Supporting E-Learning with Emotion Regulation for Students with Autism Spectrum Disorder

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ABSTRACT: Students with Autism Spectrum Disorder (ASD) in general have been found to have significantly lower academic achievement relative to their level of ability. Research has shown that students' emotional impairment with ASD severely interferes with their learning process, and academic emotions are domain-specific in nature. Therefore, the regulation of domain-specific academic emotions is an important approach to help students with ASD learn effectively. This study proposed an e-learning model that featured emotion recognition and emotion regulation to enhance mathematics e-learning for students with ASD. An emotion recognition approach based on facial recognition, an emotion regulation model, and a mathematics e-learning platform, were developed to realize the e-learning model. Two e-learning conditions: timed contest and increased difficulty of learning, were created for gathering information by observing two indexes: mathematical learning performance and negative emotional behaviors in each condition. An experiment in a mathematical e-learning context was performed to evaluate the performance of e-learning and emotion regulation effectiveness. The results of the emotion recognition classifier reached a 93.34% average recognition rate, and the participants of this experiment displayed a statistically significant decrease in targeted negative behaviors from baseline to intervention (p = .000) and significant improvements in mathematics learning performance (p = .005); however, responses to emotion regulation interventions varied among the participants. Implications for research and practice are discussed.

Keywords: Autism spectrum disorder, Emotion regulation, Emotion recognition, E-Learning, Intelligent systems, Mathematics learning

1. Introduction

Educational reformation is a global trend in the 21st century, with an emphasis on improving the learning competence of students with disabilities. However, since many students with disabilities learn differently from other students, one of the emphases of special education is to provide adaptive education in order to develop the strengths of students based on their characteristics.

As the Internet and other computer technology continue to develop rapidly, e-learning has become an emerging learning method that can provide adaptive learning services, thereby significantly improving learning effectiveness. E-learning has also been employed in the field of special education, and has demonstrated learning improvements of students with autism spectrum disorder (ASD) (Khowaja & Salim, 2013). Research has shown that children with ASD may learn more rapidly when tasks are presented by a computer rather than by a teacher (Heimann, Nelson, Tjus, & Gillberg, 1995; Moore & Calvert, 2000). In addition, e-learning enables students with ASD to use their strengths in visual-spatial skills to overcome the challenges they encounter during learning (Cheng & Ye, 2010; Swezey, 2003).

Emotional impairment, one of the significant characteristics of students with ASD, can severely affect their daily activities, such as learning, communication, and interacting with teachers and peers. Totsika, Hastings, Emerson, Lancaster and Berridge (2011) found that 74% of children with ASD and no intellectual disability had clinically significant emotional difficulties, such as anger, sadness or anxiety, compared to 18% of typically developing peers. Other investigators have also reported that 17% to 74% of individuals with ASD exhibited anxiety-related behavior (Tsai, 1999). Intense anxiety can result in syndromes such as obsessive-compulsive disorder, generalized anxiety disorder, social anxiety, panic disorder, phobia and depression (Bejerot, 2007; Leyfer, Folstein, Bacalman, Davis, Dinh, & Morgan, 2006; MacNeil, Lopes, & Minnes, 2009). Also, student with ASD often exhibit impaired cognitive flexibility (Hughes, Russell, & Robbins, 1994; Kriete & Noelle, 2015) that makes students with ASD frustrated more than typical peers when facing new and difficult problems. Furthermore, conventional learning contexts are often time-limited, such as test (Roskam, 1997) and include increased difficulties of academic demands resulting in unexpected situation - the ordeal of learning makes students with ASD cannot accomplish their learning mission in the designated time period, which then induced negative academic emotions. Ashburner, Ziviani, and Rodger (2010) compared teacher ratings of academic performance and classroom emotional and behavioral regulation of 28 students with ASD (with average range IQ) and 51 typically developing students drawn from the same mainstream classrooms, and teachers rated students with ASD as exhibiting emotional and behavioral difficulties (including attention difficulties, anxiety, depression, oppositional and aggressive behaviors) to a significantly higher level than their typically developing peers. These negative academic emotions interfere with learning, resulting in unfavorable learning outcomes (Bejerot, 2007; MacNeil et al., 2009). As shown in the study of (Ashburner et al., 2010), fifty-four percent of students with ASD were rated by teachers as under-achieving academically as compared to 8% of typically developing students. However, domain-specific academic emotions in ASD has been understudied.

Mathematics problem solving is necessary for daily life (Lerner & Kline, 2006; Roman, 2004). However, in mathematics, one of the most difficult courses (Ginsburg, 1997), negative academic emotions appear very often in the learning process, especially for students with disabilities (Georgiou, Soulis, Rapti, & Papanikolaou, 2018) and greatly affect the learning outcomes (Carey, Hill, Devine, & Szücs, 2015). Oswald, Beck, Iosif, McCauley, Gilhooly, Matter, and Solomon (2016) found that the strongest predictor of math problem solving was perceptual reasoning, followed by verbal ability and test anxiety, then the diagnosis of ASD. Thus, reducing negative emotions of students with ASD during learning may be beneficial to enhancing their math abilities. Furthermore, mathematics problem solving is a process that combines reading, thinking, and computational skills (Forsten, 2004). If there is a methodology to benefit this process, by reducing their negative emotions, wider applications of other academic subjects would be anticipated. To sum up, factors related to mathematic learning could be categorized as individual and external. Individual factors include impaired emotion and cognition, whereas external factors could include difficulty and time limitations. The interactive effect of individual and external factors may induce negative emotions during the learning process. Therefore, assistance in regulating emotions is important for students with ASD to learn effectively in both authentic and virtual learning environments.

Emotional assistance in the context of e-learning requires automatic emotion recognition and adaptive emotion regulation. Since the concept of affective computing was first proposed (Picard, 1997), e-learning platforms have evolved from intelligent tutoring systems (ITSs) (Schiaffino, Garcia, & Amandi, 2008; Curilem, Barbosa, & De Azevedo, 2007) to affective tutoring systems (ATSs) (Afzal & Robinson, 2011; Mao & Li, 2010; Shen, Wang, & Shen, 2009), in which emotion detection methods were developed to identify a student's emotional state automatically. Current methods for identifying emotional features include physiological signals, facial expressions, speech, and physical postures (Moridis & Economides, 2008). The facial-expression-based approach seems more appropriate when recognizing students' emotional states during the learning process for two reasons: First, human emotional expressions come in numerous forms, such as facial expressions, body language, and vocalizations. Among these, 55% of emotional information is conveyed by facial features (Mehrabian, 1968). Second, wearing a device for physiological sensors makes students feel uncomfortable and may cause them to be restive. Therefore, facial-expression-based recognition that does not need body-based devices would be more suitable in the learning process. However, as students with ASD have severe difficulties with communication-related emotions, their facial expressions change less than others (Bieberich & Morgan, 2004; Czapinski & Bryson, 2003).

Studies on emotional regulation have adopted various strategies and methods, including cognitive mediation strategy (Lehmkuhl, Storch, Bodfish, & Geffken, 2008; Singh, Lancioni, Singh, Winton, Singh, & Singh, 2011; Reaven, Blakeley-Smith, Leuthe, Moody, & Hepburn, 2012; Sze & Wood, 2007), attention transfer, learning context adjustment, and stepwise guides (Parkinson & Totterdell, 1999). However, previous investigations on emotion regulation for people with ASD have focused on regulating social emotions, not academic emotions. The effectiveness of emotion regulation depends heavily on the application of regulation strategies that are, in turn, based on the types of emotions, causes of negative emotions, and students' characteristics. Accordingly, a model of adaptive emotion regulation is required. The present study aimed to develop and validate an adaptive e-learning model featuring domain-specific academic emotion recognition and emotion regulation. For assessing the model's effectiveness, we attempted to answer the three other specific research questions:

(a) Are emotion regulation strategies effective in reducing negative academic emotions for students with ASD?

(b) Are emotion regulation strategies effective in enhancing learning performance for students with ASD?

(c) Are there differences in the effectiveness of emotion regulation strategies for students with mild (level 1) and moderate (level 2) ASD?

An e-learning model that featured emotion recognition and regulation to enhance e-learning for students with ASD was proposed in this study to answer these research questions. A facial expression-based emotion recognition approach, an emotion regulation model, and an e-learning platform were developed to realize the proposed e-learning model. To observe how interactive effects of individual and external factors influence learning emotion, this study manipulated external factors, including time limitation and increased difficulty of learning. Individual responses in e-learning were measured for mathematical learning performance and negative emotional behaviors in two conditions that were conducted in correspondence with the external factors: the timed contest and the increased difficulty of learning. To verify the feasibility and effectiveness of the proposed domain-specific academic emotion recognition and emotion regulation model, we conducted an experiment with 8 students with ASD. Considering the limitation of the small sample size, we aimed to provide some preliminary insights into the impact of this model on reducing negative academic emotions and improving the mathematical learning performance of students with ASD.

2. Literature review

2.1. E-Learning environment for students with ASD

E-Learning delivers a stable interactive environment that benefits not only learning but also social interaction. Various kinds of e-learning applications for ASD have been proposed, including academic learning, linguistic learning, and social interactions. This work surveyed the related literature, as follows: Colby (1973) utilized a composed voice to treat nonspeaking children with ASD and showed that 13 out of 17 children showed significant linguistic improvement. Cheng and Ye (2010) developed a collaborative virtual learning environment (CVLE-3D) to improve empathy instruction, which reached significant effectiveness. Golan and Baron-Cohen (2006) used mind-reading software to deliver emotion-related content to aid students with ASD by recognizing complex emotions. Similarly, Bernard-Opitz, Sriram, and Nakhoda-Sapuan (2001) developed an e-learning environment for instruction to help students with ASD deal with social conflict situations. Some studies used AR/VR techniques to benefit the learning process. Hu and Han (2019) used gesture-based instructions via VR technology to teach matching skills to age-schooled students with ASD. Politis, Sung, Goodman, and Leahy (2019) train people with ASD conversational skills through VR technology and demonstrates the potential of VR in participant feedback. Cakir and Korkmaz (2019) used AR-based learning materials for children with special educational needs and reached significant levels of improving learning performance, not only bringing them real-life experiences but also activating their motivation for learning.

However, the aforementioned researches only focused on improving social interactions and learning experiences; very few studies investigated methods for reducing students' academic negative emotions. Therefore, this research aimed to develop an e-learning model with emotion recognition and regulation to assist students with ASD in regulating negative emotions and improve their learning performance.

2.2. Emotion regulation

Current researches on emotion regulation for students with ASD have focused on emotions related to social interactions. Conner, White, Scahill, and Mazefsky (2020) evaluated the association between anxiety and emotion regulation from 1107 children with ASD and their parents; the result indicated emotion regulation impairment significantly predicted whether children's anxiety elevated. Konstantareas and Stewart (2006) investigated children with ASD regarding the relationship between affect regulation method and their temperament, by exposing them to a mildly frustrating situation and using the Children's Behavior Questionnaire (CBQ) to assess their temperament. The variance of the affect regulation results was more extensive than that of the controls, and the affect regulation method was thusly less effective. Farmer and Oliver (2005) assessed the social-emotional adjustment of children with pragmatic difficulties. The analytical results showed that children with ASD have more social-emotional adjustment difficulties than other children do. Sze's case study (Sze & Wood, 2007) described evidence-based cognitive-behavioral intervention and demonstrated successful treatment outcomes of an 11-years old girl with high-functioning autism (HFA). Lehmkuhl et al. (2008) demonstrated the effectiveness of the cognitive-behavioral intervention, successfully treating a 12-years-old male with ASD. Singh et al. (2011) used a mindfulness-based procedure for adolescents with Aspergers (a form of autism characterized by average or above-average intelligence, which eliminated from a subtype of ASD after DSM-V published) to control their aggressive behaviors, with no negative behavior observed near the end of the procedure. Reaven et al. (2012) recruited 24 adolescents with ASD and developed a program for the regulation of anxiety, in which nearly 46% of participants responded positively to the treatment. Conner, White, Beck, Golt, Smith, and Mazefsky (2019) proposed the emotional awareness and skills enhance (EASE) program, demonstrate significant clinical effectiveness and the feasibility.

Hilton, Ratcliff, Collins, Flanagan, and Hong (2019) examined a large data set of children from age 6 to 17 years and confirmed the need to address positive emotions and positive affect for individuals with ASD at a young age. The emotion regulation model proposed by Gross and Thompson (2007) delineated five aspects of the emotion regulation process: situ*ation selection, situation modification, attentional deployment, cognitive changes*, and *response modulation.* Quoidbach, Mikolajczak, and Gross (2015) further proposed that positive emotions can be increased through these 5 families of emotion regulation strategies. As noted in their recent review of studies which measured short-term increases in positive emotions, attentional deployment, cognitive change, and response modulation strategies have received the most empirical support (Quoidbach et al., 2015). These findings provide the basis for our research, and therefore the present study focused on developing these three types of the emotion regulation interventions that were modified and adapted to meet the needs of students of ASD.

2.3. Emotion regulation strategies

(a) *Situation modification* refers to tailoring a situation to modify its emotional impact. It is also referred to as problem-focus coping (Lazarus & Folkman, 1984) or primary control (Rothbaum, Weisz, & Snyder, 1982). To modify the situations, adapting teaching materials or curricula can be useful. McLaughlin (1993) claimed that most curriculum options of students with disabilities require adaptation to existing standard materials. Sometimes no adequate or easily adapted materials can be found; therefore, developing new curricula is needed. Furthermore, Hoover and Patton (1997) proposed that four perspectives should be considered when adapting the curriculum for students with disabilities: curriculum content, teaching strategies, teaching environment, and student behavior. When learning material is too hard, reducing the difficulty level or the amount of homework, simplifying steps, or giving tips are useful strategies. Van-Bockstaele, Atticciati, and Hiekkaranta (2020) applied situation modification in a negative situation to regulate their emotions by changing the environment.

(b) *Cognitive change* refers to selecting from the many possible meanings that may be attached to that situation. It is often used to either increase or decrease the emotional response or even change the emotion itself (Gross, 2002; Sze & Wood, 2007; Lehmkuhl et al., 2008; Chorpita & Daleiden, 2009; Reaven, 2010). Consequently, students' negative behavior can be reduced when they face difficult situations utilizing cognitive behavior therapy (CBT). Some studies have suggested that CBT, such as graded exposure and cognitive restructuring, effectively reduces anxiety in teenagers and children with ASD (Chorpita et al., 2009; Reaven, 2010; Sze et al., 2007). Maughan and Weiss (2017) pointed out CBT improved children's depression and positively affected parents across all parents in depression, emotion regulation, perceptions of their children, and mindful parenting when they joined the treatment process.

(c) *Attentional deployment* refers to how individuals direct their attention within a given situation to regulate their emotions (Gross et al., 2007). Grolnick, Bridges, and Connell (1996) pointed out that individuals use various methods to balance their emotions when facing an emotionally arousing situation. Among these, shifting attention from the arousing stimuli is useful for children, including their visual and motor exploration and passive use of objects and active engagement with substitute objects. Hamilton (2000) indicated that shiny objects could easily attract participants with ASD.

(d) *Response modulation* refers to efforts made to alter physiological, experiential, or behavioral responses in a situation (Gross et al., 2007). This family involves the modulation of the bodily component of the emotion by acting directly on the body itself (Gross, 1998). Strategies belonging to the response modulation family are muscle relaxation, deep breathing and positive imagery (Chorpita & Daleiden, 2009; Reaven, Blakeley-Smith, Nichols, Dasari, Flanigan, & Hepburn, 2009). Floress, Zoder-Martell, and Schaub (2017) combined relaxation training with social skills training and reinforcement principles to effectively increase the frequency of the targeted social skills of a student with ASD, and the effects were maintained for up to 17 weeks after the training program ended.

2.4. Classifier of emotion

To understand the emotions of students during the learning process, classifying emotion recognition is necessary. Hence, this work surveyed related recent studies on the recognition of emotions, as summarized below.

Human emotional expressions adopt numerous forms, such as facial expressions, body language, and voice. Among these, 55% of emotional information is conveyed through facial features, inferred by changes in the eyes, eyebrows, nose, and mouth (Mehrabian, 1968). Therefore, changes in facial expression are critical indicators for judging emotion.

Kapoor, Burleson, and Picard (2007) used a template-based facial landmark tracker, posture sensors, skin conductance, and mouse behavior model to detect gaming frustration, achieving 79% accuracy. Tariq, Li, Zhou, Wang, Huang, Lv, and Han (2012) extracted facial features by incorporating Hierarchical Gaussianization (HG), Scale Invariant Feature Transform (SIFT), and Optic Flow (OF), with SVMs to recognize emotions and person identification, achieving 80% accuracy. Chen and Lee (2011) used EEG (Electroencephalograph, an electrophysiological monitoring method to record the electrical activity of the brain) with SVM to detect anxiety in a web-based one-to-one language learning environment, and achieved 79.71% accuracy.

However, very few researchers have investigated emotion recognition applications in e-learning environments for students with ASD, whose facial expressions change less than those of other people (Bieberich et al., 2004; Czapinski et al., 2003). Therefore, this research aimed to develop an emotion recognition classifier specifically for students with ASD in e-learning applications, capable of recognizing happy, calm, and negative emotions, including anger and anxiety, of understanding students' mood changes during the learning process and to provide effective regulation.

3. Proposed model and methods

3.1. E-Learning model with emotion regulation

The proposed e-learning model includes pre-testing, learning path planning, adaptive learning material selection, adaptive learning, and post-testing, as shown in Figure 1. Before engaging in the learning for the first time, students are required to participate in a pre-test, including a computerized adaptive test and learning and thinking style assessments.

After the pre-test, a tentative learning path is planned based on math concepts in the student's knowledge model. Learning materials are selected according to the math concepts and mathematics error preventive strategies, and are adapted to suit the diverse traits of students based on their strengths, weaknesses, learning performances, and thinking styles. An error preventive strategy is applied to support preventive teaching by predicting mathematical errors that students may make according to their strengths and weaknesses. The purpose of this strategy is to reduce the difficulty of problems that students encounter d learning and to enhance their motivation to learn. After each stage of the adaptive learning process, remedial learning may be required according to the types of errors the students make, and the learning path will be adjusted based on students' learning status. However, the goal of this study is to support e-learning with emotion regulation for students with ASD. Therefore, to focus on the effectiveness of emotion regulation, learning style, thinking style, and learning path planning is not conducted in an experimental context.

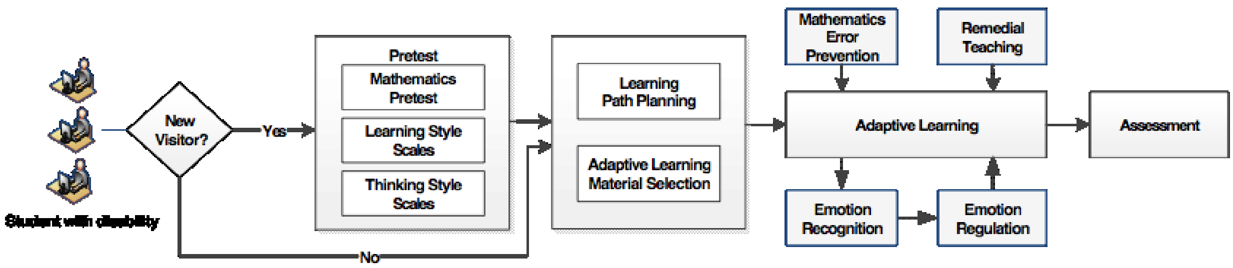


Figure 1. The proposed e-Learning model

During learning, an adaptive assessment is conducted to identify the students' learning progress and the types of errors made. This information is used to identify suitable teaching strategies for addressing these errors. Simultaneously, the affective states of students are monitored, and suitable regulation strategies are applied once unfavorable emotions are detected based on students' facial expressions. When students develop unfavorable emotions during the learning process, and regulation strategies cannot reduce these emotions, teachers can use remote support to intervene, helping students relax. After the entire learning process, the students take a computerized adaptive math test for the learning progress assessment. The next section introduces the main component of the proposed model, emotion regulation.

3.2. Emotion regulation

In this section, the categories and contents of the regulating strategies, the methods used in the decision-making for strategy selection, and the model of emotional regulation strategies are explained.

3.2.1. Emotion regulation strategies

The proposed regulation strategies can be categorized into three types: *response modulation, cognitive change, and attention deployment*.

Response modulation strategy: In this study, response modulation strategy is applied for regulating negative emotional behaviors, which involve a series of actions that will influence physiological, experiential, or behavioral responding as directly as possible (Gross et al., 2007). Strategies belonging to the response modulation family are muscle relaxation, deep breathing and positive imagery (Chorpita & Daleiden, 2009; Reaven et al., 2009). The computerized intervention sessions of the response modulation strategy were conducted with written and visual stimuli such as pictorial and graphical representations of the specific strategy steps that were presented in Figure 2. These provide students with ASD instruction on the implementation of each technique. Figure 2 illustrates an example of the computer sequence presented to a participant during the process of the response modulation strategy instruction.

Cognitive change strategy: In this work, the cognitive change strategies include social stories, self-instruction, and self-management. Appropriate strategies are selected for students to manage emotions and behaviors according to their personality traits and learning context. Each strategy involves a procedure, as well as voice and video clips. The procedure contains stepwise descriptions of the content of the cognitive intervention strategy. In each step, texts and video clips are used as tools for regulation. Students are introduced to the steps they should take to regulate their emotions and behaviors when encountering challenges. The strategy's design is inspired by Gross (2002), Sze and Wood (2007), Lehmkuhl et al. (2008), Chorpita & Daleiden (2009) and Reaven (2010). Figure 3 presents the steps that are involved in applying the social story strategy in a timed competition. The e-learning environment simulates the contexts presented in Figure 3 in the following order: descriptive sentences, perspective sentences, directive sentences, affirmative sentences, control sentences, or cooperative sentences. Integrated with a voice system, the model enables students to understand the meanings implied in the contexts and exhibit positive behaviors.

Attentional deployment strategy: This strategy helps directing the individual's attention towards positive aspects of the situation whereas focusing attention away from negative aspects (Campos, Frankel, & Camras, 2004; Gross, 1998). Positive distraction as an attentional deployment strategy, involves distracting oneself from negative emotions by engaging in activities that induce positive emotions to relax attention (Hanin, Grégoire, Mikolajczak, Fantini-Hauwel, & Van Nieuwenhoven, 2017). In this study, positive distraction included presentation of educational computer games, graphic animations, and task interspersal (Rapp & Gunby, 2016). The left image in Figure 4 presents an application of the game strategy. In this computer game, the students are instructed to draw on a whiteboard. The image on the right shows an animated geometry shape, and all animated geometry shapes (i.e., squares, rectangles, triangles, trapezoids, and polygons) were presented in a sequence order. Each shape was shown for 10 seconds, and the students with ASD were instructed to count the number of the geometry shapes that appeared during the intervention process.

The media presentation for the emotional regulation interventions was specifically designed for students with ASD and included texts, images, video clips, games, and graphic animations, which attracted learners' attention and enabled students with ASD to use their strengths in visual-spatial skills.

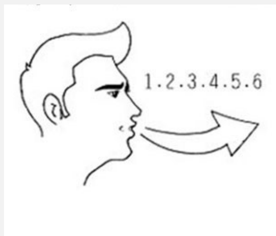
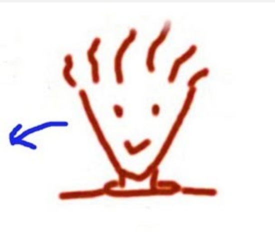
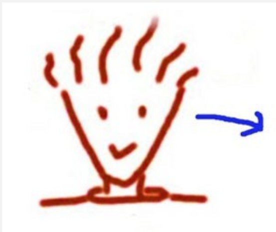
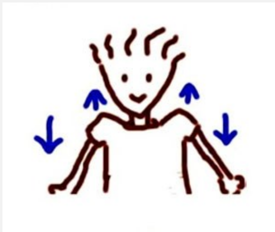
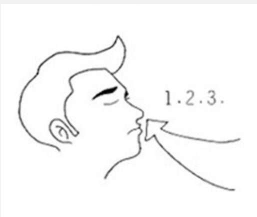
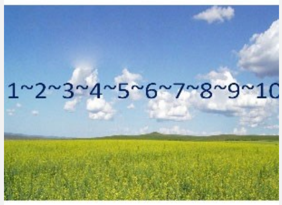
①	②	③	④
 When you are angry, you can follow these steps:	 Make yourself comfortable on a chair.	 Inhale and count to three.	 Exhale and count to six
⑤	⑥	⑦	⑧
 Make a fist with both hands and count to five.	 Relax both hands and count to five.	 Look up and count to three.	 Look down and count to three.
⑨	⑩	⑪	⑫
 Look to the left and count to three.	 Look to the right and count to three.	 Raise your shoulders toward your ears and count to three.	 Stretch your shoulders toward your back and count to five before you relax.
⑬	⑭	⑮	⑯
 Inhale and count to three.	 Lift both hands and cross your fingers over your head. Stretch your arms above your head and count to five.	 Make a fist with your left hand and use the fist to hit your right shoulder gently five times.	 Look at the picture of grass and imagine yourself lying on the grass. Count to ten.

Figure 2. Example of response modulation strategy

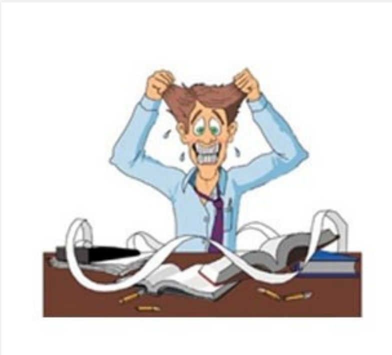
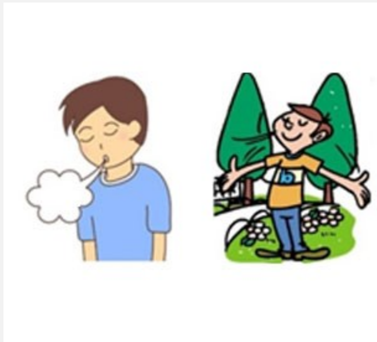
① descriptive sentences	② descriptive sentences	③ perspective sentences
 I love solving mathematical problems on the computer.	 Sometimes the homework has many questions like a test. I may not be able to finish all of them, but I must try my best.	 My mom always tells me that I must finish my homework before I can do things that I enjoy.
④ descriptive sentences	⑤ perspective sentences	⑥ directive sentences
 I realize that there are only two or three minutes left, but I still have many questions to finish.	 My mom and the teacher will worry if they see me panic.	 I can take three deep breaths and count from one to three while telling myself: "Take your time."
⑦ directive sentences		
 I can solve the problems one at a time.		

Figure 3. Example of cognitive change strategy: A social story

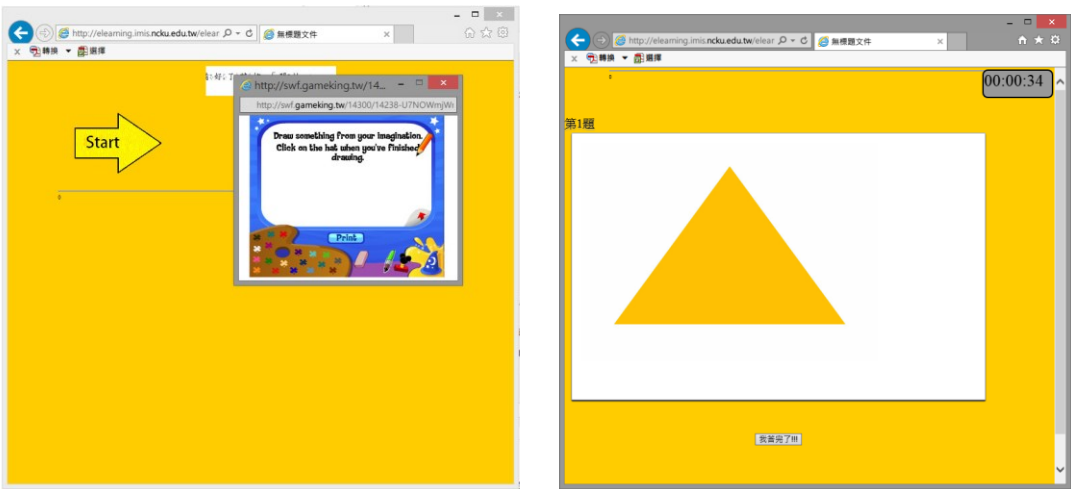


Figure 4. Example of attentional deployment strategy: Educational computer game and graphic animation

3.2.2. Model of strategy for regulating emotions

A preliminary model of emotional regulation strategies was developed based on the relations among personal background, types of learning emotions, and regulation strategies, through the following analysis: (a) the types of academic emotions that are exhibited by students with ASD, (b) the relationship between the personal background of students and their most frequent academic emotions, i.e., happiness, anxiety, anger and feeling calm, (c) the relationship between learning stress and academic emotions (Carey et al., 2015; Georgiou et al., 2018), and (d) corresponding regulation strategies.

The Fuzzy Delphi method (Dalkey & Helmer, 1963), an expert evaluation method, was employed to evaluate the preliminary model. The purpose of this step was to obtain expert opinions for the revision of the preliminary model. Based on the preliminary model, a fuzzy Delphi questionnaire was designed. Scholars and expert teachers in the ASD field were invited to complete the questionnaire by weighting the relations between types of academic emotions and corresponding strategies specified in the preliminary model. The relative significance of regulation strategies was calculated and defined. The simple center of gravity method was used to calculate the threshold values. All of the most agreed upon variables were incorporated into a Bayesian network analysis that produced a model for adaptive academic emotion regulation for students with ASD. This model was upgraded and dynamically maintained to ensure effectiveness of emotion regulation interventions by incorporating the participant data and the experts' opinion into the model during the application stage through a Bayesian network analysis (Xenos, 2004).

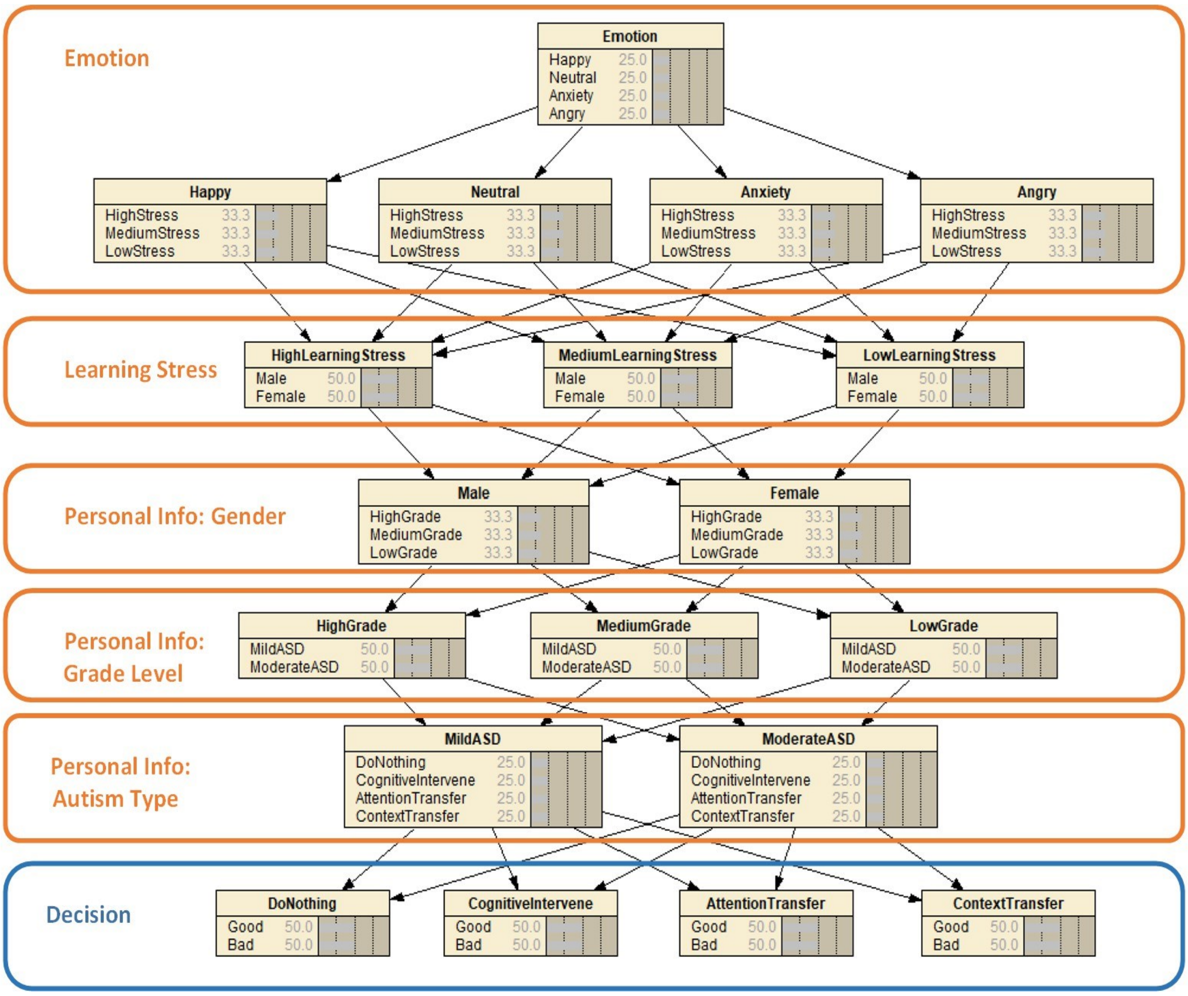


Figure 5. Structure of the Bayesian model for making decisions about choosing emotional regulation strategies

The Bayesian-based emotion regulation model has the following levels: emotion, learning stress, personal information (gender, grade, and ASD type), and the decision of strategy selection, as shown in Figure 5. The emotional state is captured from an emotion recognition classifier in real-time. Learning stress is predefined during the learning progress, which is decided by the difficulties of the current learning materials, and personal information is collected from the results of students' pretest and psychologists' diagnosis. The decision involves choosing one of the three aforementioned types of strategy from the repository of emotion regulation strategies.

3.2.3. Method for emotion regulation strategy selection

According to the principle of adaptability, choices of regulation strategies should be based on students' personal information and their specific emotional context. Numerous decision methods are accurate only when the sample is large enough. However, obtaining large amounts of above-mentioned information is often difficult and involves privacy concerns. Small samples suffice when Bayesian networks are employed to make decisions; furthermore, training, and reflections take little time (Mendes & Mosley, 2008). This method satisfies the need to use real-time emotion regulation strategies to provide rapid responses; therefore, the Bayesian network was employed to determine appropriate emotion regulation strategies.

A Bayesian network is based on a directed acyclic graph (DAG) G = (I, E), where I denotes the combination of all nodes, and E denotes the combination of all edges. Assume that $X = (X_i)_{i \in I}$ is a random variable of node *i*. If the joint probabilistic distribution of X is obtained using the following equation, then X is the Bayesian network based on graph G, where *pa(i)* is the prior probability of node *i*:

$$\mathrm{p}(\mathrm{x}) = \prod_{i \in I} p(x_i | x_{pa(i)}) \qquad - (4)$$

After the learning process is completed, the outcome is assessed to evaluate the effectiveness of the selected regulation strategy. The results are fed back to the Bayesian network model, where the probability values of the nodes are modified to yield perfected regulation criteria.

3.2.4. The classifier for academic emotion recognition

To understand the academic emotions of students with ASD during the mathematics e-learning process, this work developed a classifier for recognizing emotion. The details are described below.

Two stages were involved (see Figure 6) in developing the method for facial expression-based emotion recognition: *facial feature extraction* and *recognition model construction* (i.e., the emotion classifier). An emotion elicitation experiment was performed in a mathematical e-learning environment to collect facial-based features for training the emotion classifier. The participants of this experiment were fifteen students (14 boys) with ASD (aged 8 to 12 years) recruited from elementary schools. All participants were diagnosed with ASD by psychiatrists based on the current Diagnostic and Statistical Manual of Mental Disorders, 5th Edition (DSM-V) diagnostic criteria (American Psychiatric Association, 2013).

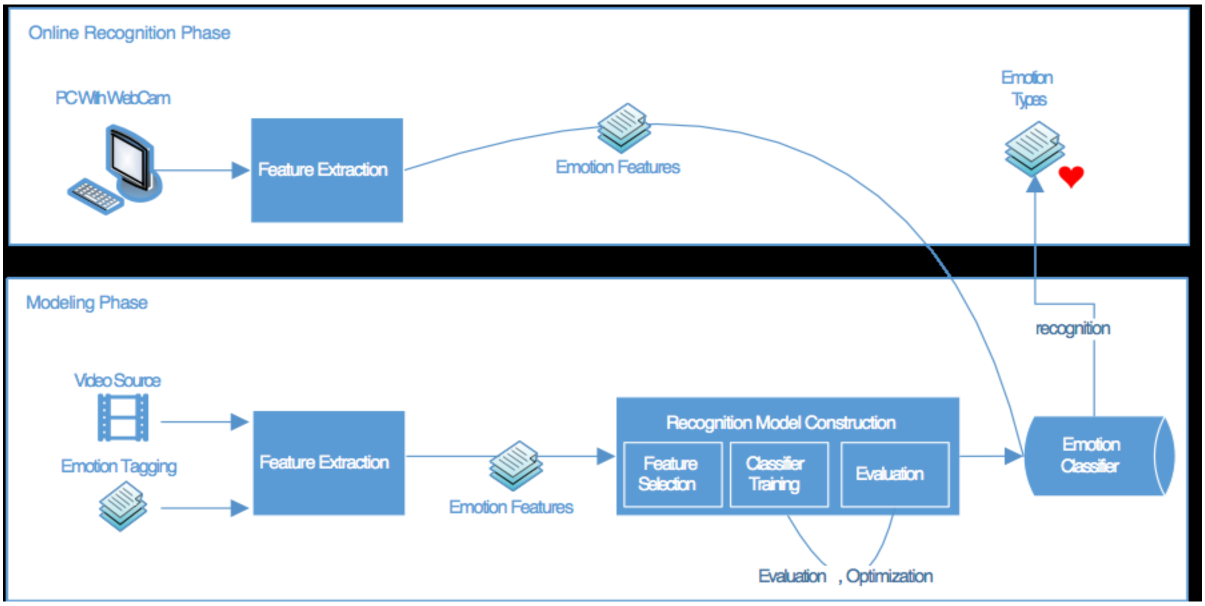


Figure 6. Emotion recognition mechanism

In the stage of feature extraction, the Face Tracking API 3.2 system was used to track facial points and calculate facial features. The obtained facial signals were combined with emotion assessments made by expert teachers and the parents of the participants regarding the participants' emotional states, and 39,067 samples were collected from the experiment.

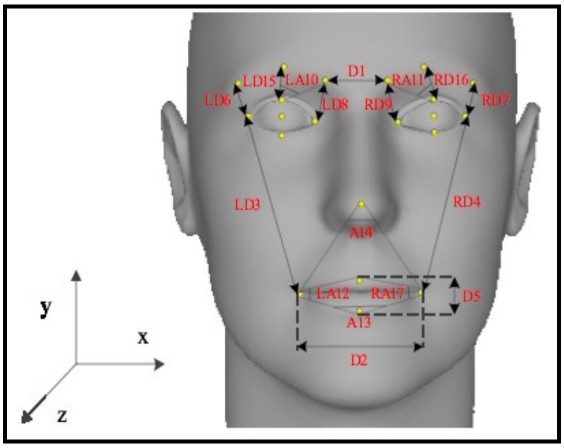
The support vector machine (SVM) (Cortes & Vapnik, 1995) was used to construct the classifier for emotion recognition. To determine robust features for emotion recognition, Information Gain (IG) (Quinlan, 1979) and Chi-Square were used for feature evaluations. The effectiveness of the classifiers with different parameters of sliding windows was also examined.

Facial Feature Extraction was used to generate feature vectors based on the facial landmark coordinate signals extracted by the Face Tracking API. This process has three steps: coordinate conversion, statistical processing, and normalization. The generated feature vectors can be used as the training samples of the classifiers. Figure 7 shows the distribution of facial features.

Coordinate conversion: Distance and angle were used as the two observable metrics to identify facial expression variations. All facial coordinates were transformed to distances and angles, yielding 12 distances and five angles, as shown in Figure 3. Equations (1) and (2) use distance D5 and angle A14 as examples.

$$D5 = \sqrt{(mP2x - mP4x)^2 + (mP2y - mP4y)^2} \quad \text{- (1)}$$

$$A14 = cos^{-1}\frac{(mP1nP)\cdot(mP3nP)}{|mP1nP|\cdot|mP3nP|} \quad \text{- (2)}$$



Where:

D5: the distance between the top and bottom of the opened mouth.
A14: the angle between both corners of the mouth is subtended at the nose.
mP1: right corner of the mouth.
mP2: center point of the upper lip.
mP3: left corner of the mouth.
mP4: center point of the bottom lip.
nP: nose.

Figure 7. Facial feature distribution

Statistical processing: To identify the trends in the signal variations, the statistics concerning the observed values were calculated; these were: maximum and minimum values, standard deviations, and means. A total of 34 features [(12 distance values + 5 angle values) × 2 statistics] were generated, yielding 34 × 1 feature vectors.

Normalization: When the range of values of a feature is relatively wide, the feature may influence the operation of the classifier. Hence, all features' ranges of values must be normalized to ensure that the features contribute proportionally. Equation (3) was used for normalization.

$$x' = \frac{x-min}{max-min} \quad \text{- (3)}$$

where

x': normalized value. x: the value of original signals. min: the minimum value of the original signal. max: the maximum value of the original signal.

Finally, the generated feature vectors are used as training samples to construct a classifier. Each sample represents the variations of the facial features and expressions exhibited by each participant within 30 sec. A sample consists of a set of feature vectors and an emotion label. The use of the samples to construct the classifier and identify useful feature combinations is explained below.

The development of the recognition model includes three steps: *feature selection, classifier training*, and *evaluation*, as shown in Figure 2. Before *classifier training*, *feature selection* was conducted to assess the features that facilitate the construction of a highly accurate classifier and to reduce the dimensionality of the input feature vectors. Thus, the performance of the classifier could be improved. To meet the requirements of practical applications, real-time recognition of negative emotions is necessary. Therefore, feature selection should reduce the dimensionality of the input vectors. Consequently, attention can be focused on critical features, reducing the response time and the classifier's construct time.

The *feature selection* algorithms used in this model included filters and wrappers. Filter algorithms evaluate all features individually, using threshold values to remove features that do not contribute enough to the classifier (Guyon & Elisseeff, 2003). Wrapper algorithms identify optimal feature combinations iteratively, using classification algorithms to evaluate various selected feature combinations (Guyon et al., 2003). Since filter algorithms take relatively little time to execute, they were used to identify the optimal feature combinations. Among the filter algorithms, Information Gain and Chi-Square methods were used to evaluate the contribution of features, and the top 50% of features were used for classifier construction.

An SVM was employed to construct the classifier by iteratively feeding each feature vector from the training set, including 39,150 facial samples. Parameters of the SVM classifier (cost C and gamma γ) were optimized by the grid search method (Huang, Chen, & Wang, 2007). We found the best (C, γ) combination to be (C = 16.0, γ = 10.0) in this work. The feature vectors generated in the feature extraction stage were used as the training set. To verify the effectiveness of the classifiers, 10-fold cross-validation was used to avoid over-fitting (Kohavi, 1995). The Precision/Recall index was used in the evaluation protocol.

In the application of e-Learning, the emotion classifier records 30 sec of facial feature variations that are exhibited by the students before converting the signals into vectors that can be used as input to the emotion recognition model. The emotions that were exhibited by the students were thus determined.

4. Experiment

This section presents the experimental design to verify the effectiveness of the proposed academic emotion recognition and regulation based mathematics e-learning model for students with ASD.

4.1. Experimental design

This was an intervention study design consisting of baseline and alternating treatments conditions, and the dependent variables of this study were the percentages of negative emotional behaviors and the rates of mathematical learning performance. In the baseline phase, emotional behaviors in computer simulation environments were initially observed in two e-learning conditions: *timed contest* and *increased difficulty of learning*. Data were collected regarding the emotions of each participant in response to each computer simulation environment. Emotions were automatically detected based on facial features (as explained in Section 3.3) during the alternating treatments conditions, which were counterbalanced to control for sequence effects. Emotion regulation strategies were used on two occasions to assist in the learning process. The first occasion was when negative emotion was detected, and the proposed Bayesian model would suggest an adaptive strategy. The other was when the teacher determined that negative emotional behavior had appeared. Finally, using observational data concerning negative emotional behaviors, the effectiveness of the emotion regulation strategies was evaluated. Data on the rates of mathematical learning performance were also collected to analyze whether reducing negative emotional behaviors may improve learning performance across the two e-learning conditions. Table 1 presents the defined negative emotional behaviors in this research (Pierce & Courchesne, 2001; Patnam, George, George, & Verma, 2017; Rivard & Forget, 2012).

Table 1. Negative emotional behaviors

Type	Presentation
Stereotyped Movement (Pierce et al., 2001)	Clicking mouse frequently, scratching, and biting fingers, shaking a leg
Verbal Behavior (Rivard et al., 2012)	Complaining, calling parents, or clucking
Facial Expression (Patnam et al., 2017)	Crying, with tears in eyes

The experiment was conducted in a bright and quiet room. Parents, a teacher, and two researchers observed participants via monitor outside the room. The descriptions of the duration and activities of each e-learning condition of the experiment are shown in Table 2. The duration of emotion regulation across two e-learning conditions was three minutes. If emotion regulation happened in the alternating treatment period, time would be extended according to how long the emotion regulation intervened. The answer time in the timed contest condition was five minutes for each question. A set of questions that slightly exceed the participants' ability would be delivered in the difficulty learning condition. When the terminating condition was satisfied, the stage would be finished. Besides this, three-minute breaks were taken in-between the two conditions in the alternating treatment period. During the break, participants were provided with drinks or snacks of their choice, allowing them to take a short rest. The process was conducted at the same time each day.

Table 2. The descriptions of the duration and activities of each e-learning condition of the experiment

Activities	Timed Contest (TC)	Difficulty Learning (DL)
Emotion regulation Intervention	3min	3min
Time limitation for solving the problems	5min	N/A
Breaks between conditions	3min	3min
The criteria for discontinuing the session	Answered 4 questions	Duration more than 20min

4.2. Participants

Eight students with ASD aged 8 to 14 (M = 9.5 years, SD = 1.92), consisting of seven boys and one girl, participated in this study. Seven participants were enrolled in special education resource rooms at an elementary school, and the remaining participant was enrolled in a special education resource room at a middle school. All participants were diagnosed with ASD by psychiatrists based on the current DSM-V diagnostic criteria. The participants attended regular classrooms for more than half of each day at school while being mentored by teachers who specialized in special education. Participants' prerequisite abilities were (a) a requirement to have basic mathematical knowledge, language, and communication skills. (b) the ability to operate the e-learning system interface using a keyboard and mouse. And (c) were evaluated using the Wechsler Intelligence Scale for Children-Third Edition (WISC-III), in which verbal or performance IQ at or above 70. All participants satisfied the above criteria. Table 3 presents the demographic information on the participants.

Table 3. Participant characteristics

	Gender	Chronological age	ASD severity
1	F	10	Moderate (Level 2)
2	M	9	Mild (Level 1)
3	M	14	Mild (Level 1)
4	M	8	Mild (Level 1)
5	M	9	Mild (Level 1)
6	M	9	Moderate (Level 2)
7	M	9	Mild (Level 1)
8	M	8	Mild (Level 1)

4.3. Method of quantitative analysis

This study observed two quantitative indicators: the percentages of negative emotional behaviors and the rates of mathematical learning performance. Negative emotional behaviors (Table 1) were evaluated with 10s-partial-interval recording, and the target behavior was recorded if the participant engaged in the behavior at any time during a given 10-s interval. Data were then converted to a percentage of occurrences of negative emotional behaviors for a given session. The mathematical learning performance rates were defined as the number of math problems the participant completed correctly per minute. A small-sample analysis (n = 8) was performed. As the Wilcoxon signed-rank test has been proven to be representative for small sample sizes (Sidney, 1956), it was used herein to evaluate the effectiveness of changes, and we assessed effect sizes by calculating d-statistics for pairwise comparisons (Dunlap, Cortina, Vaslow, & Burke, 1996).

5. Data analysis and results

5.1. Results of emotion recognition classifier

Table 4 shows the performance of emotion recognition. By using the SVM classifier and Information Gain of the feature selection, the average overall recognition rate was 93.34%. Additionally, to prove the effectiveness of the proposed emotion recognition method, this research used ROC (Receiver Operating Characteristic), AUC (Area Under Curve), and a standard technique for summarizing classifier performance over a range of trades using true positive and false positive error rates (Swets, 1988). The ROC curve is a robust method of identifying potentially optimal classifiers (Provost & Fawcett, 2001). When ROC AUC is over 0.7, the classifier has enough discernibility to recognize emotion. In Table 4, all the ROC AUC exceeded 0.7.

Table 4. Recognition rate

Emotion	Recognition rate	ROC AUC	F-measure
Calm	95.10%	.947	.921
Happy	88.40%	.939	.914
Anxiety	97.20%	.952	.936
Anger	85.70%	.927	.900
Overall	93.34%	.946	.924

These results displayed enough capability in recognizing four types of emotion and verified that the proposed e-learning model could deliver emotion regulation materials triggered in-time by emotion recognition with high accuracy.

5.2. Overall effects of the academic emotion regulation interventions for students with ASD

Table 5 shows the proportion of suggested regulation strategies by the Bayesian model. With regards to the overall changes in negative emotional behaviors and mathematical learning performance rates over time (see Table 6), Wilcoxon signed rank tests showed significant improvements in negative emotional behaviors (overall p = .000***) corresponding to large effect size (ES = 1.010). Mathematical learning performance rates significantly increased (overall p = .005*) with a moderate effect size (ES = .594) between baseline and intervention phases.

Table 5. The proportion of suggested regulation strategies by Bayesian model

Strategy type	Timed contest (TC)	Difficulty learning (DL)
Response modulation	58.8%	55.5%
Cognitive change	35.2%	38.9%
Attention deployment	5.8%	5.5%

Table 6. Changes between baseline and intervention phases

Dependent variable	Phases						*p*-value (ES)
	Baseline			Intervention			
	Median	Mean	Range	Median	Mean	Range	
NEB	53.00%	46.40%	8.42%; 90.83%	18.04%	21.86%	4.62%; 49.40%	.000*** (1.010)
MLPR	1.32	1.65	0.17; 5.22	1.66	2.51	0.28; 6.93	.005* (0.594)

Note. $^{*}p$ < .05; $^{***}p$ < .001. NEB: Negative Emotional Behavior, MLPR: Mathematical Learning Performance Rate.

5.2.1. Effects of interventions on negative emotional behaviors of students with ASD

Tables 7, 8 and 9 show change in negative emotional behaviors between baseline and intervention phases for both conditions (TC, DL), both levels of ASD (level 1, level 2) and the three different intervention strategies (RM, CC, AD). Participants demonstrated a statistically significant decrease in their negative emotional behaviors across both conditions (TC p = .004, DL p = .004) with large effect sizes (TC ES = .888, DL ES = 1.155). In addition, participants with mild (level 1) ASD showed a significant decrease during the intervention period in their negative emotional behaviors with a large effect size (p = .000, ES = .854). A moderate decrease was also observed in the participants with moderate (level 2) ASD; however, it was not statistically significant (p

= .063). This decrease was also significant for each of the strategy as shown in Table 9 (RM p = .000, CC p = .000, AD p = .004) with large effect sizes (RM ES = .987, CC ES = 1.011, AD ES = 2.720).

Table 7. Change in negative emotional behaviors between baseline and intervention phases for both conditions

Condition	Phases						p-value (ES)
	Baseline			Intervention			
	Median	Mean	Range	Median	Mean	Range	
TC	46.34%	41.66%	8.42%; 71.83%	18.04%	22.70%	4.62%; 49.40%	.004* (0.888)
DL	58.84%	51.15%	9.67%; 90.83%	17.74%	21.02%	6.53%; 46.08%	.004* (1.155)

Note. $^{*}p < .05$. TC: Timed Contest Condition, DL: Difficulty Learning Condition.

Table 8. Change in negative emotional behaviors between baseline and intervention phases for each level of ASD

Level of ASD	Phases						p-value (ES)
	Baseline			Intervention			
	Median	Mean	Range	Median	Mean	Range	
Moderate	65.92%	65.67%	40.00%; 90.83%	25.17%	25.26%	4.62%; 46.08%	.063 (2.190)
Mild	52.17%	39.38%	8.42%; 65.33%	18.04%	20.73%	6.53%; 49.40%	.000** (0.854)

Note. $^{**}p < .001$.

Table 9. Change in negative emotional behaviors between baseline and intervention phases for the different strategies

Strategy	Phases						p-value (ES)
	Baseline			Intervention			
	Median	Mean	Range	Median	Mean	Range	
RM	53.00%	46.40%	8.42%; 90.83%	22.68%	22.40%	4.95%; 49.40%	.000*** (0.987)
CC	53.00%	45.74%	8.42%; 90.83%	14.68%	20.77%	3.92%; 49.85%	.000*** (1.011)
AD	61.52%	55.94%	30.33%; 71.83%	21.80%	20.16%	3.30%; 36.10%	.004* (2.720)

Note. $^{*}p < .05$; $^{***}p < .001$. RM: Response Modulation, CC: Cognitive Change, AD: Attention Deployment.

5.2.2. Effects of interventions on mathematical learning performance rates of students with ASD

Tables 10, 11 and 12 show change in mathematical learning performance rates between baseline and intervention phases for both conditions (TC, DL), both levels of ASD (level 1, level 2) and the three different intervention strategies (RM, CC, AD). As reported in Table 10, the Wilcoxon sign-ranked test approached significant increase (p = .074). for the number of math problems completed correctly per minute between baseline and intervention in the time contest condition (M = 2.28 vs. M = 2.79) with a moderate effect size (ES = .349). The number of math problems completed correctly per minute between baseline and intervention in the difficulty learning condition showed a similar tendency increasing from the baseline level of 1.01 per minute to the intervention level of 2.24 per minute, with a large effect size (p = .071, ES = 1.069).

Table 10. Change in mathematical learning performance rates between baseline and intervention phases for both conditions

Condition	Phases						p-value (ES)
	Baseline			Intervention			
	Median	Mean	Range	Median	Mean	Range	
TC	1.86	2.28	0.53; 5.22	2.18	2.79	0.41; 6.75	.074 (0.349)
DL	0.52	1.01	0.17; 3.67	1.00	2.24	0.28; 6.93	.071 (1.069)

Note. TC: Timed Contest Condition, DL: Difficulty Learning Condition.

As shown in Table 11, considering students with mild (level 1) ASD only (n = 6), the Wilcoxon signed-ranks test yielded a significant increase (p = .0261) in the number of math problems completed correctly per minute between baseline and intervention (M = 1.79 vs. M = 2.61), with a moderate effect size (ES = .51). Considering students with moderate (level 2) ASD only, the Wilcoxon signed rank test p value was only approaching significance (p = .063), and the very small sample size of this subgroup (n = 2) associated with increased Type II error prevents us from drawing definitive conclusions. There was a very large effect size (ES = 1.387) reflecting an increase in mean MLPR from baseline (M = 1.21) to intervention (M = 2.22). This increase was also significant for each of the strategy (see Table 12) with small to moderate effect sizes, among which the response modulation strategy yielded the highest effect size of 0.778 (p = .004) for improving the mathematical learning performance rates for students with ASD, followed by the attention deployment strategy (ES = 0.646, p = .004) and the cognitive change strategy (ES = 0.463, p = .012).

Table 11. Change in mathematical learning performance rates between baseline and intervention phases for each level of ASD

Level of ASD	Phases						p-value (ES)
	Baseline			Intervention			
	Median	Mean	Range	Median	Mean	Range	
Moderate	1.17	1.21	0.33; 2.17	2.44	2.22	0.88; 3.13	.063 (1.387)
Mild	1.40	1.79	0.17; 5.22	1.22	2.61	0.28; 6.93	.026* (0.510)

Note. $^{*}p < .05$.

Table 12. Change in mathematical learning performance rates between baseline and intervention phases for the different strategies

Dependent variable	Phases						p-value (ES)
	Baseline			Intervention			
	Median	Mean	Range	Median	Mean	Range	
RM	1.32	1.65	0.17; 5.22	1.72	2.78	0.24; 8.50	.004* (0.778)
CC	0.85	1.64	0.17; 5.22	1.29	2.36	0.33; 7.71	.012* (0.463)
AD	2.09	2.60	0.33; 5.22	2.95	3.55	0.89; 6.00	.004* (0.646)

Note. $^{*}p < .05$. RM: Response Modulation, CC: Cognitive Change, AD: Attention Deployment.

6. Discussion and conclusion

This research proposed an e-learning model that features emotion recognition and regulation to enhance e-learning for students with ASD. An emotion recognition classifier, an emotion regulation method, and an emotion regulation model were then developed to realize the proposed e-learning model. To the best of our knowledge, this is the first model that integrates and performs domain-specific academic emotion recognition and emotion regulation. Based on this model, a mathematics e-learning environment was implemented, and experiments were conducted to verify the effectiveness of the proposed e-learning model and emotion regulation model. Next is a discussion of the research questions presented in Section 1:

6.1. Are emotion regulation strategies effective in reducing negative academic emotions of a student with ASD in the proposed e-Learning model?

Significant improvements in negative emotional behavior were observed between baseline and intervention phases (overall $p = .000^{***}$, TC $p = .004^{*}$, DL $p = .004^{*}$) with large effect size (overall ES = 1.010, TC ES = 0.888, DL ES = 1.155), both generally and separately in the two experiment conditions. These preliminary findings suggest that negative academic emotions of students with ASD can be improved through emotion regulation strategies embedded in the proposed e-Learning model.

6.2. Are emotion regulation strategies effective in improving the mathematical learning performance of the student with ASD in the proposed e-Learning model?

The overall improvement of mathematical learning performance was highly significant between baseline and intervention phases (overall $p = .005^{*}$) with moderate effect size (ES = .594), and the changes in the mathematical learning performance were also statistically significant between baseline and intervention phases in the *time contest* and *difficulty learning* conditions ($p = .004^{**}$) corresponding to large effect sizes (TC ES = .888, DL ES = 1.155). Despite the small sample size of this study, these preliminary findings suggest that the mathematical learning performance of students with ASD can be improved through emotion regulation strategies embedded in the proposed e-Learning model.

6.3. Are there differences in the effectiveness of emotion regulation strategies for students with mild and moderate ASD in the proposed e-Learning model?

For participants with mild (level 1) ASD, a significant difference was obtained in the percentages of negative emotional behaviors between baseline and intervention phases with a large effect size (p = .000***, ES = .854). A significant difference was also obtained in the number of math problems completed correctly per minute between baseline and intervention phases with a moderate effect size (p = .026, ES = .51). That is, the emotion regulation strategies embedded in the proposed e-Learning model significantly decreased the percentages of negative emotional behaviors and also significantly increased the rates of mathematical learning performance among the students with mild (level 1) ASD. For participants with moderate (level 2) ASD, the mean percentage of negative emotional behaviors decreased from the baseline (65.67%) to intervention phases (25.26%) which was approaching significance (p = .063), whereas the mean rate of mathematical learning performance increased from the baseline (1.21) to intervention phases (2.22) which was also approaching significance (p = .063). This result could be linked to the very small sample size of this subgroup (n = 2), and replications in larger samples studies are needed.

It has generally been recognized that there are close interactions between mathematics learning and affective, motivational, and cognitive processes and their regulation (Hanin et al., 2017). Hannula (2019) had argued that the most common type of mathematics-related effect is emotions, which are considered to be important predictors of students' self-regulation and achievement (Pekrun, 2016). Emotions related to either achievement outcomes (e.g., anxiety) or learning-related activities (e.g., enjoyment of learning, anger at the task demands) have been termed as academic emotions (Frenzel, Pekrun, & Goetz, 2007; Pekrun, 2016). Previous research with typically developing students has shown that negative academic emotions, such as anger and anxiety, can impair a student's performance at complex or difficult tasks and his/her motivation to stay on mathematics assignments (Ma, 1999), and may reduce cognitive resources and self-regulation of learning (Ahmed, Minnaert, Van der Werf, & Kuyper, 2013). In contrast, positive academic emotions may have a positive influence on the use of flexible learning strategies (Pekrun, Goetz, Titz, & Perry, 2002), and can motivate students to work on mathematics problem-solving (Liljedahl, 2005). In a recent effort to enhance the understanding of the roles of academic emotions and emotion regulation in mathematics learning, Hanin and colleagues (Hanin et al., 2017) developed the Children's Emotion Regulation Scale in Mathematics (CERS-M). This indicates an increasing acknowledgment of the importance of domain-specific academic emotion regulation.

Students with ASD have significantly higher prevalence rates of emotional difficulties, including anger and anxiety, compared to typically developing peers (Totsika et al., 2011). The data from the study by Oswald and colleagues (Oswald et al., 2016) suggest that anxiety, one of the negative academic emotions, may serve as a potential target for intervention to enhance mathematics achievement of students with ASD. Although research exists documenting the relationship between these emotional difficulties (i.e., anxiety and anger) and deficits in emotion regulation in students with ASD (Fujii, Renno, McLeod, Lin, Decker, Zielinski, & Wood, 2013; Rieffe, Camodeca, Pouw, Lange, & Stockmann, 2012), there is still a need for more empirical investigation of domain-specific academic emotion regulation interventions. Taken together, albeit the small sample size and preliminary nature of the findings, the results of the current study indicate that the proposed e-learning model featuring emotion recognition and emotion regulation had moderate to large effects on reducing negative academic emotions and improving the mathematical learning performance of students with ASD. These preliminary findings support further evaluation of the efficacy of the intervention in a larger randomized control trial.

Due to the small sample size and data not normally distributed, a nonparametric Wilcoxon signed-rank test was used in the current study to examine the statistical significance of the difference between baseline and intervention conditions for all participants. That is, within-group comparison of dependent variables was done in this study using Wilcoxon signed rank test for comparing repeated measurements on a single sample to assess whether their population mean ranks differ. The results of this study demonstrated significant differences on almost all dependent variables. Nevertheless, it is important to note that a few participants with ASD exhibited not only high within-subject variability but also high between-subject variability. This can be in part explained by the substantial inter- and intraindividual variabilities in participants' state emotions, defined as the momentary context-specific appraisals, emotions, and strategies that emerge during a person-environment transaction (Schutz & Davis, 2000) and idiosyncratic emotions (Begeer, Koot, Rieffe, Terwogt, & Stegge, 2008), often observed in ASD. That is, one of the key challenges in developing domain-specific academic emotion recognition and emotion regulation interventions for students with ASD is that this group is highly heterogeneous (Wodka, Mathy, & Kalb, 2013), and abundant inter- and intraindividual heterogeneity is often observed in their progress over time in responses to interventions.

Our results highlight the importance of domain-specific adaptive academic emotion regulation interventions for students with ASD, and indicate the need for future studies aimed at further improving the adaptive intervention models with additional intervention strategies like emotion expression and situation selection (Hanin et al., 2017) or learning contexts, such as collaborative virtual environments, single-player and multiplayer educational games, and Virtual Reality (VR) and Augmented Reality (AR) environments.

Compared to other works on affective-related e-learning that focused merely on emotion recognition or emotion regulation (Bernard-Opitz et al., 2001; Sze & Wood, 2007; Lehmkuhl et al., 2008; Chorpita et al., 2009; Reaven, 2010; Cheng et al., 2010), this research integrated the methods of emotion recognition and emotion regulation to make the e-learning environment more effective and applicable to students with ASD. Besides helping students with ASD to learn effectively by reducing emotional interference on mathematical learning processes, the e-learning platform developed in this research can also help special education teachers and parents to better understand the emotional state of students with ASD and thus provide appropriate assistance.

Finally, this research could be improved in several ways. First, a sample that included more participants with moderate ASD would yield experimental results that are more representative. Second, since some studies have found increased rates of emotional symptoms for students with ASD after entering adolescence (Keith, Jamieson, & Bennetto, 2019), and most of the participants in this research were students with ASD in elementary schools, it is suggested that adolescents with ASD or students with other disabilities can be targeted in future studies. Third, other variables related to learning performance could be investigated in future studies including, for example, the degree of commitment to learning and the motivation to learn. Fourth, individuals communicate emotional information not only through facial expression but also body posture (Bijlstra, Holland, Dotsch, & Wigboldus, 2019). A mechanism for the recognition of emotional body postures might also be incorporated into the e-learning platform to increase recognition accuracy. Fifth, recent studies (Hu et al., 2019; Sung et al., 2019; Cakir et al., 2019) demonstrate the potential of using AR/VR technologies in e-Learning, using related methodologies to design materials of emotion regulation strategy with immersive experience might further improve the effectiveness of this study.

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