Joint Emotional State of Children and Perceived Collaborative Experience in Coding Activities

Conference Paper · June 2019

DOI: 10.1145/3311927.3323145

3 authors:

Kshitij Sharma
Norwegian University of Science and Technology

Sofia Papavlasopoulou
Norwegian University of Science and Technology

Michail Giannakos
Norwegian University of Science and Technology

Joint Emotional State of Children and Perceived Collaborative Experience in Coding Activities

Kshitij Sharma, Sofia Papavlasopoulou, Michail Giannakos
Department of Computer Science
Norwegian University of Science and Technology
Trondheim, Norway
kshitij.sharma@ntnu.no,spapav@ntnu.no,michailg@ntnu.no

ABSTRACT

This paper employs facial features to recognize emotions during a coding activity with 50 children. Extracting group-level emotional states via facial features, allows us to understand how emotions of a group affect collaboration. To do so, we captured joint emotional state using videos and collaborative experience using questionnaires, from collaborative coding sessions. We define groups' emotional state using a method inspired from dynamic systems, utilizing a measure called cross-recurrence. We also define a collaborative emotional profile using the different measurements from facial features of children. The results show that the emotional cross recurrence (coming from the videos) is positively related with the collaborative experience (coming from the surveys). We also show that the groups with better experience than the others showcase more positive and a consistent set of emotions during the coding activity. The results inform the design of an emotion-aware collaborative support system.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**.

KEYWORDS

facial expressions, coding, emotional state, collaborative programming

ACM Reference Format:
Kshitij Sharma, Sofia Papavlasopoulou, Michail Giannakos. 2019. Joint Emotional State of Children and Perceived Collaborative Experience in Coding Activities. In *Interaction Design and Children (IDC '19), June 12–15, 2019, Boise, ID, USA.* ACM, New York, NY, USA, 13 pages. https://doi.org/10.1145/3311927.3323145

IDC '19, June 12–15, 2019, Boise, ID, USA

ACM ISBN 978-1-4503-6690-8/19/06…$15.00
https://doi.org/10.1145/3311927.3323145

1 INTRODUCTION

Emotions are essential on how we envision goals and challenges, they are also central to the processes tackling problem-solving. Emotions guide our behaviour, shape the group-dynamics and interactions, and inform the design of social systems [46]. Also, emotions have been found to play a central role in teaching, motivation and particularly in the context of self-regulated learning [53]. Contemporary research with children in the context of collaborative problem-solving, attempts to unveil the collaborative experience and ways of enriching it [40, 59]. Understanding the role of emotions during learning, holds the potential to enhance state-of-the-art practices [53].

During collaborative activities, people not only share their knowledge and ideas, but also share their emotions [20, 21]. In collaborative settings, the main sources of emotions are the episodes where the interaction occurs [27], or argumentation and conflicts happen [23, 29]. When collaboration among peers starts, they get to know each other and develop trust and belongingness that can raise a certain set of emotions [27]. During the collaboration, there are situations where peers need to negotiate a certain path to solve a problem, this leads to argumentation and in turn leads to showcasing of emotions [23]. For example, task-related conflicts among the peers can cause negative emotions [29]. Capturing emotions of children and then emulating them on a robot or using the emotional information to present a cue or hint in cognitive tutors is a common practice in the cases of Human Robot Interaction (HRI) [56] and Intelligent Tutoring Systems (ITS) [62, 69, 71]. This happens to keep children engaged and sustain the interaction over long periods of time. Understanding emotions would not only contribute to explain the collaboration from a socio-emotional point of view, but it can also enable the design of scaffolding systems based on the emotional states of the groups [21].

In coding activities, children tend to have an emotional repertoire [25]; for example in the beginning of a coding session, children display negative emotions (anxiety) and as they progress further, they follow a problem-solving loop, which results in a wide set of emotions [26]. However, there is a lack of quantitative measures for investigating emotions of groups in learning contexts [37]. Most assessments of emotional evaluations with children, focus on the individual child and do not consider the joint emotional state. In addition, related work uses self-reports and inferring from observations that provide limited insights into how emotional state changes over time during learning or interaction [63].

In this paper, we propose a quantitative method to capture the joint emotional profile of the group using emotions extracted from the facial features of the children. Inspired from Klaus Scherer [50], who provided a component process model of emotions that seeks to deal with both the *"dynamic, continuously fluctuating nature of emotion processes and the existence of discrete language labels referring to steady states"* (p. 75); we define the notion of joint emotional profile of children while they work collaboratively, in order to understand the evolution (dynamic) of emotions. Therefore, we tackle the following research objectives:

(1) Define the emotional profile of a collaborating group of children.
(2) Investigate the relationship between the emotional profile of a group and the quality of collaboration during coding.
(3) Identify the components of the emotional profile that affect the quality of collaboration during learning.

2 RELATED WORK

Children and Affect

Researchers in the fields of Child-Robot Interaction (CRI) and Child-Computer Interaction (CCI), have measured emotions via various modes of data collection, for example, self reports [17, 56], Electromyography (EMG) [66], facial features [24, 31, 69], Electrodermal Activity (EDA) [32, 63], gestures [6, 7, 31, 64], text [47] and audio data [10]. Children's emotional state is an important topic in CCI, with several studies focusing in the relationship between children's emotional display and various interaction constructs, such as usability [17, 69], learning processes [63], engagement [32] and enjoyment [31].

Self reported emotional states were used to study the relation between the age, gender and experiences in HRI [56]. In video-mediated communication the usability of the communication channel was evaluated with the self-reported emotions that were then evaluated from human coders who watched children's videos [17]. Furthermore, the experiences with a shared gaze channel were studied using self-reported emotions [55]. Based on the facial landmark data and a teacher/parent's manual emotion tags (happy), researchers performed a computational analysis to compare the happy emotion labels generated by the automated algorithm and the human rater [67]. Using self-reported emotions in an emotional awareness tool, and sharing the emotions between partners, engaged the peers into mutual modeling of emotions and increased the perceived intensity of positive emotions [39].

In the context of learning and problem-solving experiences, emotions were captured using EDA data [63] to study the relation between individual learning processes and emotional states of children. Emotions were also captured from a video of a wearable camera to support in-situ socio-emotional learning and communication [14]. Also, a deep neural network framework was used to obtain audio-based emotions to explain interactions to kids [4]. Postural shifts and facial expressions were used in the collaborative problem solving sessions to recognize emotions from children [24].

Emotions have also been used as a way to inform the behaviour of robots in a multitude of CRI/CCI scenario. For example, with children suffering from Down syndrome [68] or Autism Spectrum Disorder (ASD) [19, 66]. The researchers captured the emotions of children and used them to transfer the emotions to their peers [66, 68], to display them on a robot [6, 31, 41] or to inform the decision making processes in the intelligent tutors [62, 69, 71]. These efforts have shown to support social interaction [19, 47, 64], increase the engagement [6, 7, 32], enjoyment [30, 41], motivation [69] and provided the ability to sustain interaction over long periods of time [30, 31, 49, 69].

Previous research suggests that in CCI/CRI situations, emotions have been captured using a multitude of modalities, such as facial features, EDA, gesture, posture, self-reports. However, there are only a few studies [39] , which do so in a collaborative context. In this contribution, we will use facial features to quantitatively capture joint emotions of peers and investigate the relation between the joint emotional profile and collaborative coding experiences.

Emotions in Education

According to control value theory [45], happiness is related to high prospective success , anger is related to retrospective failure and sadness is related to high negative activity. Emotions were also found to be related to the competence belief, and the value students attribute to a particular domain [16]. Emotion is an essential part of studying motivation in classroom interactions since the instructional and interpersonal responses of teachers to students are often governed by the emotions [38].

There is little support for a direct relation between emotions and learning performance [34, 35]; however, frustration is a common feeling among students involved in online collaborative learning experiences [5]. There has been studies reporting on the relationship between gender, performance and emotional showcase. For example, high performing girls show less positive emotions than high performing boys [54].

Another facet of studies about emotions in educational contexts show how emotions influence the way in which information is processed. Happiness/joy results in novel and creative actions [15], positive emotions also promote the engagement in meta cognitive processing [34] which is beneficial for long term learning. On the other hand, negative emotions result in focusing on environmental specific details [3] also negative emotions lead to lack of elaboration [44]. Moreover, negative affect was associated with lower learning goals [38]; while positive affect was associated with the interest in a given topic [1].

When students collaborate they have to maintain durable relationships and acceptable levels of participation. Interactions that are associated with these aspects of the group performance can be typified as social-emotional interactions [70]. These interactions are primarily directed towards the relationship between group members [12]. In terms of collaborative learning, positive emotions were found to be correlated with effort and persistence, while negative emotions were correlated with less risk tolerance, lower learning gains and conflicts [12, 36]. Furthermore, negative socio-emotional interactions such as lack of respect and excessive criticism, have significant consequences in general quality of group learning opportunities [33] since such groups were reported to undermine commitment [36] and criticism [28] .

In learning, emotions have been mainly used as a dependent or independent variable. This restricts the ability of emotional aspects to explain the processes responsible for experiences in collaborative scenarios. In this paper, we use emotions as variables that explain processes.

3 METHODS

The coding activity

We designed and implemented a coding activity in conjunction with an initiative organized at the Norwegian University of Science and Technology (NTNU), Trondheim, Norway. The activity is based on the constructionist approach, following the main principles of "Making" [42]. The workshop was conducted in a largely informal setting, as an out-of-school activity, and lasted for four hours in total. Student groups ranging from 13–16 years old, were invited in NTNU's specially designed rooms for creative purposes to interact with digital robots and create games using Scratch and the Arduino hardware platform. Specifically, Arduino was attached to the digital robots to connect them with the computer. At that point, an extension of Scratch called Scratch for Arduino (S4A) provided the extra blocks needed to control the robots. Children who attended the workshop worked collaboratively in dyads or triads (depending on the number of children). The activity was designed for children without (or with minimum) previous experience in coding. During the activity, student assistants were supporting each team as needed. Approximately one assistant observed and helped one or two teams. Three researchers were also present throughout the intervention focusing on observing, writing notes and taking care of the overall execution of the workshop. The workshop was divided into two sections. In the first section, the children interacted with digital robots. The duration of the session was different for each team, it lasted between 45 minutes and one-and-a-half hours, and ended with a break before the next session. The second section focused on the creative implementation of simple game development concepts using Scratch. Children created their games step by step by iterative coding and testing them. After completing the games, all teams reflected and played each others games. The second section lasted approximately three hours.

Sampling

The study was conducted in Autumn 2017, children from 8^{th} to 10^{th} grade (age 13-16 years old) participated in the activity, after their school–teacher applied to attend our coding activity. The sample consisted of 105 participants in total, 69 boys and 36 girls (mean age: 14.55, SD: 0.650). During the workshops, several teams were video recorded. In particular, we collected videos from 50 children (29 females), 10 triads and 10 dyads, having the necessary consent from both the child and the legal guardian for the data collection.

From Children's Faces to Emotions

To extract the joint emotions from the videos, we followed a 6-steps process. Figure 1 provides the order of steps used to compute joint emotions from the video recordings during the collaborative coding sessions.

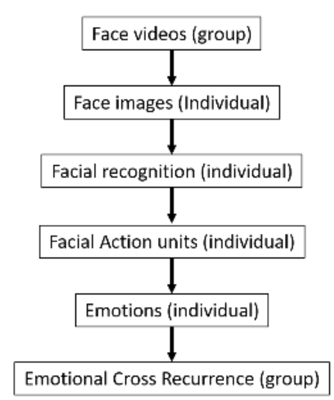

Figure 1: Summary of steps from the face videos of each group to their emotional cross recurrence.

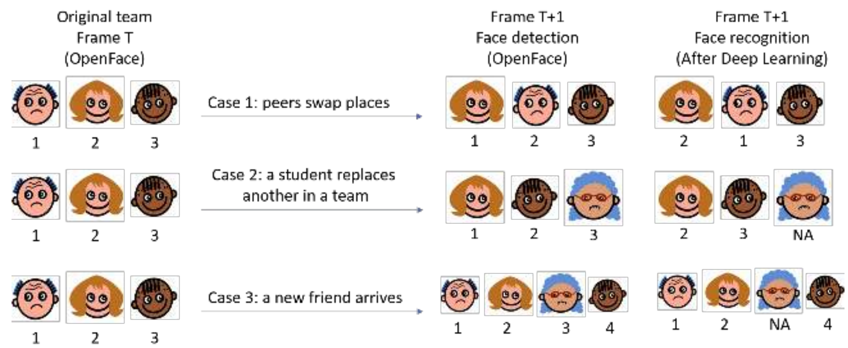

Figure 2: Three cases to show why face recognition is important for this contribution.

Multiple face detection: First, we used the OpenFace [2] library, in the videos, in order to detect the faces for every frame. Thus, each face is given a label starting from left to right (1 to N, where N is the number of faces in each frame). There are three cases where the left-to-right labelling of faces fails as shown in Figure 2. First, when students in the team swap places. Second, when someone switches teams for a small amount of time. Third, when a new student joins the team, again for a small amount of time. We need to keep the faces which composed the initial team. To achieve this, we used a pre-trained deep neural network, INCEPTION-v4 [65], to extract features from the individual face images and used a k-nearest neighbour prediction algorithm to recognize original individuals in every team. Figure 2 shows the example for all the three cases. The first 10 minutes are used to create the feature vectors for the original members in each team.

Facial Action Units System and emotions: Then, we used the face images to extract the facial Action Units (AUs) [18] using the OpenFace framework [2]. Facial Action Coding System (FACS) is taxonomy for human facial movements as they appear on the face. Movements of individual facial muscles are encoded by FACS from slight different instant changes in facial appearance. Using FACS it is possible to code nearly any anatomically possible emotion, deconstructing it into the specific Action Unit (AU) that produced the facial expression. It is a common standard to objectively describe emotions from facial expressions using such techniques [69]. Figure 3 shows the AUs detected for this paper and Table 1 shows how to define emotions from the Action units.

Measurements

To capture the quality of the collaboration we used two standardized set of questions from the literature. Perceived effectiveness of the collaboration and satisfaction from the collaboration [61].

To capture information about the emotions extracted from the videos, we used five different measurements. In particular:

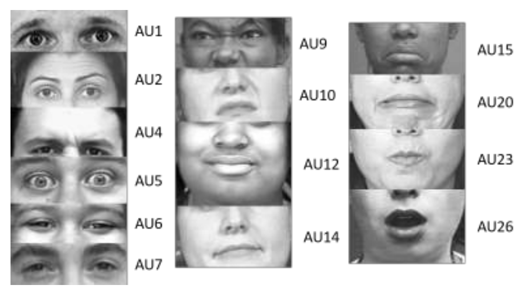

Figure 3: Action units captured for this paper.

Table 1: Emotions as defined by combination of AUs.

Emotion	AU Combination
Happiness	AU6, AU10
Sadness	AU1, AU4, AU15
Surprise	AU1, AU2, AU5, AU26
Fear	AU1, AU2, AU4, AU5, AU7, AU20, AU26
Anger	AU4, AU5, AU7, AU23
Disgust	AU9, AU15
Contempt	AU12, AU14

Proportion of emotions: Table 1 shows the combination of AUs used to define each emotion. We calculated the proportion of each emotion in a one-minute long window with an overlap of 30 seconds between two consecutive time windows. – Change of emotions (i.e., emotional entropy): From the proportions of the emotions in a given one-minute time window, we compute the Shannon entropy of proportionality vector using the following formula:

$$Entropy = -\sum_{i \in set\_of\_emotions} Proportion_i * log(Proportion_i) \tag{1}$$

A *zero* value of emotional entropy indicates that in a given time window students showed exactly one kind of emotion.

On the other hand, a high value will depict that students showcased a variety of emotions (in our case the highest possible value is $-log(1/7) = 0.85$, since there are seven emotions being captured).

Emotional consistency: From the proportions of the emotions in two consecutive one-minute time windows, we compute the emotional consistency as the cosine similarity between the two vectors using the following formula:

$$\cos(\mathbf{A}, \mathbf{B}) = \frac{\mathbf{AB}}{\|\mathbf{A}\|\|\mathbf{B}\|} = \frac{\sum_{i=1}^{n} \mathbf{A}_i \mathbf{B}_i}{\sqrt{\sum_{i=1}^{n} (\mathbf{A}_i)^2}\sqrt{\sum_{i=1}^{n} (\mathbf{B}_i)^2}} \quad (2)$$

where,
A = emotion proportionality vector at time t
B = emotion proportionality vector at time $t + 1$
N = 7, i.e., the number of emotions (happiness, sadness, anger, fear, surprise, contempt, disgust).

The theoretical limits of emotional consistency are 0 and 1. A *zero* value will depict that the set of emotions shown by the students were completely different across two consecutive time windows; while a *one* value will depict the exact distribution of emotions in the two consecutive time windows.

Joint Emotional State (i.e., Emotional Togetherness – Cross Recurrence (CR)): Once we have the emotions for every frame and each child in the video, we define a **one-minute long temporal window**, with a **30 seconds shift** and use the most frequent emotion as the main emotion in every window for each child. This results in a time series of emotion labels (happiness, sadness, surprise, fear, anger, disgust, contempt) for every child in each team. Once we have the time series for whole group, we compute "emotional togetherness" as the cross recurrence of emotion labels.

The concept of cross recurrence is widely used in the theory of dynamical systems to compute the temporal co-occurrence of states of two dynamical systems [13]. Each dynamical system can be represented as a temporal sequence of measurable states. In CSCL this measurement has been used to explain collaborative processes using collaborative eye-tracking data [22, 48, 51]. In our case, to characterize quantitatively the temporal patterns of emotions, we need an indicator that measures the relationship between the sequences of emotions exhibited by the peers. In the context of our analysis, each student can be considered as a dynamical system in which the emotion from a given time window represents the state. Thereby, cross-recurrence analysis can be used to measure how much and when peers have similar emotional states.

The principle of cross-recurrence is to build a binary matrix, called a cross-recurrence plot (CR plot), that displays similarities between two temporal sequences of states of some dynamical systems. The two-time series are represented as the two dimensions of the matrix; and every point in matrix corresponds to a time window in each time series. The value of every point indicates whether the states of the two systems for their respective time windows are recurrent (similar) or not. The construction of such a matrix for systems having discrete state values is described schematically in Figure 4. The main diagonal of the final matrix represents the perfect synchrony of states for the systems, which in our case are the emotional states of peers. The computation of CR can be extended from a 2D case (dyad) to a 3D case (triad) in a simple manner.

High Cross-recurrence episodes (number and average length): Once, we computed the time-series of the emotional CR from the face videos of the students, we computed the median for the whole coding session and used it to divide each one-minute window into high or low CR episodes. Next, we compute the episodes with high CR by merging the consecutive high CR windows. Finally, we count the number of such episodes and compute the average length of these episodes per group.

Analysis

First, to check for the bias (on the collaborative experiences: effectiveness and satisfaction) occurring because of the different group sizes (dyads vs triads), we will use ANOVA with the collaborative experiences as the dependent and the group size as the independent variables, respectively. To explore the relationship between the components of joint emotional profile and the collaborative experiences we will use Pearson correlation tests. Finally, to investigate which components of the joint emotional profile best explain the collaborative experiences, we will use Linear Models and percent of variance explained to compare different models.

4 RESULTS

Group size bias

First of all we tested a potential difference between the dyads and triads. The results didn't show any significant difference in the perceived collaboration quality for the two different group sizes. In particular, an Analysis of Variances (ANOVA) shows no significant difference between the satisfaction from the collaboration ($F[1,18] = 0.24$, $p = .62$)and the perceived effectiveness of the collaboration ($F[1,18] = 0.35$, $p = .55$) between the dyads and triads.

Performance of the face detection algorithm

To display the performance of the face detection and tracking algorithm, we computed the following proportions. The proportions are calculated based on the number of frames in the video, since all the values were computed per frame

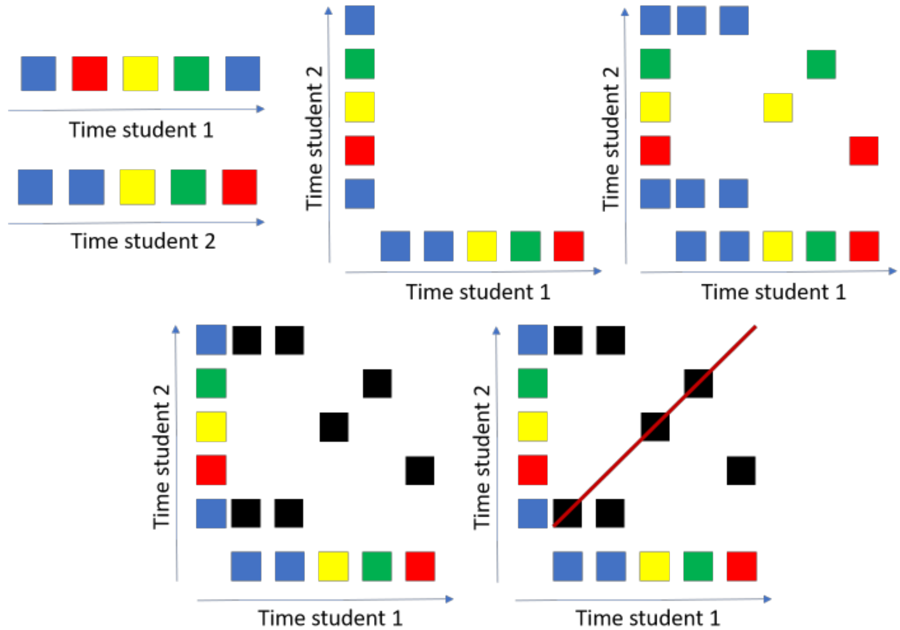

Figure 4: Summary of steps from the individual time series of emotions to group's emotional cross recurrence. Each colour represents a different emotion.

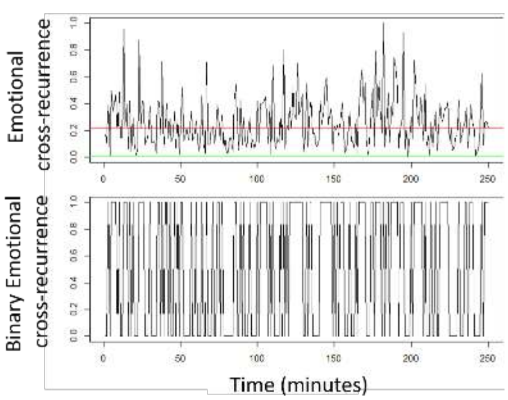

Figure 5: Example of computing the high/low CR episodes. The green line in the top panel shows the theoretical base line which is the probability of two people having the same emotion (out of 7 emotions) at the exact same moment which is $1/2^7$, i.e., 0.008. The red line in the top panel shows the median for this particular team.

Table 2: All the constituent measurements of joint emotional profile and their correlations with the perceived effectiveness of the collaboration, and satisfaction from the collaboration. (*p-value:* * < *.05;* ** *<.01*).

Variable	Correlation Effectiveness Collaboration	Correlation Satisfaction Collaboration
Happiness	0.54^*	0.51^*
Sadness	-0.62^{**}	-0.52^*
Anger	-0.56^{**}	-0.53^*
Contempt	0.60^{**}	0.41
Surprise	0.41	0.40
Disgust	0.27	0.29
Fear	-0.03	-0.14
Emotional entropy	-0.63^{**}	-0.62^{**}
Emotional stability	0.51^*	0.54^*
CR	0.66^{**}	0.55^{**}
Number of high CR episodes	0.52^*	0.61^{**}
Average length high CR episodes	0.62^{**}	0.52^*

before the pipeline was executed. For the dyads, we observe that most of the times there were at least two faces detected (mean = 87.5%, sd = 4.57%); there were three or more faces detected in 84.9% times (sd = 7.92%). For the triads, we observe that there were at least three faces detected for an average of 84.7% times (sd = 6.28 %); there were four or more faces detected in 82.35% of times (sd = 7.37%). The main reason for the frames having less than 2 (for dyads) and 3 (for triads) faces detected was that the children were free to move among different groups during the coding activity. This resulted in some of the frames having partially visible faces or completely occluded faces. For further analysis we normalized all the measures with the number of frames with required number of children being visible (2 for dyads and 3 for triads).

Performance of the emotion computation

For each face detected in the frame, OpenFace library provides a confidence value for each of the AUs detected (the values are between 0 for no detection and 1 for complete detection). To have high levels of robustness in the emotion computation process, we kept only those frames where the average confidence value of all the detected AUs was more than 0.85 and the standard deviation was below 0.05. This resulted into removal of a few more frames from further analysis (mean = 2.4% SD = 1.4%, including dyads and triads). Again, we normalized all the measures with the number of frames available with high quality action unit detection.

Proportions of emotions

We observe the following significant and positive correlations among the measures:
–a positive and significant correlation between the perceived effectiveness of collaborative sessions and the average proportion of happiness shown by the peers ($r(15) = 0.54, p < .05$). The groups having high levels of perceived effectiveness of collaboration also showcased high levels of happiness during the collaboration;
–a positive and significant correlation between the perceived effectiveness of collaborative sessions and the average proportion of contempt shown by the peers ($r(15) = 0.60, p < .01$). The groups having high levels of perceived effectiveness of collaboration also showcased high levels of contempt during the collaboration;
–a positive and significant correlation between the satisfaction from collaborative sessions and the average proportion of happiness shown by the peers ($r(15) = 0.51, p < .05$). The groups having high levels of satisfaction from collaboration also showcased high levels of happiness during the collaboration.

Next, we observe the following significant and negative correlations among the measures:
– a negative and significant correlation between the perceived effectiveness of collaborative sessions and the average proportion of anger shown by the peers ($r(15) = -0.56, p < .01$). The groups having low levels of perceived effectiveness of collaboration showcased high levels of anger during the collaboration;
– a negative and significant correlation between the perceived effectiveness of collaborative sessions and the average proportion of sadness shown by the peers ($r(15) = -0.62, p < .01$).

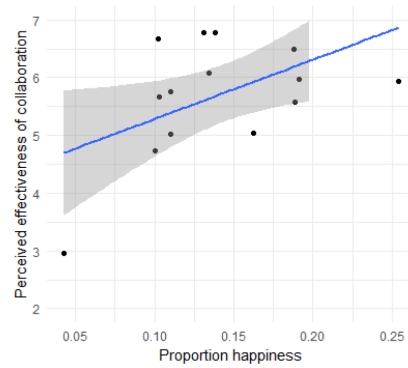

Figure 6: Perceived effectiveness and proportion of happiness, with the linear model (blue line) and the error (gray area).

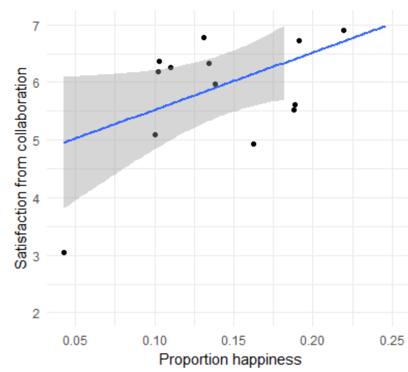

Figure 7: Satisfaction and proportion of happiness, with the linear model (blue line) and the error (gray area).

The groups having low levels of perceived effectiveness of collaboration showcased high levels of sadness during the collaboration;
– a negative and significant correlation between the satisfaction from collaborative sessions and the average proportion of anger shown by the peers ($r(15) = 0.53, p < .05$). The groups having low levels of satisfaction from collaboration showcased high levels of anger during the collaboration. – a negative and significant correlation between the satisfaction from collaborative sessions and the average proportion of sadness shown by the peers ($r(15) = -0.49, p < .05$). The groups having low levels of satisfaction from collaboration showcased high levels of sadness during the collaboration.

Emotions, such as surprise, disgust and fear were not found to be correlated with either perceived effectiveness or the satisfaction (Table 2).

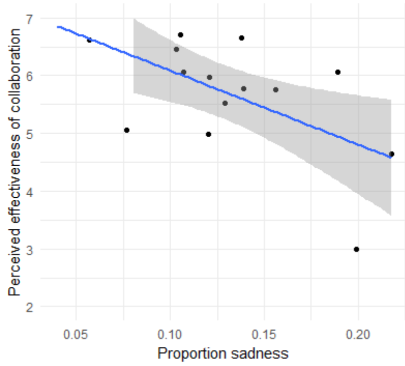

Figure 8: Perceived effectiveness and proportion of sadness, with the linear model (blue line) and the error (gray area).

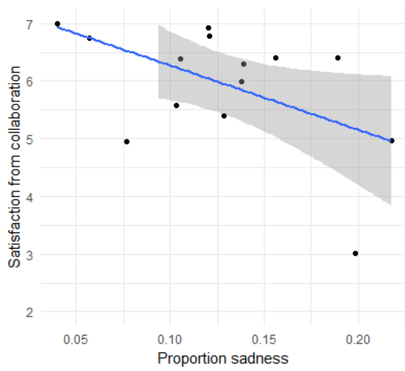

Figure 9: Satisfaction and proportion of sadness, with the linear model (blue line) and the error (gray area).

Emotional entropy

We observed a negative and significant correlation between the emotional entropy and the perceived effectiveness of the collaborative coding sessions ($r(15) = -0.63$, $p < .01$, Table 2). The groups who indicated low levels of effectiveness of the collaborative coding sessions had high levels of entropy indicating that on an average such groups showcased wide variety of emotions during the coding sessions. On the other hand, the groups considering these coding sessions highly effective, showcased fewer emotions during the coding sessions.

We also observed a negative and significant correlation between the emotional entropy and the satisfaction from the collaborative coding sessions ($r(15) = -0.62$, $p < .01$, Table 2). The groups who indicated low levels of satisfaction from the collaborative coding sessions had high levels of entropy indicating that on an average such groups showcased wide variety of emotions during the coding sessions. On the other hand, the groups considering these coding sessions to be highly satisfactory, showcased fewer emotions during the coding sessions.

Emotional consistency

We observed a positive and significant correlation between the emotional consistency and the perceived effectiveness of the collaborative coding sessions ($r(15) = 0.51$, $p < .05$, Table 2). The groups who indicated low levels of effectiveness of the collaborative coding sessions had low levels of consistency indicating that on an average such groups showcased emotions that were short lived during the coding sessions. On the other hand, the groups considering these coding sessions highly effective, showcased a set of emotions for longer periods of time during the coding sessions.

We observed a positive and significant correlation between the emotional consistency and the satisfaction from the collaborative coding sessions ($r(15) = 0.54$, $p < .05$, Table 2). The groups who indicated low levels of satisfaction from the collaborative coding sessions had low levels of consistency indicating that on an average such groups showcased emotions that were short lived during the coding sessions. On the other hand, the groups considering these coding sessions highly satisfactory, showcased a set of emotions for longer periods of time during the coding sessions.

Emotional cross recurrence (CR)

We observe the following positive and significant correlations concerning the emotional CR:
– between the perceived effectiveness and CR ($r(15) = 0.66$, $p < .01$); – between satisfaction and CR ($r(15) = 0.55$, $p < .01$);
– between the perceived effectiveness and number of episodes with high CR ($r(15) = 0.52$, $p < .05$);
– between satisfaction and number of episodes with high CR ($r(15) = 0.61$, $p < .01$);
– between the perceived effectiveness and the average length of episodes with high CR ($r(15) = 0.62$, $p < .01$);
– between satisfaction and the average length of episodes with high CR ($r(15) = 0.52$, $p < .05$).

These results suggest that the groups having high perceived effectiveness and satisfaction also had high emotional CR, moreover such groups also had higher number of high CR episodes with longer duration than the groups with low perceived effectiveness and satisfaction.

Linear Modelling

To explain the perceived effectiveness of the collaborative coding sessions, the most important measurements, contributing positively, are emotional consistency, and emotional CR; while emotional entropy and proportion of anger contribute negatively. Table 3 shows the details of the model explaining 61.6% of the variance in the perceived effectiveness of collaboration.

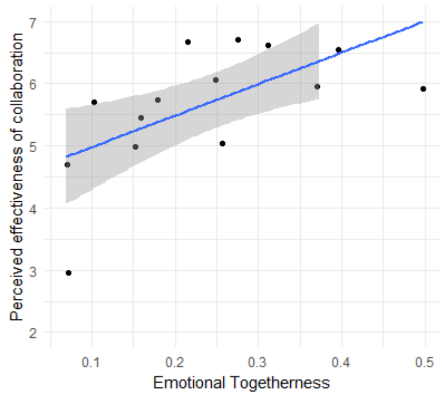

Figure 10: Perceived effectiveness and proportion of emotional cross recurrence, with the linear model (blue line) and the error (gray area).

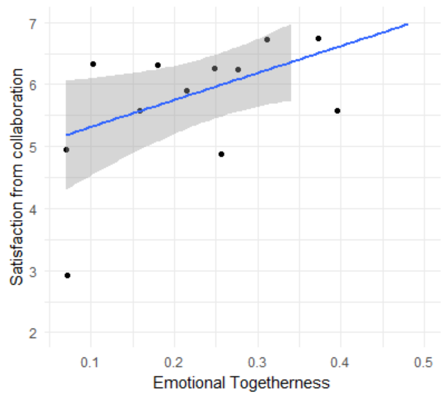

Figure 11: Satisfaction and emotional cross recurrence, with the linear model (blue line) and the error (gray area).

Table 3: Final model for perceived effectiveness of the collaborative coding sessions. Percentage of variance explained = 61.6; all p-values are less than .05

Variable	Estimate	Error	t-value
intercept	4.82	1.48	2.79
stability	1.42	0.65	2.49
entropy	-2.20	0.23	-2.36
cross-recurrence	2.32	1.02	2.65
anger	-2.76	0.47	-2.57

To explain the satisfaction from the collaborative coding sessions, the most important measurements, contributing positively, are number of episodes with high emotional CR and proportions of happiness and contempt shown; while emotional entropy and proportion of anger contribute negatively. Table 4 shows the details of the model explaining 65.3% of the variance in the satisfaction from collaboration.

Table 4: Final model for satisfaction from the collaborative coding sessions. Percentage of variance explained = 65.3; all p-values are less than .05

Variable	Estimate	Error	t-value
intercept	3.31	1.81	2.91
happiness	1.51	0.68	2.38
anger	-1.99	0.52	-2.20
contempt	3.83	0.50	2.65
entropy	-4.87	0.22	-2.51
#episodeHighCR	0.02	0.01	-2.19

5 DISCUSSION AND CONCLUSIONS

In our study, we show the relation between groups' joint emotional profile (proportions of emotions, emotional entropy and consistency, and emotional togetherness) and their collaborative experience during after-school group coding sessions. Emotions, such as happiness and contempt co-occur with high perceived effectiveness and high satisfaction from the collaborative coding. There are few possible explanations for this effect. First, the children who showcase more happiness might have an inherent interest in coding and since they get into an environment where they can learn more about it, they become happy. Second, satisfaction with the final product and with the different phases of game making and fruitful negotiations with the peers and hence they showcase higher proportions of happiness than others. There might be a correlation between such emotions and the performance as well, but more experimentation is required to confirm this hypothesis.

Negative emotions co-occur with low perceived effectiveness and low satisfaction from the collaborative coding. One of the plausible reasons could be that the groups with negative experiences had troubles with the activity and they were disappointed (anger, sadness). Further, they might have negative attitude towards coding or might be facing minor issues with the hypotheses verification in the coding (sadness upon failure) or could have involved in arguments or misunderstandings among peers.

The contingency between the proportions of emotions and the collaborative experiences (satisfaction and perceived effectiveness) is similar to some of the studies with the emotions in education [3, 5, 15, 34, 44]. These results suggest that the emotions are not only valuable to study the relation between two variables but also to understand the process. The added value in this paper is the real-time analyses and using emotions to define measurements which can explain the collaborative processes.

Next, high perceived effectiveness and high satisfaction are positively correlated with the emotional consistency and negatively correlated with the emotional entropy. A post-hoc analysis shows negative and significant correlation between the average emotional entropy of the groups and their average emotional consistency ($r(20) = -0.49$, $p < .05$). This result is not completely intuitive. Mathematically, it is more probable to have high consistency across two consecutive time frames when the entropy values are the highest. For two time frames that have uniform unit distribution will be identical. We propose to interpret entropy and consistency together. Correlations among collaborative experiences, emotional entropy and emotional consistency show that the positive experiences are accompanied by low range and consistent set of emotions. Similar results were reported with performance in pair programming [58] and eye-tracking, concerning the entropy-consistency of the exploration patterns. This paper has an advantage in terms of ease of implementation, pervasiveness, and ubiquitous nature of measuring device, i.e., web-cam.

Finally, the emotional togetherness (CR) is observed to be higher for the groups with high perceived effectiveness and high satisfaction than for the groups with low perceived effectiveness and low satisfaction. This can be explained by the fact that the groups having high effectiveness and satisfaction might also manage the collaboration in a better manner than the groups having low effectiveness and satisfaction. Collaboration management is based on initiating and sustaining long term shared understanding among the peers; the main aim of a collaborative problem solving task is to arrive at a common ground earlier in the collaboration [8] and then maintaining this common ground through sustained efforts[11]. High emotional togetherness (CR) indicates towards this effect taking place within the coding context as well.

Another interesting finding from the togetherness (CR) is about the number of high CR episodes and their average length. A post-hoc analysis shows positive and significant correlations between CR and number of episodes with high CR ($r(20) = 0.44$, $p < .05$), between CR and average length of the high CR episodes ($r(20) = 0.65$, $p < .001$) and the number of CR episodes and their average length ($r(20) = 0.51$, $p < .05$). This also shows that peers in a group with high perceived effectiveness and high satisfaction during the collaborative coding might try to initiate and maintain the common ground for the success of their collaboration more frequently and for longer periods. Regarding cross-recurrence (CR, emotional togetherness), similar results were reported from the studies with dual eye-tracking[22, 43, 52] and bio-signals[60]. Again, the added value from this contribution is the affordable and accessible instrument.

In terms of the most important components of the joint emotional profile to explain the collaborative experiences, we observe that the proportion of anger and emotional entropy appear in the models for both effectiveness and satisfaction. Moreover, these two measurements have negative coefficients showing that high proportions of anger and having a wide range of emotions in a given time period have detrimental effect on both the perceived effectiveness and satisfaction. For the satisfaction, showcasing happiness and contempt and having a large number of episodes with high levels of emotional togetherness (CR) coincide with high levels of satisfaction. On the other hand, having consistent set of emotions and a high emotional togetherness (CR) is coincidental with the high levels of perceived satisfaction.

Design implications

This study reveals promising perspectives on how to design collaboration support systems to inform the peers about each others' current emotional state. An emotional awareness tool, can sustain long term engagement from the participants [39]. Such systems might be useful in remote collaborative situations, where the peers can not see each other. This scaffolding also mitigates the need for physical co-presence in situations where emotional awareness among peers is of utmost importance. This can also be useful for collaborating children having difficulties in expressing themselves or detecting/perceiving their peers' emotions (for example children with Down syndrome or ASD). Moreover, the design implications from gaze-aware systems [9, 57] can also be used to inform the design of emotion-aware collaborative systems.

Limitations and Future work

This study uses a window based measurement which is averaged over the whole interaction of the team. Improvements of the method used would be to include more temporal measurements and modelling such as hidden Markov models. Future work also includes, incorporating dialogues, annotating the different stages of coding activities and comparison with qualitative and manually labelled data. In addition, combining entropy and consistency might provide more insights about the evolution of emotion at a higher level. Further, considering the cross-recurrence for each type of emotion separately could also inform us about which kind of emotions are jointly shown and for how long. This can help us in designing more informed scaffolding tools. Finally, future research should focus on experimenting with other independent variables, such as adaptive coding exercises according to the expertise of the children, different group composition and visual versus textual coding environments.

6 SELECTION AND PARTICIPATION OF CHILDREN

All the participants of the study were students from the Trondheim (Norway) region whose teachers have applied to participate in our workshops as an out-of school activity. Studies took place at the university campus in specially designed rooms. Data related to the study were collected after permission from the national Data Protection Official for Research, following all the regulations and recommendations for research with children. A researcher contacted the teacher and the legal guardian of each child to get a written consent that gave permission for the data collection. The children were informed about the data collection process and their participation in the study was completely voluntary. They could withdraw their consent for the data collection at any time without affecting their participation in the coding activity.

7 ACKNOWLEDGEMENTS

This work supported from the "Learning science the fun and creative way: coding, making, and play as vehicles for informal science learning in the 21st century" Project, under the European Commission's Horizon 2020 SwafS-11-2017 Program (Project Number: 787476). This article reflects the views only of the authors and it does not represent the opinion of neither the European Commission nor NTNU, and the European Commission and NTNU can not be held responsible for any use that might be made of its content. This work is also supported from the Norwegian Research Council under the projects FUTURE LEARNING (number: 255129/H20) and Xdesign (number: 290994/F20), and by NOKUT under the Centre for Excellent IT Education (Excited) (number: 16/02049).

REFERENCES

[1] Mary Ainley, Matthew Corrigan, and Nicholas Richardson. 2005. Students, tasks and emotions: Identifying the contribution of emotions to students' reading of popular culture and popular science texts. *Learning and Instruction* 15, 5 (2005), 433–447.

[2] Brandon Amos, Bartosz Ludwiczuk, and Mahadev Satyanarayanan. 2016. *OpenFace: A general-purpose face recognition library with mobile applications.* Technical Report. CMU-CS-16-118, CMU School of Computer Science.

[3] Herbert Bless. 2000. The interplay of affect and cognition: The mediating role of general knowledge structures. (2000).

[4] Yaohua Bu, Jia Jia, Xiang Li, Suping Zhou, and Xiaobo Lu. 2018. IcooBook: When the Picture Book for Children Encounters Aesthetics of Interaction. In *2018 ACM Multimedia Conference on Multimedia Conference.* ACM, 1260–1262.

[5] Neus Capdeferro and Margarida Romero. 2012. Are online learners frustrated with collaborative learning experiences? *The International Review of Research in Open and Distributed Learning* 13, 2 (2012), 26–44.

[6] Ginevra Castellano, Iolanda Leite, André Pereira, Carlos Martinho, Ana Paiva, and Peter W Mcowan. 2014. Context-sensitive affect recognition for a robotic game companion. *ACM Transactions on Interactive Intelligent Systems (TiiS)* 4, 2 (2014), 10.

[7] Ginevra Castellano, André Pereira, Iolanda Leite, Ana Paiva, and Peter W McOwan. 2009. Detecting user engagement with a robot companion using task and social interaction-based features. In *Proceedings of the 2009 international conference on Multimodal interfaces.* ACM, 119–126.

[8] Ruth Colvin Clark, Richard E Mayer, and Will Thalheimer. 2003. E-learning and the science of instruction: Proven guidelines for consumers and designers of multimedia learning. *Performance Improvement* 42, 5 (2003), 41–43.

[9] Sarah D'Angelo and Darren Gergle. 2018. An Eye For Design: Gaze Visualizations for Remote Collaborative Work. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems.* ACM, 349.

[10] Agnes Delaborde, Marie Tahon, Claude Barras, and Laurence Devillers. 2009. A Wizard-of-Oz game for collecting emotional audio data in a children-robot interaction. In *Proceedings of the International Workshop on Affective-Aware Virtual Agents and Social Robots.* ACM, 5.

[11] Pierre Dillenbourg and David Traum. 2006. Sharing solutions: Persistence and grounding in multimodal collaborative problem solving. *The Journal of the Learning Sciences* 15, 1 (2006), 121–151.

[12] Ian Dore. 2016. Shape-shifter and agenda setter: The influence of emotion in social work practice and practice education. *Social Work Education* 35, 4 (2016), 469–481.

[13] J-P Eckmann, S Oliffson Kamphorst, and David Ruelle. 1987. Recurrence plots of dynamical systems. *EPL (Europhysics Letters)* 4, 9 (1987), 973.

[14] Rana El Kaliouby and Matthew S Goodwin. 2008. iSET: interactive social-emotional toolkit for autism spectrum disorder. In *Proceedings of the 7th international conference on Interaction design and children.* ACM, 77–80.

[15] Barbara L Fredrickson. 1998. What good are positive emotions? *Review of general psychology* 2, 3 (1998), 300.

[16] Anne C Frenzel, Reinhard Pekrun, and Thomas Goetz. 2007. Girls and mathematicsâĂŤA âĂIJhopelessâĂİ issue? A control-value approach to gender differences in emotions towards mathematics. *European Journal of Psychology of Education* 22, 4 (2007), 497.

[17] Michail N Giannakos, Konstantinos Chorianopoulos, Kori Inkpen, Honglu Du, and Paul Johns. 2013. Understanding children's behavior in an asynchronous video-mediated communication environment. *Personal and ubiquitous computing* 17, 8 (2013), 1621–1629.

[18] P EKMAN-WV FRIESEN-JC HAGER. 2002. Facial Action Coding System. The Manual On CD ROM.

[19] Natalie Harrold, Chek Tien Tan, Daniel Rosser, and Tuck Wah Leong. 2014. CopyMe: an emotional development game for children. In *CHI'14 Extended Abstracts on Human Factors in Computing Systems.* ACM, 503–506.

[20] Hanna Järvenoja and Sanna Järvelä. 2005. How students describe the sources of their emotional and motivational experiences during the learning process: A qualitative approach. *Learning and instruction* 15, 5 (2005), 465–480.

[21] Hanna Järvenoja and Sanna Järvelä. 2009. Emotion control in collaborative learning situations: Do students regulate emotions evoked by social challenges. *British Journal of Educational Psychology* 79, 3 (2009), 463–481.

[22] Patrick Jermann and Marc-Antoine Nüssli. 2012. Effects of sharing text selections on gaze cross-recurrence and interaction quality in a pair programming task. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work.* ACM, 1125–1134.

[23] Norman A Johnson and Randolph B Cooper. 2009. Media, affect, concession, and agreement in negotiation: IM versus telephone. *Decision Support Systems* 46, 3 (2009), 673–684.

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

[25] Paivi Kinnunen and Beth Simon. 2010. Experiencing programming assignments in CS1: the emotional toll. In *Proceedings of the Sixth international workshop on Computing education research*. ACM, 77–86.

[26] Päivi Kinnunen and Beth Simon. 2012. My program is ok–am I? Computing freshmen's experiences of doing programming assignments. *Computer Science Education* 22, 1 (2012), 1–28.

[27] Karel Kreijns, Paul A Kirschner, and Wim Jochems. 2003. Identifying the pitfalls for social interaction in computer-supported collaborative learning environments: a review of the research. *Computers in human behavior* 19, 3 (2003), 335–353.

[28] Susanne P Lajoie, Lila Lee, Eric Poitras, Mandana Bassiri, Maedeh Kazemitabar, Ilian Cruz-Panesso, Cindy Hmelo-Silver, Jeffrey Wiseman, Lap Ki Chan, and Jingyan Lu. 2015. The role of regulation in medical student learning in small groups: Regulating oneself and otherssâĂŹ learning and emotions. *Computers in Human Behavior* 52 (2015), 601–616.

[29] Dabae Lee, Yeol Huh, and Charles M Reigeluth. 2015. Collaboration, intragroup conflict, and social skills in project-based learning. *Instructional Science* 43, 5 (2015), 561–590.

[30] Iolanda Leite, Ginevra Castellano, André Pereira, Carlos Martinho, and Ana Paiva. 2012. Modelling empathic behaviour in a robotic game companion for children: an ethnographic study in real-world settings. In *Proceedings of the seventh annual ACM/IEEE international conference on Human-Robot Interaction*. ACM, 367–374.

[31] Iolanda Leite, Ginevra Castellano, André Pereira, Carlos Martinho, Ana Paiva, and Peter W McOwan. 2009. Designing a game companion for long-term social interaction. In *Proceedings of the International Workshop on Affective-aware Virtual Agents and Social Robots*. ACM, 10.

[32] Iolanda Leite, Rui Henriques, Carlos Martinho, and Ana Paiva. 2013. Sensors in the wild: Exploring electrodermal activity in child-robot interaction. In *Proceedings of the 8th ACM/IEEE international conference on Human-robot interaction*. IEEE Press, 41–48.

[33] Germán Lescano and Rosanna Costaguta. 2018. COLLAB: Conflicts and Sentiments in chats. In *Proceedings of the XIX International Conference on Human Computer Interaction*. ACM, 33.

[34] EA Linnenbrink and PR Pintrich. 2003. Motivation, affect, and cognitive processing: What role does affect play. In *annual meeting of the American Educational Research Association, Chicago, IL*.

[35] Elizabeth A Linnenbrink and Paul R Pintrich. 2002. The role of motivational beliefs in conceptual change. In *Reconsidering conceptual change: Issues in theory and practice*. Springer, 115–135.

[36] Lisa Linnenbrink-Garcia, Toni Kempler Rogat, and Kristin LK Koskey. 2011. Affect and engagement during small group instruction. *Contemporary Educational Psychology* 36, 1 (2011), 13–24.

[37] Alex Lishinski, Aman Yadav, and Richard Enbody. 2017. Students' Emotional Reactions to Programming Projects in Introduction to Programming: Measurement Approach and Influence on Learning Outcomes. In *Proceedings of the 2017 ACM Conference on International Computing Education Research*. ACM, 30–38.

[38] Debra K Meyer and Julianne C Turner. 2002. Discovering emotion in classroom motivation research. *Educational psychologist* 37, 2 (2002), 107–114.

[39] Gaëlle Molinari, Guillaume Chanel, Mireille Betrancourt, Thierry Pun, and Christelle Bozelle Giroud. 2013. Emotion feedback during computer-mediated collaboration: Effects on self-reported emotions and perceived interaction. (2013).

[40] Jennifer Olsen, Kshitij Sharma, Vincent Aleven, and Nikol Rummel. 2018. Combining Gaze, Dialogue, and Action from a Collaborative Intelligent Tutoring System to Inform Student Learning Processes. International Society of the Learning Sciences, Inc.[ISLS].

[41] Ana Paiva, Rui Prada, Ricardo Chaves, Marco Vala, Adrian Bullock, Gerd Andersson, and Kristina Höök. 2003. Towards tangibility in gameplay: building a tangible affective interface for a computer game. In *Proceedings of the 5th international conference on Multimodal interfaces*. ACM, 60–67.

[42] Sofia Papavlasopoulou, Michail N Giannakos, and Letizia Jaccheri. 2017. Empirical studies on the Maker Movement, a promising approach to learning: A literature review. *Entertainment Computing* 18 (2017), 57–78.

[43] Sofia Papavlasopoulou, Kshitij Sharma, and Michail N Giannakos. 2018. How do you feel about learning to code? Investigating the effect of children's attitudes towards coding using eye-tracking. *International Journal of Child-Computer Interaction* (2018).

[44] Reinhard Pekmn, Thomas Goetz, Wolfram Titz, et al. 2002. Academic emotions in students" self regulated learning and achievement: A program of qualitative and quantitative research. *Educational Psychologist* 37 (2002), 91–106.

[45] Reinhard Pekrun. 2006. The Control-Value Theory of Achievement Emotions: Assumptions, Corollaries, and Implications for Educational Research and Practice. *Educational Psychology Review* 18, 4 (01 Dec 2006), 315–341. https://doi.org/10.1007/s10648-006-9029-9

[46] Reinhard Pekrun, Thomas Goetz, Wolfram Titz, and Raymond P Perry. 2002. Positive emotions in education.

[47] Daniel Perry and Cecilia Aragon. 2012. Measuring distributed affect in collaborative games. In *Proceedings of the ACM 2012 conference on Computer Supported Cooperative Work Companion*. ACM, 195–198.

[48] Daniel C Richardson, Rick Dale, and Natasha Z Kirkham. 2007. The art of conversation is coordination. *Psychological science* 18, 5 (2007), 407–413.

[49] Jyotirmay Sanghvi, Ginevra Castellano, Iolanda Leite, André Pereira, Peter W McOwan, and Ana Paiva. 2011. Automatic analysis of affective postures and body motion to detect engagement with a game companion. In *Proceedings of the 6th international conference on Human-robot interaction*. ACM, 305–312.

[50] Klaus R Scherer. 2000. Emotions as episodes of subsystem synchronization driven by nonlinear appraisal processes. *Emotion, development, and self-organization: Dynamic systems approaches to emotional development* 7099 (2000).

[51] Bertrand Schneider, Kshitij Sharma, Sébastien Cuendet, Guillaume Zufferey, Pierre Dillenbourg, and Roy Pea. 2016. Using mobile eyetrackers to unpack the perceptual benefits of a tangible user interface for collaborative learning. *ACM Transactions on Computer-Human Interaction (TOCHI)* 23, 6 (2016), 39.

[52] Bertrand Schneider, Megan Strait, Laurence Muller, Sarah Elfenbein, Orit Shaer, and Chia Shen. 2012. Phylo-Genie: engaging students in collaborative 'tree-thinking' through tabletop techniques. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*. ACM, 3071–3080.

[53] Paul A Schutz and Jessica T DeCuir. 2002. Inquiry on emotions in education. *Educational Psychologist* 37, 2 (2002), 125–134.

[54] Gerard Seegers and Monique Boekaerts. 1993. Task motivation and mathematics achievement in actual task situations. *Learning and Instruction* 3, 2 (1993), 133–150.

[55] Suleman Shahid. 2018. Computer mediated playful interactions: investigating how variations in the level of gaze affect children's gameplay. In *Proceedings of the 17th ACM Conference on Interaction Design and Children*. ACM, 427–433.

[56] Suleman Shahid, Emiel Krahmer, Marc Swerts, and Omar Mubin. 2010. Child-robot interaction during collaborative game play: Effects of age and gender on emotion and experience. In *Proceedings of the 22nd*

Conference of the Computer-Human Interaction Special Interest Group of Australia on Computer-Human Interaction. ACM, 332–335.

[57] Kshitij Sharma, Sarah D'Angelo, Darren Gergle, and Pierre Dillenbourg. 2016. Visual augmentation of deictic gestures in mooc videos. Singapore: International Society of the Learning Sciences.

[58] Kshitij Sharma, Patrick Jermann, Marc-Antoine Nüssli, and Pierre Dillenbourg. 2013. Understanding collaborative program comprehension: Interlacing gaze and dialogues. In *Proceedings of Computer Supported Collaborative Learning (CSCL 2013)*, Vol. 1. 430–437.

[59] Kshitij Sharma, Jennifer K Olsen, Vincent Aleven, and Nikol Rummel. 2018. Exploring Causality Within Collaborative Problem Solving Using Eye-Tracking. In *European Conference on Technology Enhanced Learning*. Springer, 412–426.

[60] Kshitij Sharma, Ilias Pappas, Sofia Papavlasopoulou, and Michail Giannakos. [n. d.]. Towards Automatic and Pervasive Physiological Sensing of Collaborative Learning. In *Submitted*.

[61] Hyo-Jeong So and Thomas A Brush. 2008. Student perceptions of collaborative learning, social presence and satisfaction in a blended learning environment: Relationships and critical factors. *Computers & education* 51, 1 (2008), 318–336.

[62] Samuel Spaulding, Goren Gordon, and Cynthia Breazeal. 2016. Affect-aware student models for robot tutors. In *Proceedings of the 2016 International Conference on Autonomous Agents & Multiagent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 864–872.

[63] Priyashri K Sridhar, Samantha WT Chan, and Suranga Nanayakkara. 2018. Going beyond performance scores: understanding cognitive-affective states in kindergarteners. In *Proceedings of the 17th ACM Conference on Interaction Design and Children*. ACM, 253–265.

[64] Kenji Suzuki. 2015. Social imaging technology to identify and represent social behaviors. In *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*. ACM, 907–908.

[65] Christian Szegedy, Sergey Ioffe, and Vincent Vanhoucke. 2016. Inception-v4, Inception-ResNet and the Impact of Residual Connections on Learning. *CoRR* abs/1602.07261 (2016). arXiv:1602.07261 http://arxiv.org/abs/1602.07261

[66] Yuji Takano and Kenji Suzuki. 2014. Affective communication aid using wearable devices based on biosignals. In *Proceedings of the 2014 conference on Interaction design and children*. ACM, 213–216.

[67] Tiffany Y Tang, Pinata Winoto, and Guanxing Chen. 2017. Emotion Recognition via Face Tracking with RealSense (TM) 3D Camera for Children with Autism. In *Proceedings of the 2017 Conference on Interaction Design and Children*. ACM, 533–539.

[68] Pablo Torres-Carrión, Carina González-González, and Alberto Mora Carreño. 2015. Facial Emotion Analysis in Down's syndrome children in classroom. In *Proceedings of the XVI International Conference on Human Computer Interaction*. ACM, 15.

[69] Tzu-Wei Tsai, Hsiao Yu Lo, and Kai-Shao Chen. 2012. An affective computing approach to develop the game-based adaptive learning material for the elementary students. In *Proceedings of the 2012 Joint International Conference on Human-Centered Computer Environments*. ACM, 8–13.

[70] Wouter Van Diggelen and Maarten Overdijk. 2007. Small-group face-to-face discussions in the classroom: a new direction of CSCL research. In *Proceedings of the 8th iternational conference on Computer supported collaborative learning*. International Society of the Learning Sciences, 727–736.

[71] Li Zhang. 2008. Metaphorical affect sensing in an intelligent conversational agent. In *Proceedings of the 2008 International Conference on Advances in Computer Entertainment Technology*. ACM, 100–106.