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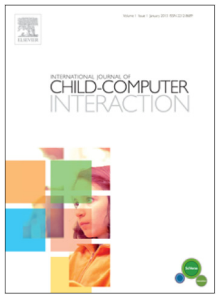

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Coding Games and Robots to Enhance Computational Thinking: How Collaboration and Engagement Moderate Children's Attitudes?

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Abstract: Collaboration and engagement while coding are vital elements for children, yet very little is known about how children's engagement and collaboration impact their attitudes toward coding activities. The goal of the study is to investigate how collaboration and engagement moderate children's attitudes about coding activities. To do so, we designed an study with 44 children (between 8 and 17 years old) who participated in a full-day coding activity. We measured their engagement and collaboration during the activity by recording their gaze, and their attitudes in relation to their learning, enjoyment, team-work and intention by post-activity survey instruments. Our analysis shows that there is a significant moderating effect of collaboration and engagement on children's attitudes. In other words, highly engaging and collaborative coding activities significantly moderate children's attitudes. Our findings highlight the importance of designing highly collaborative and engaging coding activities for children and quantifies how those two elements moderate children's attitudes.

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Abstract

Collaboration and engagement while coding are vital elements for children, yet very little is known about how children's engagement and collaboration impact their attitudes toward coding activities. The goal of the study is to investigate how collaboration and engagement moderate childrens attitudes about coding activities. To do so, we designed an study with 44 children (between 8 and 17 years old) who participated in a full-day coding activity. We measured their engagement and collaboration during the activity by recording their gaze, and their attitudes in relation to their learning, enjoyment, team-work and intention by post-activity survey instruments. Our analysis shows that there is a significant moderating effect of collaboration and engagement on children's attitudes. In other words, highly engaging and collaborative coding activities significantly moderate children's attitudes. Our findings highlight the importance of designing highly collaborative and engaging coding activities for children and quantifies how those two elements moderate children's attitudes.

Keywords:
eye-tracking; computational thinking; coding activity; programming; informal learning; attitudes; children programming; interaction design and children; collaborative eye-tracking

1. Introduction

Children's engagement during a learning activity, is considered the holy grail of learning [95]. It is associated with several important aspects of the design and implementation of contemporary learning activities and is clearly associated with students attitudes [33]. Engagement changes over time and is dependent on interventions, social interactions and changing contexts [27]. In collaborative learning activities, the level and quality of collaboration between young students has also been found to have direct influence in the quality of learning processes and persistence [11] as well as in improving students attitudes (e.g., about mathematics) [41]. Thus, when investigating learning activities for children, it's important to look closely how collaboration and engagement might moderate the interplay of other important attitudes.

Computational thinking and coding activities for young students are becoming an integral part of contemporary informal learning in different contexts (e.g., in makerspaces, after school activities, museums, libraries etc.). It is evident that young students should begin developing computational thinking skills early [101], and thus, more and more organizations design and deliver coding activities, as part of their curriculum or their outreach program. Properly designed coding activities for children have shown to be beneficial, since they enhance problem solving skills, critical thinking and creativity among other [7]. The design of these activities is important to enhance collaboration and engagement in a meaningful way [101], yet very little is known about the role of collaboration and engagement and their connections with other attitudes that empower children's participation (e.g., positive attitudes like enjoyment, intention etc.).

Therefore, in this contribution we seek to investigate how collaboration and engagement moderate the relationship between central attitudes of children when coding (i.e., team-work, intention to participate, perceived learning and enjoyment).

To tackle the aforementioned proposition, we conducted a study with 44 children participating to a full-day coding activity. We used eye-tracking techniques to measure their engagement and collaboration during the activity and post-activity surveys to measure their attitudes in relation to learning obtained, sense of enjoyment, team-work and intention to participate in a similar activity in the future. By investigating the role of collaboration and engagement we provide a quantified evidence of how those two important elements moderate other attitudes and enable various insights for the design of future coding activities. In particular, our paper makes the following contributions:

- We present insights from a study that collects data related to children's behaviour (eye-tracking) and attitudes (surveys) during a coding activity.

- We show that collaboration and engagement moderates the relationship between children's attitudes

The remainder of the paper is organized as following. The second section presents the related work on investigating the relationship between attitudes and behaviour in primarily educational/organizational settings. Third section highlights the conceptual model and research hypotheses of our paper. The fourth section provides the methodology of the study, the coding activity, participants, variables used for the analysis and the analysis itself. The fifth section shows results from data analysis, and the last section discusses the implications of the results and concludes the paper with future work and limitations.

2. Related work

2.1. The importance of attitudes in learning activities

An important issue related to the success of coding activities is their adoption by children. A number of models and theories have been developed and utilized to understanding the relationships between the attitudes towards a new technologies and the experiences and outcomes of using the technology (e.g., UTAUT or its initial form Technology Acceptance Model-TAM, [19]). TAM is a model connecting the ease of use, intention to use, user behaviour and the usage outcomes (enjoyment, engagement, learning to name a few). Various studies have used this model as a basis for their analyses or extending the basic model given by Davis (1989) [19].

Attitudes have been central in educational research for several years. For instance, in an organizational learning context, humans' intention to use new technology was found to be positively correlated with their motivation to learning and transfer learning [24].In another study, perceived enjoyment is another element that has been reported to be closely associated with intention. This association has been reported in studies concerning both the teachers [100] and young students [2]. In another study pre-service teachers showed that the perceived enjoyment was positively associated with their intention to use new technology [100]. Finally, in the context of gaming it is found that the intention to play games had a positive significant correlation with the enjoyment in the games [106].

Enjoyment and learning are also associated, this has been proven through different studies in educational settings [9; 58; 26]. For instance, in a face-to-face class about data analysis where the teacher focused on the dialectic relation between theory and data, the students who enjoyed this method, believed that it helped them with their learning [9]. Similarly, based on the surveys in another face to face classroom setting, the results stipulated a positive correlation between enjoyment and learning performance [65]. The results from a survey about a web-based class management system, showed a positive correlation between enjoyment and the learning goal orientation [58]. In a reading study with eighth graders, the authors found the correlation between the enjoyment in reading text and the perception about learning to be significantly positive [26]. In a study based on PISA tests, the perceived enjoyment was positively correlated with the science knowledge, for students across different countries (USA, Columbia, Estonia, Sweden) [1].

One of the most intuitive relations, among the various constructs included in TAM, is between enjoyment and engagement when it comes to technology usage. These studies (mostly using survey data) were conducted at different educational levels, such as pre-university level [54], high school [32], primary and secondary levels [107; 53]. Therefore, if an experience provides enjoyment to the participant, it is likely that it would also be engaging in long-term. For example, a study using PISA tests showed (N > 400,000, 57 countries) a positive correlation between activation enjoyment and engagement with learning science [1]. Considering high school students in different years (10–13 grade) the students showed a positively significant correlation between their enjoyment at and engagement with the school [32]. This correlation was also consistent across the different years. In a study with children aged between 7 and 8 years using educational games, the children who enjoyed the games also showed higher levels of engagement than the children with lower levels of enjoyment [53]. Among pre-university students, the results showed a negative correlation between disengagement and various constructs such as enjoyment at school and class participation [54]. In a study with tangible user interfaces involving children, the results showed a positive correlation between childrens engagement with the tangible game and their perceived enjoyment [107]. Further, within a teacher-student laboratory paradigm [70] the students who reported high levels of enjoyment also reported high levels of engagement. To summarize, from the literature it is evident that attitudes are highly associated with the adoption of a learning activity by young students, as well as, the learning obtained from the activity.

2.2. Engagement and collaboration in learning

Many studies have reported a positive relation between collaborative learning and engagement [8; 73; 36; 35]. In a collaborative learning scenario with clickers in the classroom, there was a significant positive association between engagement and active learning [8]. The proponents of Computer Supported Collaborative Learning (CSCL) argue that introducing technology to facilitate the collaboration might increase engagement with the learning activities and hence learning outcomes [73; 35]. Jarvela and Jarvenoja [36] identified engagement as one of the key factors for the success of self-regulated learning. Kreijns and colleagues

[44] argue that there might be two different ways in which mutual engagement and learning are related. First, because of mutual engagement individuals can gain knowledge that could not be done prior to the collaboration. Second, mutual engagement facilitates the co-creation of knowledge and hence leads to better individual learning outcomes.

Furthermore, Lipponen and colleagues [51] highlight the need of engagement in collaborative learning by stating that just by putting two or more individuals together one cannot foster collaborative learning, one should make the collaborative task active enough to engage the collaborators. Engagement has also been shown to be related with team work [105; 28; 48; 40]. In a group writing study, there were negative effects of restricted communication over engagement of students within different groups [28]. A study with hockey players, showed that with positive attitude towards the team work, novice players showed more willingness to come to practice [105]. Similar results were reported in the context of basketball players [48]. In a study with educational robotics, the authors found a positive correlation between group work and engagement levels with robots [40].

2.3. Eye-tracking as a means to understand engagement and collaboration

Eye-tracking provides a direct access of users' attentional patterns to the researchers. Eye-tracking has been used in multiple educational settings to provide an understanding of cognitive processes responsible for learning and collaboration [91]. Eye-tracking has been historically known as a data source to measure engagement in various research contexts. Shagass et. al. [84], Navab et. al. [59] and Sanchez et. al. [78], used eye-tracking to detect attentional disengagement in psychotic, autistic, and depression-effected patients, respectively. Eye-tracking has also been used to capture the engagement in marketing studies (for a comprehensive review see [104]). Dalzel and colleagues [17] used eye-tracking to compare the engagement patterns in a intelligent agent based learning scenario. Moreover, it has also been used to measure engagement in learning scenarios (for a comprehensive review see [63; 46]).

Eye-tracking has been widely used to measure collaboration in different dual eye-tracking experiments. In the past studies, collaboration and engagement measures have been used to correlate the collaboration levels to various constructs like expertise [38], collaboration quality [37], task based performance [87] and learning outcomes [81]. Two synchronous eye-trackers can be used for studying the gaze of two persons interacting to solve a problem. It gives a chance to understand the underlying cognition and social dynamics when people collaborate to solve problems at hand [62]. In a collaborative task of finding bugs in a program, Stein et. al. [99] showed that the pairs who had their gaze displayed to their partners took less time in finding the bugs than those pairs who had no information about their partners' gaze. From a collaborative concept map experiment , Liu et. al. [52] found that the gaze data of the pair is predictive of the expertise in the collaboration. The authors framed the whole interaction as a sequence of concepts looked at. The authors then use Hidden Markov Models to predict the outcome of post-test and achieved an accuracy of 96.3%.

Eye-tracking has been used to capture communication and referencing in collaborative scenarios, which are essential for creating and maintaining mutual ground among collaborators. Grounding is an essential part of the communication [13]. Clark and Brennan define grounding as the "coordination of process" – which entails sharing information (or common ground) – which includes mutual knowledge, beliefs, assumptions [14; 15]. In a dual eye-tracking experiment, the authors measured the time lag between the speaker looking and referring at a specific actor and the listeners looking at the same actor. This time lag was termed as the cross-recurrence between the participants. The average cross-recurrence was found to be between 1200 and 1400 milliseconds. This time was consistent with the additions of eye-voice span [31] and voice eye-span [3]. The cross-recurrence [16] (the amount of time spent by the collaborators while looking at the same object) is one of the most common measurements to assess the collaboration quality. Recently, Sharma and colleagues [87] proposed a temporal and more distributed and robust version of the cross-recurrence known as gaze-similarity (the amount of time spent by the collaborators while looking at the same set of objects in a given time window). Thus, eye-tracking is an established approach to quantify both collaboration and engagement during an activity.

2.4. *Eye-tracking as a means to understand cognitive processes during collaborative learning*

Collaborative eye-tracking has been used in previous research in collaborative learning scenarios to shed light on the socio-cognitive mechanisms responsible for learning gains such as, joint-attention [37; 93] , mutual understanding [79; 21], misunderstandings [12], memorization [82]. In a pair programming study with collaborative eye-tracking data, the results depicted that the students which were able to provide correct answers to the comprehension questions had more joint-attention (measured by cross-recurrence or gaze similarity) than the students who could not give correct answers [37; 93]. Furthermore, in a collaborative concept map study, the joint-attention was found to be correlated with the learning gains of the pair [88]. In a similar study with collaborative concept maps, participants' gaze on a Knowledge Awareness Tool (KAT) to assess the peer's domain expertise was reported to be correlated with high levels of mutual understanding between the pair [79]. Mutual understanding had been shown to be one of the main socio-cognitive construct responsible for high level collaborative learning outcomes [55; 21; 61; 49]. Sangin and colleagues [80] used a knowledge awareness tool (KAT) to inform the pair about their partners' knowledge about a certain topic in a collaborative concept map task. From the gaze data analysis, the authors found that there was a positive correlation between the gaze on the KAT and participants' relative learning gain.

In terms of collaborative eye-tracking and dialogues during the collaborative learning situations, Cherubini and colleagues showed that the distance between the places looked at by peers is predictive of their level of misunderstanding [12]. The misunderstanding was measured by the mistakes (made by the listener) in disambiguation the (speaker's) verbal references in a shared learning system, which was a detrimental factor for the learning outcome [12].

In a collaborative learning task, the gaze of the peers was indicative of the processed responsible for memorization and analysis of new concepts [81]. In a similar study the unbalanced participation (division of labour, as measured by eye-tracking) was found to be negatively correlated with learning gains of the collaborating pairs [82]. Moreover, sharing gaze among collaborating peers, resulted in a better division of labour [10], better understanding of the content [89], and better attention spans from the students [86]. In this contribution, we attempt to use the gaze as a measurement of the behaviour of the peers and examine the effect of a certain behaviour on the relationship between the different attitudes of children towards coding.

3. Conceptual model and research hypotheses

As presented in the previous section, relevant literature has shown positive correlations among the different constructs related to attitudes (intention to participate, attitude towards team work, enjoyment and perceived learning) and indicators of behaviour (collaboration and engagement). Behaviour is seldom considered as a factor which can affect these relationships; rather it is considered as a factor in the correlational analyses while most of these studies use subjective questionnaires. In addition, eye-tracking has been widely used to provide a direct access of users' attentional patterns and provide an understanding of cognitive processes responsible for learning and collaboration [91]. In this study, we propose objective measures of behaviour as a pivoting factor, and have a hypothesis that behaviour can affect the strength and/or the polarity of the relationship between attitudes of children in coding activities. Therefore, we measured behaviour using eye-tracking data. Specifically, we used gaze uniformity to measure the level of children's engagement and gaze similarity to measure Children's level of collaboration during the coding activity. Furthermore, our study is guided by the following research question:

How does the gaze behaviour moderates the relationship between different attitudes when it comes to coding activity with children?

In order to investigate the effect of children's behaviour (capture via gaze) in their attitudes (captured via survey responses) during coding activities (see conceptual model in figure 1), we divide the overall challenge into smaller hypotheses, as described below. Responding to the following three hypotheses offers important insights into the general feasibility of the problem. Specifically, our study attempts to verify the following research hypothesis:

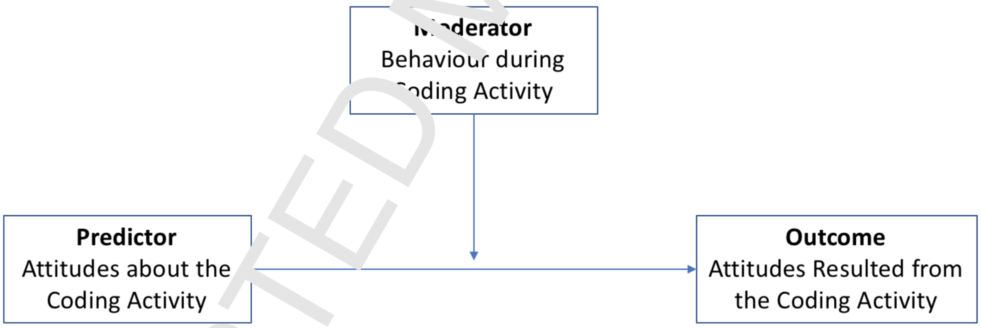

Figure 1: The Conceptual Model of our Study

- H1a: Children's engagement (gaze uniformity) has a significant moderating effect on the relationship between children's Intention and Enjoyment during a coding activity.
- H1b: Children's engagement (gaze uniformity) has a significant moderating effect on the relationship between children's Intention and Learning during a coding activity.
- H2a: Children's level of collaboration (gaze similarity) has a significant

moderating effect on the relationship between children's Team Work and Enjoyment during a coding activity.

- H2b: Children's level of collaboration (gaze similarity) has a significant moderating effect on the relationship between children's Team Work and Learning during a coding activity.

In the following diagram presented in Figure 2, the research hypotheses of our study are summarized.

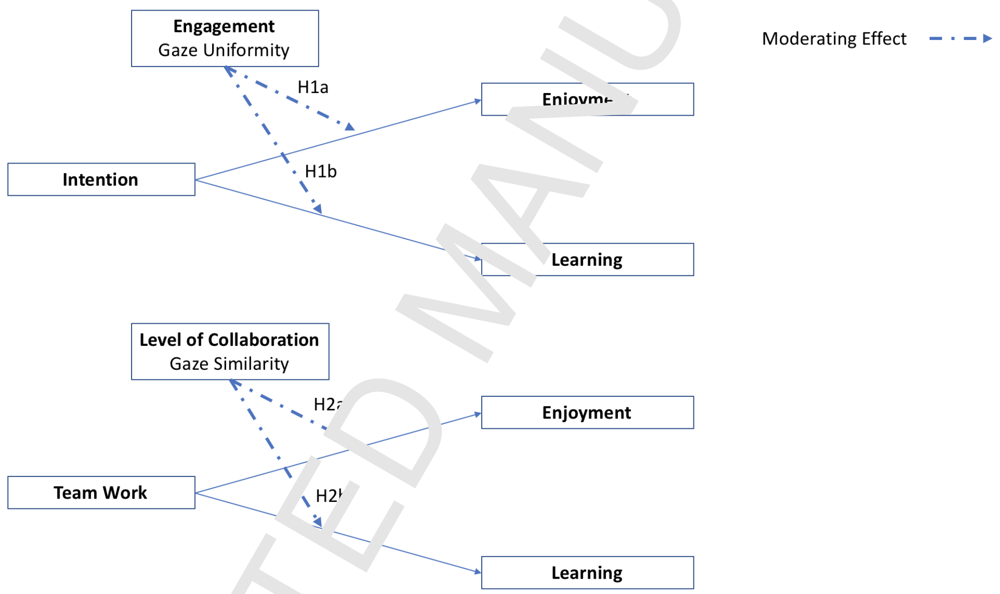

Figure 2: The research hypotheses of our study

4. Methodology

In this section, we present the methodological details of our study, like, the measurements used and the data analysis implemented.

4.1. The coding activity

Based on the constructionist approach and its main principle, learning by doing [72], we conducted a coding workshop at the Norwegian University of Science and Technology Trondheim, Norway. Our coding workshops are out-of-school activities, in which children from 8 to 17 years old are invited in a specially designed room in the university's premises to interact with digital robots, using Scratch for Arduino (S4A), and then code their own game using the Scratch programming language. At each workshop the children work for approximately four hours. Five assistants with previous experience in similar activities are responsible for instruction and the procedure for the workshop. The workshop consists of two main parts, interaction with the robots and creating games with Scratch, described below.

Interaction with robots: During the first part of the coding activity, the children interact with digital robots. The assistants give a brief presentation of the workshop's activities. Then, the children use a paper tutorial with instructions (Figure 3) for how to make the robots react to the physical environment with visual effects using simple loops of Scratch for Arduino (e.g. to make the tongue of the snake robot move when there is less light in a sensor). The first part of the workshop provides a smooth start for the participants as they playfully interact with tangible objects. Showing the connection with the physical world through digital robots, gives an opportunity to the children to understand STEM subjects better and handle difficult problems [5]. For this activity children by using Scratch for Arduino (S4A) are also introduced to Scratch logic while they get motivation and inspiration. The duration of the first part varies from 45 to 90 minutes. When all the children have finished, they have a break before the next section begins.

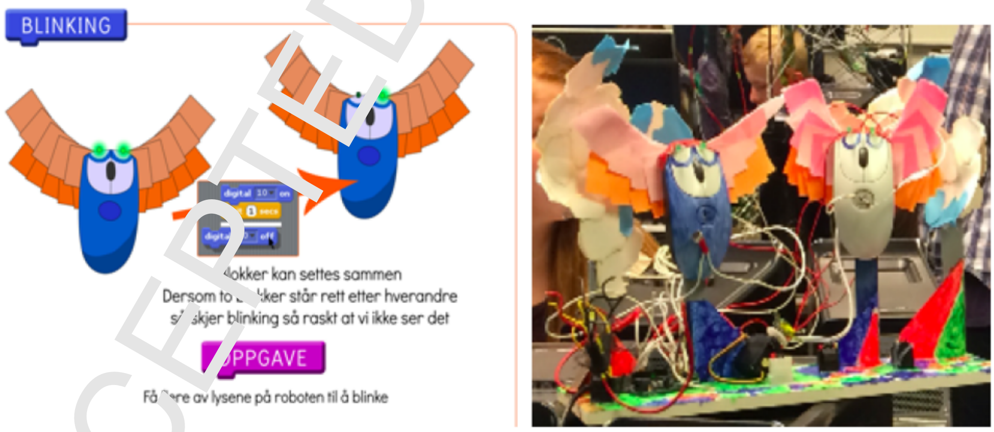

Figure 3: Left: Example of the robots tutorial. Right: example robot.

Creating games with Scratch: This section is the main activity of the workshop and lasts approximately three hours, without the presence of the robots. The goal is to successfully develop a simple game, coding in Scratch. To achieve this goal, the assistants give another paper tutorial with examples of all the basic Computer Science concepts, possible loops they should use to complete their own game, and how to manage the process of game development (Figure 4).They were advised that, first, they should think and decide the story for their game and then create a draft storyboard. When they had finished, they started coding using Scratch. The children can ask for support from the assistants whenever they need it throughout the activity in order to successfully complete their games. Finally, the children reflected on and played each others games.

Figure 4: Left: example of the tutorial; Middle: children interacting with Scratch; Right: example of developed game.

4.2. Participants

We conducted the study at a dedicated lab space at the Norwegian University of Science and Technology Trondheim, Norway. Specifically, the study lasted two weeks during Autumn 2016, with 44 children from the eighth to twelfth grades (aged 8–17 years old), 12 girls (mean age: 12.64, standard deviation (SD): 2.838) and 32 boys (mean age: 12.35, SD: 2.773). Five workshops were held in total, all following the same process for the coding activity, addressed to novices in coding. Some of the participants in the sample (13–17 years old) were recruited from the local schools who had applied to take part in our activity. The other set of participants (8–12 years old) were youngsters who attend local coding clubs as an after-school activity.The children were carefully selected regarding their age so at each of the workshops, the participants were at the same grade or within a small age range. All 44 children comprising the sample of this study were eye-tracked volunteering their participation; the legal guardians provided a written informed consent form for their child, giving permission for the data collection.

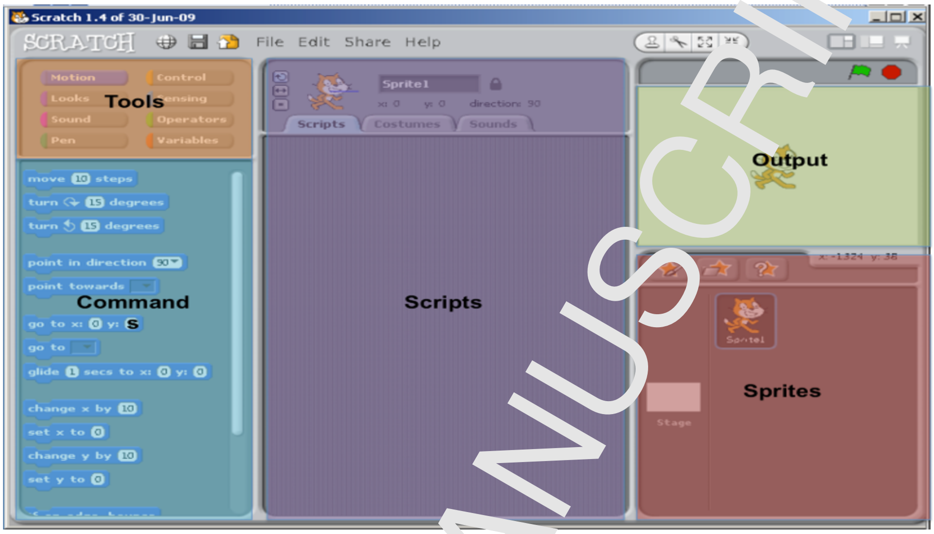

Figure 5: The five areas of interests (AOI) for the screen, the sixth AOI was the robot.

4.3. Measures

As mentioned before, this study is one of the few so far utilizing children's gaze. We recorded children's gaze while they were coding using the Scratch environment during both parts of the activity. The eye-tracking data was collected using four SMI and one Tobii eye-tracking glasses. The sampling rate for all the eye-tracking glasses was set to be 30 Hz for the binocular eye-tracking. The average accuracy for both SMI and Tobii glasses was 0.5 degrees at a distance of 40 Centimetres. The visual field was divided into six areas of interests (AOIs). Five of them are shown in the Figure 5. Once we have the gaze data on these six AOIs, we extracted the following variables to include in our analysis for this contribution:

Level of Collaboration: To measure the level of collaboration of children during the coding activity, we calculate the gaze similarity. Gaze similarity captures the proportion of the time spent by the participants looking at the similar set of AOIs in a given time window. This is computed as the cosine similarity of the vectors comprising of the proportion of time spent in each AOI within a given time window.

$$Similarity(X,Y) = \frac{\sum_{i=1}^{N} X_i Y_i}{\sqrt{\sum_{i=1}^{N} X_i^2}\sqrt{\sum_{i=1}^{N} Y_i^2}} \quad (1)$$

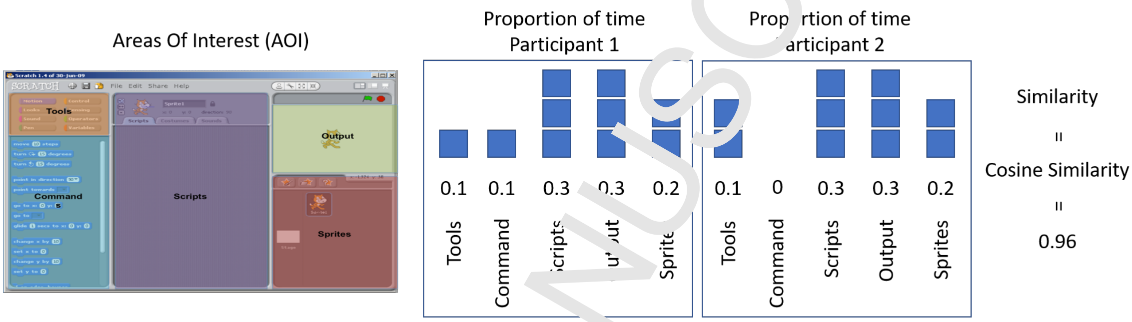

Figure 6: A typical example of computing gaze similarity from the time spent on the different AOIs.

Engagement: To measure engagement of children during the coding activity, we calculate gaze uniformity. Gaze uniformity captures the uniformity of the time spent on all AOIs. The distribution is computed as a vector of length six (there are six AOIs) comprising of the proportion of time spent in each AOI. The uniformity is computed as the inverse of the Kullback-Leibler divergence between the original proportionality vector and a uniform distribution with the same minimum and maximum limits as the original vector.

$$Uniformity(X,Y) = \sum_{i=1}^{N} X_i log\frac{X_i}{Y_i} \quad (2)$$

At the end of the activity, the children completed a paper-based survey. The survey gathered feedback on the childrens attitudes regarding the coding activity. The children were asked to rate their experience with the coding activity regarding their four different variables: team work, their intention to participate in future similar activities, their enjoyment during the activity and how much they thing they learned (i.e., perceived learning). For all the measures, we used a five-point Likert-scale questionnaire. Table 1 shows the operational definitions of the four factors.

4.4. Data Analysis

In this contribution, we address the following analysis question: *"how does the behaviour moderates the relationship between different attitudes when it comes*

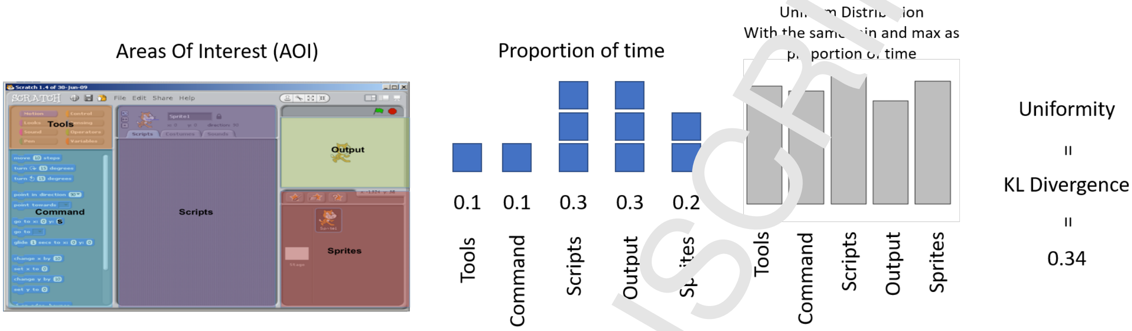

Figure 7: A typical example of computing gaze uniformity from the time spent on the different AOIs.

to coding?". Figure 1 shows the relation between the constructs, measurements and variables used in this study. To find how the behaviour affects the relation between the different attitudes towards coding, we chose to conduct moderator analysis [47]. Moderator is a variable that affects the strength and/or direction of the relationship between two variables. In terms of ANOVA or correlational analyses, this variable is added as an independent variable that does not have a direct effect on the dependent variable, but when combined with the main independent variable, shows a significant interaction effect. In the present analyses, we use intention and team work as the independent variables; enjoyment and learning as the dependent variables; and gaze behaviour (similarity and uniformity) as the potential moderator variables.

5. Results

5.1. Descriptive Results

Children expressed high learning and enjoyment (4.7/5 and 4.6/5, respectively) for the coding activity. Additionally, they expressed slightly lower intention and attitudes towards team work (4.4/5 and 4.2/5, respectively). High levels of these attitudes indicate positive views concerning their learning performance and benefits regarding their engagement with coding activities. The descriptive statistics about childrens attitudes and eye-tracking measures are summarized in Table 2.

To assess the correlation between individual items on the questionnaire, Pearsons correlation coefficient between the factors was used. Pearson quantifies the

Table 1: The attitudinal factors and their respective questions, operational definitions and sources.

Factor	Operational Definition	Item/Question	Source
Perceived learning	The degree to which children indicate their performance.	Please indicate if you learned new things during the coding activity (Not at all Very much)	[45]
Intention	The degree of children s willingness to participate in a similar activity.	Please indicate how much you want to attend similar coding activities in the future (Not at all Very much)	[30]
Enjoyment	The degree to which children indicate their enjoyment during the activity	Please indicate how much you enjoyed your participation in the coding activity (Not at all Very much)	[30]
Team Work	The degree to which children indicate their enjoyment of working in a team during the activity	Please indicate how much you enjoyed working in a team (Not at all Very much)	[96]

strength of the relationship between the variables. Table 3 shows the pairwise correlations among attitude towards team work, intention to participate, learning, and enjoyment. We observe that all the correlations are significant and positive. This allows us to proceed with the investigation for the moderation effects. In the following subsections we present four different moderation analysis for the different variables measuring attitudes and behaviour.

5.2. *Level of Collaboration as Moderator*

First, we focus on the relation between attitude towards team work and learning; we test if this relation is significantly moderated by the level of collaboration of the participants. Table 4 shows the model fitting details and the Figure 8 (left) shows the trends for the main effect (dashed line) the high collaboration (blue line) and the low collaboration categories (red line). We observe a significant interaction effect of collaboration and attitude towards team work on the learning. From Figure 8 (left) it can be observed that the relation between the attitude towards team work and learning is stronger for participants who experienced high level of collaboration. Thus our data provide strong evidence that children's level of

Table 2: Descriptive statistics for the variables used in this contribution.

	Mean	Std. Dev.	Minimum	Maximum
Uniformity (0–1)	0.48	0.35	0.004	0.97
Similarity (0–1)	0.34	0.26	.002	0.96
Intention (scale 1–5)	4.45	0.73	3	5
Team work (scale 1–5)	4.24	0.87	2	5
Enjoyment (scale 1–5)	4.55	0.51	4	5
Perceived Learning (scale 1–5)	4.65	0.98	1	5

Table 3: Pearson correlation matrix for the attitude variables used in the analysis. *** *p-value < .001; ** p-value < .01; * p-value < .05*

		1	2	3	4
Team Work	**1**	-	0.37**	0.32*	0.30*
Intention to Participate	**2**	-	-	0.45**	0.56***
Learning	**3**	-	-	-	0.65***
Enjoyment	**4**	-	-	-	-

collaboration during coding activities moderates the relationships between their attitude about team-work and learning (accepting H2b).

Second, concerning the moderating effect of the level of collaboration for the relation between attitude towards team work and enjoyment, Table 4 shows the details for the model and the Figure 8 (right) shows the trends similar to that of Section 5.2. We observe a significant moderating effect of collaboration and attitude towards team work on the enjoyment. From Figure 8 (right) it can be observed that the relation between the attitude towards team work and enjoyment is stronger when the participants experience high levels of collaboration than in the case participants experience low levels of collaboration. Thus our data provide strong evidence that children's level of collaboration during coding activities moderates the relationships between their attitude about team-work and enjoyment (accepting H2a).

5.3. Engagement as a Moderator

Investigating how engagement moderates the relation between intention to participate and perceived learning, Table 5 shows the details for the model and the Figure 9 (left) shows the trends similar to that of Section 5.2. We observe a significant moderation effect of engagement and intention to participate on perceived learning. From Figure 9 (left) it can be observed that the relation between

Table 4: Testing the moderating effect of the level of collaboration, on the team work to enjoyment and team work to learning relationships.

Model for Perceived learning					
	Estimate	**Error**	**t-value**	**p-value**	**Hypothesis**
intercept	4.62	0.10	38.71	.00001	H2b Accepted
Team work	0.44	0.18	2.42	.01	
Similarity	0.33	0.43	0.77	.44	
interaction	1.20	0.58	2.04	.04	
Model for Enjoyment					
intercept	4.62	0.10	44.34	.00001	H2a Accepted
Team work	0.36	0.15	5.62	.02	
Similarity	-0.45	0.33	1.38	.17	
interaction	1.43	0.67	2.11	.04	

intention to participate and perceived learning is stronger when the participants experience high engagement than in the case the participants experience low engagement. Thus our data provide strong evidence that children's level of engagement during coding activities moderates the relationships between their intention to participate in the activity and learning (accepting H1b).

Finally, we consider how engagement moderates the relation between intention to participate and enjoyment, Table 5 shows the details for the model and the Figure 9 shows the trends similar to that of Section 5.2. We observe a significant moderating effect of engagement in the relationship between intention to participate and enjoyment. From Figure 9 (right) it can be observed that the relation between intention to participate and enjoyment is stronger for the highly engaged participants than the case of non-engaged ones. Thus our data provide strong evidence that children's level of engagement during coding activities moderates the relationships between their intention to participate in the activity and enjoyment (accepting H1a).

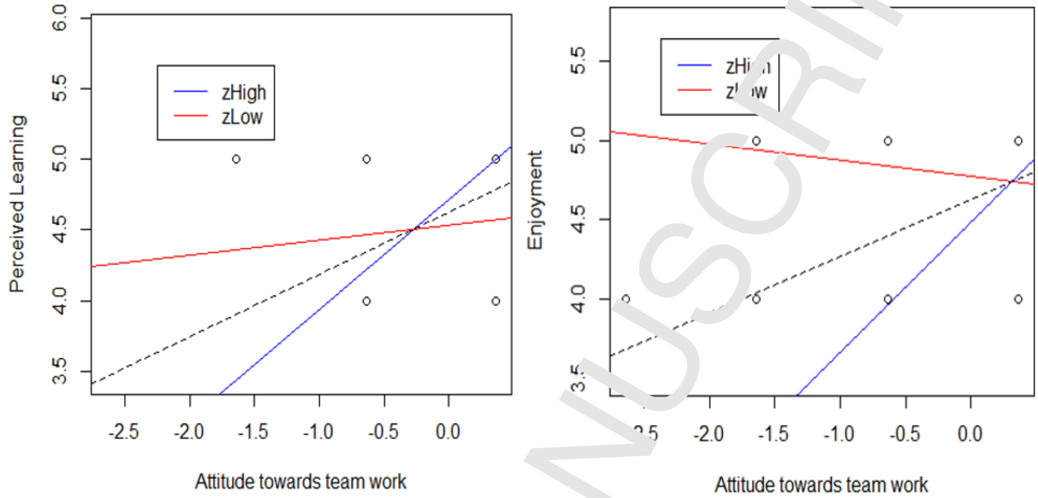

Figure 8: Trends from the models shown in the Table 4. The red and blue lines show fitted model with low and high collaboration (gaze similarity) values, respectively. The dashed line shows the main effect.

6. Discussion and Conclusions

We presented analysis of data from a study with children coding games and interactive robots. We captured children's behaviour while coding using eye-trackers. Moreover, we also captured their attitude towards coding using questionnaires. In this contribution, we investigated the role of gaze-behaviour as a moderator for the relationship between the different attitudes. The results show that gaze-behaviour does moderate the relationship between the attitudes about a coding activity with the ones resulted from the coding activity.

The first behavioural measure is the level of collaboration (measure via gaze similarity). The results show that the level of collaboration affects the relationship between childrens attitudes. High level of collaboration shows children's ability to share the learning experience, this fosters their enjoyment from the process. Moreover, high level of collaboration also indicates high level of mutual understanding (common ground) [37; 16] and better division of labour[10], that is critical for group learning activities. In addition, through the collaborative process of coding, children share their learning by interacting and making decisions together[20]. This could reinforce learning (as also indicated from the perceived learning measure). A few studies have also reported similar results where the lack of shared gaze among the participants turns out to be detrimental for children's learning (e.g., [85]).

Table 5: Moderator effect model for perceived learning and enjoyment using attitude towards intention and gaze uniformity as the independent and moderating variables, respectively.

Model for Perceived learning					
	Estimate	**Error**	**t-value**	**p-value**	**Hypothesis**
intercept	4.70	0.10	45.34	.00001	
Intention	0.63	0.14	4.33	.0001	H1b Accepted
Uniformity	-0.25	0.36	-0.69	.049	
interaction	1.44	0.48	2.98	.004	
Model for Enjoyment					
intercept	4.06	0.08	53.85	.00001	
Intention	0.66	0.11	5.62	.0001	H1a Accepted
Uniformity	-0.61	0.34	-1.75	.09	
interaction	1.09	0.39	2.77	.008	

The differences in children's coding level of competence, even if they had positive attitude towards team work, made them feeling that they didn't learn enough. Differences in children's coding competence could have also made it difficult to communicate and coordinate with the partner. This can be the reason that they also enjoyed the activity less than those who were in more homogeneous groups, and were able to communicate and coordinate well with peers. These results are inline with the previous work related to learn new concepts and the gaze-togetherness [82; 92]; and the lack of gaze-togetherness and the high levels of misunderstandings [12].

The second behavioural measure we used was children's engagement (measured via gaze uniformity). Engagement moderated the relationship between childrens attitudes (influence of intention to participate to enjoyment and learning). Higher engagement shows confidence and children explore different parts of the interface and navigate in all parts of the screen [64]. Also, the activities were designed in a manner that all parts of the interface were equally important for success (task based). Children who pay equal attention to all the feel more successful in learning the concepts than those who did not. Their familiarization with the learning environment (Scratch) and being able to understand all its different parts and their functionalities influenced their enjoyment and learning. The ability of accomplishing a task provides an overall positive experience and offers positive results like fun and enjoyment [69; 83].

Collaboration promotes better perspective taking and reflection among students [56; 18], which in turn enables higher learning gains and better collab-

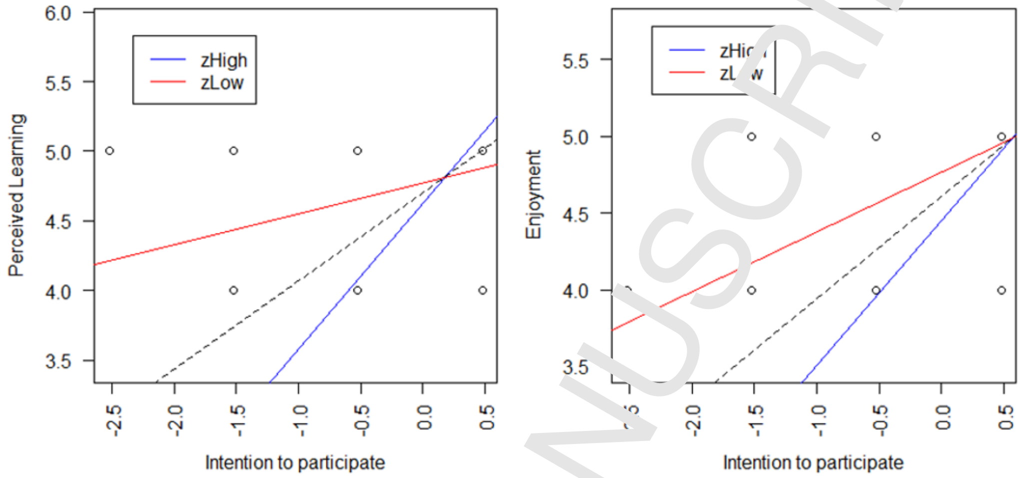

Figure 9: Trends from the models shown in the Table 5. The red and blue lines show fitted model with low and high gaze similarity values, respectively. The dashed line shows the main effect.

orative learning experiences [98; 71; 67; 66]. Moreover, the engagement with collaborative tasks can offer opportunities for the children to learn the domain related [42; 25; 57] as well as the collaborative skills[23]. These relations have also been highlighted in the case of pair-programming at a classroom level [6]. Collaboration among the students has also been found to be fruitful in acquiring other computer literacy skills[59] beyond programming skills.

It is shown that co-located collaboration has certain educational benefits [68; 103] such as, externalization of thought processes [60] and reduced cognitive load [43]. This supports our results where we found that relation between the attitude towards team work and learning is stronger for participants who experienced high level of collaboration. The groups with high levels of collaborative work and a more positive attitude towards collaboration were able to talk about the programming processes and concepts more than the groups with lower collaborative work and hence they were able to achieve higher learning gains. By designing for these mechanisms one can achieve higher collaborative outcomes [34]. For example, while working together and sharing insights and problems with each other, the peers might benefit from a reflection tool [76].

Other studies with collaborative learning with children have argued about the benefit of collaboration [77; 94; 4] specifically, in learning computational thinking skills [77; 39; 102]. Our results consists of two benefits over the previous studies. First, most of the studies reported in Section 2 addressed the pairwise relations among behaviour and attitudes, while this contribution focuses on more intricate nature of the triumvirate relationship. Second, the behaviour was used in the reported eye-tracking studies [84; 59; 16; 97] more as a process variable for the plausible explanation of the relation between success/expertise/collaboration/perception, while our results show that it could be used as a moderator. This fact will allow us to provide feedback in real time to affect both attitudes and experiences in positive manner.

6.1. Theoretical and practical implications

Our results show that the behaviour is key to understand the relation between attitudes towards learning, specifically when it comes to learning to code. Both gaze similarity and gaze uniformity influenced childrens relationship among attitudes. This highlights the importance of both individual and collaborative measures to understand learners behavior during coding activities and act accordingly to enhance their learning experiences.

Considering the relationships between the intention, learning and enjoyment; and how they are moderated by gaze uniformity, our results seem to extend the Technology Acceptance Model (TAM) [19]. According to TAM the perceived ease of use, intention to use and the actual usage are correlated [19]. Our results suggest that the children with high gaze uniformity on the interface have a higher correlation between the intention and enjoyment; and between the intention and perceived learning than those children who have low gaze uniformity. This shows that the gaze behaviour moderates the relationship between intention to use technology and the other attitudes (enjoyment and learning). This is inline with TAM, which also shows significant correlations between the intention to use, the behavioural use, and the attitudes towards technology. In this contribution we propose to use the behaviour as a moderator of the relationship between different attitudes. The results enhances our understanding of how children's behaviour can impact their attitudes towards a new technology, since most of the children participating in the workshop were novices.

In practical terms, the gaze uniformity translates to exploring the interface in a uniform manner to learn most of the functions provided by the environment. Gaze uniformity can be calculated in real-time, which could allow us to provide feedback while the children are coding. This might enhance the learning experiences and outcomes for them. Gaze uniformity can also be used to develop post-coding reflection tools as well. One can use the gaze data to show how the children explored the interface and help them understand what they missed. This might help them to have better exploration and understanding in the future coding activities.

In any collaborative scenario, where the coordination of the collaborators is essential for the successful completion of the task such as collaborative programming, collaborative problem solving, collaborative learning, it is essential to have a common ground between the team members [13]. According to the grounding theory in communication [13] – grounding is basic to all the communications – and hence, it is important to have a measurement for the process of grounding the conversations. Mutual gaze is the process by which two or more collaborators initiate and maintain the common ground [74]. Mutual gaze can be initiated by a diactic gesture (verbal or physical) by one of the team members [75]. When John refers (talks about or points) at a certain part of the Scratch interface to initiate a conversation he has to look at that particular part of the screen. At the same time, if following what John's discourse, Susan looks at the same part of screen to make sense of what John is saying. This results in gaze similarity. Our results show that the teams with high gaze similarity have a higher correlation between the attitude towards team work and both learning and enjoyment (Table 4 and Figure 8). This is inline with results reported in previous research with collaborative processes and conversations [87; 29; 16; 37]. The results in the present contribution highlight the importance of having a common ground among collaborators at young ages as well.

In practical terms, the moderator effect shown by the gaze similarity could be exploited to provide gaze-aware feedback to the collaborating partners. In video based learning scenarios gaze-awareness has been shown to improve learning experiences [90] and outcomes [86]. In collaborative problem solving sharing the gaze of partners leads to better collaborative outcomes [22; 29; 10]. Children might benefit from having an additional support for sharing a common ground with their team-mates since their verbal referencing capabilities might not be as good as adults due to lack of experience.

6.2. Limitations

This study is the one of the few ones (to the best of our knowledge) to explore the relationship between the objective behaviour and the attitudes of children towards coding activities. The eye-tracking data provided us a proxy for the behaviour. However, there were many difficulties faced while collecting the data, which affected the quality of data in certain ways. For example the eye-tracking glasses are made to fit adult sized heads and the participants were eight to seventeen years old. A few of the children obviously had small head sizes. This created a few problems while calibrating and post-processing the data. Another limitation of the current contribution comes from the fact that this was an experiment conducted with a visual programming tool (Scratch) and following specific instructions and learning goals. Although, we would expect the findings to generalize across other visual programming tools and coding activities, it is difficult to generalize for text-based programming environments and formal coding activities.

6.3. Future Work

This contribution opens up varied directions for further extension of research. First, this paper focuses on eye-tracking as an objective proxy of behaviour, which is not ideal for ecological validity and hence one should explore other options for behavioural proxy. Some examples are, facial features, interaction patterns with the programming interface, arousal data collected through devices such as wristbands. Second, our results show that there is potential to use eye-tracking data to provide feedback to children while they are learning how to code. Our results can provide a first step towards designing a gaze-aware feedback system to enhance the learning experiences and the learning outcomes. Third, a logical extension of the present contribution can be to look into the temporal dynamics of the gaze behaviour to observe how engagement and collaboration evolve for different groups of children with different characteristics (e.g., competence in coding, experience, age groups etc.).

6.4. Conclusions

In this paper we present analytics to understand the relationships between attitudes and behaviour of children while solving coding problems. We proposed to use the behaviour, as measured by gaze, as a moderator of the relationship between the different attitudes. The results show that the behaviour is an important factor while examining such relations. We found that behaviour does moderates the relation between the intention to learn, attitude towards team work, enjoyment and perceived learning. We also demonstrate that the results are inline with existing theories and contemporary research. This encourages us to work in this direction for future towards enhancing our understanding about kids coding patterns.

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We confirm that the manuscript has been read and approved by all named authors. We further confirm that the order of authors listed in the manuscript has been approved by all of us.

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