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Dear Prof/Dr/Mr/Mrs: Suresh G,

It is my great pleasure to inform you that your paper entitled "Classroom Behavior Mining in Adolescents: A Cognitive and Data-Driven Approach Using BEHAVE_Apriori" is initially ACCEPTED and will be published in the International Journal of Informatics and Communication Technology (IJ-ICT), an open-access peer-reviewed journal indexed by Scopus. This journal was accepted for Scopus indexing on November 9, 2023, and it is now available on the Scopus source page, with coverage starting in 2023 (https://www.scopus.com/sourceid/21101199360). Congratulations!

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International Journal of Informatics and Communication Technology (IJ-ICT) http://ijict.iaescore.com

International Journal of Informatics and Communication Technology (IJ-ICT)
Vol. 99, No. 1, Month 2099, pp. 1~1x
ISSN: 2252-8776, DOI: 10.11591/ijict.v99i1.pp1-1x

Classroom Behavior Mining in Adolescents: A Cognitive and Data-Driven Approach Using BEHAVE_Apriori

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Article Info

Article history:

Received month dd, yyyy
Revised month dd, yyyy
Accepted month dd, yyyy

Keywords:

Cognitive Psychology
Classroom Behaviour Analysis
Feature Selection
Apriori Algorithm

ABSTRACT

Adolescence is a critical developmental stage that leads about essential changes in social, emotional, and cognitive domains that affect conduct in the classroom. Students' perceptions, processing, and reactions to their learning environment are better-understood thanks to cognitive psychology. However, contemporary data mining techniques frequently ignore the environmental, emotional, and cognitive elements influencing teenage behaviour in learning environments. This research presents a comprehensive approach to analyzing teenage college students' classroom behavior by integrating cognitive psychology with data-driven methods to identify key behavioral traits shaped by both external and internal factors. A brand-new algorithm called the Behavioural Evaluation via Hybrid Attributes and Valuable Extraction using the Apriori (BEHAVE_Apriori) approach is presented. Also, a variety of feature selection (FS) strategies, including information gain (IG), chi-squared (CS), and tree-based approaches are used for feature selection (FS). Then, using the Apriori algorithm, association rules are found that relate behaviour patterns to elements like family history, academic involvement, and peer influence. The IG-based feature selection (FS) combined with the Apriori algorithm delivered the best performance, generating 95 rules in 0.0241 seconds, outperforming CS (154 rules, 0.0629s) and tree-based FS (251 rules, 0.1394s), while the unfiltered dataset produced 514 rules in 0.2853 seconds.

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1. INTRODUCTION

Psychology has always placed a high priority on the scientific research of the human intelligence and behaviour. Psychology as the science intentions to understand how persons think, sense, and perform in different settings. It covers various subjects, including personality, mental health, development, emotions, and interpersonal interactions. Cognition researches mental developments like awareness, memory, reasoning, and problem-solving abilities that help us comprehend and interact [1]. Cognitive psychology studies how the brain processes data such as perception, attention, memory, and language to understand how anyone think, learn, and behave. The problem-solving and decision-making capabilities are higher-level cognitive activities that entail analyzing possibilities, applying data to novel circumstances, and choosing the best courses of action. From selecting a professional route to solving a math problem, these skills are critical for day-to-day living [2]. Most data mining models now concentrate on finding statistical correlations rather than addressing the underlying causal mechanisms rooted in cognitive psychology [3]. Although peer impact is recognized, these models frequently overlook the cognitive mechanisms involved in social learning, including internalization, mimicry, and observational learning [4]. Stress, motivation, emotions, and cultural background greatly affect cognition, but are often overlooked or lack strong psychological validation in research. In most mining methodologies, classroom behaviour, which is frequently influenced by cognitive load and task complexity, is not thoroughly examined [5].

A review by Kaur and Puri [6] emphasizes that cognitive psychology shapes classroom behavior by aligning teaching strategies with adolescents' cognitive development, enhancing motivation, emotional regulation, and learning outcomes. Zhou et al. [7] found that physical activity positively impacts cognitive ability in adolescents, especially those with lower baseline cognition, with learning habits and self-education expectations acting as mediators. Fourie and Schlebusch [8], through SEM and HLM, revealed that cognitive and metacognitive engagement improves information processing. Lavie and Hobbiss [9] found that by age 12, adolescents display selective attention abilities similar to adults. Kumari and Biswas [10] revealed that classroom management techniques like clear rules, positive reinforcement, and Social Emotional Learning (SEL) promote positive social behavior and reduce disruptions. Huang and Wan [11] demonstrated that emotional characters in parenting increases social supports of the children and emotion guideline, lowering bullying risk, whereas excessively protective parenting rises vulnerability to mistreatment by weakening confidence and communication abilities. Yang et al. [12] examined daily fluctuations in early adolescents and how classroom interpersonal climate moderates these associations. Morishima et al. [13] examined individual - and classroom-stages advantagnges related to help-seeking behaviors by using generalized mixed-effects models (GMEM). Hillekens, Stark, and Phalet [14] investigated how earlier adolescents' social individualities and behaviors relate to relationship associations in minority-based class networks using Exponential Random Graph Models (ERGM).

Prasad and Khan [15] examined the effects of perceived parenting styles on classroom anxiety and risky behavior among adolescents by employing Structural Equation Modeling (SEM) and PROCESS macro models. Chang, Cai, and Chen [16] developed and validated a model by integrating Sense of Place (SOP), conservation agency, and Pro-Nature Conservation Behavior (ProCoB) using Structural Equation Modeling (SEM). Yajun [17] developed a DL-based model by employing an improved You Only Look Once version 3 (YOLOv3) with Darknet-47 for feature extraction and Histogram of Oriented Gradients (HOG) features for local shape representation. Novak and Reysen [18] examined violence by employing path modeling with data from the LONGSCAN consortium. Petropoulou et al. [19] examined social–cognitive factors among Greek vocational high school students using path analysis and other statistical methods. Yan and Yuan [20] examined how peer interactions affect efficient computer-based problem-solving by utilizing Network Analysis (NA) to model behavioral patterns. Bommersbach, Olfson, and Rhee [21] investigated depressive symptoms by using data from the Youth Risk Behavior Survey (YRBS) and multivariable-adjusted logistic regression analysis. Cai et al. [22] examined alterations in School-Based Health Center (SBHC) utilization employing negative binomial regression and staff interviews. Jarraya et al. [23] employed DL network integrating TimeDistributed layers and BiLSTM layers. Speight, Murphy, and Fitzgerald [24] investigated the effects of the Classwide Functioning Intervention Teams (CW-FIT) classroom-level interdependent group contingency model. Johnstone et al. [25] analyzed the impacts of Class-wide Function-related Intervention Teams (CW-FIT), a positive behavior support classroom management interventions. Giray et al. [26] introduced the Generative AI (GenAI) approach for academic duplicitous, assisted by the Theory of Planned Behavior (TPB).

This research presents an approach to analyzing teenage college students' classroom behavior by integrating cognitive psychology with data-driven methods to identify key behavioral traits shaped by both external and internal factors. A brand-new algorithm called the Behavioural Evaluation via Hybrid Attributes and Valuable Extraction using the Apriori (BEHAVE_Apriori) approach is presented. Also, a variety of feature selection (FS) strategies, including information gain (IG), chi-squared (CS), and tree-based approaches are used for feature selection (FS). Then, using the Apriori algorithm, association rules are found that relate behaviour patterns to elements like family history, academic involvement, and peer influence.

2. METHODS

Finding and choosing the most informative features in a dataset that substantially contribute to the prediction variable or desired output is known as FS. Its objectives include minimizing the computational overhead to speed up model training and prediction, improving prediction performance on unseen data by keeping just the most significant features, and removing redundant or unnecessary features to stop the model from learning noise. Additionally, by avoiding the curse of dimensionality, choosing only the most important features can save the costs of data collection and storage while facilitating efficient management of high-dimensional data. This study employed two filter selection techniques: the CS test and IG, and one embedded FS technique, the tree-based FS technique.

2.1. CS FS Technique

One popular filter-based FS technique is the CS (χ^2) test, which works well for classification problems with categorical features and targets. Assessing the independence of each characteristic from the target variable is the aim of the CS test. More target-dependent features are chosen because they are thought to be more informative. Under the premise of independence, the CS test calculates the difference between observed and anticipated frequencies [27]. A higher CS value shows a larger deviation from independence, which suggests that the feature is more significant for forecasting the target variable.

2.2. Tree Based FS Technique

The automatic determination of feature importance during model training makes tree-based FS techniques popular in ML. Decision trees and ensemble techniques like GB and RF are methods that recurrently divide the dataset into subcatagories according to feature values to reduce a loss function (mean squared error, entropy, or Gini impurity). They automatically assess the significance of every feature throughout this procedure. Following training, the model generates feature significance scores that indicate each feature's relative value or utility in building the trees [28].

2.3. IG FS Method

Many input features are used for classification models; however, not all help make predictions. A metric from information theory called IG is frequently employed in decision trees and FS to assist in determining which features are most pertinent [29]. It calculates the numbers of "information" a feature offers about the target variable or, to put it another way, the amount of uncertainty about the target class that is eliminated once the feature is known. IG enables us to recognize the features that more efficiently provided to precise forecasts by measuring this decrease in uncertainty.

2.4. Apriori Algorithm

In 1994, R. Agrawal and R. Srikant presented the basic algorithm Apriori, which generates Boolean association rules and identifies frequently occurring item sets [30]. It uses the guiding heuristic that subsets of recurrent element sets must likewise be regular. Using an iterative, level-wise approach, the technique creates candidate items of size k+1 through the sets of size k (k-item sets).

3.5. BEHAVE_Apriori Algorithm for Classroom Behaviour Analysis

Adolescent boys and girls between 16 and 25 participated in this study by being questioned in person. The interviews aimed to determine adolescents' issues in their interactions with peers and family.

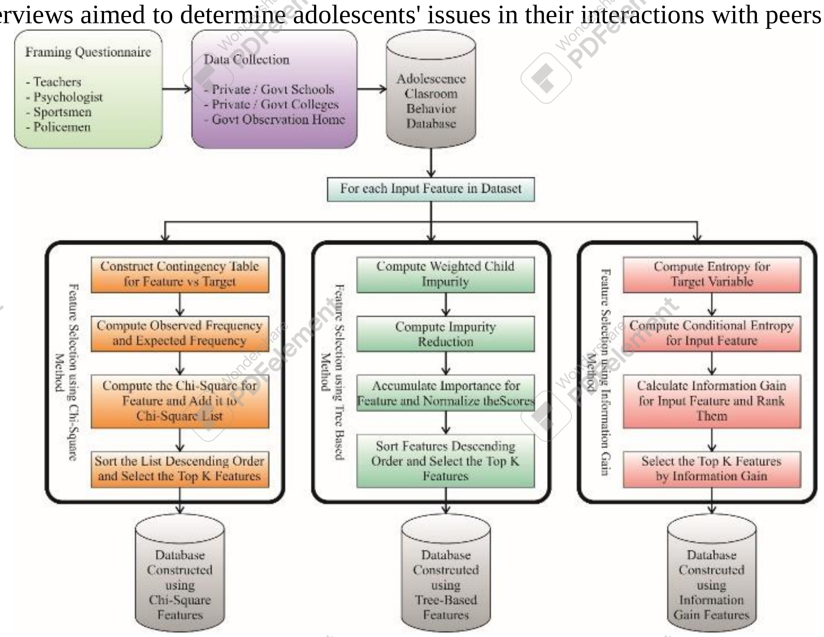

Figure 1. The FS module presents in the BEHAVE_Apriori model

Professional opinions were also sought from psychologists, physicians, athletes, and law enforcement to gain a deeper comprehension of the emotional and personal struggles that college students experience. A thorough, closed-ended questionnaire was created using these observations as a basis. There are 45 questions on the classroom behaviour analysis questionnaire, and questions 1 through 13 ask for personal information, including name, age, and educational background. A total of 2,083 college students

(729 males, 1,354 females) from various institutions in Tamil Nadu's Cuddalore, Chengalpattu, Villupuram, and Sivagangai districts participated in a survey on classroom behavior, using a 32-item closed-ended questionnaire. Most students were aged 16–19 (1,551), followed by 19–23 (501), 23–25 (27), and above 25 (4). The study included both government and private colleges and universities. To analyze the classroom behaviour of teenage college students, this research presents the Behavioural Evaluation via Hybrid Attributes and Valuable Extraction using Apriori (BEHAVE_Apriori) Algorithm. The algorithm functions in two main stages. Figure 1 illustrates the initial FS process using three modules: Correlation-based Selection (CS), tree-based FS, and IG. Each method selects the top k features to create three refined versions of the Classroom Behaviour Dataset. In the next step, shown in Figure 2, the Apriori Association Rule Mining Algorithm is applied separately to each dataset using varied support and confidence thresholds. Metrics like lift, representativity, leverage, and conviction evaluate the results. The combined association rules provide insights to help teachers enhance student-teacher interactions.

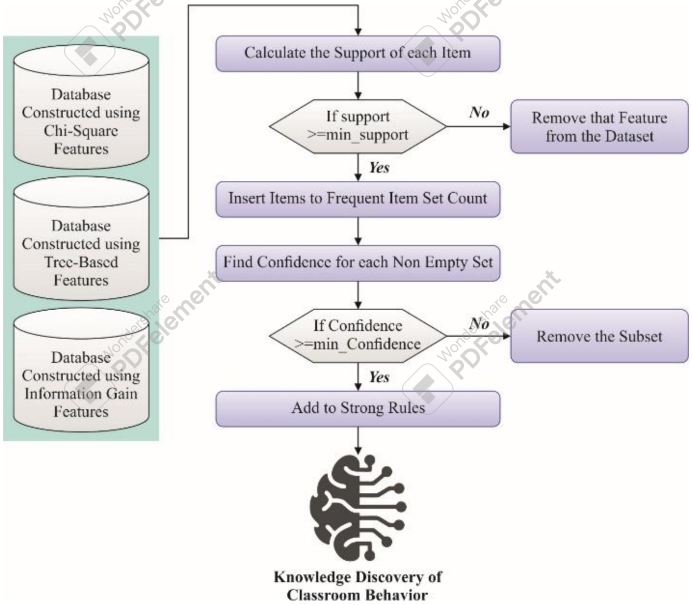

Figure 2. The Apriori algorithm module present in the BEHAVE_Apriori model

3. RESULTS AND DISCUSSION

3.1. FS using CS Method

In the BEHAVE_Apriori method, the CS FS method is implemented using key Python libraries, including NumPy and Pandas for effective data manipulation and Matplotlib.pyplot and Seaborn for data visualization. According to this method, the target variable, which is stored in y and situated at index 130 of the dataset, is assigned to feature matrix X and all other input characteristics. By converting category labels into integer values, the LabelEncoder converts the target variable into a numerical format to aid supervised learning. The CS test is used to assess the statistical dependence between each feature and the target variable by applying the chi2 technique from sklearn.Featual Selection module.

Table 1. Greatest 12 association rules produced by ACT-mine model for attributes chosen by CS FS technique

Rules	Antecedents (LKS)	Consequents (RHS)	Support	Confidence	Coverage	Lift
R1	{'FamilyBackground_rural', 'Parentrelationship_together' }	{'Parentoccupation_Daily wages', 'Course_UG'}	0.75	0.89	0.84	1.37
R2	{'Age_16_to_19', 'Gender_female', 'Parentrelationship_together' }	{'Parentoccupation_daily wages', 'Schoolboard_stateboard'}	0.72	0.88	0.82	1.29
R3	{'Parentoccupation_daily wages', 'Age_16_to_19', 'Gender_female'}	{'Schoolboard_stateboard' }	0.66	0.89	0.74	1.27
R4	{'Parentoccupation_Daily	{'Parentrelationship_toget	0.75	0.85	0.88	1.25

	wages'}	her'}				
R5	{'Age_16_to_19', 'Gender_female', 'Parentrelationship_together' }	{'Schoolboard_stateboard' }	0.68	0.84	0.82	1.23
R6	{'Parentoccupation_Daily wages', 'Schoolboard_stateboard', 'Medium_Tamil'}	{'Age_16_to_19'}	0.61	0.82	0.74	1.22
R7	{'Medium_Tamil', 'Parentoccupation_Daily wages', 'Schoolboard_stateboard', 'Parentrelationship_together' }	{'Age_16_to_19'}	0.72	0.82	0.88	1.22
R8	{'Parentoccupation_Daily wages', 'Age_16_to_19', 'Medium_Tamil'}	{'Schoolboard_stateboard' , 'Parentrelationship_together'}	0.68	0.81	0.84	1.21
R9	{'Age_16_to_19', 'Schoolboard_stateboard', 'Gender_female', 'Parentrelationship_together' }	{'Parentoccupation_Daily wages'}	0.61	0.81	0.75	1.21
R10	{'Ugnature_Boys Only'}	{'Parentoccupation_Daily wages', 'Parentrelationship_together'}	0.68	0.84	0.82	1.20
R11	{'Parentoccupation_Daily wages', 'Age_16_to_19', 'Course_UG', 'Parentrelationship_together' }	{'Schoolboard_stateboard' }	0.61	0.82	0.74	1.19
R12	{'Medium_Tamil', 'Age_16_to_19'}	{'Parentoccupation_Daily wages'}	0.72	0.88	0.82	1.16

The CS values are found in the output chi_scores[0], where larger values denote a feature's greater importance. The mutual information between each feature and the target variable is also calculated using the mutual_info_classif method. This measure, with scores ranging from 0 (no reliance) to 1 (full dependency), assesses the amount of information shared across variables. The outcomes are similarly converted into pandas.series, arranged in decreasing order, and presented in an interpretable bar chart. The SelectKBest approach, which finds and keeps the top k features (in this example, k = 50) based on their CS scores, is used to choose the most pertinent features.

3.2. Frequent Pattern Mining using Apriori Algorithm

The dataset was handled and altered using the panda's Python package. The time library was imported to monitor the algorithm's execution time. The lxtend.frequent_patterns library includes the association_rules function and the apriori technique for pattern mining. The time.time() method, which is written at the start and finish of the apriori process, was used to measure the beginning and ending times. The total records (rows) in the dataset are determined using the num_transactions method, and the total number of frequent itemsets in the classroom behaviour datasets is determined using the num_frequent_itemsets method. The num_association_rules method was employed for calculating the total number of association rules produced via the Apriori Algorithm. The Apriori algorithm's complete performance measurements and other outputs were methodically assembled and exported to an Excel file for additional examination and interpretation. Table 1 illustrates the greatest 12 association rules created by ACT-mine method.

Table 2. Comparitive evalution of performance metrics for four Apriori-based methods

	Apriori	Apriori-Chisquare	Apriori-Treebased	Apriori-Infogain
Execution Time	0.2853 sec	0.0629 sec	0.1394 sec	0.0241 sec

Numbers of transactions	2083	2083	2083	2083
Numbers of frequent Itemsets	514	154	215	95
Number of Association Rules Generated	1155	304	225	188
Representativity	1	1	1	1
Leverage	0.009	0.009	0.011	0.008
Conviction	1.123	1.136	1.143	1.134
Zhangs_Metric	0.046	0.049	0.059	0.045
Jaccard	0.432	0.449	0.436	0.469
Certainty	0.083	0.080	0.095	0.079
Kulczynski	0.648	0.659	0.646	0.673

The original classroom behaviour analysis dataset and the three databases created by FS approaches were assessed to the Apriori Algorithm. The performance metrics displayed in Table 2 were used to gauge the effectiveness of Apriori method. The IG-based dataset had the quickest execution time (0.0241 seconds) out of the four analyzed datasets, whereas the raw dataset took the longest (0.2853 seconds) because of its higher dimensionality. All datasets maintained a constant number of transactions (2083) despite differences in FS methods, guaranteeing consistency in the study. The IG-based dataset yielded the fewest frequent itemsets (95), while the raw dataset produced the most (514). This decrease is ascribed to the IG method's stricter and more restrictive criteria, which only keep the most pertinent characteristics. The creation of association rules showed a similar pattern: the raw dataset produced the most rules (1155), while the IG-based dataset produced the fewest (188), suggesting a better-targeted and less redundant set of rules.

4. CONCLUSION

Using cutting-edge data mining techniques and cognitive psychology concepts, this research introduces the BEHAVE_Apriori algorithm as a new and efficient method for examining teenage classroom behaviour. The model efficiently determines the most pertinent behavioural characteristics using hybrid FS techniques like IG, CS, and tree-based approaches while drastically lowering the Apriori algorithm's computing complexity. The results show that in addition to improving rule generation efficiency, the suggested paradigm offers profound insights into how environmental, emotional, and cognitive aspects affect teenage behaviour in learning environments. By bridging the gap between algorithmic analysis and cognitive theory, this model provides educators, psychologists, and policymakers with a valuable tool for creating a more encouraging and productive learning environment. In the long run, the BEHAVE_Apriori algorithm advances targeted treatments for behavioural support, leadership development, and ethical education while advancing the understanding of adolescent growth. The limitations include contextual settings, which may limit the generalization across various sectors. Future work should concentrate on analyizing the model with wide datasets, longitudinal designs, and real-world applications to strengthen robustness and practical impact.

ACKNOWLEDGEMENT: Not Applicable
FUNDING STATEMENT: The authors are received no funding for this study.
DATA AVAILABILITY STATEMENT: data sharing not applicable to this article as no datasets were generated or analyzed during the current study.
AUTHOR CONTRIBUTIONS:

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
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S. Muthukumaran		✓	✓		✓	✓		✓	✓	✓	✓	✓		
B. Kamatchy	✓		✓	✓	✓		✓			✓	✓		✓	✓
N. Kalaichelvi		✓		✓		✓	✓	✓	✓	✓	✓	✓		
K. Nandhini	✓		✓	✓	✓		✓		✓	✓	✓		✓	✓

CONFLICT OF INTEREST: The authors declare that they have no conflict of interest. All authors have given approval to the final version of the manuscript.

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