Exploring the Importance of Individual Differences to the Automatic Estimation of Emotions Induced by Music

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ABSTRACT

The goal of this study was to evaluate the impact of the inclusion of listener-related factors (individual differences) on the prediction of music induced affect. A group of 24 subjects listened to a set of music excerpts previously demonstrated to express specific emotional characteristics (in terms of Arousal and Valence), and we collected information related to listeners' stable (personality, emotional intelligence, attentiveness, music preferences) and transient (mood, and physiological activity) states. Through a series of regression analysis we identified those factors which have a significant explanatory power over the affective states induced in the listeners. Our results show that incorporating information related to individual differences permits to identify more accurately the affective states induced in the listeners, which differ from those expressed by the music.

Categories and Subject Descriptors

H.1.2 [**Information Systems**]: Human factors

Keywords

Perceived music emotion, affect induction, personality, emotional intelligence, mood states, physiological signals, music liking, attention

1. INTRODUCTION

It is well known that listening to music interacts with listeners' affective (and cognitive) states, as demonstrated by numerous studies in the interdisciplinary field of music psychology (see, for instance, [15, 29] for overviews). One of the core processes that underlies the emotional power of music is a strong connection between the acoustic building blocks of music and the communication of emotional and affective meaning [11]. Nonetheless, communicated and *perceived* emotions are different from *induced (felt)* emotion [2]. A piece of music can convey certain emotion, but the same emotion may not be induced in the listener [17, 31]. This is because emotional responses are inherently subjective, and the role of individual differences is prominent in this process [29]. According to [29], individual factors affecting emotional responses to music can be broadly categorized as stable dispositions and transient states. Stable dispositions refer to individual differences such as age, gender, personality, while transient states refer to motivational state, concentration, and mood, among all. These differences can alter both perceived and induced (felt) emotional response.

Some studies have addressed the role of individual factors on music perceived emotions [24, 23, 10, 19, 12, 22, 29, 30], but very few have studied their impact on induced emotions. The focus of this paper is toward *induced* emotions, that is, how individual factors lead to differentiated emotional experiences while listening to music. In this domain, researchers developed systems to predict induced emotion from psychoacoustic features of music (loudness, pitch level,...) and physiological cues (skin conductivity) [7, 18]. However, these studies ignored the individual difference as a mediating variable in affect induction.

In the following we briefly review the factors we considered in our study and have promising effects on emotion induction from music:

- **Traits**. Vuoskoski and Eerola found some relationships between Big-Five (BF) personality traits and felt emotions [33]. For example, they found a positive relationship between extraversion and the experience of happiness, sadness, and tenderness in response to music. In another study, the same authors found that Trait Empathy can influence the rating of sadness while listening to music [34]. Kallinen and Ravaja found that in participants with high neuroticism and anxiety, listening to music increases positive Electroencephalography (EEG) alpha activation [16] and they rate with higher difference between perceived and felt arousal (i. e., they tend to evaluate stimuli as more emotional) [17].

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- **Emotional Intelligence**. Emotional Intelligence (EI) is another indicative of stable dispositions which is strongly connected to the emotional perception and response. In the music domain, the effects of EI on music consumption [5, 6] has been investigated. Additionally, Petrides and Furnham found that individuals with high trait EI exhibit greater sensitivity to emotion induction than low trait EI individuals and they identify faster emotional expressions [22].

- **Attentiveness**. Given the complex interaction between cognition and emotion in music (see [9]), various individual factors related to cognitive processes modulate emotional responses to music. For instance, keeping attention to the emotional stimuli can affect the felt emotion [26]. Scherer also suggested that high focus on stimulus events is needed to elicit emotions [28]. Consequently, lack of attention (such as day-dreaming, mind-wandering, mindful-attention) can alter the level of induced emotions.

- **Mood**. In relation to transient states, not only music can elicit moods in a listener, but the listener's current mood state can also alter the emotional impact of music. Schellenberg and colleagues [27] found that the intensity of induced emotion is higher when listening to two consecutive music excerpts (as emotion inducers) with contrasting emotions. Cantor and Zillman also found that the music rating is influenced by prior emotion induction [4].

- **Gender** also affects the emotion induction with music stimuli; women tend to show hypersensitivity to aversive musical stimuli [21].

In this study, our goal is to quantify the importance of a group of listener-related transient and stable characteristics to the prediction of emotional responses after listening to music communicating particular emotions. In particular, we investigate the role of age, gender, personality, EI, attentiveness, and music preferences (stable dispositions), as well as mood and physiological states (transient states) on the emotion induced by music. The affective responses to music (as dependent variables) were quantified using the Geneva Music-Induced Affect Checklist (GEMIAC)[8].

Beside emotional response, we also investigated the music rating (in terms of liking) with the same above-mentioned factors. The closest study to ours is from Vuoskoski and Eerola [33]. Nevertheless, our contribution is the inclusion of EI, attentiveness, physiological signals and mood, as well as the use of regression method.

2. EXPERIMENT

2.1 Participants

Twenty-four volunteers (students and employees of the Technische Universität München from eleven nationalities) participated in the experiment (16 males/8 females, mean age = 31, SD = 4.7, range = 21 - 40 years). Some of the participants had received musical training or they played music as a hobby, but they were not selected according to any musical background or skill. The participants signed an informed consent form before participation.

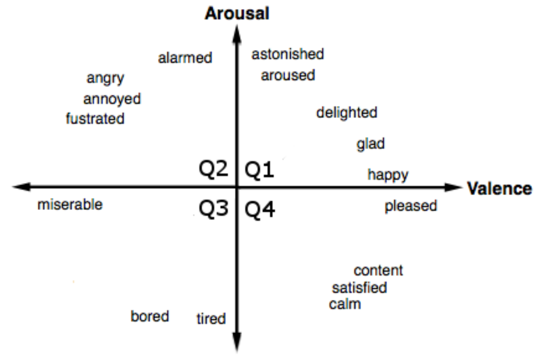

Figure 1: Schematic of the 2DES. Arousal describes the intensity level of an emotion (on a continuous scale ranging from low - bottom - to high - top) and Valence characterizes the hedonic value of an emotion (ranging from bad or unpleasant - left - to good or pleasant - right). The superimposed emotion words indicate the approximate location of typical terms used in everyday life to describe specific emotions according to Russell [25].

2.2 Materials

The stimuli consist of 16 excerpts of instrumental music pieces. The excerpts were selected based on their potential to induce in the listeners a wide range of affective states (irrespective of genre). In order to determine the emotional character of each piece we used the MediaEval 2014 "Emotion in Music" (ME14) dataset gold standard. From that set we selected pieces in the extremes of the two-dimensional emotional space (2DES) as described by Valence and Arousal affective dimensions (see Fig. 1). Specifically, we selected four pieces from each affective quadrant: high Arousal/positive Valence (Quadrant 1; Q1), high Arousal /negative Valence (Quadrant 2; Q2), low Arousal/negative Valence (Quadrant 3; Q3), and low Arousal/positive Valence (Quadrant 4; Q4). Because the ME14 dataset lacked in pieces that fall onto extremes of Q2 and Q4, we selected 8 music excerpts from other resources and verified by a music psychologist. The list of music excerpts is provided in Table 1.

Participants were also asked to complete three different questionnaires for measuring stable individual traits and dispositions related to personality, EI, attentiveness and their music preference. Personality was assessed using the Ten-Item Personality Inventory (TIPI). The TIPI is a brief measure of the Big-Five personality dimensions [13], the most widely used and researched model of personality. This framework quantifies individual differences in personality in terms of five broad dimensions: Agreeableness (A), Conscientiousness (C), Neuroticism (N), Extraversion (E), and Openness to Experience (O). EI was measured using the 68-item Barchard's questionnaire [1], measuring seven potential components in EI: Positive Expressivity, Negative Expressivity, Attending to Emotions, Emotion-based Decision Making, Responsive Joy, Responsive Distress, and Empathic Concern. In TIPI and EI cases, participants respond to the items using 7-point and 5-point scales, respectively. Furthermore, the participants complete the Short Test Of Music Preference-Revised (STOMP-R) [24], as a self-report

Table 1: Selected music excerpts. Q: Quadrant.

Q	Composer	Name	Genre
Q1	Patrick Lee	Quittin' Time	Electronic
	Latché Swing	Songe D'Automne	Jazz
	Jahzzar	Birthday Cake	Pop
	Anamanaguchi	Helix Nebula	Rock
Q2	Cannibal corpse	Make them suffer	Death metal
	Hatebread	Another day, another vendetta	Hardcore
	Jacob Lizotte	This Present Darkness	Metalcore
	Paths of possession	Darklands	Death metal
Q3	Stephan Siebert	When	Classical
	Blear Moon	Cold Summer Landscape	Electronic
	LJ Kruzer	Chantiers Navals 412	Pop
	Ergo Phizmiz	Simon Cowell	Pop
Q4	DeepMindRelaxation	Venus meditation	New age
	Unknown	Relaxing music	Relaxing
	Fridrik Karlsson	Make a Wish	Healing
	Michael Fesser	Relaxing background music	Relaxing

tool to assess music preference which are related to personality variables, self-views, and cognitive abilities. It consists of 23 items of 7-point ratings, and its subscales are: reflective & complex, intense & rebellious, upbeat & conventional, and energetic & rhythmic. Additionally, during listening, the participants may detach their mind from music listening to unrelated thoughts and consequently their ratings will be affected. Therefore, we assessed their attentiveness in terms of Daydreaming Frequency Scale (DDFS)[32], Mind-Wandering (MWQ)[20] and Mindful Attention Awareness Scale (MAAS)[3].

To assess the participants' current mood, they completed a mood questionnaire before the start of the first trial. This questionnaire consists of six 7-point bipolar items: Bad–Good, Sad–Happy, Displeased–Pleased, Calm–Excited, Tired–Energetic, and Sedate–Aroused.

Finally, to quantity the induced mood, we used the Geneva Music-Induced Affect Checklist (GEMIAC; [8]), an extension of the popular Geneva Emotional Music Scale (GEMS) [36]. The GEMIAC comprises 14 affective dimensions (see Table 2). Participants were asked to rate each item after listening to each excerpt in a 5-point Likert scale according to the emotion they felt.

2.3 Procedure

The participants were asked to sit inside a sound proof booth (see Fig. 2). Music was played with two speakers at a convenient volume level tuned by the subject. Each subject listened to 8 music excerpts (two from each 2DES quadrant) according to a balanced Latin square design (to reduce carryover and fatigue effect), and therefore every music piece was rated by at least 12 participants. Each trial lasted for 1'20": 30 seconds of silence followed by 50 seconds of music. After listening to each piece, participants filled in GEMIAC and indicated how much they liked the music. They were also asked to point out whether they knew the music. 85% (=164) of the trials were rated as "I didn't know it", 15% (=28) as "I think I heard it before", and 0% as "definitely knew it". Since there is not much variance in this variable, we omit it from the calculations. In between each trial there is about 2 minutes rest period for filling the questionnaires and to recover emotionally.

Figure 2: A participant inside the booth with the electrodes attached to her just before the experiment.

2.4 Physiological measurement

The physiological signals were acquired using the ProComp Infiniti encoder and the BioGraph Infiniti software suite (Thought Technology, Canada). We recorded Electrocardiogram (ECG), Skin Conductivity (SC) between the middle and index fingers, and respiration (to obtain heart-rate variability). The sampling rate for ECG was set to 2048Hz, while the other sensors were recorded with the rate of 256Hz. For each trial we extracted physiological features from the last 20 seconds of silence and music period. These features are mean and standard deviation of heart rate (HR) and heart rate variability (HRV), and standard deviation of high-pass filtered (0.5Hz-) skin conductivity (SC). We used the ratio of these features between each music period and its prior silence period.

2.5 Regression approach

We focused on estimating the relationships between emotional characteristics of music, listener's stable dispositions, physiological responses to music, and participants ratings of affective state for particular music pieces. Therefore, each affective state from GEMIAC was set as the dependent variable, and the other normalized variables as explanatory.

To predict each of the affective states, we used a Genetic Algorithm (GA) approach to select the variables which lead to the maximum likelihood[1]. Binary strings with the length of the number of variables were used to represent chromosomes (i. e., if the variable is selected then "1", otherwise "0"). Three sets of variables were tested; using only perceived music emotion, using perceived music emotion and physiological signals, and using perceived music emotion, stable dispositions and mood. Additionally, we added the interaction between each variable with the perceived music emotion (Arousal/Valence). A generalized linear regression model with proportional odds was used for prediction, since it is more suitable for ordinal discrete response variables.

We ran 16 times the GA process to avoid local minima and to take the maximum possible likelihood. The GA iteration is set to 300 for each run. During GA operation, we penalized the models where one or more variables (except intercepts) were not significantly different from zero ($p > 0.05$). This ensures that all the variable coefficients are significantly not equal to zero and no extra variable is inflating the correlation.

Once we found the effective variables, we tested them by using a one-subject-out cross validation; a new model with the same selected variables was created, but the coefficients were obtained by using N-1 subjects' trials. Then, this model was tested on the remaining subject. Finally, the correlation (ρ) between the true outputs and the predicted outputs was calculated.

Additionally, we performed the same steps to predict music liking from the same set of variables. This was to understand better the relationships between emotions in music and music preference given stable dispositions or physiological signals. Furthermore, we compared the liking prediction from self-rated emotional state and the liking prediction from stable dispositions and physiological signals. This was to find out if in the presence of a perfect emotion predictor we could gain more information on music liking prediction.

3. RESULTS

Table 2 depicts the selected variables which yield to the maximum likelihood for each affective state as well as liking rating. Once a variable without interaction is selected we marked it as "X", and once its interaction with music arousal or music valence is selected, we marked it as "A" or "V", respectively. In Table 2(a) we only included music Arousal and Valence as candidates. Interesting points regarding these results are that music arousal is not involved in "filled with wonder, amazed" measure and music valence has no effect on being "nostalgic, sentimental", "powerful, strong", "energized, lively", and "being bored, indifferent". For the other measures both arousal and valence are effective. Furthermore, correlation (ρ) varies between 0.22 and 0.63 for affective state and is 0.57 for music liking.

In Table 2(b), we included physiological signatures (Skin Conductivity, Heart Rate Variability, and Heart Rate) into the GA process. The important points we can conclude from this table are that physiological signatures are not involved in feeling "peaceful, relaxed", "powerful, strong", "energized, lively", or "moved, touched". Skin conductivity is only affected while being "sad, melancholic", and HRV is only selected for predicting "filled with wonder, amazed", "feeling of transcendence, sublime", "fascinated, captivated", and "tenderness, feeling of attraction". In addition in the presence of physiological signatures, music arousal is not any more selected for being "fascinated, captivated" and for music liking. Instead, the interaction of music valence with HRV and HR are selected, respectively. A significance test based on Fisher's Z-transformation has been taken to compare the correlations with the ones obtained in Table 2(a). We found no significant improvement (Fisher's Z-transformation with $p < 0.05$) in any of the affective states by inclusion of physiological signals.

In Table 2(c), instead of physiological signals, we included stable disposition (TIPI, EI, STOMPR, Attentiveness), age, gender, and mood state (POMS). Age is not affecting the predictions except for "filled with wonder, amazed". TIPI is not involved in "feeling of transcendence, sublime", EI subscales is not selected for "feeling of beauty, perfection" and "joyful, wanting to dance", attentiveness is not adding information in predicting "fascinated, captivated", and "moved, touched", and finally mood states are not involved in "being bored, indifferent". In addition, "feeling of affection, tenderness" and "sad, melancholic" vastly rely on TIPI as five variables are selected from this. Similarly, seven variables related to EI are selected for predicting "nostalgic, sentimental", STOMPR is affecting "powerful, strong" and music liking. Attentiveness and POMS are also promising candidates for predicting "feeling of transcendence, sublime". The Fisher's Z-transformation significance test also has been taken to compare the correlations with the ones in Table 2(a) and (b). In all the affective states except "Feeling of beauty, perfection", and "Joyful, wanting to dance", there are significant improvements ($p < 0.05$). In general, the mean correlation increase over all the affective states is 0.19 (SD = 0.07). This improvement is greater than when using any physiological signals. It suggests that the level of induced emotions are more tied to the listener's stable disposition, rather than changes in the physiological signals.

In addition, there is a significant improvement in predicting music liking by 12% with respect to only considering emotional characteristics of music. Liking music is affected by only STOMPR and mood state, while personality trait, emotional intelligence, attentiveness, age and gender have no effect on it. This could be because of the fact that STOMPR is a well-defined instrument for music preference.

3.1 Music liking prediction from induced affect

The same analysis has been taken to predict the liking rate from self-assessed induced affect, emotional characteristics of music, age, and gender. This is to assess in the presence of a perfect affect predictor how much gain we can achieve for prediction of liking. Using the same GA approach, nine affective states are selected (cf. Table 3).

[1]We have avoided using step-wise approaches (such as forward backward selection) because the may not reach to an optimal solution[14].

Table 2: Selected variables for predicting music induced affect by incorporating (a) Music Arousal and Valence, (b) Music Arousal and Valence and Physiological signals, (c) Music Arousal and Valence and stable disposition and mood states. (X) denotes the variable is selected without interaction, (A) and (V) depict the variable that is selected with its interaction with Music Arousal and Music Valence, respectively. The shaded area denotes the spaces that no variable is selected for certain modality (for reading facilitation). Asterisks denote the level significance: *$\equiv p < 0.001$, **$\equiv p < 0.01$, *$\equiv p < 0.05$, .$\equiv p < 0.1$.**

		Filled with wonder, amazed	Feeling of transcendence, of the sublime	Feeling of beauty, of perfection	Fascinated, captivated	Tenderness, feeling of affection	Nostalgic, sentimental	Peaceful, relaxed	Powerful, strong	Energized, lively	Joyful, wanting to dance	Moved, touched	Sad, melancholic	Tense, nervous	Bored, indifferent	Like
(a)	# of selected vars	1	2	2	2	2	1	2	1	1	2	2	2	2	2	2
	ρ	0.22	0.38	0.57	0.41	0.34	0.3	0.63	0.49	0.54	0.6	0.27	0.49	0.54	0.26	0.57
Music	Arousal		X	X	X	X	X	X	X	X	X	X	X	X	X	X
	Valence	X	X	X	X	X		X			X	X	X	X	X	X
(b)	# of selected vars	3	5	3	2	4	5	2	1	1	4	2	3	3	2	2
	ρ	0.28	0.43	0.57	0.42	0.37	0.4	0.63	0.49	0.54	0.61	0.27	0.49	0.55	0.26	0.57
Music	Arousal		X	X		X	X	X	X	X	X	X	X	X	X	
	Valence	X	X	X	X	X		X			X	X	X	X	X	X
Physiology	SC												A			
	Mean HRV		XV		V	A										
	Std HRV	V														
	Mean HR					X	A							V		V
	Std HR	A	X	A			XAV				AX					
(c)	# of selected vars	14	13	10	8	15	16	13	16	13	8	12	16	14	14	10
	ρ	0.51	0.56	0.65	0.6	0.56	0.66	0.74	0.68	0.69	0.69	0.53	0.67	0.75	0.47	0.69
	Significance to (a) and (b)	***	*		**	**	***	*	**	**	.	**	**	***	**	*
Music	Arousal		X	X	X	X	X	X	X	X	X	X	X	X	X	X
	Valence	X	X	X	X		X	X	X		X		X	X	X	X
TIPI	Extraversion	XA			A			XV	X		X				XA	
	Agreeableness			X	A	A	A	X			XA	X	X	X	A	
	Conscientiousness						X				V			V	A	
	Emotinoal stability			X		XA			AV	A			AV			
	Openness to experience			V		XV				A		A	AV			
EI	Positive expressivity		X			X	X	A					X		X	
	Negative expressivity	V				A	XA								X	
	Attending to emotions				X	X	X		V				X	V		
	Emotion based dec. making		V				XA			X					X	
	Responsive joy	X					A		V							
	Responsive distress									A					A	
	Empathic concern											A		X	A	
STOMPR	Reflective, complex	A							AV	A			V		X	
	Intense, rebellious	X		X	X			X	AV	A		A				XAV
	Upbeat, conventional			A		X	X					A	X			AV
	Energetic, rhytmic		X						X					X	X	
Attentiveness	DDFS score		A							XAV	V			V		
	MWQ score	A	X	A		X		X					X	X	X	
	MAAS score	X	X				XV			A			X			
POMS	Bad		X			A		X	X			V		XA		
	Sad		X					V	A	A		X				
	Displeased				A				X							X
	Calm		X		X									X		X
	Tired	XA	XV	V		V							XA			V
	Sedate	A		X		X	X	XA		X	X	XA	V			
	Age	A														
	Gender	A				A	A	X	V			AV		XA		

Table 3: Selected parameters for prediction of music liking rate from induced affect. (X) denotes the variable is selected without interaction, (V) depicts the variable that is selected with its interaction with Music Valence.

	Like
# of selected vars	9
ρ	0.84
Music Arousal	
MusicValence	X
Filled with wonder, amazed	X
Feeling of transcendence, of the sublime	X
Feeling of beauty, of perfection	
Fascinated, captivated	
Tenderness, feeling of affection	
Nostalgic, sentimental	
Peaceful, relaxed	X
Powerful, strong	
Energized, lively	
Joyful, wanting to dance	XV
Moved, touched	X
Sad, melancholic	
Tense, nervous	X
Bored, indifferent	X
Age	
Gender	

The correlation coefficient (ρ) is 0.83 which is 15% higher (Fisher's Z-transformation with $p < 0.001$) than using stable disposition and mood (ρ=0.69) and 27% higher (Fisher's Z-transformation with $p < 0.001$) than using physiological signals (ρ=0.57). This means that with a perfect emotion predictor, we can gain higher performance in predicting music liking.

4. CONCLUSION

Music has been widely used for inducing affect in listeners. However, due to the psycho-physiological differences between listeners, this induction may not be effective as expected. In this study we investigated the possible individual factors (differences) that can influence the emotion induction to a music listener. These factors are: stable dispositions (Big-Five personality traits, emotional intelligence, attentiveness, personality related to music liking), mood, and physiological signals. Given perceived music emotions, we used variable selection and regression to select the variables which are involved in the prediction of the induced affective states. We found for each type of affect, certain factors are mediating between perceived and felt emotion. This finding suggests that in any scenario if a certain affect is needed to be induced, only certain individual differences need to be taken into account. This can reduce the time for administration of questionnaires. In addition, inclusion of the stable dispositions and mood factors adds significant information about the felt emotion, while physiological signals provide less information.

Furthermore, we found from stable dispositions, using only personality related to music liking ([24]) collaborating with mood states provide significant information about music liking. Moreover, having a perfect emotion predictor we can boost the performance of music liking predictor. The results can be used in personalized music recommenders to boost their performance by incorporating mood and individual differences.

The limitation of our study is that only 24 participants ($\simeq$ 192 trials) from various nationalities were participated. This low number may not reflect between- and within-individual differences precisely. However, we found that adding more participants (> 21) does not change the selected variables drastically. Nevertheless, we plan to recruit more participants. In addition, in this study we used a limited number of music excerpts with already annotated perceived music emotion. However, the annotations may not be available in real scenarios. In this case, an automatic approach can be used to predict perceived emotion from acoustics [7, 35] in tandem operation with an emotion regulator.

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