World Academy of Science, Engineering and Technology
International Journal of Educational and Pedagogical Sciences
Vol:14, No:12, 2020

Pattern Discovery from Student Feedback: Identifying Factors to Improve Student Emotions in Learning

Angelina A. Tzacheva, Jaishree Ranganathan

Abstract—Interest in (STEM) Science Technology Engineering Mathematics education especially Computer Science education has seen a drastic increase across the country. This fuels effort towards recruiting and admitting a diverse population of students. Thus the changing conditions in terms of the student population, diversity and the expected teaching and learning outcomes give the platform for use of Innovative Teaching models and technologies. It is necessary that these methods adapted should also concentrate on raising quality of such innovations and have positive impact on student learning. Light-Weight Team is an Active Learning Pedagogy, which is considered to be low-stake activity and has very little or no direct impact on student grades. Emotion plays a major role in student's motivation to learning. In this work we use the student feedback data with emotion classification using surveys at a public research institution in the United States. We use Actionable Pattern Discovery method for this purpose. Actionable patterns are patterns that provide suggestions in the form of rules to help the user achieve better outcomes. The proposed method provides meaningful insight in terms of changes that can be incorporated in the Light-Weight team activities, resources utilized in the course. The results suggest how to enhance student emotions to a more positive state, in particular focuses on the emotions 'Trust' and 'Joy'.

Keywords—Actionable pattern discovery, education, emotion, data mining.

I. Introduction

EDUCATION is considered to be an indispensable need in today's world. It is continuously evolving to meet the challenges of the fast-changing and unpredictable globalized world. There is a lot of importance and attention paid to improve students educational outcomes throughout the world [1]. Therefore the educational institutions and the instructors are expected to innovate the theory and practice of teaching and learning, and other aspects of the organization to ensure quality preparation of all students to life and work [2]. In 1964 the book "Innovation in Education" [3] states that changes and revolution are in progress in education. It is almost 55 years since then, even now it is of high demand that education at all level needs renewal [2]. According to Merriam Webster Dictionary Innovation is the introduction of a new idea, or change made to existing idea. When we think of innovation in terms of education, it can be applied as a teaching technique, pedagogical approach, learning style or process, and institutional structure.

Active Learning is one such pedagogy or approach that is gaining attention and popular in higher education. Lightweight teams are an Active Learning approach where students work together in a group, but they have very little or no direct impact on their final grades [4]. There are lot of works on this area, but none of them use the psychological perspective of identifying student emotions and identifying patterns to suggest how to enhance student emotions.

Emotion is a primary concern in younger generation students that have major impact on the productivity in school. The emotional influence does not stop at high school or university but may have lifelong consequences in future career outcomes. Emotion influences the thought and behavior of individuals. It is associated with different psychological phenomena, including personality, mood, and motivation. How students feel or their emotion towards a classroom, teaching style, and learning approach helps motivate them to achieve better outcomes. There is an increasing effort by universities all over the world to collect student feedback. Besides various limitations, the student survey of teaching and learning provides valuable insights [5]–[8].

In this paper, we propose an approach of using student feedback for courses labeled with emotion and provide suggestions on how to enhance emotions, Fig. 1. This in turn leads to better teaching style, learning outcomes and a comprehensive environment. For this purpose we use actionable pattern discovery method. Actionable patterns are patterns that help benefit the user to achieve better outcomes. Action rule mining is one of the actionable pattern mining approach. Action Rule mining is a rule based data mining method that helps extract Action Rules. Action Rules are extracted from a decision system that suggest possible transition of data from one state to another [9]. Such rules can be used to benefit the user.The formal definition of Action Rule [9] is defined as in (1).

$$[(\omega) \wedge (\alpha \rightarrow \beta)] \Rightarrow (\phi \rightarrow \psi) \quad (1)$$

where ω is conjunction of fixed condition features shared by both groups, $(\alpha \rightarrow \beta)$ represents changes in flexible attributes, and $(\phi \rightarrow \psi)$ is the desired change in the decision attribute or attribute whose change benefits the user. In literature authors have used actionable patterns for wide range of applications including medicine, business, social media [10], [11]. There is no work in the area of education data mining especially use of emotion mining from student feedback and actionable pattern discovery. The reminder of the paper is as follows: Section II - related works, Section III - methodology, Section IV - experiments and results followed by conclusions and future works.

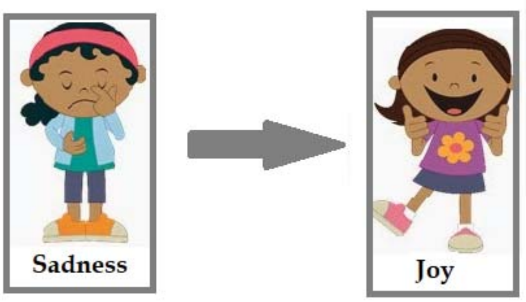

Fig. 1 Enhance Student Emotions

II. Related Work

There is a wide range of research in the field of education and data mining with different methods and applications. The applications are categorized as (1) applications that focus on the objective of the task and (2) applications that focus on the end user. In this section we have a brief discussion about such literature in the field of education.

Bakhshinategh et al. [12] classify the Education Data Mining tasks into different subcategories based on their applications. One of them is representing the cognitive aspects of students. Some of the works in this area include predicting student performance [13], identifying their motivational level [14], use of clustering and classification methods to predict undesirable student performance [15].

Sentiment Analysis has gained popularity in the recent years in the field of education. Several researchers focus on the task of identifying sentiments (positive, negative, or neutral) from students comments. The main objective of their work is to understand the effect of teaching by using student ratings and feedback. Jagtap et al. [16] propose hybrid approach combining Hidden Markov Model and Support Vector Machine for classifying student feedback data into ‘positive’ and ‘negative’ categories. Rajput et al. [17] utilize sentiment dictionary to derive sentiment scores on student feedback data and compare the scores with Likert-scale based teacher evaluation. They also use word cloud along with sentiment scores and provide insights about teacher’s performance.

Qualitative student feedback is used to identify fine grained emotion. In [18], [19] authors collect end of semester student feedback and process the qualitative text comments. They propose approach of automatic labeling of text comments with fine grained emotions such as ‘joy’, ‘anticipation’, ‘trust’, ‘anger’, ‘fear’, ‘disgust’, ‘sadness’, ‘surprise’. and assess the effectiveness of the Light-weight team teaching model. They have used visualization of the emotion labeled data for the purpose of analyzing the effectiveness of Active Learning pedagogies. These applications provide information to educators on how certain strategies or teaching methodology helps in the learning process and student outcomes.

All of the above applications focus only on identifying if certain tasks work well or not in the education setting. In this work we propose an approach of using student feedback data with fine grained emotion to identify patterns and suggest improvements. This helps teachers and the management to understand various factors that need attention or change for betterment of both teaching and learning.

III. Methodology

In this section we present our proposed approach of Data Collection and Actionable Pattern mining methods.

A. Data Collection

Web-based student survey data are collected from a public research university in the United States. The survey was designed to provide insight on how students feel about the courses that include Active Learning pedagogies and other factors that help in their learning process. The data collected is part of the courses that implemented and followed the same teaching methodology and style. This dataset has close to 50 attributes. The details of data collection process is described in Fig. 2.

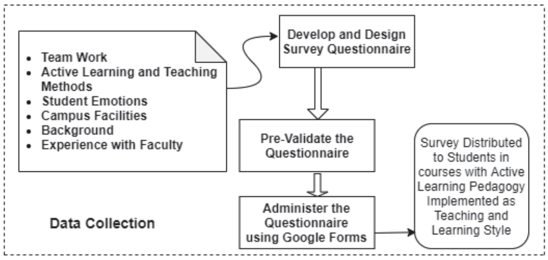

Fig. 2 Data Collection Process

Table I shows some of the sample questions on the survey.

TABLE I
Sample Survey Questions

Survey Questions
Did you gain any Benefits from Group Assignments?
Course group helped me get acquainted with students from different background
The class discussions are with the subject matter

TABLE II
Dataset Properties: Student Survey Data

Property	Student Survey Data
Attributes	59 attributes including - Team-Sense of Belonging - Team Member Responsibility - Team Work Helped Diversity - Group Assignment Benefits - Video Case Assignments - Helpfulness - Active Learning Method - Rating - Flipped Class Helped Better Learning - Peer Teaching Helped Better Learning - Student Emotion

The survey collected basic demographic information including gender, ethnicity, school year. Fig. 3 shows the gender distribution in the collected data including ‘Male’, ‘Female’, ‘Other’, and ‘Prefer Not to Answer’.

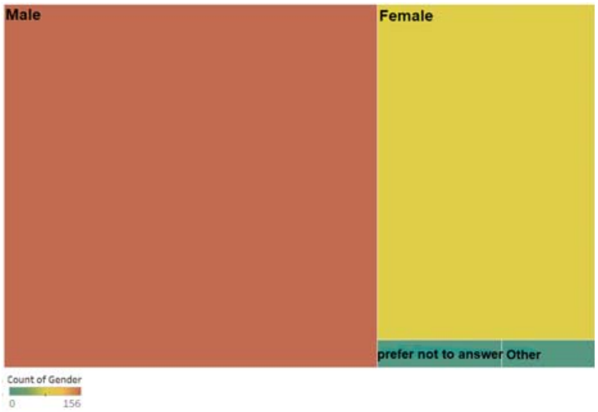

Fig. 3 Gender Distribution in the Dataset

The student population include students from both graduate and undergraduate courses. The survey included options of freshman, sophomore, junior, senior or more and Masters. We could see the distribution of data based on School year in Fig. 4.

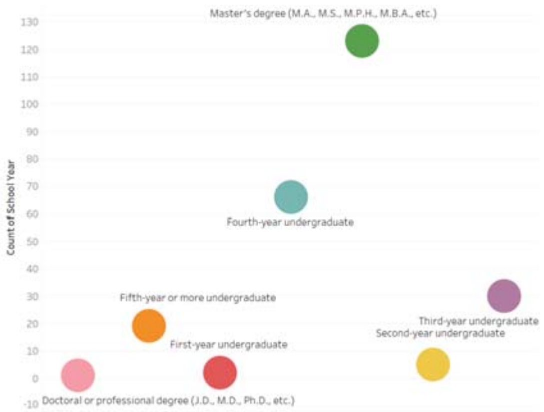

Fig. 4 School Year Distribution in the Dataset

The student population, Fig. 5, includes students from different ethnicity, with majority White, and Asian.

B. Data Processing

The data are pre-processed in order for it to be suitable for pattern discovery process. Pre-processing involves removal of special characters like '-', spaces, '/'. The whole survey data consisted upto 60 attributes in the following categories: Team Work, ActiveLearning and TeachingMethod, Emotions, Experience with Faculty, Background, Campus Facilities. These categories are used to split the data into three parts to provide meaningful insights from the experiments, Table III

C. Action Rule Mining

In this paper, we propose to use the approach of hybrid Action Rule generation, combining the rule based and object based approach of Action Rule mining [20] for enhancing student emotions. The hybrid algorithm is implemented in Spark [21], runs separately on each subtable

TABLE III
DATA CATEGORIES

S.No	Category
Data1	TeamWork, Student Emotion
	ActiveLearning
Data2	TeachingMethod
	StudentEmotion

and does transformations like map(), flatmap(), join() and other distributed operations. The algorithm pseudocode is given in Algorithm 1.

Algorithm 1: Hybrid Action rule Mining

Result: Action Rules
Input: certainRules, decisionFrom, decisionTo, support, confidence;
while *Rule r in certainRules* **do**
  instructions;
  if *consequent(r) equals decisionTo* **then**
    Form ActionRuleSchema(r);
    ARS = ActionRuleSchema(r);
  else
    continue;
  end
end
while *schema in ARS* **do**
  Identify objects satisfying schema;
  Form subtable;
  Generate frequent action sets using Apriori;
  Combine frequent action sets to form Action Rules;
  Result = Action Rules
end

TABLE IV
INFORMATION SYSTEM Z

X	A	B	C	E	F	G	D
x_1	A_1	B_1	C_1	E_1	F_2	G_1	D_1
x_2	A_2	B_1	C_2	E_2	F_2	G_2	D_3
x_3	A_3	B_1	C_1	E_2	F_2	G_3	D_2
x_4	A_1	B_1	C_2	E_2	F_2	G_1	D_2
x_5	A_1	B_2	C_1	E_3	F_2	G_1	D_2
x_6	A_2	B_1	C_1	E_2	F_3	G_1	D_2
x_7	A_2	B_3	C_2	E_2	F_2	G_2	D_2
x_8	A_2	B_1	C_1	E_3	F_2	G_3	D_2

We now give an example of how the algorithm works with the help of Decision System, Table IV. The information system in Table IV is denoted as Decision system if the attributes M are classified into flexible M_{fl} , stable st and decision d, *mathdsM* $= (M_{st}, M_{fl}, \{d\})$. From Table IV M_{st} = $\{A, B, C\}$, M_{fl} = $\{E, F, G\}$, and d = D. In this example we intend to re-classify the decision attribute D from $D_2 \rightarrow D_1$. First the algorithm Algorithm 1 uses LERS method to extract the certain classification rules and generate Action Rule schemas as given in (2) and (3). Then the algorithm proceeds

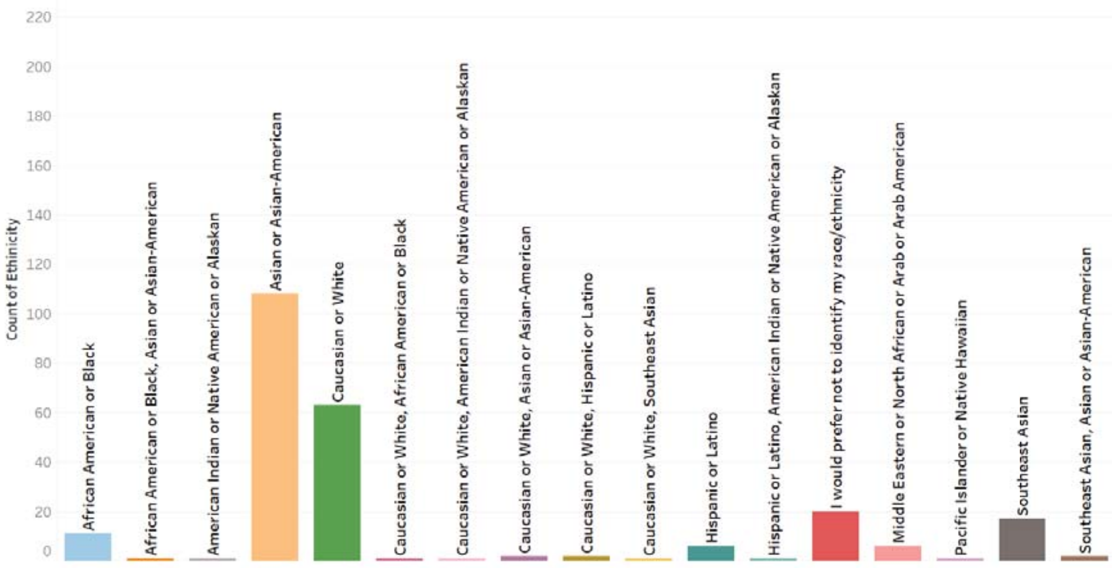

Fig. 5 Ethnicity Distribution in the Dataset

by creating subtable based for each of the Action Schema. For instance (2) generates the subtable Table V.

$$[\mathrm{B}_1 \wedge \mathrm{C}_1 \wedge (\mathrm{F}, \rightarrow \mathrm{F}_1) \wedge (\mathrm{G}, \rightarrow \mathrm{G}_1)] \rightarrow (\mathrm{D}, \mathrm{D}_2 \rightarrow \mathrm{D}_1). \quad (2)$$

$$[(\mathrm{E}, \rightarrow \mathrm{E}_1)] \rightarrow (\mathrm{D}, \mathrm{D}_2 \rightarrow \mathrm{D}_1). \quad (3)$$

TABLE V
SUBTABLE FOR ACTION RULE SCHEMA

X	B	C	F	G	D
x_1	B_1	C_1	F_2	G_1	D_1
x_3	B_1	C_1	F_2	G_3	D_2
x_6	B_1	C_1	F_3	G_1	D_2
x_8	B_1	C_1	F_2	G_3	D_2

Association Action Rule extraction is an exhaustive Apriori based method which extracts complete set of Action rules by taking all possible combinations of the action terms. It is an iterative procedure and does not scale very well in case of dense and high dimensional dataset. In this work we create subtables by using the Action Rule Schema in a highly dense data as explained above. We perform Association Action Rule extraction algorithm on each of the subtables in parallel which allows the algorithm to complete and generate rules in a much faster time compared to the existing algorithms and systems. In our sample dataset example, the algorithm generates following Action Rules, (4) based on the subtable Table V.

$$[\mathrm{B}_1 \wedge \mathrm{C}_1 \wedge (\mathrm{F}, \rightarrow \mathrm{F}_1) \wedge (\mathrm{G}, \mathrm{G}_3 \rightarrow \mathrm{G}_1)] \rightarrow (\mathrm{D}, \mathrm{D}_2 \rightarrow \mathrm{D}_1). \quad (4)$$

The overall operating methodology is shown in Fig. 6.

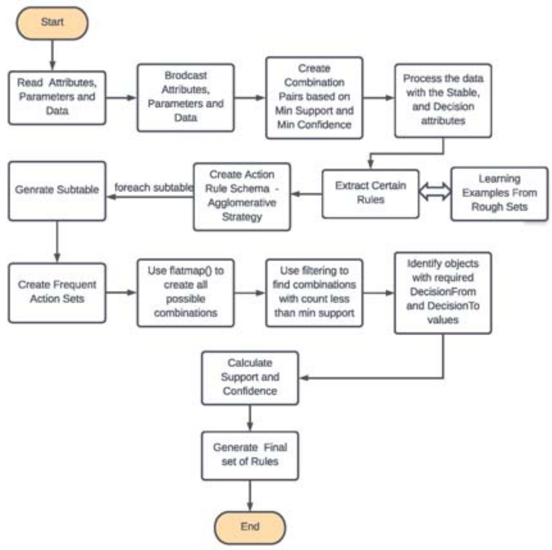

Fig. 6 Hybrid Action Rule Algorithm - Flowchart

IV. EXPERIMENTS AND RESULTS

The original dataset is replicated for scalabilty testing which include approximately 50,000 instances. We divided the dataset into two parts depending on the questions in the survey and conducted separate experiments for each of the data parts.

A. Student Survey Data 1 - Team Work and Student Emotion

These data consist of 8 attributes and the corresponding student emotion. These attributes are derived from the survey questions that focus on the Light-Weight team work activities and assignments. Table VI shows sample action rules extracted using this data.

Let us consider the action rule AR_{AT1}. This rule suggests that if the team members are technically effective, number of members in the team are in the range of 5 to 7 students,

TABLE VI
SAMPLE ACTION RULES - DATA 1 - TEAM WORK AND STUDENT EMOTION

Enhance Student Emotion - Anticipation → Trust

1) AR_{AT1} : $(LikeTeamWork, 4QuiteaBit \rightarrow 5VeryMuch) \wedge (TeamSenseofBelonging, 3AverageSenseofBelongingtotheTeam \rightarrow 4CompleteSenseofBelongingtotheTeam) \wedge (TeamMemberResponsibility, HelpfulMembers \rightarrow TechnicallyEffectiveMembers) \wedge (NumberofTeamMembers = 5to7) \implies (StudentEmotion, Anticipation \rightarrow Trust)[Support : 108, Confidence : 100\%]$
2) AR_{AT2} : $(TeamMemberResponsibility, HelpfulMembers \rightarrow TechnicallyEffectiveMembers) \wedge (TeamWorkHelpedDiversity, 2Occasionally \rightarrow 2Occasionally) \wedge (GroupAssignmentBenefit, SharedKnowledge \rightarrow AllofThem) \implies (StudentEmotion, Anticipation \rightarrow Trust)[Support : 108, Confidence : 75.3\%]$

Enhance Student Emotion - Sadness → Joy

1) AR_{SJ1} : $(LikeTeamWork, 3Somewhat \rightarrow 5VeryMuch) \wedge (GroupAssignmentBenefit, EliminateStress \rightarrow AllofThem) \implies (StudentEmotion, Sadness \rightarrow Joy)[Support : 36, Confidence : 100\%]$
2) AR_{SJ2} : $(TeamFormation = 3Average) \wedge (TeamSenseofBelonging = 3AverageSenseofBelongingtotheTeam) \wedge (TeamMemberResponsibility, ResponsibleMembers \rightarrow TechnicallyEffectiveMembers) \wedge (GroupAssignmentBenefit, EliminateStress \rightarrow AllofThem) \implies (StudentEmotion, Sadness \rightarrow Joy)[Support : 36, Confidence : 50\%]$

and they feel a complete sense of belonging in the team then the student emotion could be changed from 'Anticipation' to 'Trust'. This provides an useful insight to the course instructor, that more attention is required when forming team members. The instructor should consider the technical complexity of the assignments or activities. Based on the complexity, the instructor could choose to have a poll at the beginning of the semester requesting students to state their level of expertise in each area required for the assignments in general. These results may provide a basic idea on the technical capability of students in the class, based on which the instructor could then form the teams. This way the Team Members formation would be more efficient and helpful to the students. Also the rule suggests that students feel better with 5 to 7 members in the team.

B. Student Survey Data 2 - Active Learning, Teaching Method, and Student Emotion

These data consist of 11 attributes and the corresponding student emotion. These attributes are derived from the survey questions that focus on the Active Learning method adopted for the courses and the teaching method.

Table VII shows sample action rules extracted using this data.

TABLE VII
SAMPLE ACTION RULES - DATA 2 - ACTIVE LEARNING, TEACHING METHOD, AND STUDENT EMOTION

Enhance Student Emotion - Anticipation → Trust

1) AR_{AT3} : $(ExamPrepGuidesSampleQuestions Helpfulness, 3 \rightarrow 5) \wedge (SyllabusAssignmentsPriorAvailabilityHelped = 5) \wedge (VideoCasesAssignmentsHelpful = 5) \wedge (IndividualAssignments, 3 \rightarrow 5) \implies (StudentEmotion, Anticipation \rightarrow Trust)[Support : 148, Confidence : 66.4\%]$
2) AR_{AT4} : $(ExamPrepGuidesSampleQuestions Helpfulness, 3 \rightarrow 4) \wedge (ActiveLearningMethodologyVs TraditionalMethod, 3 \rightarrow 5) \implies (StudentEmotion, Anticipation \rightarrow Trust)[Support : 110, Confidence : 60.99\%]$

Enhance Student Emotion - Sadness → Joy

1) AR_{SJ3} : $(OpenBookExamHelpsLowerAnxiety = 5) \wedge (ExamPrepGuidesSampleQuestionsHelpfulness, 3 \rightarrow 4) \wedge (SyllabusAssignmentsPriorAvailabilityHelped, 1 \rightarrow 5) \wedge (PeerTeachingInTeamsHelpSelfLearning = 4) \implies (StudentEmotion, Anticipation \rightarrow Trust)[Support : 37, Confidence : 100\%]$
2) AR_{SJ4} : $(VideoCasesAssignmentsHelpful, 3 \rightarrow 5) \wedge (FlippedClassHelpsBetterLearning, 2 \rightarrow 4) \wedge (PeerTeachingHelpedUnderstanding = 2) \implies (StudentEmotion, Anticipation \rightarrow Trust)[Support : 36, Confidence : 100\%]$

Let us consider the action rule AR_{AT5}. This rule suggests that there is needed some improvement in terms of exam preparation guides provided for the students. In other words if $(ExamPrepGuidesSampleQuestionsHelpfulness, 3 \rightarrow 5)$ and the Individual assignment $(IndividualAssignments, 3 \rightarrow 5)$ then there is a good chance that students feel better in the learning process, which would ultimately lead to better outcomes.

V. LIMITATIONS

It is evident from this kind of survey data using the suggested methods of Action Rule Mining, we can extract meaningful insights in terms of the advantages, and improvements of teaching style, material provided, and learning methods adopted. This study was conducted in a single institution with limited number of participants in courses offered in computer science. The results as part of this study are exploratory and provide approaches for such analysis that helps in innovation in education, but does not provide conclusive evidence. This is especially because of the limitation in the number of participants.

VI. CONCLUSIONS AND FUTURE WORKS

In this study we propose an approach of identifying patterns and enhancing student emotions based on Student Survey Data. We propose to use Actionable Pattern Mining framework called Action Rule Mining. The data collected for this study are original data, with specifically designed questions, collected by the authors, from a public research university in United States. This kind of data collected in educational setting combined with the Action Rule Mining method provides intuitive information on how student emotions can be altered from negative $\rightarrow$ positive, or neutral $\rightarrow$ positive, including classroom environment, teaching style, teamwork, and school facilities. In future we plan to apply the results to classroom teaching and online courses. Then collect the data for further analysis of the results, in terms of student performance and emotions. This helps us identify the generalized nature of the actionable suggestions obtained and how the results obtained from previous data is applicable when the student population changes.

REFERENCES

[1] V. Svenja, K. David, K. Eckhard, and B. Sonja, *TALIS teaching practices and pedagogical Innovations evidence from TALIS: Evidence from TALIS*. OECD Publishing, 2012.

[2] P. Serdyukov, "Innovation in education: what works, what doesnt, and what to do about it?" *Journal of Research in Innovative Teaching & Learning*, vol. 10, no. 1, pp. 4–33, 2017.

[3] M. B. Miles, *Innovation in education*. Bureau of Publication, Teachers College, Columbia University, 1964.

[4] C. Latulipe, N. B. Long, and C. E. Seminario, "Structuring flipped classes with lightweight teams and gamification," in *Proceedings of the 46th ACM Technical Symposium on Computer Science Education*. ACM, 2015, pp. 392–397.

[5] E. Santhanam, B. Lynch, and J. Jones, "Making sense of student feedback using text analysis–adapting and expanding a common lexicon," *Quality Assurance in Education*, vol. 26, no. 1, pp. 60–69, 2018.

[6] L. Alderman, S. Towers, and S. Bannah, "Student feedback systems in higher education: A focused literature review and environmental scan," *Quality in Higher Education*, vol. 18, no. 3, pp. 261–280, 2012.

[7] L. Harvey, "The nexus of feedback and improvement," in *Student Feedback*. Elsevier, 2011, pp. 3–26.

[8] S. Palmer, "Student evaluation of teaching: keeping in touch with reality," *Quality in higher education*, vol. 18, no. 3, pp. 297–311, 2012.

[9] Z. W. Ras, A. Dardzinska, L.-S. Tsay, and H. Wasyluk, "Association action rules," in *IEEE/ICDM Workshop on Mining Complex Data (MCD 2008), Pisa, Italy, ICDM Workshops Proceedings,*. IEEE Computer Society, 2008, pp. 283–290.

[10] J. Ranganathan, A. S. Irudayaraj, A. Bagavathi, and A. A. Tzacheva, "Actionable pattern discovery for sentiment analysis on twitter data in clustered environment," *Journal of Intelligent & Fuzzy Systems*, vol. 34, no. 5, pp. 2849–2863, 2018.

[11] J. Ranganathan and A. Tzacheva, "Emotion mining in social media data," in *Proceedings of the 23rd International Conference on Knowledge-Based and Intelligent Information & Engineering Systems: KES2019, Procedia Computer Science journal*, vol. 159. Elsevier, 2019, pp. 58–66.

[12] B. Bakhshinategh, O. R. Zaiane, S. ElAtia, and D. Ipperciel, "Educational data mining applications and tasks: A survey of the last 10 years," *Education and Information Technologies*, vol. 23, no. 1, pp. 537–553, 2018.

[13] L. D. Miller, L.-K. Soh, A. Samal, K. Kupzyk, and G. Nugent, "A comparison of educational statistics and data mining approaches to identify characteristics that impact online learning." *Journal of Educational Data Mining*, vol. 7, no. 3, pp. 117–150, 2015.

[14] M. Cocea and S. Weibelzahl, "Can log files analysis estimate learners' level of motivation?" in *LWA*. University of Hildesheim, Institute of Computer Science, 2006, pp. 32–35.

[15] J. Bravo and A. Ortigosa, "Detecting symptoms of low performance using production rules." *International working group on educational data mining*, 2009.

[16] B. Jagtap and V. Dhotre, "Svm and hmm based hybrid approach of sentiment analysis for teacher feedback assessment," *International Journal of Emerging Trends & Technology in Computer Science (IJETTCS)*, vol. 3, no. 3, pp. 229–232, 2014.

[17] Q. Rajput, S. Haider, and S. Ghani, "Lexicon-based sentiment analysis of teachers evaluation," *Applied Computational Intelligence and Soft Computing*, vol. 2016, p. 1, 2016.

[18] A. Tzacheva, J. Ranganathan, and R. Jadi, "Multi-label emotion mining from student comments," in *Proceedings of the 2019 4th International Conference on Information and Education Innovations*, ser. ICIEI 2019. New York, NY, USA: ACM, 2019, pp. 120–124. [Online]. Available: http://doi.acm.org/10.1145/3345094.3345112

[19] A. Tzacheva and J. Ranganathan, "Emotion mining from student comments a lexicon based approach for pedagogical innovation assessment," *The European Journal of Education and Applied Psychology*, pp. 3–13, 2018.

[20] J. Ranganathan, S. Sharma, and A. Tzacheva, "Hybrid action rules: Rule based and object based," in *Proceedings of the 2020 International Conference on Compute and Data Analysis*. ICCDA, 2020, pp. 1–5.

[21] M. Zaharia, M. Chowdhury, M. J. Franklin, S. Shenker, and I. Stoica, "Spark: Cluster computing with working sets." *HotCloud*, vol. 10, no. 10-10, p. 95, 2010.

Open Science Index, Educational and Pedagogical Sciences Vol:14, No:12, 2020 publications.waset.org/10011679/pdf