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Expectations of Students from Classroom Rules: A Scenario Based Bayesian Network Analysis

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Classroom rules are a fundamental aspect of classroom management and ensuring compliance with established rules is crucial. Previous research has shown that students often pay little attention to the development of classroom rules. This quantitative study aims to investigate the expectations that students have concerning classroom rules. To this end, a 4-point Likert scale questionnaire consisting of 30 items was administered to 356 secondary school students. The Bayesian Search method and expert opinion were used to obtain a Bayesian Network model. The findings of the study indicate that students expect rules to be determined at the beginning of the academic year, wish to be involved in the determination process, and prefer minimal changes to the rules. They also expect a limited number of rules and reinforcement from teachers for displaying desirable behavior. Additionally, the study found that students are more likely to adhere to classroom rules in a clean and uncrowded environment, and prefer that their parents are not informed about these rules. The results also suggest that increased adherence to classroom rules leads to increased class inclusion, while decreased adherence results in decreased class inclusion. Furthermore, the study found that adoption of classroom rules leads to increased in-class cohesion, while non-adoption results in decreased cohesion. These findings contribute to the existing body of knowledge concerning student expectations of classroom rules.

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Introduction

In a society, rules serve to maintain harmony and foster healthy relationships. Classrooms, being small societies themselves, provide a space for students to learn and adhere to social norms. However, managing student behavior in the classroom can be a complex task, as problematic behaviors may arise. According to research, challenging student behaviors are often cited as the most difficult issue that teachers face on a daily basis (Alter & Haydon, 2017; Browers & Tomic, 2000; Coalition for Psychology in Schools and Education, 2006; Westling, 2010). These behaviors can also cause stress and frustration for both teachers (Lampert & Graziani, 2009) and students. Disruptive behaviors can limit instruction time, negatively impact peer interactions, and hinder learning in the classroom (Pas et al., 2015). Therefore, "effective management is a key factor contributing to a positive classroom environment" (Hue & Li, 2008, p.3).

Classroom management can be defined as "creating and maintaining a learning environment that supports instruction and increased student achievement" (Brophy, 1999, p. 43) and "the actions teachers take to create an environment that supports and facilitates both academic and social-emotional learning" (Evertson & Weinstein, 2006, p. 4). To achieve successful classroom management, non-negotiable rules should be established. The aim of establishing rules is to create a healthy teaching environment where students can learn the good behavior expected from them and predict possible situations (Wayson, 1985). These rules are "statements that teachers present to describe acceptable and unacceptable behavior" (Alter & Haydon, 2017, p. 115). Proper rules can eliminate disruptive behaviors of students (Kerr & Nelson, 2006), contribute to the academic achievement of students (Korpershoek et al., 2016; Schwab & Elias, 2015), avert chaos to create a healthy interaction among students, and increase teaching time (Weinstein, 1996). The creation of a regular and safe classroom environment requires the establishment and implementation of a set of classroom rules meticulously. If there are problems with the students' behaviors in the classroom and there exist no classroom rules that lead the students, chaos is indispensable, and desired learning and teaching in such a mismanaged environment have little chance to occur (Marzano et al., 2003).

Classroom rules provide two-way benefit since they protect the rights of the teachers and the students (Stiggins et al., 2004). In terms of the teacher, the classroom rules provide taking effective decisions, acting impartially, legalizing authority, and ensuring undivided instructional activities. In terms of students, classroom rules provide establishing a healthier relationship with their peers, accepting awards and punishment without personalizing, creating a safer environment by protecting them from physical damage, and ensuring the self-confidence-morale-success trilogy. Rules are the main reference point in determining whether the students' behavior in the classroom is right or wrong. A behavior is positive-good to the extent that it conforms to the rule, otherwise, it is negative-bad.

Classroom rules form the basis of effective classroom management, "the foundation on which effective teaching is constructed" (Billingsley et al., 2018, p.1). Effective teaching contributes to student learning and engagement. For this to happen, effective classroom management has a key role (Garwood et al.,2017). Effective classroom management is also important for students' academic achievements (Wang et al., 1997). Teachers' readiness and in-service training reveal that teacher competence is very important for effective classroom management. Handling problematic behaviors in the classroom proactively can create more time for instruction and increase student engagement (Sugai & Horner, 2002). The students' challenging behaviors regarding classroom management are defined as verbal disruptions, objections, and being off-task behaviors (i.e., unfettered) (Rose & Gallup, 2005). In this case, teachers often ask for administrative help for challenging student behaviors (Alter et al., 2013). Failures in classroom management are seen as the main reason that adversely affect students' social and academic achievement and teachers' self-efficacy and increase their frustration and burnout (Algozzine et al., 2011; Ingersoll & Smith, 2003; Kokkinos et al., 2005). In addition, one of the most important factors negatively affecting teacher satisfaction is student discipline problems (Ingersoll & Smith, 2003).

One of the most important indicators of effective classroom management is achievement outcomes or results. To observe the success of the students and teachers in the classroom discipline, numerous studies have been conducted with classical statistical methods (e.g. Alter & Haydon, 2017). Regression, correlation, ANOVA, and factor analysis (Guney et al., 2012) are mostly preferred in the assessment of the efficiency of classroom rules. Since the variables used in these analyses are mostly continuous, there are various assumptions and sometimes these assumptions cannot be realized. In cases where assumptions cannot be achieved, the results of the analyses are weak, and the interaction of the variables is not clear. In contrast to the aforementioned deficiencies, the Bayesian Networks approach used in the current study has advantages in terms of the lack of assumptions that affect the outcome of the analysis, analysis with binary, nominal and ordinal variables, including the prior knowledge in the analysis, and the interaction between the variables. In this respect, the Bayesian Network approach (Friedman et al., 1997) has become popular as an analysis method with a dynamic, interactive, and easily understandable graphical structure.

In educational sciences, Bayesian Networks are used in the estimation of learning patterns (Botsios et al., 2007; Carmona et al., 2008; García et al., 2005; García et al., 2007), in the examination of the relationships of performance indicators (Fernández et al., 2011), in the assessment of students' learning performances (Conati et al., 1997; Martin & VanLehn 1995; Mayo & Mitrovic, 2001; Millán et al., 2010; Wei, 2014), in the support of learning processes (Gertner, et al., 1998), in the assessment of education (Almond et al., 2015), and modeling of students' behaviors (Xenos, 2004).

Understanding the underlying reasons why some students obey classroom rules while others disregard these rules is important to create a favorable classroom environment. Research on the subject has been mostly limited to the analysis of classroom rules in terms of teachers, indicating the need to investigate the issue in terms of the students, one of the major components of the classroom environment. Therefore, this study aims to investigate students' expectations and suggestions for setting classroom rules. To this end, answers to the following questions were sought to determine students' expectations in setting classroom rules:

(1) What method should be used in setting the rules?
(2) What is the role of teachers in setting and applying the rules?
(3) What is the relational structure of students' expectations of classroom rules in setting and applying the rules?

Methodology

Research Design

This study adopts a quantitative approach to investigate the expectations of the students from classroom rules. To this end, a 30-item questionnaire consisting of a 4-point Likert scale was applied to 356 secondary school students. A Bayesian Network model was obtained with the Bayesian Search method and expert opinion.

Bayesian Network (BN) consists of a node-arc (arrow) and is the graphical structure used by researchers to explain the probabilistic relationship between nodes (Heckerman, 2008). In the relations of nodes in the network, the node in which the arc begins is referred to as the parent node and the arc pointing to the node is referred to as the child node (Pearl, 2008). A simple BN model is represented below in Figure 1.

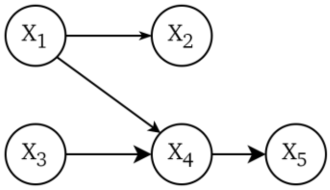

Figure 1. Simple Bayesian Network Model

BNs are different from classification, regression, and clustering methods and have several advantages such as determining the relationship between variables, simultaneously observing the dynamic query, and responding to possible scenarios. Learning BN is a graphical structure learning. There are two methods to determine the network: by direct expert opinion or the network structure from the data with the help of structure learning algorithms. Constructing a BN model with expert opinion is possible by knowing completely the causal relationship between the variables. If there is not enough information about each variable in the data set, it is preferable to create a Directed Acyclic Graph (DAG) structure through an existing algorithm. In BNs created by an existing algorithm, there is no causal relationship between variables, but there is only a probabilistic dependency relationship. In the current study, Greed Thick Thinning (GTT) (Cheng et al., 1997) and Bayesian Search Method (BSM) (Cooper & Herskovits, 1992) were used to learn the BN model then the causal relationship between variables was discussed.

GTT is one of the high-performance BN learning methods (Cheng et al., 1997). The nodes start with a fully connected graphical structure. It gives a score to the network and modifies the network by removing the arcs, which reduces the score in the network via the Prototypical Constraint (PC) algorithm. GTT is a deterministic method that presents the BN structure to the user when it achieves the highest network score.

Bayesian Search Method (BSM) is another heuristic search method in the same group as the GTT. BSM gives the best non-deterministic BN structure to the user as a result of random repetitions (Tonda et al., 2013). The local probability values of the variables (nodes) in the network are calculated by using the Expectation Maximization (EM) algorithm with the conditional probability table values from the data (Dempster et al., 1977; Lauritzen, 1995). BSM and GTT heuristic search methods have been used to learn the BN structure of data. The DAG model that is constructed with BSM, which has a higher success than GTT, has been supported by expert opinion and the BN is obtained. The analysis is performed with the default settings of the GeNie / SMILE program (Druzdzel, 1999).

Data Set

The population of the current research consisted of students studying at secondary school. The study sample consisted of randomly selected 356 voluntary 6th, 7th, and 8th-grade secondary school students in Istanbul (Bakirkoy, Gungoren, and Bagcilar), Turkey. The gender distribution among students is 56% male and 44% female. The research was conducted with a multi-stage cascade sampling method. The dataset consisted of a demographic information section and a 30-item questionnaire that includes a four-point Likert scale (Disagree, Partially Agree, Agree, Totally Agree) to measure the students' view of the classroom rules and their expectations from the classroom (Koktas, 2009). The questionnaire was applied to the 356 students and there was no missing data. According to the total score of the students' responses to the questionnaire, a dummy decision variable was formed by giving a score of 0 (low) for each student below the sample average and 1 (high) for each student above the sample average. The questionnaire statements are given in Appendix.

Findings

The correlations of responses are given in Figure 2. It is observed that there are medium and low-level correlations between statements. As seen in Figure 2, the existence of a correlation between the statements reveals that there is a relationship between the variables (Demir, 2020) and the data can be examined by BNs. The graph shows the relationship between the variables roughly. These relationships are given in more detail in Table 1.

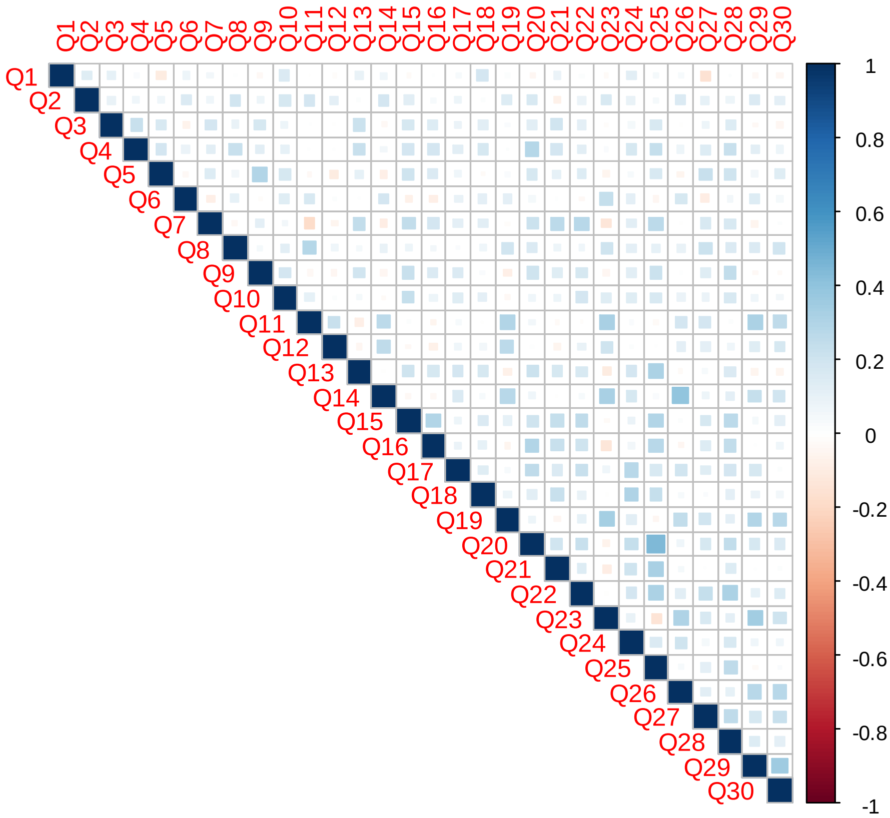

Figure 1. The Correlations of the Questionnaire Statements

Table 1**.** The Correlations of the Questionnaire Statements

Question	Mean	Sd	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Q16	Q17	Q18	Q19	Q20	Q21	Q22	Q23	Q24	Q25	Q26	Q27	Q28	Q29	Q30
Q1	2.04	1.11																														
Q2	2.82	1.11	0.13																													
Q3	3.20	0.95	0.11	0.09																												
Q4	3.46	0.82	0.03	0.07	0.22																											
Q5	3.47	0.78	-0.11	0.06	0.16	0.19																										
Q6	2.51	1.08	0.07	0.16	-0.06	0.08	-0.04																									
Q7	3.14	0.94	0.05	0.06	0.19	0.13	0.15	-0.08																								
Q8	2.87	1.07	0.01	0.19	0.10	0.22	0.05	0.10	-0.04																							
Q9	3.44	0.89	-0.04	0.07	0.18	0.13	**0.30**	-0.01	0.12	0.05																						
Q10	2.85	1.04	0.16	0.18	0.07	0.10	0.17	0.14	0.05	0.13	0.18																					
Q11	2.33	1.12	0.00	0.18	0.00	0.00	-0.03	0.17	-0.19	0.28	-0.04	0.10																				
Q12	2.08	1.12	-0.02	0.12	0.00	0.01	-0.11	0.02	-0.05	0.06	-0.05	0.01	0.23																			
Q13	3.28	0.89	0.09	0.02	0.21	0.22	0.10	0.00	0.24	0.05	0.19	0.05	-0.09	-0.05																		
Q14	1.96	1.20	0.07	0.18	-0.04	0.05	-0.08	0.19	-0.09	0.09	-0.04	-0.02	0.27	0.26	-0.01																	
Q15	2.98	0.97	-0.02	0.12	0.17	0.18	0.21	-0.08	0.24	0.08	0.22	0.23	0.02	-0.03	0.21	-0.04																
Q16	3.31	0.90	0.00	0.04	0.15	0.19	0.15	-0.08	0.18	0.05	0.15	0.08	-0.05	-0.07	0.17	-0.03	0.29															
Q17	2.63	1.17	0.03	0.07	0.09	0.13	0.06	0.10	0.12	0.02	0.16	0.13	0.03	0.06	0.18	0.16	0.07	0.08														
Q18	2.64	1.04	0.18	0.02	0.13	0.17	-0.02	0.11	0.13	0.07	0.03	0.11	0.00	0.06	0.17	0.03	0.15	0.10	0.14													
Q19	2.28	1.16	0.02	0.14	0.03	0.01	0.03	0.11	-0.02	0.19	-0.09	-0.04	0.29	0.26	-0.07	0.28	0.11	-0.06	0.03	0.08												
Q20	3.24	0.93	-0.04	0.16	0.13	0.28	0.17	0.05	0.21	0.16	0.21	0.06	0.06	0.01	0.21	0.07	0.20	0.29	0.25	0.12	0.08											
Q21	3.36	0.86	0.08	-0.08	0.20	0.18	0.11	0.01	0.26	0.08	0.14	0.08	-0.03	-0.05	0.18	0.00	0.23	0.23	0.16	0.22	-0.05	0.19										
Q22	3.15	0.84	0.02	0.09	0.11	0.13	0.14	-0.03	0.27	0.06	0.18	0.19	-0.01	0.09	0.16	0.04	0.26	0.20	0.22	0.10	0.10	0.23	0.14									
Q23	2.18	1.13	-0.02	0.16	-0.01	0.02	-0.06	0.23	-0.13	0.20	-0.05	0.14	**0.32**	0.20	-0.10	**0.32**	-0.03	-0.14	0.07	-0.01	**0.34**	-0.07	-0.10	-0.01								
Q24	2.56	1.10	0.13	0.09	0.05	0.17	0.03	0.11	0.13	0.12	0.12	0.14	0.03	0.01	0.18	0.17	0.09	0.05	0.28	**0.30**	0.13	0.23	0.20	0.18	0.09							
Q25	3.11	0.96	0.05	0.04	0.17	0.23	0.17	-0.05	0.27	0.10	0.22	0.16	-0.02	0.00	**0.31**	0.02	0.29	0.28	0.17	0.24	-0.04	**0.45**	**0.32**	**0.31**	-0.15	0.16						
Q26	2.02	1.18	0.03	0.16	-0.01	0.07	-0.05	0.18	0.00	0.09	0.01	0.09	0.19	0.11	-0.02	**0.39**	0.02	-0.04	0.20	0.04	0.24	0.06	0.04	0.13	**0.31**	0.21	0.04					
Q27	2.96	1.04	-0.15	0.10	0.07	0.15	0.22	-0.10	0.16	0.21	0.13	0.09	0.19	0.11	0.03	0.07	0.17	0.15	0.13	0.03	0.20	0.17	0.00	0.23	0.17	0.05	0.12	0.13				
Q28	2.89	1.00	0.01	0.08	0.14	0.23	0.20	0.06	0.16	0.15	0.25	0.16	0.02	0.06	0.16	0.12	0.26	0.24	0.19	0.12	0.11	0.24	0.15	**0.31**	0.12	0.17	0.26	0.10	0.25			
Q29	2.73	1.12	-0.03	0.16	-0.03	0.12	0.06	0.14	-0.06	0.15	-0.03	0.06	**0.32**	0.14	-0.05	0.24	0.04	0.00	0.17	0.08	0.29	0.17	0.01	0.10	**0.35**	0.06	-0.03	0.28	0.18	0.15		
Q30	2.78	1.10	-0.04	0.11	-0.04	0.08	0.13	0.05	0.01	0.19	-0.02	0.05	0.26	0.18	-0.06	0.19	0.11	0.06	0.02	0.05	0.27	0.15	0.01	0.14	0.21	0.07	0.02	0.28	0.22	0.11	**0.35**	
Decision	0.49	0.50	0.18	0.29	0.21	**0.33**	0.20	0.17	0.25	**0.34**	0.22	**0.30**	0.23	0.14	0.24	0.27	**0.34**	0.26	**0.36**	**0.31**	0.25	**0.39**	**0.32**	**0.38**	0.22	**0.34**	**0.33**	0.29	**0.34**	**0.41**	**0.32**	**0.30**

The means, standard deviations of the variables used in the model, and the relationship between the variables are given in Table 1. When the correlations are examined, it is seen that the highest correlation (0.45) is between Q25 and Q20. Secondly, it is seen that there is a correlation of 0.41 between Decision and Q20. In the related table, correlations greater than 0.30 are shown in blue, and correlations between 0.20-0.29 are in red. As can be seen, the dyadic relations of the variables are at a medium or lower level. But this does not mean that these variables do not affect each other and indirectly other variables. BN analysis should be done to clearly understand whether the variables affect other variables from the first or second level, or which variables, directly and indirectly, affect each other as a whole.

Bayesian Network Results

GTT and BS methods are applied to the data set and the log scores of the model were calculated as follows.

Table 2. Log-scores of Algorithms Used in Bayesian Network Model Construction

Heuristic Search Methods	**Log-scores (*Log(p)*)***
Greedy Thick Thinning	-11258.844984
Bayesian Search	-12180.557090

*Randomize the initial parameter with seed-123 and uniformed

DAG models are obtained with BS and GTT methods without expert opinion. The log score of the DAG model obtained by the BS method (Heckerman & Shachter, 1995) is smaller than the GTT method, showing that the BS method is more successful than the GTT method for this sample. Therefore, the DAG structure of the BS method, which offers more successful results in the construction of the BN model for this data, is preferred in Figure 3.

Logic errors can be found in the causality relationship between the nodes in the DAG structure that are obtained by the methods used in the learning structure of the BN from the data. Logic errors can occur because the relationship between the nodes is based on the conditional probability table values. In the BN model, to prevent the logic errors that may arise in the causality relationship between the nodes, expert opinion is required. For this reason, the direction of the arcs showing the relationships between nodes in the BN model obtained from the data set is determined by expert opinion in Figure 3. For example, the BS method is presented a network model where the relationship between Q25: ‘I can easily adapt to the rules which are specified at the beginning of the semester and Q13: ‘I can easily obey the rules if I am informed previously’ is not clear. According to the expert opinion, if students know the classroom rules at the beginning of the semester, the students will comply with those rules. Thus, the direction of the arc is designated as Q25→Q13. The evidence probability of nodes is given in Figure 3.

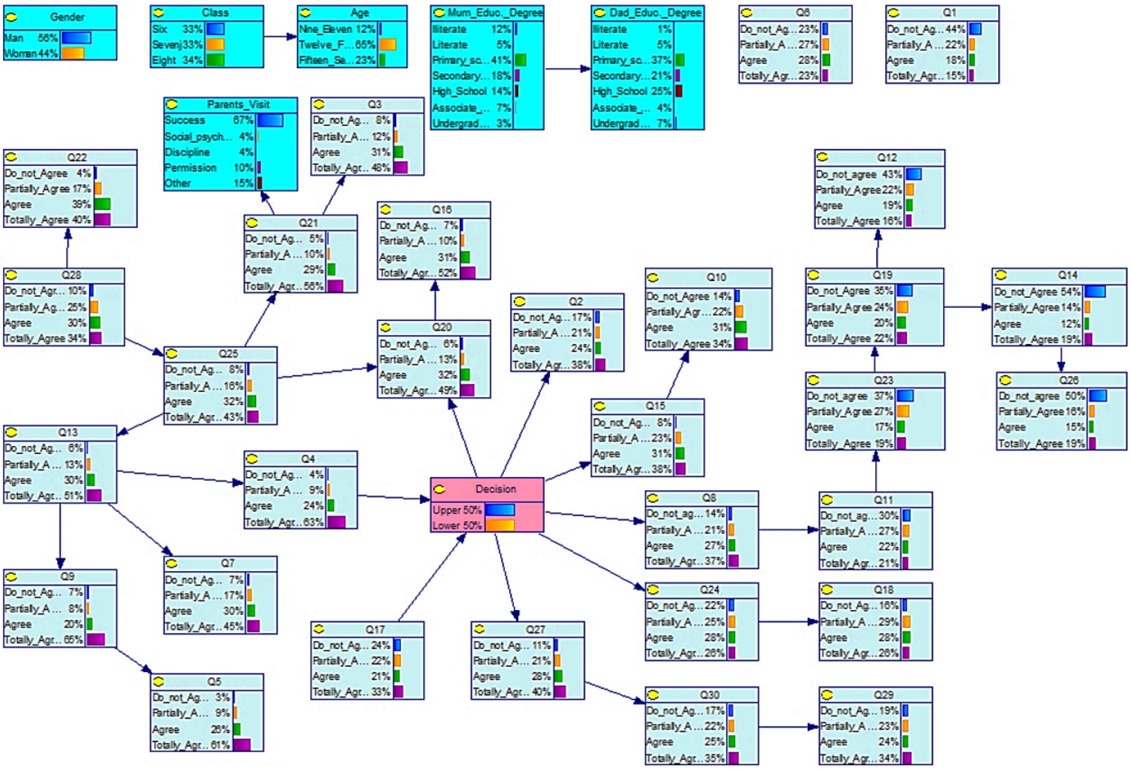

Figure 3. The BN model of students' expectations from classroom rules and evidence probability values of nodes

The conditional relations between the nodes and the posterior probability values of these relations are seen as percentages in Figure 3. There is no significant relationship between demographic nodes and questionnaire statements in this sample. So, these nodes are not linked with arcs. Therefore, the nodes that have no relation to other nodes were removed from the model. Thus, the normalized values of the strength of influences (Koiter, 2006) of the nodes in the BN model are shown in Figure 4.

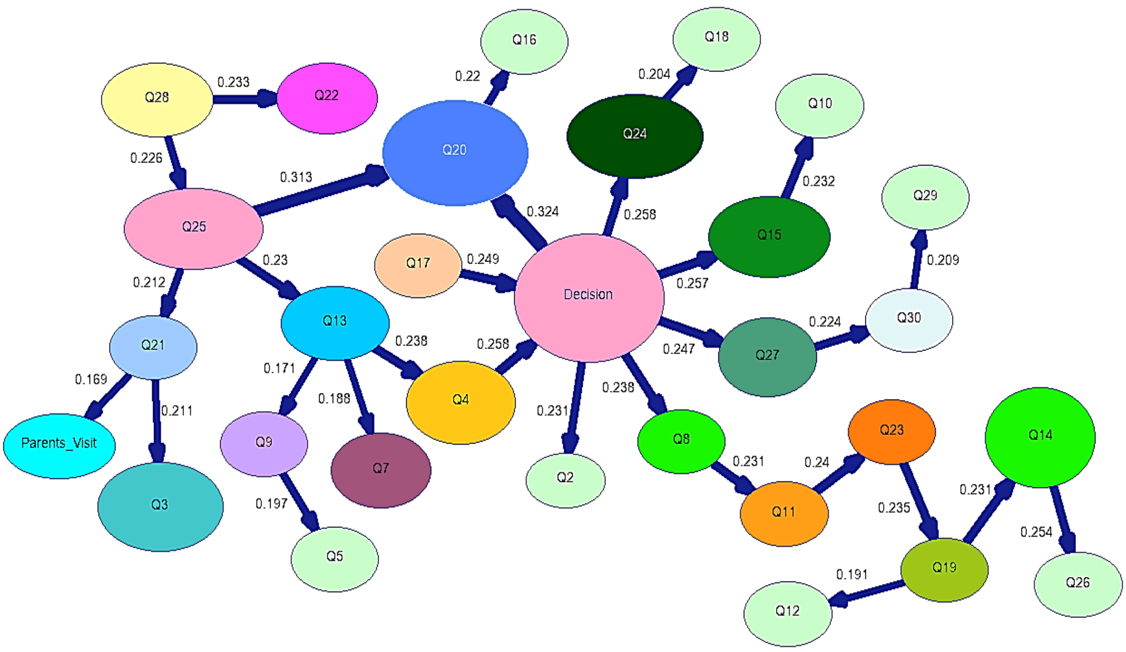

Figure 4. The BN model of students' expectations from the classroom rules and the normalized values of the strength of influences

The values above the arcs between the nodes are shown as the normalized values of the strength of influences of the nodes. As can be seen from these values, the strength of influences between Q20: ‘I can easily adapt to the rules when my teacher supports my positive behavior’ statement and the decision node has the highest conditional probability value of 0.324. In other words, the activities of the teacher towards reinforcing the students’ behaviors are among the expectations of the students from the classroom rules.

When the model is examined based on the influencing (parent) and affected (child) nodes, it is seen that the posterior probability of the decision node is influenced by the prior probabilities of Q28, which is affecting the other nodes related to Q25 and Q25. Similarly, the posterior probabilities of the model are influenced by the prior probabilities of Q8 affecting the other nodes associated with Q11 and Q11.

One of the important advantages of BN is to analyze how the posterior probabilities of nodes may change under different conditions. Accordingly, scenarios for 3 different situations are created to examine the expectations of students from the classroom rules and to analyze the direction changes in the students' expectations within the possible scenarios. These scenarios are given below:

Scenario 1

The Q2, Q8, Q27, Q15, Q24, and Q20 nodes are affected by the low or high value of the decision node. Possible contingent probability values of these variables according to the probability values of the decision node are given in Table 3.

Table 3. The Conditional Probability Values (%) of Nodes According to the Low and High Status of the Decision Node

Parent				**Child**								
		Probability			**Probability**							
					Evidance				**Scenarios**			
Nodes	**State**	**Evidance**	**Scenario**	**Nodes**	**Do not Agree**	**Partially Agree**	**Agree**	**Totally Agree**	**Do not Agree**	**Partially Agree**	**Agree**	**Totally Agree**
Q31: Decision (Dummy)	**Lower**	49.54	100	Q20	6.45	12.78	31.78	48.99	9.96	18.16	37.21	34.66
				Q2	17.07	20.92	24.45	37.56	22.24	29.42	23.90	24.45
				Q15	8.16	23.11	31.16	37.58	12.29	33.84	30.52	23.34
				Q8	14.22	21.50	27.01	37.27	22.24	28.87	24.45	24.45
				Q24	22.06	24.84	27.52	25.58	29.42	32.73	27.21	10.64
				Q27	11.45	20.88	27.63	40.03	18.37	31.08	21.69	28.87
	Upper	50.46	100	Q20	6.45	12.78	31.78	48.99	3.01	7.50	26.45	63.04
				Q2	17.07	20.92	24.45	37.56	12.06	12.57	25.00	50.42
				Q15	8.16	23.11	31.16	37.58	4.10	12.57	31.78	51.55
				Q8	14.22	21.50	27.01	37.27	6.36	14.27	29.52	49.86
				Q24	22.06	24.84	27.52	25.58	14.83	17.09	27.82	40.25
				Q27	11.45	20.88	27.63	40.03	4.66	10.88	33.47	50.99

The above table contains two different scenarios depending on the low and high values of the decision node. In Table 3, the values below the 'Evidence' column show the evidence probability values and the values below the 'Scenario' column indicate the new conditional probability values that the nodes receive when the value of the decision node is the lowest (100%) or the highest (100%).

In case of the decision variable is the lowest (100%), the probabilities of the students' responses to the Q2:‘ I cannot adapt to rules in crowded classes’, Q8:‘ If the rules often change, I may be negatively affected’, Q27:‘ If the rules are applied to the student inequitably, I may be affected negatively’, Q15:‘ Compatibility between the rules of the school and class is affected me positively, Q24:‘ When my parents are informed about the rules I easily adapt to them’ and Q20:‘ I can easily adapt to the rules when my teacher supports my positive behavior’ are negatively decreased. For example, the percentage of students who responded to the Q20 and Q27 statements as totally agree decreased from 48.99% to 34.66% and from 40.03% to 28.87% respectively. Similar decreases existed in other nodes. The low value of the decision node means that the students do not adopt the classroom rules due to excuses such as crowded classrooms, frequent changes in the classroom rules, and notification of the parents about the rules.

When the value of the decision node is the highest (100%), the probabilities of the students' responses to the Q2, Q8, Q27, Q15, Q24, and Q20 statements are positively increased. For example, the percentage of students who responded to the Q15 and Q20 statements as totally agree increased from 37.58% to 51.55% and from 48.99% to 63.04% respectively. Similar increases existed in other nodes. The high value of the decision node means that the adoption of the classroom rules by the students brings many positive situations. For instance, teachers' reinforcement of the behavior of the students who comply with the classroom rules allows the students to adopt the school rules and obey the classroom rules. Thus, a student profile that obeys the rules can be created.

Scenario 2

The change of Q28→Q25→Q13→Q4→Decision←Q17 nodes, which directly and indirectly affect the decision node, is examined in this scenario. According to the status (disagree and totally agree) of the nodes that affect the decision node, the posterior conditional probability values of the decision node are given in Figure 5.

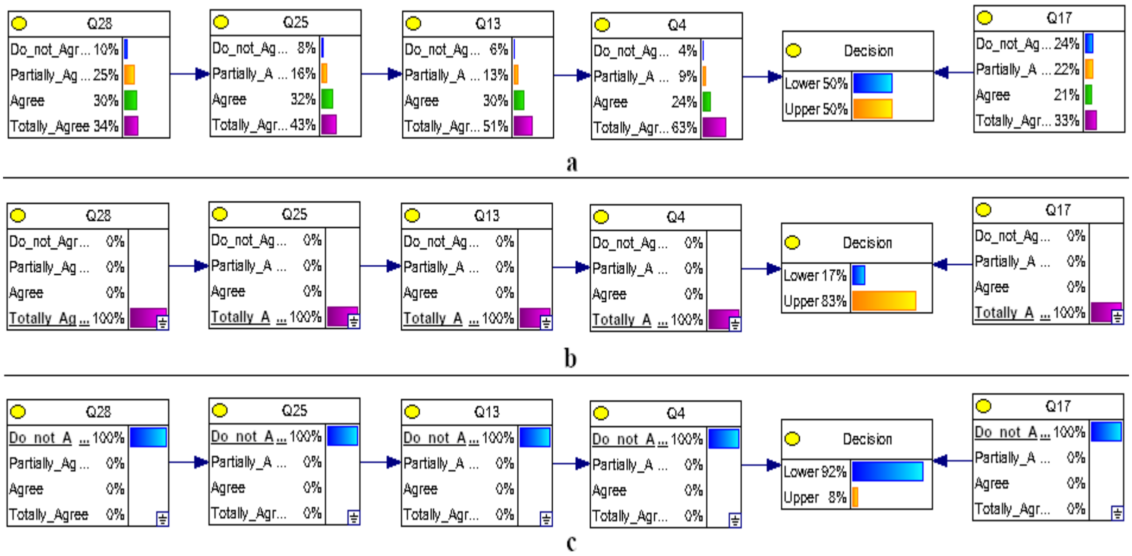

Figure 5. For the nodes, which are directly or indirectly affected by the decision node a-) Evidence probability values (%) b-) While the status is totally agreed, Conditional probability value (%) of the decision node c-) While the status is not agreed, Conditional probability value (%) of the decision node

In the case of the status of Q28: 'If the rules are realistic, I may easily adapt to them', Q25: 'I easily adapt to the rules which are determined at the beginning of the semester', Q13: 'I can easily obey the rules if I am informed previously', Q4: 'I can easily adapt rules in tidy and clear classes' and Q17: 'I easily adapt to the rules if there is punishment and award consequences' nodes that directly or indirectly affect the decision node is totally agreed and the probability of the decision node is positively increased from 50% to 83%. A positive change is observed in the decision node with positive feedback from the nodes affecting the decision node. The fact that the direction of the affected node (positive-negative) is the same as the nodes that affect, emphasizes the importance of the effect indirectly. Therefore, the students' adoption of the classroom rules is positively affected by the classroom rules, which are oriented toward the classroom environment and are determined at the beginning of the semester. In addition, cleaning the classes and controlling the rules with awards and punishment are among the expectations of the students.

In the case of the status of the nodes, which are affected by the decision node "disagreed", the decision node decreased from 50% to 92%. It is observed that not knowing the classroom rules before, not controlling the classroom rules by award and punishment, cleanness of the classes, not relating the classroom rules with the class environment and environmental factors are the reasons why the students do not adopt the classroom rules.

Scenario 3

The change of Q8→Q11→Q23→Q19→Q12, Q14→Q26 nodes, which directly and indirectly affected the decision node, are examined in this scenario. Depending on whether the decision node value is the highest or the lowest, the posterior conditional probability values (%) of the associated nodes are given in Figure 6.

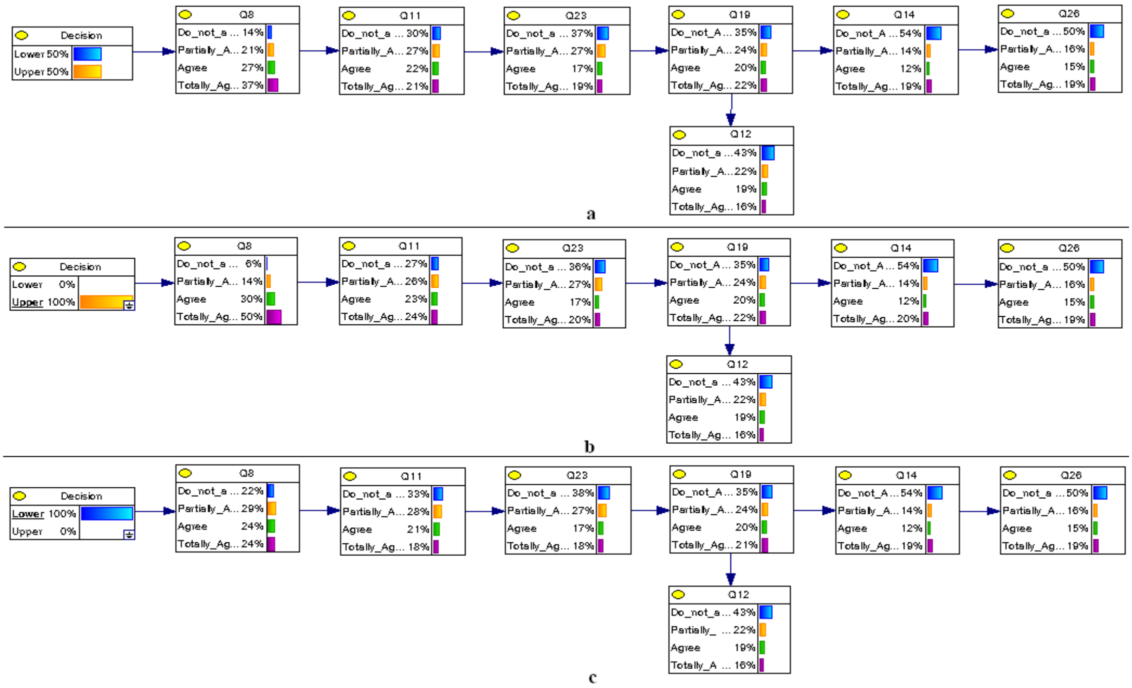

Figure 6. For the nodes, which are directly or indirectly affected by the decision node a-) Evidence probability values (%) of the nodes b-) While the status of the decision node is the highest, Conditional probability values (%) of the nodes c-) While the status of the decision node is the lowest, Conditional probability values (%) of the nodes

When the value of the decision node is the highest, there is a positive change in the Q8: 'If the rules often change, I may be negatively affected', Q11: 'I can be negatively affected if there are large numbers of rules', Q23: 'If the teacher often reminds me the rules I may be affected negatively' nodes. However, there is no change in the conditional probability values of Q19: 'If the same rules are valid throughout the semester, I may adapt to the rules unwillingly', Q12: 'The rules remind me of lack of discipline', Q14: 'Gender of my teacher affects me positively' and Q26: 'My teacher's age has an effect on me to obey the rules' nodes. For instance, there is a positive increase from 37% to 50% in Q8 and from 21% to 24% in Q11, while no change is observed in conditional probability values of Q19, Q12, Q14, and Q26 nodes. In adopting the classroom rules, although the students are negatively affected by the frequent change of the classroom rules and a large number of the classroom rules, they are not affected by the gender and the age of the teachers and the continuous application of the classroom rules.

While the value of the decision node is low, there is a decrease in the conditional probability values of the Q8, Q11, and Q23 nodes. There is no change in the conditional probability values of Q19, Q12, Q14, and Q26 nodes. In the case of the classroom, rules are not adopted, changing of classroom rules, the number of classroom rules, and the gender and the age of teachers who apply the classroom rules are not changed the students' behaviors.

The Q19, Q12, Q14, and Q26 nodes, which are unchanged in the highest and the lowest value of the decision node, show that the continuous application of the classroom rules is an indicator of the class has lack of discipline and the gender and the age of teachers are not influential in the adoption of the classroom rules by the students. This deduction can be easily seen from the level of relationship of the nodes with the decision node. The influence of the decision node approximates zero on the fourth and higher-level nodes. In other words, the effect of the decision node on Q19 and later nodes can be ignored.

Discussion

The successful management of a classroom is partially dependent on the establishment of clear and effective classroom rules. Determining and applying them effectively has a direct effect on the success of students and teachers. These rules serve to minimize disruptive behaviors among students and create a positive and healthy classroom learning environment. The BN model used in this study allows us to analyze the effects of classroom rules dynamically, effectively, and successfully on classroom discipline and the expectations of students from these rules. As a result of the analyses, the BN model which supports the relationship between variables with an expert opinion has been established. The statistical relationship between the nodes in the model is supported logically. When the feedback obtained from the students is analyzed and modeled with BN, it provides valuable insights into the expectations of the students from classroom rules.

The current study revealed that too many classroom rules have a negative effect on the adoption of classroom rules. This finding is consistent with those studies in the literature. The well-accepted approach in terms of the number of classroom rules is the few are better (Alberto & Troutman, 2013; Kerr & Nelson, 2006; Kokkinos et al., 2005; Simonsen et al., 2008). Madsen's study concluded that the number of class rules should be around 5-6 (Madsen et al., 1968). It is concluded that students prefer few and easy-to-understand classroom rules. It may be concluded that students experience difficulty in obeying the classroom rules when there are many rules.

The current study supports the idea of creating and implementing classroom rules at the beginning of the semester. It is suggested the determination of rules and implementation of them from the beginning of the semester, that is as early as possible, can allow the teachers to prevent disruptive behaviors early and keep the rate of these behaviors low throughout the year, which in turn facilitates effective classroom management (Emmer et al., 1980). In fact, "Classroom management begins long before the students come into the classroom. Effective teachers plan their classroom management before the school year begins and know what tasks they will need to undertake at the beginning and throughout the year" (Simonsen et al., 2008, p. 366). Also, these rules should be compatible with the rules of the school and the students should take active roles in determining the classroom rules to internalize them. It is stated that the active role of the students in determining the classroom rules would enable more effective classroom management (Emmer et al., 1980). If students internalize the rules, they are less likely to be influenced negatively when they display misbehavior (Aelterman et al., 2019). Students also expect teachers are consistent in the application of these rules. Moreover, it is seen that the frequent changes in the rules affect the students negatively. In addition, students prefer to know the classroom rules beforehand and do not want frequent reminders of the classroom rules by the teacher.

The participants in the current study suggested that they are less inclined to obey the classroom rules in crowded and untidy classes. Crowded classes can bring about behavioral problems (Maxwell, 1996). Having more space may have a positive effect on the students obeying the classroom rules. In addition, an interesting finding of the study is that participants do not want their parents to know the classroom rules. Moreover, the idea that classroom rules should be linked to positive and/or negative consequences (Alter & Haydon, 2017) is supported in the current study. The classroom rules should be associated with awards and punishment. A student should know the consequences of violating a classroom rule (Harris & Garwood, 2015). In addition, the reinforcement of the behavior of the students who comply with the classroom rules facilitates the adoption of school rules.

Conclusion

An effective classroom management creates a conducive learning environment free from disruptive student behaviors. Classroom rules play a key role in this regard. The current study revealed student expectations and suggestions regarding the determination of classroom rules. The graphical representation of questionnaire items obtained through Bayesian Networks (BNs) demonstrated the verbal relationship between these items. Providing this relationship with a mathematical method revealed the logical integrity of the students in determining the classroom rules.

The findings of the study indicated that students expect the determination of the rules at the beginning of the academic year, do not want to see frequent changes in these rules. They also advocate for consistent application of the rules by their teachers. While the inherent invariance of the rules and the follow-up of their implementation are reiterated by the students, it is also evident that they want to participate in the rule-making process. It is hoped that the instinctive control mechanism will come into play when they follow the rules they establish.

The results also revealed that students want to be involved in the rule-making process, potentially because doing so facilitates internalization of the rules and promotes self-control and social pressure. Students also desire all classmates to adhere to mutually determined classroom rules without exception, and prefer fewer rules with reinforcement from teachers for desired behaviors in accordance with these rules. Additionally, the results indicate that students are more likely to follow classroom rules when the physical environment is not crowded and is clean and tidy and do not want their parents to know these rules.

Taken together, these findings suggest that including students in the rule-making process can facilitate internalization of the rules and create a more desirable learning environment. However, it is necessary to exercise caution in interpreting these results due to the small sample size and specific study group Further research utilizing different age groups, such as high school students, may be necessary to confirm and extend these findings.

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Appendix

Table A1. Questionnaire statements (Koktas, 2009).

Question	Statements
Q1	I can easily adapt to imperative rules
Q2	I cannot adapt to rules in crowded classes
Q3	I can easily adapt rules which are constituted by the teacher
Q4	I can easily adapt to rules in tidy and clean classes
Q5	I easily adapt to rules of which I know the purpose
Q6	My point of view on the rules is different when I am inside the friends' group
Q7	I believe that the rules of the class changed my treatment positively
Q8	If the rules often change, I may be negatively affected
Q9	I can be positively affected when my teacher obeys the rules
Q10	I can easily adapt to the rules that my classmates are participated in democratically
Q11	I can be negatively affected if there are a large number of rules
Q12	The rules remind my lack of discipline
Q13	I can easily obey the rules if I am informed previously
Q14	The gender of my teacher affects me positively
Q15	Compatibility between the rules of the school and class is affected me positively
Q16	If my teacher cares about the rules I am inclined to obey them
Q17	I can easily adapt to the rules if there are punishments and award consequences.
Q18	I can easily adapt to rules if they are in written form
Q19	If the same rules are valid throughout the semester, I may adapt to the rules unwillingly
Q20	I can easily adapt to the rules when my teacher supports my positive behavior
Q21	Positively stated rules affect me more than negative ones
Q22	If the rules include observable behaviors it is easier for me to obey the rules
Q23	If the teacher often reminds me of the rules I may be affected negatively
Q24	When my parents are informed about the rules, I easily adapt to them
Q25	I easily adapt to the rules which are determined at the beginning of the semester
Q26	My teacher's age affects me to obey the rules
Q27	If the rules are applied to the student inequitably, I may be affected negatively
Q28	If the rules are realistic, I may easily adapt to them
Q29	If there are too many rules, this negatively affects me.
Q30	The strict rules are inversely proportional to obedience