A computational model of emotion and personality in e-learning environments

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ABSTRACT

One of the currently most important discussions in artificial intelligence is modeling personality and emotion in artificial intelligence, chiefly in Human-Computer-Interaction (HCI). The purpose of this research is designing a general model that identifies a user's affective status based on user's personality and emotion. The proposed model is composed of two main modules: personality and emotion modules. The personality module detects personality type of a user based on two approaches: determining personality through users' actions in a system and using sequential behavioral pattern mining to determine personality. In the emotion module, we propose a computational model to calculate a user's desirability based on personality in e-learning environments. The desirability of an event is one of the most important factors in determining a user's emotions. The proposed model has been evaluated in simulated and real e-learning environments. The results show that the model formulates the relationship between personality and emotions with adequate accuracy.

Keywords: Personality, Emotion, Desirability, Learning Styles

1. INTRODUCTION

Nowadays, one of the most used computer applications is in E-learning. The main idea of E-learning is learning anywhere and anytime, but this type of education has brought new problems. It usually lacks dynamism and does not establish necessary interactions to attract learners' attention.

For instance, it's clear that during a learner's interaction with a computer, the learner's emotional states changes [1] which depends on his/her individual characteristics. Positive emotions play an important role in creativity and flexibility for solving problems while negative emotions block the thinking process and prevent sound reasoning [2] [3] [4]. Then, the learner's emotional states in E-learning environments must be taken into account [2].

Besides, individuals have different personalities, and individuals with different personalities show different emotions in facing events. Also, individuals with different personalities have different learning style.

Consequently, developers ought to concentrate designing interactive user interfaces based on user's affective status, and personality aiming to make them more realistic and attractive [5].

In this paper, we present a computational model to determine the desirability [6] of events, as one of the important emotions in human-human and human-computer interaction, based on personality of users. To the best of our knowledge, it is the first model relating the desirability of events to the personality of a user in E-learning environments.

2. RELATED WORKS

Several studies have been carried out in order to consider human characteristics in human computer interaction [7] [8] [9] [10] [11] [12] [13].

Jin Du and his colleagues [14] handled the model of learner based on the Cattell's 16 Personality Factor. In 2011, Gong and Wang [9] used Support Vector Machine (SVM) in order to determine learning styles in the E-learning environment. Haron suggested a learning system, including a learning module which can be adapted to each learner and utilizes fuzzy logic and MBTI personality test [12]. Abrahamian and his colleagues designed an interface for computer learners according to learners' personality type using MBTI test [15]. In [5], a Bayesian network was used to detect the learners' learning style in a tutoring system. In [16], the authors presented a framework for automatic detection of the learner's learning style based on the Felder-Silverman model. Fatahi and her colleagues [17] [18] [19] [20] designed and implemented a virtual tutor and virtual classmate agent that had personality and emotion characteristics as a human being. They used the Ortony, Clore and Collins (OCC) model for emotion modeling and MBTI for personality modeling.

As mentioned above, several studies have been carried out in order to consider human characteristics in human computer interaction especially in E-learning environments. Despite all these efforts, to the best of our knowledge, there is no work modeling the relationship between personality and emotion to improve the e-learning experience. Consequently, we have proposed a model to show a relationship between personality and one of the most important variables in determining emotions [6] called desirability. Based on the OCC model, a person could alternatively have three types of focus which are consequence of events, actions of people, and aspects of objects [6]. The first type of emotions includes emotions which are consequences of the events that have occurred. These consequences are obtained according to the desirability or undesirability level of the events and the person's goals. Based on the desirability level, the first branch of emotions in OCC model can calculate.

In addition, in this research, we used MBTI for personality modeling and the OCC model for emotion modeling. The results show the effectiveness of the proposed approaches.

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3. PROPOSED MODEL

In this research, we focus on designing a computational model that identifies a user's affective status based on personality and emotion. During the user's interaction with a computer, and depending on events happening in the environment and his personality, the user's emotion changes. In this situation, an intelligent system should be responsive to the user's emotions. The proposed model is composed of two main modules: the personality and emotion modules.

Personality module: The goal of this module is detecting personality type of users based on two approaches: determining personality through users' actions in a system and using sequential behavioral pattern mining to determine personality. These approaches are automatic. Also, we use MBTI questionnaire to detect users' personality manually. It should be mentioned that the manual method of personality detection is used as a ground truth for automatically personality detection.

Emotion module: A lot of models have been designed for emotion modeling. One of the most famous ones is OCC model [6] that is used in most studies. The OCC model calculates intensity of emotion based on a set of variables. The variables are divided into two groups: global and local. The desirability is one of the most important factors in determining a user's emotion [6].

In this research, we focus on designing a computational model which calculates a user's desirability based on the user's personality and his/her goals. The overall architecture of the model is illustrated in Fig. 1. In the following, each module is explained in more detail.

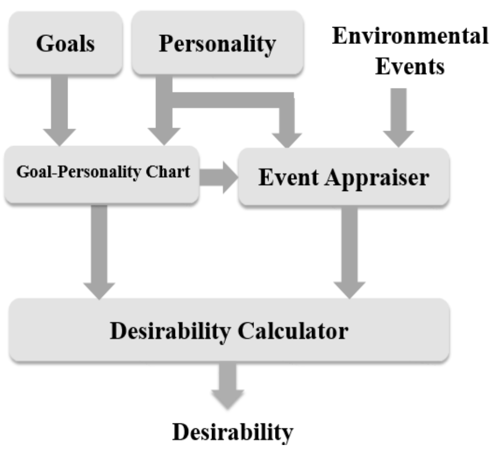

Figure 1. The general view of the proposed model

Goals: In every environment, individuals have different goals which can be determined based on different theories. For example, according to the Ames (1990) theory, in learning environments, there are two categories of people based on their goals: performance motivational orientation (PMO) and mastery motivational orientation (MMO). For example, PMO learners have three goals which are "please the teacher and parents", "do better than other colleagues", and "show a high-level of competence".

Goal-Personality Chart: Based on the fact that there is a relationship between goals and personality [21], the most related goals and their importance to a personality type can be determined based on expert knowledge. For example, ENTJ type people fall into MMO category since they always tend to collect information and increase their skill levels [22]. Thus, ENTJ type people have the three MMO's goals, i.e. "develop new skills", "learn new things", and "improve their level of competence". On the other hand, each goal, in the related set of goals to a personality type, has its importance value in determining desirability. For example, based on the characteristics of an ENTJ type person, the importance value of "develop new skills" and "learn new things" are high and the impact value of "improving their level of competence" is low. The output of Goal-Personality chart to the event appraiser module is set of goals corresponding to the user's personality. On the other hand, the output of this module to the desirability calculator is the importance value of each goal in determining the desirability based on the user's personality.

Event appraiser: The aim of this module is to calculate the impact of environmental events on achieving the goals which are determined by the Goal-Personality chart. In other words, the output of this module determines how much the goals are achieved based on the events.

This is based on lot of evidences that show there is a relationship between personality dimensions and the events that causes individuals with different personality react in different ways. For example, asking help from a teacher in an e-learning environment is an environmental event which happened through learner. This event is related to extroversion/introversion dimension. As we know, extroverted individuals like to ask for help from others and they like to help others. In contrast, introverted individuals prefer to perform their tasks alone without help. That is why we use the relationship between personality dimensions and events to calculate impact of environmental events on achieving the goals.

Desirability calculator: As mentioned earlier, based on the OCC model, to calculate the desirability or undesirability level of an event, it is essential to know how much an event is in line with a user's goals. That is why the inputs to this module are the importance values of the goals, provided by the goal-personality chart, and the impact of environmental events on achieving the goals, given by the event appraiser. These inputs are used to calculate the desirability using Eq. 1.

$$Desirability = \frac{\sum_{i=1}^{n} l_i * w_i}{\sum_{i=1}^{n} w_i} \quad l_i \in [-1,1] \tag{1}$$

in which n is the number of goals, w_i, given by the Goal-Personality chart, is the importance of the i[th] goal. Furthermore, l_i is the achieved level of the i[th] goal, which is calculated based on the impact of the triggered events and the corresponding personality dimensions. Finally, $Desirability$ represents how much the triggered events are desirable based on the user's goals and personality. The desirability is normalized between -1 and 1 in which desirable events range between 0 and 1 while undesirable events range between 0 and -1. l_i is calculated using Eq. 2 in which the impact of events and the personality dimensions' levels (*pdl*) are considered through a linear relation between these two.

$$l_i = \sum_{i=1}^{m} e_i * pdl_i \tag{2}$$

in which *m* is the number of events, and e_i is the i[th] event.

4. IMPLEMENTATION AND RESULTS

4.1. Personality module

We use an E-learning environment in order to evaluate our proposed model. Since Furnham and Jackson clearly expressed that the learner's learning style is a subset of his/her personality [23] and MBTI is the personality model which has a learning style model, we use MBTI learning style model in e-learning environment instead of personality.

To evaluate proposed personality module, we use a blended learning environment for the "Introduction to computing systems and programming" (ICSP) course. The course is taught to the first-year students at the school of electrical and computer engineering at the University of Tehran in Iran. The course runs for 18 weeks, and 355,155 interaction records were collected of the two hundred and twenty-six students from the Moodle's log file. Each record includes "time", "IP address", "action", "URL", "info", "username", "first name", "last name" and "email of the corresponding student". The "time" shows the duration of time students did an activity and the "info" includes an id uniquely assigned to the page accessed/used by the students.

We define two groups of features: Learning Activity Feature (LAF) and Context-based Learning Activity Feature (CLAF). To determine the best features for predicting the learning styles, we run many important clustering methods through Weka tools. K-means (k=2) was the suitable method for separating two MBTI dimensions. K-means gives best result when data set are distinct or well separated from each other. The results show that there are nine CLAF of 112 features that separate people with different learning styles. Table 1 shows an example of the results.

Table 1. Context-based learning activity features to determine LSs in T/F dimension

Feature	Measure	Thinking	Feeling
The number of messages sent in the chat rooms	Precision	0.61	0.87
	Recall	0.94	0.39
	Accuracy	0.67	0.67
	F-measure	0.74	0.54

The number of messages sent in the chat rooms is the best feature to separate feeling students from thinking ones. This feature confirms that feeling people tend to interact and relate to other students through discussion rooms. Table 1 shows that feeling students used chat rooms more than thinking people.

In the next step, to extract frequent behavioral sequences, we have collected the data from two hundred and fifteen students who registered in the "Introduction to computing systems and programming" (ICSP) course. We run Generalized Sequential Pattern Mining (GSP) algorithm which is an apriori-based algorithm on data. Finally, we found a lot of frequent behavioral sequences in each dimension of MBTI which some of them can be meaningful and usable to discriminate individuals. Some examples of frequent sequences are presented here:

{Results of Quizzes} {Lessons} {Extra Exercises} {Add/Delete Posts} → Introvert

{Extra Exercise} {Quiz}{Results of Quizzes} {Lessons} → Extrovert

{Review}{Quiz}{Results of Quizzes} {Lessons}→ Thinking

{Quiz}{Quiz}{Results of Quizzes} {Lessons}{Add/Delete Posts}→ Feeling

{Review}{Quiz}{Quiz}{Results of Quizzes} {Extra Exercises}→ Perceiving

{Lessons}{Quiz}{Add/Delete Posts} {Extra Exercises}→Judging

{Add/Delete Posts} {Quiz}{Quiz}{Results of Quizzes}→iNtuition

{Quiz}{Results of Quizzes} {Lessons}{Quizzes}→Sensing

The sample of results show that there are different sequences of behaviors for different dimension of learning style. Also, we can predict the learning style of learners based on these sequences with high accuracy.

4.2. Emotion module

To evaluate the emotion module, we used a simulated and a real e-learning environment. In the simulated e-learning environment, 1878 artificial intelligence agents were used. The agents had different personality types, different goals based on their personality types, and different levels of knowledge generated randomly based on a normal random distribution. The five events generated randomly in the simulated e-learning environment and the agents responded to them. These event are "finish the proposed activities", "receive appropriate help", "lack of request for help", and "low/high effort". The simulated e-learning environment calculated the desirability of the agents based on Eq. 1 for agents. On the other hand, the level of desirability for each agent, based on the agent's activities, personality type, and events, was labeled by seven experts as our ground truth. After that, a dataset was collected which included: agent's personality type, agent's goals, the event happened, the level of desirability which calculated based on the proposed model, and the level of desirability which was labeled by the experts. The dataset was used to train the two FCMs (Fuzzy Cognitive Maps) have been designed to modeling relationship between environmental events, user's goals, personality dimensions and desirability. These FCMs show the relationship between events, a user's goals, the user's personality, and the user's desirability. After training mode, we test the model to predict desirability. To evaluate the model for the PMO and MMO FCMs, we computed 10-fold cross validation on the data set. Results are reported in table 2.

Table 2. Accuracy rate of predication of desirability with simulated data

Personality types	The accuracy of the predicted desirability
ESFJ	84.26%
ENFP	85.82%
ESTP	85.57%
ENFJ	82.06%
ISFP	83.27%
ENTJ	84.69%
ENTP	81.38%
ESFP	83.82%
ESTJ	82.47%
INFJ	80.81%
INFP	86.03%
INTJ	81.04%
INTP	84.19%
ISFJ	81.92%
ISTJ	83.42%
ISTP	81.51%

In the next step of this research, we tested the model using real data. A real e-learning environment is implemented for the "Introduction to computing systems and programming" (ICSP) course. We have collected the data from a hundred and thirty-one students who participated in this study. Since the number of real data which was collected for INTJ, INTP, ISTJ and ISTP type was reasonable to test the model, we evaluated the model on these types. The results in table 3 show the desirability prediction accuracy for this test.

Table 3. Accuracy rate of predication of desirability with real data

Personality	The accuracy of the weights
INTJ	75.22%
INTP	68.82%
ISTJ	75.83%
ISTP	68.04%

The results in table 2 and 3 show that our hypothesis about the relationship between events and achieving goals and mapping between the personality dimensions and achieving goals are correct and our expectation in desirability prediction is satisfied.

5. CONCLUSION

In this research, we focused on designing a user computational model that identifies the user status based on personality and emotions. To evaluate the proposed module, we used a simulated and a real e-learning environment.

In the future, we want to incorporate mood in our modeling to improve the desirability prediction by incorporating the relationship between mood, emotion, and personality. Furthermore, it is necessary to collect further data to improve the system's accuracy. Also, modeling of other factors in emotions needs to be investigated.

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