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A Machine Learning Approach to Evaluate Variables of Math Anxiety in STEM Students

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ARTICLE INFO	ABSTRACT
	The relationships between math anxiety and other variables such as students' motivation and confidence have been extensively studied. The main purpose of the present study was to employ a machine learning approach to provide a deeper understanding of variables associated with math anxiety. Specifically, we applied classification and regression tree models to weekly survey data of science, technology, engineering, and mathematics (STEM) students enrolled in calculus. The tree models accurately identified that the level of confidence is the primary predictor of math anxiety. Students with low levels of confidence expressed high levels of math anxiety. The academic level of students and the number of weekly hours studied were the next two predictors of math anxiety. The junior and senior students had lower math anxiety. Also, those with a higher number of hours studied were generally less anxious. Weekly tree diagrams provided a detailed analysis of the interrelations between math anxiety and variables including academic level, number of hours studied, gender, motivation, and confidence. We noticed that the nature of such interrelations can change during the semester. For instance, in the first week of the semester, confidence was the primary factor, followed by academic level and then motivation. However, in the third week, the order of the interrelation changed to confidence, academic level, and course level, respectively. In summary, decision tree models can be used to predict math anxiety and to provide a more detailed analysis of data associated with math anxiety. **Keywords:** math anxiety, motivation, confidence, machine learning

INTRODUCTION

Statistical models have been traditionally used for data analysis and forecasting different outcomes. In the past two decades, a significant increase in computational power has cleared the way for automated analytical model building techniques, which are known as machine learning methods. A major goal of machine learning is to use the ever-growing computational power to extract information, make predictions, and ultimately make informed decisions applicable to a variety of task domains (Carbonell et al., 1983). Reddy (2021) provided a concise survey of various machine learning methods including support vector machines, decision trees, Bayes classifiers, and k-nearest neighbors techniques. These machine learning methods have been used in healthcare, science, engineering, and education.

In recent years, machine learning has been increasingly used in the field of education. Machine learning approaches for evaluating large amounts of educational data can provide vital information, potentially with large impacts on future education (Bienkowski et al., 2012). For example, highly accurate machine learning models have been constructed to predict the time students are required to generate a response and to estimate the likelihood that the student's response was correct (Inaba et al., 2000). Saarela et al. (2016) used a combination of unsupervised and supervised learning algorithms to predict student performance on math scores, which is a unique way of learning directly from large-scale educational assessment studies' (LSAs) data. In another research, Lezhnina and Kismihók (2021) employed random forest algorithm applications to provide a more complete view of the connections between attitudes toward information and communication technology (ICT) and mathematical and scientific literacy, with an emphasis on the multilayered structure of the data.

In addition, machine learning techniques have lately made significant progress in data analysis and prediction, as well as in evaluating learning quality. Assessing students' academic progress is challenging, but machine learning techniques can aid both students and instructors in this process. Wang and Zhang (2020) investigated the application of machine learning algorithms in an educational quality evaluation model. In their investigation, the machine learning technique was successful in tackling tough challenges such as classification, fitting, and pattern identification. This technique may be used to evaluate university instructors'

classroom teaching performance in a more thorough, reasonable, and efficient way. The goal of developing a teaching quality assessment index is to establish a link between the learning quality evaluation index and the teaching effect.

Predictive student performance statistical models have been created with the goal of forecasting mathematics performance. Because a single tool cannot be easily scaled from one circumstance to another, a variety of learning approaches have been investigated and compared to determine the best prediction model (Sokkhey & Okazaki, 2019). In the present study, we utilize the CRT machine learning method to provide a deeper analysis of factors (gender, confidence, motivation, academic level, etc.) associated with math anxiety. We chose decision tree models because they have a tree-like structure and are easy to grasp, handle predictions, classification, and factor importance (Al-batah, 2014). In the following, we provide a review of existing literature related to the connections between the above-mentioned factors and math anxiety.

To model math anxiety's relationship to confidence, previous researchers have utilized traditional statistical methods for decades. For example, math anxiety has been inversely correlated to high school students' self-confidence (i.e., self-esteem and self-efficacy) (Akin & Kurbanoglu, 2011; Naderi Dehsheykh et al., 2021). Likewise, Tapia and Marsh (2004) found that students with lower math anxiety had significantly more confidence than students with high math anxiety. Rozgonjuk et al. (2020) concluded that reducing students' mathematics anxiety could be helpful in boosting their mathematics confidence. Broadly speaking, the literature indicates that confidence in mathematics has a significant impact on math anxiety.

Confidence is not the only factor, though; motivation can also impact math anxiety. Having a positive attitude might help to minimize anxiety about learning and increase motivation to succeed (Chen et al., 2018). The relationship between math anxiety and motivation has been frequently studied, and a negative correlation between the two has been observed (Chang & Beilock, 2016; Gunderson et al., 2018; Wang et al., 2015; Zakaria & Nordin, 2008). However, in some cases, the relationship between math anxiety and motivation remains ambiguous (Wang et al., 2018). Wang et al. (2018) discovered eight unique profiles in a sample of 927 high school students (13-21 years old) defined by varying combinations of math anxiety and motivation. Simply put, they found some math-anxious students are highly motivated, while the current understanding in the literature is anxious students often have low motivation.

Researchers have also found a connection between gender and math anxiety. The relationship between math anxiety and gender has sparked debate and controversy (Rubinsten et al., 2012). Studies have found distinct gender disparities in certain populations. Hembree's (1990) meta-analysis analyzed 151 studies, including 49 journal articles, 23 ERIC documents, 75 Ph.D. dissertations, and four reports from additional investigations. According to the results, females had higher levels of math anxiety than males at the collegiate level. Other researchers have found similar results (Betz, 1978; Woodard, 2002). Xie et al. (2019) revealed women showed a higher level of math anxiety compared to men at a high school level, as well. On the other hand, Tapia and Marsh's (2004) study shows math anxiety is unrelated to gender in their sample of university students, though the other literature shows a significant relationship between the two.

Despite extensive and traditional research on the binary relationship between math anxiety and different factors such as motivation or confidence, there are fewer studies analyzing the relation between math anxiety and all the above-mentioned factors combined. The main goal of the present study is to utilize machine learning to identify and measure the interrelation between math anxiety and factors such as confidence, motivation, gender, and academic level in a population of STEM students. For instance, is math anxiety prevalent in certain subpopulations such as freshman students with low confidence? How would the association of math anxiety and factors such as motivation, confidence, and academic level change over time (throughout the semester)? In the mediation of math anxiety, which variable is a crucial factor? Is there any difference in math anxiety levels between academic levels? Which factor is perhaps the least impactful among other factors? Is there a difference in confidence and motivation between males and females? In the present study, we aim to answer these questions using a machine learning approach rather than traditional statistical methods. Specifically, we employ a classification and regression tree (CRT) to identify factors associated with math anxiety in a population of college students taking online calculus courses during the COVID-19 pandemic. Therefore, the present study provides new insights into the interconnection between math anxiety, confidence, motivation, the number of hours studied, gender, and academic level.

The research approach and the data utilized to carry out the experiment is described in the next section. We first looked at the demographics of the participants and provide a summary statistic of the survey data we collected. Then, we explained the applied CRT machine learning method to the data prepared for the modeling. After that we presented the main results. Finally, we discussed the main results.

MATERIALS AND METHODS

This section describes the study's participants, data sources, and analyses. CRT is a decision tree machine learning algorithm that is used to classify students into subgroups to better understand the modulating effects of independent variables influencing whether students become anxious about mathematics.

Participants

This study's data were automatically collected by Canvas, a learning management system used at the University of Missouri-Kansas City (UMKC). The sample for the study included students' participating in fully online semester-length mathematics courses offered in the Summer 2020 semester. Course topics included "calculus II" and "calculus III". The final sample included all 45 students who participated in both classes. Among the two courses included in the analysis, calculus II contained 30 (66.7%) total participants—12 (40.0%) females and 18 (60.0%) males, 25 (83.3%) F/S and 5 (16.7%) J/S. Calculus III contained 15 (33.3%)

total participants—6 (40.0%) females and 9 (60.0%) males, 5 (33.3%) F/S and 10 (66.7%) J/S. All analyses were conducted using SPSS (version 27.0). 45 students participated in the nine-week study and contributed to 405 individual observations.

Context

Due to COVID-19, the University of Missouri-Kansas City (UMKC) suspended in-person classes and continued them in an online synchronous format at their normal hours beginning in March 2020. For the whole Summer 2020 semester, campus closures and online learning were in place. Thus, in the Summer 2020 semester, calculus II and calculus III were taught for the first time in an online synchronous format—previously, these programs were exclusively offered in person at UMKC. Some students were enrolled from various states in the United States, while others were participating in similar programs as part of their home country.

Monday through Thursday, calculus II and calculus III sessions were split into two 50-minute sections with a 10-minute break in between. All classes and office hours were conducted through Zoom. These classes were worth four credits each. In the former grading process, a passing grade of 60% was required; however, due to COVID-19, it was cut to 55%.

During the Summer 2020 semester, students learned about integration techniques, definite integral applications, improper integrals, sequences and series, power series, Taylor series and convergence, and analytic geometry in calculus II class. Additionally, students learned about vectors, solid analytic geometry, vector functions, and multiple variable functions, partial derivatives, multiple integrals, line and surface integrals, and their applications in calculus III class.

Measures

We developed an instrument to measure students' self-reported math anxiety across a number of factors including their math assignments, upcoming exams, course meetings, grades, etc. (see **Appendix A**). The instrument further asked students to report usage of math and emotional supports (e.g., supplemental instruction, math tutoring, and the counseling center, among other options, and no options). Finally, it inquired about students' math confidence, their desire to study, and their weekly experience with COVID-19 as related to their math anxiety or ability to succeed in class. The six-question instrument was created based on the researchers' experience with prior survey creation and guidance from Fowler Jr's (2013) principles for good survey practice.

This instrument was created as an online survey in the Canvas learning module that students could access via the "quiz" tab on their calculus II and calculus III Canvas course sites. During the COVID-19 pandemic, students answered the same survey questions one week prior to the beginning of the semester and during each of the eight weeks of the semester. Thus, survey data was used to extract levels of students' anxiety as it related to examinations, motivation, confidence, and weekly hours studied. For the eight-week Summer 2020 semester, students' answers were gathered once a week through Canvas and one week prior to the start of the semester. The results were then presented to a mathematical education specialist who evaluated the data for validity and intelligibility.

Data Preparation

We pooled data from both calculus classes for all statistical analyses performed in this study due to the small number of participants. To minimize unintended effects (such as students not taking the survey or providing inaccurate self-assessments), the surveys were given in the form of a weekly quiz with bonus points. During the semester, we randomly monitored the survey data to identify human error and asked some participants to provide answers within the given range of values (e.g., level of anxiety should be between 1 and 7). Weekly reminders were sent to students which encouraged them to take the survey. Consequently, we had a high participation rate of 84.9% (45 out of 53 students).

Students were asked to rate their experiences on a numerical scale in a weekly survey. For example, question 4 stated, "how would you rate your desire to study this week?" (1=no desire to study, 7=very motivated to study)." We selected and used MS Excel software to compile and organize the data for statistical analysis after gathering nine weeks of student answers in Canvas. We cleaned the data (removing non-essential information such as timestamps and duplicate information from across the nine-week study duration, such as student identification numbers) and gave numeric codes to each response choice as appropriate.

We divided student replies to complicated questions into groups when coding them. For example, we defined three categories for question 4: low motivation (scores 1-2), medium motivation (scores 3-5), and high motivation (scores 6-7). Students' replies to yes or no questions were categorized in a dichotomous manner, with "yes" equaling 1 and "no" equaling 0. The data was then totaled by groups and weeks, and the results were organized.

Following that, we carefully put the data into SPSS (version 27.0) and ran classification statistical analyses. Demographic variables including gender and academic level were plotted against weekly hours studied, confidence, motivation, and the effects of COVID-19 on self-reported math anxiety. The practical implications of these findings were then clarified and addressed in further depth.

Classification and Regression Tree

Decision tree models, which have an easy to grasp tree-like structure, perform prediction and classification, and evaluate factor importance (Alkhasawneh et al., 2014). Decision tree analysis, a non-parametric approach for expressing how examples from a sample are categorized into increasingly smaller subgroups until reaching the final or terminal child nodes in a tree diagram, was used to perform this study. Because of data sparsity among collected responses, this technique was chosen.

The regularity in which participants modify their predictions to match those of the model, as well as their self-reported levels of trust in the model, show that claimed accuracy has a substantial influence on people's trust in a model (Yin et al., 2019).

In this study, we used the IBM SPSS (version 27.0) software as one of a variety of machine learning techniques. This tool assisted us in creating decision tree models that will present data in an easy-to-understand format. We imported all of the cleaned data

Table 1. Average data values for each variable on gender (male, female) & academic level (freshman, sophomore, junior, & senior)

	Hours studied	Confidence	Motivation	Exam anxiety
W1	10.4, 4.4, (7.8, 7.2, 3.4, 13)	4.7, 5.2, (4.8, 4.6, 5.7, 5.1)	4.2, 5.6, (4.9, 4.4, 5, 4.7)	3.9, 3.8, (3.9, 4.9, 2.4, 4.3)
W2	14, 12.3, (10.6, 14.9, 16.3, 15)	5.3, 5.3, (4.9, 5.1, 6.2, 5.6)	4.3, 5.4, (4.8, 5, 4.3, 4.6)	3.7, 4.2, (4.3, 5.1, 1.8, 3.7)
W3	17.6 ,15.7, (12.3, 19.6, 25.2, 18.3)	5, 4.7, (4.8, 4.6, 6, 4.7)	4.4, 5, (4.6, 5.1, 4.5, 4.4)	4.1, 4.6, (4.5, 4.4, 3.4, 4.5)
W4	16.9, 15.2, (10.9, 20.2, 25.7, 16.4)	5, 4.8, (4.6, 5.1, 5.5, 5)	4.5, 4.9, (4.2, 5.6, 4.3, 4.9)	5.1, 5.1, (5.2, 5.8, 4.7, 5)
W5	15.4, 17.6, (12, 19.2, 21, 18.4)	5, 4.9, (4.8, 5.1, 5.4, 4.6)	4.4, 5, (4.5, 5, 4, 4.7)	3.9, 4.6, (4, 4.8, 3.6, 4.3)
W6	16.8, 16.6, (11.9, 19.4, 24.2, 18.7)	4.8, 4.6, (4.5, 4.7, 5.4, 4.9)	4.5, 4.8, (4.3, 5.7, 3.6, 4.7)	4.3, 5, (4.2, 4.5, 4.4, 5.5)
W7	16.2, 16.3, (11, 19.3, 20.4, 23.4)	4.6, 4.2, (4.3, 4.9, 4.8, 4.1)	4.4, 4.7, (4.3, 5, 4.4, 4.7)	4.8, 5.5, (5.1, 4.5, 4.6, 5.8)
W8	18.6, 17.1, (12.7, 16.6, 25, 26.9)	4.6, 3.8, (4.1, 3.9, 5, 4.7)	4.6, 4.3, (4.1, 4.9, 4.2, 5)	5.1, 5.7, (5.4, 5, 4.8, 6.1)
W9	16.9, 17.4, (11.9, 16.8, 22.3, 26.1)	4.8, 3.6, (4.3, 4, 4.3, 4.7)	4.7, 4.6, (4.3, 5, 4.2, 5.6)	5, 6, (5.1, 5.5, 5.2, 6.3)

from MS Excel into the SPSS software to perform the analysis. Data cleaning entails determining the optimal method for dealing with missing information. SPSS gave us a few algorithmic choices to model the decision trees. A classification and regression tree were used (CRT) in this study. The CRT divides instances into forecast-dependent variable values based on independent variable values. We applied this method for each individual week of data in addition to all data collected over the entire nine-week study.

Regarding the dependent variables, the CRT divides the data into segments that are as homogenous as possible (IBM, 2012). The independent variables can be continuous, ordinal, nominal, or scale. For example, we identified the dependent variables of interest as "yes" (anxious) and "no" (non-anxious). Also, we used this category for the classification of independent variables. This approach was used for each week of study as well as the entirety of the nine-week period. Each parent node divides into just two child nodes as the tree grows. We used one case for parent nodes and one case for child nodes in the default value category. Occasionally, CRT produced trees without any nodes below the root node. This helped us to produce more useful results.

Once a model has been adapted to a specific set of data, it might have a worse predictive value when applied to other data sets. This concern addresses a model's specificity and correctness. The capacity of a model to anticipate a positive result and be right in its forecast is known as correctness. To assess the models' correctness, we used a 10-fold cross-validation technique. Our model's overall percentage accuracy indicates how effectively it predicted if there would be a yes (anxious) or a no (non-anxious).

Pearson Correlation Analysis

During the Summer 2020 semester, the surveyed data were collected from 45 students enrolled in calculus II and calculus III courses. The classification and regression tree techniques were performed during preliminary statistical analysis to better understand the anxiety levels of students as they related to the studied independent variables. Participants were split into groups based on gender and academic level in the second portion of the analysis. The relationship between the dependent and independent variables was determined using a Pearson correlation. Only the strength of the linear relationship between the two variables is measured by correlations and the Pearson correlation implies that both variables have normal distributions (DeCoster & Claypool, 2004).

Table 1 displays the correlation coefficients and their related significance levels. SPSS software was used to conduct this analysis. The main goal of this study is to see if there is a relationship between math anxiety as a dependent variable and independent variables such as exam anxiety, confidence, motivation, and weekly hours studied.

RESULTS

We began surveying students one week prior to the start of the eight-week Summer 2020 semester. **Table 1** shows average values in reported hours studied (varying between 0 and 96 hours), confidence, motivation, and exam anxiety. Students were asked to rate their confidence, motivation, and exam anxiety on a scale of 1 to 7, where 1 represented low confidence/motivation/exam anxiety and 7 represented high confidence/motivation/exam anxiety. The first column demonstrates that on average male students tended to study more hours than female students surveyed.

Data in **Table 1** are formatted as follows. For each entry, the first two numbers are the average values reported by male and female students, respectively, and the numbers within parenthesis correspond to average values among freshman, sophomore, junior, and senior students. Observe that in most cases, the junior and senior students studied longer hours compared to freshman and sophomore students. Also, in most cases, male students had slightly more confidence than female students. Furthermore, junior and senior students exhibited mainly higher levels of confidence than freshman and sophomore students. In all groups, the average exam anxiety went up during exam weeks 4, 7, and 9.

The correlation analysis of the survey data has been summarized in **Table 2**. As expected, math anxiety is directly correlated with exam anxiety in most subpopulations. We also noted that the number of hours studied and being a junior is negatively correlated with math anxiety. In other words, the higher number of hours studied, the lower the level of math anxiety. Surprisingly the correlation between the number of hours studied and math anxiety in the sophomore population was positively correlated. This suggests that the more hours sophomore students studied, the more confused and anxious they became. We also noticed a positive correlation between motivation and anxiety in the sophomore students. Whereas in senior students, lower motivation was correlated with higher levels of anxiety. In all subpopulations, confidence and anxiety were negatively correlated. The COVID-19 pandemic disproportionately affected female, junior, and senior students. In both subpopulations (senior and junior), COVID-19 was positively correlated with math anxiety.

Table 2. Person's correlation between model variables & math anxiety within each subpopulation during the Summer 2020

	Exam anxiety	Hour studied	Motivation	Confidence	COVID-19
Female	0.337**	0.142	0.1	-0.277**	0.246**
Male	0.291**	-0.085	-0.059	-0.172*	-0.076
Freshman	0.378**	-0.083	-0.114	-0.304**	-0.082
Sophomore	0.609**	0.289**	0.262*	-0.097	0.075
Junior	0.336*	-0.384**	-0.031	-0.069	0.318*
Senior	-0.017	-0.021	-0.204	-0.342**	0.198
F/SP	0.451**	0.109	0.02	-0.214**	-0.034
J/S	0.174	-0.142	-0.108	-0.215*	0.246**
All students	0.322**	-0.012	-0.021	-0.219**	0.053

Note. F/S: Freshman & sophomore; J/S: Junior & senior; **Correlation is significant at the 0.01 level(2-tailed); *Correlation is significant at the 0.05 level(2-tailed)

Table 3. Model accuracy and main predictors of math anxiety for each week 1-9, as well as the entire semester

Week	Model accuracy	Primary nodes	Secondary nodes
W#1	93.3% (O), 88.9% (N), 94.4% (Y)	Confidence (4)	Academic level (F/SP/J/S)
W#2	86.7% (O), 62.5% (N), 100% (Y)	Motivation (3)	Academic level (F/SP/J/S) & Hours studied (22)
W#3	93.3% (O), 75% (N), 100% (Y)	Confidence (6)	Academic level (F/SP/J/S) & Hours studied (28.5)
W#4	93% (O), 66.7% (N), 100% (Y)	Hours studied (47)	Academic level (F/SP/J/S) & COVID-19
W#5	97.8% (O), 92.9% (N), 100% (Y)	Calculus II or III	Confidence (6) & COVID-19
W#6	95.6% (O), 91.7% (N), 97% (Y)	Confidence (4)	Hours studied (10) & Gender (F/M)
W#7	88.9% (O), 50% (N), 100% (Y)	Confidence (3)	Motivation (2)
W#8	97.8% (O), 87.5% (N), 100% (Y)	Motivation (4)	Academic level (F/SP/J/S) & Hours studied (11)
W#9	95.6% (O), 75% (N), 100% (Y)	Confidence (4)	Hours studied (37) & Hours studied (4.5)
W#1-9	86.2% (O), 49% (N), 98% (Y)	Confidence (4)	Calculus II or III

Note. F: Freshman; SP: Sophomore; J: Junior; S: Senior; F: Female; M: Male; Model accuracy is summarized by percentage correct for overall (O), no anxiety (N), and those with anxiety (Y)

Table 4. Weekly importance of factors (IF) associated with math anxiety determined by the decision tree models

Week #	1st IF	2nd IF	3rd IF	4th IF	5th IF	6th IF	7th IF
W#1	HS	C	M	AL	C2/3	G	C-19
W#2	HS	M	C	AL	G	C2/3	C-19
W#3	M	HS	C-19	C2/3	C	AL	G
W#4	HS	C	AL	C2/3	C-19	M	G
W#5	HS	C	AL	M	C-19	C2/3	G
W#6	HS	M	C	C-19	G	AL	C2/3
W#7	HS	C	M	G	AL	C-19	C2/3
W#8	HS	C	C2/3	M	AL	G	C-19
W#9	HS	C	M	AL	G	C-19	C2/3
W#1-9	HS	M	C	AL	C-19	G	C2/3

Note. IF: Important factor; HS: Hours studied; M: Motivation; C: Confidence; C2/3: Calculus II or III; AL: Academic level; G: Gender; C-19: COVID-19; The number of hours studied (HS), confidence (C), and motivation (M) were the top three predictors of math anxiety throughout the semester

Next, we applied the CRT method to further analyze the survey data. We constructed decision tree models for each week of survey data as well as the entire data. For each decision tree model, the dependent variable was math anxiety, and the independent variables were confidence, motivation, weekly hours studied, gender (F/M), academic level (F/SP/J/S), the relative effects of COVID-19, and course level. **Table 3** provides a summary of the model accuracies and main predictors of decision tree models for weeks 1-9 and all weeks. As it can be seen all CRT models have high levels of overall accuracies. Observe that confidence is the main predictor for most cases (i.e., weeks 1, 3, 6, 7, 9, and all weeks). Whereas academic level and the number of hours studied are the second most important predictors of math anxiety (see the columns primary and secondary nodes).

Table 4 is a summary of the importance of variables to each CRT model. Again, note that confidence, number of hours studied, and academic level are the top three variables in the prediction of math anxiety.

The tree diagram of each CRT model has been included in the supplementary document. In the following paragraphs, we will summarize the results of tree diagrams for weeks 1-9 and the diagram modeled the entire semester. See **Table 3** for the accuracy and key outputs of each decision tree model.

In the first week, all students who reported confidence levels with less than four also reported anxiety. Whereas students with confidence greater than four had different results based on the academic level. Namely 50% of J/S students were anxious as compared to 83% of F/SP students (see **Figure 1** in **Appendix B**).

During the second week, 22% of students who reported a level of motivation less than three were anxious. Within this group, F/SP students reported they were not anxious, while 50% of J/S students reported they were. Among those students with a level of motivation of more than three, 75% of students reported they were anxious. Under the same category, 72% of students who studied less than 22 hours were anxious, while 100% of students who studied more than 22 hours were anxious (see **Figure 2** in **Appendix C**).

In week 3, 78% of students with a level of confidence less than 6 reported that they were anxious. By contrast, 40% of students who reported with a level of confidence more than six were anxious. Among those students with a level of confidence less than six, all S students were anxious compared to 73% of F/SP/J students. All students who reported a level of confidence with more than six and who studied less than 28.5 hours were not anxious, while all students who studied more than 28.5 hours were anxious (see **Figure 3** in **Appendix D**).

In week 4, the students' exam week, 83% of students have reported anxiety if they studied less than 47 hours that week. By contrast, 33% of students who studied for more than 47 hours were anxious. Among those students who studied less than 47 hours, all S students were anxious versus 80% of F/SP/J students. Of those who studied more than 47 hours, all students who reported experiencing adverse effects due to the COVID-19 pandemic were anxious. By contrast, all students who reported no adverse effects of the COVID-19 pandemic reported no anxiety (see **Figure 4** in **Appendix E**).

In week 5, 80% of calculus II students reported feeling anxious, as compared to 47% of calculus III students. Among those calculus II students, 88% of students who reported with a level of confidence less than 6 were anxious. By contrast, 40% of students who reported with a level of confidence of more than six were anxious. 42% of calculus three students reported feeling anxious if they reported no adverse effects due to the COVID-19 pandemic, while 67% of students who experienced effects were anxious (see **Figure 5** in **Appendix F**).

In week 6, 90% of students who reported with a level of confidence less than 4 were anxious, while only 60% of students who reported with a level of confidence more than four were anxious. Among those students with a level of confidence of less than four, 71% were anxious if they reported less than 10 weekly hours studied. By contrast, all students who studied for more than 10 hours were anxious. Among those with a level of confidence greater than four, 73% of M students were anxious as compared to 40% of F students (see **Figure 6** in **Appendix G**).

During the second exam week, week 7, all students who reported with a level of confidence less than three were anxious while only 70% of students who reported with a level of confidence more than three were anxious. Within the level of confidence with more than three, all students who reported a level of motivation less than two were not anxious as compared to the 72% of students who were anxious (see **Figure 7** in **Appendix H**).

Throughout week 8, 95% of students who reported with a level of motivation less than four were anxious, while only 73% of students who reported with a level of motivation more than four were anxious. 50% of J students who reported a level of motivation with less than four were anxious as compared to 100% of F/SP/S students. Among those students who reported a level of motivation of more than four, 50% of students who studied less than 11 hours were anxious. By contrast, 88% of students who studied for more than 11 hours were anxious in the level of motivation with more than four (see **Figure 8** in **Appendix I**).

During finals week, week 9, 95% of students who reported with a level of confidence less than four were anxious. By contrast, 72% of students who reported with a level of confidence more than four were anxious. Within the level of confidence less than four, all students who reported were anxious if they reported less than 37 weekly hours studied. By contrast, 50% of students who studied for more than 37 hours were anxious. Among those students who reported a level of confidence of more than four, all students who studied less than four and a half hours were not anxious. By contrast, 78% of students who studied for more than four and a half hours were anxious (see **Figure 9** in **Appendix J**).

Throughout the semester, 88% of students who reported with a level of confidence less than four were anxious (see **Figure 10 (a)** in **Appendix K**). Within this group, 90% of F/SP/S students reported they were anxious, while 64% of J students reported they were anxious. By contrast, 70% of students who reported with a level of confidence more than four were anxious (see **Figure 10 (b)** in **Appendix L**). Among those students who reported with a level of confidence more than four, 75% of calculus II students reported feeling anxious, versus 58% of calculus III students (see **Figure 10 (b)** in **Appendix L**).

DISCUSSION

The purpose of the present study was to utilize the power of machine learning to have a deeper understanding of the factors associated with math anxiety in college students. Applying the CRT method to the survey data of the Summer 2020 semester calculus students, we identified the interrelationships between math anxiety and factors including students' motivation, confidence, weekly hours studied, academic level, and gender. The tree diagrams of the CRT method revealed temporal variations of these factors over the course of the semester. Specifically, from weeks 1-9, there was an interchange between the level of confidence and motivation (less than three or four) as the significant predictors of math anxiety which is consistent with the results of previous research (Akin & Kurbanoglu, 2011; Rozgonjuk et al., 2020; Tapia & Marsh, 2004; Zakaria & Nordin, 2008). There was an exception for week 4 and week 5, where the number of hours studied, and course level became the primary predictors of math anxiety. This could be due to the fact that the students had a midterm exam on the fourth week. This study distinguishes itself from other studies on math anxiety in two important aspects. First, we collected longitudinal survey data to analyze the temporal changes to math anxiety affected by the abovementioned variables. Secondly, it illustrates the capabilities of machine learning methods over the traditional statistical models to extract crucial information about education and the level of math anxiety in college students.

The list of primary and secondary nodes and the accuracies of weekly CRT models are summarized in **Table 3**. Note that all CRT models have reasonably good accuracies that suggest that confidence is the first primary factor involved in the mediation of math anxiety. Students who report a confidence level of less than a four out of seven were significantly more anxious than those with higher levels of confidence in the proposed model. Another finding of the present study showed the academic level and the number of hours studied were the top factors involved in the production or negation of math anxiety in half of our CRT models. In

addition, our study indicates that J/S students tend to study more hours than F/SP students and therefore are more confident and less anxious (**Table 1**). Interestingly, the first column of **Table 1** demonstrates that on average, male students tend to study more hours than female students surveyed, which is inconsistent with the results obtained by Smail (2017). Smail (2017) mentioned that female students are more likely to have math anxiety and study math more than male students.

Furthermore, the adverse effects of the COVID-19 pandemic had the least impact among other factors on math anxiety in calculus students. The effects of the COVID-19 pandemic as a secondary factor causing math anxiety only occurred in two of the ten CRT models which is consistent with the results of previous research (Ludwig, 2021; Soysal et al., 2022; Velazco et al., 2021). For example, Velazco et al. (2021) claim that the level of math anxiety increased due to COVID- 19. However, one study measuring the magnitude of math anxiety in students found relatively low levels during COVID-19 (Ariapooran & Karimi, 2021). Ariapooran and Karimi (2021) found that 67.21% of students showed minimal mathematics anxiety in the COVID-19 pandemic.

In addition to machine learning methods, and for the purpose of drawing connections to earlier studies on math anxiety, we performed a correlation analysis of the survey data. There was significant correlation between math anxiety and the factors mentioned on Pearson's correlation analysis in **Table 2**. We also observed that confidence was negatively correlated with math anxiety based on Pearson's correlation analysis in **Table 2**, which is consistent with the results obtained from previous research (Akin & Kurbanoglu, 2011; Ashcraft & Ridley, 2005; Hembree, 1990; Naderi Dehsheykh et al., 2021; Samuel & Warner, 2021).

In this study, the population of interest was a random population of UMKC students who were taking a calculus course in a given semester. In particular, the population (n=45) consisted of those who were STEM majors and enrolled in an online synchronous calculus II (or calculus III) course during the Summer 2020 semester. Our findings are generalizable to public institutions and to students who are taking online calculus classes. However, there could be some limitations to generalizability perhaps due to the effects of the COVID-19 pandemic on the circumstances at the time, although we did control for the effects of participants' COVID-19 anxiety in our analysis.

The limitations of the present work are as follows: first, it should be noted that the collected data related to the number of hours studied and levels of anxiety, motivation and confidence are self-reported data. Although we eliminated incorrect data, we could not validate the full accuracy of self-reported data. Secondly, the participants in this study were students enrolled in a summer course rather than fall or spring courses. This may create a slight selection bias in the collected data. For example, some students may not have enrolled because of the COVID-19 pandemic or perhaps did not enroll because it was an online summer course. Thirdly, there may have also been other unexplained biases in the data related to this particular institution, and thus there is some sampling/selection bias present. Lastly, a limitation of this study is that environmental factors (such as parents, teachers, ethics, etc.) may enhance the association between math anxiety and the factors which we used in this study. However, we believe that these findings offer considerable insight into strengthening academic achievement in higher education. Moving forward, the results of this study should be validated using larger samples of STEM students across different college-level math courses. It is our profound hope that the results of this study will serve as a foundation to build upon as other researchers continue to develop the field. In addition, the present work shows that researchers in the field of education can use machine learning methods to provide a deeper analysis of data associated with math anxiety and attitudes toward math education. In conclusion, the present study underlines the importance of machine learning methods to extract detailed and accurate information from survey data in the field of mathematics education.

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APPENDIX A

QUESTION 1: Please rank the level of math anxiety you are feeling today: 1-7 (1=Lowest level of anxiety, 7=Highest level of anxiety)

a) Upcoming assignment

b) Upcoming midterm or final exam

c) Upcoming Zoom meeting

d) Your anticipated grade in this course

e) Other reasons (specify)

f) I am not feeling anxious about math today (enter yes if this is the case. Otherwise, leave blank)

Copy this and paste it in the following box to enter your answers: (b) (c) (d) (e) (f)

QUESTION 2: What type of help did you seek for your math anxiety this week? (Enter 1 for all that apply and 0 for those that do not)

a) Supplemental instruction

b) UMKC tutoring

c) Office hours

d) Online tutoring (net tutor)

e) Classmates

f) Private tutor

g) UMKC Counseling Center (https://info.umkc.edu/counseling-services/)

h) Other (specify)

i) I did not seek any help

j) I did not have any math anxiety this week

Copy this and paste it in the following box to enter your answers: (a) (b) (c) (d) (e) (f) (g) (h) (i) (j)

QUESTION 3: Aside zoom meetings and My Math Lab videos, how many hours have you approximately spent studying for this class this week?

QUESTION 4: How would you rate your desire to study this week? (1-7) 1=No desire to study, 7=Very motivated to study)

QUESTION 5: How confident are you today that you will pass this class with a B or better? (1=Not confident at all, 7=Very confident)

QUESTION 6: Are you or any of your family members currently affected by COVID-19 in a way that is influencing your ability to succeed in this class or increasing your math anxiety? Enter Yes/No.

Also, include any comment if you would like to.

APPENDIX B
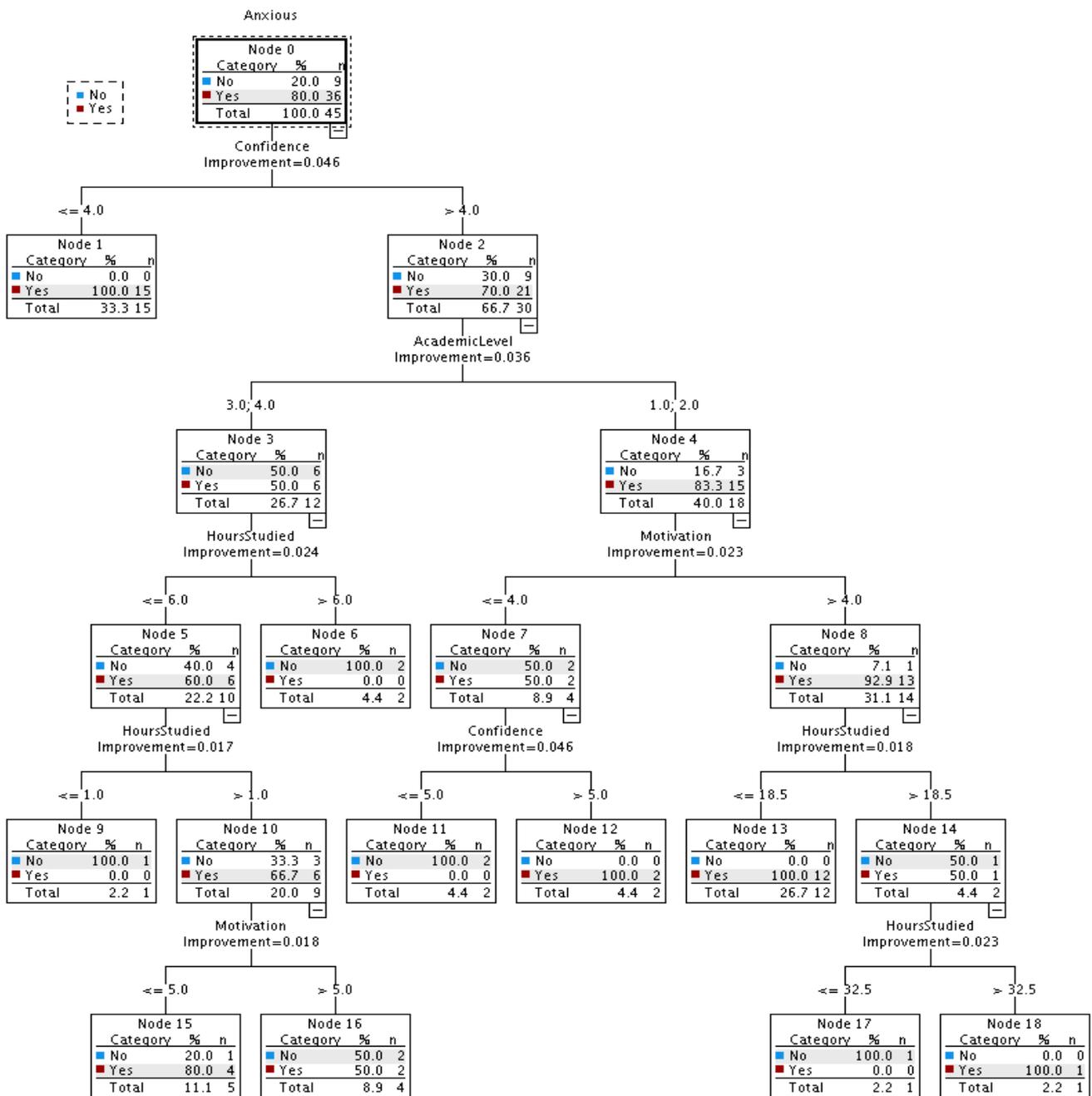
Figure 1. The output tree diagram of the CRT model fitted to survey data of the first week
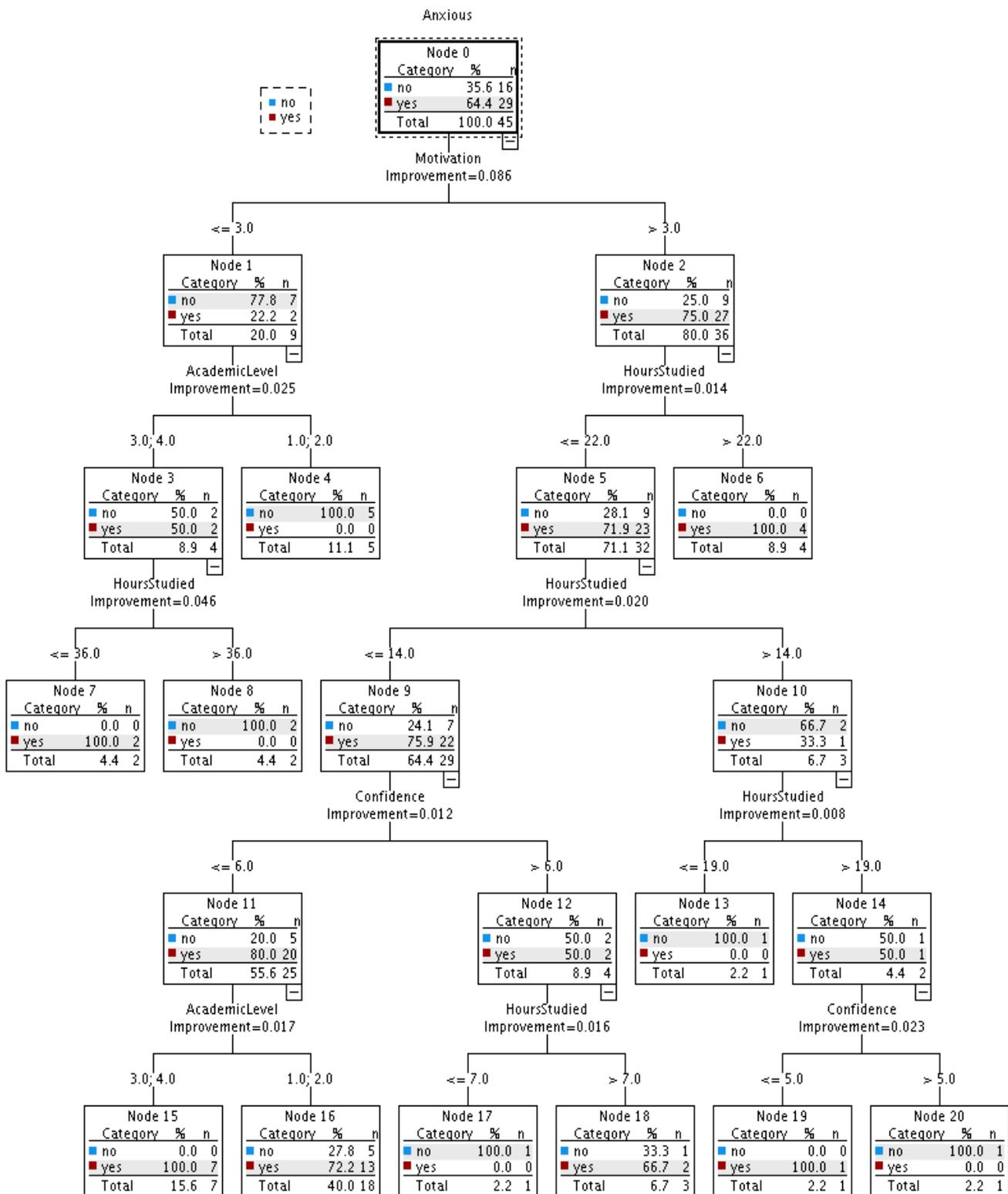
APPENDIX C

Figure 2. The output tree diagram of the CRT model fitted to survey data of the second week
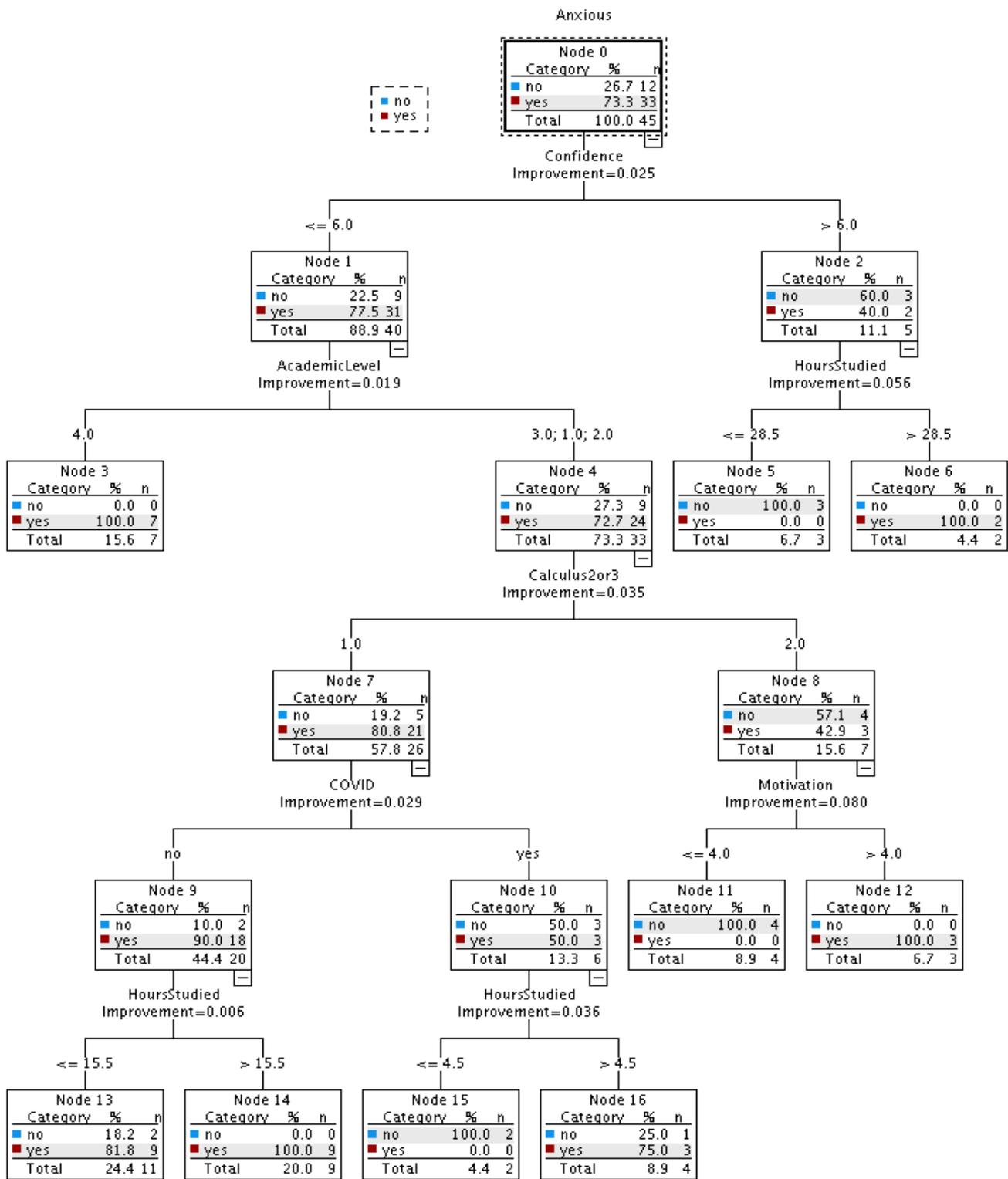
APPENDIX D

Figure 3. The output tree diagram of the CRT model fitted to survey data of the third week
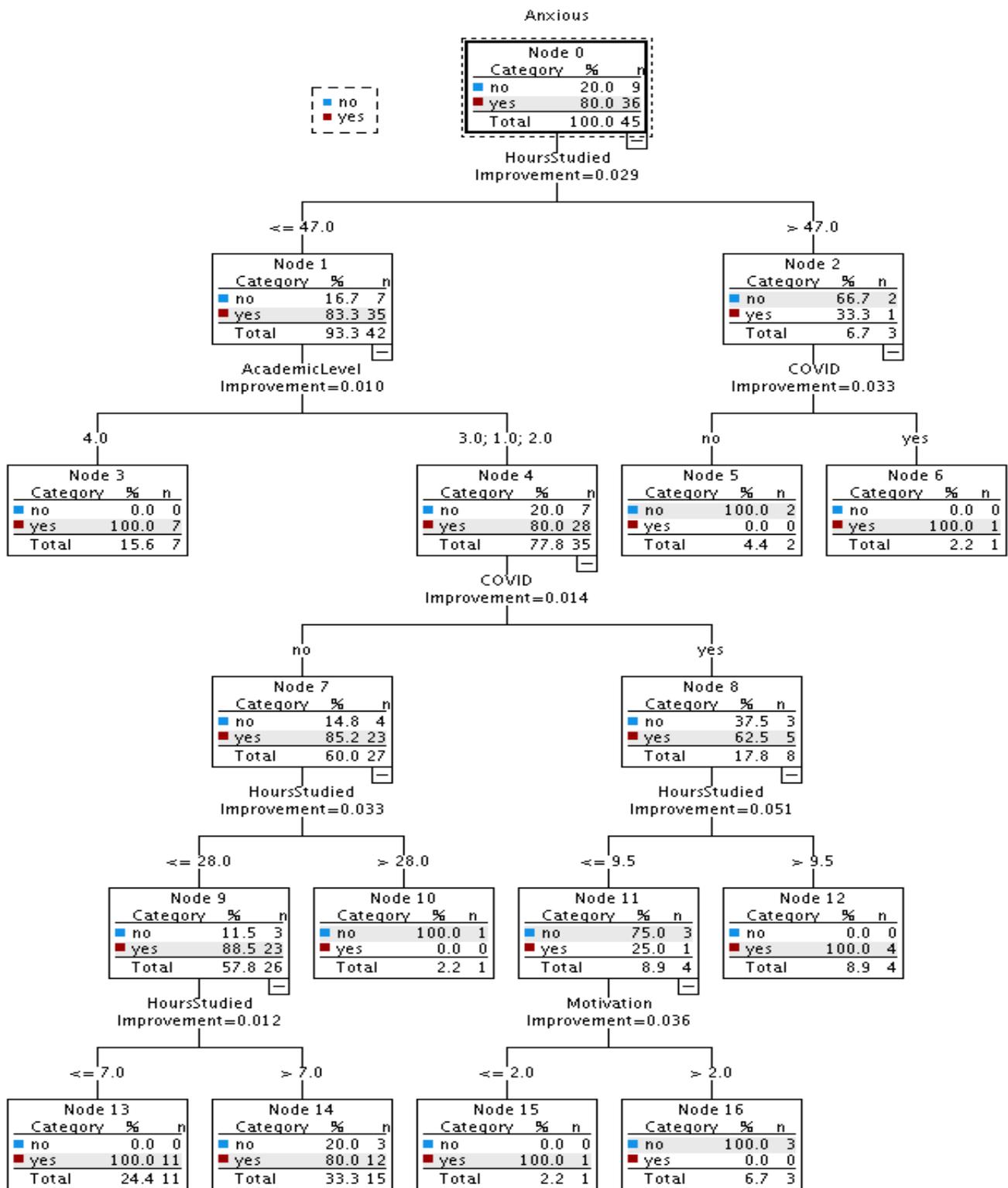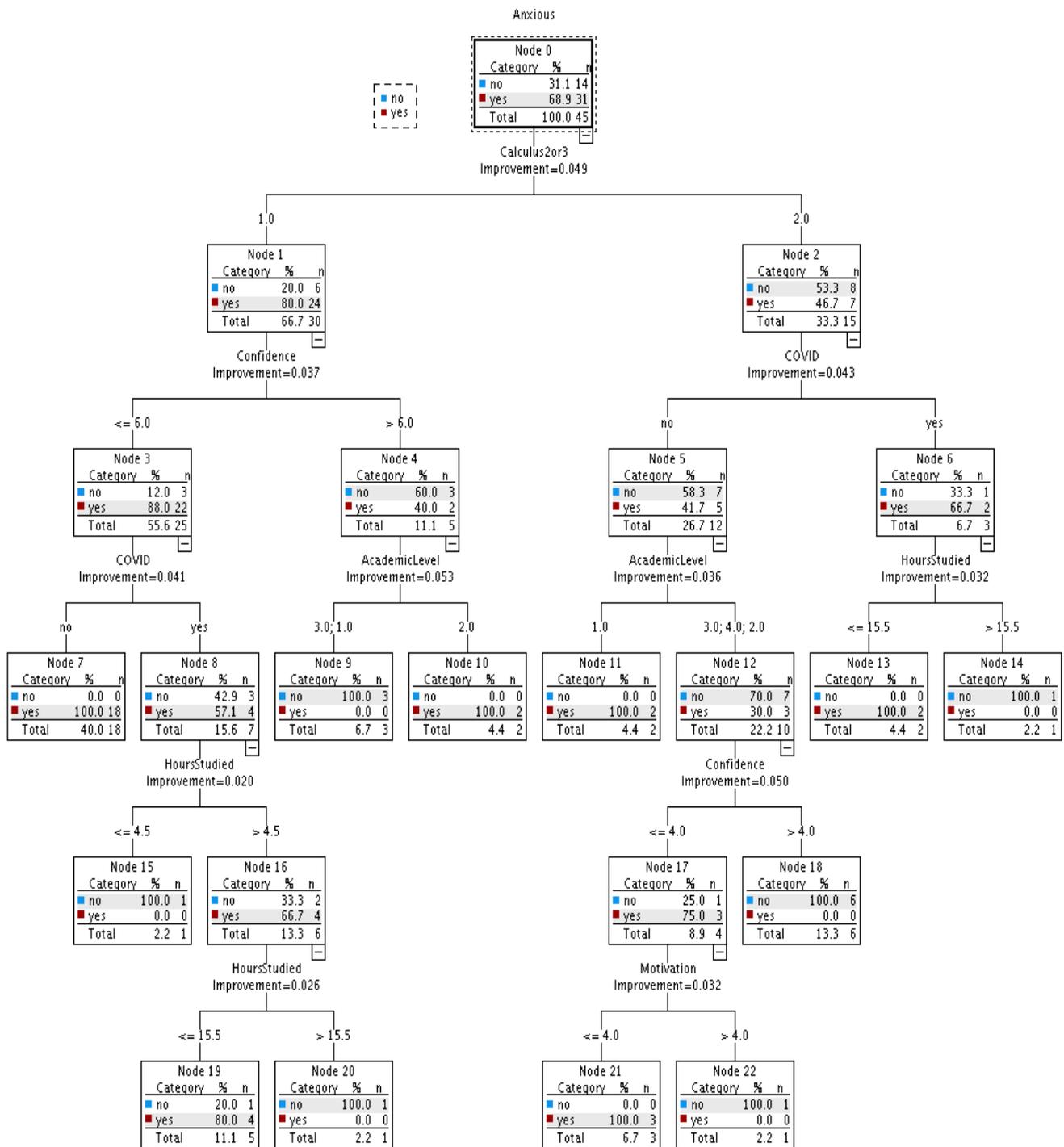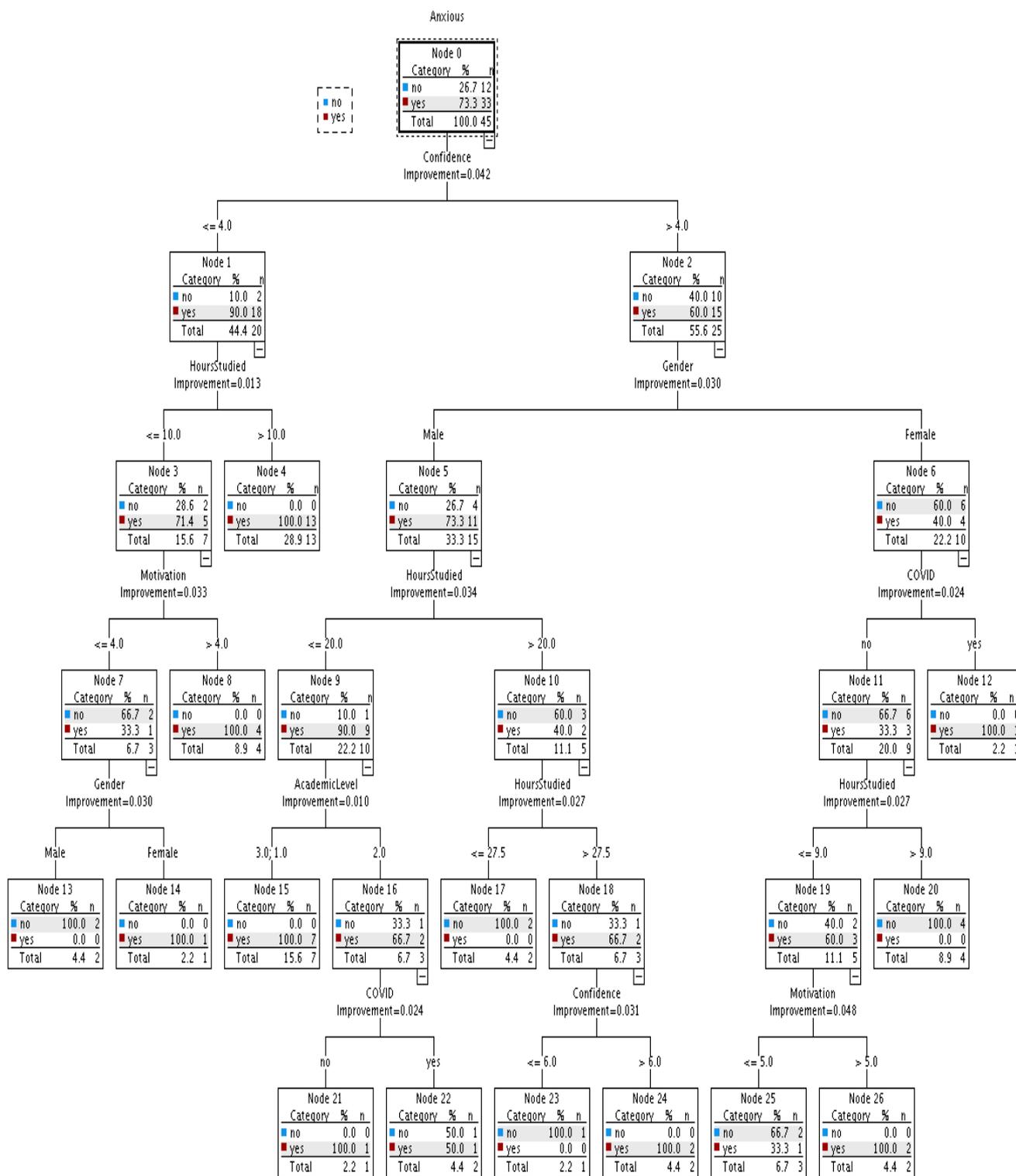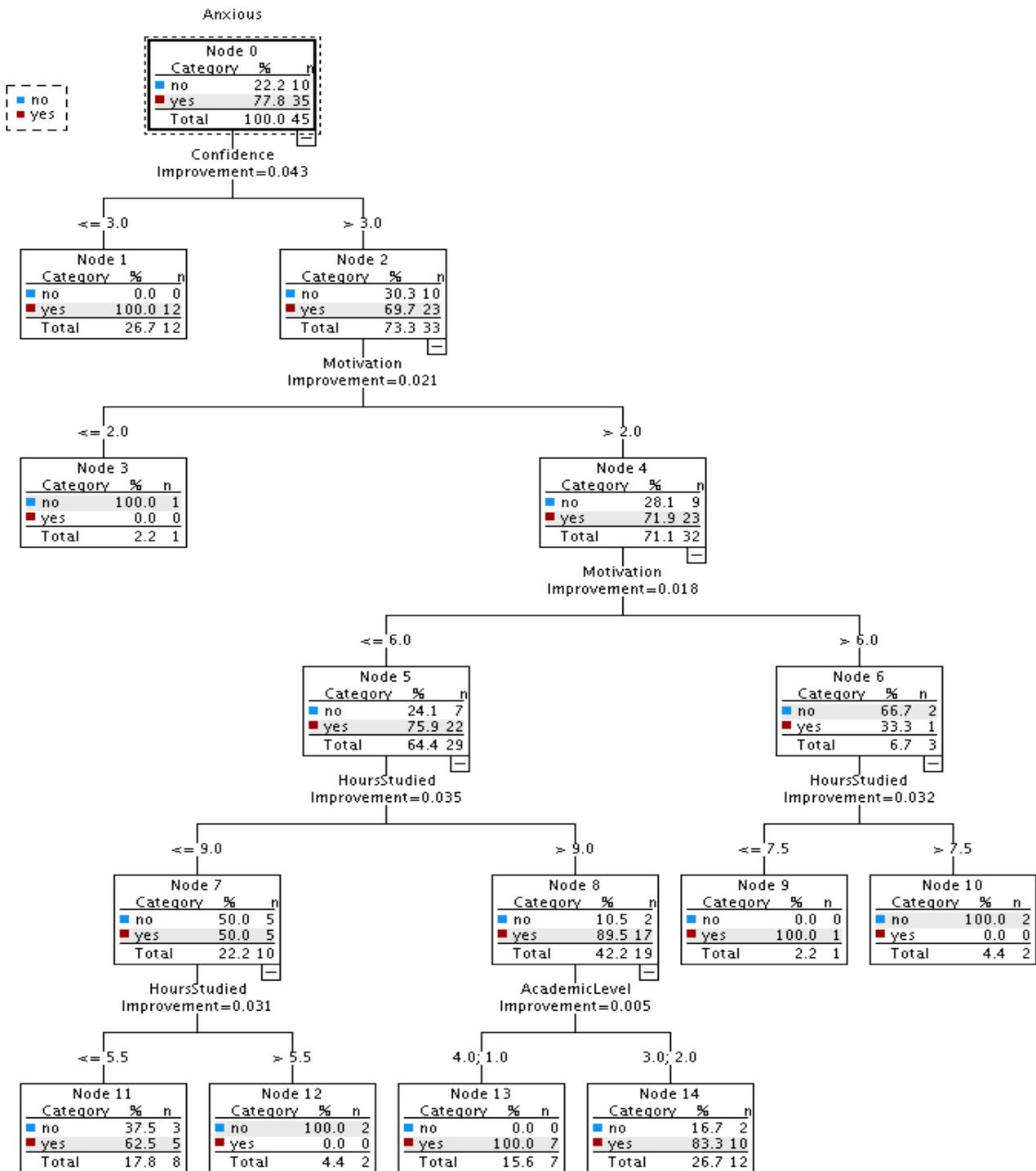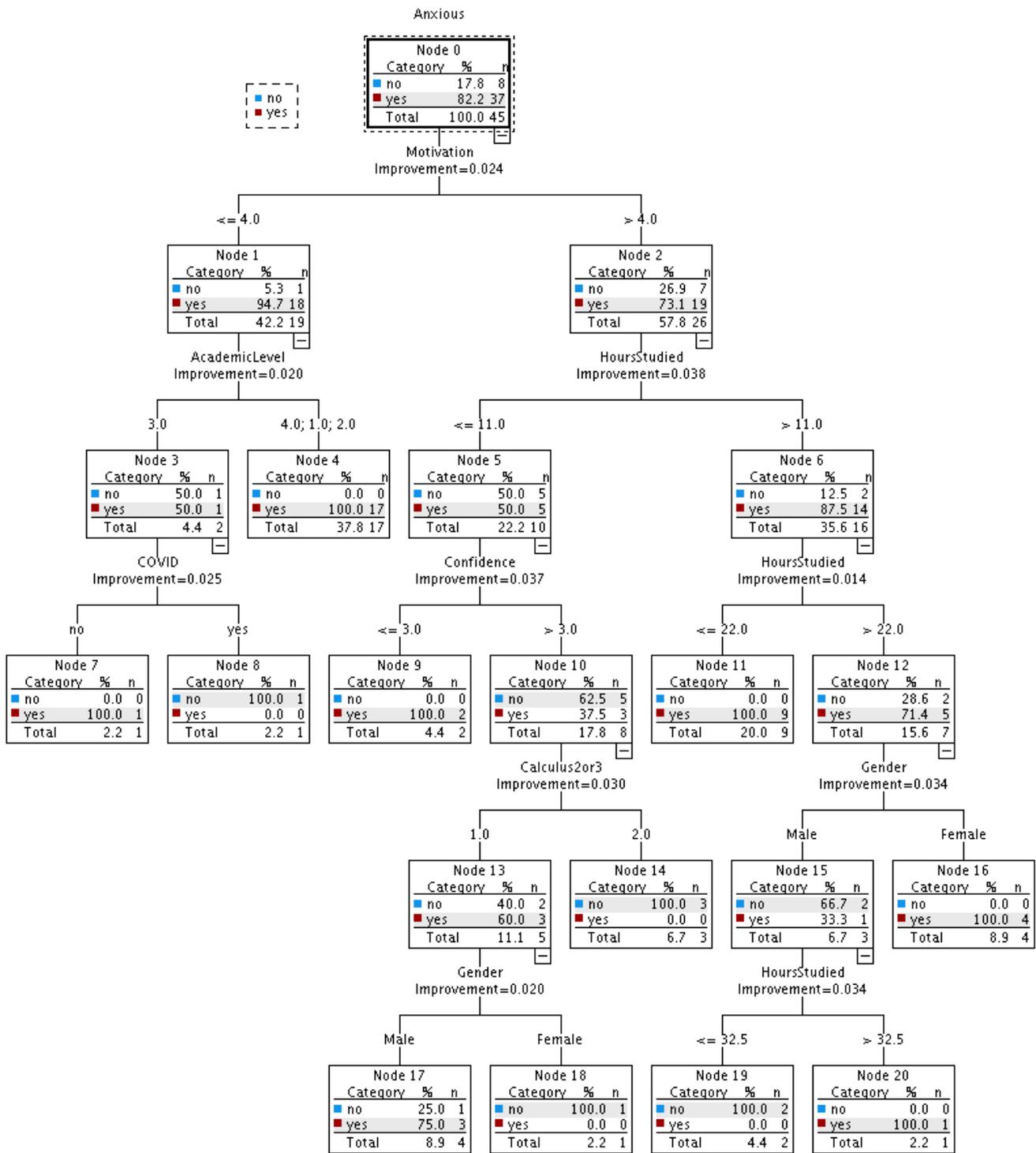
APPENDIX E

Figure 4. The output tree diagram of the CRT model fitted to survey data of the fourth week
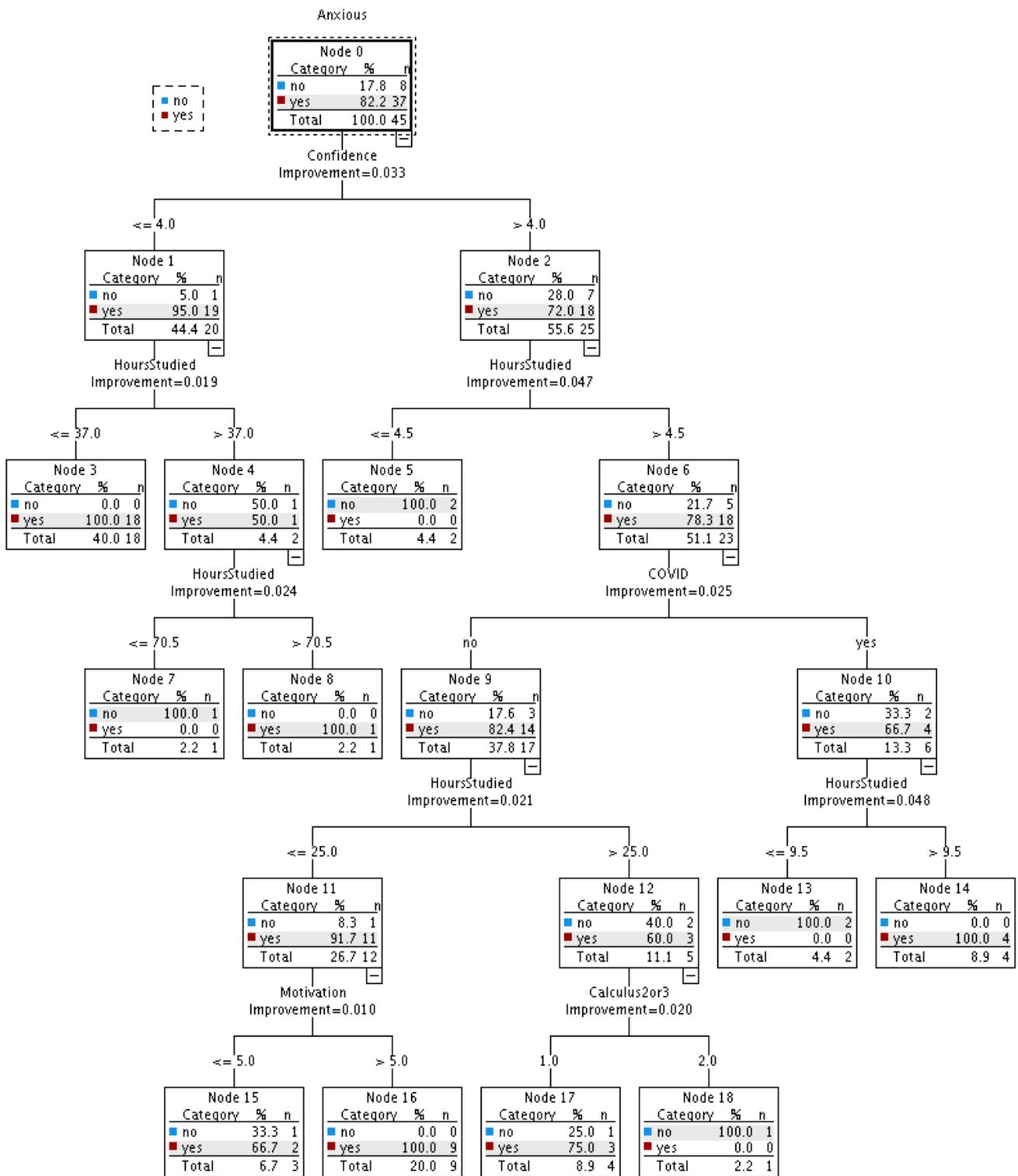
APPENDIX F

Figure 5. The output tree diagram of the CRT model fitted to survey data of the fifth week

APPENDIX G

Figure 6. The output tree diagram of the CRT model fitted to survey data of the sixth week

APPENDIX H

Figure 7. The output tree diagram of the CRT model fitted to survey data of the seventh week

APPENDIX I

Figure 8. The output tree diagram of the CRT model fitted to survey data of the eigth week

APPENDIX J

Figure 9. The output tree diagram of the CRT model fitted to survey data of the ninth week
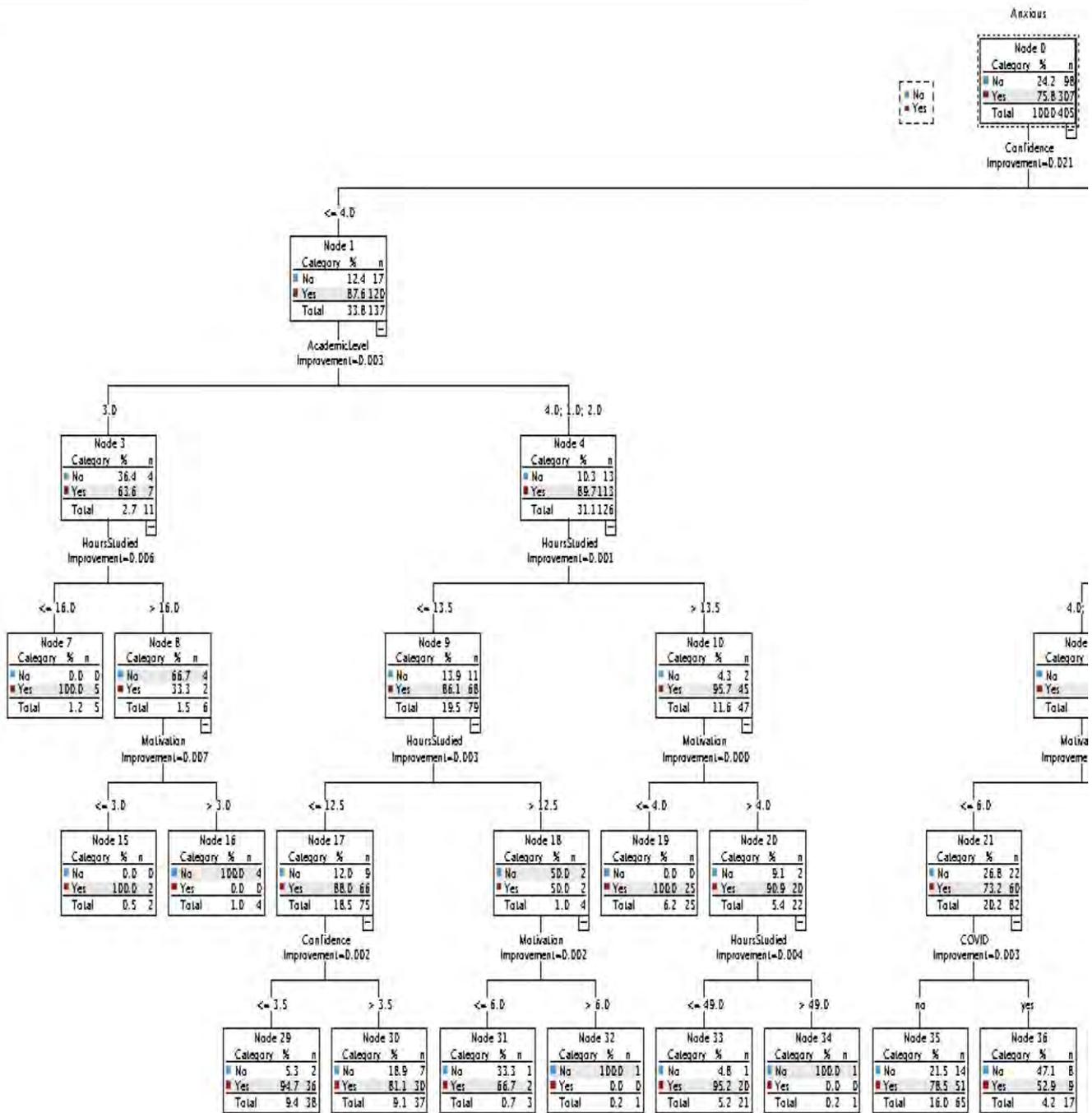
APPENDIX K

Figure 10 (a). The output tree diagram of the CRT model fitted to survey data of the one to ninth week
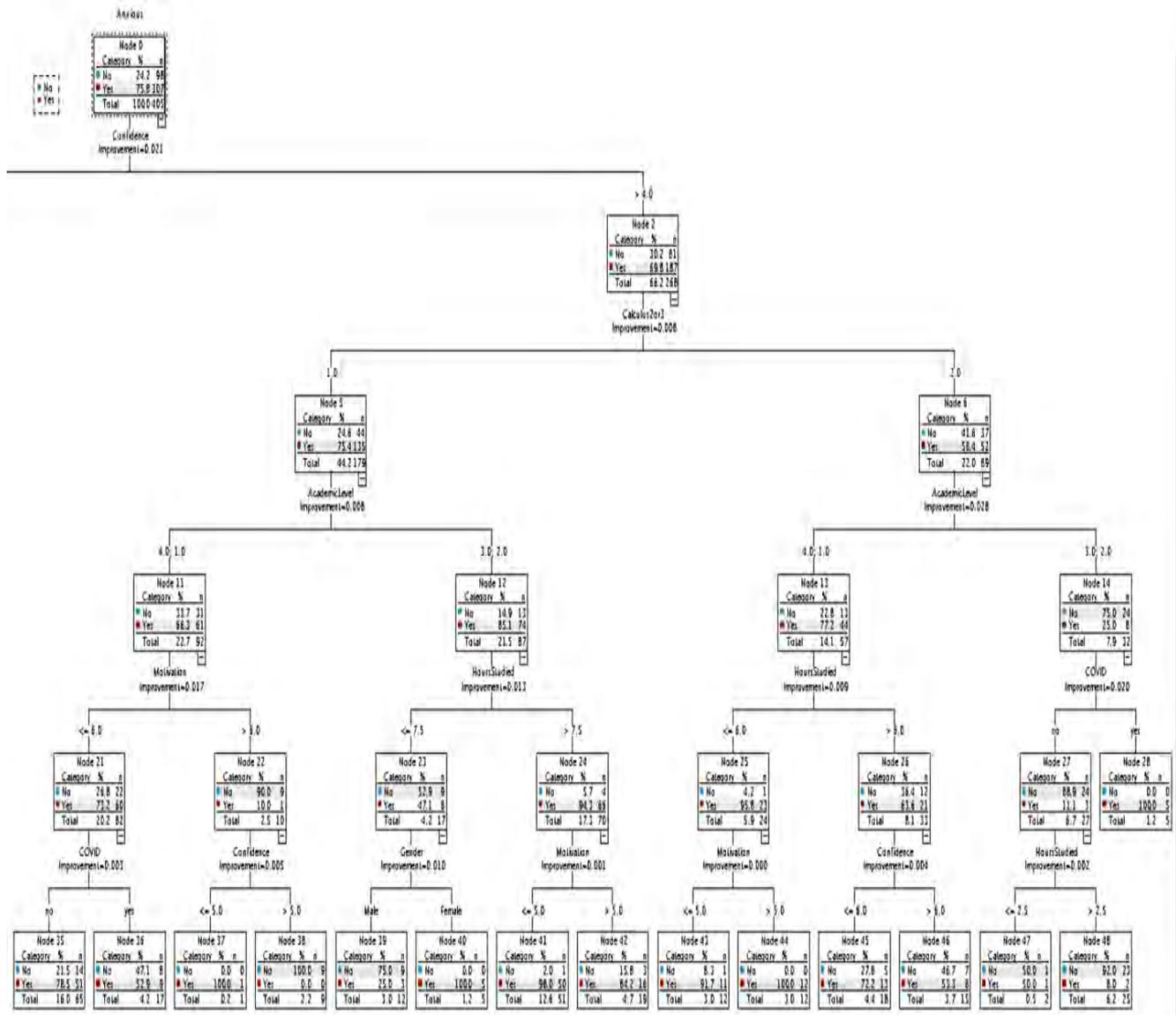
APPENDIX L

Figure 10 (b). The output tree diagram of the CRT model fitted to survey data of the one to ninth week