Modeling Self-Efficacy Across Age Groups with Automatically Tracked Facial Expression

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Abstract. Affect plays a central role in learning. Students' facial expressions are key indicators of affective states and recent work has increasingly used automated facial expression tracking technologies as a method of affect detection. However, there has not been an investigation of facial expressions compared across age groups. The present study collected facial expressions of college and middle school students in the CRYSTAL ISLAND game-based learning environment. Facial expressions were tracked using the Computer Expression Recognition Toolbox and models of self-efficacy for each age group highlighted differences in facial expressions. Age-specific findings such as these will inform the development of enriched affect models for broadening populations of learners using affect-sensitive learning environments.

Keywords: Affect, Facial Expression Recognition, Nonverbal Behavior, Self-Efficacy, Game-based Learning Environments.

1 Introduction

Affect plays an important role in learning. While learning, students transition through a wide range of cognitive-affective states, such as *confusion*, *boredom*, *engagement*, and *frustration* [1]. These states may signal—or promote—effective learning while also interacting with broader constructs, such as motivation and self-efficacy. With a growing recognition of the importance of affect, new learning theories have begun to incorporate affective states into models of learning [2, 3].

Despite the significant body of work in facial expression tracking of learning-centered affect [4], there has not been an investigation that compared facial expressions across age groups. The present study provides the first examination of facial expression tracking of middle school and college students in an identical task: solving a science mystery with the aid of a human tutor in a game-based learning environment, CRYSTAL ISLAND, during a series of Wizard of Oz studies. Facial expressions were tracked using the Computer Expression Recognition Toolbox (CERT) and models of self-efficacy constructed for each age group highlighted differences in facial expressions, with only mouth dimpling appearing across models.

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These results suggest that there are key differences in facial expression between middle school and college students. Further analyses in this vein will contribute to the development of future learning environments, as affect detector functionalities will likely need to be tailored to specific age groups.

2 CRYSTAL ISLAND Wizard of Oz Studies

The CRYSTAL ISLAND game-based learning environment provides an effective “laboratory” for studying affect because students are engaged in deep learning while exploring an immersive virtual environment, experiencing cognitive-affective states related to challenge and enjoyment during the learning task. CRYSTAL ISLAND Wizard of Oz studies were conducted in order to build an automated director agent built on human narrative interventions [5]. The human “wizard” controlled narrative progress by guiding the student through reading information, testing objects in the environment, and developing a diagnosis to solve the mystery.

A middle school study was conducted with 32 students, including surveys and identical multiple-choice pretest/posttest on microbiology and the scientific method. The surveys consisted of demographics, the Big Five personality inventory (not analyzed here), a presence questionnaire, and self-efficacy for self-regulated learning [6]. An initial pilot study was also conducted with 38 college students to test the CRYSTAL ISLAND Wizard of Oz interface and protocol. Only the self-efficacy survey was administered during that pilot study. Webcam video, audio, and data logs were collected during both studies. Consent for image publication was not received, therefore no participants are shown in this paper.

3 Modeling Self-Efficacy Across Age Groups

Students' motivation and self-efficacy impact learning [2, 3]. In our prior research, we found that self-efficacy was associated with distinct nonverbal behaviors over the course of a tutoring session [7]. In the present study, models of self-efficacy were constructed for middle school and college students. Each model was built using relative frequencies of facial expression features provided by the Computer Expression Recognition Toolbox [8].

The models were constructed with the JMP statistical software. Features were standardized and model averaging was used to identify the top forty features based on the absolute value of a ratio between coefficient estimate and standard error. Then, stepwise forward linear regression was run with leave-one-student-out cross-validation. After a feature was selected at each step, all other features from the same CERT output channel were excluded in order to prevent over-fitting to a single output channel (e.g., selecting AU2 would then exclude further AU2). Bayesian Information Criterion (BIC) was used to select models that balanced model complexity with performance. The model of self-efficacy for middle school students is shown in Figure 1 and the model of self-efficacy for college students is shown in Figure 2.

Self-Efficacy =	***p***
0.66 * AU2 (*mean-center, threshold=0.05*)	<0.001
0.46 * AU12 Left (*z-score, threshold=0.5*)	<0.001
-0.26 * Fear Brow (*mean-center, threshold=0.45*)	0.057
-0.22 * AU14 Right (*mean-center, threshold=0.45*)	0.096
0.01 (intercept)	1
Leave-One-Student-Out Cross-Validated R^2 = 0.670	

Fig. 1. Model of self-efficacy for middle school students (*N*=31)

Self-Efficacy =	***p***
0.56 * AU4 (*orig., threshold=0*)	<0.001
0.39 * Contempt (*orig., threshold=0.1*)	0.041
0.31 * AU14 (*orig., threshold=0*)	0.074
0 (intercept)	1
Leave-One-Student-Out Cross-Validated R^2 = 0.434	

Fig. 2. Model of self-efficacy for college students (*N*=31)

4 Discussion

Models of self-efficacy constructed for each age group showed key differences in facial expressions. AU2 was most associated with self-efficacy for middle school students, with no analogous feature for college students. Similarly, AU4 was most associated with self-efficacy for college students, but did not appear in the model for middle school students. The “fear brow” facial expression was associated with lower self-efficacy in middle school students and has been previously correlated with anxiety [9]. Lower face features played a role in both models, with lip corner pulling (AU12) associated with middle school students and mouth dimpling (AU14) appearing in the model for college students. The prototypical contempt facial expression involves unilateral mouth dimpling (AU14 on either the right or left side). Contrary to the “basic” emotion interpretation, AU14 facial movement may be related to mental effort during learning, as evidenced in our prior research [10]. Thus, the model of self-efficacy for college students may be related to moments of mental effort (evidenced by AU4 and AU14) that did not result in negative affect, such as *frustration*. In contrast, middle school students with high self-efficacy may have smiled more, as evidenced by AU12. Collectively, these models provide empirical evidence of facial expression differences associated with self-efficacy across middle school and college students.

5 Conclusion

Recognizing and responding to affect during learning is a central requirement of affect-sensitive learning environments. Recent theories of learning incorporate affect as a vital component of student success and a growing body of research has aimed to recognize learning-centered affect using facial expression tracking. The present study provided first evidence of differences in middle school and college students' facial expressions during an identical task. Models of self-efficacy constructed for each age group incorporated different features, with only mouth dimpling appearing across models. These results provide insight into how facial expressions related to learning phenomena differ across age groups.

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