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Real-time Feedback based on Emotion Recognition for Improving Children's Metacognitive Monitoring Skill

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ABSTRACT

In this extended abstract, we outline a PhD project which investigates the relationship between emotion and metacognition in children with Autism Spectrum Disorder (ASD) in order to design and develop an automatic Machine Learning based tool with real-time feedback to support metacognitive process of both Typically Developing (TD) children and children with ASD.

CCS CONCEPTS

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

KEYWORDS

Metacognitive monitoring process, Emotion, Self-regulated learning, Children, Automatic tool

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1 RESEARCH TOPIC

The learning experience of children with Autism Spectrum Disorder (ASD) may be negatively affected due to impaired social communication, restricted interests, and repetitive behaviour. There is a great distance in learning attainment for some children with ASD to their Typically Developing (TD); the mathematics learning gap is one instance of such a distance [5, 27]. The reason why some children diagnosed with ASD have difficulties in mathematics is that it requires a comprehensive accurate cognitive process to understand mathematics concepts. To support mathematics learning, one of the most cost-efficient educational interventions is to support one's metacognition [15]. Metacognition is described as 'thinking about one's thinking' [25]. It is the ability to understand and control one's learning by comparing features of learning experience with the standards of experience, and it is directly related to one's mathematics performance [11]. Evidence from research experiments have revealed that children with ASD have impairment on the metacognitive process. A significant difference is shown in the metacognitive monitoring score between a group of children with ASD and a group of Typically Developing (TD) children [4, 6, 13, 24]. An impaired metacognitive monitoring process is unfavorable for children with ASD because the metacognitive monitoring process is one important part of self-regulation of learning (SRL), which is one's ability to understand and control one's learning environment [16]. The impaired metacognitive monitoring process could explain why children with ASD have difficulties with SRL and perform a delayed performance in the mathematics study.

Current interventions which improve children's mathematics learning by supporting metacognitive monitoring ability can be categorised into traditional-based and computer-based interventions. Based on research experiments, the mathematics performance of children or adolescents with ASD are improved after working on these interventions [8, 10, 14, 17, 18, 27]. Compared with traditional-based interventions, computer-based interventions have additional advantages for children with ASD. First, the computer-based intervention can build a more comfortable learning environment for children, since children with ASD tend to enjoy themselves and be engaged when interacting with computers as these interactions occur in a safe and trustworthy environment [32]. Second, the computer-based intervention can use technological devices and algorithms to collect and analyse more precise features from children such as emotion, temperature, body motions, and learning performance [17] which can be used to improve the quality of support. Third, computer-based interventions are replicable so that every child with ASD can be supported by one independent machine [8] to receive more specific targeted support.

In the proposed research, such 'support' of metacognitive monitoring ability appears in the form of some feedback about the judgement of learning activity [17]. One limited aspect of the traditional feedback in the proposed research is having to be provided after children finish the learning process because the feedback is based on children's postdictive judgement of their answers. Such a delay in providing feedback can not support children's metacognitive monitoring process in real-time, whilst active learning is in progress [33]. To evaluate the metacognitive monitoring process in real-time, research groups have focused on exploring the relationship between emotion and metacognitive monitoring accuracy of TD children [9, 29, 30]. It has been studied that typical emotions such as 'boredom' and 'surprising' have a significant relationship with metacognitive monitoring accuracy [9, 30]. However, the relationship between emotion and metacognitive monitoring accuracy of children with ASD is still emerging. The Facial Emotion Expression (FEE) of children with ASD can not be recognised with a reliable accuracy [3, 22, 26, 31], because children with ASD have

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unique and impaired emotion expressions [2, 28]. Thus our research project aims to fill the following gaps:

(1) Current interventions can not provide feedback in real-time and omit the heterogeneous behaviours of children [17, 30].
(2) Research has shown emotions can have a positive influence on the metacognitive process, but the relationship between emotion and metacognitive monitoring accuracy has not been investigated in children with ASD [12, 30].
(3) It needs to be explored which patterns of emotional expression are significantly different in children with ASD [26].

1.1 Key-terms Descriptions

In this subsection, we will illustrate all key terms we used in this review.

Self-regulated learning (SRL): Self-regulated learning refers to one's ability to understand and control one's learning environment. It include goal setting, self-monitoring, self-instruction, and self-reinforcement.
Metacognitive monitoring accuracy: Metacognitive monitoring accuracy represents the accuracy of one individual's metacognitive monitoring process when monitoring the cognitive error [33].
Emotion change: The term 'emotion change' represents the change of one's emotion evidence score such as joy, anger, surprise, boredom, etc [30].
Traditional feedback: The traditional 'feedback' is provided to children after completing required tasks such as the the rate of accuracy, the scores obtained, the goal reminder, and the strategy for the next action [17, 18].

1.2 Problem Statement

We build on evidence that children with ASD have impaired metacognitive monitoring ability when engaging in complex and constrained problems [4, 6, 13, 24, 33]. This impairment in metacognition can explain why the mathematics performance of some children with ASD is poorer than their peers. Based on two research outcomes: first, Maras and Brosnan [17] studied that traditional feedback which supports metacognition can improve children's mathematics performance; second, Taub [30] has investigated the relationship between emotional change and metacognition in TD children, we will investigate the relationship between emotional change and metacognitive monitoring accuracy in children with ASD and explore how an automatic Machine Learning (ML) tool can be designed to provide feedback in real-time based on emotional changes to support metacognitive monitoring skills in children with ASD.

1.3 Research Aim and Objectives

In this research project, we aim to design and build automatic computer-based learning tools for TD children and children with ASD, to improve their mathematics performance by providing personalized real-time feedback to support their metacognitive monitoring accuracy. To achieve this aim, the objectives below need to be accomplished:

1. Validate the accuracy of emotion recognition tool for TD children and children with ASD.
2. Explore the relationship between emotion change and metacognitive monitoring accuracy in children with ASD.
3. Analyze the effect of feedback generated in real-time on metacognitive monitoring accuracy of TD children and children with ASD.

2 RESEARCH QUESTIONS

To solve the research problem and accomplish our research objectives, there are two research questions that will drive the research work in this project:
RQ 1: *Can the emotion recognition tool improves the metacognitive monitoring accuracy of TD children and children with ASD?*

This question is focusing on whether the metacognitive monitoring accuracy of children (TD and ASD) can be increased if we provide feedback in real-time to children based on their expected emotional changes such as boredom and surprise.
RQ 2: *Which emotional expressions are significantly different in children with ASD while engaging in the metacognitive monitoring process?*

As children with ASD have unique facial expressions, to monitor their emotional change in RQ 1, this question needs to explore which emotions are significantly different, and how to classify and measure these emotions in children with ASD.

3 CURRENT WORK DONE SO FAR

Building on two research outcomes (Maras et al. and Taub et al.) mentioned in Sec.1.2, now we aim to explore whether providing real-time feedback which based on emotional change can improve children's metacognitive monitoring accuracy and thereby improving the mathematics performance. As recognising facial emotional expressions is a vital procedure in this project, we need to validate the accuracy of the emotion recognition tool for children (the first objective in Sec.1.3). To be aware of unique behaviours of facial expression with small training dataset, transfer learning algorithms have been applied on training Neural Networks (NN) to classify emotions [1, 20, 21]. We tested the accuracy of a transfer learning algorithm (loss-reweighting) [7] and deep learning neural network (NN) in classifying emotions in ChildEFES[1], the result (see Fig.1) showed that the transfer learning algorithm can improve the accuracy of facial emotional classification based on a generic classifier and a personalized classifier (see (a), (b) in Fig.1 that the mean accuracy in middle is higher than both end), and this result is consistent with the experiment in [22, 23, 26]. Now we are requesting the permission of accessing an emotional dataset of children with ASD to test the accuracy of emotional classifier on children with ASD.

4 NEXT STEPS

Next, a 'between-groups study design' will be employed, where each group will be exposed to one of the following conditions: C1 - learning without feedback support; C2 - learning with traditional feedback support; C3 - learning with real-time feedback support.

[1]ChildEFES [19] is a photo and video database of 4-to-6-year-olds expressing the seven induced and posed universal emotions (happy, disgust, surprise, fear, sad, anger, contempt) and a neutral expression.

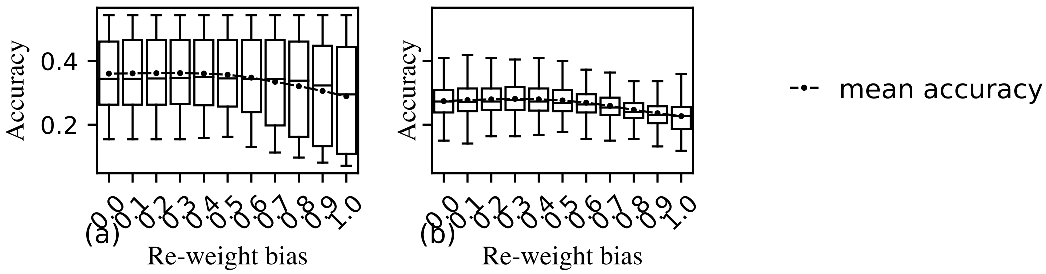

Figure 1: The accuracy of loss-reweighting on ChildEFES: (a) re-weight between gender aware NN (when bias=0.0) and generic NN (when bias=1.0), (b) re-weight between nationality aware NN (when bias=0.0) and generic NN (when bias=1.0).

The difference between C2 and C3 is that C2 will get feedback at the end of the learning task, while C3 will get feedback when children's metacognitive monitoring process is keeping lower than usual. We expect to answer whether the real-time feedback based on emotional change can improve the metacognitive monitoring accuracy and mathematics performance.

With our PhD project, we will fill up the research gap about the relationship between emotion and metacognition in children with ASD and will provide a reliable approach to evaluating children's metacognitive monitoring accuracy in real-time for the research community. The metacognitive monitoring processed of children are expected to be improved from real-time feedback. This will offer a direction for future research to provide high-quality feedback for TD children and children with ASD to support their metacognitive process.

REFERENCES

[1] MAH Akhand, Shuvendu Roy, Nazmul Siddique, Md Abdus Samad Kamal, and Tetsuya Shimamura. 2021. Facial Emotion Recognition Using Transfer Learning in the Deep CNN. *Electronics* 10, 9 (2021), 1036.

[2] R James R Blair. 1999. Psychophysiological responsiveness to the distress ofothers in children with autism. *Personality and individual differences* 26, 3 (1999), 477–485.

[3] Kellen Briot, Adrien Pizano, Manuel Bouvard, and Anouck Amestoy. 2021. New Technologies as Promising Tools for Assessing Facial Emotion Expressions Impairments in ASD: A Systematic Review. *Frontiers in psychiatry* 12 (2021), 530.

[4] Mark Brosnan, Hilary Johnson, Beate Grawemeyer, Emma Chapman, Konstantina Antoniadou, and Melissa Hollinworth. 2016. Deficits in metacognitive monitoring in mathematics assessments in learners with autism spectrum disorder. *Autism* 20, 4 (2016), 463–472.

[5] Jennifer C Bullen, Lindsay Swain Lerro, Matthew Zajic, Nancy McIntyre, and Peter Mundy. 2020. A Developmental Study of Mathematics in Children with Autism Spectrum Disorder, Symptoms of Attention Deficit Hyperactivity Disorder, or Typical Development. *Journal of autism and developmental disorders* 50, 12 (2020), 4463–4476.

[6] Katie L Carpenter, David M Williams, and Toby Nicholson. 2019. Putting your money where your mouth is: examining metacognition in ASD using post-decision wagering. *Journal of autism and developmental disorders* 49, 10 (2019), 4268–4279.

[7] Justin Chen, Edward Gan, Kexin Rong, Sahaana Suri, and Peter Bailis. 2019. Crosstrainer: Practical domain adaptation with loss reweighting. In *Proceedings of the 3rd International Workshop on Data Management for End-to-End Machine Learning*. 1–10.

[8] Caitlyn Clabaugh, Kartik Mahajan, Shomik Jain, Roxanna Pakkar, David Becerra, Zhonghao Shi, Eric Deng, Rhianna Lee, Gisele Ragusa, and Maja Matarić. 2019. Long-term personalization of an in-home socially assistive robot for children with autism spectrum disorders. *Frontiers in Robotics and AI* 6 (2019), 110.

[9] Elizabeth B Cloude, Franz Wortha, Daryn A Dever, and Roger Azevedo. 2020. How do Emotions Change during Learning with an Intelligent Tutoring System? Metacognitive Monitoring and Performance with MetaTutor.. In *CogSci*.

[10] MeganClaire Cogliano, Matthew L Bernacki, and CarolAnne M Kardash. 2020. A metacognitive retrieval practice intervention to improve undergraduates' monitoring and control processes and use of performance feedback for classroom learning. *Journal of Educational Psychology* (2020).

[11] Annemie Desoete and Brigitte De Craene. 2019. Metacognition and mathematics education: An overview. *ZDM* 51, 4 (2019), 565–575.

[12] Sidney D'Mello, Arvid Kappas, and Jonathan Gratch. 2018. The affective computing approach to affect measurement. *Emotion Review* 10, 2 (2018), 174–183.

[13] Catherine Grainger, David M Williams, and Sophie E Lind. 2016. Metacognitive monitoring and control processes in children with autism spectrum disorder: Diminished judgement of confidence accuracy. *Consciousness and Cognition* 42 (2016), 65–74.

[14] Beate Grawemeyer, Hilary Johnson, and Mark Brosnan. 2015. Can young people with autism spectrum disorder benefit from an open learner model?. In *International Conference on Artificial Intelligence in Education*. Springer, 591–594.

[15] Steve Higgins, Maria Katsipataki, AB Villanueva-Aguilera, Robbie Coleman, P Henderson, LE Major, R Coe, and Danielle Mason. 2016. The Sutton Trust-Education Endowment Foundation Teaching and Learning Toolkit. (2016).

[16] Randy M Isaacson and Frank Fujita. 2006. Metacognitive knowledge monitoring and self-regulated learning: Academic success and reflections on learning. *Journal of Scholarship of Teaching and Learning* 6, 1 (2006), 39–55.

[17] Katie Maras, Tim Gamble, and Mark Brosnan. 2019. Supporting metacognitive monitoring in mathematics learning for young people with autism spectrum disorder: A classroom-based study. *Autism* 23, 1 (2019), 60–70.

[18] Napoleon A Montero et al. 2021. The Impact of a Metacognitive Intervention using IMPROVE Model on Grade 7 Students' Metacognitive Awareness in Mathematics. *Turkish Journal of Computer and Mathematics Education (TURCOMAT)* 12, 3 (2021), 3881–3894.

[19] Juliana Gioia Negrão, Ana Alexandra Caldas Osorio, Rinaldo Focaccia Siciliano, Vivian Renne Gerber Lederman, Elisa Harumi Kozasa, Maria Eloisa Famá D'Antino, Anderson Tamborim, Vitor Santos, David Leonardo Barsand de Leucas, Paulo Sergio Camargo, et al. 2021. The child emotion facial expression set: a database for emotion recognition in children. *Frontiers in psychology* 12 (2021), 1352.

[20] Hong-Wei Ng, Viet Dung Nguyen, Vassilios Vonikakis, and Stefan Winkler. 2015. Deep learning for emotion recognition on small datasets using transfer learning. In *Proceedings of the 2015 ACM on international conference on multimodal interaction*. 443–449.

[21] Min Peng, Zhan Wu, Zhihao Zhang, and Tong Chen. 2018. From macro to micro expression recognition: Deep learning on small datasets using transfer learning. In *2018 13th IEEE International Conference on Automatic Face & Gesture Recognition (FG 2018)*. IEEE, 657–661.

[22] Ognjen Rudovic, Jaeryoung Lee, Miles Dai, Björn Schuller, and Rosalind W Picard. 2018. Personalized machine learning for robot perception of affect and engagement in autism therapy. *Science Robotics* 3, 19 (2018), eaao6760.

[23] Ognjen Rudovic, Yuria Utsumi, Jaeryoung Lee, Javier Hernandez, Eduardo Castelló Ferrer, Björn Schuller, and Rosalind W Picard. 2018. Culturenet: A deep learning approach for engagement intensity estimation from face images of children with autism. In *2018 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*. IEEE, 339–346.

[24] Alyssa CP Sawyer, Paul Williamson, and Robyn Young. 2014. Metacognitive processes in emotion recognition: Are they different in adults with Asperger's disorder? *Journal of Autism and Developmental Disorders* 44, 6 (2014), 1373–1382.

[25] Gregory Schraw and Rayne Sperling Dennison. 1994. Assessing metacognitive awareness. *Contemporary educational psychology* 19, 4 (1994), 460–475.

[26] Zhonghao Shi, Thomas R Groechel, Shomik Jain, Kourtney Chima, Ognjen Rudovic, and Maja J Matarić. 2021. Toward Personalized Affect-Aware Socially Assistive Robot Tutors in Long-Term Interventions for Children with Autism. *arXiv preprint arXiv:2101.10580* (2021).

[27] Nur Choiro Siregar, Roslinda Rosli, Siti Mistima Maat, Aliza Alias, Hasnah Toran, Kannamah Mottan, and Siti Muhibah Nor. 2020. The Impacts of Mathematics Instructional Strategy on Students with Autism: A Systematic Literature Review. *European Journal of Educational Research* 9, 2 (2020), 729–741.

[28] Mary E Stewart, Natalie Russo, Jennifer Banks, Louisa Miller, and Jacob A Burack. 2009. Sensory characteristics in ASD. *McGill Journal of Medicine: MJM* 12, 2 (2009).

[29] Michelle Taub and Roger Azevedo. 2018. Using Sequence Mining to Analyze Metacognitive Monitoring and Scientific Inquiry Based on Levels of Efficiency and Emotions during Game-Based Learning. *Journal of Educational Data Mining* 10, 3 (2018), 1–26.

[30] Michelle Taub, Roger Azevedo, Ramkumar Rajendran, Elizabeth B Cloude, Gautam Biswas, and Megan J Price. 2021. How are students' emotions related to the accuracy of cognitive and metacognitive processes during learning with an intelligent tutoring system? *Learning and Instruction* 72 (2021), 101200.

[31] Dominic A Trevisan, Maureen Hoskyn, and Elina Birmingham. 2018. Facial expression production in autism: A meta-analysis. *Autism Research* 11, 12 (2018), 1586–1601.

[32] Katherine Valencia, Cristian Rusu, Daniela Quiñones, and Erick Jamet. 2019. The impact of technology on people with autism spectrum disorder: a systematic literature review. *Sensors* 19, 20 (2019), 4485.

[33] Philip H Winne. 2011. A cognitive and metacognitive analysis of self-regulated learning. *Handbook of self-regulation of learning and performance* (2011), 15–32.