

Positive Affective Learning Improves Memory

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Abstract. It is well documented that affective learning materials can impact learning process, but it is unclear that what the role of affective learning-irrelevant stimuli is. To tackle this issue, this study provided evidence that affective value of irrelevant stimuli can be transferred to learning materials and influences the learning process. Using a variant of minimal affective learning paradigm, the experiment demonstrated that only one occasion of neutral-affective pairing can lead to affective learning, and showed an advantage of positive affective learning on the improvement of face memory. Implications for the design of affective human-computer interactive system are discussed.

Keywords: affective learning, affective interaction, face learning, memory.

1 Introduction

Information technology has reshaped learning and instruction, and more and more learning activities are undergoing with interactive tutorial systems. Research has shown that users tend to interact with the virtual agents in tutorial system in the same way as they would with humans [1]. Human-computer interaction could be improved if machines can naturally adapt to their users, and response in an adaptive manner according to the users' affective state as well as cognitive state. The research on affective computing have proved that it is important to interact with emotional information involved, possibly including expressions of frustration, confusion, disliking, interest, and more [2]. Affective computing expands human computer interaction by including emotional communication together with appropriate means of handling affective information [2].

Emotional interaction is essential for emotional intelligence [3], and humans assess emotional signals from themselves and/or others, with varying degrees of accuracy. The goal of affective computing is to give computers skills of emotional intelligence, including the ability to recognize and express emotion as a person might [4]. Researchers in educational technology field had make great effort to make the educational systems more customized for the affective states of the learners [5]. Emotional interaction is especially important for learning system, given that emotions are well known to play significant role in learning. During the learning activities, humans tend to generate affective experiences, and emotions permeate educational contexts and

affect everyone in the learning process [6]. On the one hand, the user will feel a number of emotions during their interaction with this kind of system. For example, the user may enjoy the learning process when he/she thinks the system is helpful, or become frustrated when her/his expectations are not satisfied. On the other hand, emotional outcomes of learning will play a highly important role in learning performance. For example, negative emotions experienced by the user can affect their perception of the interface, and prevent them from concentrating on and remembering information [7], and, thus, lead to lower learning performance.

However, not only can the learning outcomes, but also the affective aspects of the system interface lead to affective processing, e.g., the virtual emotional behavior and affective characteristics of the agents. During social communication in reality, we pay attention to not only the biological characteristics of the communicators, such as one's age, gender, race and so on, and also social aspects of the persons, such as emotional state and attractiveness. These sorts of information can bias our social behaviors as well as cognitive process in social communication. For example, teachers may show different emotions ranging from anxiety to joy and pride in the classes, and both teaching and learning involve emotional understanding [8]. Thus, teaching is a form of emotional behaviors, and teachers' emotion may play an important role in interactions in classroom and learning performance [8]. By being impolite in online system, virtual agents are not viewed as technologically deficient, but they are more likely believed as humans by the users. Therefore, the virtual emotional behavior of the agents is also very important for the interaction during learning, and might have a significant impact on learning performance [9].

Although it has been evident for the relationship of virtual emotional behaviors and learning, it remains unclear whether the affective characteristics of the agents also impact learning. In a recent study, Plass et al. (2014) provided evidence in support that the affective design of multimedia learning materials can be used to foster positive emotions, and such positive emotions can facilitate learning [10]. They found that round face-like shapes both alone and in conjunction with warm color induced positive emotions; and comprehension task was facilitated by warm colors and round face-like shapes, independently as well as together, and transfer learning was facilitated by round face-like shapes when used with neutral colors. Magner et al. (2014) found the affective interface design, e.g., learning-irrelevant decorative illustrations, can foster learning for near transfer for those students with high prior knowledge [11]. It was suggested that affective decorative illustrations might foster situational interest and, thus, ease the learner's focusing of attention and reducing effort of cognitive activation. These results suggest that affective characteristics of the learning system interface can impact learning. Thus, it is reasonable to postulate that affective characteristics of virtual agents can also impact learning.

Nevertheless, irrelevant affective decorative illustrations can also hinder learning (e.g., near transfer) [11]. To interpret this fact, it was suggested that decorative illustrations can be considered as seductive details that require investment of cognitive resources that might then not be available for processing essential information. Mayer et al. (2005) suggested that cognitive resources during learning may be available as a result of optimized design of the learning environment [12]. This is a cognitive

account, but not affective account. Thus, although it is evident that affective value of learning materials can impact learning process [10], it is unknown that whether this is the case for affective values of learning-irrelevant stimuli (e.g., decorative illustrations).

It has been well documented that affective stimuli are more efficiently encoded, consolidated, and retrieved than neutral stimuli [13-14]. In this line of study, memory for faces is a crucial topic for psychology and social science since the processing and the encoding of emotional signals conveyed by faces is used to form impressions, to evaluate the intentions of others and to adapt future behavior [15]. The affective characteristic of face (e.g., facial expression and attractiveness) is also proved to play a key role in affective and social behavior as well as facial encoding and recognition memory.

Apart from the affective characteristics conveyed by face, the individual behavior description [16] can be also affective. Those affective personal descriptions and faces integrate together will become a unify characterization in memory. For example, neutral face will be impressed as more attractive if it has been associated with positive trait (e.g. honest) [17]. However, it is unknown whether face memory is influenced by paired irrelevant affective information during learning phase.

Research on affective learning has accumulated evidence that affective values of learning-irrelevant stimuli can be transferred to neutral learning materials. That is, when the neutral learning contents are accompanied with emotional context, they may acquire affective value via affective learning process [18]. There is accumulating evidence that people can learn the affective value of individuals from detailed behavioral descriptions of those targets. However, it remains unclear how the transferred affective value influence learning process. The present study was to tackle this issue and investigated the mechanism of affective learning effect on memory using simple affective stimuli. In this study, face learning task was used as an analogous task to simulate the role of learning-irrelevant affective characteristics of virtual agents in learning. We used face encoding as learning task, and face recognition memory as learning performance.

2 Method

2.1 Participants

Eleven undergraduates (6 males and 5 females, the average age is 21.9 years ($SD = 2.1$)) participated in this experiment for a small payment. All had normal or corrected-to-normal vision. Participants in the experiment were naive about the purpose of the study.

2.2 Stimuli

Forty photographs of Chinese faces taken by the researchers were used in the face learning task (20 for learning targets and 20 for distractors). Half of the photos were male faces. Each photo shows a close-up full face with a neutral expression. The face

covers approximately 80% of the photo, posed against a plain light-colored background. The size of each photo is 220×300 pixels and results in a visual angle of 5.3°×12.6° at the distance of about 60 cm. Each photo was assigned a unique name, occupation, and residence (i.e., a city/town and a state/province of participants' residence). The names were randomly selected from telephone books. All names contain three characters.

2.3 Design and Procedure

It was a one-factor design with affective valence (positive, negative) of the trait descriptions as within-participant variable.

A variant of the minimal affective learning paradigm (Bliss-Moreau et al., 2008) was introduced. The stimuli were presented on a 17" computer monitor with an E-prime program. The experiment consisted three phases: learning phase, filling phase, memory test phase and affective evaluation phase. Four practice trials were provided before the actual encoding task to familiarize participants with the task.

During the learning phase, participants viewed 20 sequentially presented face-sentence pairs for 5 s and were told to learn and remember the pictures. Each of the twenty target faces was paired with a unique descriptive sentence that was positive or negative in affective tone. The descriptions are sentences introducing the name, the occupation, the residence of the person in each photo, and whether s/he is a good/evil person. Each trial started with a centered fixation cross for 1000 ms, then replaced by a photo presented for 5000 ms, along with a simultaneously presented description below it. A 1000-ms blank screen was presented as an inter-stimulus interval before proceeding to the next trial.

During the filling phase, participants completed some unrelated arithmetic tasks for 5 min to prevent rehearsal.

During the memory test phase, the 20 target faces in learning phase and 20 novel faces were sequentially presented. Each trial started with a centered fixation cross for 1000 ms, followed by a photograph. The photo was terminated by a key press response before moving to the next trial. Participants were asked to judge whether the face was old one in the learning phase.

During affective evaluation phase, the 20 target faces in learning phase and 20 novel faces were sequentially presented again. Participants were told to make two judgments: valence categorization task and liking rating task. Each trial started with a centered fixation cross for 1000 ms, followed by a photograph. Participants were asked to judge whether the face was positive, neutral, or negative and how s/he likes the picture based on a 5 points scale.

3 Result and Discussion

3.1 The Affective Learning Effect

The valence categorization results are shown in Figure 1. A repeated-measures analysis of variance (ANOVA) showed that more faces were categorized as negative when paired with negative information ($F(2, 20) = 6.65, p < .01$), whereas more faces were

categorized as positive when paired with positive information ($F(2, 20) = 4.42, p < .05$). These results confirmed that participants learned affective value for neutral faces only with one occasion of pairing, contrast to two or four occasions of face-sentence pairs in the original minimal affective learning paradigm [18], and suggested that affective learning is a robust phenomenon.

The liking rating results are shown in Figure 2. A repeated-measures analysis of variance (ANOVA) showed that liking score for faces paired with positive information were higher than for faces paired with positive information and new faces ($F(2, 20) = 6.87, p < .01$). This result suggested that the learned positive affective value for neutral faces evoked a more positive affect.

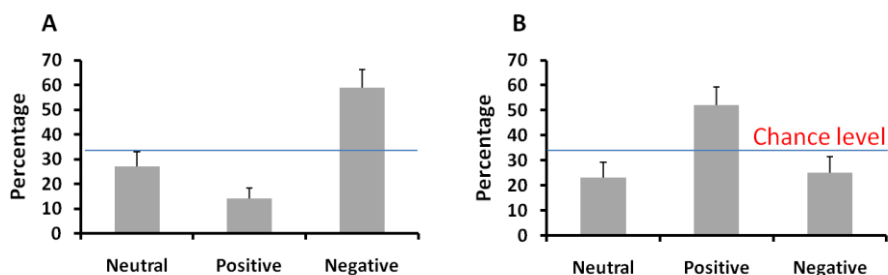


Fig. 1. Affective categorization for faces paired with negative (A) and positive (B) information

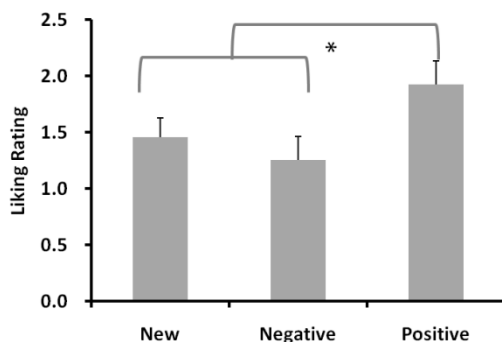


Fig. 2. Affective evaluation scores for new faces and old faces paired with negative and positive information

3.2 The Impact of Affective Learning on Recognition Memory

The old/new judgment data are shown in Figure 3. A repeated-measures analysis of variance (ANOVA) showed that faces paired with positive information are better recognized than with negative information ($F(1, 10) = 8.53, p < .05$). This result provided evidence that affective learning do influence the learning performance. Although the accompanied sentence might induce unnecessary processing demands and

distract from learning [12], our result suggested that it is also possible to evoke positive affect, which may, in return, reduce or cancel the additional effort of cognitive activation [19].

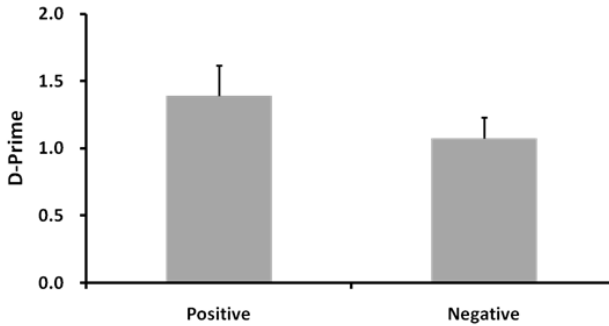


Fig. 3. Recognition memory for faces paired with negative and positive information

3.3 Implications of the Present Study

We found that affective learning occurred for faces paired with affective information, and positive affective learning may improve the learning performance, compared with negative affective learning. Furthermore, only one occasion may be very common for the human-computer interactive system. In fact, multimedia learning materials may be designed to associated with affective values (e.g., warm color [10]), and the interface design of learning system can be served as affective companion of the learning materials (e.g., decorative illustrations [11]). In these settings, the learning materials is always paired with affective stimuli, and affective learning is very possible to occur and influence the learning performance. Therefore, affective learning should be taken into account in the interactive system involving human learning.

In human-computer interaction, each main event will be subjectively evaluated by the user, depending on whether the event represents progress or an obstacle towards his or her aims, as appraisal theories imply [20]. The present study provided further evidence that affective context of the event and/or system reactions may also play a highly important role in emotional and learning outcomes. This implication has potential significance to improve several aspects of the interaction such as the interface design, user perception, and task performance. Under affective context, the users may be more stimulated and engaged in the interaction, and can better understand and memorize information because the attention can be modulated by the affective context.

To make machines naturally adapt to their users according to the users' affective state, research on affective computing has focused largely on algorithms that can recognize the affective state of the users. However, Virtual agents that learn naturally from interacting with human may be more essential [21]. According to the finding of this study, affective agents may be served as affective context to modulate the users'

learning. In fact, the use of animated pedagogical agents with emotional capabilities in an interactive learning environment has been found to have a positive impact on learners [22]. Further work may focus on modeling of the affective preferences of the user, the user's emotional response to the interactive interface and agent, as well as the personality and affective responses of the agent to the individual user, and how it will benefit learning performance. It is important that theories and models should concern affective and cognitive mechanisms used in human computer interaction.

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