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Emotional patterns in a simulated virtual classroom supported with an affective recommendation system

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Abstract

The purpose of this study is to explore the effects of an affective recommendation system on the developmental trajectories of prospective teachers' emotional patterns, integrated with a Simulated Virtual Classroom (SVC) platform called SimInClass. SVC exposes teachers to a range of student discourses in the form of unexpected stimuli. Fifteen prospective teachers participated in a study consisting of two practicum sessions in the SVC. Participants did not receive any affective recommendation after the first session but did receive it after the second session. Additional data were collected during both sessions in the SVC, including the physiological responses, such as electroencephalogram (EEG), galvanic skin response (GSR), and facial expressions. L metric and Lag sequential analysis were employed in determining teachers' transitional emotional patterns. The results showed that participants did not maintain disgust after receiving affective recommendations, although they maintained sadness. This result indicates that the given affective recommendation has an inherent effect on negative emotions that are felt less intensely. Different or longer-term interventions may be needed for more intense and long-lasting negative discrete emotions such as sadness. Also, participants transitioned to happiness and sadness instead of maintaining their neutral status after receiving an affective recommendation. This result demonstrates that affective recommendations encourage participants to use the cognitive reappraisal necessary for emotion regulation. When the participants' emotional patterns are examined on the basis of student discourse, the results are more complex and the emotional patterns differ according to the function of the discourse triggered by virtual students.

KEYWORDS
emotion, emotional patterns, prospective teachers, simulated virtual classroom

Practitioner notes

What is already known about this topic

- Teachers experience different emotional states during teaching.
- Teachers' emotions affect their behaviour management, teaching process and student engagement.
- It is beneficial to increase opportunities for prospective teachers' classroom experience and provide them with sufficient guidance and advice during this difficult process.

What this paper adds

- The affective recommendation system has intervened in the persistence of short-term and low-intensity negative emotions.
- The affective recommendation system enabled prospective teachers to try to reach optimal emotional conditions through cognitive reappraisal processes.
- When emotional patterns are examined in light of the types of student discourse, it is noted that happy prospective teachers maintain their emotions when confronted with unexpected stimuli. However, prospective teachers in a negative valance displayed a descending pattern of activation in response to an unexpected stimulus.

Implications for practice and/or policy

- Teacher emotions need to be taken into account in teacher education programs.
- SVCs can be utilized as useful tools for teacher education programs.
- In subsequent studies, it is suggested to explore the stimulus-based effects of the affective recommendation system by increasing the number of stimuli according to different types of discourse and behaviour patterns.

INTRODUCTION

Teaching is an emotionally charged profession (Hargreaves, 1998; Pekrun & Linnenbrink-Garcia, 2014) wherein three basic functions of the nervous system—perception, processing and response occur dynamically (Rodriguez, 2013). Teachers experience different emotional states such as anxiety, pleasure and anger during teaching (Sutton & Wheatley, 2003).

They also feel positive if their efforts are supported, they reach their teaching goals and classroom conditions match with their ideals (Lasky, 2000). On the contrary, students' misbehaviour and academic failures, teachers' perceived inability to feel in control and physical classroom conditions are reported to be the sources of teachers' negative emotions (Taylor et al., 2020).

Due to the contagious nature of emotions, a teacher's emotions can affect their teaching process as well as the students involved. Positive emotions can create a positive classroom environment, whilst negative emotions may induce negative emotions for students (Frenzel et al., 2009; Yan et al., 2011). However, it should be noted that a teacher's positive emotions can sometimes be counterproductive (Anttila et al., 2017). For example, it is known that negative emotions, such as anger, can be beneficial in achieving learning and motivational goals (Tamir, 2009). In this context, it is emphasized that teachers may experience an entire range of emotions in the classroom, and the essential element is to reach a balance between both positive and negative emotions (Anttila et al., 2017). To achieve this balance, it is important for the teacher to be aware of their emotions in the classroom and observe the antecedents and effects of such emotions (Barrett et al., 2001).

Yet, it may not always be easy for prospective and novice teachers to become emotionally aware and balance their emotions. Moreover, it is emphasized that the emotional confusions are reduced with increasing teaching experience (Lortie & Clement, 1975). Therefore, first, it may be beneficial to provide them with sufficient guidance and advice during this difficult process. Second, it would be beneficial to increase prospective teachers' classroom experiences. Simulated Virtual Classrooms (SVC) are usually coined with the idea of dispelling the shortcomings in practice.

SVCs are expected to be a replica of an authentic classroom environment so that participants could utilize their skills such as problem-solving, attention, and scheduling in order to improve their teaching skills. Dieker et al. (2017) indicated that as the use of SVC increases, the frequency of asking questions, and specific feedback for students increases in prospective teachers' actual classroom experiences. SVC affords frequent rehearsal experiences, enhancing classroom management skills, improving the use of teaching methods (Donehower Paul et al., 2020). Currently, the idea of a need for an affective recommendation system has been raised in the literature, but no SVC is utilized to provide an affective recommendation in order to support the emotional development of prospective teachers.

The idea of affective recommendation was born out of the effect of emotion on cognitive structures, especially for decision making (Desautels, 2016). In the educational context, affective recommendation is used to provide support for different purposes such as providing affective support or feedback according to the emotional state of the user in the learning environment, directing the student to the appropriate learning material, providing a recommendation to the student in need by the peer-user or teacher (Salazar et al., 2021). There is no single methodology agreed upon in the design of affective support in the literature. According to one approach, a knowledge-based method should be adopted both to provide support to users in a collaborative way (Karampiperis et al., 2014), taking the user and the context into account (Santos & Boticario, 2012). Another approach posits that participants should either be directed to the learning material according to their affect state (Leony et al., 2013), or utilize the TORMES (Tutor Oriented Recommendations Modelling for

Educational Systems) protocol (ie, Santos & Boticario, 2011), in which the knowledge of the literature is used together with the support from experts (Santos et al., 2014).

The affective recommendation system is designed to fulfil two main functions. First, it is intended to recognize and describe prospective teachers' emotional states during a teaching session in association with the co-occurring classroom events (eg, misbehaviour and discourse). Second, it gives recommendations to the prospective teachers based on their experienced emotions and their teaching performances. In other words, the system consists of two main structures: (1) the emotion recognition module and (2) the affective recommendation module. Technical characteristics are explained in detail under Method section. In addition, a general view showing the functions of the system is given in Appendix 1.

The overall goal in this study is, first, to understand the pedagogical effects of the affective recommendation system; and, to examine the emotions and emotional patterns experienced by prospective teachers in a simulated virtual classroom. Teacher-talk and unexpected student discourse may interfere with teachers' classroom behaviour, especially for novice teachers. Since emotions are short-lived compared to moods due to their nature, and that various emotional states can be felt by individuals as a result of cognitive appraisal of existing conditions (Scherer, 1993), it is thought that examining the sequential emotional pattern is important in order to discover the effect of the recommendation system, especially on the basis of stimuli (ie, unexpected student discourse). In this context, the following research questions were sought to be answered:

1. Does the use of an affective recommendation system integrated with SVCs influence prospective teachers' emotions?
2. What are the prospective teachers' sequential emotion patterns whilst teaching in an SVC? Would an affective recommendation system contribute to a change in these patterns?
3. How do various student discourses subjected to prospective teachers in an SVC affect their sequential emotion patterns? Would an affective recommendation system contribute to a change in these patterns?

THEORETICAL FRAMEWORK

Emotions are intense conscious mental responses that can last from minutes to hours that are subjectively experienced and cause physiological and behavioural changes towards a specific goal (Merriam-Webster, 2019). In addition to the theories explaining how emotion is formed on a physiological, cognitive and neural basis discrete and dimensional emotion theories explain how emotions are classified.

In the discrete emotion approach, emotions differ from each other in terms of appraisal, antecedent, and physiological characteristics (Ekman, 1999). According to Ekman (1970), emotions are revealed in every individual with similar psychological and physical patterns. Basic emotions are universal, but the factors that reveal emotions are cultural (Ekman, 1970). Ekman and Friesen (1971) argue that there are six basic emotions: happy, sad, disgust, surprise, fear and anger and that other emotions are a combination of these emotions. Another model based on the Discrete emotion approach is Plutchik's wheel model. In this model, anticipation and trust have been added to the six basic emotions defined by Ekman. Plutchik (2001) states that other emotions emerge with the decrease in intensity and combination of eight basic emotions. In this approach, emotions are grouped and labelled according to their common characteristics. However, due to the difficulty of labelling some complex emotions and the multidimensional nature of emotion, dimensional theories are often taken as a basis in research in the literature.

It is noteworthy that models that examine the formation of emotions in the educational context are often based on Appraisal Theory (Frenzel et al., 2009). Appraisal theory explains how emotions are formed from a cognitive perspective. According to the Appraisal theory, situations and events do not directly trigger emotions, primarily situations are valued. This process is a cognitive appraisal process and creates situational emotions (Scherer, 1993; Smith & Lazarus, 1993). Roseman and Smith (2001) stated that appraisals are determinants of different emotions, and there are seven components that directly affect emotions. These components are expectations, compliance with the goal, motivational situation, probability of an event occurring, the situation that mediates the event, the source of the problem and the control potential. With these components, the intensity of the emotion and the quality of the emotional response are determined. According to this theory, the individual enters the cognitive reappraisal process and experiences a new emotional state with the change of these components (Frenzel et al., 2009).

Literature review

Han et al. (2021) examined the affect state of 72 seventh grade students with sequential analysis to examine how participants perform using affective regulation and investigate the effectiveness of an intelligent learning system that provides emotional support. The study was designed with an experimental method. Whilst the experiment group worked in the intelligent tutoring system (ITS), the control group participated in a non-ITS learning environment. Both groups performed a 25-minutes learning phase, during which video recordings of the participants were taken. Two experts reviewed the video recordings and coded time-dependent moods according to the facial expressions of the participants for every 30 seconds. Then, the emotional states of the participants were confirmed by interviewing them. Because frustration and surprise were rare, those emotions were excluded from the study. In the study, flow, neutrality and confusion were the most frequently experienced emotions. Boredom and delight were experienced less frequently. The results show a difference between the experimental and control groups, especially when switching from negative emotions to positive emotions. The experimental group switched from neutral to delight and from boredom to delight significantly more frequently than the control group. However, the control group switched from neutral to confusion significantly more frequently. In this study, it is recommended to use automatic collection and identification of data through channels such as video and audio for future studies.

Rebolledo-Mendez et al. (2021) examined the dynamics of affect over time in an ITS prepared for teaching mathematics. He also investigated the relationship between learners' meta-affective competencies (eg, awareness and self-regulation) and learning outcomes. Data were collected from 54 students from the secondary level through self-report. Students rated the emotional state they felt at ten-minute intervals whilst interacting with the system. Although the results showed that participants with meta-affective competence experienced positive and neutral affective states longer than negative states, the sequential analysis of affective states revealed the pattern of transition from negative to positive in individuals with high meta-affective skills was not statistically significant. Participants who did not show meta-affective proficiency exhibited statistically significant patterns in the learning process from boredom to frustration and concentration to neutral. In the study, it was stated that the data collection method was limited, and it was suggested to use data collection tools that provide automatic and instant identification of emotion.

Anttila et al. (2017) conducted a study to investigate the academic emotions of prospective teachers, the patterns they show, and the sources of their emotions. Data were collected by interviewing 19 prospective teachers. It was observed that the participants mostly showed positive and changing emotional patterns, and sometimes they produced negative, ascending and descending emotional patterns. It was concluded that the emotional patterns are related to whether the expectations are met, the competence of abilities and social support. It was stated that examining the emotional pattern of prospective teachers in different learning environments will be useful in illuminating this complex and dynamic structure.

D'Mello and Graesser (2012a) determined the affect state of learners with a retrospective judgment protocol in a computer-assisted learning environment lasting 32 minutes. The affective transition was examined with the L metric. Surprise and delight were rarer than other mood states. Flow, engagement, confusion, boredom, frustration were frequent emotional states. When the time-dependent affect transition is examined, it has been observed that individuals who are engaged and experience flow experience cognitive disequilibrium and confusion when they encounter a difficulty or a conflict and cannot reach their goals. According to the model presented in the study, if the individual can overcome the obstacles in front of him, he can be re-engaged. But if he cannot solve the problems, he experiences frustration that will lead to boredom.

Rodrigo (2011) aimed to examine students' cognitive-affective states, focusing on boredom, engagement, delight, surprise, neutral, frustration and confusion in a math game. One hundred sixty-four seventh-grade students participated in the study. The students' emotional states were determined by the eight observers' facial expressions, body language, words and actions. The emotion determination process was carried out every 200 seconds for each student. Analyses were carried out by creating the affect transition metric (L) regarding cognitive and emotional states. The results showed that boredom is a long-term emotional state, and there is no transition from boredom to engagement. After the confusion, the students were able to engage, and the feeling of delight did not bring confusion. For this reason, it was emphasized that boredom is an undesirable state to be felt in the learning environment, and confusion is the desired state to be felt in learning environments as it brings engagement with content.

In addition to studies investigating emotional transitions, there are studies exploring the effects of affective interventions. These studies have utilized different terms interchangeably such as affective support, affective feedback, and affective recommendation. In a study, eg, DeFalco et al. (2018) explored whether an affective intervention would increase the learning performance of the participants in a serious game. Participants were 124 students who took military training, and their frustration levels were determined by log activities and their posture data. According to the participants' frustration feelings, it was seen that the group that was given feedback to improve self-efficiency showed better learning outcomes than the control group.

Aslan et al. (2018) examined the effect of emotion aware intervention on the emotional state in an online reading environment used in an English course. Twelve high school students participated in the study. Participants' emotions during learning activities were collected through a webcam. The video recordings were examined by experts and the emotional states of the participants were labelled. In addition, self-report data regarding the emotions of the participants were collected in certain parts of the learning sessions. With the self-label data collected, the instant emotional intervention was applied to the participants. It was found that the satisfied state of the students increased significantly after the intervention.

In the study of Arevalillo-Herráez et al. (2017), affective support was provided to 38 secondary education school students in an intelligent tutoring system (ITS) during a problem-solving task. The affected state of the participants was collected with a self-assessment manikin test. Whilst affective support was provided to the experimental group through ITS, no support was provided to the control group. Both groups were attended two different sessions at ITS. At the end of sessions, students were presented with an affective report showing their valance, activation and autonomy levels. The results showed that the learning performance of the experimental group increased between the first and second applications, while there was no change in the control group.

In their study, D'Mello and Graesser (2012b) compared supportive AutoTutor with affect detection feature and regular AutoTutor in terms of a number of variables related to learning, engagement, enjoyment and tutor quality. Supportive AutoTutor was designed to guided students by recognizing students' emotions and responding to students' negative emotions. A total of 84 graduate students participated in the study. Students participated in two learning sessions in these two different environments. The mood of the participants was determined through body posture and eye-tracking data. The results showed that the tutor's features were not effective on participants' enjoyment, engagement, and learning.

Robison et al. (2010) examined the interaction between affective feedback and learning in a three-dimensional learning environment according to personality profiles. 115 middle school students participated in the study, and data on their affective states were collected by self-report. In the study, it was found that students with different personality traits in positive moods reacted differently to affective feedback, and some of them changed from positive valance to negative after affective feedback.

Robison et al. (2009) evaluated the emotions of the participants by giving affective feedback in a three-dimensional learning environment. A total of 35 graduate students participated in the study. The data on the emotional states of the participants in the learning environment were collected by a self-report measurement tool. It has been found that the appropriate affective intervention was found to be effective in maintaining a positive affective state such as flow and delight. It was stated that the effect of the affective intervention on frustration and confusion was less clear.

Chaffar et al. (2009) wanted to induce positive emotion with their recommendation to 16 learners in an intelligent tutoring system. In the study, emotional states were determined by electromyography (EMG). It has been observed that students with moderate and low achievement have increased positive emotions after receiving the recommendation.

In summary, affective intervention, or affective feedback/support or recommendation leads to positive learning outcomes (DeFalco et al., 2018) and it can increase positive states in the learning process (Arevalillo-Herráez et al., 2017; Aslan et al., 2018; Chaffar et al., 2009; Robison et al., 2009). Yet, these studies were generally learning performance-oriented and emotion detection was determined either by self-report measurement tools or by utilizing physical or physiological data alone. It has been noted that affect transition studies are needed in future studies. Only in the study of Anttila and colleagues (2017), the affect transition of prospective teachers was examined in an intelligent tutoring system, educational games, and real classrooms. Some researchers emphasized that for an effective affective recommendation, it is important to correctly detect the affect and configure the recommendation in a context-sensitive manner (see, DeFalco et al., 2018). In addition to detecting affect accurately, it is essential to determine affect intensity, duration, and antecedent for affect-related effective instructional strategies (D'Mello et al., 2014). Hence, this study aims to consider the aforementioned limitations and the suggestions of the affect intervention and affect transition studies. The contributions of this study to the literature are as follows: (1) determining the teacher's emotions during the teaching task, (2) for emotion recognition using physiological and physical sources together, (3) reporting the type, duration, intensity and antecedent of discrete emotions and presenting them to the teacher candidates and (4) giving context-sensitive affective recommendations to encourage prospective teachers to enter the process.

METHOD

In this study, a single group experimental method was used to determine the effectiveness of the affective recommendation system embedded in an SVC. Fifteen prospective teachers studying at the Department of Computer Education and Instructional Technology voluntarily participated in this study. The participants were healthy individuals aged 20–22, who have no vision problems, who stated that they slept an average of 7 hours before the experiment. Selected participants were all prospective teachers who had previously taken classroom management and teaching practice courses and taught practicum sessions at two different levels in the SVC. In the selected levels, the number of students, classroom seating and challenging tasks are kept similar; yet, the only difference between them was that participants attended different subject topics.

Process and materials

Ethical permissions required for the study were obtained from the ethics committee of a state university. Before the experimental procedure took place, the participants received information about the research being carried out and signed a consent form. Before the experiment, the participants were asked not to apply gel-cream-like cosmetic materials on their scalp and hands that would impair conductivity. The calibration of the sensors feeding the emotion recognition module was adjusted for each participant. This process included dressing the EEG cap following the 10–20 electrode system, controlling the EEG signals, placing the GSR electrodes on the thumb and middle finger knuckles, and evaluating the artefacts for both sensors. On the contrary, the participant was asked to sit in a position where the camera would fully detect his/her face, moving as little as possible. With all these adjustments, it was aimed to collect the best quality data. The screen recording in Figure 1 was taken whilst a participant was experiencing SVC.

The implementation process started with the participation of the prospective teachers in the trial session. After the trial session, each participant was requested to teach the first practicum session in the SVC. During the first practicum session, they did not receive any affective recommendation. However, when the first session was over, the affective recommendation report for this session was generated from their actual teaching performance data and was presented to the participants in detail. After the participants studied the affective recommendation report regarding their teaching experiences with a mentor, they then attended the second practicum session, whose difficulty level and stimuli were similar to the first session and taught another practicum session in the same SVC. The implementation process was summarized in Figure 2.

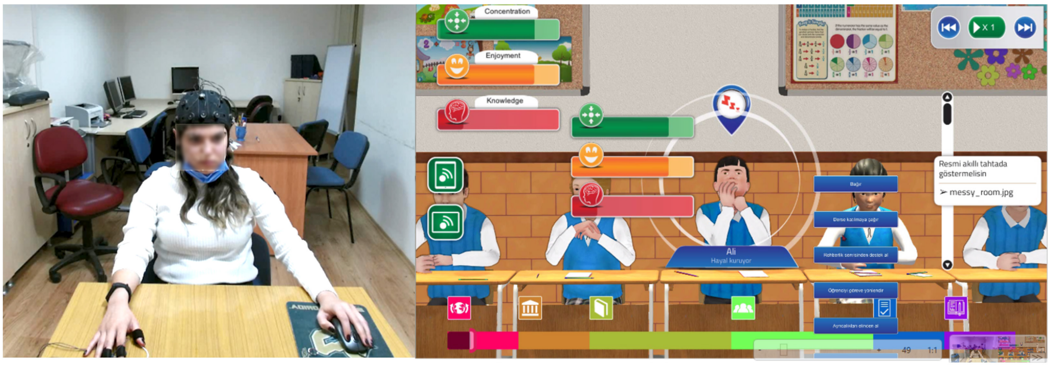

FIGURE 1 Participant experiencing SVC

FIGURE 2 Implementation process

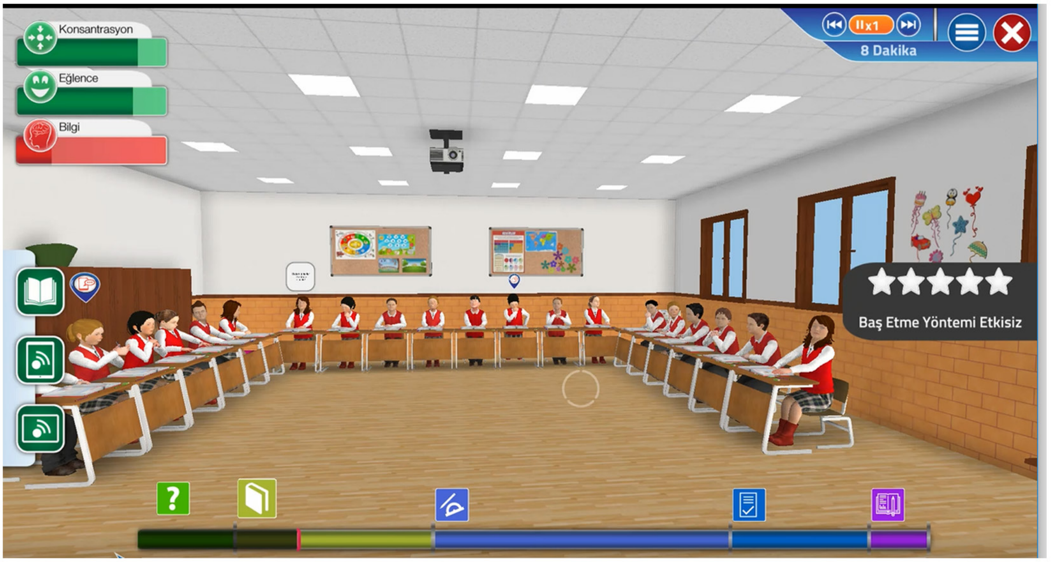

FIGURE 3 Simulated virtual classroom-SimInClass

Simulated virtual classroom-'SimInClass'

'SimInClass' is a three-dimensional, Artificial Intelligence (AI)-based-simulated virtual classroom developed to improve teachers' classroom management, planning and teaching skills in technology-supported classrooms (Kelleci & Aksoy, 2020). SimInClass includes virtual students who behave unpredictably, based on AI-based algorithms in varying classroom designs. Using 'SimInClass', prospective teachers have the opportunity to practice in a technology-supported classroom with those virtual students to practice their classroom management and teaching skills. Whilst teaching in SimInClass, the prospective teachers are expected to plan the lesson, carry out the teaching, observe the reactions and behaviours of the virtual students and make sound decisions about their misbehaviours in the virtual classroom.

In our study, prospective teachers were requested to plan their teaching process by taking into consideration the objectives of the course they would deliver in the SVC. The planning process is set to include three parts: Introduction to the course, teaching process, measurement and evaluation. Second, prospective teachers were requested to deliver their lessons in the simulation environment. During their practice teaching, prospective teachers were advised to keep the level of concentration, enjoyment and content assimilation levels of virtual students at the highest level with the activities they prepared. During course delivery, there are occurrences of misbehaviour and student talk in the virtual classroom, similar to a conventional classroom (Figure 3). In order to create discourse units, transcripts of teacher-student speech were prepared from video-audio recordings of 16 natural classroom environments. Then, discourse analysis was carried out. Discourse units were voiced by virtual students in SVC within the rules created by considering the emotions of the prospective teachers and the part of the course. Eight different types of discourse, namely demand, initiate, response, evaluate, comment, clarification, negotiation, and steering were performed by virtual students at different parts of the simulated lesson. Yet, this study has mainly focused on the interactions with the two mostly occurring types of student discourse in a typical classroom, 'demand' and 'initiate discourse'. Thus, the findings in the study are limited to only these two types of discourse.

In the demand discourse type, sentences with four different functions were used by virtual students: asking for help, rule-governed process question, factual question and service. In the initiate type, sentences with five functions, namely inquiry, greeting, interrogative, authentic question and report an event, were directed to prospective teachers by virtual students.

Affective recommendation system

The affective recommendation system is designed to function like an expert system, which offers various suggestions, recommendations and guides to inexperienced users (Negnevitsky, 2005), based on their emotions during teaching in SimInClass. As in the case of the TORMES methodology used for the design of the recommendation, the interactions most appropriate for the support to be provided were examined by means of a literature review to identify the situations in which emotional support is commonly needed. The recommendations/supports were created by evaluating the design on the basis of students' and experts' opinions.

The recommendations were presented both in visual and text-based modalities. The visual modalities included graphics representing the antecedents of the users' emotions during the simulation and information about the context and how long those emotions lasted. Moreover, information about when classroom discourse (student–teacher interactions) and student misbehaviour occurred and how the individual participant felt at the time was also included in the graphs. The emotions experienced during different parts of the lesson and the exact time stamp were shown on an event-related basis. Through using the graphics, the aim was to raise awareness among the prospective teachers of the antecedents of the emotions they experienced in the classroom. With regard to the textual representation, the related recommendations were described in a paragraph intended to present a behaviour/decision recommendation to the user. The textual representations were structured with the support of prior literature in order to reflect the effects of different emotional states on the cognitive structures, behavioural outputs, classroom climate, and students during the virtual lessons delivered by the prospective teachers. For example, the paragraph shown to a prospective teacher who predominantly experienced happiness during the lesson was as follows:

> Happiness brings with it environmental clues and decision making with shortcuts. Therefore, it may lead to less accurate decision making. Yet, happy individuals are more successful in relation to displaying creativity and adapting to changing conditions. Teachers' positive emotions create a positive climate in the classroom, increase motivation and satisfaction with the learning material and teaching, facilitate learning and support academic success.

On the contrary, the information presented to the prospective teacher whose dominant mood is sadness is as follows:

> Sadness can lead to being more detail-oriented, more analytical, more organized and more alert in information processing. However, it reduces working memory performance. Negative teacher emotions trigger negative student emotions, reducing motivation and satisfaction with learning.

Recommendations were given through a system-generated report at the end of a lesson experienced by prospective teachers in SVC. The report includes (a) graphics showing users' emotions, the intensity and duration of their emotions according to time, context and classroom events, (b) texts in which the graphics are interpreted based on the event and (c) literature-supported recommendations according to the dominant mood felt throughout the process. Figure 4 provides an example of part of the affective recommendation report.

Emotion recognition system

It is noteworthy that nearly all emotional theories consider emotion as a holistic structure that includes physical, neurological and cognitive evaluations. This multidimensionality brings along diversity in the definition and measurement of emotion. Emotions can be defined according to the physical and physiological signals of individuals. Facial expression, gesture and speech are physical signals frequently used in emotion recognition (Shu et al., 2018). Since physical signals can be hidden or manipulated by individuals, it is known that physiological signals will also be useful in emotion identification. Physiological signals, which are reflections of the central nervous system and autonomic nervous system, are not easily controlled by the individual (Shu et al., 2018). Electroencephalogram (EEG), electrocardiogram (ECG), galvanic skin response (GSR) and electromyogram (EMG) are some of the physiological signals. Studies emphasize that the use of multiple physical and physiological signals together is significant in recognizing emotions. In this study, an emotion recognition system was utilized in order to identify EEG, GSR and facial expression using a hybrid fusion strategy (EEG, GSR, and facial expressions), considering the multidimensional nature

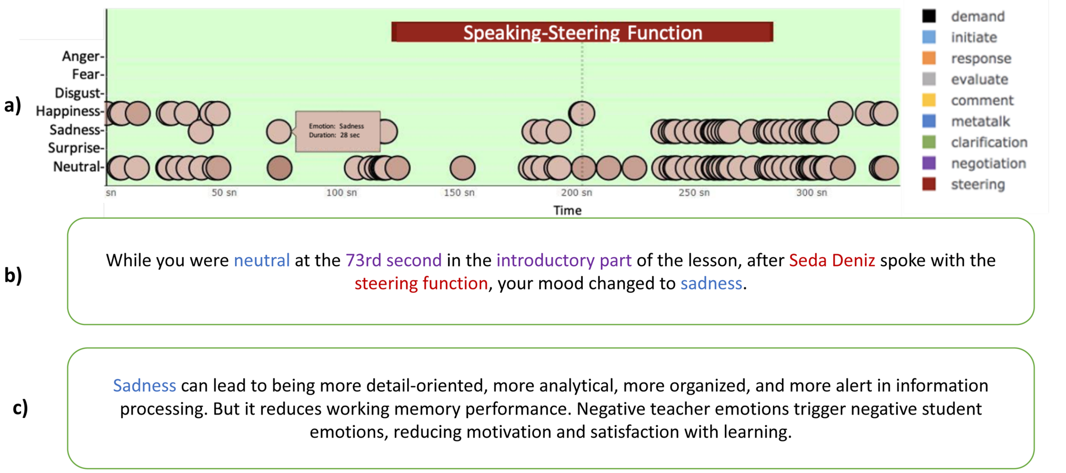

FIGURE 4 Part of the affective recommendation report

of emotion (see Cimtay et al., 2020). The probability array representing the valance dimension of emotion is taken from the EEG modality. The probability array regarding the arousal dimension of emotion was used in the model through the combined data obtained from EEG and GSR. A discrete emotion probability array is provided by face modality. Three different InceptionResnetV2 Convolutional Neural Networks (CNN) models were used in the described hybrid model: CNN_V for valance, CNN_A for arousal, and CNN_F for discrete emotion.

This system was tested for seven basic emotional states (happy, surprised, neutral, afraid, angry, disgust, sad) using the Database for Emotion Analysis using Physiological Signals (DEAP). One subject out mean accuracy in DEAP was 37.1% only for face data and 32.5% for physiological data (GSR+EEG). The combined use of face data and physiological data produces a maximum one-subject out the accuracy of 91.5% and a mean accuracy of 53.8%. Also, the emotion recognition system has been tested for sad, neutral and happy with the multimodal emotion dataset LUMED-2. In the LUMED-2 dataset, mean accuracy was found to be 47.2% for face data only, and 52.2% for physiological data (GSR+EEG). When the model is tested with the use of face data and physiological data together, for these three emotional states representing different valance, produce a maximum one-subject out accuracy of 81.2% and a mean accuracy of 74.2%.

Data sources

In this study, the emotional states of the participants were predicted in real-time through a previously developed multimodal emotion recognition system, which includes monitoring EEG, GSR and facial expressions (Cimtay et al., 2020). EEG records the electrical activity of the brain. The 8-channel Neuroelectrics Enobio EEG headset was used that has a sampling rate of 500 Hz and a bandpass of 0.1–50 Hz. On the scalp, the electrodes were positioned in Fp1, Fp2, F3, F4, F7, F8, T7 and T8 according to the 10–20 electrode placement system. Sintered Ag-AgCl electrodes were applied using a cap. Data from all channels were referenced to the right and left mastoids.

The GSR was used to measure the instantaneous changes in the electrical conductivity of the skin. Empatica E4 Wristband was used to collect the GSR data during the trials, which has a sampling frequency of 64 Hz and would not physically affect the use of the SVC. Facial expressions of participants were captured with Microsoft Kinect. Kinect can recognize facial features and their locations via its multisensory camera and facial mapping algorithm. Good data quality was ensured by asking participants not to wear significant makeup that could impair facial expression recognition performance. Other conditions that required careful adjustment to optimize the data collection quality involved the ambient light and proper insulation of the room that would otherwise impair the EEG signal quality.

Data analysis

Through the emotion recognition system, discrete emotions were tagged at 500 ms during the participant's time in the SVC. These are angry, afraid, disgust, happy, neutral, sad and surprised. It was thought that it would be more meaningful to examine the sequential change of emotions in order to see the effects of the affective recommendation system.

Two methods were used for sequential analysis in this study. The transition likelihood metric 'L' developed specifically for the affective path (D'Mello et al., 2007) was used to examine the difference in the transition of emotion during the two implementations. L*, the modified version of L, is recommended to be used in cases where the self-transition is removed (Matayoshi & Karumbaiah, 2020). However, the purpose of this study was not only to focus on emotion change, but since the persistence of emotion was also important, self-transitions were included, and the L metric was used. Indeed, Karumbaiah et al. (2019) criticize that excluding self-transitions will reveal too many emotional patterns.

There was a total of 24,783 teachers' emotion codes for the first implementation and 20,664 for the second implementation. A transitional frequency matrix was created from emotion codes. Then, the L value was calculated for each student. Twenty-two transition variables (nine from the first implementation and thirteen from the second implementation), which were found to have no transition from one emotion to another, were removed from the dataset.

The L value gives information about the probability and direction of the transition from the base frequency to the destination state (D'Mello et al., 2007). A two-tailed *t*-test for one sample was applied to test whether the transitions were statistically significant. After calculating the mean L metric for both implementations, the post hoc control method of Benjamini and Yekutieli (2001) was applied, as suggested for controlling false discoveries (See, Matayoshi & Karumbaiah, 2021).

According to Student discourses, when the emotion pattern was examined, it was seen that short sequences emerged because an event-related approach was followed. Bosch and Paquette (2021) found that Lag sequence analysis is more suitable for short sequences than other transition measurements when examining transition. For this reason, the statistical significance of the sequential relationships between each event was examined via lag sequential analysis (Bakeman & Gottman, 1997). As Bakeman and Gottman (1997) suggested, a coding scheme listing the emotions of prospective teachers in chronological order according to discourse was prepared. Then, a transitional frequency matrix was created by calculating the frequency of each emotion category following another emotion category. In order to test the significance between the transitions, Z value was calculated using the transitional frequency. It is accepted that Z values greater than +1.96 reach a significant level ($p < 0.05$).

RESULTS

Does the use of an affective recommendation systems integrated with SVCs influence prospective teachers' emotions and emotion patterns?

As shown in Table 1, the descriptive analysis of our data indicates that the prospective teachers experienced happiness, neutral and sadness predominantly during the first and the second trials. Disgust, surprise and fear were not experienced as much as the former

TABLE 1 Frequency of emotions

Frequency	First Implementation	Second Implementation
Happiness	7427	5816
Sadness	2887	1470
None	5931	7478
Anger	18	11
Disgust	798	201
Surprise	135	192
Fear	374	226

TABLE 2 Results of Wilcoxon Signed Ranks Test

Emotion	Second Trial-First Trial	N	Mean Ranks	Sum of Ranks	Z	p
Happiness	Negative Ranks	7	9.00	63.00	−0.170	0.865
	Positive Ranks	8	7.13	57.00		
	Ties	0				
Sadness	Negative Ranks	10	8.35	83.50	−1.335	0.182
	Positive Ranks	5	7.30	36.50		
	Ties	0				
Neutral	Negative Ranks	7	6.29	44.00	−0.909	0.363
	Positive Ranks	8	9.50	76.00		
	Ties	0				
Anger	Negative Ranks	3	2.83	8.50	−0.271	0.786
	Positive Ranks	2	3.25	6.50		
	Ties	10				
Disgust	Negative Ranks	12	7.25	87.00	−2.906	0.004[a]
	Positive Ranks	1	4.00	4.00		
	Ties	2				
Surprise	Negative Ranks	5	4.7	23.50	−0.771	0.441
	Positive Ranks	3	4.17	12.50		
	Ties	7				
Fear	Negative Ranks	9	8.11	73.00	−1.289	0.197
	Positive Ranks	5	6.40	32.00		
	Ties	1				

[a]Based on negative ranks.

two, and they were observed in certain time periods only, whereas anger was the least experienced emotion. These findings indicate that the ranking of the perceived emotions in the first and the second implementations was similar. Since it is an important question, ie, whether the use of an affective recommendation system affects the prospective teachers' emotions or not, further analyses have been carried out.

Wilcoxon Signed Ranks Test was applied to examine whether there is a difference between the prospective teachers' emotions before and after the use of the affective recommendation system. As shown in Table 2, the results indicate that the use of affective recommendation system significantly reduced the occurrence of the feeling of disgust [$z = -2906$, $p > 0.05$]. Participants experienced similar frequencies of Anger and Surprised in both trials.

What are the prospective teachers' sequential emotional patterns whilst teaching in an SVC? Would an affective recommendation system change these patterns?

Considering that emotion is a variable structure depending on the situation and the individual, how the prospective teachers' emotional patterns were affected was also investigated. The mean value of L and standard error obtained from the transition frequencies between

TABLE 3 Mean value of L and standard errors

	Happiness	Sadness	Neutral	Anger	Disgust	Surprise	Fear
Happiness							
I1	0.64*	0.19	−0.72	–	0.24	–	0.27
	(0.03)	(0.06)	(0.9)		(0.07)		(0.08)
I2	0.57*	0.010	0.09	–	0.15	–	0.2
	(0.06)	(0.03)	(0.05)		(0.05)		(0.09)
Sadness							
I1	0.02	0.4*	−0.82	–	0.06	–	0.11
	(0.01)	(0.06)	(0.91)		(0.02)		(0.06)
I2	−0.009	0.39*	−0.045	–	0.012	–	0.06
	(0.03)	(0.06)	(0.09)		(0.014)		(0.37)
Neutral							
I1	0.11	0.2	0.45*	0.95	0.18	–	0.16
	(0.03)	(0.05)	(0.04)	(0.07)	(0.06)		(0.06)
I2	0.18*	0.23*	0.53*	0.02	0.31	–	0.17
	(0.04)	(0.05)	(0.05)	(0.02)	(0.09)		(0.07)
Anger							
I1	−0.002	0.03	−0.934	0.09	0.02	–	−0.0001
	(0.003)	(0.02)	(0.9)	(0.07)	(0.016)		(0.0001)
I2	−0.03	0.006	−0.09	0.03	–	–	–
	(0.03)	(0.01)	(0.09)	(0.02)			
Disgust							
I1	0.17	0.02	−0.91	0.15	0.29*	–	0.03
	0.01	0.008	0.91	(0.09)	(0.07)		(0.02)
I2	−0.02		−0.08		0.02		0.083
	(0.03)		(0.08)		(0.05)		(0.06)
Surprise							
I1	−0.00	0.007	−0.92	–	0.002	–	0.018
	(0.004)	(0.007)	(0.91)		(0.002)		(0.009)
I2	−0.02	−0.004	−0.08	–	0.01	–	–
	(0.03)	(0.005)	(0.09)		(0.008)		
Fear							
I1	0.006	0.057	−0.91	−0.0003	0.022	–	0.16
	(0.005)	(0.032)	(0.91)	(0.000)	(0.01)		(0.05)
I2	−0.02	0.037	−0.07	–	0.01	–	0.08
	(0.033)	(0.033)	(0.09)		(0.01)		(0.03)

Note: 'I1' represents the first implementation, 'I2' represents the second implementation. Directions of the transitions are row to column.

*Statistically significant relationships

the emotions experienced by the prospective teachers in the first implementation is given in Table 3.

There are 49 possible transitions for seven discrete emotions. For the first implementation data, 9 of them and 13 of them did not have sufficient frequency for the second implementation data. Therefore, the transitions mentioned above were not included in the statistical analysis.

As shown in Table 3, four cyclical transitions were significantly more likely than chance in the first implementation ($p < 0.05$). In the study, only the adjusted p-values obtained after post hoc analysis were reported. Happiness ($M = 0.64$, SD = 0.12) $t(14) = 19.6$, $p < 0.01$, sadness ($M = 0.4$, SD=0.27) $t(14)$=5.63, $p < 0.01$, neutral ($M = 0.45$, SD = 0.17) $t(14) = 10.22$, $p < 0.01$ and disgust ($M = 0.29$, SD = 0.27) $t(14) = 4.2$, $p < 0.01$ states were found to be persistent.

For the second implementation, five transitions were significantly more likely than chance in the second implementation ($p < 0.05$). As in the first implementation, the cyclical transitions of happiness ($M = 0.57$, SD = 0.24) $t(14) = 8.95$, $p < 0.01$, sadness ($M = 0.39$, SD = 0.25) $t(14) = 6.08$, $p < 0.01$, and neutral ($M = 0.53$, SD = 0.20) $t(14) = 10.23$, $p < 0.01$ were statistically significant. Neutral states were significantly more likely than chance to transition to happiness states ($M = 0.18$, SD = 0.17) $t(14) = 4.05$, $p < 0.01$ and sadness states ($M = 0.23$, SD = 0.20) $t(14) = 4.39$, $p < 0.01$).

How do various student discourses subjected on to prospective teachers in an SVC affect their sequential emotion patterns? Would an affective recommendation system change these patterns?

Within the scope of this question, the emotional patterns experienced by prospective teachers according to the types of discourse between student and teacher were examined. In this way, it was thought that the change of emotions against common stimuli and the effects of the affective recommendation system in SVC would be better understood. There are eight different types of discourse implemented in the SVC we used, which are triggered randomly using an internal logic. In this study, sufficiently many data samples have been collected for the following student discourse types: ‘initiate’ and ‘demand’. Therefore, our findings focus mainly on these two types of discourse (Figure 5).

Table 4 includes the transitional probability matrix on the emotions of the prospective teacher for the type of discourse that functions as ‘initiate’. In the first session, it was observed that individuals who experienced happiness before a stimulus to initiate discourse continued to experience happiness after the stimulus ($p_{I1}^{tr} = 0.79$, $z = 2.51$, $p < 0.05$). The repetition pattern of happiness continued in the second session ($p_{I2}^{tr} = 0.88$, $z = 2.39$, $p < 0.05$). It was noted that the transition pattern from happiness to happiness was significant in both sessions for the ‘initiate the discourse’-type stimulus. It was observed that the prospective teachers who experienced sadness in the first session continued to experience this feeling following the triggered stimulus and this pattern was significant ($p_{I1}^{tr} = 0.75$, $z = 4.11$, $p < 0.05$). In the second session, although it did not reach a statistically significant level, the prospective teachers who experienced sadness tended to switch to happy ($p_{I2}^{tr} = 0.50$) or neutral ($p_{I2}^{tr} = 0.50$). In the first session, when prospective teachers who had the emotional state of fear encountered a stimulus of discourse initiation by virtual students, they experienced disgust following the stimulus, and this pattern was statistically significant ($p_{I1}^{tr} = 0.67$, $z = 2.61$, $p < 0.05$). The pattern of transition from surprise to neutral was significant in the first session ($p_{I1}^{tr} = 1$, $z = 4.00$, $p < 0.05$). Similarly, in the second session, although not significant, a transition from surprised to neutral ($p_{I2}^{tr} = 0.67$) and happiness ($p_{I2}^{tr} = 0.33$) was experienced. In the second session, the transition pattern from disgust to sadness was found to be statistically significant ($p_{o2}^{tr} = 1$, $z = 3.74$, $p < 0.05$). Although it did not reach a statistically significant level in the first session, the individuals who experienced disgust continued to experience this feeling following the stimulus ($p_{o1}^{tr} = 0.50$) or they had a transition to happiness ($p_{o1}^{tr} = 0.50$).

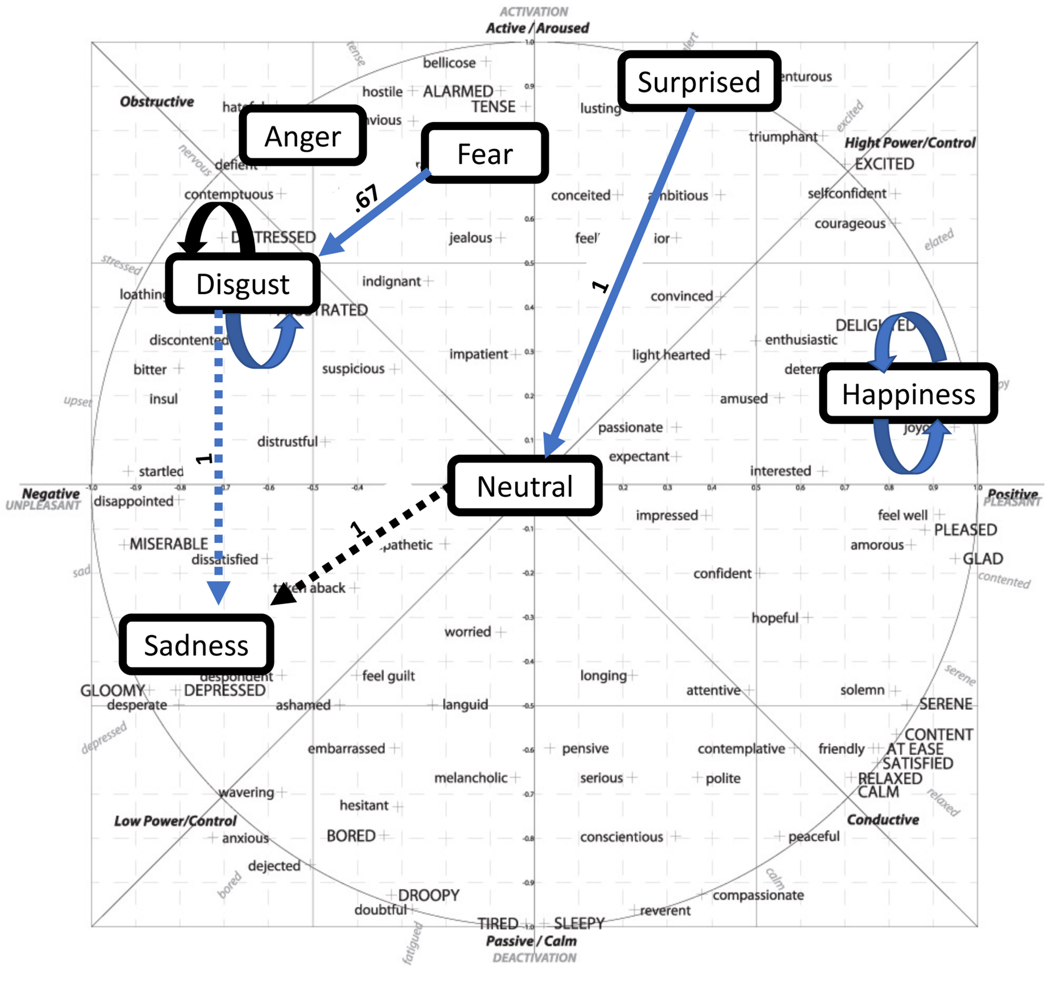

FIGURE 5 Prospective teachers' emotional patterns based on the student discourse type. Solid lines represent the first implementation, dashed lines represent the second implementation. Blue arrows indicate the stimulus type 'discourse initiation', and black arrows indicate the stimulus type 'demand'. 2-D valence-arousal circumplex model was taken from Paltoglou and Thelwall's (2013) research.

TABLE 4 Emotion transition probability matrix for discourse initiation stimulus

Transitional probability matrix	Happiness		Sadness		Neutral		Disgust		Surprise	
	I1	I2	I1	I2	I1	I2	I1	I2	I1	I2
Happiness	0.79*	0.88*			0.05	0.13	0.11		0.05	
Sadness	0.25	0.50	0.75*			0.50				
Neutral	0.75	0.20		0.20		0.20			0.25	
Fear			0.33				0.67*			
Disgust	0.50			1*			0.50			
Surprise		0.33			1*	0.67				

Note: 'I1' represents the first implementation, 'I2' represents the second implementation. Directions of the transitions are row to column.

*$p < 0.05$.

TABLE 5 Transition probability matrix for stimuli in the function of demand discourse

Transitional probablity matrix	Happiness		Sadness		Neutral		Disgust	
	I1	I2	I1	I2	I1	I2	I1	I2
Happiness	0.78	0.75		0.08	0.22	0.17		
Sadness	1							
Neutral				1*				
Disgust		1					1*	

Note: 'I1' represents the first implementation, 'I2' represents the second implementation. Directions of the transitions are row to column.
*$p < 0.05$.

Table 5 shows the transitional probability matrix of the emotions of the prospective teacher for the 'demand' discourse type. Whilst the pattern of continuing disgust after the stimulus was significant in the first session ($p_{I1}{}^{tr} = 1$, $z = 4.58$, $p < 0.05$), the transition from neutral to sadness pattern was significant in the second session ($p_{I2}{}^{tr} = 1$, $z = 2.54$, $p < 0.05$). In addition, it was seen that prospective teachers who encountered a stimulus of this function tended to show a continuity of the happiness pattern for both sessions ($p_{I1}{}^{tr} = 0.78$, $p_{I2}{}^{tr} = 0.75$). The probability of transition from happiness to a neutral state in the first session was higher than in the second session ($p_{I1}{}^{tr} = 0.22$, $p_{I2}{}^{tr} = 0.17$), although it was not seen at all during the first session, there was a possibility of transition to sadness in the second session. ($p_{I2}{}^{tr} = 0.08$).

DISCUSSION

The dominant emotions for both implementations were happiness, sadness and neutral. The least experienced emotion was anger. As a matter of fact, Bächler et al. (2018) stated in their studies with teachers that participants frequently experienced happiness and sadness during teaching. Neutral is also one of the situations frequently experienced in learning-teaching environments (ie, Han et al., 2021).

Sutton and Wheatley (2003) found that teachers frequently felt positive emotions such as pleasure and satisfaction during teaching, and teachers who failed to achieve their teaching goals experienced negative emotions such as sadness, anger and fear. Some of the teaching goals are to achieve good quality teaching, create a positive classroom climate and optimize learning. Considering that emotion is the product of a cognitive evaluation, it is thought that it is meaningful for the teacher to experience different emotions in different situations encountered during teaching. However, it is known that being aware of the emotions in the classroom and trying to reach a balance is important for teaching. The most crucial evidence of achieving balance is whether the prospective teacher has entered the reappraisal process. Emotion is a product of the cognitive appraisal process. Teachers' feelings emerge by reviewing the current conditions in the classroom, their teaching ideals, their current capacity, and their self-efficacy (Frenzel et al., 2009). The changing conditions over time are reviewed by the teacher, the reappraisal process is experienced, and a new emotional state emerges. After the use of the affective recommendation system, affect transition is examined to understand whether reappraisal occurs.

It was noted that the level of disgust felt by the prospective teachers after receiving affective recommendation decreased significantly. Disgusted individuals mostly want to get away from the things related to the goal, and their desire to reach the goal is reduced (Scherer, 1993). For this reason, it is possible to say that the use of the affective recommendation system has a triggering role in reaching the goal of the prospective teachers regarding the teaching performed in SVC.

In the second question of the study, the affect transition of the participants were examined. It was observed that the cyclical transitions of happiness, sadness, neutral and disgust were statistically significant for the first implementation. For the second implementation, cyclical transitions of happiness, sadness and neutral were statistically significant. Emotion is a phenomenon experienced from minutes to hours, changing with environmental conditions and individual evaluations. The emotion recognition system used in this study can detect the changes in a participant's emotion in a time frame of 500 msec. Considering both the sampling frequency and the nature of emotion, it is an expected and desired result that these cyclical transitions are meaningful. Similar to these results, Robison et al. (2009) found that appropriate affective intervention was effective in maintaining a positive affective state such as flow and delight. In addition to these results, studies in the literature show that the cyclical transitions of negative emotions such as boredom are statistically significant (ie, Andres & Rodrigo, 2014; Guia et al., 2013; Rodrigo et al., 2012). The critical point is that disgust's cyclical transition is meaningful in the first implementation but not in the second implementation.

On the contrary, it is noteworthy that the other negative emotion, sadness, maintains its persistence in both implementations. In the study of Guia et al. (2013), frustration persistence, which is one of the emotions in the negative value, continued to be preserved. It is thought that this situation is entirely related to the nature of emotional states. Disgust has the shortest intensity and duration among negative emotions (Brans & Verduyn, 2014). In contrast, sadness is the emotion with the highest intensity and the most extended duration, unlike disgust (Brans & Verduyn, 2014; Verduyn et al., 2011). Therefore, disgust, which has less intensity and short duration, may be manipulated by the given affective recommendation. It is also curious how the persistence of stronger negative emotions will change with prolonged use of the affective recommendation system.

In the first implementation, only the cyclical transitions were significant, whereas, in the second implementation, the transitions from neutral to happiness and from neutral to sadness were both statistically significant. This finding provides evidence that the affective recommendation is effective in two regards. First, the prospective teachers began the cognitive reappraisal process by considering the current conditions, rather than maintaining the persistence of the neutral situation. Second, after receiving the affective recommendation, the prospective teachers preferred to display their emotions, even if they were negative, rather than maintaining the neutral state. These outcomes are thought to be related to the structure of the affective recommendation given to the prospective teachers. With the recommendations provided, the aim was to encourage prospective teachers to begin the cognitive reappraisal process by evaluating the antecedents and consequences of their emotions. In fact, Frenzel et al. (2020) recommended supporting teachers in changing their emotions by means of cognitive reappraisal.

However, this finding shows that after receiving the affective recommendation, transitions both from neutral to positive valence and from neutral to negative valence occurred. In their study, Botelho et al. (2018) found evidence of a transition from neutral to frustration and boredom. Moreover, Han and colleagues (2021) found there to be a transition from neutral to delight. Neutral to positive valence transition pattern is matched with overcoming a challenge, trusting one's capacity and holding control (Anttila et al., 2017). They accepted the ascending pattern as a situation that shows that the prospective teachers are in Zone of Proximal Development. It is emphasized that it is one of the most optimal periods for new learning and skill acquisition. In addition, in some studies, it was found that participants' positive emotions increased after the affective intervention (Aslan et al., 2018), and especially low and moderate-performing individuals felt more positive after such interventions (Chaffar et al., 2009). Happiness is a discrete emotion characterized by reciprocal transmission from teacher to student (Frenzel et al., 2018). It appears that individual cognitive factors may have an effect on the transition to negative valence following the affective recommendation. For example, individuals with low meta-affective efficacy exhibit significant patterns during the transition to negative emotions (Rebolledo-Mendez et al., 2021). There are experimental studies showing that the effect of affective intervention on negative emotions was not clear (Robison et al., 2009) or that the affective recommendation had no effect on enjoyment (D'Mello & Graesser, 2012b). In addition, another study found that participants with certain personality traits experienced a transition from positive emotions to negative emotions after an affective intervention (Robison et al., 2010). Therefore, the transition from neutral to both positive and negative states after receiving an affective intervention may have resulted from the individual differences of the participants (cognitive, behavioural or personality type), the type of affective recommendation given, or the study being limited to only two sessions. Yet, it should be noted that positive emotions do not always bring about positive results, whilst negative emotions do not always lead to negative results (Pekrun, 2006). Goran and Negoescu (2015) emphasize that sometimes the negative emotions felt by the prospective teachers can be effective in having emotionally optimal conditions, improving students' learning capacity and attention.

When sequential emotion patterns are examined according to unexpected student discourse, it is noted that happy prospective teachers maintain their emotions against unexpected stimuli. However, prospective teachers in a negative valance displayed a descending pattern of activation in response to an unexpected stimulus. Although there are ascending patterns that are not statistically significant, especially for student discourse in the initiate function, it has been found that there is very little possibility of ascending patterns in the demand type. Demand-type stimuli, especially those discourses that are not related to the ongoing lesson (eg, 'Can I go to the toilet?'), may trigger negative emotions as they may be interpreted as an external obstacle to the prospective teacher in achieving their goal, as stated in the appraisal theory. The presence of the ascending patterns in the second implementation for the initiate type of discourse suggests that as the use of SimInClass and the affective recommendation system increases, the prospective teachers may shape the re-appraisal process for such stimuli.

CONCLUSIONS

Since it is known that emotion is a cognitive evaluation product, prospective teachers can experience emotions in different categories according to their individual situation, class conditions and student behaviour. However, based on the fact that positive emotions are not always adaptive (Pekrun, 2006) and negative emotions are not always incompatible, it is emphasized that it is important for teachers to try to reach a balance of emotional states in the classroom.

In this study, affect transitions were examined by giving affective recommendations to prospective teachers delivering a course in the SVC. The results show that the persistence of short-term negative emotional states, especially non-intense, such as disgust, ceases after the affective recommendation. On the contrary, prospective teachers who received the affective recommendation experienced a transition to happiness or sadness instead of remaining neutral. They preferred to express their emotions rather than suppress them. This result shows that prospective teachers entered the cognitive reappraisal process after receiving an affective recommendation. It is thought that the teacher's involvement in the cognitive reappraisal process represents the effort to reach balance. In this respect, the effect of the affective recommendation on reducing negative emotions and informing prospective teachers about the possible cognitive-behavioural outcomes of their emotions in the teaching process allows prospective teachers to discover the optimal emotional state and encourages them to reach these optimal affective conditions. Affective optimal conditions are also known to improve their teaching performances.

So far, existing studies heavily focused on affect transitions for learning. This study, however, mainly focused on the least explored phenomenon, affect transition for teaching with the participation of prospective teachers. In addition, it focuses on basic emotional states, not epistemic emotions such as confusion and curiosity. Thirdly, emotions were determined through physical (facial expression) and physiological data (EEG and GSR). Finally, the intensity, duration and antecedent of the determined emotion were presented to prospective teachers and affective recommendations were presented. In subsequent studies, it is suggested to explore the stimulus-based effects of the affective recommendation system by increasing the number of stimuli according to different types of discourse.

The affective recommendation system is promising, especially in terms of its effect on non-intense emotions and encouraging cognitive reappraisal. However, some limitations of the study should be stated. First, although prospective teachers with similar experiences participated in the study, factors such as cognitive-individual differences and past experiences were ignored. In future studies, the effect of cognitive-individual differences on emotional states and affect transitions can be investigated. Another limitation is that the experiment was conducted with a single group. The effects of the affective recommendation can be explored better by using a control group in future studies.

Finally, it should be kept in mind that teacher emotions are a factor to be taken into account in teacher education programs. In teacher education programs, prospective teachers acquire knowledge of the subject area and develop their pedagogical and classroom management skills. However, it should not be forgotten that emotions are one of the factors that affect their ability to use all the information they have acquired and to fully dominate their work.

Last but not the least, although teaching in a simulated virtual classroom cannot replace teaching in the actual environment, it is thought that the SVCs are beneficial for a few reasons. First, teacher trainees could have the opportunity to experience diverse classroom contexts in those environments. When they attend only the real classrooms, their overall experience would have been limited to what they get in the given conditions. Second, feedback and recommendations from their mentors and/or peers might not have been in depth embedded in their actions. With the help of the affective recommendations, they could have the chance to observe and reflect on how they did and felt at different parts of their classes.

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CONFLICT OF INTEREST

The authors state that they have no conflicts of interest.

ETHICS STATEMENT

This study was approved by the Ethics Boards and Commissions of Hacettepe University.

DATA AVAILABILITY STATEMENT

Researchers may contact the authors to access the data.

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REFERENCES

Andres, J. M. L., & Rodrigo, M. M. T. (2014). The incidence and persistence of affective states while playing Newton's playground. In *7th IEEE International Conference on Humanoid, Nanotechnology, Information Tech., Communication and Control, Environment, and Management*, Palawan, Philippines.

Anttila, H., Pyhältö, K., Soini, T., & Pietarinen, J. (2017). From anxiety to enthusiasm: Emotional patterns among student teachers. *European Journal of Teacher Education*, *40*(4), 447–464. https://doi.org/10.1080/02619768.2017.1349095

Arevalillo-Herráez, M., Arnau, D., Ferri, F. J., & Santos, O. C. (2017). Gui-driven intelligent tutoring system with affective support to help learning the algebraic method. In *2017 IEEE international conference on systems, man, and cybernetics (SMC)* (pp. 2867–2872). IEEE.

Aslan, S., Alyuz, N., Okur, E., Mete, S. E., Oktay, E., & Esme, A. A. (2018). Effect of emotion-aware interventions on students' behavioral and emotional states. *Educational Technology Research and Development*, *66*(6), 1399–1413. https://doi.org/10.1007/s11423-018-9589-7

Bächler, R., Pozo, J. I., & Scheuer, N. (2018). How do teachers conceive the role of emotions in teaching and learning? An analysis of the affective component of their beliefs. *Infancia y Aprendizaje*, *41*(4), 733–793.

Bakeman, R., & Gottman, J. M. (1997). *Observing interaction: An introduction to sequential analysis*. Cambridge University Press.

Barrett, L. F., Gross, J., Christensen, T. C., & Benvenuto, M. (2001). Knowing what you're feeling and knowing what to do about it: Mapping the relation between emotion differentiation and emotion regulation. *Cognition & Emotion*, *15*(6), 713–724. https://doi.org/10.1080/02699930143000239

Benjamini, Y., & Yekutieli, D. (2001). The control of the false discovery rate in multiple testing under dependency. *Annals of Statistics*, *29*(4), 1165–1188. https://doi.org/10.1214/aos/1013699998

Bosch, N., & Paquette, L. (2021). What's next? Sequence length and impossible loops in state transition measurement. *Journal of Educational Data Mining*, *13*(1), 1–23.

Botelho, A. F., Baker, R. S., Ocumpaugh, J., & Heffernan, N. T. (2018). Studying affect dynamics and chronometry using sensor-free detectors. In *Proceedings of the 11th International Conference on Educational Data Mining* (pp. 157–166).

Brans, K., & Verduyn, P. (2014). Intensity and duration of negative emotions: Comparing the role of appraisals and regulation strategies. *PLoS One*, *9*(3), 92410. https://doi.org/10.1371/journal.pone.0092410

Chaffar, S., Derbali, L., & Frasson, C. (2009). Inducing positive emotional state in intelligent tutoring systems. In V. Dimitrova, R. Mizoguchi, B. Du Boulay, & A. Graesser (Eds.), *Proceedings of 14th international conference on artificial intelligence in education* (pp. 716–718). IOS Press.

Cimtay, Y., Ekmekcioglu, E., & Caglar-Ozhan, S. (2020). Cross-subject multimodal emotion recognition based on hybrid fusion. *IEEE Access*, *8*, 168865–168878. https://doi.org/10.1109/ACCESS.2020.3023871

DeFalco, J. A., Rowe, J. P., Paquette, L., Georgoulas-Sherry, V., Brawner, K., Mott, B. W., Baker, R. S., & Lester, J. C. (2018). Detecting and addressing frustration in a serious game for military training. *International Journal of Artificial Intelligence in Education*, *28*(2), 152–193. https://doi.org/10.1007/s40593-017-0152-1

Desautels, L. (2016). *How emotions affect learning, behaviors, and relationships*. https://digitalcommons.butler.edu/cgi/viewcontent.cgi?referer=https://scholar.google.com/&httpsredir=1&article=1114&context=coe_papers

Dieker, L. A., Hughes, C. E., Hynes, M. C., & Straub, C. (2017). Using simulated virtual environments to improve teacher performance. *Journal of the National Association for Professional Development Schools*, *10*(3), 62–81.

D'Mello, S., Blanchard, N., Baker, R., Ocumpaugh, J., & Brawner, K. (2014). I feel your pain: A selective review of affect sensitive instructional strategies. In R. Sottilare, A. Graesser, X. Hu, & B. Goldberg (Eds.), *Design recommendations for adaptive intelligent tutoring systems: Adaptive instructional strategies* (Vol. 2, pp. 35–48). US Army Research Laboratory.

D'Mello, S., & Graesser, A. (2012a). Dynamics of affective states during complex learning. *Learning and Instruction*, *22*(2), 145–157. https://doi.org/10.1016/j.learninstruc.2011.10.001

D'Mello, S., & Graesser, A. (2012b). Malleability of students' perceptions of an affect-sensitive tutor and its influence on learning. In G. Youngblood & P. Mccarthy (Eds.), *Proceedings of 25th Florida Artificial Intelligence Research Society Conference* (pp. 432–437). AAAI Press.

D'Mello, S., Taylor, R., & Graesser, A. (2007). Monitoring affective trajectories during complex learning. In D. McNamara & J. Trafton (Eds.), *Proceedings of 29th Annual Cognitive Science Society* (pp. 203–208). Cognitive Science Society.

Donehower Paul, C., Bukaty, C. A., & Dieker, L. (2020). Teacher professional learning using simulation: A Delphi study. *Teacher Development*, *24*(1), 21–32. https://doi.org/10.1080/13664530.2019.1694574

Ekman, P. (1970). Universal facial expressions of emotions. *California Mental Health Research Digest*, *8*(4), 151–158.
Ekman, P. (1999). Basic emotions. In T. Dalgleish & T. Power (Eds.), *The handbook of cognition and emotion* (pp. 45–60). Wiley.
Ekman, P., & Friesen, W. V. (1971). Constants across cultures in the face and emotion. *Journal of Personality and Social Psychology*, *17*(2), 124–129. https://doi.org/10.1037/h0030377
Frenzel, A. C., Becker-Kurz, B., Pekrun, R., Goetz, T., & Lüdtke, O. (2018). Emotion transmission in the classroom revisited: A reciprocal effects model of teacher and student enjoyment. *Journal of Educational Psychology*, *110*(5), 628–639. https://doi.org/10.1037/edu0000228
Frenzel, A. C., Fiedler, D., Marx, A. K., Reck, C., & Pekrun, R. (2020). Who enjoys teaching, and when? between- and within-person evidence on teachers' appraisal-emotion links. *Frontiers in Psychology*, *11*, 1092. https://doi.org/10.3389/fpsyg.2020.01092
Frenzel, A. C., Goetz, T., Stephens, E. J., & Jacob, B. (2009). Antecedents and effects of teachers' emotional experiences: An integrated perspective and empirical test. In P. A. Schutz & M. Zembylas (Eds.), *Advances in teacher emotion research: The impact on teachers' lives* (pp. 129–152). Springer.
Goran, L., & Negoescu, G. (2015). Emotions at work. The management of emotions in the act of teaching. *Procedia-Social and Behavioral Sciences*, *180*, 1605–1611.
Guia, T. F. G., Rodrigo, M. M. T., Dagami, M., Sugay, J., Macam, F., & Mitrovic, A. (2013). An exploratory study of factors indicative of affective states of students using SQL-Tutor. *Research & Practice in Technology Enhanced Learning*, *8*(3), 411–430.
Han, J.-H., Shubeck, K., Shi, G.-H., Hu, X.-E., Yang, L., Wang, L.-J., Zhao, W., Jiang, Q., & Biswas, G. (2021). Teachable agent improves affect regulation: Evidence from Betty's brain. *Educational Technology & Society*, *24*(3), 194–209.
Hargreaves, A. (1998). The emotional practice of teaching. *Teaching and Teacher Education*, *14*(8), 835–854. https://doi.org/10.1016/S0742-051X(98)00025-0
Karampiperis, P., Koukourikos, A., & Stoitsis, G. (2014). Collaborative filtering recommendation of educational content in social environments utilizing sentiment analysis techniques. In N. Manouselis, H. Drachsler, K. Verbert, & O. C. Santos (Eds.), *Recommender systems for technology enhanced learning* (pp. 3–23). Springer.
Karumbaiah, S., Baker, R. S., & Ocumpaugh, J. (2019, June). The case of self-transitions in affective dynamics. In *International Conference on Artificial Intelligence in Education* (pp. 172–181). Springer.
Kelleci, Ö., & Aksoy, N. C. (2020). Using game-based virtual classroom simulation in teacher training: User experience research. *Simulation & Gaming*, *52*, 204–225. https://doi.org/10.1177/1046878120962152
Lasky, S. (2000). The cultural and emotional politics of teacher–parent interactions. *Teaching and Teacher Education*, *16*(8), 843–860. https://doi.org/10.1016/S0742-051X(00)00030-5
Leony, D., Parada Gélvez, H. A., Munoz-Merino, P. J., Pardo Sánchez, A., & Delgado Kloos, C. (2013). A generic architecture for emotion-based recommender systems in cloud learning environments. *Journal of Universal Computer Science*, *19*(14), 2075–2092.
Lortie, D. C., & Clement, D. (1975). *Schoolteacher: A sociological study*. University of Chicago Press.
Matayoshi, J., & Karumbaiah, S. (2020). Adjusting the L statistic when self-transitions are excluded in affect dynamics. *Journal of Educational Data Mining*, *12*(4), 1–23.
Matayoshi, J., & Karumbaiah, S. (2021, April). Using marginal models to adjust for statistical bias in the analysis of state transitions. In *LAK21: 11th International Learning Analytics and Knowledge Conference* (pp. 449–455). Association for Computing Machinery.
Merriam-Webster. (2019). Emotion. In Merriam-Webster.com dictionary. Retrieved January 19, 2019, from https://www.merriam-webster.com/dictionary/emotion
Negnevitsky, M. (2005). *Artificial intelligence: A guide to intelligent systems*. Pearson Education, Addison-Wesley.
Paltoglou, G., & Thelwall, M. (2013). Seeing stars of valence and arousal in Blog posts. *IEEE Transactions on Affective Computing*, *4*(1), 116–123.
Pekrun, R. (2006). The control-value theory of achievement emotions: Assumptions, corollaries, and implications for educational research and practice. *Educational Psychology Review*, *18*(4), 315–341. https://doi.org/10.1007/s10648-006-9029-9
Pekrun, R., & Linnenbrink-Garcia, L. (Eds.). (2014). *International handbook of emotions in education*. Routledge.
Plutchik, R. (2001). The nature of emotions: Human emotions have deep evolutionary roots, a fact that may explain their complexity and provide tools for clinical practice. *American Scientist*, *89*(4), 344–350. https://doi.org/10.1511/2001.4.344
Rebolledo-Mendez, G., Huerta-Pacheco, N. S., Baker, R. S., & du Boulay, B. (2021). Meta-affective behaviour within an intelligent tutoring system for mathematics. *International Journal of Artificial Intelligence in Education*, *32*, 1–22.

Robison, J., McQuiggan, S., & Lester, J. (2009, September). Evaluating the consequences of affective feedback in intelligent tutoring systems. In *2009 3rd international conference on affective computing and intelligent interaction and workshops* (pp. 1–6). IEEE.
Robison, J., McQuiggan, S., & Lester, J. (2010, June). Developing empirically based student personality profiles for affective feedback models. In *International Conference on Intelligent Tutoring Systems* (pp. 285–295). Springer, Berlin, Heidelberg.
Rodrigo, M. M. T. (2011). Dynamics of student cognitive-affective transitions during a mathematics game. *Simulation & Gaming*, *42*(1), 85–99. https://doi.org/10.1177/1046878110361513
Rodrigo, M. M. T., Baker, R., Agapito, J., Nabos, J., Repalam, M., Reyes, S., & San Pedro, M. O. C. (2012). The effects of an interactive software agent on student affective dynamics while using; an intelligent tutoring system. *IEEE Transactions on Affective Computing*, *3*(2), 224–236. https://doi.org/10.1109/T-AFFC.2011.41
Rodriguez, V. (2013). The human nervous system: A framework for teaching and the teaching brain. *Mind, Brain, and Education*, *7*(1), 2–12. https://doi.org/10.1111/mbe.12000
Roseman, I. J., & Smith, C. A. (2001). Appraisal theory. In K. R. Scherer, A. Schorr, & T. Johnstone (Eds.), *Appraisal processes in emotion: Theory, methods, research* (pp. 3–19). Oxford University Press.
Salazar, C., Aguilar, J., Monsalve-Pulido, J., & Montoya, E. (2021). Affective recommender systems in the educational field. A systematic literature review. *Computer Science Review*, *40*, 100377.
Santos, O. C., & Boticario, J. G. (2011). TORMES methodology to elicit educational oriented recommendations. In *International Conference on Artificial Intelligence in Education* (pp. 541–543). Springer, Berlin, Heidelberg.
Santos, O. C., & Boticario, J. G. (2012, September). Affective issues in semantic educational recommender systems. In N. Manouselis, H. Draschler, K. Verber, & O. C. Santos (Eds.), *Proceedings of the 2nd Workshop on Recommender Systems forTechnology Enhanced Learning* (Vol. *896*, pp. 71–82). http://ceur-ws.org/Vol-896/paper6.pdf
Santos, O. C., Saneiro, M., Salmeron-Majadas, S., & Boticario, J. G. (2014, July). A methodological approach to eliciting affective educational recommendations. In *2014 IEEE 14th International Conference on Advanced Learning Technologies* (pp. 529–533). IEEE.
Scherer, K. R. (1993). Studying the emotion-antecedent appraisal process: An expert system approach. *Cognition & Emotion*, *7*(4), 325–355. https://doi.org/10.1080/02699939308409192
Shu, L., Xie, J., Yang, M., Li, Z., Li, Z., Liao, D., Xu, X., & Yang, X. (2018). A review of emotion recognition using physiological signals. *Sensors*, *18*(7), 2074.
Smith, C. A., & Lazarus, R. S. (1993). Appraisal components, core relational themes, and the emotions. *Cognition & Emotion*, *7*(3), 233–269. https://doi.org/10.1080/02699939308409189
Sutton, R. E., & Wheatley, K. F. (2003). Teachers' emotions and teaching: A review of the literature and directions for future research. *Educational Psychology Review*, *15*(4), 327–358.
Tamir, M. (2009). What do people want to feel and why? Pleasure and utility in emotion regulation. *Current Directions in Psychological Science*, *18*(2), 101–105. https://doi.org/10.1111/j.1467-8721.2009.01617.x
Taylor, L. P., Newberry, M., & Clark, S. K. (2020). Patterns and progression of emotion experiences and regulation in the classroom. *Teaching and Teacher Education*, *93*, 103081. https://doi.org/10.1016/j.tate.2020.103081
Verduyn, P., Van Mechelen, I., & Tuerlinckx, F. (2011). The relation between event processing and the duration of emotional experience. *Emotion*, *11*(1), 20–28. https://doi.org/10.1037/a0021239
Yan, E. M., Evans, I. M., & Harvey, S. T. (2011). Observing emotional interactions between teachers and students in elementary school classrooms. *Journal of Research in Childhood Education*, *25*(1), 82–97. https://doi.org/10.1080/02568543.2011.533115

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APPENDIX 1. A WORKING SCENARIO

To illustrate, when a prospective teacher teaches a class in the SVC, the system collects data about their emotional states. The analysed data is presented visually in the affective recommendation system according to the options selected by the user from the 'Event' and 'Panel' sections. Figure A1 shows a graph of Course Section Related Emotions during the Speaking Event.

If the user selects the Event-Related Emotions option from the panel, he/she is informed with a text showing that his/her emotions have changed depending on the corresponding event in this process (See. Figure A2).

If the user chooses the Affective recommendation, they will be presented with texts on their three most dominant emotions they have experienced in the SVC (See Figure A3).

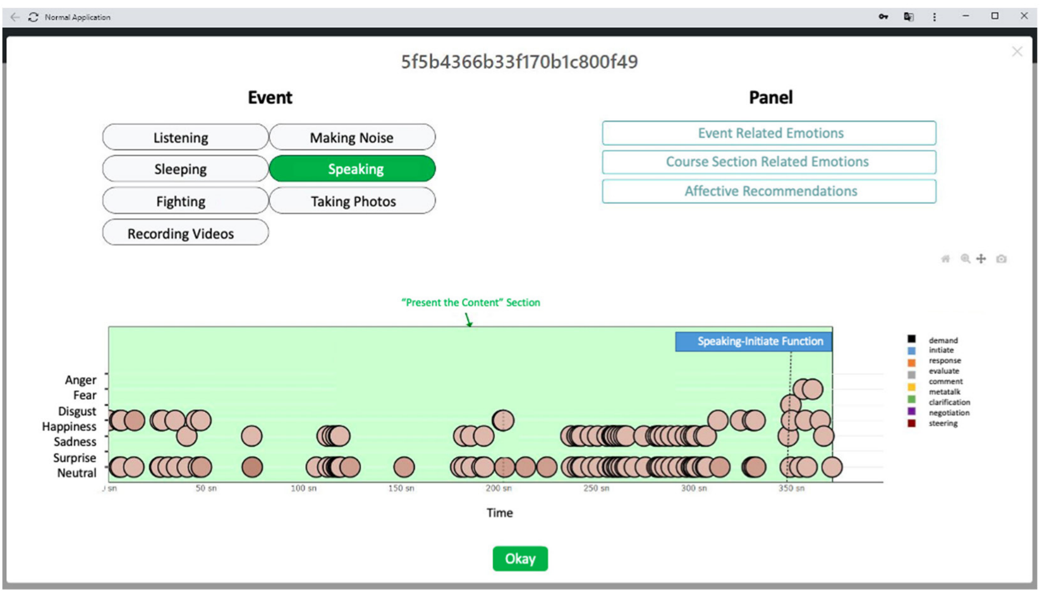

FIGURE A1 Visual representation of course section related emotions

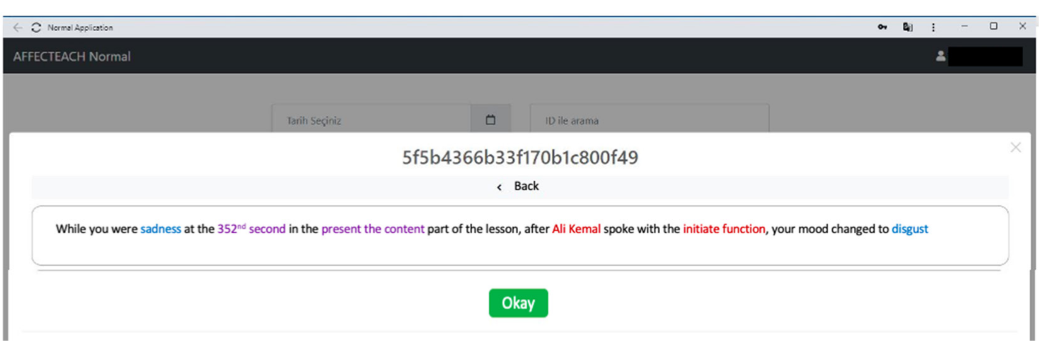

FIGURE A2 Event-related emotions

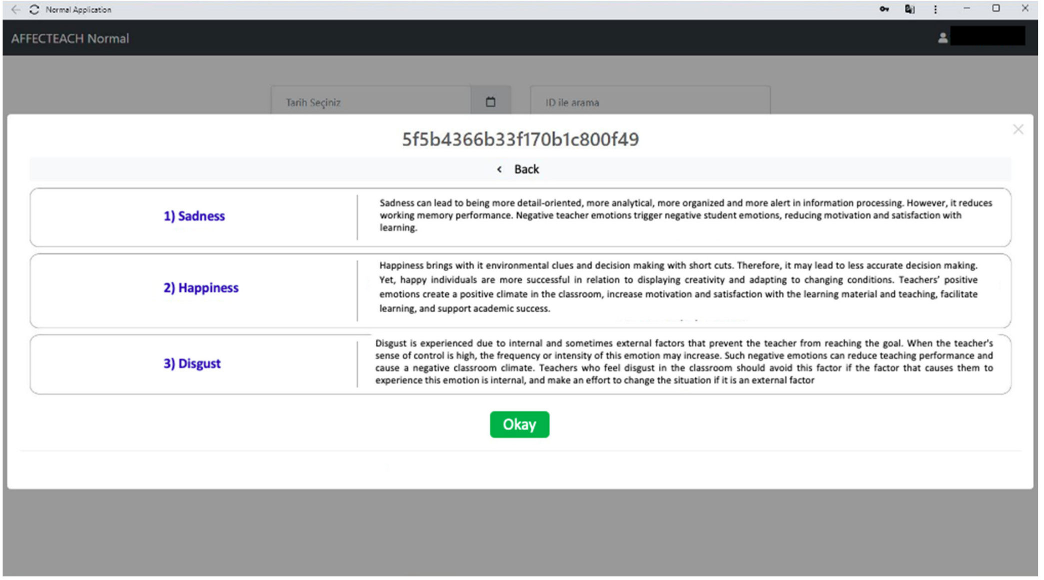

FIGURE A3 Textual view of the affective recommendations