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Use of Personality Profile in Predicting Academic Emotion based on Brainwaves Signals and Mouse Behavior

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***Abstract*— The academic emotion of learners is difficult to predict using EEG data, unless these brainwaves data undergo some extensive pre-processing operations. However, we show some evidence that it can be predicted somewhat more accurately for certain personality profiles. Twenty-five (25) college students were asked to use a math tutoring system while their brainwaves signals and mouse-click activities were being captured. Brainwaves signals were recorded using an Emotiv EEG device while the mouse behavior was based on the number of clicks, the duration of each click and the distance traveled by the mouse. The personality of the learners was evaluated based on the Big-Five Personality Test of *Extroversion, Inquisitiveness, Accommodation, Emotional Stability* and *Orderliness*. For each group based on personality type, the frequency of each self-reported academic emotion of *confidence, excitement, frustration* and *interest* was recorded and two classifiers, kNN and C4.5, were trained for each personality type. The accuracy rate of the classifiers built using only data instances from those assessed to be "low" in "orderliness", as well as only from those assessed to be "high" in "orderliness", performed significantly better compared to the classifiers that were trained for all personality types combined. The experiments also revealed that for almost all the 5 personality types, the percentage of instances where the learners reported themselves to be *confident* or *frustrated* differed significantly depending on whether they were assessed as "low" or "high" in the five personality types.**

Keywords- affective computing; academic emotion; brainwaves; mouse; personality

I. Introduction

Intelligent Tutoring Systems (ITS) were primarily developed to help students improve their learning through the help of a computer tutor who acts like a human teacher who guides, provides learning materials and interacts with the students accordingly based on their current cognitive state. Recent developments in the design of tutoring systems have attempted to render these systems more adaptive not only to the learner's cognitive state but also to his/her affective state. In the case of these systems, usually referred to as affective tutoring systems, affective states may be recognized using the tutor context and user profile [4] and sometimes in combination with signals from hardware sensors such as a camera, microphone [9] and various other physiological sensors that capture EEG signals, EMG signals, skin conductance levels, heart rate, and respiration rate [1][5][6][7][8][14].

Recent work in affective systems have investigated the potential of using brainwaves signals and standard mouse data for affect detection and prediction [3]. Brainwaves may be captured using an electroencephalogram (EEG) device. The EEG device measures the electrical activity along the scalp caused by the firing of neurons within the brain. Designed for clinical diagnosis, EEG sensors have recently been explored for measuring user alertness, cognitive engagement [17] and affect detection. Another device that is not much explored but may be useful for affect detection is the standard mouse. An inexpensive device that has the closest contact with a computer user, the mouse may provide useful information about the user's behavior. Some researches have explored the potential of special and standard mouse devices to measure affect [20]. On the other hand, the static user profile such as personality traits were found to be correlated to a person's reaction to certain events as explored in the work of [8] and [21]. While the research in [3] had included the personality personality profiles as features in classifying affect, for this study, the personality profiles were not taken as features for classification but were used to group the student subjects according to their personality types.

II. Affective Computing

Affective tutoring systems have studied the influence of emotions in the learning process of a learner. These emotions, also referred to as academic emotions, play an important role in the success of learning [16]. In a tutoring system scenario, these academic emotions may be recognized based on the learner's interaction with the system and/or on the physiological signals captured by hardware sensors.

To some extent, some systems are able to detect affect without using any hardware sensor. These systems rely solely on the recorded student's logged activities such as scores from the previous tasks, response time in performing tasks,

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frequency of getting hints, etc. Since emotions are naturally complex and are expressed in different modalities (i.e. face, voice, gesture, physiological signals), most affective tutoring systems have explored the multimodal approach for affect detection because the single modality approach poses some limitations. For instance, face detection is extremely sensitive to the positioning of the head or the face. For yet other systems, the performance was shown to further improve with the combination of contextual information and physiological signals [8]. In [8], Conati & Maclaren for example, used the details of student and agent actions together with personality traits to infer student goals, interaction patterns, student actions in a system and even emotions by applying the OCC cognitive theory of emotion. Similarly, Benadada et al. in [5] explored the use of personality traits on learner emotional reaction to a tutor event and performance.

According to [22], "extraversion facilitates the mental effort and mobilization of energy required to deal with different tasks that engage attention, either experimental or real life. Introverts deal better with easy tasks but become overly aroused when the tasks become more difficult. On the other hand, extroverts are not aroused sufficiently on easy tasks until the tasks become more demanding." In other words, extroverts seem to mobilize well their energy and mental effort and that they increase their arousal only when faced with a more demanding task.

More recent work on tutoring systems have added several affective hardware sensors to improve the accuracy rate in predicting student emotions. This multimodal approach for affect detection in tutoring systems has shown some promising results. For example, Arroyo and his group were able to predict affective states such as confident, frustrated, excited, and interested with high accuracy using such special devices as a facial expression camera, posture chair, pressure mouse, and skin conductance [1]. A similar multimodal system is the learning companion [14] that fuses information from cameras, posture chair, pressure-sensitive mouse, skin sensor and task state to predict frustration - in order to determine when the user needs help. Finally, Autotutor uses information from conversation cues, posture and facial features to predict student boredom, flow/engagement, confusion and frustration [9].

Some researches have been investigating the potential of using electroencephalogram (EEG) devices for affect detection. In [19], the student's level of frustration, distraction and cognitive workload were observed while the student is engaged in different activities in a multimedia-learning environment. Similar works in [2][3] have investigated the use of brainwaves to detect the affect of students while using a math software. The work described in [12] explored the accuracy of using EEG and emotional dimensions in predicting the correctness of the student's answers. Furthermore, the use of a biometric mouse to measure a user's emotional state and productivity was described in [20]. The study attempts to use the mouse as a proxy for physiological data (skin conductance, heart rate, blood pressure, respiration, pupillary dilation, EEG, or muscle actions) and motor-behavioral (skin conductance, amplitude of hand tremble, and skin temperature) information.

While a number of research works have focused on using expensive sensors for affect detection, not much work has explored the use of a standard mouse. The work of [18] has shown that this has the potential to measure student frustration. Mouse events such as mouse-clicks have been used to measure behavioral responses and some patterns were found in their mouse behavior when subjects were presented with frustration-eliciting events. According to [15], emotions and mood would have an effect on a person's motor movements. The mouse clicks, frequency of mouse movement and duration of mouse clicks tend to correlate with the grade on the valence and arousal dimensions of emotions. A user tends to click more when they are frustrated with the system (such as when there are lags and delays) [10].

Despite the positive results that were reported by such affective tutoring systems, much remain to be explored. In particular, the potential of combining physiological signals and mouse click data in order to improve the accuracy of predicting the affective state of the user has yet to be studied more extensively [3].

III. Experimental Set-Up

Twenty-five computer science undergraduate students (14 male and 11 female) who were mentally healthy and right-handed were taken as subjects in this study. The participants were asked to learn a tutoring software called Aplusix [23] which teaches algebra. The students were asked to solve 4 algebra equations of varying difficulty levels for about 15 minutes. While the students were learning using the software, signals from an EEG sensor attached to their head were recorded. Also, the details of their mouse clicks, click duration and movement were automatically captured and stored in 2 different mouse log files - one for the clicks and duration and another for the movement.

The EEG sensor that was used in the experiment is the Emotiv EPOC sensor. A commercial product typically used for gaming purposes, the Emotiv EPOC sensor is equipped with 14 channels based on the International standard 10-20 locations. A service program was created to capture the raw EEG signals from each of the channels.

Prior to the learning session, each participant was asked to fill-up a web-based Big Five Personality (or Five Factor Model) questionnaire (http://similarminds.com) to measure his or her personality traits such as extroversion, orderliness, emotional stability, accommodation and inquisitiveness. The traits were presented as percentile scores. Common traits of each personality type are described below.

- Extroversion/Extraversion. People who scored high on this trait prefer to spend more time with others than alone. They are characterized by positive emotions, energetic and action-oriented individuals. They can easily express emotions and have the tendency to seek out stimulation and the company of others.
- Orderliness/Conscientiousness. People who scored high on this trait are typically systematic, organized,

serious, prefer structure and predictability of routine and habit and success driven.

- Emotional Stability. Those who are high on this trait are typically calm, patient, secured, self-confident and not quick tempered. The low pole of this trait is referred to as neuroticism. Neuroticism is the tendency to experience negative emotions such as anger, anxiety or depression.
- Accommodation/Agreeableness. Those who are high on this trait have the tendency to be compassionate and cooperative. They are typically warm, caring and generous and enjoy helping others.
- Inquisitiveness/Openness. Those who are high on this are typically intellectually curious, appreciative of art, emotion, unusual ideas and imagination and willing to try new things. They are problem solver and feel best when working.

After the personality test, each participant, with an EEG sensor attached to the head, was asked to close his/her eyes and relax for a period of 3 minutes in order to create the baseline EEG data [24]. After this period, brief instructions were given on how to use the software. The participants were also informed that they will self-report the intensity of each of the 4 emotional experience: confidence, excitement, frustration and interest through a window that automatically pops up every 2 minutes. The window has a sliding bar with values from 1-100 for each emotion. During the learning session, an observation module was developed to capture raw EEG signals and mouse data.

IV. Data Preprocessing and Preparation

Two sets of EEG data were taken from each subject: one from the relaxed period and one from the tutorial session. The mean of each EEG channel for each subject during the relaxed period were computed and served as the baseline EEG data of that particular subject, as mentioned earlier. The raw EEG channel values taken during the tutorial session were filtered by computing the difference between the raw value of the channels and the mean value of corresponding channels from the baseline (relaxed state) data.

All the pre-processed EEG data, mouse data, and self-reported emotion tags are summarized below. These data were carefully synchronized, merged and uniformly segmented into 2-second windows with 1-second overlaps [24]. Each segment was treated as a single instance in each subject's dataset. The full dataset had a total of 17 features: 14 for the EEG channels and 3 for mouse behavior. The self-reported emotion serves as the tag for each recorded instance. The features used for emotion classification are:

- EEG channels : AF3 F7 F3 FC5 T7 P7 O1 O2 P8 T8 FC6 F4 F8 AF4
- Mouse Behavior : Number of Clicks, Distance Traveled, Click Duration
- Self-reported Emotion : Frustrated, Interested, Confident, Excited

Eleven datasets were formed for all the personality groups. The first dataset is composed of all the subjects, i.e all personality types, while the rest are for the individual personality types, as shown in Table I and the percentage distribution by personality group appears in Table II. Since there were 5 personality traits (extroversion, orderliness, emotional stability, accommodation and inquisitiveness) that were measured, two sets of data were created for each trait: one for those whose percentile scores are less than 50% while the other was for those who scored 50% or higher. Each dataset was split into two subsets - around 80% for the training subset while around 20% for the testing subset. Table I also presents the number of students that were used for the training and testing subsets. Note that each subject appears only either in a training subset or in a testing subset. Note further that although the number of students/learners that were grouped according to personality types may seem small, the actual number of <u>instances</u> collected during the entire training session is actually huge for each and every dataset used. As mentioned earlier, the sample (training and test) features were collected every two seconds, with one second overlaps.

V. Results and Discussions

Table III shows the percentage distribution of emotions as they were self-reported by the learners. If we consider each personality type and if we check for which emotions they vary significantly between the "low" and "high" groups (marked in bold for those that differ by at least 8%), we readily notice that it is for the emotions *confidence* and *frustration* were most of the variations are seen. This can be said of all the personality types, except for the *confidence* emotion of the "low" and "high" groupings of the "accommodation" personality type. For example, those assessed to be "low" in "extroversion" (i.e. introverted) only reported themselves to be frustrated during 26.83% of the various portions of the learning session, while as much as 38.88% of the time, highly extroverted learners reported themselves to be frustrated. On the other hand, those rated "low" on "orderliness" were frustrated 35.02% of the time, while those "high" on orderliness reported themselves to be frustrated only 18.02% of the time.

Some examples as far as the confidence emotion can likewise be cited. For those who are highly inquisitive, they reported themselves to be confident in 44.49% of the time, while only 36.46% of the time were they confident among those who were rated low in inquisitiveness. Those who were rated "high" in orderliness reported themselves to be confident in 45.68% of the time, while among those "low" in orderliness, in only 35.52% of the time did they feel confident. These examples would confirm that learners of different personality profiles do react differently to the various segments of the learning session, especially as far as being frustrated and confident are concerned.

Aside from a cursory comparison of the various academic emotions experienced by the students depending on their personality type, different datasets were also constructed and used to compare the accuracy rate of emotion classification when using kNN (*k=5* & *k=9)* and C4.5 machine learning algorithms. WEKA, a machine learning tool was used to compute the accuracy results [11]. The accuracy performance of kNN and C4.5 on different datasets are presented in Table IV while the detailed performance of the two are presented in Table V.

TABLE I. DATASETS FOR EMOTION CLASSIFICATION

Personality Group	No. of Students			No. of Instances		
	Train	*Test*	*Total*	*Train*	*Test*	*Total*
All Personalities	20	5	25	7556	1606	9162
Low Extroversion	11	3	14	4490	1123	5613
High Extroversion	9	2	11	3046	503	3549
Low Orderliness	11	3	14	3829	1103	4932
High Orderliness	9	2	11	3727	503	4230
Low Emotional Stability	11	3	14	3913	1103	5016
High Emotional Stability	9	2	11	3340	806	4146
Low Accommodation	3	1	4	1004	320	1324
High Accommodation	17	4	21	6552	1286	7838
Low Inquisitiveness	15	4	19	5928	1336	7264
High Inquisitiveness	5	1	6	1628	270	1898

TABLE II. DISTRIBUTION OF PERSONALITY GROUPS

Personality Group	Percentage (%)
All Personalities	100
Low Extroversion	56
High Extroversion	44
Low Orderliness	76
High Orderliness	24
Low Emotional Stability	56
High Emotional Stability	44
Low Accommodation	56
High Accommodation	44
Low Inquisitiveness	84
High Inquisitiveness	16

TABLE III. PERCENTAGE DISTRIBUTION OF SELF-REPORTED EMOTIONS

Personality Group	Emotion			
	Interest (%)	*Confidence (%)*	*Excitement (%)*	*Frustration (%)*
Low Extroversion	8.87	41.81	22.48	26.83
High Extroversion	14.34	30.99	15.78	38.88
Low Orderliness	10.35	35.52	19.11	35.02
High Orderliness	13.44	45.68	22.87	18.02
Low Emotional Stability	11.9	30.12	17.38	40.59
High Emotional Stability	9.89	46.7	22.91	20.5
Low Accommodation	14.7	39.84	17.27	28.18
High Accommodation	6.67	35.04	22.93	35.37
Low Inquisitiveness	10.7	36.46	20.08	32.75
High Inquisitiveness	12.69	44.49	18.73	24.09

It is very clear from both Tables IV and V that the prediction of the academic emotion of a learner based on EEG data and mouse click behavior is very difficult. This is so for EEG data that have not been processed using more advanced techniques (using FFT, for example), such as the data used for the experiments reported here. We have conducted experiments using more advanced pre-processing of the EEG data and the prediction results are significantly better. These results would be published elsewhere.

Nevertheless, it is interesting to note that the specialized classifiers to predict *frustration* that were trained using just those learners who were assessed as “high” in orderliness have performed significantly better. Notice from Table V that only at most one third (f-measure of 0.29 to 0.33) of the instances have been correctly classified when the classifier is built for all personality types combined. When a specialized classifier is built using data coming exclusively from learners who were assessed to be “high” in “orderliness”, the f-measures for the K-NN and C4.5 classifiers have gone up to .052 to 0.54. These prediction rates are not impressive still, but are just the same significantly better that when all personality types are combined.

The same can be said of the significantly better prediction of the *confidence* emotion among those rated “low” in orderliness. The high accuracy rates of these classifiers may be attributed to the similarity of the emotional experience of a certain personality type thereby contributing to a more homogeneous dataset that in turn would contribute to higher prediction rates. Subjects with the same personality type seem to react similarly to the same stimulus based on the pattern of brainwaves signals and mouse behavior.

There are various other cases where precision and recall rates are quite high, such as a recall rate of 0.72 for the recall of the *confidence* emotion among those who are “low” in “orderliness”. But in all these other cases, the f-measures are really not all that impressive, even for classifiers that are specialized for certain personality types.

Further tests need to be done to know whether the classifiers (kNN and C4.5) that were trained using all traits combined, but used to predict only those data from the low extroversion would also register also higher prediction rates. In that case, then perhaps these results can be explained away as being due to the fact that the academic emotions of the learners for this group can really be more easily predicted than those of the other groups.

VI. Conclusion and Future Work

The use of a learner's personality profile in predicting academic emotions, particularly *confidence* and *frustration*, based on brainwaves and mouse behavior features, has the potential of increasing the predictive performance of classifiers. Even when using EEG data that have not been pre-processed extensively, some significant improvement in the prediction rate for two personality profiles ("high" in "orderliness" and "low" in "orderliness") has been observed.

Further tests need to be done to investigate performance rates of the classifiers, that were trained using all traits combined, in predicting the academic emotions of learners of a given personality type. Also, the use of EEG data that have undergone more advanced pre-processing techniques have to be explored. Nevertheless, the preliminary results presented here would seem to suggest that tutoring systems to be designed in the future should consider using personality-dependent classifiers when trying to predict the academic emotion of the user/learner.

TABLE IV. Accuracy of emotion classification

Personality Group	Classifier		
	KNN (k=5)	*KNN (k=9)*	*C4.5*
All Personalities	28.39	27.40	30.45
Low Extroversion	21.55	21.28	25.64
High Extroversion	18.09	19.28	27.04
Low Orderliness	31.00	30.00	35.99
High Orderliness	34.19	33.60	32.80
Low Emotional Stability	29.10	30.00	22.03
High Emotional Stability	21.34	19.73	22.33
Low Accommodation	28.44	27.19	40.00
High Accommodation	28.62	29.47	28.30
Low Inquisitiveness	27.10	28.29	30.16
High Inquisitiveness	4.44	2.96	16.30

TABLE V. Detailed Performance Of kNN and C4.5 on Different Personalities

All Personalities									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.06	0.02	0.02	0.07	0.01	0.02	0.28	0.07	0.12
Confidence	0.27	0.47	0.35	0.27	0.49	0.35	0.36	0.47	0.41
Excitement	0.20	0.18	0.19	0.19	0.17	0.18	0.18	0.41	0.25
Frustration	0.38	0.30	0.33	0.35	0.26	0.30	0.37	0.24	0.29
Low Extroversion									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.01	0.04	0.02	0.02	0.04	0.02	0.02	0.04	0.02
Confidence	0.26	0.49	0.34	0.24	0.40	0.30	0.29	0.50	0.36
Excitement	0.05	0.24	0.07	0.10	**0.58**	0.16	0.04	0.24	0.07
Frustration	**0.53**	0.09	0.16	0.44	0.11	0.17	**0.70**	0.15	0.25
High Extroversion									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.12	0.04	0.06	0.18	0.07	0.10	0.47	0.26	0.33
Confidence	0.19	**0.51**	0.28	0.18	0.49	0.27	0.23	0.49	0.31
Excitement	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Frustration	**0.55**	0.12	0.20	0.50	0.14	0.22	**0.56**	0.20	0.30
Low Orderliness									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.05	0.02	0.03	0.06	0.02	0.03	0.05	0.02	0.03
Confidence	**0.34**	**0.58**	**0.43**	**0.33**	**0.58**	**0.42**	**0.39**	**0.72**	**0.51**
Excitement	0.25	0.20	0.22	0.26	0.19	0.22	0.43	0.28	0.34
Frustration	0.36	0.20	0.03	0.30	0.16	0.21	0.28	0.12	0.17
High Orderliness									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.00	0.00	0.00	0.33	0.02	0.04	0.19	0.05	0.08
Confidence	0.21	0.39	0.27	0.17	0.33	0.22	0.20	0.27	0.23
Excitement	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Frustration	**0.61**	**0.45**	**0.52**	**0.61**	**0.45**	**0.52**	**0.69**	**0.45**	**0.54**
Low Emotional Stability									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.07	0.01	0.02	0.14	0.02	0.04	0.06	0.03	0.04
Confidence	0.33	0.48	0.39	0.34	**0.51**	0.41	0.34	0.30	0.32
Excitement	0.30	0.27	0.28	0.27	0.24	0.25	0.13	0.19	0.16
Frustration	0.22	0.22	0.22	0.24	0.23	0.24	0.06	0.03	0.04
High Emotional Stability									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.05	0.03	0.04	0.03	0.02	0.02	0.00	0.00	0.00
Confidence	0.16	0.50	0.24	0.15	0.48	0.23	0.17	0.50	0.26
Excitement	0.19	0.23	0.21	0.18	0.21	0.20	0.06	0.09	0.07
Frustration	**0.66**	0.15	0.24	0.56	0.14	0.22	**0.59**	0.22	0.32
Low Accommodation									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Confidence	0.25	0.36	0.30	0.24	0.38	0.30	0.38	**0.51**	0.44
Excitement	0.30	0.30	0.30	0.64	0.43	**0.51**	0.33	0.05	0.08
Frustration	0.43	0.22	0.30	0.30	0.15	0.20	0.44	0.41	**0.43**

High Accommodation									
	KNN (k=5)			KNN (k=9)			C4.5		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.02	0.00	0.01	0.00	0.00	0.00	0.40	0.08	0.13
Confidence	0.30	**0.53**	0.38	0.29	0.53	0.38	0.31	0.50	0.38
Excitement	0.16	0.21	0.18	0.17	0.20	0.18	0.08	0.17	0.12
Frustration	0.39	0.29	0.33	0.38	0.33	0.35	0.42	0.27	0.33
Low Inquisitiveness									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.09	0.05	0.06	0.11	0.03	0.04	0.16	0.04	0.07
Confidence	0.34	0.41	0.37	0.32	0.43	0.37	0.20	0.38	0.26
Excitement	0.20	0.30	0.24	0.24	0.33	0.28	0.38	0.38	0.38
Frustration	0.28	0.20	0.23	0.26	0.20	0.23	0.33	0.29	0.31
High Inquisitiveness									
	KNN (k=5)			**KNN (k=9)**			**C4.5**		
Emotion	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***	***Pr***	***Rec***	***FM***
Interest	0.00	0.00	0.00	0.00	0.00	0.00	**0.59**	0.24	0.35
Confidence	0.03	**1.00**	0.07	0.03	**1.00**	0.06	0.01	0.25	0.02
Excitement	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Frustration	0.50	0.03	0.05	0.00	0.00	0.00	**0.62**	0.10	0.18

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