Automated Detection of Facial Expressions during Computer-Assisted Instruction in Individuals on the Autism Spectrum

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ABSTRACT

It has been suggested that computer-assisted instruction (CAI) is a promising method for educating students on the autism spectrum. We aimed to determine whether automated recognition of facial expressions aided in predicting CAI engagement and learning performance. Seven youth with autism (mean age = 12.7, SD = 4.2) interacted with a CAI program, TeachTown Basics, for 15 consecutive sessions. Video recordings of the participants' faces were collected during these sessions and facial expressions from these videos were analyzed using CERT, an algorithm that automatically outputs intensity values for each facial action unit (AU). Using these data, we attempted to operationally define two engagement indices: (1) behavioral engagement, the proportion of time a participant had their face oriented to the computer screen; and (2) emotional engagement, the activation of AUs previously associated with CAI. Our results suggest that both indices strongly correlated with one another, but that emotional (not behavioral) engagement predicted test performance. CAI knowledge domain, participant sex, and developmental age also contributed to the prediction.

Author Keywords

Emotion/Affective Computing; Education/Learning; Quantitative Methods; Computer Vision; Individuals with Disabilities & Assistive Technologies

ACM Classification Keywords

K.4.2 Social Issues: Assistive technologies for persons with disabilities

INTRODUCTION

Engagement, Learning, and CAI

Current research on student academic engagement defines it as a multifaceted construct including both emotional and behavioral components. Behavioral engagement refers to observable skills required to achieve positive learning outcomes, such as participation and attendance. Emotional engagement refers to a student's feelings in reaction to the learning process [9]. Although the link between engagement and learning has been well established, it is less clear how engagement interacts with and influences achievement outcomes, especially during CAI [11].

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Craig et al. [5] assessed facial affect in neurotypical undergraduate students during CAI. Participants verbalized their affective states while video of their faces was simultaneously recorded. Videos were coded using the Facial Action Coding System (FACS), which categorizes 46 anatomical facial movements as distinct "action units" (AU) [6]. The authors reported that frustration, confusion, boredom, and eureka (the "joy of discovery") were most prominently expressed and that AU activations coincided with these self-reported emotions. AUs 1 (outer brow raise), 2 (inner brow raise), and 14 (dimpler) were associated with *frustration*; 4 (brow lowerer), 7 (lid tightener), and 12 (lip corner puller) with *confusion*; and 45 (eye closure) with *boredom*.

Computer Expression Recognition Toolbox

Although FACS allows observers to reliably identify fine-grained facial movements, manual coding is time-intensive. The Computer Expression Recognition Toolbox (CERT) is a computer vision tool that detects the presence of a face, and the intensity of AUs within it, from video data [17]. Although CERT was trained on adult faces, it has also been used to collect meaningful data from children [29]. Grafsgaard [7] used CERT to analyze facial expressions of neurotypical undergraduates as they interacted with a CAI tool. They reported that AUs 1, 2, 4, 7, and 14 were most commonly expressed in their sample, which was consistent with previous findings based on manual coding [5]. Interestingly, they also demonstrated that self-report of performance was positively predicted by AU14 activation, and that objective performance (student differences in pre- and post-test scores) were positively predicted by AU14 and negatively predicted by AU2. Henrie [9] has further suggested that the expression of positive and negative emotions can indicate engagement and disengagement, respectively. However, these results imply that negative emotions can accompany engaged and productive learning as well. Additional work is needed to characterize the relationship between emotional engagement and learning in CAI, not only in the general population, but especially in populations who cannot easily self-report their affective states [13,14,30].

CAI and Autism

Autism is a lifelong neurodevelopmental condition associated with difficulties in social interaction and communication, and repetitive or stereotyped behaviors [2]. Despite these common diagnostic characteristics, there is great heterogeneity in the clinical presentation of autism [18]. Carnahan [4] noted that many children with autism experience more difficulty in social situations, including traditional learning environments. Thus, their engagement in learning may require specialized support. Reviews of the current literature have highlighted how CAI programs can support individuals with autism by focusing attention, increasing motivation, bypassing potentially stressful social contexts, and providing a more structured learning environment [20,22,23,25,28].

Furthermore, a meta-analysis of technology-based interventions for autism reported that the proposed efficacy of CAI in this population is supported, but that individuals with average or above average IQ were overrepresented, comprising 67.8% of study participants [8]. Additional work is needed to expand the autism CAI literature to include more severely impacted individuals, especially those who cannot verbalize their learning processes.

Prior work has indicated that children with autism produce emotional facial expressions spontaneously, but that they may be infrequent or ambiguous relative to typically developing children's expressions [21]. Prior work has also demonstrated that children with autism have reduced capacity to self-report their emotional states [14]. Given the above, we sought to determine whether computational measures could be used to assess engagement and learning processes in those who have trouble self-reporting emotional states, with the longer-term goal of producing better CAI learning outcomes for all specialized learners. The current study used TeachTown Basics (http://web.teachtown.com/products/teachtown-basics), a commercially available CAI program whose efficacy as a teaching tool for students with autism has been previously demonstrated [31,32]. That is, children with autism who interacted with the program showed statistically significant gains in language and cognitive skills relative to those in a control group.

The present study sought to determine whether computationally-derived computer vision measurements of engagement were predictive of CAI learning outcomes in severely impacted youth with autism. The specific research questions examined were: How can we quantitatively characterize engagement in a CAI learning task? Is engagement, as we measured it, related to test performance? What factors moderate CAI learning performance in severely impacted youth with autism?

METHOD

Sample

Seven youth with autism (4 male, 3 female) with a mean age of 12.7 (range = 8-19 years) were recruited from a day program serving children with developmental disabilities. Diagnoses were confirmed by a licensed psychologist familiar with autism using DSM-IV guidelines, the Childhood Autism Rating Scale (CARS), and previous psychiatric reports [18]. Participant cognitive abilities as assessed by standardized intelligence measures (Stanford-Binet-IV, Leiter) or scales of cognitive development (Bayley Scales) ranged from 24-38 (M = 31) and 5-24 months, respectively. Scores on the CARS ranged from 31.5-43.5 (M = 39), placing our participants in the moderately to severely autistic range. Five of the youth were white, and two were African American/Black.

Procedure

All participants interacted with TeachTown Basics, and completed its self-contained academic lessons (discrete trials). Trials consisted of multiple-choice questions with 3 to 8 possible answers. The subject matter of the trials varied between 5 learning domains: adaptive skills, cognitive skills, language arts, language development, mathematics, and social and emotional skills. TeachTown Basics also presents learners with interactive reward games for 15-45 seconds between discrete trial tasks as reinforcement. In the present study, trials of the same type were grouped into tests. Every participant worked through several tests within a session, which lasted approximately 30 minutes each.

Each participant repeated their interaction with TeachTown Basics for at least 15 sessions. Although some participants had more than 15 sessions, only the first 15 were included in the present analysis to establish data consistency. Sessions were less than a week apart and often took place on consecutive days. The learning domain tested and number of tests administered varied across sessions.

Data Collection

Video

During each session, video of the participants' faces were recorded at approximately 30 frames per second. The camera was positioned above the computer screen, directly facing the participants.

Performance and Timing Information

TeachTown Basics produces a detailed, time-stamped report of each session, including all learning activities and responses that take place. We focused specifically on two activities, discrete trials (learning tasks) and interactive games (animated reward sequences displayed upon completion of a test). The software also reports the percentage of trials answered correctly for each test.

Facial Expression Recognition

Video from the first 15 sessions for each participant was passed through CERT, which produced a frame-by-frame analysis of AU intensity levels. We extracted AUs 1, 2, 4, 6, 7, 12, 14, 17, and 45 based on prior work implicating them in engagement during CAI [5,7]. Intensity levels for each frame of video were subtracted from each AU's session-wide average to allow for between-participant comparisons, because baseline AU activation can vary across individuals [7]. CERT-generated intensity levels of 0.25 or higher have been shown to indicate a threshold level of activation that reasonably avoids false-positives [7]. Thus, we calculated AU frequency scores by taking proportion of segment times when AU intensities were above threshold levels. These scores were defined as computational proxy indices of emotional engagement.

We also attempted to define a metric for engagement related to gross physical behavior. CERT outputs an empty value for a frame of video if it cannot detect the components of a face required to measure AU activations, including the eyes and mouth. We calculated the proportion of frames with empty values to characterize how much time participants' faces were oriented toward the screen, which was defined as a proxy index of behavioral engagement.

CERT results were segmented based on the activities reported from TeachTown Basics, such that for each discrete trial and reward video we obtained emotional and behavioral engagement index scores as described above. Additionally, for each test, we obtained the learning domain and the percentage of trials answered correctly, along with engagement scores for the duration of that test. We also considered chronological age, developmental age, and sex of the student participants as covariates.

RESULTS

Engagement Measures

Correlation

We sought first to investigate how the two quantitative engagement scores we defined were related. Spearman's correlations were performed between the mean frequency score of each AU of interest ("emotional engagement") and the mean percentage of time participants had their faces oriented toward the screen ("behavioral engagement") during activities. Data for all participants and for all 15 sessions were combined for this analysis.

Nine correlations were performed, resulting in a Bonferroni-corrected significance threshold of $p = 0.05/9 = 0.0055$. Four AUs significantly correlated with behavioral engagement after threshold correction ($p < 0.0055$): AU2 (rho = -0.19), AU4 (rho = -0.41), AU7 (rho = -0.28), and AU45 (rho = -0.19).

Linear Mixed Model Analysis

We specified a model to determine whether behavioral engagement was predicted by emotional engagement while also considering individual differences and the effect of time. Additionally, we sought to identify whether and how the categorical variable "activity" (learning trial or reward video) influenced behavioral engagement scores. A linear mixed model was defined with participant ID and session number as fixed effects, and with CAI activity, AU2, AU4, AU7, AU45, chronological age, developmental age, and sex as random effects.

Predictor	Estimate (Std. Error)	Chi-sq (df = 1)	p
AU4	-2.09 (0.34)	31.93	4.06E-09
AU7	-1.52 (0.91)	3.56	0.091
Chr. Age	0.03 (0.006)	11.30	0.00077
Dev. Age	0.11 (0.019)	7.16	3.78E-05
Sex	0.10 (0.023)	10.15	0.0014

Table 1. Model statistics and likelihood ratio tests for a model predicting behavioral engagement scores.

To reduce the model to its most parsimonious state, we calculated the Akaike Information Criterion (AIC) [1]. AIC is a measure of a model's information loss; when comparing models, the preferred model is that which has the minimum AIC (lower is better). We calculated the second-order "corrected AIC" (AICc), which factors in an increased penalty for extra parameters. This was done for the full model, and for the model with each of its predictors removed separately [10,19].

Removing AU45 and CAI activity parameters had a negative effect on AICc, and therefore a positive effect on goodness-of-fit. We removed these parameters from further consideration, which reduced AICc from -100.7 to -105.6. Additionally, removing AU4 had a substantially greater positive effect on AICc relative to other predictors.

We then performed likelihood ratio tests to gauge each predictor's contribution to the model (Table 1). Each predictor was removed individually and tested against the full model. All predictors except AU7 significantly influenced model likelihood at a threshold of $p < 0.05$.

Emotional engagement indices (AU4 and AU7) yielded a negative model estimate, indicating that increases in the frequency of those AUs decreased behavioral engagement prediction. The demographic covariate estimates showed that increasing age resulted in an increase in the prediction, but to a much smaller degree.

Test Performance

We specified a linear mixed model to identify factors moderating test performance. The initial model included a subset of AUs selected based on prior work [5,7]. Behavioral engagement, developmental age, chronological age, knowledge domain of the test, and sex were included as random effects. Test performance – the percentage of correct answers – was set as the outcome variable.

As in the prior section, a model selection procedure based on AICc comparisons was performed and the parameters AU1, 2, 7, 14, 17, 45, behavioral engagement, and age were removed.

Predictor	Estimate (Std. Error)	Chi-sq (df = 1)	p
Domain	-	12.1	0.0335
AU4	29.97 (14.9)	3.82	0.051
AU6	-42.04 (11.96)	12.59	0.00039
AU12	33.7 (9.20)	13.54	0.00023
Dev. Age	-8.37 (2.24)	10.5	0.0012
Sex	20.44 (6.10)	9.33	0.0023

Table 2. Model statistics and likelihood ratio tests for a model predicting test performance. Model estimates for the learning domain predictor are addressed in the main text.

Likelihood ratio tests revealed that all remaining predictors, except AU4, significantly influenced model likelihood (Table 2). The model estimates indicate that AU6 and AU12 had a negative and positive influence, respectively, on predicted test performance. Within the knowledge domain predictor, the "Social and Emotional" category had the largest effect on the prediction (-8.94, SE = 3.44), while the effects of the other domains were negligible (the estimates +/- their standard errors overlapped zero).

DISCUSSION

Using computer vision, we sought to define automated quantitative proxy indices of emotional and behavioral engagement with CAI and evaluate their relative contributions to learning outcomes in severely affected youth with autism. Four out of the nine AUs that comprised our emotional engagement index correlated with behavioral engagement. Of these, only AU4 (brow lowerer) survived model selection and likelihood ratio testing. AU4 negatively affected the prediction of behavioral engagement. This finding echoes prior work that associated AU4 activation with negative learning outcomes, such as finding a learning session not worthwhile [7].

We also found that knowledge domain, sex, developmental age, and AUs 6 (cheek raise) and 12 (lip corner puller) were influential in a model predicting test performance. However, our proxy measure of behavioral engagement did not improve model fit. This result indicates that head orientation towards the CAI program was not as closely linked to participants' successful learning as was their emotional experiences measured by facial expressions contingent on learning materials. Increased AU6 frequency led to a decrease in predicted test performance, while increases in AU12 led to an increase. AU12 produces smiling expressions [3,15,12]. AU6 raises the cheeks and narrows the eye openings, and has been associated with both smiles [3] and pain [16].

Limitations and Future Work

It is important to note that AUs are not singly correlated to discrete emotions. Emotions are often associated with multiple AUs activating in concert, and each AU can play a role in many emotional expressions. Future work is needed to further assess relationships among AUs in addition to their individual effects on student CAI outcomes.

A significant drawback of focusing solely on automated facial expression recognition is loss of contextual information surrounding AU activations. Although prior work has demonstrated the validity and accuracy of CERT in identifying facial expressions in children and adults (during CAI and in other contexts) [7,29,33], we recognize that false positives can be expected even after activation thresholding.

Critically, we acknowledge that our proxy measure of behavioral engagement lacks corroboration from manual coding or self-report in this study. CERT may have failed to detect a face despite a student being engaged; for example, due to the occlusion of facial features. Interestingly, however, students with more severe forms of autism may intentionally use a "looking away" strategy to reduce visual stimulation and better concentrate [26], suggesting a need for more sensitive metrics in this population.

Research involving minimally verbal individuals on the autism spectrum is constrained by idiosyncratic behaviors and severe deficits in communication [13,24,30]. This often precludes obtaining ground truth labels from self-report questionnaires, or from observers without clinical expertise. We hope that our preliminary findings inspire collaborative research between clinical psychologists and computing researchers to collect multimodal data. Developing prediction models of CAI engagement using these data would be especially useful for understanding and supporting the learning processes of students who cannot reliably provide self-reports.

CONCLUSION

We believe our study is the first to translate theoretical constructs of engagement to quantitative indices of facial orientation and expression, including their associations with CAI learning performance. Additionally, we demonstrated feasibility for automated emotion recognition (via CERT) in youth with more severe forms of autism. Most work in autism focuses exclusively on "high-functioning" populations. We found that facial expressions were strong predictors of test performance in our sample, but that facial orientation towards the screen was not. This result differentiates between behavioral and emotional components of student engagement in CAI, and may thus provide a useful measure for future studies of CAI in more severely affected youth with autism.

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REFERENCES

1. Hirotogu Akaike. 1998. Information Theory and an Extension of the Maximum Likelihood Principle. In *Selected Papers of Hirotugu Akaike*, Emanuel Parzen, Kunio Tanabe and Genshiro Kitagawa (eds.). Springer New York, New York, NY, 199–213. http://doi.org/10.1007/978-1-4612-1694-0_15
2. American Psychiatric Association. 2013. *DSM 5*. American Psychiatric Association.
3. Nigel Bosch, Sidney K D'Mello, Jaclyn Ocumpaugh, Ryan S Baker, and Valerie Shute. 2016. Using Video to Automatically Detect Learner Affect in Computer-Enabled Classrooms. *Acm Transactions on Interactive Intelligent Systems* 6, 2. http://doi.org/10.1145/2946837
4. Christi Carnahan, Shobana Musti-Rao, and Jody Bailey. 2015. Promoting Active Engagement in Small Group Learning Experiences for Students with Autism and Significant Learning Needs. *Education and Treatment of Children*, 32, 1: 37–61.
5. Scotty D. Craig, Sidney D'Mello, Amy Witherspoon, and Art Graesser. 2008. Emote aloud during learning with AutoTutor: Applying the Facial Action Coding System to cognitive–affective states during learning. *Cognition & Emotion* 22, 5: 777–788. http://doi.org/10.1080/02699930701516759
6. Paul Ekman and Wallace V. Friesen. 1978. *Facial Action Coding System.* Consulting Psychologists Press.
7. Joseph F. Grafsgaard, Joseph B. Wiggins, Kristy Elizabeth Boyer, Eric N. Wiebe, and James C. Lester. 2013. Automatically recognizing facial expression: Predicting engagement and frustration. *International Conference on Educational Data Mining*.
8. Ouriel Grynszpan, Patrice L. (Tamar) Weiss, Fernando Perez-Diaz, and Eynat Gal. 2014. Innovative technology-based interventions for autism spectrum disorders: A meta-analysis. *Autism* 18, 4: 346–361. http://doi.org/10.1177/1362361313476767
9. Curtis R. Henrie, Lisa R. Halverson, and Charles R. Graham. 2015. Measuring student engagement in technology-mediated learning: A review. *Computers & Education* 90: 36–53. http://doi.org/10.1016/j.compedu.2015.09.005
10. Clifford M. Hurvich and Chih-Ling Tsai. 1989. Regression and time series model selection in small samples. *Biometrika* 76, 2: 297–307. http://doi.org/10.1093/biomet/76.2.297
11. Michel Janosz. 2012. Part IV Commentary: Outcomes of Engagement and Engagement as an Outcome: Some Consensus, Divergences, and Unanswered Questions. In *Handbook of Research on Student Engagement*, L Sandra Christenson, L Amy Reschly and Cathy Wylie (eds.). Springer US, Boston, MA, 695–703. http://doi.org/10.1007/978-1-4614-2018-7_33
12. Takeo Kanade, Jeffrey F. Cohn, and Yingli Tian. 2000. Comprehensive database for facial expression analysis. *Proceedings Fourth IEEE International Conference on Automatic Face and Gesture Recognition (Cat. No. PR00580)*: 46–53. http://doi.org/10.1109/AFGR.2000.840611
13. Connie Kasari, Nancy Brady, Catherine Lord, and Helen Tager-Flusberg. 2013. Assessing the minimally verbal school-aged child with autism spectrum disorder. *Autism Research* 6, 6: 479–493. http://doi.org/10.1002/aur.1334
14. Jasna Legiša, Daniel S. Messinger, Enzo Kermol, and Luc Marlier. 2013. Emotional responses to odors in children with high-functioning autism: Autonomic arousal, facial behavior and self-report. *Journal of Autism and Developmental Disorders* 43, 4: 869–879. http://doi.org/10.1007/s10803-012-1629-2
15. James Jenn-Jier Lien, Takeo Kanade, Jeffrey F. Cohn, and Ching-Chung Li. 2000. Detection, Tracking, and Classification of Action Units in Facial Expression. *Robotics and Autonomous Systems* 31, 3: 131–146.
16. Gwen C. Littlewort, Marian Stewart Bartlett, and Kang Lee. 2009. Automatic coding of facial expressions displayed during posed and genuine pain. *Image and Vision Computing* 27, 12: 1797–1803. http://doi.org/10.1016/j.imavis.2008.12.010
17. Gwen C. Littlewort, Jacob Whitehill, Tingfan Wu, et al. 2011. The computer expression recognition toolbox (CERT). *IEEE International Conference on Automatic Face and Gesture Recognition and Workshops, FG 2011*: 298–305. http://doi.org/10.1109/FG.2011.5771414
18. Catherine Lord, Ann Wagner, Sally Rogers, et al. 2005. Challenges in Evaluating Psychosocial Interventions for Autistic Spectrum Disorders. *Journal of Autism and Developmental Disorders* 35, 6: 695–708. http://doi.org/10.1007/s10803-005-0017-6
19. Marc J. Mazerolle. 2016. AICcmodavg: Model selection and multimodel inference based on (Q)AIC(c). R package version 2.0-4. http://CRAN.R-project.org/package=AICcmodavg.
20. David Moore and Jill Taylor. 2000. Interactive Multimedia Systems for Students with Autism. *Journal of Educational Media* 25, 3: 169–177. http://doi.org/10.1080/1358165000250302
21. Heather J. Nuske, Giacomo Vivanti, and Cheryl Dissanayake. 2013. Are emotion impairments unique to, universal, or specific in autism spectrum disorder? A comprehensive review. *Cognition & Emotion* 27, 6: 1042–1061. http://doi.org/10.1080/02699931.2012.762900

22. Samuel L. Odom, Julie L. Thompson, Susan Hedges, et al. 2015. Technology-Aided Interventions and Instruction for Adolescents with Autism Spectrum Disorder. *Journal of Autism and Developmental Disorders* 45, 12: 3805–3819. http://doi.org/10.1007/s10803-014-2320-6
23. Robert C. Pennington. 2010. Computer-Assisted Instruction for Teaching Academic Skills to Students With Autism Spectrum Disorders: A Review of Literature. *Focus on Autism and Other Developmental Disabilities* 25, 4: 239–248. http://doi.org/10.1177/1088357610378291
24. Kathleen Ann Quill. 1995. *Teaching Children with Autism: Strategies to Enhance Communication and Socialization*. Delmar Publishers.
25. Sathiyaprakash Ramdoss, Wendy Machalicek, Mandy Rispoli, Austin Mulloy, Russell Lang, and Mark O'Reilly. 2012. Computer-based interventions to improve social and emotional skills in individuals with autism spectrum disorders: A systematic review. *Developmental Neurorehabilitation* 15, 2: 119–135. http://doi.org/10.3109/17518423.2011.651655
26. Deborah M. Riby, Gwyneth Doherty-Sneddon, and Lisa Whittle. 2012. Face-to-face interference in typical and atypical development. *Developmental Science* 15, 2: 281–291. http://doi.org/10.1111/j.1467-7687.2011.01125.x
27. Eric Schopler, Robert J. Reichler, and Barbara R. Renner. 1986. *The childhood autism rating scale (CARS): for diagnostic screening and classification of autism*. Irvington, New York.
28. Frederick Shic and Matthew S. Goodwin. 2015. Introduction to Technologies in the Daily Lives of Individuals with Autism. *Journal of Autism and Developmental Disorders* 45, 12: 3773–3776. http://doi.org/10.1007/s10803-015-2640-1
29. Karan Sikka, Alex A. Ahmed, Damaris Diaz, et al. 2015. Automated Assessment of Children's Postoperative Pain Using Computer Vision. *Pediatrics* 136, 1: 1–8. http://doi.org/10.1542/peds.2015-0029
30. Helen Tager-Flusberg, Daniela Plesa Skwerer, Robert M. Joseph, et al. 2016. Conducting research with minimally verbal participants with autism spectrum disorder. *Autism*: 1362361316654605. http://doi.org/10.1177/1362361316654605
31. Christina Whalen, et al. 2006. Positive behavioral changes associated with the use of computer-assisted instruction for young children. *Journal of Speech and Language Pathology and Applied Behavior Analysis* 1, 1: 11–26.
32. Christina Whalen, Debbie Moss, Aaron B. Ilan, et al. 2010. Efficacy of TeachTown: Basics computer-assisted intervention for the Intensive Comprehensive Autism Program in Los Angeles Unified School District. *Autism: the international journal of research and practice* 14, 3: 179–197. http://doi.org/10.1177/1362361310363282
33. Jacob Whitehill, Zewelanji Serpell, Yi-Ching Yi-Ching Lin, Aysha Foster, and Javier R. Movellan. 2014. The Faces of Engagement: Automatic Recognition of Student Engagementfrom Facial Expressions. *IEEE Transactions on Affective Computing* 5, 1: 86–98. http://doi.org/10.1109/TAFFC.2014.2316163