Enriching the Student Model in an Intelligent Tutoring System

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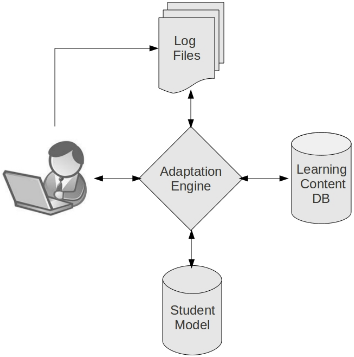
Outline

Objective

To create a model to detect and respond to affective states of the students when they interact with an Intelligent Tutoring System (ITS).

Intelligent Tutoring System (ITS)

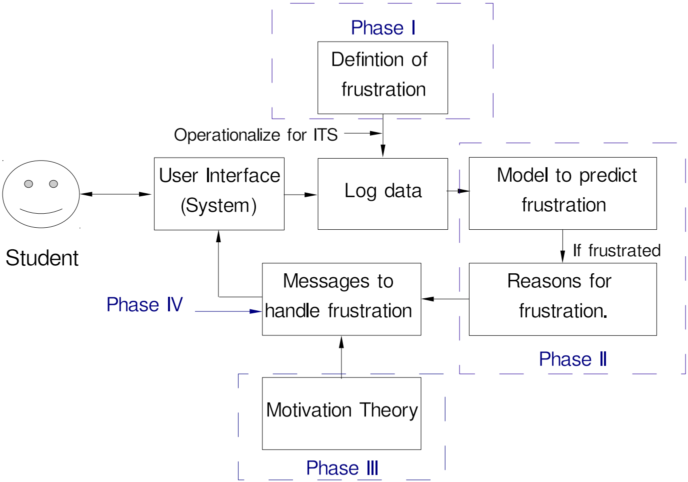
ITS dynamically adapts the learning content based on learner's needs and preferences.



Affective components in Student Model

- The learning process involves both cognitive and affective processes and the consideration of affective processes has been shown to achieve higher learning outcomes [29].
- The importance of the students' motivation and the affective component in learning has led adaptive systems such as ITS to include learners' affective states in their student models.
- Affective states used in affective computing research: Frustration, Boredom, Confusion, Engaged Concentration, Delight, and Surprise.

Methodology



Affect Recognition

- To include affective states in the student model, students' affective states should be identified and responded to, while they interact with the ITS.
- In affective computing, detecting affective states is a challenging, key problem as it involves emotions–which cannot be directly measured; it is the focus of several current research efforts [32], [9].

Affect Recognition

In order to respond to students' affective states, the following methodologies are employed to identify affective states of students while they interact with ITS.

1. Human observation [18], [47], [4]
2. Learner's self reported data [5], [6]
3. Using sensing devices such as physiological sensors [7], [8], [83], [84]
4. Face-based emotion recognition systems [29], [102], [79], [80], [81], [82]
5. Mining the data from the student log [30], [31], [27], [46]
6. Modeling affective states [6], [10]

Affect Recognition

- Identifying affective states using the sensor signals is possible in laboratory settings, but difficult to implement at a large scale. Also, the physiological sensors are intrusive to the users.
- Facial analysis methods use a web-cam to analyze the facial expressions of the users. In the real-world scenario, keeping the camera in the right position, and expecting users to face the camera all the time is not feasible.
- Voice and text analysis methods can only be used in the ITS that considers voice and subjective answers as an input from the users.

Our Context

System: Mindspark, a commercial ITS implemented in large scale.

Affective State: Frustration.

Method: Modeling the data from student log.

- A commercial mathematics ITS developed by Educational Initiatives India (EI-India)
- Incorporated into the school curriculum for different age groups (grade 3 to 8) of students [21].
- Mindspark is currently being implemented in more than hundred schools and being used by 80,000 students across India.
- Mindspark adaptation logic is based on student's response to the question, question's difficulty level and student's education background.
- Sparkies are the reward points to motivate the students.

Related Work - Predicting Affective States

Table: Research Works, that Identify Frustration Using the Data from Student Log File, with Number of Features, Detection Accuracy and Classifiers used

Ref Number	ITS/Game used	Features used	Method of selecting the feature	Detection Accuracy	Classifiers used
[30]	AutoTutor	Data from students' interaction	Correlation analysis	78%	17 classifier like NB, DT from Weka[50]
[46]	Crystal Island	Data from students' interaction and Physiological senors	All features	88.8%	NB, SVM, DT
[31]	Introductory Programming Course Lab	Data from students' interaction	Correlation analysis	Regression coefficient r=0.3168	Linear regression model
[10]	Crystal Island	Students' learning pattern and data from questionnaires	All features	28%	DBN
[6]	Prime Climb	Students' learning pattern and data from questionnaires	All features	For joy = 69% and for distress = 70%$	DDN

NB- Nave Bayes, SVM- Support Vector Machine, DT - Decision Tree, DBN - Dynamic Bayesian Network, DDN - Dynamic Decision Network, $ = this system was not detecting frustration

Related Work - Predicting Affective States

- Crystal Island [10], and Prime Climb [6] creates a Dynamic Bayesian Network (DBN) model to capture the users' affective states.
- The users' affective states are predicted by applying the theory.

The reason identified by the system helps to respond to user's affective state based on the reasons for it.

Disucssion

- Accuracy in data-mining approaches is in the range of 77% to 88%.
- Accuracy for emotions reported by using DBN and DDN model is comparatively less, 28% to 70%.
- Affective state modeling captures not only the affective states but also why the user is in that state.

Related Work - Addressing Affective States

Table: Related Research Works to Respond to Student's Affective States along with the Theories used, Experiment Method and Results

Ref Number	ITS/Game used	Theory used to respond to frustration	Experiment Method	Results
[52]	Affect-Support computer game	Active listening, emotional feedback, sympathy statement [181]	Factorial study, 2 (level of frustration) x 3 (interactive design), N = 71. Self reporting using questionnaire	On an average the affect support group played more minutes compared to non-affect support group.
[4]	Scooter the Tutor	Agents were given emotions	Control-experiments group study. N = 60. Human observation	Reduction in frustration instances. There is no significant difference in observed affect between control and experimental group.
[19]	Wayang Outpost	Agent to reflect student's affective states and messages based on Dweck's messages [78], [77]	N = 34, physiological sensor data to detect affective states	Initial studies results that students change their behavior based on digital interventions

N = Number of participants

Theory-Driven Approach

The theory-driven approach to detect affective states is given below:

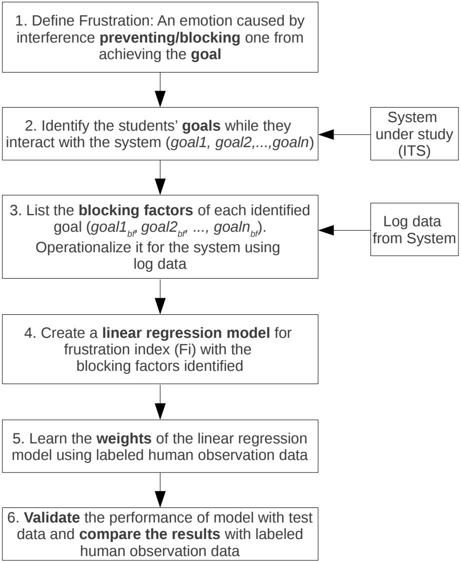
1. Operationalize the theoretical definition of affective state for the system under consideration.
2. Construct features from the system's log data; based on the theoretical definition of affective state.
3. Create a model using the constructed features to detect the affective state.
4. Conduct an independent method to detect affective state and use the data from independent method to train the weights of model.
5. Validate the performance of the model by detecting the affective state in the test data and compare the results with the data from independent method.

Definitions of Frustration

The following factors of frustration are considered in our research to model the student's frustration.

- Frustration is the blocking of a behavior directed towards a goal [25].
- The distance to the goal is a factor that influences frustration [88].
- Frustration is cumulative in nature [146].
- Time spent to achieve the goal is a factor that influences frustration [55].
- Frustration is considered as a negative emotion, because it interferes with a student's desire to attain a goal [88], [146].

Theory-Driven Approach to Detect Frustration



Generic Linear Regression Model for Frustration

We formulate a linear function F_i, as the frustration index at i^{th} question based on the blocking behaviour of student's goals.

Linear regression formulation of frustration

$$F_i = \alpha[w_0 + w_1 * goal1.bf + w_2 * goal2.bf + ...$$

$$+w_n * goaln.bf + w_{n+1} * t_i] + (1 - \alpha)[F_{i-1}$$

$W_0, W_1, ...W_n$ are weights, will be determined during training.

$\propto$ is to accommodate the cumulative nature of frustration.

t_i is the response time at i^{th} question.

Human Observation & Data Collection

- Independent method to identify the student's frustration while they interact with Mindspark

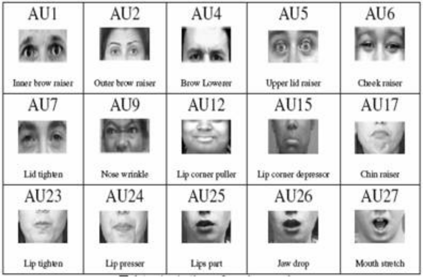


Figure: Facial Action Coding System (FACS) [62]

Human Observation & Data Collection

- Students' facial expressions during the interaction with Mindspark is recorded using a web camera
- The student's interaction with Mindspark is recorded using Camstudio[1], open source free streaming video software.
- 932 facial expression form the 27 student's interaction video.
- Based on guidelines given in [48] and [47] the student's facial expressions such as outer brow raise, inner brow raise, pulling at her hair, statements like "what", "this is annoying", and so on are considered as frustration.
- 80% of time observers agree to other observers facial expression coding and Cohen's κ was found to be 0.74, a substantial agreement.

we recorded 932 observations from 27 students. Among those, 137 observations were classified as frustration (Frus) and remaining as non-frustration (Non-Frus).

[1] www.camstudio.org

Metrics

Human Observation

		Frustrated	Non-Frustrated
Model	**Frustrated**	True Positive (TP)	False Positive (FP)
Data	**Non-Frustrated**	False Negative (FN)	True Negative (TN)

$$Precision = \frac{TP}{TP + FP}, \; Recall = \frac{TP}{TP + FN}$$

$$Accuracy = \frac{TP + TN}{TP + FP + FN + TN}$$

F1 score and Cohen's kappa are measured to check the performance of our model compared to random guess.

Frustration Model for Mindspark Log Data

Table: Student Goals and Blocking Factors for Mindspark

Student Goal	Blocking factor
*goal*1: To get the correct answer to the current question	*goal*1.*bf*: Answer to the current question is wrong
*goal*2: To get a Sparkie (answer three consecutive questions correctly)	*goal*2*a*.*bf*: Answers to two previous questions are correct and to the current question is wrong *goal*2*b*.*bf* : Answer to the previous question is correct and to the current question is wrong
*goal*3: To reach the Challenge Question (answer five consecutive question correctly)	*goal*3*a*.*bf*: Answers to four previous questions are correct and to the current question is wrong *goal*3*b*.*bf*: Answers to three previous questions are correct and to the current question is wrong
*goal*4: To get the correct answer to the Challenge Question	*goal*4.*bf*: Answer to the Challenge Question is wrong

Frustration Model for Mindspark Log Data

$$F_i = \alpha[w_0 + w_1 * goal1.bf + w_2 * goal2.bf + w_3 * goal3.bf + w_4 * goal4.bf + w_5 * t_i] + (1 - \alpha)[F_{i-1}]$$

Solving Linear Regression Model

Human Observation, B_i at the i^{th} instance, $B_i = 0$ for non-frustration and $B_i = 1$ for frustration.

Predicted frustration P_i, $P_i = 0$ if $F_i < 0.5$ and $P_i = 1$ if $F_i > 0.5$, 0.5 - threshold.

Our Goal:

$$min(P_i - B_i)^2$$
$$by\ varying\ w_0, w_1, w_2, w_3, w_4, w_5$$

GNU Octave[2] is used to solve the above optimization problem. We used gradient decent algorithm with step size $= 0.001$.

[2] http://www.gnu.org/software/octave/

Results

Table: Contingency Table

Human Observation

		Frustrated	Non-Frustrated
Pred	**Frustrated**	45	12
Result	**Non-Frustrated**	92	783

Table: Performance of our Approach

Metrics	Results
Accuracy	88.84%
Precision	78.94%
Recall	32.85%
Cohen's kappa	0.41
F1 Score	0.46

Performance of Related Data-Mining Approaches Applied to the Data from Mindspark Log File

System	Classifiers	Accuracy in %	Precision in	Recall in %
AutoTutor	Logistic Model Tree	88.63	65.97	46.71
Crystal Island	Decision Tree	86.05	52.63	51.09
Programming lab	Linear regression	r = 0.583		
Our Approach	Linear Regression	88.84	78.94	**32.85**

Our approach performed comparatively better than other approaches in precision of 79.31%

Performance of Theory-Driven Features using Different Classifiers

Order of Polynomial Model	Precision	Recall	Accuracy	Kappa
First	78.94%	32.85%	88.84%	0.41
Second	85.1%	29.2%	88.84%	0.3889
Third	82.4%	30.7%	88.84%	0.3989
Fourth	77.4%	29.9%	88.4%	0.3808

Classifiers	Precision	Recall	Accuracy	Kappa
Naive Bayes	55.24%	57.66%	86.91%	0.4873
Logistic	77.94%	38.69%	89.38%	0.4649
Bagging Pred	60.18%	49.64%	87.77%	0.4741
Logistic Model Tree	79.69%	37.23%	89.38%	0.4566
Decision Table	68.97%	43.80%	88.84%	0.4759

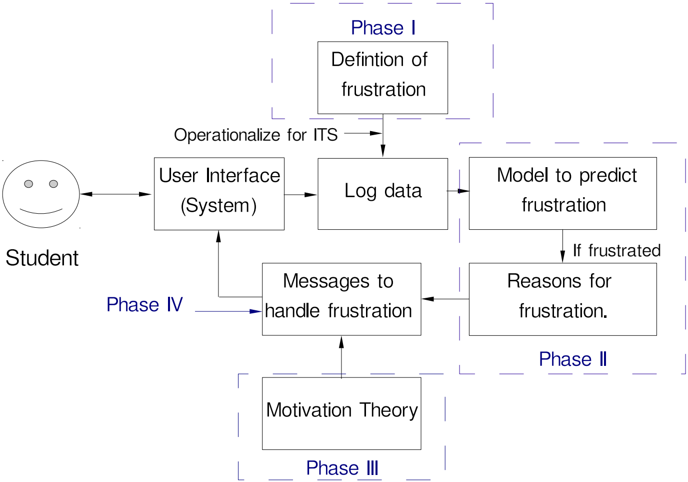
Discussion

- The advantage of the theory-driven approach is that the features identified provides the reasons for students' frustration.
- The reason for frustration provides information on which variables to control while responding to students' frustration.

Limitations:

- The frustration model is specific to Mindspark.
- To apply our theory-driven approach to other systems, careful thought is required to operationalize the blocking factors of goals.
- The goals of the students when they interact with the system should be captured; this is a limitation in the scalability of our approach.
- The results of the theory-driven approach are dependent on how well the goals are captured and how well the blocking factors of the goals are operationalized.

Methodology



Our Approach to Respond to Frustration

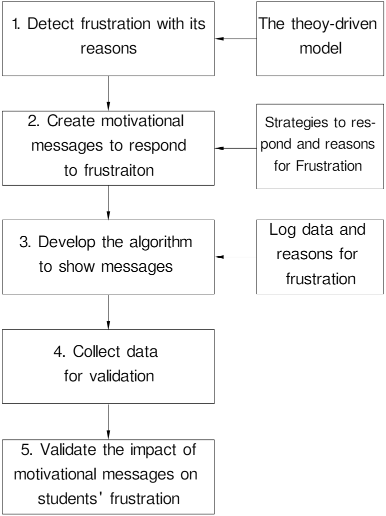


Figure: Steps of our Approach to Respond to Frustration

Strategies

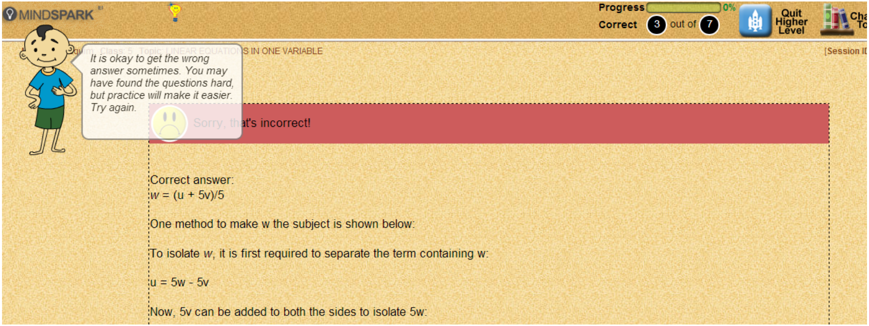
- Create motivational message to attribute the students' failure to achieve the goal to external factors [76].
- Create messages to praise the students' effort instead of outcome [77].
- Create messages with empathy, which should make the student feel that s/he is not alone in that affective state [52].
- Create message to request student's feedback [121].
- Display messages using an agent [182], [121].

Sample Algorithm

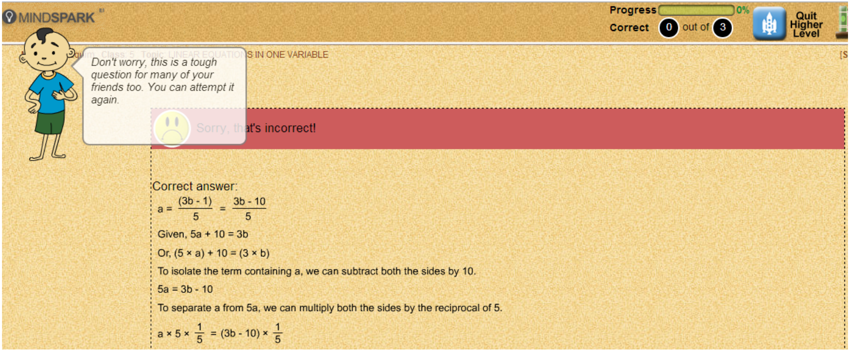
Algorithm 2 To display motivational messages

Require: Res Time, FrusInst, Question Type.
  return Message
  if FrusInst = 1 & Question Type is Normal then
    Create Message: Based on the response time, concatenate the messages from Table and display it to the students.
  else if FrusInst = 1 & Question Type is Challenge then
    Create Message: Based on the response time, concatenate the messages from Table and display it to the students.
  else if FrusInst = 2 & Question Type is Normal then
    Message: It is okay to get the wrong answer sometimes. You may have found the question hard, but practice will make it easier. Try again
  else if FrusInst = 2 & Question Type is Normal then
    Message: Dont worry, this is a tough question for many of your friends too. You can attempt it again.
  else if FrusInst = 3 then
    Message: Would you like to give your feedback?
  end if

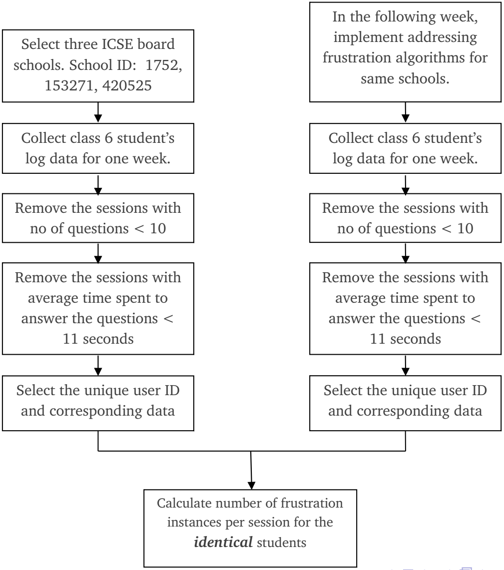
Integration with Mindspark



Sample Screenshot



Data Collection - Methodology



Data Collection - Details

Table: Details of the data collected from three schools to measure the impact of motivational messages on frustration

School Code	Number of students in Class 6	Mindspark topic in first week (Without motivational Messages)	Mindspark topic in second week (with motivational messages)	Number of matching students' sessions considered for analysis
1752	326	Integers	Integers	54
153271	279	Decimals	Decimals	72
420525	164	Algebra	Geometry	62
Total				188

Results

Table: Median and Median Absolute Deviation (MAD) of number of frustration instances from the Mindspark session data from three schools

Number of Mindspark Sessions	Median of Frustration Instances	MAD of Frustration Instances
188 sessions without motivational messages	2	2.1942
188 sessions with motivational messages	1	1.4628

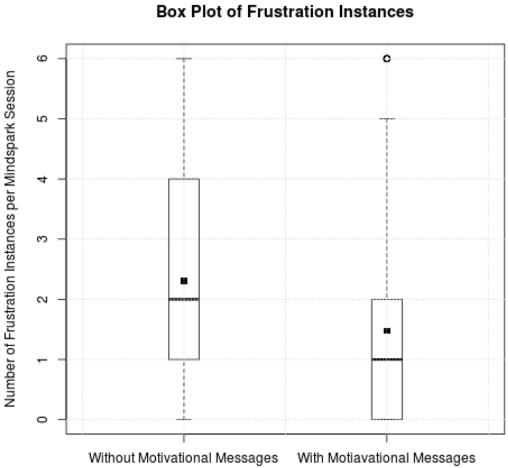
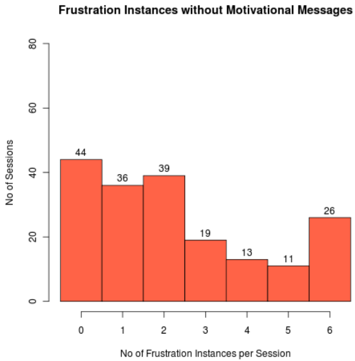
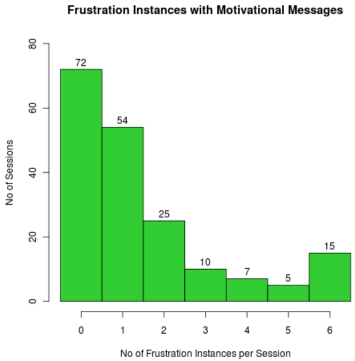


Figure: Box plot of Frustration instances from 188 sessions without and with motivational messages. Box = 25th and 75th percentiles; bars = minimum and maximum values; center line = median; and black dot = mean.

Results





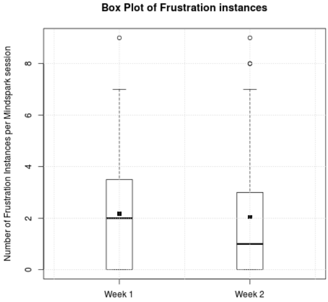
Number of frustration instances is reduced in from very high to less due to the motivational messages.

Results

Table: Impact of motivational messages on frustration in three schools

School Code	Number of Sessions	Without Motivational Message		With Motivational Messages		Mann-Whitney's Significance Test
		Sum of Frustration instances	Median	Sum of Frustration instances	Median	
1752	54	92	1	57	0	$P < 0.05$
153271	72	212	3	148	1	$P < 0.05$
420525	62	130	2	72	1	$P < 0.05$

Validation of Impact of Motivational Messages



School Code	Number of Sessions	First Week Data		Second Week Data		Mann-Whitney's Significance Test
		Sum of Frustration instances	Median	Sum of Frustration instances	Median	
1752	99	215	2	203	1	$P > 0.05$

Analysis on Ordering Effects - Removal of Motivational Messages

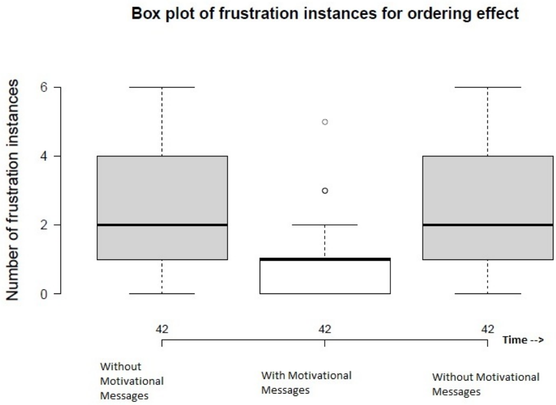


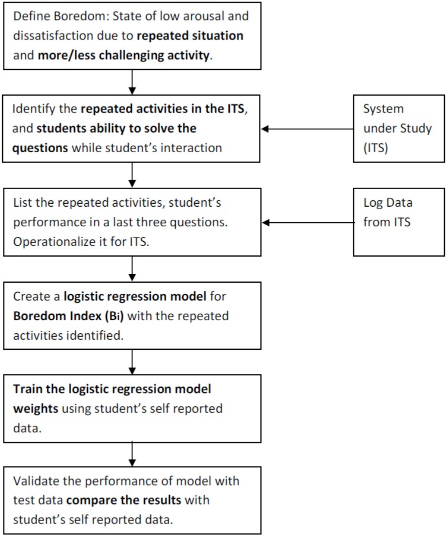
Figure: Box plot of Frustration instances from 42 session in each week. First week without motivational messages, second week with motivational messages and third week without motivational messages.

Discussion

- From the histograms, the frustration instances of students are reduced in the sessions with motivational messages.
- There is a statistically significant reduction in the number of frustration instances per session due to the approach to respond to frustration.
- The significant reduction in the frustration instances is independent of the schools analyzed and topics used in the Mindspark sessions.
- The approach to respond to frustration has a relatively higher impact on the students whose performance in the sessions is low.
- The approach to respond to frustration has a relatively higher impact on the students who spend more time to answer the questions in Mindspark session.

Approach to Detect Boredom

The theory-driven approach to model boredom



Definition of Boredom Used in Our Research

The most common feature in all existing work on boredom is repetitiveness and monotonous stimulation [189], [191]. The other key features of boredom are

1. Conflict between whether to continue the current situation or not due to lack of motivation [190].
2. The student is forced to do the an uninteresting activity. Non-interest occurs when the student not challenged enough [37], [194].
3. The student is prevented from doing a desirable action or forced to do an undesirable action [191].
4. The student lost the interest in outcome of the event [193].

Boredom Model

The logistic regression model to detect boredom is given below:

$$B_i = w_0 + w_1 * f1 + w_2 * f2 + w_3 * f3 + ... + w_n * fn \tag{1}$$

Independent Method -Self Reporting

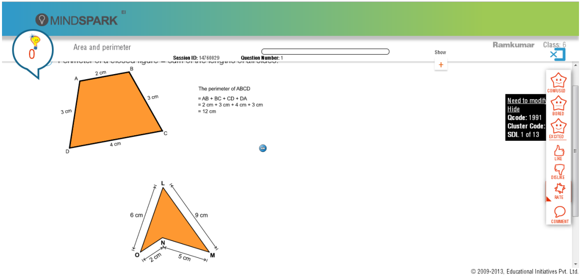


Figure: EmotToolbar integrated with Mindspark user interface to collect students' emotions. The emote bar is in right side of the figure.

The emotToolbar consists of six options for the students to choose from as

Figure: The EmotToolbar

Sample

- We collected 1617 instances of student's answering the questions in Mindspark from 90 students.
- Out of 1617, 442 instances are self reported as boredom (Bored) by students, the remaining instances are marked as (Non-Bored).
- The dataset is stratified at questions (instances) level. Unit of analysis is the instances where students respond to questions in Mindspark.

Results

Table: Results of Boredom Model when Applied to Mindspark Log Data

		Self Reported Data	
		Bored	**Non-Bored**
Pred	**Bored**	98	46
Result	**Non-Bored**	344	1129

The values from Table 9 are used to calculate the performance of our model. The results are given in Table 10.

Table: Performance of our Approach Shown Using Various Metrics when Applied to Mindspark Log Data

Metrics	**Results**
Accuracy	75.88%
Precision	68.1%
Recall	22.22%
Cohen's kappa	0.23
F1 Score	0.33

Major Contributions

- Theory-driven Approach: We developed an approach to detect affective states using data from the students' interaction with the system. Our approach uses only the data from log files, hence, it can be implemented in the large scale deployment of ITS. We have tested our approach on a math ITS to detect frustration. Moreover, we validated the likelihood of generalizing the theory-driven approach to detect other affective states by creating a model to detect boredom in an ITS.
- Frustration Model: We developed a linear regression model to detect frustration in a math ITS – Mindspark, using the theory-driven approach. The detection accuracy of our model is comparatively equal to the existing approaches to detect frustration. Additionally, our model provides the reasons for the frustration of the students.
- Respond to Frustration: We provided an approach to avoid the negative consequences of frustration, such as dropping out, by using the motivational messages. The messages to respond to frustration are created based on the reasons for frustration. The impact of motivational messages was analyzed and it was found that our approach significantly reduced the number of frustrations per session.

Publications Arising Out of this Thesis

- A Theory-Driven Approach to Predict Frustration in an ITS, *Ramkumar Rajendran, Sridhar Iyer, Sahana Murthy, Campbell Wilson, and Judithe Sheard*, IEEE Transactions on Learning Technologies, Vol 6 (4), pages 378–388, Oct-Dec 2013.
- Responding to Students' Frustration while Learning with an ITS, `To be submitted to the IEEE Transactions on Learning Technologies.`
- Literature Driven Method for Modeling Frustration in an ITS, *Ramkumar Rajendran, Sridhar Iyer, and Sahana Murthy*, International Conference on Advanced Learning Technologies (ICALT), 2012, Rome, Italy.
- Automatic identification of affective states using student log data in ITS, *Ramkumar Rajendran*, Doctoral Consortium in International Conference on Artificial Intelligence in Education (AIED), 2011, Auckland, New Zealand.

Thank You

Bibliography I

Zhao Ying, Quan Bingzhe, and Jin Chunzhao.
On intelligent tutoring system.
CNKI Journal on Computer Science, 04, 1995.

Chung Leung, Elvis Wai, and Qing Li.
An experimental study of a personalized learning environment through open-source software tools.
IEEE Transactions on Education, Vol 50(No. 4), Nov 2007.

Elizabeth J. Brown, Timothy J. Brailsford, Tony Fisher, and Adam Moore.
Evaluating learning style personalization in adaptive systems: Quantitative methods and approaches.
IEEE Transactions on Learning Technologies, 2:10–22, 2009.

M. M. T. Rodrigo, R. S. J. d. Baker, J. Agapito, J. Nabos, M. C. Repalam, S. S. Reyes, and M. O. C. Z. S. Pedro.
The effects of an interactive software agent on student affective dynamics while using an intelligent tutoring system.
IEEE Transactions on Affective Computing, 3(2):224 –236, 2012.

D. Cooper, I. Arroyo, B. Woolf, K. Muldner, W. Burleson, and R. Christopherson.
Sensors model student self concept in the classroom.
In *User Modeling, Adaptation, and Personalization*, pages 30–41. Springer, 2009.

Bibliography II

C. Conati and H. Maclaren.
Empirically building and evaluating a probabilistic model of user affect.
User Modeling and User-Adapted Interaction, 19(3):267–303, 2009.

K. Brawner and B. Goldberg.
Real-time monitoring of ecg and gsr signals during computer-based training.
In *Intelligent Tutoring Systems*, pages 72–77, 2012.

M. S. Hussain, H. Monkaresi, and R. A. Calvo.
Categorical vs. dimensional representations in multimodal affect detection during learning.
In *Intelligent Tutoring Systems*, pages 78–83, 2012.

Z. Zeng, M. Pantic, G.I. Roisman, and T.S. Huang.
A survey of affect recognition methods: Audio, visual, and spontaneous expressions.
IEEE Transactions on Pattern Analysis and Machine Intelligence, 31(1):39–58, 2009.

Jennifer Sabourin, Bradford Mott, and James C. Lester.
Modeling learner affect with theoretically grounded dynamic bayesian networks.
In *International Conference on Affective Computing and Intelligent Interaction*, pages 286–295, 2011.

Elvira Popescu.
Evaluating the impact of adaptation to learning styles in a web-based educational system.
In *ICWL '009: Proceedings of the 8th International Conference on Advances in Web Based Learning*, pages 343–352, 2009.

Bibliography III

Chin-Ming Hong, Chih-Ming Chen, Mei-Hui Chang, and Shin-Chia Chen.
Intelligent web-based tutoring system with personalized learning path guidance.
Advanced Learning Technologies, IEEE International Conference on, 0:512–516, 2007.

Tom Murray.
Authoring intelligent tutoring systems: An analysis of the state of the art.
International Journal of Artificial Intelligence in Education, 10:98–129, 1999.

Trifonova Anna and Ronchetti Marco.
Where is mobile learning going?
In *Proceedings of World Conference on E-Learning in Corporate, Government, Healthcare, and Higher Education.*, pages 1794–1801, Chesapeake, VA, USA., 2003.

A.W. Bates.
Technology, E-Learning And Distance Education.
Routledge; 2nd edition, London, 2005.

Robin Mason and Frank Rennie.
Broadband: A solution for rural e-learning?
International Review of Research in Open and Distance Learning, 5(1):19, 2004.

M. Cocea and S. Weibelzahl.
Disengagement detection in on-line learning: Validation studies and perspectives.
Learning Technologies, IEEE Transactions on, 2010.

Bibliography IV

Ryan S. J. d. Baker, Sidney K. D'Mello, Ma. Mercedes T. Rodrigo, and Arthur C. Graesser.
Better to be frustrated than bored: The incidence, persistence, and impact of learners' cognitive-affective states during interactions with three different computer-based learning environments.
International Journal of Human-Computer Studies, 68(4):223 – 241, 2010.

Beverly Woolf, Winslow Burleson, Ivon Arroyo, Toby Dragon, David Cooper, and Rosalind W Picard.
Affect-Aware Tutors: Recognising and Responding to Student Affect.
Int. J. Learn. Technol., 4(3/4):129–164, 2009.

Angel de Vicente and Helen Pain.
Motivation diagnosis in intelligent tutoring systems.
In *Proceedings of the 4th International Conference on Intelligent Tutoring Systems*, ITS '98, pages 86–95, 1998.

Suchismita Srinivas, Muntaquim Bagadia, and Anupriya Gupta.
Mining information from tutor data to improve pedagogical content knowledge.
In *Educational Data Mining*, 2010.

Ivon Arroyo and Beverly Park Woolf.
Inferring learning and attitudes from a bayesian network of log file data.
In *AIED*, pages 33–40, 2005.

V. R. C. Castillo, K. B. V. Villaflor, R. L Rodriguez, and M. M. T Rodrigo.
Modeling student affect and behavior using biometric readings, log files and low fidelity playbacks.
In *Philippine Computing Society Congress*, 2010.

Bibliography V

Cynthia D. Fisherl.
Boredom at Work: A Neglected Concept.
Human Relations, 46(3):395–417, 1993.

Clifford T. Morgan, Richard A. King, John R. Weisz, and John Schopler.
Introduction to Psychology.
McGraw-Hill Book Company, seventh edition edition, 1986.

Cristina Conati and Heather Maclare.
Evaluating a probabilistic model of student affect.
In *Intelligent Tutoring Systems*, pages 55–66. 2004.

Ashish Kapoor, Winslow Burleson, and Rosalind W. Picard.
Automatic prediction of frustration.
Int. J. Hum.-Comput. Stud., 65:724–736, August 2007.

Toby Dragon, Ivon Arroyo, Beverly P. Woolf, Winslow Burleson, Rana Kaliouby, and Hoda Eydgahi.
Viewing student affect and learning through classroom observation and physical sensors.
In *Proceedings of the 9th international conference on Intelligent Tutoring Systems*, ITS '08, pages 29–39, 2008.

Sidney K. D'Mello, Scotty D. Craig, Jeremiah Sullins, and Arthur C. Graesser.
Predicting affective states expressed through an emote-aloud procedure from autotutor's mixed-initiative dialogue.
Int. J. Artif. Intell. Ed., 16:3–28, January 2006.

Bibliography VI

Sidney K. D'Mello, Scotty D. Craig, Amy Witherspoon, Bethany Mcdaniel, and Arthur Graesser.
Automatic detection of learner's affect from conversational cues.
User Modeling and User-Adapted Interaction, 18:45–80, February 2008.

Ma. Mercedes T. Rodrigo and Ryan S. J. d. Baker.
Coarse-grained detection of student frustration in an introductory programming course.
In *Proceedings of the fifth international workshop on Computing education research workshop*, ICER '09, pages 75–80, 2009.

Rafael A. Calvo and Sidney K D'Mello.
Affect detection: An interdisciplinary review of models, methods, and their applications.
IEEE Transactions on Affective Computing, 1:18–37, 2010.

Peter Brusilovsky and Eva Milln.
User models for adaptive hypermedia and adaptive educational systems.
In *The Adaptive Web, LNCS 4321*, pages 3–53, 2007.

Jeff Johns and Beverly Woolf.
A dynamic mixture model to detect student motivation and proficiency.
In *Proceedings of the 21st national conference on Artificial intelligence - Volume 1*, pages 163–168, 2006.

C. Romero and S. Ventura.
Educational data mining: A review of the state of the art.
Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on, 40(6):601 –618, nov 2010.

Bibliography VII

Huey-Ing Liu and Min-Num Yang.
QoI guaranteed adaptation and personalization in e-learning systems.
Education, IEEE Transactions on, 48(4):676 – 687, nov 2005.

William L. Mikulas and Stephen J. Vodanovich.
The essence of boredom.
Psychological aspects, 43(1):3, 1993.

Reed W. Larson and Maryse H. Richards.
Boredom in the middle school years: Blaming schools versus blaming students.
American Journal of Education, 99(4):pp. 418–443, 1991.

Ulrike E. Nett, Thomas Goetz, and Nathan C. Hall.
Coping with boredom in school: An experience sampling perspective.
Contemporary Educational Psychology, 36(1):49 – 59, 2011.
Students' Emotions and Academic Engagement.

Reinhard Pekrun, Thomas Goetz, Lia M. Daniels, Robert H. Stupnisky, and Raymond P. Perry.
Boredom in achievement settings: Exploring control-value antecedents and performance outcomes of a neglected emotion.
Journal of Educational Psychology, 102(3):531 – 549, 2010.

Bibliography VIII

Richard Farmer and Norman D. Sundberg.
Boredom proneness–the development and correlates of a new scale.
Journal of Personality Assessment, 50(1), 1986.

Marvin Zuckerman, Sybil B. Eysenck, and H.J. Eysenck.
Sensation seeking in england and america: Cross-cultural, age, and sex comparisons.
Journal of Consulting and Clinical Psychology, 46(1):139 – 149, 1978.

Anna Sierpinska, Georgeana Bobos, and Christine Knipping.
Sources of students' frustration in pre-university level, prerequisite mathematics courses.
Instructional Science, 36:289–320, 2008.

Markku S. Hannula.
Affect in mathematical thinking and learning: Towards integration of emotion, motivation, and cognition.
J. Maasz, W. Schloeglmann (Eds.), New Mathematics Education Research and Practice, pages 209–232, 2006.

Markku Hannula, Jeff Evans, George Philippou, and Rosetta Zan.
Affect in mathematics education-exploring theoretical frameworks. research forum.
In *Proceedings of the 28th Conference of the International Group for the Psychology of Mathematics Education*, pages 107–136, 2004.

Bibliography IX

Scott W. Mcquiggan, Sunyoung Lee, and James C. Lester.
Early prediction of student frustration.
In *Proceedings of the 2nd international conference on Affective Computing and Intelligent Interaction*, ACII '07, pages 698–709, 2007.

Ma. Mercedes T. Rodrigo, Ryan S. J. d. Baker, Maria C. V. Lagud, Sheryl A. L. Lim, Alexis F. Macapanpan, Sheila A. M. S. Pascua, Jerry Q. Santillano, Leima R. S. Sevilla, Jessica O. Sugay, Sinath Tep, and Norma J. B. Viehland.
Affect and usage choices in simulation problem-solving environments.
In *Proceeding of the 2007 conference on Artificial Intelligence in Education: Building Technology Rich Learning Contexts That Work*, pages 145–152, 2007.

Sidney K. D'Mello, Scotty D. Craig, Barry Gholson, and Stan Franklin.
Integrating affect sensors in an intelligent tutoring system.
In *In Affective Interactions: The Computer in the Affective Loop Workshop at 2005 Intl. Conf. on Intelligent User Interfaces, 2005*, pages 7–13. AMC Press, 2005.

M. Grant and S. Boyd.
CVX: Matlab software for disciplined convex programming, version 1.21.
`http://cvxr.com/cvx`, apr 2011.

Hall Mark, Frank Eibe, Holmes Geoffrey, Pfahringer Bernhard, Reutemann Peter, and Ian H. Witten.
The weka data mining software: An update.
SIGKDD Explorations, 11, 2009.

Bibliography X

Reed. Lawson.
Frustration; the development of a scientific concept.
Critical issues in psychology series. Macmillan, 1965.

J Klein, Y Moon, and R W Picard.
This computer responds to user frustration: Theory, design, and results.
Interacting with Computers, 14:119–140, Jan 2002.

Naveen Nair, Ganesh Ramakrishnan, and Shonali Krishnaswamy.
Enhancing activity recognition in smart homes using feature induction.
In *Proceedings of the 13th international conference on Data warehousing and knowledge discovery*, DaWaK'11, pages 406–418, 2011.

M. S. Hussain, Omar AlZoubi, Rafael A. Calvo, and Sidney K. D'Mello.
Affect detection from multichannel physiology during learning sessions with autotutor.
In *Proceedings of the 15th international conference on Artificial intelligence in education*, AIED'11, pages 131–138, 2011.

Jonathan Lazar, Adam Jones, Mary Hackley, and Ben Shneiderman.
Severity and impact of computer user frustration: A comparison of student and workplace users.
Interact. Comput., 18(2):187–207, mar 2006.

Paul Ekman.
Strong evidence for universals in facial expressions: a reply to Russell's mistaken critique.
Psychology Bulletin, 115(2):268–287, 1994.

Bibliography XI

Hillary Anger Elfenbein and Nalini Ambady.
On the universality and cultural specificity of emotion recognition : A meta-analysis.
Psychology Bulletin, 128(2):203–235, 2002.

M. K. Mandal, M. P. Bryden, and M. B. Bulman-Fleming.
Similarities and variations in facial expressions of emotions: Cross-cultural evidence.
International Journal of Psychology, 31(1):49–58, 1996.

K. Gottlicher, S. Stein, and D. Reichardt.
Effects of emotional agents on human players in the public goods game.
In *3rd International Conference on Affective Computing and Intelligent Interaction and Workshops, ACII 2009.*, 2009.

Sidney K D'Mello, Scotty D Craig, Karl Fike, and Arthur C Graesser.
Responding to learners' cognitive-affective states with supportive and shakeup dialogues.
In *Human-Computer Interaction. Ambient, Ubiquitous and Intelligent Interaction*, pages 595–604, 2009.

Takeo Kanade, Yingli Tian, and Jeffrey F. Cohn.
Comprehensive database for facial expression analysis.
In *Proceedings of the Fourth IEEE International Conference on Automatic Face and Gesture Recognition*, pages 46–53, 2000.

Bibliography XII

Yan Tong, Wenhui Liao, and Qiang Ji.
Inferring facial action units with causal relations.
In *IEEE Computer Society Conference on Computer Vision and Pattern Recognition*, pages 1623 – 1630, 2006.

Sandra Graham, Bernard Weiner, DC Berliner, and RC Calfee.
Theories and principles of motivation.
Handbook of educational psychology, 4:63–84, 1996.

T. T. K. Munia, A. Islam, M. M. Islam, S. S. Mostafa, and M. Ahmad.
Mental states estimation with the variation of physiological signals.
In *International Conference on Informatics, Electronics & Vision*, pages 800–805, 2012.

A. Amsel.
Arousal, suppression, and persistence: Frustration theory, attention, and its disorders.
Cognition & Emotion, 4(3):239–268, 1990.

A. Ortony, G. L. Clore, and A. Collins.
The cognitive structure of emotions.
Cambridge university press, 1990.

S. Geisser.
Predictive Inference: An Introduction.
Monographs on Statistics and Applied Probability. Chapman & Hall, 1993.

Bibliography XIII

D. Michie, D.J. Spiegelhalter, C.C. Taylor, and J. Campbell.
Machine learning, neural and statistical classification.
Ellis Horwood London, 1994.

G. Salton.
Automatic Text Processing; the Transformation, Analysis, and Retrieval of Information by Computer.
Addison-Wesley, 1989.

Y. Yang.
An evaluation of statistical approaches to text categorization.
Information retrieval, 1(1):69–90, 1999.

N. L. Stein and L. J. Levine.
Making sense out of emotion.
In W. Kessen, A. Ortony, and F. Kraik, editors, *Memories, thoughts, and emotions: Essays in honor of George Mandle*, pages 295–322. 1991.

Robert E Thayer.
The biopsychology of mood and arousal.
Oxford University Press on Demand, 1989.

James Paul Gee.
What video games have to teach us about learning and literacy.
Computers in Entertainment (CIE), 1(1):20–23, 2003.

Bibliography XIV

James Paul Gee.
Learning and games.
The ecology of games: Connecting youth, games, and learning, 3:21–40, 2008.

F. Heider.
The Psychology of Interpersonal Relations.
Lawrence Erlbaum Associates, 1958.

Bernard Weiner.
An attributional theory of achievement motivation and emotion.
Psychological review, 92(4):548–573, 1985.

Carol S. Dweck.
Messages that motivate: How praise molds students' beliefs, motivation, and performance (in surprising ways).
In *Improving Academic Achievement*, pages 37 – 60. Academic Press, 2002.

Carol S Dweck.
Motivational processes affecting learning.
American psychologist, 41(10):1040–1048, 1986.

B. T. McDaniel, S. K. D'Mello, B. G. King, Patrick Chipman, Kristy Tapp, and A. C. Graesser.
Facial features for affective state detection in learning environments.
In *Proceedings of the 29th Annual Cognitive Science Society*, pages 467–472, 2007.

Bibliography XV

Marian Stewart Bartlett, Gwen Littlewort, Mark Frank, Claudia Lainscsek, Ian Fasel, and Javier Movellan.
Fully automatic facial action recognition in spontaneous behavior.
In *7th International Conference on Automatic Face and Gesture Recognition.*, pages 223–230, 2006.

Maja Pantic and Ioannis Patras.
Dynamics of facial expression: recognition of facial actions and their temporal segments from face profile image sequences.
Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 36(2):433–449, 2006.

Hatice Gunes and Massimo Piccardi.
Bi-modal emotion recognition from expressive face and body gestures.
Journal of Network and Computer Applications, 30(4):1334–1345, 2007.

Rafael A Calvo, Iain Brown, and Steve Scheding.
Effect of experimental factors on the recognition of affective mental states through physiological measures.
In *AI 2009: Advances in Artificial Intelligence*, pages 62–70. Springer, 2009.

Changchun Liu, Karla Conn, Nilanjan Sarkar, and Wendy Stone.
Physiology-based affect recognition for computer-assisted intervention of children with autism spectrum disorder.
International journal of human-computer studies, 66(9):662–677, 2008.

Bibliography XVI

Ashish Kapoor and Rosalind W Picard.
Multimodal affect recognition in learning environments.
In *Proceedings of the 13th annual ACM international conference on Multimedia*, pages 677–682, 2005.

Abram Amsel.
Frustration theory: Many years later.
Psychological bulletin, 112(3):396–399, 1992.

Reinhard Pekrun.
The impact of emotions on learning and achievement: Towards a theory of cognitive/motivational mediators.
Applied Psychology, 41(4):359–376, 1992.

Paul E Spector.
Organizational frustration: A model and review of the literature.
Personnel Psychology, 31(4):815–829, 1978.

Bernard Weiner.
Theories of motivation: From mechanism to cognition.
1972.

Sandra Graham.
A review of attribution theory in achievement contexts.
Educational Psychology Review, 3(1):5–39, 1991.

Bibliography XVII

Charles Darwin.
The expression of the emotions in man and animals.
Oxford University Press, 1998.

Paul Ekman.
Universals and cultural differences in facial expressions of emotion.
In *Nebraska symposium on motivation*. University of Nebraska Press, 1971.

Paul Ekman and Wallace V Friesen.
Unmasking the face: A guide to recognizing emotions from facial clues.
Malor Books, 2003.

Carroll E Izard.
The face of emotion.
Appleton-Century-Crofts, 1971.

Carroll E Izard.
Innate and universal facial expressions: evidence from developmental and cross-cultural research.
Psychological Bulletin, 115(2):288–299, 1994.

Craig A Smith and Phoebe C Ellsworth.
Patterns of cognitive appraisal in emotion.
Journal of personality and social psychology, 48(4):813–838, 1985.

Bibliography XVIII

Stanley Schachter and Jerome Singer.
Cognitive, social, and physiological determinants of emotional state.
Psychological review, 69(5):379, 1962.

Ira J Roseman.
Cognitive determinants of emotion: A structural theory.
Review of Personality & Social Psychology, 1984.

Farman Ali Khan, Sabine Graf, Edgar R. Weippl, and A Min Tjoa.
An approach for identifying affective states through behavioral patterns in web-based learning management systems.
In *Proceedings of the 11th International Conference on Information Integration and Web-based Applications & Services*, iiWAS '09, pages 431–435, 2009.

Rosalind W Picard.
Affective computing.
MIT press, 2000.

Gianluca Donato, Marian Stewart Bartlett, Joseph C. Hager, Paul Ekman, and Terrence J. Sejnowski.
Classifying facial actions.
Pattern Analysis and Machine Intelligence, IEEE Transactions on, 21(10):974–989, 1999.

Rana El Kaliouby and Peter Robinson.
Real-time inference of complex mental states from facial expressions and head gestures.
Springer, 2005.

Bibliography XIX

Michel F Valstar and Maja Pantic.
Fully automatic recognition of the temporal phases of facial actions.
Systems, Man, and Cybernetics, Part B: Cybernetics, IEEE Transactions on, 42(1):28–43, 2012.

Chul Min Lee and Shrikanth S Narayanan.
Toward detecting emotions in spoken dialogs.
Speech and Audio Processing, IEEE Transactions on, 13(2):293–303, 2005.

Diane J Litman and Kate Forbes-Riley.
Predicting student emotions in computer-human tutoring dialogues.
In *Proceedings of the 42nd Annual Meeting on Association for Computational Linguistics*, pages 351–358, 2004.

Cecilia Ovesdotter Alm, Dan Roth, and Richard Sproat.
Emotions from text: machine learning for text-based emotion prediction.
In *Proceedings of the conference on Human Language Technology and Empirical Methods in Natural Language Processing*, pages 579–586. Association for Computational Linguistics, 2005.

Taner Danisman and Adil Alpkocak.
Feeler: Emotion classification of text using vector space model.
In *AISB 2008 Convention Communication, Interaction and Social Intelligence*, volume 2, pages 53–59, 2008.

Bibliography XX

Weiyuan Li and Hua Xu.
Text-based emotion classification using emotion cause extraction.
Expert Systems with Applications, (0):–, 2013.

Ivon Arroyo, David G Cooper, Winslow Burleson, Beverly Park Woolf, Kasia Muldner, and Robert Christopherson.
Emotion sensors go to school.
In *Artificial Intelligence in Education*, volume 200, pages 17–24, 2009.

Mark Coulson.
Attributing emotion to static body postures: Recognition accuracy, confusions, and viewpoint dependence.
Journal of nonverbal behavior, 28(2):117–139, 2004.

Selene Mota and Rosalind W Picard.
Automated posture analysis for detecting learner's interest level.
In *Computer Vision and Pattern Recognition Workshop, 2003. CVPRW'03. Conference on*, volume 5, pages 49–49. IEEE, 2003.

Sidney K D'Mello and Art C Graesser.
Automatic detection of learner's affect from gross body language.
Applied Artificial Intelligence, 23(2), 2009.

Bibliography XXI

Nadia Bianchi-Berthouze and Christine L Lisetti.
Modeling multimodal expression of users affective subjective experience.
User Modeling and User-Adapted Interaction, 12(1):49–84, 2002.

Johannes Wagner, Jonghwa Kim, and Elisabeth André.
From physiological signals to emotions: Implementing and comparing selected methods for feature extraction and classification.
In *Multimedia and Expo, 2005. ICME 2005. IEEE International Conference on*, pages 940–943. IEEE, 2005.

Kyung Hwan Kim, SW Bang, and SR Kim.
Emotion recognition system using short-term monitoring of physiological signals.
Medical and biological engineering and computing, 42(3):419–427, 2004.

Tanja Bänziger, Didier Grandjean, and Klaus R Scherer.
Emotion recognition from expressions in face, voice, and body: the multimodal emotion recognition test (mert).
Emotion, 9(5):691–704, 2009.

A. Panning, I. Siegert, A. Al-Hamadi, A. Wendemuth, D. Rosner, J. Frommer, G. Krell, and B. Michaelis.
Multimodal affect recognition in spontaneous hci environment.
In *Signal Processing, Communication and Computing (ICSPCC), 2012 IEEE International Conference on*, pages 430–435, 2012.

Bibliography XXII

Henry A Feild, James Allan, and Rosie Jones.
Predicting searcher frustration.
In *Proceedings of the 33rd international ACM SIGIR conference on Research and development in information retrieval*, pages 34–41. ACM, 2010.

Rich Caruana and Alexandru Niculescu-Mizil.
An empirical comparison of supervised learning algorithms.
In *Proceedings of the 23rd international conference on Machine learning*, pages 161–168. ACM, 2006.

Joseph F Grafsgaard, Joseph B Wiggins, Kristy Elizabeth Boyer, Eric N Wiebe, and James C Lester.
Automatically recognizing facial expression: Predicting engagement and frustration.
In *Proceedings of the 6th International Conference on Educational Data Mining*, 2013.

Kate Hone.
Empathic agents to reduce user frustration: The effects of varying agent characteristics.
Interacting with Computers, 18(2):227–245, 2006.

Saul Rosenzweig and Gwendolyn Mason.
An experimental study of memory in relation to the theory of repression.
British Journal of Psychology. General Section, 24(3):247–265, 1934.

Rosalind W Picard.
Affective computing.
Technical report, Cambridge, MA, 1997.

Bibliography XXIII

ELENA Verdu, LUISA M Regueras, MARÍA JESÚS Verdu, JUAN PABLO de Castro, MA Pérez, Qing Li, SY Chen, and Anping Xu.
Is adaptive learning effective? a review of the research.
In *WSEAS International Conference. Proceedings. Mathematics and Computers in Science and Engineering*, number 7. World Scientific and Engineering Academy and Society, 2008.

Peter Brusilovsky, Elmar Schwarz, and Gerhard Weber.
Elm-art: An intelligent tutoring system on world wide web.
In *Intelligent tutoring systems*, pages 261–269, 1996.

Susanne P Lajoie and Alan Lesgold.
Apprenticeship training in the workplace: Computer-coached practice environment as a new form of apprenticeship.
Machine-Mediated Learning, 3(1):7–28, 1989.

Chris Eliot and Beverly Park Woolf.
Reasoning about the user within a simulation-based real-time training system.
In *Fourth International Conference on User Modeling, Hyannis Cape Cod, Mass*, pages 15–19, 1994.

Erica Melis and Jörg Siekmann.
Activemath: An intelligent tutoring system for mathematics.
In *Artificial Intelligence and Soft Computing-ICAISC 2004*, pages 91–101. Springer, 2004.

Bibliography XXIV

Steven Ritter, John R Anderson, Kenneth R Koedinger, and Albert Corbett.
Cognitive tutor: Applied research in mathematics education.
Psychonomic bulletin & review, 14(2):249–255, 2007.

John R Anderson, Albert T Corbett, Kenneth R Koedinger, and Ray Pelletier.
Cognitive tutors: Lessons learned.
The journal of the learning sciences, 4(2):167–207, 1995.

Mia Stern, Joseph Beck, and Beverly Park Woolf.
Adaptation of problem presentation and feedback in an intelligent mathematics tutor.
In *Intelligent tutoring systems*, pages 605–613. Springer, 1996.

CR Beal, JE Beck, and BP Woolf.
Impact of intelligent computer instruction on girls math self concept and beliefs in the value of math.
In *Poster presented at the annual meeting of the American Educational Research Association, San Diego*, 1998.

Kenneth R Koedinger, John R Anderson, William H Hadley, Mary A Mark, et al.
Intelligent tutoring goes to school in the big city.
International Journal of Artificial Intelligence in Education (IJAIED), 8:30–43, 1997.

Bibliography XXV

Kurt VanLehn, Pamela W Jordan, Carolyn P Rosé, Dumisizwe Bhembe, Michael Böttner, Andy Gaydos, Maxim Makatchev, Umarani Pappuswamy, Michael Ringenberg, Antonio Roque, et al.
The architecture of why2-atlas: A coach for qualitative physics essay writing.
In *Intelligent tutoring systems*, pages 158–167. Springer, 2002.

Arthur C Graesser, Katja Wiemer-Hastings, Peter Wiemer-Hastings, and Roger Kreuz.
Autotutor: A simulation of a human tutor.
Cognitive Systems Research, 1(1):35–51, 1999.

Steven Ritter, John Anderson, Michael Cytrynowicz, and Olga Medvedeva.
Authoring content in the pat algebra tutor.
Journal of Interactive Media in Education, 98(9), 1998.

Albert T Corbett, Kenneth R Koedinger, and John R Anderson.
Intelligent tutoring systems.
Handbook of humancomputer interaction, pages 849–874, 1997.

Arthur C Graesser, Kurt VanLehn, Carolyn P Rosé, Pamela W Jordan, and Derek Harter.
Intelligent tutoring systems with conversational dialogue.
AI magazine, 22(4):39–51, 2001.

Arthur C Graesser, Patrick Chipman, Brian C Haynes, and Andrew Olney.
Autotutor: An intelligent tutoring system with mixed-initiative dialogue.
Education, IEEE Transactions on, 48(4):612–618, 2005.

Bibliography XXVI

Ryan S J d Baker, Albert T Corbett, and Vincent Aleven.
More accurate student modeling through contextual estimation of slip and guess probabilities in bayesian knowledge tracing.
In *Intelligent Tutoring Systems*, pages 406–415. Springer, 2008.

Stacy Marsella, Jonathan Gratch, and Paolo Petta.
Computational models of emotion.
A Blueprint for Affective Computing-A Sourcebook and Manual, pages 21–46, 2010.

Phoebe C Ellsworth and Klaus R Scherer.
Appraisal processes in emotion.
Handbook of affective sciences, pages 572–595, 2003.

Ira J Roseman, Martin S Spindel, and Paul E Jose.
Appraisals of emotion-eliciting events: Testing a theory of discrete emotions.
Journal of Personality and Social Psychology, 59(5):899–915, 1990.

Richard S Lazarus.
Emotion and adaptation.
Oxford University Press New York, 1991.

Saul Rosenzweig.
A general outline of frustration.
Journal of Personality, 7(2):151–160, 1938.

Bibliography XXVII

John Dollard, Neal E Miller, Leonard W Doob, Orval Hobart Mowrer, and Robert R Sears.
Frustration and aggression.
1939.

Valerie J Shute and Joseph Psotka.
Intelligent tutoring systems: Past, present, and future.
Technical report, DTIC Document, 1994.

Etienne Wenger.
Artificial intelligence and tutoring systems.
International Journal of Artificial Intelligence in Education, 14:39–65, 2004.

JR Hartley and Derek H Sleeman.
Towards more intelligent teaching systems.
International Journal of Man-Machine Studies, 5(2):215–236, 1973.

William J Clancey.
Intelligent tutoring systems: A tutorial survey.
Technical report, DTIC Document, 1986.

Derek Sleeman and John Seely Brown.
Intelligent tutoring systems.
Computer and people series. London Academic Press, 1982.

Bibliography XXVIII

Elena Verdú, Luisa M Regueras, María Jesús Verdú, Juan Pablo De Castro, and María Ángeles Pérez.
An analysis of the research on adaptive learning: the next generation of e-learning.
WSEAS Transactions on Information Science and Applications, 5(6):859–868, 2008.

Clark Hull.
Principles of behavior.
1943.

John William Atkinson.
An introduction to motivation.
Van Nostrand, 1964.

Matthew C Jadud.
An exploration of novice compilation behaviour in BlueJ.
PhD thesis, University of Kent, 2006.

Landowska Agnieszka.
Affect-awareness framework for intelligent tutoring systems.
In *Human System Interaction (HSI), 2013 The 6th International Conference on*, pages 540–547. IEEE, 2013.

Mindspark: Improve your math skills.
`http://www.mindspark.in/`.
Accessed Feb 20, 2014.

Bibliography XXIX

Richard R Burton and John Seely Brown.
An investigation of computer coaching for informal learning activities.
International Journal of Man-Machine Studies, 11(1):5–24, 1979.

Edward Hance Shortliffe.
Computer-based medical consultations, MYCIN.
Elsevier Science Publishers, 1976.

William J Clancey.
Tutoring rules for guiding a case method dialogue.
International Journal of Man-Machine Studies, 11(1):25–49, 1979.

John Seely Brown, Richard R Burton, and Alan G Bell.
Sophie: A step toward creating a reactive learning environment.
International Journal of Man-Machine Studies, 7(5):675–696, 1975.

James D Hollan, Edwin L Hutchins, and Louis Weitzman.
Steamer: An interactive inspectable simulation-based training system.
AI magazine, 5(2):15–27, 1984.

Roger C Schank.
Dynamic memory: A theory of reminding and learning in computers and people.
Cambridge University Press, 1982.

Bibliography XXX

Chris Dede, Marilyn C Salzman, and R Bowen Loftin.
Sciencespace: Virtual realities for learning complex and abstract scientific concepts.
In *Virtual Reality Annual International Symposium, 1996., Proceedings of the IEEE 1996*, pages 246–252, 1996.

Sandra Katz and Alan Lesgold.
The role of the tutor in computer-based collaborative learning situations.
Computers as cognitive tools, pages 289–317, 1993.

Nicola Capuano, Marco Marsella, and Saverio Salerno.
Abits: An agent based intelligent tutoring system for distance learning.
In *Proceedings of the International Workshop on Adaptive and Intelligent Web-Based Education Systems, ITS*, 2000.

Peter Brusilovsky.
Adaptive hypermedia.
User modeling and user-adapted interaction, 11(1-2):87–110, 2001.

Ryan S. J. d Baker, Albert T Corbett, and Kenneth R Koedinger.
Detecting student misuse of intelligent tutoring systems.
In *Intelligent tutoring systems*, pages 531–540, 2004.

Ling-Hsiu Chen, Yi-Chun Lai, and Yi-Hsu Weng.
Intelligent e-learning system with personalized misconception diagnose and learning path guidance.
In *International Conference on Electronic Business*, 2009.

Bibliography XXXI

Barry Kort, Rob Reilly, and Rosalind W Picard.
An affective model of interplay between emotions and learning: Reengineering educational pedagogy-building a learning companion.
In *Advanced Learning Technologies, IEEE International Conference on*, pages 0043–0046. IEEE Computer Society, 2001.

Edward Vockell.
Educational psychology: A practical approach.
Purdue University, 2004.

Sadia Batool, Muhammad Imran Yousuf, and Qaisara Parveen.
A study of attribution patterns among high and low attribution groups: An application of weiners attribution theory.
Anthropologist, 14(3):193–197, 2012.

Jyotirmay Sanghvi, Ginevra Castellano, Iolanda Leite, André Pereira, Peter W McOwan, and Ana Paiva.
Automatic analysis of affective postures and body motion to detect engagement with a game companion.
In *Human-Robot Interaction (HRI) 2011, 6th ACM/IEEE International Conference on*, pages 305–311, 2011.

Bibliography XXXII

Mohammad Adibuzzaman, Niharika Jain, Nicholas Steinhafel, Munir Haque, Ferdaus Ahmed, Shiekh Iqbal Ahamed, and Richard Love.
Towards in situ affect detection in mobile devices: a multimodal approach.
In *Proceedings of the 2013 Research in Adaptive and Convergent Systems*, pages 454–460. ACM, 2013.

Sidney DMello, Rosalind Picard, and Arthur Graesser.
Towards an affect-sensitive autotutor.
IEEE Intelligent Systems, 22(4):53–61, 2007.

Blair Lehman, Melanie Matthews, Sidney DMello, and Natalie Person.
What are you feeling? investigating student affective states during expert human tutoring sessions.
In *Intelligent Tutoring Systems*, pages 50–59. Springer, 2008.

Allan Wigfield and Jacquelynne S Eccles.
Expectancy–value theory of achievement motivation.
Contemporary educational psychology, 25(1):68–81, 2000.

Marylène Gagné and Edward L Deci.
Self-determination theory and work motivation.
Journal of Organizational behavior, 26(4):331–362, 2005.

Edward L Deci and Richard M Ryan.
Self-Determination.
Wiley Online Library, 2010.

Bibliography XXXIII

Thomas Gordon.
PET: Parent Effectiveness Training.
New American Library, 1970.

William R Nugent and Helene Halvorson.
Testing the effects of active listening.
Research on Social Work Practice, 5(2):152–175, 1995.

Helmut Prendinger and Mitsuru Ishizuka.
The empathic companion: A character-based interface that addresses users' affective states.
Applied Artificial Intelligence, 19(3-4):267–285, 2005.

Timo Partala and Veikko Surakka.
The effects of affective interventions in human–computer interaction.
Interacting with computers, 16(2):295–309, 2004.

Craig C Pinder.
Work motivation in organizational behavior .
Psychology Press, 2008.

Diane F Halpern, Joshua Aronson, Nona Reimer, Sandra Simpkins, Jon R Star, and Kathryn Wentzel.
Encouraging girls in math and science.
2007.

Bibliography XXXIV

Allan Wigfield and Kathryn R Wentzel.
Introduction to motivation at school: Interventions that work.
Educational Psychologist, 42(4):191–196, 2007.

Edwin A Locke and Gary P Latham.
What should we do about motivation theory? six recommendations for the twenty-first century.
Academy of Management Review, 29(3):388–403, 2004.

Friedrich Försterling.
Attributional retraining: A review.
Psychological Bulletin, 98(3):495, 1985.

Richard P Smith.
Boredom: A review.
Human Factors: The Journal of the Human Factors and Ergonomics Society, 23(3):329–340, 1981.

Joseph E Barmack.
The effect of benzedrine sulfate (benzyl methyl carbinamine) upon the report of boredom and other factors.
The Journal of Psychology, 5(1):125–133, 1938.

James F O'Hanlon.
Boredom: Practical consequences and a theory.
Acta psychologica, 49(1):53–82, 1981.

Bibliography XXXV

Jonathan SA Carriere, J Allan Cheyne, and Daniel Smilek.
Everyday attention lapses and memory failures: The affective consequences of mindlessness.
Consciousness and cognition, 17(3):835–847, 2008.

Jennifer J Vogel-Walcutt, Logan Fiorella, Teresa Carper, and Sae Schatz.
The definition, assessment, and mitigation of state boredom within educational settings: A comprehensive review.
Educational Psychology Review, 24(1):89–111, 2012.

Mihaly Csikszentmihalyi.
Finding flow: The psychology of engagement with everyday life.
Basic Books, 1997.

R. S. J. d. Baker, Sujith M Gowda, Michael Wixon, Jessica Kalka, Angela Z Wagner, Aatish Salvi, Vincent Aleven, Gail W Kusbit, Jaclyn Ocumpaugh, and Lisa Rossi.
Towards sensor-free affect detection in cognitive tutor algebra.
International Educational Data Mining Society, 2012.