A Computational Model to Determine Desirability of Events Based on Personality for Performance Motivational Orientation Learners

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Abstract. One of the most important discussions in artificial intelligence is the modeling of human behaviors in virtual environments. The factors such as personality, emotion, and mood are important to model human behaviors. In this paper, we propose a computational model to calculate a user's desirability as one of the most important factors which in determining the user's emotions. The main purpose of this research is to find a relationship between personality and emotion in virtual learning environments. The model has been evaluated in a simulated virtual learning environment and the results show that the proposed model formulates the relationship between personality and emotions with high precision.

Keywords: Personality · Emotion · User's status · Desirability

1 Introduction

The goal of Human Computer Interaction (HCI) is to make computing systems more useful and usable. To achieve this goal, computer interfaces should be able to recognize and track users' behaviors (Zeng et al. 2009). Identifying a user's status enables machines to understand his/her needs and react to them accordingly (Trabelsi and Frasson 2010). Until now, several studies have been carried out to consider human characteristics in human computer interaction. Rosis and his colleagues (2003) implemented a 'realistic' 3D embodied agent called Greta. The affective components of personality and emotions were located in the agent's mind component. This component simulated how emotions are triggered and decayed over time based on the agent's personality. Egges and his colleagues (2004) implemented a generic model for personality, mood, and emotions in a conversational virtual humans. The model could update the emotion and mood considering the history of emotion and mood using linear regression. Also, Mehdi and his colleagues (2004) attempted to develop a model that comprises emotion, mood, and personality factors. The model considers personality as a parameter that defines the threshold of the appearance of emotions and mood as a filter for moderating the intensity of the emotions. They applied the model in a virtual reality training

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tool for firemen. The results show that the fireman agent can reproduce the stress emotion felt in a real emergency fire incident. Moshkina (2006) presented an integrative behavior framework for affective agent called TAME. TAME combined personality traits, attitudes, mood, and emotions to generate affective behaviors. Moshkina evaluated the TAME framework in a human-robot application. The results show that affective behavior provides many benefits such as ease of use and pleasantness of interaction. In 2008, Dang and Duhau (2008) proposed a generic model called GRACE (Generic Robotic Architecture to Create Emotions). They combined the OCC model and Lazarus-Scherer theory for its emotion component, and used MBTI for its personality component. In this model, the intensity of an emotion is related to the personality type. Fatahi and her colleague (2010) designed a model of personality and emotion that was used in an E-learning framework. The results of the model evaluation showed that the presence of the intelligent agents with same features as humans increases the learning rate. Santos and his colleagues (2011) used artificial intelligence agents that have personality, emotion, and mood in a group decision-support system. Their goal was to improve the negotiation process through argumentation using the affective characteristics of the involved participants. Kazemifard and his colleagues (2011) presented a new computational emotional model that maps the environmental events and agents' actions into emotional states to generate human like decision-making behavior. Hwang and Lee (2013) used Fuzzy Cognitive Map (FCM) to represent causal relationships between a user's personality and the target system. They ran several scenarios in which they showed that a user's personality has relation to the personality of the target system. In addition, FCM helped them to predict a human's personality but they didn't consider the human's emotion.

It could be observed that all of the recent researches focus on modeling the emotion and personality in artificial intelligence agents by using FFM as a personality model. Most of previous studies did not use computational modeling in their researches, however there was some studies which used the computational modeling, but they was not able to identify and predict user's neither the emotion nor personality.

The novel contribution of this study is in proposing a computational model to predict users' emotions based on his/her personality. We presented and evaluated this computational model, which uses the OCC and MBTI models, in a virtual E-learning environment which showed desirable performance.

2 Psychological Principles

2.1 Emotion

Many studies have proven that emotion affects reasoning, memorizing, learning and decision-making (Damasio 1994; Chaffar et al. 2007; Kort and Reilly 2001). Also, these studies show that the learner's emotional state influences his/her performance and it is an important factor in learning environments so should be considered in user modeling (Chaffar and Frasson 2004).

There are many psychological model for emotion modeling in computer science. One of the most famous of these is the OCC model (Ortony et al. 1988) that is employed in many studies. It is a computational emotion model that applied in artificial characters. The OCC model has three branches. The first branch includes the emotions which are consequences of the events faced. These consequences are obtained according to the desirability or undesirability level of the events compared to the agents' goals. The second branch includes the emotions that are results of agent actions based on approving or disapproving relative to a set of standards. The third branch consists of emotions that are the consequences of the agent's which either like or dislike his/her goals compared to the agent's position and attitude. The OCC model calculates intensity of emotions based on a set of variables. The variables are divided into two groups: global and local. One of the most important variable to calculate first branch emotions is desirability. In this research we use the OCC model and we try to calculate desirability variable based on finding its relationship with personality dimensions.

2.2 Personality

Personality comprises thoughts, feelings, desires and behavioral tendencies that exist in every person (Hartmann 2006). Each psychologist presents a different classification of personality based on his/her research. Jung's type theory specifies three dimensions: Extraversion/Introversion (E/I); Sensing/Intuition (S/N) and Thinking/Feeling (T/F). In 1920, Kathrin Briggs and Isabel Myers Briggs (Schultz and Schultz 2008) added another dimension to Jung's typological model and presented the MBTI personality model. A further fourth dimension is Judging/Perceiving (J/P) (Pittenger 1993). MBTI uses four two-dimensional functions based on Jung's theory. Sixteen personality types result from mixing four two-dimensional functions. For example, people in ESTJ group are all extravert, sensing, thinking, and judging. Based on MBTI theory, every person has instinctive priorities that specify his/her behavior in different conditions (Retrieved from http://www.myersbriggs.org/my-mbti-personality-type/mbti-basics/). Although there are many models of personality in the literature, MBTI is the best-known tool used to determine personality. According to the Center for Applications of Psychological Type, MBTI is the most commonly used personality inventory in history; approximately 2,000,000 people use MBTI for their personality detection every year. Moreover, the validity of the MBTI model has been widely recognized (Kim et al. 2013). Also, MBTI is the most popular method to specify the personality type in learning environments especially in E-learning environments (Hall and Moseley 2005; Niesler and Wydmuch 2009; Haron and Salim 2006). Since we design our model in a virtual learning environment, it seems that MBTI is the best choice.

3 The Proposed Model

In this paper, our focus is on designing a computational model that identifies a user's status based on factors which include personality and emotions. It is noteworthy that people with different personalities express different emotions to deal with an event. Figure 1 shows the general view of the model showing the relationship between personality dimensions and emotion.

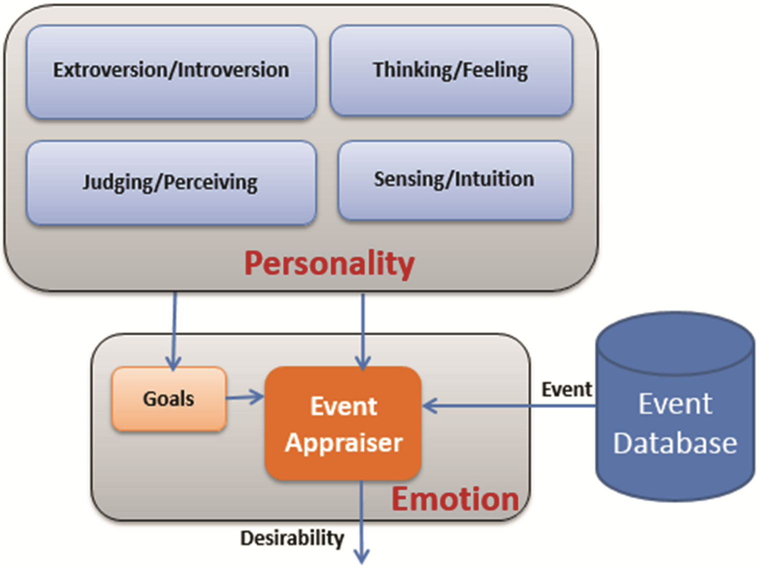

Fig. 1. General view of the proposed model

The personality module includes four dimensions of MBTI that generate sixteen personality types which influence emotions. The relationship between personal goals and personality (Reisz et al. 2013; Salmela-Aro et al. 2012) is used to model the impacts of personality on emotions. This module helps us to determine a user's personality and her/his goals based on the personality.

The emotion module is based on the OCC model in which the consequences of events are obtained according to the desirability or undesirability level of the events considering the users' goals. The event database includes many events that happen which affect users' emotions.

3.1 Calculating Desirability

To calculate desirability of an event, the following steps should be taken:

- Determine the user's personality
- Determine the user's goals based on his/her personality using the MBTI model
- Determine the importance value, i.e. the weight, of the user's goals
- Determine the relationship between personality type of the user and the event
- Determine the relationship between events and goals

In this method, the goals and their importance are shown as vectors named Goals and G, respectively (Eq. 1):

$$\text{Goals} = \begin{pmatrix} \text{Goal}_1 \\ \text{Goal}_2 \\ \ldots \\ \text{Goal}_n \end{pmatrix}, \; G = \begin{pmatrix} g_1 \\ g_2 \\ \ldots \\ g_n \end{pmatrix} \qquad \forall i \in [1, n], \; gi \in [0, 1] \tag{1}$$

In which, g_i is the importance of Goal_i. To show the impact of events on goals, an Impact matrix is used. Each element of the impact matrix is the impact degree of the i_{th} event on the j_{th} goal; where m is the number of events and n is the number of goals (2):

$$\text{Impact}(e_i, g_j) = \begin{pmatrix} \alpha_{11} & \alpha_{12} \cdots & \alpha_{1n} \\ \alpha_{21} & \alpha_{22} \cdots & \alpha_{2n} \\ & \cdots & \\ \alpha_{m1} & \alpha_{m2} \cdots & \alpha_{mn} \end{pmatrix} \tag{2}$$

The desirability of each event can be computed as follows (Eq. 3):

$$\text{Desirability}(e_i) = \frac{\sum_{j=1}^{n} \alpha_{ij} g_j}{\sum_{j=1}^{n} g_j} \; \forall j \in [1, n] \; and \, \forall i \in [1, m] \; \text{Desirability}(e_i) \in [-1, 1] \tag{3}$$

3.2 E-learning Environment Example

To show the effectiveness of the proposed model, we applied it to an E-Learning environment. A few events and goals in an E-Learning environment are considered and the model is used to predict students' desirability.

To determine the goals, we used Ames (1990) theory in which students are divided in two groups: mastery motivational orientation and performance motivational orientation. In this study, we have focused on performance motivational orientation group. When students have performance motivational orientation, they believe that performance is important and want to show that they have abilities. They feel successful when they please their teacher or do better than other students, rather than when they learn something new. When these students experience difficulty, they are not likely to increase their effort because this shows lack of ability. As they are primarily motivated by extrinsic factors (grades, parent approval, etc.), they are also called extrinsically motivated. There are three goals for performance motivational orientation students. These include: please the teacher and parents, do better than other colleagues, and show a high-level of competence.

To determine the relationship between personality and goals, we used MBTI studies to define a mapping between MBTI personality types and these goals (Durling et al. 1996; Higgs 2001; Jessee et al. 2006; Vincent and Ross 2001). In general, ENFJ, ESTP, ESFJ, ENFP and ISFP types include goals that cover the goals for performance motivational orientation in learning environments (Table 1).

Table 1. Relationship between MBTI Personality types and Goals in learning environments

Personality	Please the teacher and parents	Do better than other colleagues	Show that has a high level of competence
ESFJ	✓	-	-
ENFP	-	-	✓
ESTP	-	✓	✓
ENFJ	-	✓	-
ISFP	✓	-	-

As mentioned before, people with different personalities show different emotions in facing an event so that each event has a different degree of impact on each personality. To test our model, five events are considered. In addition, based on experts' recommendation, that the influence of each MBTI dimension on each event is defined (Table 2).

Also, based on the expert's knowledge we determined the relationships between the students' goals and personality dimensions (Table 3).

Table 2. Relationship between MBTI dimension and events in virtual learning environments

Event	E/I	T/F	S/N	J/P
Provide a correct response to the exercises	–	T	–	–
Finish the proposed activities	–	–	–	J
Receive appreciate help	E	–	–	–
Do not ask for help	I	–	–	–
Low effort	E	–	–	–

Table 3. Relationship between MBTI dimension and students' goals

Goals	E/I	T/F	S/N	J/P
Please the teacher and parents	–	F	–	–
Do better than other colleagues	–	–	N	–
Show that has a high level of competence	–	–	N	–

Finally, we designed a cognitive map to show the relationship between events, user's goals, user's personality and emotions variable in virtual learning environments (Fig. 2).

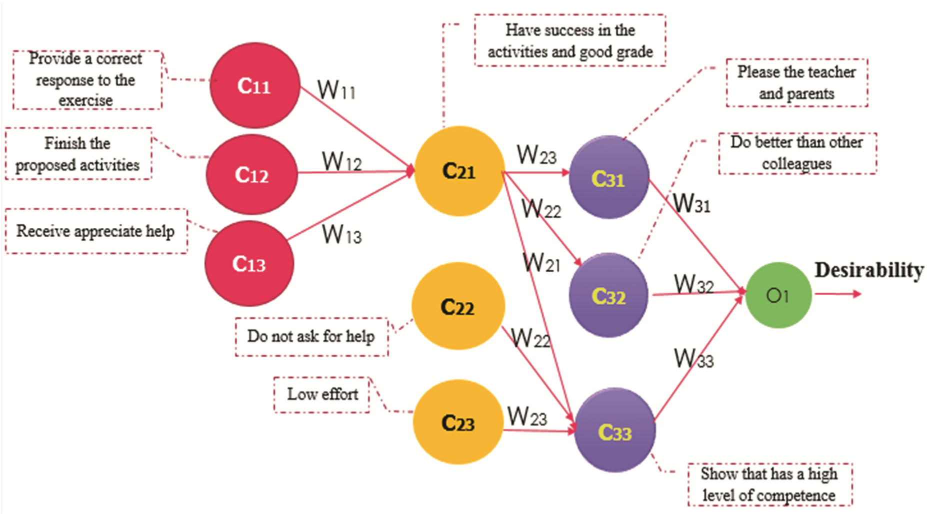

Fig. 2 The cognitive map in learning environments

Based on Fig. 2, desirability of a user is calculated according the following (4) and (5).

$$C_{21} = \sum_{i=1}^{3} C_{1i} * W_{1i},\ C_{31} = C_{21} * W_{23},\ C_{32} = C_{21} * W_{22},\ C_{33} = \sum_{i=1}^{3} C_{3i} * W_{3i} \quad (4)$$

$$\mathrm{O}_1 = \sum_{i=1}^{3} C_{3i} * W_{3i} \quad (5)$$

4 Results

To evaluate the proposed model we simulated a virtual learning environment which includes 580 agents with different personalities (ISFP, ESTP, and ESFJ with 118 agents each, 115 agents with ENFP, and 111 agents with ENFJ personality type). The agents have different goals based on their personality types and different level of knowledge which is set randomly based on a normal distribution. The five mentioned events happen randomly in the simulated environment and the agents respond to them and their emotion changes accordingly. An agent's response depends on its knowledge and personality. The simulated environment records the desirability of the agents based on Eq. 4. Also, the level of desirability for each agent is labeled by an expert. Finally, the weights of the cognitive map (Fig. 2) are learned from these data for each personality type. Weight of each layer are reported in Table 4. According to our proposed model, we expect weights with positive or negative values for each personality. For example in the ESFJ case, we expect weights which are related to E, F and J to be positive and weights which are related to T and N dimensions to be negative. Table 5 shows the accuracy of the weights for each type of personality based on our expectation.

Table 4. Weights of cognitive map for evaluating the proposed model

Personality	Weights of Layer 1	Weights of Layer 2
ESFJ	W11 (Thinking) = −1.25 W12 (Judging) = 0.24 W13 (Extroversion) = −0.68	W23 (Feeling) = −0.32 W22 (Intuition) = −1.06 W21 (Intuition) = −1.11 W22 (Introversion) = −1.91 W23 (Extroversion) = 1.89
ENFP	W11 (Thinking) = 0.50 W12 (Judging) = 0.52 W13 (Extroversion) = 1.33	W23 (Feeling) = 0.59 W22 (Intuition) = 0.34 W21 (Intuition) = 0.39 W22 (Introversion) = −0.22 W23 (Extroversion) = 0.24
ESTP	W11 (Thinking) = 0.38 W12 (Judging) = 0.18 W13 (Extroversion) = 0.60	W23 (Feeling) = −0.34 W22 (Intuition) = −0.45 W21 (Intuition) = 1.20 W22 (Introversion) = −0.42 W23 (Extroversion) = 0.18
ENFJ	W11 (Thinking) = 1.34 W12 (Judging) = −0.37 W13 (Extroversion) = 1.23	W23 (Feeling) = 0.66 W22 (Intuition) = 0.37 W21 (Intuition) = 0.69 W22 (Introversion) = −2.09 W23 (Extroversion) = 4.02
ISFP	W11 (Thinking) = −0.72 W12 (Judging) = −0.74 W13 (Extroversion) = −0.23	W23 (Feeling) = −0.52 W22 (Intuition) = −0.16 W21 (Intuition) = −0.06 W22 (Introversion) = 0.86 W23 (Extroversion) = −2.09

Table 5. Accuracy of the weights for each type of personality in train mode

Personality	Percent accuracy of weights
ESFJ	75 %
ENFP	75 %
ESTP	75 %
ENFJ	75 %
ISFP	88 %

We consider another dataset as a test dataset and evaluate the map with obtained weights. Results are reported in Table 6.

Table 6. Accuracy of the weights for each type of personality in test mode

Personality	Percent accuracy of weights
ESFJ	87.97 %
ENFP	89.16 %
ESTP	90.87 %
ENFJ	88.39 %
ISFP	87.80 %

5 Discussion

This paper aimed at modeling the relationship between emotion and personality in calculating user's desirability. Results in Table 5 show that our hypothesis in Tables 2 and 3 is correct. Based on psychology studies, we designed a cognitive map as shown in Fig. 2.

We consider a positive relationship between dimensions I in the MBTI test and "Do not ask for help" in events group. Since the introverted people are more interested in working alone, they refuse to ask for help from other people. In contrast, extroverted people have many tendencies for teamwork so we expected there is a positive relationship between "Receive appreciate help" and E dimension. Also, extroverted people, who tend to be fast in doing tasks, act quickly and sometimes without thought do not have high effort, and according to expectations, there should be a positive relationship between "low effort" and E dimension. The judging people prefer a systematized life and they care about activities which they can do on time so we expect there is a positive relationship between "Finish the proposed activities" and J dimension. Thinking people have a tendency for everything to be ideal then we expect there must be a positive relationship between "Provide a correct response to the exercises" and T dimension.

In the second layer, we expect personality type shows its effect on the user's goals. Feeling people are encouraged by others and so other people can affect their feelings. Also, feeling people cares about what others say and there should be a relationship between them. Intuitive people like to be different from other people so there should be a relationship between N dimension, and "Do better than other colleagues" and "Show that has a high level of competence".

After evaluating the proposed model with train data set, the results in Table 5 confirm our proposed model. For example for the ISFP type (Introverted Sensing Feeling Perceiving), we expected the weights related to the first layer (e.g. T, J and E) would be negative. Results in Table 5 confirm this.

In the second layer, according to ISFP type, we expected a positive value for F and I dimensions and a negative value for N and E dimensions. Results in Table 5 show the four weights are correct and just one of them is wrong.

Table 6 shows the percentage of weight correctness in the cognitive map designed for evaluating the proposed model in test mode.

It is plainly visible that there are a wide range of variables in determining user's desirability and many factors affect a user's emotion; nevertheless our results seems to be valid. The proposed model shows that we have found a significant correlation between emotions and personality using the OCC and the MBTI models.

6 Conclusions

In this paper we presented a general computational model for emotion and personality in humans. We used the MBTI model for personality and the OCC model for emotion modeling. This research focused on the personality and emotions of a user to calculate the user's desirability. We evaluated the proposed model in a virtual learning environment.

The most significant contribution of this paper is the introduction of a new computational model for determining users' desirability, based on the evaluation of events. Also, results show that our hypotheses on the relationship between emotion and personality is correct with high precision.

In future, we will add a mood module to model the relationship between mood, emotion, and personality.

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