An Adaptive Color Change of User-interface Based On User's Mood and Emotion, Using Memory-based System

Fariba Noori[1], Mohammad Kazemifard[1*], Jahangir Karami[2]

1. Razi University, Faculty of Electrical and Computer Engineering, Department of Computer Engineering, Baghe Abrisham, Kermanshah, Iran, fariba.noori70@gmail.com, m.kazemifard@razi.ac.ir
2. Razi University, Faculty of Social Science, Department of Psychology, Beheshti Blvd, Kermanshah, Iran, J.karami@razi.ac.ir

Abstract

With the increased use of computers, electronic devices and human interaction with computer in the broad spectrum of human life, the role of controlling emotions and increasing positive emotional states becomes more prominent. If a user's negative emotions increase, his/her efficiency will decrease greatly as well. The reduced effectiveness not only increases the number of errors, it may also cause great irreparable problems for professional users. Emotional control helps one avoid negative emotional states. On the other hand, with an increase in computer programs, graphical interfaces of applications play a major role in computer programs by establishing direct communication with users. Furthermore, research has shown that colors are to be considered as one of the most influential basic functions in sight, identification, interpretation, perception and senses. It can be said that colors have impact on individuals' emotional states and can change them. In this paper, by learning the reactions of users with different personality types against each color, communication between the user's emotional states and personality and colors were modeled for the variable "emotional control". For the sake of learning, we used a memory-based system with the user's interface color changing in accordance with the positive and negative experiences of users with different personalities. For evaluation and testing, we used a C++ programming language system in three different modes: (1) basic mode without any color change, (2) color change via AUBUE method, and (3) color change using the memory-based learning method. Each method was tested by 8 men and 8 women separately. In addition, this tool was used by 30 individuals for testing the third method, and one-way ANOVA was used for the data analysis. The end result of comparison of the testing methods demonstrated the superiority of memory-based learning in all three parameters of emotional control, enhancement of positive emotional states and reduction of negative emotional states. Moreover, the accuracy of memory- based learning method was almost 70 % percent. Hence, by learning about users' experiences of each color and by considering their personality, we can control users' emotional states precisely enough.

Keywords: Human-Computer Interaction, Coping Strategy, Memory-Based learning, Adaptive Color Interface, Personality

1. Introduction

Due to the extensive use of computers and electronic devices in human daily lives, the role of emotion regulation and increasing positive emotional state becomes more and more prominent. If the negative emotions of users increase, user efficiency will also decrease greatly [1]. This reduced effectiveness only increases the number of errors made by ordinary users, while it may cause irreparable problems for professional users who are responsible for sensitive tasks [1]. To enhance positive emotional states, one can control his/her emotional states and change them into positive emotional states; in fact emotional control can actually help one prevent his/her negative states[1, 2]. One of the uses of emotional control is in educational and tutorial systems [3, 4], where emotional control prevents fatigue and lack of interest in users [4].

Thus, the importance of emotional control has become more prominent with the increased use of computers and interaction of humans with computers. On the other hand, with an increase in computer programs, graphical interfaces of applications play a more significant role in computer programs due to direct communications with the users [5]. Graphical interface are considered to be one of the fundamental parts of applications for human interaction with computer [5]. Adaptable interface that can automatically change and adapt it based on its task and interaction is one of the most important topics for research [6]. Hence, excitement can be controlled by using adaptive graphical interfaces.

Colors are one of the most influential basic functions in sight, identification, interpretation, perception and senses [7]. Colors have impact on emotional states [7-9] and can change them. Bright colors like yellow and blue have positive emotional states, while dark colors like black and gray are associated with negative emotions [10]. So, one may change emotional states by using user interface color [11]. As it is possible to change emotional states using color change, we can thus control the emotional states and lead them to positive emotional states. The main hypothesis of this article is: "emotional states can be controlled through a change in the user interface color".

Some reasearchers investigate the effect color in business for example effect color on customers in restaurant, hotel or in stores and so on [12-14]. Lee et al [13] investigate tourists' emotional wellness and hotel room colour and show that calmness is the most dominant dimension of emotional wellness. In addition, their results indicated that a cool colour-themed guest room, particularly green, is preferable. The purpose of Tantanatewin et al [14] study is to explore the relationship between emotional response to interior color and restaurant entry decision. Data analysis of this study also showed that restaurant scenes with high value color and warm-tone color received higher scores for pleasure. In [12] "focused on how the effects of the novel correspondences between somatosensory and visual (warmth and color lightness) perceptions extend from the capture of visual attention to the formation of preferences, as well as on how attitudes toward sensory experiences (i.e., positive reactions to sensory experiences) play critical roles in preference formation. The results showed the existence of crossmodal correspondences between feeling warm and light colors (Study 1), and such crossmodal correspondences influenced consumers' visual attention. Physical warmth increased the visual attention directed toward light-colored goods (Study 2). Although this correspondence did not directly influence consumer preferences (Study 3), it did increase consumer preferences for light-colored goods under conditions of comfortable (but not uncomfortable) warmth (Study 4)" [12].

In this paper, we decided to learn the reactions of users with different personality types versus each color for control emotion by modeling of the communication between the user's emotional states and user personality. For this purpose, we used a memory-based system for learning and interface color changes according to the different positive and negative experiences of users with different personalities. In this paper, to evaluate we used the five-factor personality of NEO-FFI in order to evaluate personality [15]. In addition, we implemented a training tool as C ++ programming language in order to test the system.

Correct response in human-computer interaction which is based on emotions relies on two main parts [16]: (1) emotion recognition and (2) response generation. Errors made when generating an appropriate response are due to two reasons: errors arising from emotion recognition and errors made when making responses. The main purpose of this study is to make use of the correct experience-driven response in the user interface. Therefore, emotion recognition phase was removed in order to minimize the errors and the Self-Assessment Manikin (SAM) non-verbal pictorial assessment test was used to determine the emotional state [17].

The memory system is made up of two parts; episodic memory and semantic memory. Episode memory saves the details of the experienced significant events, while semantic memory demonstrates the abstract of episodic memory contents. Usable memory system has the ability to learn and will be completed as it is used more and more. The memory model used in this study is learning based on actions and emotions. But a typical learning system such as Q-learning is learning only on the basis of the best practice in a given situation. In conventional methods of learning, useful details such as the time of the action, the intensity of emotion, and the subject and object are not taken into account. In other words, Q-learning loses the details, while the memory-based learning model, which has been used in this article, is based on the details of an experience. In this study, attempts were made to control the emotional states of users and lead them to positive emotional states. In fact, for users with different personality traits, we tried to use their prior experience and select user-friendly colors as background and prevent the user from creating negative emotional states. In simple terms, commensurate with users' personality and experiences, the individuals' emotional states may be controlled through user interface color and changed into balanced and positive emotional states. One-way ANOVA analysis was used in this study for the assessment process with results revealing the significant effectiveness of the memory-based learning model.

This paper is organized as follows. First, we describe the related works. Then, we present the background of the study including the memory, personality, mood and SAM. In the fourth section, we will present the memory-

based learning and explain the details of this framework. We will then describe implementation of a C++ programming language learning tools developed to evaluate the framework, after which the results of the evaluation will be presented and the last section will deal with the conclusion.

2. Related Works

Suk and Irtel [9] performed some experiments so as to find the relation between emotional states and colors. The purpose of this article was to describe emotional responses to color perception in terms of emotional state dimensions. Finally, they proposed a table mapping colors and emotional states. Their research also showed that the color characteristics will influence the emotional states. Unlike light and chroma, hue has no effect on emotional states. The effects of personality have been neglected in the study conducted by Suk & Irtel.

OU and his colleagues [18] examined the relation between color and age. Their results showed that users' age is associated with their color preferences. They found out that older adults prefer stronger colors with more Chroma, while the younger people prefer chromatic colors. We have used a sample from a particular age range in this study in order to obtain more appropriate results.

Epps and Kaya [10] carried out some studies so as to examine emotional states as associated with colors vision. They found out that bright colors like yellow and blue are associated with positive emotions (like happy), whereas dark colors like black and gray are associated with negative emotions (like sad, anger) and yellow and red are associated with more anxiety than are blue and green.

Sokolova and colleagues [19] investigated the relationship between emotion regulation and color preference. Kurt and Osueke [7] showed that colors affect the emotional states and vice versa. The main aim of their study was to explore the effects of colors psychology on individuals. Colors may change states and are actually one of the basic functions in sight, identification, interpretation, perception and senses. They found that cold colors such as blue and green are relaxing, while warm colors which including red and yellow are energy-making.

Noori et al [20] introduced an intelligent interface named AUBUE - An Adaptive User-Interface Based on Users' Emotions- adapting its colors based on emotional states of users. In this intelligent interface, which can recognize emotions based on users' interactions through a keyboard and accordingly change the background color in such a way that it decreases the negative emotions in users. This interface consists of 4 sections: Keyboard Interpreter, Event Interpreter, Mood Update and Color Selector. Keyboard Interpreter analyzes the user's interaction with keyboard and converts them into a number of events. Event Interpreter converts keyboard events into fuzzy and then maps them onto emotions and OCC model has been used in order to use emotions. Mood Update receives the list of the active emotions and their intensity as the input, obtaining the user's current mood based on the user's current mood and emotions and sending it to Color Selector. In the Color Selector, when the user's emotional state was determined, the appropriate color mode is selected. The appropriate color for a mode is a color which overrides the current mode. They showed that the use of colors can affect controlling the emotional states, but it was confronted with some problems and effectiveness of colors was not significant. Among the problems were: 1) Low number of the recognized emotional moods, 2) lack of accuracy in the emotion recognition procedure 3) Ignoring users' personality and 4) lack of learning from users' experience.

We seek in this study to solve the problems posed by Noori et al [20] and to assess the possibility of controlling emotions by using colors. In order to solve the first and second problems, we removed the emotional state diagnostic phase and used the SAM phase instead. Users had different expectations from color change. In other words, users with different personalities expected different colors. Users with different feelings may have different color expectations. People with different personalities may react differently in dealing with a particular event [16] and each color has different impacts on different people with different personalities [21]. Some studies have also dealt with the effect of individuals' personality on their favorite colors. In fact, it can be said that the basic problem set forth in Noori et al [20] was lack of the system learning process in both interactions and choice of colors. Hence, adding the learning ability can have a significant effect on controlling emotions. So we have used in this study a memory-based learning model in order to solve the third and fourth problems by taking the user's personality into consideration.

The aim of this research is to control emotional states using learning model by taking into account the users' personalities and through the use of user interface graphic color when interacting with the software.

3. Background

3.1. Machine Understanding

The components of an understanding system and the conditions of understanding are displayed in Fig 1. An operating system A can understand the entity of B (including entity, relation and attribute) if the following three conditions are met [4, 22-24]:

1. The meta-model C exists about Bs so that it can display the knowledge of Bs and A can have access to C. Meta-model refers to the knowledge related to the entity that is to be understood.
2. System A can analyze B in order to construct D as its perception of B.
3. System A can compare B based on the meta-model C in order to produce the product of the understanding process.

Therefore, as the function analysis of the understanding system in Fig 2 shows, the understanding system has a meta-model, an analyzer and an evaluator [24]. The meta-model stores the knowledge related to B. Evaluator can compare the understanding created of B with the meta-model so that it can obtain more information about B, such as non-visible attributes, and find about how this instance of B is related to other Bs. This product of the understanding process has the following characteristics [24]:

1. It is dependent on the understanding system; that is, another system may have a different understanding of the same entity.
2. For a system A, understanding is dependent on (1) the meta-model, (2) the analyzer, and (3) the evaluator. For example, with the same meta-model, a different analyzer or evaluator may lead to a different understanding.

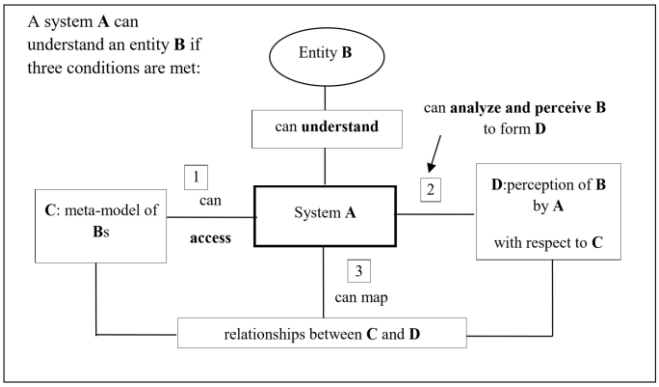

Fig 1. Elements of an understanding system (adopted from [24, 25])

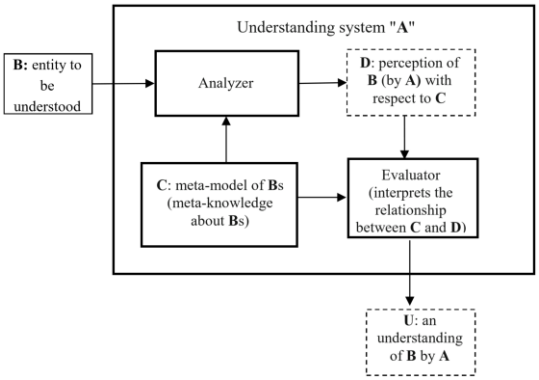

Fig 2. Functional decomposition of an understanding system. Arrows indicate information flow (adopted from [24])

3.2. Memory

Short-term memory and long-term memory are two large divisions of human memories. Short-term memory holds and keeps the experienced events only temporarily. These events are either happening at the moment or have happened just a few seconds ago [26]. Long-term memory is the same as short-term memory with the exception that it keeps events in our mind for a longer period of time (permanently). This memory can be divided into two types: declarative memory and procedural memory.

Declarative memory keeps "explicit knowledge that we can express and are aware of" [27]. Procedural memory keeps "the knowledge of how to do things that are implicit" [27]. This study has been designed and conducted based on the memory framework and system presented in Kazemifard and colleagues' paper [24]. The declarative memory, with two types of episodic memory and semantic memory, has been used in this framework. The following is a brief explanation about these memories. But for more comprehensive information, you may refer to Kazemifard's paper [24].

- Episodic memory: stores details of the remarkable experienced events
- Semantic memory: can store up general knowledge. This section of memory has not been used in this paper.
- Semantic graphs: are a kind of semantic networks displaying an abstract of the event memory contents. Semantic graph has been conceived as a component added to semantic memory and capable of learning.
- General graph: is a kind of semantic graph, which is an abstract of semantic graphs and includes general knowledge about all of the factors involved.

Since the main purpose of this study is to use experiences, only that part of memory which is capable of learning has been used in this study. In other words, the part of semantic memory of the memory model which has no learning capability has not been used in this study.

3.2.1. episodic memory

Episodic memory stores the details of the main events and consists of the following phases [26]:

1. Encoding: Encoding sends the information of an important and outstanding event into memory [28]. To determine the importance of an event, we can use the emotion intensity [29].
2. Storage: Storage refers to keeping data in memory over time [26].
3. Retrieval: This retrieves the experiences to the working memory for later use [26].

Four aspects of each experience are recorded in episodic memory to record the events (action i, type j, emotion k, and intensity). These four aspects mean that an individual with the personality type j against the background color i, has experienced the emotional state k with an intensity. In fact, this system will be able to retrieve the user's previous experiences.

The emotion intensity that a person feels during an experience can influence the retrieval of that experience from episodic memory [24]. Episodic memory can be used as a machine learning method which (1) has memory; (2) both correct and incorrect responses of the system are considered as experiences, and (3) the addition of each experience affects the retrieval of other experiences.

3.2.2. Semantic graph

Semantic graphs refer to a kind of semantic networks that display an abstract of the event memory contents. Semantic graphs are known as a component added to the semantic memory, which is capable of learning. Semantic graphs are complementary to the restrictions of episodic memory. Episodic memory retrieves the most recent experience, while the most recent experience may not be useful in the following cases:

1. When the episodic memory has several experiences for response to a request, and the most recent experience is not an appropriate response.
2. When the episodic memory has unforeseen emotional responses due to the inaccurate classifications, the changed purposes and criteria or the changed effect of events or actions on goals and criteria. These responses bring about inconsistencies in experiences.

Semantic graphs are weighted graphs in which the weights are the certainty factor. A certain semantic graph is used for each personality type. All nodes in the graph are connected to a central node. There is no edge among the nodes. We can have different semantic graphs depending on the needs of the problem. Emotions (Emotion k) in nodes, actions (action i) in edges and weights are the certainty factor (CF) of the semantic graph.

Semantic graphs allow a comparison of several candidate experiences by use of the certainty factor [30]. The certainty factor is used for false arguments. The certainty factor indicates the degree of belief that an action creates a target emotion in a kind of agent. Newness of experience and emotion intensity are used to calculate the certainty factor of the storage time, To calculate the overall certainty factor which creates a target emotional action in a personality type, you must make sure to calculate all the experiences that create an emotion in that personality type. For this purpose, Equation (1) is used.

$$CF(action, emotion) = \frac{\dfrac{\text{time of storage}}{\text{time of most recent experience}} + \dfrac{\text{intesity of emotion}}{100}}{2} \tag{1}$$

Table 1 shows an example of a number of experiences. For example, to calculate the certainty factor of experience1, we have:

CF(action_1, emotion_1) = ((50/100) + (70/100)) / 2 = .60

Equation (2) calculates the overall certainty factor that an action creates a target emotion in a type of individual. This equation uses the certainty factors obtained from Equation (1).

$$CF_{overall}(action, emotion) = \begin{cases} CF_1 + CF_2 * (1 - CF_1) & CF_1 \geq 0 \quad and \quad CF_2 \geq 0 \\ \dfrac{CF_1 + CF_2}{1 - \min\{|CF_1|, |CF_2|\}} & \begin{matrix} CF_1 \leq 0 \quad and \quad CF_2 \geq 0 \\ CF_1 \geq 0 \quad and \quad CF_2 \leq 0 \end{matrix} \\ CF_1 + CF_2 * (1 + CF_1) & CF_1 \leq 0 \quad and \quad CF_2 \leq 0 \end{cases} \quad or \tag{2}$$

Table 1. A part of episodic memory with certainty factors for the target emotion of happiness Using Equation (1), we have obtained the certainty factor of each action in creating the emotion of happiness.

Experience	Time	Action	Type	Emotion	Intensity	CF(action, joy)
1	50	1	2	1	70	0.60
2	60	1	2	1	80	0.70
3	65	1	2	1	70	0.67
4	70	3	2	7	100	-0.85
5	74	1	2	7	40	-0.57
6	80	1	2	4	40	-0.60
7	90	2	2	1	30	0.60
8	96	2	2	1	30	0.60
9	100	3	2	1	60	0.80

For example, in the following, using Equation (2), the overall certainty factor of Action 1, Action 2 and Action 3 have been calculated, creating Emotion 1 in a person with type 2:

CF(action_1, emotioin_1) = 0.75
CF(action_2, emotioin_1) = 0.85
CF(action_3, emotioin_1) = - 0.25

These certainty factors are placed in the semantic graph. Fig 3 shows the semantic graph of a person based on the experiences of Table 1. Each person has a separate semantic graph for each individual type.

When more than one action become candidates to create the target emotion, the action with the highest degree of certainty is selected. As shown in Fig 3, three actions (actions 1, 2 and 3) can create the happiness emotion in a person with type 2. Using the semantic graph, we can select an action with the highest certainty factor (Action 2).

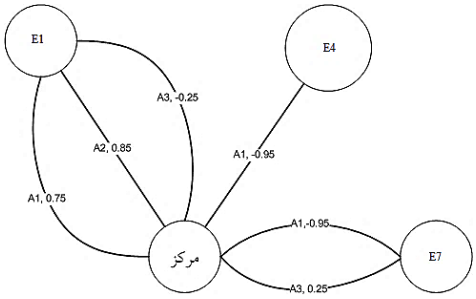

Fig 3. Semantic graph for actions 1, 2 and 3 for the Type-2 person based on experiences

3.2.3. General Graph

This graph is a kind of semantic graph which an abstract of semantic graphs and includes general knowledge about all subjects. Anderson's abstraction laws have been inspired here [24, 27]:

1. "If a fact about a concept is frequently repeated, that fact will be stored with that concept."
2. "The more frequently a fact about a concept is repeated, the more that fact is associated with that concept".

Our abstraction law for semantic graphs is that if an experience is repeated in more than half of the semantic graphs, that experience is added to the general semantic graph. Therefore, the experiences of the general semantic graph are for all types of people. For example, if more than half of the semantic graphs contain an experience that Action 1 creates emotion 1, this experience is added to the general semantic graph. This graph suggests that Action 1 may create emotion 1 in other types of people who have not yet experienced Action 1.

3.3. Personality

Personality has been defined as a set of distinct and stable thoughts, emotions and behaviors that shows our adaptation with the world. McCrae and Costa (1990) have defined the personality traits as the dimensions of individual differences in the tendency to show stable patterns of thought, feeling and action. They identified five powerful factors in understanding human personality traits [31, 32]. Based on this model, human personality was divided into five main dimensions including Extraversion, Agreeableness, Conscientiousness, Neuroticism and Openness to experiences [15, 31, 33]. These dimensions are commonly known as the Big Five personality traits and can be summarized as follow [34]:

- **Extraversion (E):** extroverts are socially-oriented, but sociability is just one of their attributes. Loving the people around, preferring large groups and conventions, being active, courageous and being too talkative are among their attributes.
- **Neuroticism (N):** a general tendency to negative emotions such as fear, sadness, confusion, anger and feeling of guilt and hatred constitutes neurosis.

- **Agreeableness (A):** the agreeable people are basically altruists, feeling compassion towards others and eager to help them and believing that others are mutually helpful.
- **Openness (O):** resilient people are curious about the inner and outer world and their life is rich in terms of experience. They are willing and eager to accept new ideas and unconventional values and experience positive and negative emotions more highly and deeply than inflexible individuals.
- **Conscientiousness (C):** purposeful conscientious people are strong-willed, determined, precise and reliable.

3.4. Mood

In fact, a person's mood is their status with higher durability than emotions and has many effects on cognitive processes and learning [35]. The PAD model has been used in this study in order to display and process a person's mood [36]. This model has defined a person's mood as their medium mental condition in different situations. The mood in PAD space has three dimensions: P (Pleasure), A (Arousal) and D (Dominance), considered to describe and measure a specific emotional response. Pleasure (P) evaluates the quality of pleasant-unpleasant emotional experience. Arousal (A) refers to physical activity and psycho-physiologic changes and Dominance (D) defines a sense of control or lack of control in a specific situation [36, 37]. Each dimension is defined as a variable that can take values between -1 to 1. If the variables are classified according to whether they are positive or negative, 8 modes can be defined in as presented in Table2. The important question raised here is whether or not these eight emotional states mutually contradict one another, the answer of which has been shown by a study to be positive [38]. These eight emotional states are in mutual conflict with one another.

Table 2. Categorization of modes based on their dimensional signs

+P+A+D = Exuberant	-P-A-D = Bored
+P+A-D = Dependent	-P-A+D = Disdainful
+P-A+D = Relaxed	-P+A-D = Anxious
+P-A-D = Docile	-P+A+D = Hostile

3.5. Self-Assessment Manikin (SAM)

Several methods have been used for detecting emotional states and have been embedded in different systems for testing [8, 39-43]. In general, three methods can be used to detect the emotional states [44]:

1. Physiological [45]: such as skin conductance, heart rate, blood pressure, electroencephalography (EEG) [46, 47], and so on.
2. Psychological: verbal description of an emotion or emotional state, standardize check list, questionnaire, and so on.
3. Behavioral: facial expression[48], and so on.

In other words, it can be said that there are two ways to tag emotional states, one is done automatically by diagnostic tools and the other is done by humans. SAM [17] is a method of tagging by humans. SAM is used more often in most automated methods so as to help one determine the accuracy of their work [1, 42, 43, 46, 47].

Self-Assessment Manikin(SAM) is a test used for evaluation of emotion with reliability coefficient ranging between 0.55 and 0.78 and the concurrent validity ranging between 0.56 and 0.78 [37]. SAM is a visual representation of the PAD dimensions developed by Lang as an alternative to self-report scales [17]. Lang developed SAM as a functional visual scale for evaluation of pleasure, arousal and dominance. Its displays in each dimension is along with a visual feature on a 5-point scale among which the respondents are to choose what they feel. SAM uses manikins for each emotional dimension in a scale. The answer to each row rates one of the three PAD variables, which can help identify an individual's emotional state. As previously mentioned, the emotion detection phase was removed so as to minimize the errors and self-assessment manikin was used instead.

4. Method

The learning based memory framework developed by Kazemifard et al [24] is presented in Fig 4. This framework includes (1) meta-model, (2) analyzer, (3) evaluator, and (4) a memory modulator. Meta-model includes episodic memory, semantic memory, semantic graph and general semantic graph .Analyzer is a perceptual categorization mechanism. Assessment provides and represents understanding of perceptions (output analyst) according to memories content (meta-model). "Memory modulator" updates memories. The following information describes the applied changes.

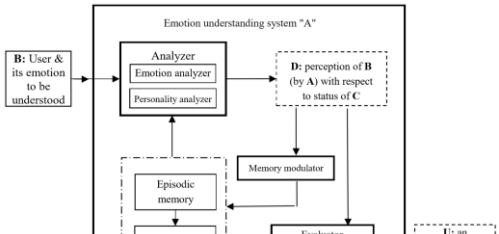

Table 3. Table of colors

P	A	D	Color
+	+	+	
+	+	-	
+	-	+	
+	-	-	
-	+	+	
-	+	-	
-	-	+	
-	-	-	

Fig 3. The framework of emotion understanding (adopted from [24]).

As mentioned above the details of the highlighted events will be saved in the episodic memory. In the episodic memory module, four aspects of each experience will be recorded (action_i, group_j, emotion k, and intensity). These four aspects mean that an individual with group_j personality in front of the background color i, has experienced the emotional state k with an intensity. In fact, using this method, this system will be able to retrieve the user's previous experiences. As mentioned previously, all memory modules presented in Kazemifard et al [24] have been used in this study. The four aspects of each experience (that will be recorded) are described in the following.

- **Action:** In this study, the operations are a set of background colors. Due to the wide range of colors, we have used color communication with emotional states in Suk et al [9]. They obtained a set of colors for every emotional state but there are different color themes in each emotional state, and from our point of view the diversity of colors in every emotional state is due to the user's personality. For elicitation of the user's feedback, the set of colors related with each emotional state is demonstrated in each emotional state. Because of the low number of colors in some certain emotional states, we made some changes in colors based on the results of the articles [7, 10] so as to improve and increase the number of colors to be chosen. At the time of testing the tools, after receiving the emotional state of the user, a set of colors associated with that emotional state is displayed and a question is asked about the color that represents that emotional state. But at the time of the test after determining the emotional state, if emotional state is positive, color selection is done according to the experience and for that positive emotional state. But when the user is in a negative emotional state, color selection will be done according to experience for the emotional state contrasting that negative emotional state, meaning that an opposite color is displayed so that it may create a positive emotional state. Table3 shows the colors used in this study.
- **Type:** In this system, persons are divided into different classes based on their differences in character. These classes help us organize the experiences based on the users' personality type. An experience about a personality type can be applied to all people with the same type of personality. As the number and degree of importance of the goals and criteria are the same (assumed for simplicity), only personality is used for classification. The classification methods have three characteristics as described in the following [24]:
    1. Accuracy: An accurate classification means that the system has the same emotions in response to the same action for two same-class persons.
    2. Dynamicity: Not all people are classified just once. Each person is classified when he or she starts working with the system. Here, the number of types is unknown and the classification method must be capable of adding new types and update the previous types by integrating two types, dividing one type into two distinct types or moving a person from one type to another. For example, not all users start to interact with an intelligent agent just suddenly in an interactive system; rather, they interact one by one. Therefore, the number of the types of users is unknown for the agent.
    3. Maintenance of the previous knowledge: When there is a dynamic classification method, the type dedicated to one user may change. If two types are integrated or a type is divided into two types, the history of the previous experiences with the previous type is lost. This feature has a relationship with dynamicity. If the classification method is dynamic, the method cannot hold the previous knowledge and vice versa.

  Considering the aforementioned explanations, the paper of [24] investigated and evaluated three classification methods. They came to the conclusion that the third method, namely the modified version of k-means has had the best result. To find the most similar persons, we have used the classification based on people's personality dimensions and the modified k-means method which has more accuracy.

- **Emotional state:** eight PAD emotional states have been used in this study, which have been explained in section's Mood.
- **Intensity:** as mentioned earlier, the intensity of the user's emotional states can influence the retrieval of an experience from the episodic memory. This is why each user is asked about the intensity of generated emotional states and will select a number in the range (0-100) as excitement intensity.

The recovery operations are also done based on the article written by Kazemifard et al [24], in which only minor changes were made. Here, when the system interacts with a user, if it has an experience about the user, it will exactly use that experience. But if the user is a new one and has not already used the system, or has had no experience about the generated state, the retrieval of experience will occur based on the memory model [24].

Emotional states (emotion_ k) in nodes, actions (action_ i) the edges and weights are certainly factor (CF) in semantic graph. Semantic graph allows us to compare some experienced candidates by using the certainly factor [24]. To calculate the certainly factor, we use saving time, new experience, and excitement intensity. For calculating the overall certainly factor, the certainly factor of all experiences that make an emotional state in an individual with a particular personality type needs to be calculated. When more than one action are present, the action with the highest degree of certainly factor is selected.

General semantic graph is also a kind of semantic graph and is actually an abstraction of semantic graphs and includes general knowledge about all human beings with different personality types. The general law of abstraction for semantic graph is that if an experience is repeated in more than half of the semantic graphs, that experience will be added to the general semantic graph [24]. Thus, semantic graph experience may be used for all types of people.

4.1. Retrieval from memory

For retrieval of actions, we have also used [24] paper along with modifications. Here, when the system is interacting with a user, it uses the same experiences that it exactly has about that user. However, if the user is new and has not previously worked with the system, or if the used does not have experiences about the created state, retrieval of experiences makes use of other methods. Different modes of memory retrieval:

1. Existence of experiences closely related to the user and the goal
    - The existence of only one experience → retrieval of the result from the episodic memory
    - The experience of several experiences → the use of semantic graph to retrieve the final result.
2. Lack of experiences closely related to the user and goal. The use of the experiences of the most similar person,
    - The existence of only one experience → retrieval of the result from the episodic memory
    - The experience of several experiences → the use of semantic graph to retrieve the final result.
3. Lack of experiences closely related to the user and the goal, and lack of experience related to the most similar person
    - The use of the general graph to retrieve the final result
    - The lack of a result from the general graph→ ask the user

5. Implementation

A C++ programming language tool was used in this study for programming learning. Nowadays, computer programs are widely used for education. This educational tool was created to learn the rules of the programming language. It is also easy to use for those who have just recently begun programming. The tool can be used by those developers who are slow at typing. The main page of tool is shown in Fig 5. In the interaction stage, the interaction of the learning system with the data users was recorded and SAM was used to record the user's emotional state (Fig 6).

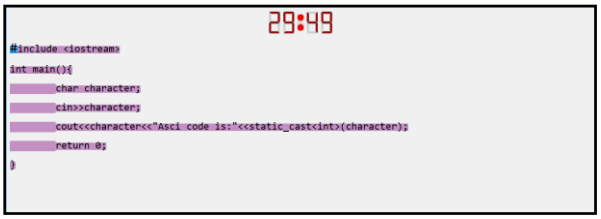

Fig 4. The main page of tool

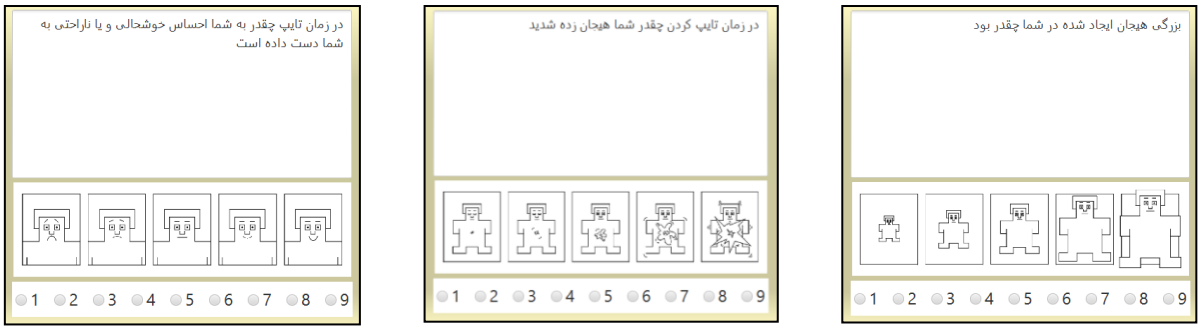

Fig 5. Self-Assessment Manikin as (SAM) non-verbal pictorial assessment test [17]

The purpose was to use a low-cost and common method for ordinary users, so only the keyboard was used to detect the emotional state. Recognizing the emotional state just through the keyboard, has lower accuracy, as shown in Noori et al [20] . By adding several parameters to the parameters used in the study [20], we sought to improve its diagnostic power. Various methods were used on the obtained data, but all had relatively low accuracy. Only one of the methods had the best results, improving the detection accuracy up to 79% through Fuzzy Mining method, with which the main problem was its not being live. In addition, the main objective of this study is to give the users an appropriate and learning-based response, and errors in diagnosis will lead to errors and inaccuracy in learning. Therefore, as previously described, the SAM was used for this purpose in this study.

In this educational tool, attempts were made to include all programming rules. In the case of a typo (typing error) made by the user, the application will warn him; for instance, when the user is typing the wrong letter, that letter will be shown in red color and bigger than the rest of the text, and the application will not allow the user to continue typing. Users' errors are notified in variety of ways, the details of which we avoid mentioning here in order to be able to explain the main stages of users' interaction with the application:

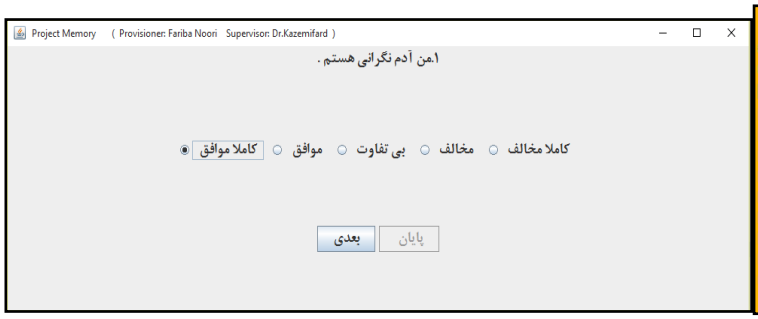

Fig 6. ask questions in the questionnaire (NEO-FFI) in tool

Fig 7. Changed background color

- **Step One- Personality Test:** First, for the user's personality detection, he/she will respond to the personality assessment questionnaire. (It shows how the questionnaire is displayed in the software item by item **Fig 7**).
- **Step Two - Classification:** Classification determines the user's personality type. This classification is used to determine the most similar people to the individual who is working with the system. This step is actually used to retrieve from memory.
- **Step Three- typing the program:** In order to get familiar with the system, the user types a short program.
- **Step Four – determining the emotional state:** by Using SAM, the user is asked about his/her emotional state.
- **Step Five – Retrieving an operation (i.e. color) from memory:** As described in the Methods section, the memory retrieves an operation and the background color will change in accordance with that color (**Fig 8**).
- **Step Six - Receiving User's Feedback:** The new program is displayed and after typing some parts of the program, the user will be asked about the background color. This process is used to receive the user's feedback and update the memory.
- **Step Seven – Updating the Model:** if the user is satisfied with the proposed colors and those colors represent his /her emotional state, the feedback will be stored, the model will be updated, and the user will continue the program. However, if the user is not satisfied with the proposed colors, and states that the presented color does not express his/her emotional state, this negative feedback will also be stored in the memory and the model will be updated. Then the user will type the program code. Upon completion of the code, the user will return to the third step so as to start typing another code.

6. Evaluation

System evaluation is done based on the user evaluation method. Therefore we used user's viewpoint for assessment in different parts. In fact, for evaluation of the memory system and assessment of the accuracy rate of the memory system's response to the gained experiences, the user is asked about how satisfied he/she is with the colors. At the end, after the user worked with the system, his/her feedback will be collected through a questionnaire. A questionnaire is used for several reasons:

1. The system is made for users and they should comment about the system and thus help the designers in the construction and designing of the system.
2. The user's structured responses to the designers' purposeful questions can be much more effective than the measurements methods which are not free from errors.
3. Instead of asking for a complex feedback from experts, ordinary users can use the questionnaire.
4. It is easier for users to compare the performance of multiple systems.
5. After working with the system, the users will respond to the questionnaire including demographic questions and also questions used in order to get feedback from users concerning emotional state control and positive and negative emotions.

6.1. Experiment

For evaluation, the tools were tested and evaluated in three different modes:

1. Base mode without changing the color
2. Color change and via AUBUE method
3. Color change by memory-based learning

Users worked with C++ programming language learning tool. The total number of users in the test was 48 people; 16 members, 8 women and 8 men tested each mode. In addition, for testing the memory-based learning method, some users needed to interact with the system so that it could collect the primitive data. 30 users, 15 women and 15 men did this. The mean age of the users in the study was 23.5 years; with SD of 2 years. Each user typed at least 6 programs in C++ language. Furthermore, each user worked with the educational tool in one of the modes of testing and evaluation. The users responded the questionnaire items after they finished working with the system.

6.2. Data analysis

In the questionnaire, the whole data were obtained via a 7-point scale [49], with 1 showing the weakest and 7 representing the highest degrees. One-way ANOVA was used to analyze the data. Analysis was done for the main hypothesis of the research, i.e. emotional control, and also a positive emotional state and negative emotional state. In fact, the emotional control should help increase the positive emotional states and decrease the negative emotional ones. Three comparisons were made in different modes for three variable of this study:

1. Comparison of the base mode with color change by AUBUE method
2. Comparison of the base mode with color change by memory-based learning model and
3. Comparison of the color change mode by AUBUE method with that by memory-based learning model.

The accuracy of memory model developed in [24] was determined but due to the changes made in the model, the accuracy parameters were measured again. In fact, we can state that accuracy is the ratio of the number of the correctly retrieved actions to the total number of the retrieval ones. Errors were determined based on users' feedbacks. In other words, the user's dissatisfaction with the presented color is considered as error, and ultimately the accuracy for the memory model was obtained 70.213.

6.2.1. Controlling the emotional states

The results of evaluating the emotional state control parameter are given in Table4. The number of participants in each method was 16, and the mean values obtained for emotional state control in the three methods were 2.94, 3.56 and 5.31 respectively. This means that the amount of emotional state control is greater for the memory-based learning model than for the other modes. Table5 shows the analysis of variance for emotional state control, which generally showed that the mean difference is significant at a significance level of 0.05 ($F_{(2,45)} = 24.250$, $P<0.001$). Table6 shows the results of the comparison of three experimental methods (base mode, color change by AUBUE mode, color change by memory-based method) in an emotional state control parameter.

Color change method using AUBUE was better than the base method but the results had not enough superiority. A comparison of the first and second methods showed that the effect of the conditions was not significant for the variable the emotional state control. The change color method using AUBUTE was shown to be better than the base method, but the results showed no considerable superiority. The results of a comparison of the first method

with the memory-based method was shown to be significant and the effect of situations was significant with effectiveness of 2.18. As a result, memory-based method is better than the base state with significant efficacy.

In addition, the result of comparison between AUBUE and memory-based method showed the superiority of memory-based method with 1.83 effectiveness. The results of the comparison showed the superiority of the memory-based learning method in emotional state control parameter over other methods with a noticeably high effectiveness.

Table 4. Descriptive table about the results of evaluation of the emotional state control parameter

	N	Mean	Std. Deviation	Minimum	Maximum
Base	16	2.94	.772	2	4
ChangeColorNoMemory	16	3.56	.512	3	4
ChangeColorMemory	16	5.31	1.401	3	7
Total	48	3.94	1.390	2	7

Table 5. The efficiency table on analysis of variance for emotional state Control parameter

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	48.500	2	24.250	25.790	.001
Within Groups	42.313	45	.940		
Total	90.813	47			

Table 2. Comparison between three experimental method results (base mode, color change by AUBUE mode, color changes by memory-based method) in an emotional state control parameter

		Mean Difference (I-J)			95% Confidence Interval	
(I) Type	(J) Type		Std. Error	Sig.	Lower Bound	Upper Bound
Base	ChangeColorNoMemory	-.625	.343	.174	-1.46	.21
	ChangeColorMemory	-2.375*	.343	.001	-3.21	-1.54
ChangeColorNoMemory	Base	.625	.343	.174	-.21	1.46
	ColorMemory	-1.750*	.343	.001	-2.58	.92
ChangeColorMemory	Base	2.375*	.343	.001	1.54	3.21
	ChangeColorNoMemory	1.750*	.343	.001	.92	2.58

*. The mean difference is significant at the 0.05 level.

6.2.2. Positive emotional state

The results of evaluation of the positive emotional state parameter are given in Table7. The number of participants in each method was 16 people, and the mean values for the positive emotional state parameter in all of the three methods were 2.94, 3.56 and 5.00 respectively. It means the amount of the positive emotional state parameter is greater for the memory-based learning model than for the rest.

Table8 shows the analysis of variance for the positive emotional state, and generally showed that a mean difference is significant at a significance level of 0.05 ($F(2,45) = 24.496$, $P<0.001$). Table9 shows comparison between three experimental method results (base mode, color change by AUBUE mode, color changes by memory-based method) in a positive emotional state parameter.

Color change method using AUBUE was shown to be better than the base method, although the results did not show considerable superiority. The compared results of base method with the third method show that the memory-based method is significant and the effect of situations was significant with 2.18 effectiveness. As a result, the memory-based method is better than the base state and had a significant efficacy.

In addition, the result of comparison between AUBUE and memory-based method showed the superiority of memory-based method with 1.73 effectiveness. The results of the comparison showed the superiority of the memory-based learning method in positive emotional state parameter over the other methods, with noticeably high effectiveness.

Table 7. Descriptive table about results of evaluation of positive emotional state parameter

	N	Mean	Std. Deviation	Minimum	Maximum
Base	16	2.94	.854	1	4
ChangeColorNoMemory	16	3.56	.629	2	4
ChangeColorMemory	16	5.00	1.033	4	7

Total	48	3.83	1.209	1	7

Table 8. The efficiency table on analysis of variance for the positive emotional state

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	35.792	2	17.896	24.496	.001
Within Groups	32.875	45	.731		
Total	68.667	47			

Table 9. Comparison between three experimental method results (base mode, color change by AUBUE mode, color changes by memory-based method) in a positive emotional state parameter

(I) Type	(J) Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Base	ChangeColorNoMemory	-.625	.302	.108	-1.36	.11
	ChangeColorMemory	-2.063*	.302	.001	-2.79	-1.33
ChangeColorNoMemory	Base	.625	.302	.108	-.11	1.36
	ColorMemory	-1.438*	.302	.001	-2.17	- .71
ChangeColorMemory	Base	2.063*	.302	.001	1.33	2.79
	ChangeColorNoMemory	1.438*	.302	.001	.71	2.17

*. The mean difference is significant at the 0.05 level.

6.2.3. Negative emotional state

The results of evaluating the negative emotional state parameter are presented in Table10. The number of participants in each method was 16 people, and the mean values for the negative emotional state parameter in all three methods were 4.50, 3.75 and 2.38 respectively. This means that the amount of negative emotional state parameter was less for the memory-based learning model than for the rest. In this variable, the lower value indicates a better result because in negative emotional state parameter, the goal is to reduce the negative emotional state.

Table11 shows the analysis of variance for the positive emotional state, and in general showed that a mean difference is significant at a significance level 0.05 ($F(2,45) = 19.561$, $P<0.001$). Table12 shows comparison between three experimental method results (base mode, color change by AUBUE mode, color changes by memory-based method) in a negative emotional state parameter.

Color change method using AUBUE was better than the base method but the results showed no considerable superiority. The compared results of base method with third method show that the memory-based method is significant and the effect of situations was significant with 1.95 effectiveness. As a result, memory-based method is better than the base state and had a significant efficacy.

In addition the result of comparison between AUBUE and memory-based method showed the superiority of memory-based method with 1.66 effectiveness. The results of the comparison showed the superiority of the memory-based learning method in negative emotional state parameter over the other methods with noticeably high effectiveness.

Table 10. Descriptive table about results of evaluation of negative emotional state parameter

	N	Mean	Std. Deviation	Minimum	Maximum
Base	16	4.50	.966	3	6
ChangeColorNoMemory	16	3.75	.683	3	5
ChangeColorMemory	16	2.38	1.204	1	5
Total	48	3.54	1.304	1	6

Table 11. The efficiency table on analysis of variance for the negative emotional state

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	37.167	2	18.583	19.561	.001
Within Groups	42.750	45	.950		

Total	79.917	47	

Table 12. Comparison between three experimental method results (base mode, color change by AUBUE mode, color changes by memory-based method) in a negative emotional state parameter

(I) Type	(J) Type	Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	95% Confidence Interval Upper Bound
Base	ChangeColorNoMemory	.750	.345	.086	-.09	1.59
	ChangeColorMemory	2.125*	.345	.001	1.29	2.96
ChangeColorNoMemory	Base	-.750	.345	.086	-1.59	.09
	ColorMemory	1.375*	.345	.001	.54	2.21
ChangeColorMemory	Base	-2.125*	.345	.001	-2.96	-1.29
	ChangeColorNoMemory	-1.375*	.345	.001	-2.21	-.54

*. The mean difference is significant at the 0.05 level.

7. Discussion

Although the findings of this research shows absolute superiority of memory-based learning model with considerable impact in all three parameters (emotional control, enhancing positive emotional state and reducing negative emotional state), there are some limitations that we aim to address in future work. First, in particular, people may need more time to get used to play with the game. As a result, a long term study may reveal more reliable results. Second, a limited number of users are used in the study that may impair the final outcome and the statistical tests. Third, using a questionnaire to measure emotional state can be problematic because the reflection of the user's emotion towards the continuous question of the system for each experience may increase negative feelings in the long term choosing an appropriate method with high accuracy in understanding the emotional states is another part of this dissertation to be dealt with in future. We are currently working on these issues that will appear in future work.

8. Conclusion

In this study, an adaptive user interface was implemented so that the user interface color will change in accordance with the user's emotion. Also, by learning about the reactions of users with different personality types against each color, communication between the user's emotional state and personality and suitable color has been modeled to control the emotions. For modeling the user’s experiences, the memory-based learning system was used.

The memory system used here includes two parts, namely episodic memory and semantic memory. Episode memory saves the details of experienced significant events, while semantic memory demonstrates an abstract of the episodic memory contents. The used Memory system is capable to learn and will be completed as used more often. NEO_FFI was used for personality assessment and the user’s point of view was also used for evaluation of the model in the form of a questionnaire.

We used C ++ programming language for the evaluation and testing. In addition, the evaluation was done in three different modes: (1) Base mode without color change, (2) Color change via AUBUE method and (3) Color change via memory-based learning. Then the three states were compared and assessed two by two. Each method was tested by 16 individuals, 8 women and 8 men. Due to having the testing phase, this tool was used in the third method by 30 people for learning. One way ANOVA test was used for data analysis. The following three Comparisons were made:

1. Comparison of the base mode with color change by AUBUE method
2. Comparison of the base mode with color change by memory-based learning model and
3. Comparison of the color change by AUBUE with color change mode by memory-based learning model.

The end result showed absolute superiority of memory-based learning model with considerable impact in all three parameters (emotional control, enhancing positive emotional state and reducing negative emotional state). Also the accuracy of the memory model was almost 70 percent.

One way to improve the effectiveness of this study is planning to produce outputs. Planning can improve the outputs of the framework. For example, if the user has the sensation of conis worried, but the system wants to show him/her to be happy, it may be necessary to run an action sequence. For example, first it guides the user towards peace, then leads him/her to happiness. This sequence will be possible through planning. Adding more planning to the framework will be dealt with in this dissertation.

As mentioned before, the reflection of the user's emotion towards the continuous question of the system for each experience may increase negative feelings in the long term. Detection of the excitement state through the keyboard, mouse, audio and video processing also has inaccuracy. Investigation on this issue will help us to make this framework more practical and use it more in applications. Choosing an appropriate method with high accuracy in understanding the emotional states is another part of this dissertation to be dealt with in future.

Use system and smartphones that have touch screens has greatly expanded. One of the most important future works of this dissertation will be use this framework in installable applications on the phones to recognize emotional state through the touch screen. In other words, by adding emotional control and using appropriate diagnostic methods, one may help improve the psychological lives of people and prevent the destructive effects of using smart devices or at least take steps towards reduction of their bad effects and better use of them. Making completely smart training tools using this framework in several areas is another part of this thesis to be done in future.

References

[1] C. Epp, M. Lippold, and R. L. Mandryk, "Identifying Emotional States using Keystroke Dynamics," presented at the In Proceedings of the 2011 Annual Conference on Human Factors in Computing Systems (CHI 2011), Vancouver, BC, Canada, 2011.

[2] K. N. Ochsner and J. J. Gross, "The cognitive control of emotion," *Trends in Cognitive Sciences,* vol. 9, no. 5, pp. 242-249, 5// 2005.

[3] M. Kazemifard and N. Ghasem-Aghaee, "Virtual Tutor," presented at the Fifteenth Conference on Electric Engineering, 2007. Available: http://www.civilica.com/Paper-ICEE15-ICEE15_260.html

[4] T. I. Ören, "Systems with Understanding Ability: Toward Advanced Agents," presented at the A series of invited doctoral lectures, University of Barcelona, Barcelona, Spain, 2006.

[5] W. O. Galitz, *The Essential Guide to User Interface Design: An Introduction to GUI Design Principles and Techniques, 3rd Edition*. John Wiley & Sons, Inc, 2007, p. 888.

[6] S. A. Tzvetanova, "A design methodology for emotional interface," PhD, Hong Kong Polytechnic University, 2008.

[7] S. Kurt and K. K. Osueke, "The effects of color on the moods of college students," *SAGE Open,* vol. 4, no. 1, p. 2158244014525423, 2014.

[8] O. Hilborn, "A Serious Game for Training in Emotion Regulation: From Design to Evaluation," 2015.

[9] H.-J. Suk and H. Irtel, "Emotional response to color across media," *Color Research & Application,* vol. 35, no. 1, pp. 64-77, 2010.

[10] N. Kaya and H. H. Epps, "Relationship between color and emotion: A study of college students," *College student journal,* vol. 38, no. 3, p. 396, 2004.

[11] P. Valdez and A. Mehrabian, "Effects of color on emotions," *Journal of experimental psychology: General,* vol. 123, no. 4, p. 394, 1994.

[12] K. Motoki, T. Saito, R. Nouchi, R. Kawashima, and M. Sugiura, "Light colors and comfortable warmth: Crossmodal correspondences between thermal sensations and color lightness influence consumer behavior," *Food Quality and Preference,* vol. 72, pp. 45-55, 2019/03/01/ 2019.

[13] A. H. Lee, B. Denizci Guillet, and R. Law, "Tourists' emotional wellness and hotel room colour," *Current Issues in Tourism,* vol. 21, no. 8, pp. 856-862, 2018/05/24 2018.

[14] W. Tantanatewin and V. Inkarojrit, "The influence of emotional response to interior color on restaurant entry decision," *International Journal of Hospitality Management,* vol. 69, pp. 124-131, 2018/01/01/ 2018.

[15] G. V. Caprara, C. Barbaranelli, L. Borgogni, and M. Perugini, "The "big five questionnaire": A new questionnaire to assess the five factor model," *Personality and Individual Differences,* vol. 15, no. 3, pp. 281-288, 1993/09/01 1993.

[16] S. Fatahi, "Design and Implementation of a Model based on Emotion and Personality in Virtual Learning," MSc Thesis, Department of Computer, University of Isfahan, 2008.
[17] M. M. Bradley and P. J. Lang, "Measuring emotion: The self-assessment manikin and the semantic differential," *Journal of Behavior Therapy and Experimental Psychiatry*, vol. 25, no. 1, pp. 49-59, 1994/03/01 1994.
[18] L. C. Ou, M. R. Luo, P. L. Sun, N. C. Hu, and H. S. Chen, "Age effects on colour emotion, preference, and harmony," *Color Research & Application*, vol. 37, no. 2, pp. 92-105, 2012.
[19] M. V. Sokolova, A. Fernández-Caballero, L. Ros, J. M. Latorre, and J. P. Serrano, "Evaluation of color preference for emotion regulation," in *Artificial Computation in Biology and Medicine*: Springer, 2015, pp. 479-487.
[20] F. Noori and M. Kazemifard, "AUBUE: An Adaptive User-Interface Based on Users' Emotions," (in en), *Journal of Computing and Security*, vol. 3, no. 2, pp. 127-145, 04/01 2016.
[21] A. Kargere, *Color and Personality*. Red Wheel/Weiser, 1979.
[22] T. I. Ören, "Understanding: A Taxonomy and Performance Factors," in *FOODSIM'2000*, Nantes, France, 2000, pp. 3-10.
[23] T. I. Ören, N. Ghasem-Aghaee, and L. Yilmaz, "An Ontology-Based Dictionary of Understanding as a Basis for Software Agents with Understanding Abilities," in *Spring Simulation Multiconference (SpringSim'07)*, Norfolk, VA, 2007, pp. 19-27.
[24] M. Kazemifard, N. Ghasem-Aghaee, B. Koenig, and T. Ören, "An emotion understanding framework for intelligent agents based on episodic and semantic memories," (in English), *Autonomous Agents and Multi-Agent Systems*, vol. 28, no. 1, pp. 126-153, 2014/01/01 2014.
[25] T. I. Ören, "Understanding Systems: A Taxonomy and Performance Factors," *Proceedings of FOODSIM*, pp. 3-10, 2000.
[26] M. Solms and O. Turnbull, *The Brain and the Inner World: An Introduction to the Neuroscience of Subjective Experience*. Other Press, 2003.
[27] J. R. Anderson, *Cognitive Psychology and its Implications* Fifth ed. New York: Worth Publishers, 2000.
[28] D. L. Schacter, *Searching for Memory: The Brain, the Mind, and the Past*. NewYork: Basic Books, 1996.
[29] P. A. Allen, K. P. Kauta, and R. R. Lord, "Emotion and episodic memory," in *Handbook of Behavioral Neuroscience: Episodic Memory Research*, vol. 18, E. Dere, A. Easton, L. Nadel, and J. P. Huston, Eds. Oxford, UK: Elsevier, 2008, pp. 115-132.
[30] E. H. Shortliffe and B. G. Buchanan, "A model of inexact reasoning in medicine," *Mathematical Biosciences*, doi: DOI: 10.1016/0025-5564(75)90047-4 vol. 23, no. 3-4, pp. 351-379, 1975.
[31] M. Gurven, C. von Rueden, M. Massenkoff, H. Kaplan, and M. Lero Vie, "How universal is the Big Five? Testing the five-factor model of personality variation among forager–farmers in the Bolivian Amazon," *Journal of personality and social psychology*, vol. 104, no. 2, p. 354, 2013.
[32] V. L. Zammitto, "Gamers' personality and their gaming preferences," Communication, Art & Technology: School of Interactive Arts and Technology, 2010.
[33] B. Ferwerda and M. Schedl, "Enhancing Music Recommender Systems with Personality Information and Emotional States: A Proposal," in *UMAP Workshops*, 2014.
[34] I. Cantador, I. Fernández-Tobías, and A. Bellogín, "Relating personality types with user preferences in multiple entertainment domains," in *CEUR Workshop Proceedings*, 2013: Shlomo Berkovsky.
[35] P. Gebhard, "ALMA: a layered model of affect," presented at the Proceedings of the fourth international joint conference on Autonomous agents and multiagent systems, 2005.
[36] A. Mehrabian, "Pleasure-arousal-dominance: A general framework for describing and measuring individual differences in Temperament," *Current Psychology*, vol. 14, no. 4, pp. 261-292, 1996.
[37] Mohammad Ali Nazari, Ghasim Nabizadeh Chianeh, Shahram Vahedi, and M. Rostami, "Validity and Reliability of Self-Assessment Manikin," *Journal of Research in Psychological Health* vol. 6, no. 2, 2012.
[38] P. Gebhard and K. Kipp, "Are Computer-Generated Emotions and Moods Plausible to Humans?," in *Intelligent Virtual Agents*, vol. 4133, J. Gratch, M. Young, R. Aylett, D. Ballin, and P. Olivier, Eds. (Lecture Notes in Computer Science: Springer Berlin Heidelberg, 2006, pp. 343-356.
[39] A. Alhothali, "Modeling user affect using interaction events," 2011.
[40] N. M. Ali *et al.*, "Exploring user experience in game using heart rate device," *Asia-Pacific Journal of Information Technology and Multimedia*, vol. 1, no. 2, pp. 28-36, 2012.
[41] C. Ennis, L. Hoyet, A. Egges, and R. McDonnell, "Emotion capture: Emotionally expressive characters for games," in *Proceedings of Motion on Games*, 2013, pp. 53-60: ACM.
[42] I. A. Khan, W.-P. Brinkman, and R. Hierons, "Towards estimating computer users' mood from interaction behaviour with keyboard and mouse," *Frontiers of Computer Science*, vol. 7, no. 6, pp. 943-954, 2013.

[43] A. Kolakowska, "A review of emotion recognition methods based on keystroke dynamics and mouse movements," in *Human System Interaction (HSI), 2013 The 6th International Conference on*, 2013, pp. 548-555.

[44] P. Zimmermann, S. Guttormsen, B. Danuser, and P. Gomez, "Affective computing—a rationale for measuring mood with mouse and keyboard," *International journal of occupational safety and ergonomics*, vol. 9, no. 4, pp. 539-551, 2003.

[45] S. Jerritta, M. Murugappan, R. Nagarajan, and K. Wan, "Physiological signals based human emotion Recognition: a review," in *Signal Processing and its Applications (CSPA), 2011 IEEE 7th International Colloquium on*, 2011, pp. 410-415.

[46] D. Oude Bos, "EEG-based emotion recognition-The Influence of Visual and Auditory Stimuli," *Capita Selecta (MSc course)*, 2006.

[47] X.-W. Wang, D. Nie, and B.-L. Lu, "EEG-Based Emotion Recognition Using Frequency Domain Features and Support Vector Machines," in *Neural Information Processing: 18th International Conference, ICONIP 2011, Shanghai, China, November 13-17, 2011, Proceedings, Part I*, B.-L. Lu, L. Zhang, and J. Kwok, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2011, pp. 734-743.

[48] C. P. Sumathi, T. Santhanam, and M. Mahadevi, "Automatic facial expression analysis: a survey," *International Journal of Computer Science & Engineering Survey*, Academic Journal vol. 3, no. 6, p. 47, 2012.

[49] R. Likert, "A technique for the measurement of attitudes," *Archives of psychology*, 1932.