Faces Don't Lie: Analysis of Children's Facial expressions during Collaborative Coding

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ABSTRACT

Educational research has used the information extracted from facial expressions to explain learning performance in a variety of educational settings like collaborative learning. Leveraging this, we extracted the emotions of frustration, confusion and boredom from videos with children aged 13-16 years old while they were collaborating to create games using Scratch. After we computed the groups' coding performance, based on the created artifacts, we divided them into high and low performance and compared them on the basis of individual emotions' duration and the transitions among the emotions. The results show that the children from the high performing teams show more confusion and frustration and more often from confusion and frustration to delight and neutral. The low performing teams show more boredom and move to this emotion from any other. Based on the results, we suggest implications both for the instructors and students.

CCS CONCEPTS

• **Human-centered computing** → **HCI theory, concepts and models**.

KEYWORDS

Frustration, Boredom, Confusion, Delight, Facial Expressions, Emotions, Affect, Collaborative learning, Collaborative coding

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1 INTRODUCTION

Computational thinking and coding activities for children in K-12 education have been growing over the past years. Many European countries have already incorporated computer science (CS) into the school curricula some years now [9] while several other followed [6, 80]. Organizations like Computer Science Teachers Association (CSTA), Informatics Europe, the Cyber Innovation Center, to mention few, support and encourage CS education with practices, while others, like the "Code.org", "code the future" are offering many resources to support coding. In addition, the existence of low-cost mini-computers such as Micro: Bit and Raspberry Pi, together with educational programming languages like Scratch, Alice and Blockly have contributed to a large scale adoption from children. More and more coding activities appear in both in- and out- of school settings during which children have the opportunity to develop digital skills, turn into creative developers of their own projects and gain confidence at different levels following technology that transforms our digital society. Many times, CS and coding activities are based on Papert's constructionism [54] that emphasizes the importance of how the process of creating a shared and meaningful artifact is the key of gaining knowledge. Available educational child-friendly tools and practices (e.g., Scratch, K-12 CS framework) are good examples can offer fruitful learning experiences to children allowing them to learn how to code, enhance their computational thinking, problem-solving and collaborative skills, [18, 52] .

Collaborative making and coding activities for children are valued not only for their engagement and building of knowledge, but also for enhancing the social setting. During these activities, children share their experience and together interact having a common purpose; they overcome possible difficulties they meet on the process and share their emotions related to the individual, the interaction with technology and the group dynamics [17, 33, 72]. In technology-based settings, emotions are important drivers of learning and can be shaped by the different aspects of the settings and learners' experience [46]. Kort et al. 2001 [40] listed the emotions involved in learning and proposed a model with the phases of learning in emotions that cycle from positive to negative. For example, a student may start dealing with a task with confusion possibly due to difficulty, followed by frustration and then by happiness related to success [38, 39]. Individual and/or collaborative emotional behaviors from children during activities like coding are crucial to be studied closely to better understand the learning experience and consequently design systems and activities to support them efficiently. Compared to performance and learning gains, learner's emotions are harder to be measured [59]. Most of the times, affect in learning contexts and specifically in coding activities has been examined through qualitative and/or quantitative measurements like questionnaires, observations and interviews [20, 35, 57, 84]. However, there are some efforts that suggest systems detecting surface level affect behaviors based on gaze, facial expressions, head movements and gestures [36], extraction of joint

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emotional states from videos [69] or to develop an instrument that focuses "in the moment" individual and collaborative interactions during computing collaborations [33]. Learning is a multifaceted phenomenon and this study is a step towards better understanding how individual emotional state changes over time during children's learning experience and interaction with coding tasks and interaction within a team. The goal of this study is to explore how children (age 13-16 years old), who participate in our making-based coding activity, experience the process of collaboratively learning how to code while creating a shared artifact (i.e. a game). Therefore, we propose a quantitative analysis to capture the emotional state of the children during the activity using video recordings from a webcam. In addition, we collected and analyzed the created artifacts as an indication of their task-based performance (high and low). Specifically we address the following research questions:
RQ1 What is the relation between children's individual educational emotions (i.e., frustration, boredom, confusion, delight) and their collaborative coding performance?
RQ2 How do these emotions change during the coding sessions based on the children's performance levels? In the next sections we present an overview of the related work, then the methodology and the coding workshop is described. The forth section presents the results and lastly we discuss the finding providing implications, the limitations and suggestions for future work.

2 RELATED WORK

2.1 Collaborative learning and coding in CCI

During K-12 CS/CT activities, children have often the chance to not only work individually on tasks but depending on the design of the activity, engage in a collaborative coding experience with peers. Although it is not an easy process, collaboration is an important part of learning CS and coding (Tsan et al., 2018) [79]. Building on Vygotsky (1978) [82] and Dewey (1938) [19], it is shown that through collaboration children construct meaning and knowledge. A common purpose gives children the chance to learn from each other, share responsibilities and confront difficulties. Compared to working alone, when children work in teams can be engaged in discussions relevant to the completion of the task, be aware of their own learning, be persistent in challenging tasks and confront struggles [28, 31, 83]. Roschelle 1992 and Teasley and Roschelle 1993 refer to the notion of joint problem space (JpS) which is essential for collaborative learning as it includes the shared conception, goals and knowledge [64, 76]. As children collaborate to find a solution to a problem their metacognitive thinking is also uncovered [42]. Children's thinking process is shown from their interactions and negotiations; the way children approach these actions will then have a result in the outcome of collaboration.

The development of computational artifacts is not simple or linear, on the contrary, it is an iterative process of decisions, trials and testing [7]. Studies show the benefits of collaborative learning for children's performance and cognition [4, 11]. During the process of creating and debugging a game, girls who had an effective collaboration, were trying more on their own before asking for help from the instructors [16]. In their study, Jordan and McDaniel, focused on how 5th grade students influenced each other during their collaboration in a robotics engineering activity. While working on problem solving, students experienced content but also uncertainty that was either directly resolved or followed by supportive or unsupportive ways of action for the peers [35]. Denner et al. showed that middle school children with low prior computer use who worked in pairs using Alice programming environment, increased their programming knowledge [17]. Their study suggests that when one of the partners has more experience the other can still learn. Sullivan, F. R., & Wilson, N. C. (2015) suggested playful talk as a way to avoid conflicts and competitive attitude of students working in coding and other physics/robotics' curriculum tasks [73]. In this way the tensions are decreased and opportunities to learn opened for low status group members.

2.2 Emotions in education and CCI

Children's emotions and their affective states are and have been a major direction of CCI research, with several studies evaluating and/or exploring performance [69], enjoyment [44], usability [26, 78], engagement [45] and learning processes [71]. Emotions in CCI research have been measured through multiple data collection modes such as facial features [37, 44, 78], physiological data [15, 45, 71, 75], and self reports [26, 66].

There are two primary strands when it comes to utilising the emotions that are considered important in educational settings. The first set is derived from the Control Value Theory (e.g., sadness, happiness, surprise, anger, disgust) [56] and the second set comprises of the affective states (e.g., confusion, frustration, boredom, delight) [23]. Previous research, with the control value theoretic emotions, has shown that happiness to be correlated with success [25] and anger is correlated with failure [5]. Furthermore, concerning the affective states, frustration was found as being a common feeling among students who are involved in online collaborative learning [47]; whereas, boredom and confusion are related to poor academic performance [2, 22]. Moreover, emotions/expressions/affective states have been used in educational research to improve students' interaction [30, 58, 74], provide feedback [70, 78, 85], and evaluate/understand task-based performance [34]. An interesting systematic literature review has been conducted about affective states and emotions in educational settings [61].

When students collaborate in front of a computer, accomplishing a coding task (co=located collaboration), there is a certain level of social engagement and a common goal which is the creation of a functioning artifact [53]. An important issue to consider is to keep acceptable levels of participation and strong relationships while students' collaborate [43]. The associated interactions with these aspects of the group performance can be characterised as social-emotional interactions [43] and these, are primarily directed towards the relationship between group members [32].

During collaboration, confusion occurs when the groups have to reinforce their pre-existing mental models with new information [13, 23]. On the other hand, frustration, during collaborative learning sessions, was found to be eminent during online interaction [10] and online discussion forums [12]. Frustration and confusion were shown to lead to impasses in collaborative learning [81]. Lastly, when the problem at hand is far too easy or repetitive boredom is the emotion that is mainly observed[51]; and the same happens with individual learning [14]. Based on a selective meta-analysis with 21 studies [20], in this paper, we decided to focus on these three emotions along with delight and neutral because they were found to be most prominent.

3 METHODS

3.1 The coding workshop

Our coding activity in Norwegian University of Science and Technology (NTNU), Trondheim, Norway, is designed based on the constructionist approach and making [52]. It is a coding workshop which takes place in an informal environment at the University's premises and specially designed rooms. School classes from the region are invited to participate in a one-day out of school activity. The main goal of the workshop is to introduce CS and programming to children in a playful and interactive way and does not require any previous coding experience from them. The total duration of the workshop is 4 hours and has two sessions. Especially, children 13-16 years old are introduced to block-based programming through Scratch environment. The purpose for them is to work collaboratively in dyads or triads; they imagine, create and modify their own games by iteratively coding and testing them. Children's teams are instructed by student assistants who are showing and explaining the coding tasks that need to be done to successfully code their games. Although the main instructions for the tasks are the same, children in each team make the their own decisions for their games interact and discover their own knowledge. Therefore, each of the instructors provides also help as requested, to one or two teams during the activities. During the workshops, three researchers are also present to observe, take field notes and make sure of the smooth execution of it. When all teams have completed their games, children shuffle around and play each others' games.

3.2 Sampling and data collection

We collected the data from the coding workshops happened during Autumn 2017 and children from 8^{th} to 10^{th} grade (age 13-16 years old) participated. The sample consisted of 105 participants in total, 69 boys and 36 girls (mean age: 14.55, SD: 0.650). We collected the videos from 10 dyads and 10 triads while they were working to code their games. For all children we had previously collected the necessary consent from the legal guardian and each child's participation in the study was voluntary. Also, the project is reported to Norwegian Center for Research Data and all recommendations and regulations for research are followed. The data collection included:

Video recording: In order to capture children's facial expressions and extract their emotions when they were coding their game, we used a wide-angle Logitech Webcam. The web camera was placed in the computer the teems were working and was zoomed at 150% into the children's faces capturing video at 10 FPS. The collected videos were from 50 children (29 females), 10 triads and 10 dyads.

Artifacts (the created games): During the coding workshop's process we collected four versions' of the games as artifacts created from each of the teams. Starting from the first version, which was saved 45 minutes after the start of the workshop, the next game versions were saved every 45 minutes. This time-frame was suggested from the instructors who are responsible for the coding workshops and run them for many years and have gained experience on how children are experiencing the learning process. Their suggestion derived from defining which is the best timing for us to be able to monitor children's progress without loosing important information of their progression, but at the same time not to disturb them or leave too short time between the different versions that would have shown no progress.

3.3 Measurements

We will use two set of measurements for this paper. First, the durations of the facial expressions who indicate the emotions. Second, the transitions from one to other expressions. Before we explain these two set of measurements, we will present how do we get from the facial videos of the teams to the individual expressions. Following are the steps to compute the emotions from the facial video of the collaborating children:

(1) Detect the faces in every frame of the video (Figure 2 left).
(2) Align the faces across the frames so that same faces are being tracked and assigned the same ID in every frame by using the method described in Sharma et. al. [69] (Figure 2 right).
(3) Once we have the faces with correct IDs, use OpenFace [1, 3] to compute the Action Units (AUs) [29] for each frame (Figure 1 left).
(4) From the AUs compute the probabilities of the five emotions: frustration, boredom, confusion, delight, and neutral [48] for every frame of the video.

3.3.1 Emotions' Durations. Once we have the facial action units from the video for each child in the study, we then computed the proportion of time they displayed each of the five Expressions: confusion, boredom, delight, frustration and neutral. We used the combination of action units to compute individual expressions (inspired by [48]) shown in the table 1:

Table 1: Group of Action Units corresponding to each emotions.

Expression	Combination of action units
Boredom	AU4, AU7, AU12
Frustration	AU12, AU43
Confusion	AU1, AU4, AU7, AU12
Delight	AU4, AU7, AU12, AU25,AU26

3.3.2 Transitions among the emotions. The second set of measurements were the transition probabilities from one expression to another. The typical transitions are shown in the right panel of the figure 1. We did not consider the self loops in this paper, because we are already using the proportion of the duration of each individual expression as the first set of measurements.

3.4 Dependent Variable – Coding Performance

We computed coding performance from the every 45 mins' collected artifacts(Scratch code) monitoring their progress. In order to do that, we used a tool called DrScratch [49]. DrScratch has been often used to analyse Scratch projects because it gives a detailed analysis and at the same time supports the assessment of computational thinking (CT) skills, using seven CT components: parallelism, logic, flow control, data representation, abstraction, user interactivity,

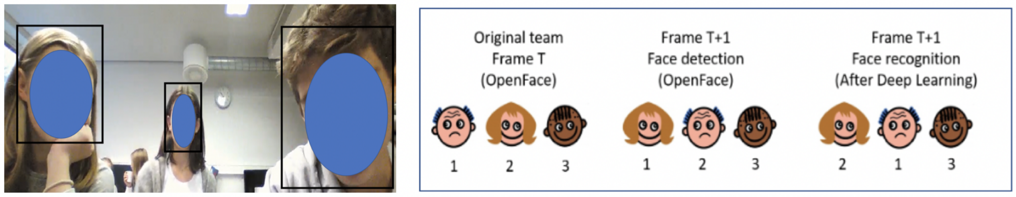

Figure 1: Left: Example of multiple face detection in one frame. Right: Mitigation scheme for countering the movement of the children during the coding workshop.

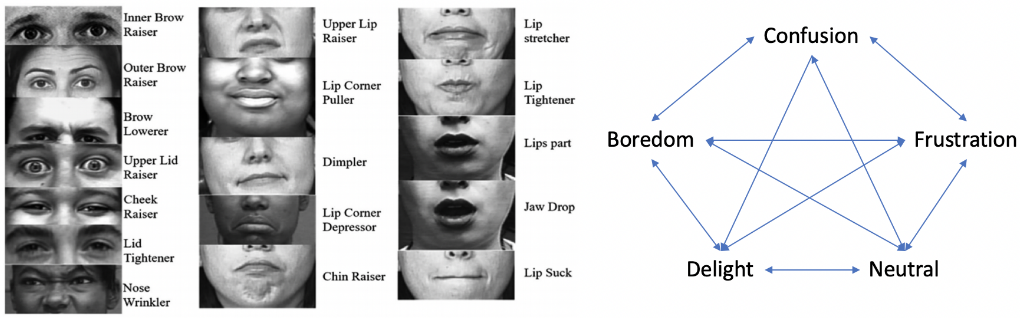

Figure 2: Left: Action units that could be detected. Right: Typical transition diagram.

and synchronisation. DrScratch is an automatic, easy and quick way to analyse Scratch projects offering feedback using a score [49] and its results indicate comparable assessment with the one of a human expert [50]. Troiano et al. 2019 used DrScratch to examine the progress of each CT component while students were designing their games. [77].

Our collected projects (i.e. the four versions of the games created from each of the teams) were uploaded and analysed by DrScratch online. The results gave us a general score to the project (i.e., max 21) which is computed from summing up the individual scores the project gets at each of the seven CT components (i.e., from 1 to 3). Figure 3 shows two examples from the analysis. For the rest of this paper, we will refer to "coding performance measure" as "performance score". We continued our analysis on the four performance scores by using a median cut to split the children's teams into high and low performing groups for all the phases. The medians for the four phases were 6, 10, 12.5 and 13, respectively. **We labelled a group "high" performing if in at least two out of the four phases the team had higher than the median points for that particular phase. Otherwise, the team was labelled as "low" performing.**

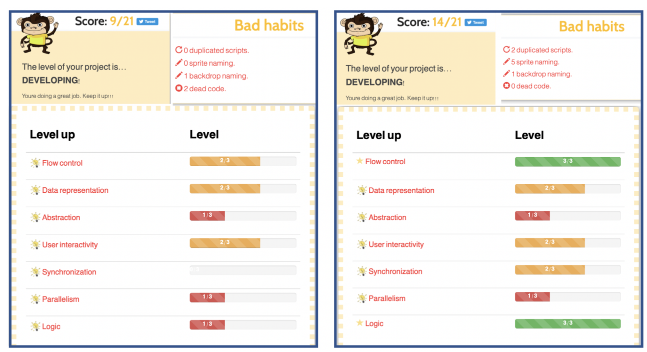

Figure 3: Two examples from the second (left) and the third (right) phases of the coding activity.

3.5 Data Analysis

To answer the first research question (**relation between the expressions an children's performance**) we use t-test with the duration of expressions as the dependent variable and the performance levels (high/low) as the independent variable. Further, to answer the second research question (**how do the expressions change during the coding activity**) we use t-test with the transition among expressions as the dependent variable and the performance levels (high/low) as the independent variable. For testing the normality, we used the Shapiro-Wilk test [65] and for testing the homoscedasticity, we used the Breusch-Pegan test [8].

4 RESULTS

We examined the expressions' proportions and the transitions for bias based on the team size (dyads versus triads). We did not find any differences in the proportions or transitions between the dyads and triads. Next, we present the results from comparing the expressions' proportions (**Research Question 1**) and the transitions among expressions (**Research Question 2**) across the two levels of performance (high/low).

4.1 Coding performance and expressions' proportions

Figure 4 shows the comparison of expressions' proportions between individuals from high and low performing teams, and Table 2 shows the mean, standard deviations, and the t-test results. We observe that the individuals in the high performing groups show significantly higher proportions of confusion ($t(41.09) = 5.81$, $p < .00001$) and frustration ($t(41.74) = 6.13$, $p < .00001$) than those from the individuals in the low performing groups. On the other hand, the individuals in the high performing groups show significantly lower proportions of boredom ($t(46.45) = -10.65$, $p < .00001$) than the boredom displayed by the individuals in the low performing groups. Finally, we did not find any difference in the proportions of neutral and delight between the individuals from high and low performing teams (Table 2, Figure 4).

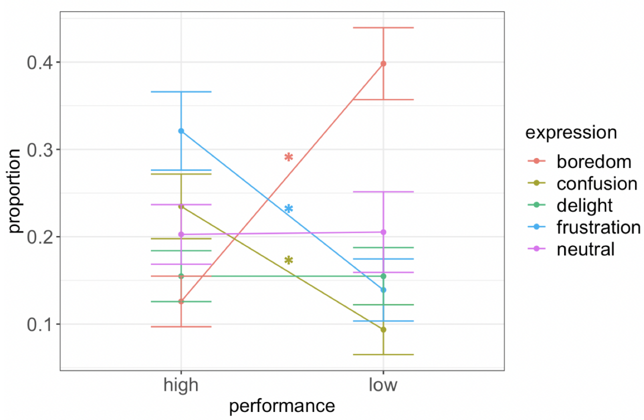

Figure 4: Comparing the proportional duration of the expressions for the two levels of performance (high/low). The asterisk show the significant differences. The vertical bars are the 95% confidence interval.

4.2 Coding performance and expression transitions

Figure 5 and table 1 show the results for comparing the transitions among the expressions, i.e., confusion, boredom, delight, neutral and frustration, for the two levels of performance (high/low).

Regarding the transitions from the confusion (Figure 5, top-left), we observe that the individuals from the high performing teams move from confusion to delight ($t(42.86) = 5.79$, $p < .000001$) and neutral ($t(47.82) = 10.73$, $p < .000001$) significantly more than the individuals from the low performing teams. On the other hand, the individuals from the low performing teams move from confusion to boredom ($t(40.61) = -15.10$, $p < .000001$) significantly more than the individuals from the low performing teams. There is no difference in moving from confusion to frustration based on the performance levels.

When it comes to the transitions from the frustration, (Figure 5, top-right), we observe that the individuals from the high performing teams move from frustration to delight ($t(47.81) = 6.43$, $p < .000001$) and neutral ($t(47.85) = 8.97$, $p < .000001$) significantly more than the individuals from the low performing teams. On the other hand, the individuals from the low performing teams move from frustration to boredom ($t(47.84) = -13.21$, $p < .000001$) significantly more than the individuals from the low performing teams. There is no difference in moving from frustration to confusion based on the performance levels.

Considering the transitions from the boredom, (Figure 5, middle), we observe that the individuals from the high performing teams move from boredom to neutral ($t(42.41) = 16.46$, $p < .000001$) significantly more than the individuals from the low performing teams. On the other hand, the individuals from the low performing teams move from boredom to frustration ($t(46.99) = -26.26$, $p < .000001$) significantly more than the individuals from the low performing teams. There is no difference in moving from boredom to confusion and boredom to delight based on the performance levels.

Concerning the transitions from the delight, (Figure 5, bottom-left), we observe that the individuals from the high performing teams move from delight to confusion ($t(47.78) = 4.23$, $p < .0001$) and frustration ($t(47.92) = 3.40$, $p < .001$) significantly more than the individuals from the low performing teams. On the other hand, the individuals from the low performing teams move from delight to boredom ($t(46.62) = -11.78$, $p < .000001$) significantly more than the individuals from the low performing teams. There is no difference in moving from delight to neutral based on the performance levels.

Finally, with the transitions from the neutral, (Figure 5, bottom-right), we observe that the individuals from the high performing teams move from neutral to confusion ($t(46.08) = 5.50$, $p < .00001$) and frustration ($t(47.67) = 3.83$, $p < .001$) significantly more than the individuals from the low performing teams. On the other hand, the individuals from the low performing teams move from delight to boredom ($t(45.75) = -7.91$, $p < .000001$) significantly more than the individuals from the low performing teams. There is no difference in moving from neutral to delight based on the performance levels.

5 DISCUSSION

We observe from the analysis that there are clear differences between the individuals from the high performing teams and the low performing teams on the account of both the durations of emotions (Research Question 1) and transitions among the emotions (Research Question 2). In this paper, we chose to utilise the education theoretic emotions (i.e., frustration, boredom, confusion, delight, neutral) instead of the control value theoretic emotions (i.e., happy, sad, angry, surprise, disgust, contempt, neutral). The main reason for this decision was that the education theoretic emotions are increasingly being used more and more in the past few years in related fields of Learning Analytics (LAK) [41], User Modeling (UMUAI) [62]; and the fact that there are not many direct relations between the control value theoretic emotions and the task based performance [69] or academic performance in general [5, 25]. In this section, we will provide plausible explanations for the results presented in the results section.

The first research question caters for the difference between the durations of the individual emotions shown by the individual team members from the high and low performing teams. The results show that the individuals from the high performing teams show more confusion and frustration while individuals from the low

Table 2: Comparing the proportional duration of the expressions for the two levels of performance (high/low). All the mean, SD and t-values are rounded to two significant digits. For consistency of effect sizes, all the effect sizes are calculated with degree of freedom = 48. This is the ceiling of the maximum degree of freedom in this contribution.

	High perf.	Low perf.	t-test results		
Expression	**Mean (SD)**	**Mean (SD)**	**t.val**	**p.val**	**effect size**
Confusion	0.23 (0.03)	0.09 (0.02)	5.81	0.00001	0.84
Frustration	0.32 (0.04)	0.13 (0.03)	6.13	0.00001	0.88
Delight	0.15 (0.02)	0.15 (0.03)	0.003	0.99	0.00
Neutral	0.20 (0.03)	0.20 (0.04)	-0.08	0.92	0.01
Boredom	0.12 (0.02)	0.39 (0.04)	-10.65	0.00001	1.53

Table 3: Comparing the transitions among the expressions for the two levels of performance (high/low). conf = confusion; frust = frustration; nut = neutral; bore = boredom; del = delight; Prob = transition probability; SD = standard deviation. All the mean, SD and t-values are rounded to two significant digits. For consistency of effect sizes, all the effect sizes are calculated with degree of freedom = 48. This is the ceiling of the maximum degree of freedom in this contribution.

	High Performance		Low Performance		t-test results		Effect Size
Transition	**Prob**	**Prob SD**	**Prob**	**Prob SD**	**t.val**	**p.val**	
conf–>frust	0.13	0.03	0.13	0.03	-0.29	0.76	0.04
conf–>del	0.36	0.04	0.18	0.03	5.79	0.000001	0.83
conf–>nut	0.44	0.02	0.18	0.03	10.73	0.000001	1.53
conf–>bore	0.07	0.02	0.51	0.05	-15.10	0.000001	2.16
frust–>conf	0.18	0.03	0.18	0.03	-0.10	0.91	0.01
frust–>del	0.36	0.03	0.18	0.03	6.43	0.000001	0.92
frust–>nut	0.40	0.03	0.19	0.03	8.97	0.000001	1.29
frust–>bore	0.13	0.03	0.53	0.04	-13.21	0.000001	1.95
nut–>bore	0.15	0.03	0.37	0.03	-7.91	0.000001	1.14
bore–>conf	0.09	0.03	0.11	0.02	-0.69	0.48	0.10
bore–>frust	0.09	0.02	0.68	0.03	-26.26	0.000001	3.77
bore–>del	0.13	0.02	0.11	0.03	1.21	0.23	0.17
bore–>nut	0.64	0.04	0.17	0.03	16.46	0.000001	2.38
del–>conf	0.31	0.03	0.20	0.04	4.23	0.0001	0.61
del–>frust	0.34	0.04	0.22	0.05	3.40	0.001	0.49
del–>nut	0.25	0.04	0.24	0.02	0.38	0.69	0.05
del–>bore	0.08	0.02	0.32	0.03	-11.78	0.000001	1.70
nut–>conf	0.30	0.03	0.16	0.03	5.50	0.000001	0.79
nut–>frust	0.27	0.03	0.17	0.03	3.83	0.0003	0.55
nut–>del	0.23	0.04	0.27	0.03	-1.30	0.20	0.18

performing teams show more boredom. The recent results from the individual learning scenarios show that students' boredom could be detrimental for their academic and task-based performance [2, 22]. On the other hand, confusion and frustration could actually be beneficial for the students' learning outcomes [47, 62]. While collaborating on the given coding problem, the students might enter a behavioural loop in which their previous mental models are being challenged by the task at hand and try to understand the problem which might increase their confusion when the code does not work as per their hypothesis [21]. Similarly, they might try and understand what caused the problem, and this can increase their frustration [22]. However, in certain cases the students can also disengage with the problem and that can raise the levels of boredom [23]. From our results it appears that the individuals from the high performing teams might get involved with the problems and the reasons for the problems and hence show more confusion and frustration than the individuals from the low performing teams. Whereas, the individuals from the low performing teams do not engage in active problem solving and therefore show more boredom than the individuals from the high performing teams.

Understanding the basic differences in durations of these emotions present one side of the observations from the study where we are only comparing the emotions' durations across the different levels of performance. However, this does not encompass the transitions among the different emotions. Our second research question looks at the basic temporality of the emotions from a Markovian

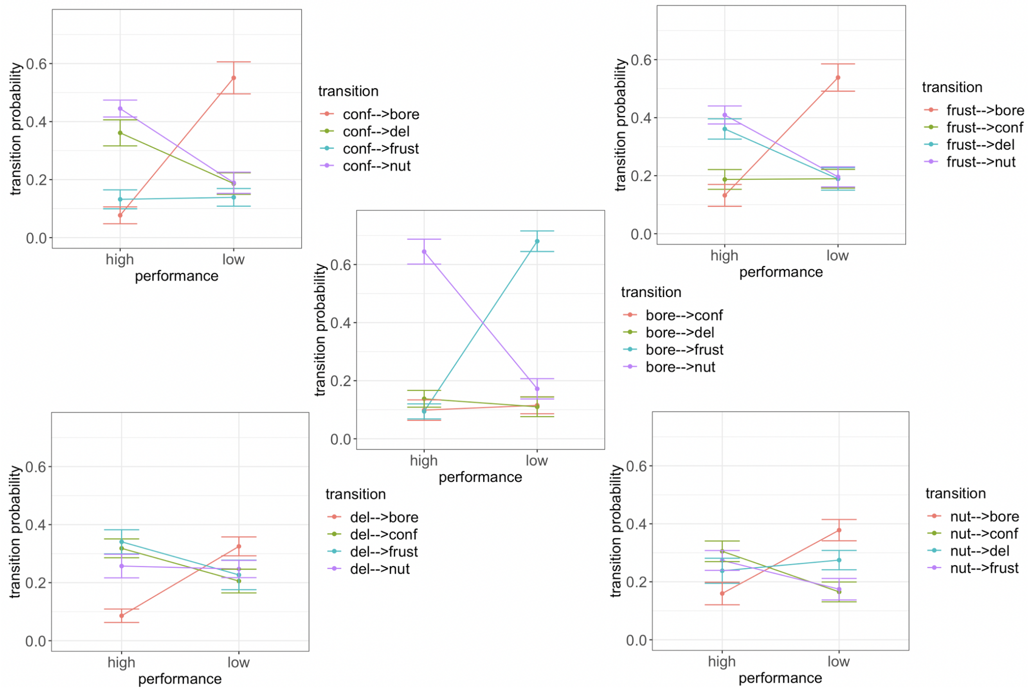

Figure 5: Comparing the transitions among the expressions for the two levels of performance (high/low). Top-left: transitions from confusion; Top-right: transitions from frustration; Middle: transitions from boredom; Bottom-left: transitions from delight; Bottom-right: transitions from neutral; conf = confusion; frust = frustration; nut = neutral; bore = boredom; del = delight. The vertical bars are the 95% confidence interval.

point of view. This question addresses the differences between the individuals from the high and low performing teams on the basis of the transition among the emotions. The results show that the high performing teams move from confusion and frustration to delight and neutral and vice versa; while the low performing teams move from every emotion to boredom. These results, when combined with the results from the first research question provide an interesting insight about the process. On one hand, for the high performing teams, we observe that individuals from these teams move from frustration and confusion to delight and neutral more often than the individuals from the low performing teams. We also know that these individuals have shown more confusion and frustration (from RQ1). This shows that when the high performing teams are trying to understand the problem (confusion) and/or trying to find the cause of the problem (frustration), they are moving to delight and neutral more often than the low performing teams. The emotions with non-negative connotations are often the results of solving the problem (delight) or having understood the cause of the problem (neutral) [23]. The high performing teams could be in similar situation, as reflected from their scores. On the other hand, for the low performing teams, we observe that the individuals from these teams move to boredom from any other emotion more often than the individuals from the high performing teams. This shows that the students in the low performing teams often disengage from the short-term problem solving processes [2, 23], which might lead to low performance.

This study is a first step to better understand the affective states of children during coding activities working in teams. This approach will help instructors understand more on how children face the learning process and gain insights on how to respond on them. For example, help them with seeking requests and trigger help from their peers or the instructors to scaffold their behaviour [33] Also, this research will help us give more "in the moment" reactions in the interactions that naturally happen during k-12 CS/CT activities [33]. Benefits vary depending on the specific task and how the group is formed [4]. Collaboration is critical for shared engagement in problem-solving and managing of learner's feelings of helplessness [33], also, individual characteristics together with the group dynamics are equally important [72]. When children debug a problem may experience difficulties and need to negotiate their process. For example, in our case we found that low performing teams experience more boredom which can be due to the not good communication between team members. It is possible that one child is getting the control in coding without spending time or effort to involve the other team members in the process and this results in disengagement and boredom. However, it can be that in the high performing teams, confusion and frustration lead to delight because the team members had different levels of experience before this coding workshop. In a study with Alice programming environment, the higher knowledge gains were for the students with low prior experience in computer use showing that in pair programming students who work with someone with more experience they can learn

[17]. Pair programming has benefits for computational thinking and coding knowledge acquisition, especially for the less experienced students [17]. Moreover, Rodrigo and Baker 2009, showed that the feelings of confusion and boredom were associated with lower achievement in a CS course [63].

Although there is an intuition on how to help children to be engaged in an effective learning experience in coding tasks, it is useful to have studies that can show how to subjectively extract children's emotions. This can benefit future real time systems that can support instructors in action by showing them the emotional flow the learners are having. Sridhar et al. 2018 stated that there is a need to understand affective states with respect to cognitive load. For example, a learner who is curious but remains engaged is different than someone who is overloaded and anxious having as a result not being able to continue with the tasks [71]. Therefore instructors' actions should respond to the learner's needs accordingly helping them to confront emotional struggles and difficulties during the learning process. Better understanding of the affective states of children during their interaction with coding and working as a team will help us design affect-sensitive learning environments. Those can be systems that may include affective responses into their cycles and help students shift into emotions that will help them facilitate the learning process and have the desirable outcomes [2].

Instructors and educators can benefit from the knowledge about the relation between the emotional and/or affective processes during collaborative learning settings and the collaborative learning outcome/quality. For example, the instructors and educators can provide content-based help to the students when the groups are showing confusion and/or frustration, because in these two cases the students are either struggling from a mismatch between their knowledge model and the actual content (confusion, [24]) or they are struggling with the content itself because the content is too difficult for them (frustration, [14]). On the other hand, the instructors/educators can provide affective/motivational support to the teams who are displaying more boredom than others because either the activities are too easy for them [14] or the team is not performing well [43], or they are not interested in the activity at all.

Another approach would be to view children's dialogue as is important for the interaction in the teams. For example, encouraging children into more playful talk [60] between them can be an answer to a situation of a negative emotion that persists over time. Overall, what is the most important aspect to consider is on how to support children move on with their emotions during a coding activity. It is natural that a wide range of emotions appear in the learning process and not only the positive ones are the ones to be valued. We need to support and keeping the learners flow into the cycle of positive and negative emotions recognizing their value [40].

In this paper, we are focusing only on the affective states from only one data source (i.e., the facial features). In the recent times, with the advancements in the physiological sensors [67] and multimodal learning analytics [27] it has become easier to incorporate more modalities to understand other affective states such as stress and arousal; and also to include cognitive processes, such as attention, cognitive load and mental effort; and social processes such as dialogues. By doing this we could gain a holistic understanding of the collaborative coding processes. Moreover, in this paper, we only focus on the educational emotions, whereas in the future, we will investigate other emotions derived from the control value theory such as, happiness, sadness, anger to name a few.

Moreover, on the analytical front, this paper utilises only Markovian analysis when it comes to the temporal analysis, which has certain disadvantages [68], in the future, we will incorporate a longer history than just the previous timestamp and move away from Markov assumption to more temporal analysis. Morevoer, since in this paper data are presented as aggregate per team, in future we will investigate, if there were specific individuals who had major impact on the results of each team, or acted as "influencers" (i.e., their emotions gradually affected the rest of the team). Further, this paper presents the relation between various variables in the terms of correlations and regressions, in HCI there is a call for the shift towards causality among the peers and among the different expressions [55]. We will also explore the causal relations between the individual emotions and joint-emotions in the future.

6 CONCLUSIONS

This study presents an analysis of individual emotions' durations and the transitions among them across two levels of performance. We observe clear differences between high and low levels of performance. We showed that the high performing teams have higher levels of confusion and frustration than the low performing teams. On the other hand, low performing teams show higher level of boredom than the high performing teams. Further, there are significant differences in the individual transitions among the five expressions studied in this contribution. The results extend the current models of students' emotions and provide guidelines for further design and research. In the future, we will extend this analysis not only with more time-dependent methods being included but also by using other theoretical aspects (e.g., control value theory) to have a more generalizable set of findings.

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