Severe nomophobia

The 10 predictive rules as shown in Table 3 can be explained as follows: rule 1- if Q15 = Agree, Q4 = Agree and Q7 = Agree, then severe nomophobia can be predicted. This indicates that the subject feels anxious because a constant connection to his/her family and friends would be broken. The subject would be annoyed is the scale score = agree. If the subject cannot use his/her smartphone and/or its capabilities when he/she wants to, the scale score = agree. If the subject did not have a data signal or could not connect to Wi-Fi, and he/she constantly checked to see if he/she had a signal or could find a Wi-Fi network, the scale score = agree. Prediction results show that there was a risk of nomophobia. It was at a severely level.

A limitations of the research are the amount of samplers that are quite small and the sampler groups that responded the questionnaires are entirely narrow. So that they affected the results of the predictive model rules.

Suggestions for further researches may consider other factors that affect the nomophobia: the samplers' general data and smartphone usage behaviors. In addition, there is a need to review additional literatures about other factors that can be used in data analysis. Finally, the predictive rules derived from modeling can be further developed into a system or application to predict the risk level of nomophobia. This would complete the research in terms of the benefits for users.

7. CONCLUSION

The developed model based on the studied details was able to create 126 prediction rules. Each rule indicates the relationship between each factor allowing you to know the factors affecting the disease, and be able to predict the extent of nomophobia. In addition, the decision tree model is able to be developed as a system or an application of predicting risk level of nomophobia from smartphone usage behavior in order to assess the risk level of users' addicting smartphones, to make the smartphone users to be aware of the risk, and to find a way to prevent and change behavior of nomophobia.

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