The Role of Emotion and Context in Musical Preference

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PhD thesis

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Abstract

The powerful emotional effects of music increasingly attract the attention of music information retrieval researchers and music psychologists. In the past decades, a gap exists between these two disciplines, and researchers have focused on different aspects of emotion in music. Music information retrieval researchers are concerned with computational tasks such as the classification of music by its emotional content, whereas music psychologists are more interested in the understanding of emotion in music. Many of the existing studies have investigated the above issues in the context of classical music, but the results may not be applicable to other genres. This thesis focusses on musical emotion in Western popular music combining knowledge from both disciplines.

I compile a Western popular music emotion dataset based on online social tags, and present a music emotion classification system using audio features corresponding to four different musical dimensions. Listeners' perceived and induced emotional responses to the emotion dataset are compared, and I evaluate the reliability of emotion tags with listeners' ratings of emotion using two dominant models of emotion, namely the categorical and the dimensional emotion models.

In the next experiment, I build a dataset of musical excerpts identified in a questionnaire, and I train my music emotion classification system with these audio recordings. I compare the differences and similarities between the emotional responses of listeners and the results from automatic classification.

Music emotions arise in complex interactions between the listener, the music, and the situation. In the final experiments, I explore the functional uses of music and musical preference in everyday situations. Specifically, I investigate emotional uses of music in different music-listening situational contexts. Finally, I discuss the use of emotion and context in the future design of subjective music recommendation systems and propose the study of musical preference using musical features.

I, Yading Song, confirm that the research included within this thesis is my own work or that where it has been carried out in collaboration with, or supported by others, that this is duly acknowledged below and my contribution indicated. Previously published material is also acknowledged below.

I attest that I have exercised reasonable care to ensure that the work is original, and does not to the best of my knowledge break any UK law, infringe any third party's copyright or other Intellectual Property Right, or contain any confidential material.

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Details of collaboration and publications:
All collaborations and earlier publications that have influenced the work and writing of this thesis are fully detailed in Section 1.4.

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Glossary of Technical Terms

- **Ground Truth** refers to data which includes input data for a particular task together with the corresponding desired output. It is typically used for training (also known as learning), validation, and/or testing for models. For example, in the studies of music emotion recognition, a subjective listening test is often conducted to collect the ground truth needed for training the computational model of emotion prediction.

- **Machine Learning** explores the study and construction of algorithms that can learn from and make predictions on data. Machine learning tasks are typically classified into three broad categories, depending on the nature of the learning "signal" or "feedback" available to a learning system. These are *supervised learning*, *unsupervised learning*, and *reinforcement learning*. Applications in which the training data comprises examples of the input data along with their corresponding output are known as supervised learning problems. Unsupervised learning is used when the training data consists of a set of input data without any corresponding output. The technique of reinforcement learning is concerned with the problem of finding suitable actions to take in a give situation in order to maximise a reward. Here the learning algorithm is not give examples of optimal outputs, in contrast to supervised learning, but must instead discover them by a process of trial and error.

- **Support Vector Machines (SVMs)** are supervised learning models with associated learning algorithms that analyse data and recognise patterns, used for classification and regression analysis. An SVM model is a representation of the examples as points in space, mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted to belong to a category based on which side of the gap they fall on. In addition to performing linear classification, SVMs can efficiently perform a non-linear classification using what is called the kernel trick, implicitly mapping their inputs into high-dimensional feature spaces. Some common non-linear kernels include *dth-degree polynomial*, *Gaussian radial basis*, and *neural network*. SVMs have been used in a variety of classification tasks, such as isolated handwritten digit recognition, speaker identification, object recognition, face detection, and vowel classification.

- **k-Nearest Neighbours (k-NN)** is a simple algorithm that stores all available cases and classifies new cases based on a similarity measure (e.g., distance functions). It is a non-parametric method used for classification and regression. A case is classified by a majority vote of its neighbours, with the case being assigned to the class most common amongst its K nearest neighbours measured by a distance function. If $k = 1$, then the object is simply assigned to the class of that single nearest neighbour. A shortcoming of the k-NN algorithm is that it is sensitive to the local structure of the data.

- **Random Forests (RF)** are a combination of tree predictors such that each tree depends on the values of a random vector sampled independently and with the same distribution for all trees in the forest. A Random Forest consists of an arbitrary number of simple trees, which are used to determine the final outcome. For classification problems, the ensemble of simple trees vote for the most popular class. In the regression problem, their responses are averaged to obtain an estimate of the dependent variable. Using tree ensembles can lead to significant improvement in prediction accuracy (i.e., better ability to predict new data cases).

- **Deep Belief Networks (DBN)** are probabilistic generative models that are composed of multiple layers of stochastic, latent variables. The latent variables typically have binary values and are often called hidden units or feature detectors. The top two layers have undirected, symmetric connections between them and form an associative memory. The lower layers receive top-down, directed connections from the layer above. The states of the units in the lowest layer represent a data vector. Deep belief networks have been used for generating and recognising images, video sequences, and motion-capture data.

List of Abbreviations

AMC	Audio Mood Classification
ANEW	Affective Norms for English Words
APIs	Application Programming Interfaces
ANOVA	Analysis of Variance
BBC	British Broadcasting Corporation
BOW	Bag-of-Words
C4DM	Centre for Digital Music
CBM	Content-base Model
CF	Collaborative Filtering
CM	Categorical Model
DBN	Deep Belief Network
DM	Dimensional Model
ECG	Electrocardiogram
EEG	Electroencephalograph
ESM	Experience Sampling Method
GEMS	Geneva Emotional Music Scale
GMM	Gaussian Mixture Model
Gold-MSI	Goldsmiths Musical Sophistication Index
HCDF	Harmonic Change Detection Function
k-NN	K-Nearest Neighbour
K-S	Kolmogorov-Smirnov
LIWC	Linguistic Inquiry and Word Counts
MER	Music Emotion Recognition
MFCC	Mel-Frequency Cepstral Coefficients
MIR	Music Information Retrieval
MIREX	Music Information Retrieval Evaluation eXchange

MSD	Million Song Dataset
MT	Musical Training
OST	Online Social Tags
PAD	Pleasure-Arousal-Dominance
PLSA	Probabilistic Latent Semantic Analysis
QBSH	Query By Singing/Humming
RBF	Radial Basis Function
RF	Random Forests
RMS	Root Mean Square
SVMs	Support Vector Machines
SCR	Skin Conductance Response
TF-IDF	Term Frequency-Inverse Document Frequency
VA	Valence-Arousal

Chapter 1

Introduction

This thesis is concerned with the role of emotion and context in musical preference. In this chapter, the motivations and aims of my work are described in Section 1.1. The thesis is outlined in Section 1.2, and a summarisation of contributions are presented in Section 1.3. Finally, publications associated with this thesis are listed in Section 1.4.

1.1 Motivation and Aim

With the emergence of digital music in the past two decades, the Internet has become a major source of retrieving multimedia information such as video, book, and music. The nature of music experience has changed at a fundamental level, and traditional ways of exploring and listening to music from radio stations and record stores have been partially replaced by music discovery web sites such as AllMusic[1], iTunes[2], Last.FM[3], Pandora[4], Spotify[5], and Youtube[6] (Casey et al., 2008). Additionally, the rapid growth of portable digital devices has made music available almost everywhere. A study of recreational activities (watching television, listening to music, reading books, and watching movies) showed that people listen to music more often than any of the other activities (Rentfrow and Gosling, 2003). Due to the tremendous expansion of digital music libraries, personal collections of music can also easily exceed practical limits on the time we have to listen to them (Casey et al., 2008). For music researchers, the large collection of music recordings has also raised a major challenge for searching, retrieving, and organising musical

[1] `http://www.allmusic.com/`
[2] `https://www.apple.com/music/`
[3] `http://www.last.fm/`
[4] `http://www.pandora.com/`
[5] `https://www.spotify.com/`
[6] `https://www.youtube.com/`

content.

In the last fifteen years, music information retrieval (MIR) techniques have been developed to deal with common issues such as identification, recognition, and recommendation of music. Music recommendation systems, an effective application of discovering and filtering musical information, have been widely discussed (Celma, 2009). A good music recommendation system is capable of automatically modelling users' musical preferences and generating playlists accordingly. The development of music recommendation systems also provides a great opportunity for industry to aggregate users who are interested in music and have similar musical preference. At present, the majority of commercial music recommendation systems are metadata-based, which provides search functionality based on the artist's name, track title, album, and genre. In recent years, although MIR researchers have achieved relative success in content-based music recommendation systems by measuring inter-song similarity, there is still a lack of personalised design, involvement of human subjects, and user interactions with music recommendation systems.

The experience of music is highly subjective. It not only can convey and express emotion, but it can also regulate a listener's emotion (Schubert, 2013; Eerola and Vuoskoski, 2013). People reported that their primary motivation for listening to music lies in its emotional effects (Juslin and Laukka, 2004; Juslin et al., 2008). In addition, Sloboda et al. (2009) reported that a substantial amount of music listening in contemporary Western society is deliberately chosen. People choose to listen to music for different reasons and to achieve various goals. Lamont and Greasley (2009) advocated that musical preferences and motivations for music listening are also context-dependent.

Companies such as Musicovery[7], Songza[8], and Stereomood[9] have attempted to integrate more subjective elements into the implementation of music recommendation systems, and have used emotional and contextual tags to help people discover music. However, these tags have been mostly manually annotated by experts. The process is very expensive and laborious. Furthermore, many questions on the practicality of emotion- and context-based music recommendation systems remain unclear. The development of subjective music recommendation system is handicapped due to the lack of empirical studies on musical emotion and music-listening context (Uitdenbogerd and Van Schyndel, 2002).

In music psychology, an extensive body of research is dedicated to the understanding of

[7] http://musicovery.com/
[8] http://daily.songza.com/
[9] http://www.stereomood.com/

music and emotion (Schubert, 2007b; Juslin and Sloboda, 2010; Eerola and Vuoskoski, 2013). Such research in music psychology literature has highlighted the importance of context in music listening (North and Hargreaves, 1996; Sloboda et al., 2001; North et al., 2004; Juslin et al., 2008; Greasley and Lamont, 2011). It is important to combine the knowledge from these two fields, music information retrieval and music psychology, in order to further advance in our understanding.

This thesis focusses on Western popular music, and the aim of my work is to investigate music and emotion using approaches from both MIR and psychology, and explore its relationship with music-listening context, functions, and musical preference. By carrying out this research, I am hoping to bring together research in MIR and music psychology.

1.2 Thesis Structure

Chapter 2 covers background knowledge for the research on music and emotion. It starts with the definitions used in this thesis and discusses different emotional processes in relation to music. The models of musical emotion, along with the advantages and disadvantages are described. Research in two different fields, music information retrieval and music psychology, is reviewed. A brief summary of stimuli used in previous research is presented, and the problems identified are discussed at the end.

Chapter 3 describes the terminology related to research of musical preference and music-listening context. A review of previous research on context is provided. Furthermore, three different aspects: emotional uses of music, functions of music listening, and musical preference are presented in detail.

Chapter 4 investigates the first element, emotion. This chapter provides the “ground truth” music emotion data collection of Western popular music. Features in four musical dimensions are extracted. Machine learning techniques are applied to classification of emotional content in music. I further investigate musical emotions and the reliability of social tags using two popular models of emotion, the categorical model and the dimensional model. The results of two listening tests using these two models are shown, and discussed in detail. In addition, the differences in music emotion classification accuracy between machine and human are compared.

Chapter 5 explores the second element, music-listening context. A questionnaire on daily usage of music is presented to participants. I compare the functional uses of music, musical preference, and emotional responses to music in everyday situations. Answers for the questions such as "What are the functions of listening to music?" and "How do different styles of music serve different situations?" can be found in this Chapter. For the study of emotional responses for different situations, this chapter focusses on the expected emotional responses from the impact of music. The emotion changes due to the presence of music is investigated in Chapter 6.

Chapter 6 addresses the emotional uses of music, and further discusses the relationships between emotional responses and functional uses of music. Based on the activity selected in Chapter 5, thirteen activities are chosen and presented to participants. This chapter compares the emotional responses with and without the presence of music, and examines the effects of individual factors such as age, gender, and musical training on the experience of music listening. Five emotional uses of music, namely to maintain, intensify, diminish, create, and to change emotion, are also identified.

Chapter 7 concludes the thesis, summarises the doctoral project, and provides ideas for future studies on music and emotion using psychophysiological measurements, musical feature analysis of musical preference, and the use of emotion and context in the design of subjective music recommendation systems.

1.3 Contributions

The following list contains the main contributions of this thesis and the chapters they appear in:

- Chapter 4: Creation of a Western popular music dataset ($N = 2904$) for music emotion classification using social tags "happy", "sad", "angry", and "relaxed" from Last.FM.
- Chapter 4: Evaluation of audio features for music emotion classification with the collected emotion dataset.
- Chapter 4: Comparison of induced and perceived emotional responses using the categorical and the dimensional models of emotion.
- Chapter 4: Implementation of a music emotion classifier trained with a participant-suggested emotion dataset ($N = 207$) and comparison of human versus machine emotion recognition.

- Chapter 5: Exploration of musical preference in twenty everyday situations.
- Chapter 5: Categorisation of expected emotional responses to music for each activity on a valence-arousal space.
- Chapter 6: Investigation of functional uses of music in various contexts, and a proposal of five emotional uses of music.

1.4 Associated Publications

The research was carried out by the author between September 2011 and August 2015 in the Centre for Digital Music at Queen Mary University of London. Most of the work in the thesis has been presented at international conferences or in journals.

Peer-Reviewed Journal Articles

i (Song et al., 2015c) - **Song, Y.**, Dixon, S., Pearce, M. T., and Halpern, A. R. (2016). Perceived and induced emotion responses to popular music: Categorical and dimensional models. *Music Perception: An Interdisciplinary Journal*, in press.

ii (Song et al., 2015b) - **Song, Y.**, Dixon, S., Pearce, M. T., and Eerola, T. (2016). Functional uses of music vary across everyday situations, emotions and music preferences. In preparation.

iii (Song et al., 2015a) - **Song, Y.**, Dixon, S., Pearce, M. T., and Eerola, T. (2016). Emotional and functional uses of music in various contexts. In preparation.

Peer-Reviewed Conference Papers

iv (Song and Dixon, 2015) - **Song, Y.**, Dixon, S. (2015). How well can a music emotion recognition system predict the emotional responses of participants?. In *Proceedings of the 12th Sound and Music Computing Conference (SMC)*, Maynooth, Ireland.

v (Song et al., 2013b) - **Song, Y.**, Dixon, S., Pearce, M. T., and Halpern, A. R. (2013). Do online social tags predict perceived or induced emotional responses to music?. In *Proceedings of the 14th International Society for Music Information Retrieval Conference (ISMIR)*, pp. 89-94, Curitiba, Brazil.

vi (Kosta et al., 2013) - Kosta, K., **Song, Y.**, Fazekas, G., and Sandler, M. (2013). A study of cultural dependence of perceived mood in Greek music. In *Proceedings of the 14th International Society for Music Information Retrieval Conference (ISMIR)*, pp. 317-322, Curitiba, Brazil.

vii (Song et al., 2013a) - **Song, Y.**, Dixon, S., Pearce, M. T., and Fazekas, G. (2013). Using tags to select stimuli in the study of music and emotion. In *Proceedings of the 3rd International Conference on Music and Emotion (ICME)*, Jyväskylä, Finland.

viii (Song et al., 2012b) - **Song, Y.**, Dixon, S., and Pearce, M. T. (2012). Evaluation of musical features for emotion classification. In *Proceedings of the 13th International Society for Music Information Retrieval Conference (ISMIR)*, pp. 523-528, Porto, Portugal.

ix (Song et al., 2012a) - **Song, Y.**, Dixon, S., and Pearce, M. T. (2012). A survey of music recommendation systems and future perspectives. In *Proceedings of the 9th International Symposium on Computer Music Modelling and Retrieval (CMMR)*, pp. 395-410, London, UK.

Chapters 1 and 7 are based on some of the work published in `ix`. Publications `i`, `iv`, `v`, `vii`, and `viii` are the basis for Chapter 4. Articles `ii` and `iii` are the basis for Chapters 5 and 6.

In addition to the research supervised by Simon Dixon and Marcus Pearce, for publication `vi`, the author also worked with Andrea Halpern on publications `i` and `v`. During the 2-month research visit at Finnish Centre of Excellence in Interdisciplinary Music Research at University of Jyväskylä from June to July, 2013, Tuomas Eerola supervised the project "emotional and functional uses of music in everyday life" (see publications `ii` and `iii`).

In publications `i`, `ii`, `iii`, and `v`, I conducted all the experiments and wrote the articles. Co-authors (Simon Dixon, Marcus Pearce, Andrea Halpern, and Tuomas Eerola) provided ideas for experimental design and data analysis. The manuscripts were also checked by co-authors throughout the submission and review process. In publication `iv`, Simon Dixon offered some insights into method and data analysis. In publication `vi`, I proposed different hypotheses, conducted data analysis, and wrote results and conclusion sections. Katerina Kosta collected Greek music dataset, wrote introduction section, and helped data analysis. György Fazekas worked on experimental design and wrote background and introduction sections. In publications `vii`, `viii`, and `ix`, I wrote the articles and conducted the experiments. Simon Dixon and Marcus Pearce provided their advices on writing and analysis, and György Fazekas kindly assisted me with the online experiments setup.

Chapter 2

Background in Music and Emotion

This chapter describes background knowledge for the research on music and emotion. Section 2.1 defines the concepts that are used throughout this work. Next, two forms of emotional processes in relation to music, perception and induction of musical emotions, are described in Section 2.2. Section 2.3 covers an overview of the models of emotion in music. Previous studies are then explained in Section 2.4, particularly in the fields of computer science (see Section 2.4.1) and music psychology (see Section 2.4.2). In Section 2.5, I briefly discuss the stimuli used in previous research. Finally, a review of the gap between research from different fields is presented in Section 2.6.

2.1 Definition

Given the importance of emotion in music, researchers have paid increasing attention to the study of music and emotion in the past two decades (Juslin and Sloboda, 2001, 2010; Eerola and Vuoskoski, 2013). Previous studies have used the terms *emotion* and *mood*, and sometimes they are referring to the same concept. Also when people describe their "emotional experience" in music, they may choose other words such as *feeling* and *affect* (Juslin and Sloboda, 2010). Scherer (2005) has stated that the definition of emotions, distinguishing them from other affective states or traits, is a notorious problem and constant challenge for emotion researchers. For example, the differences among these terms are not always stated by music information retrieval researchers (Huq et al., 2010; Yang and Chen, 2012; Watson and Mandryk, 2012), whereas the distinction is often made by psychologists (Scherer, 2004; Juslin et al., 2008; Saari and Eerola, 2014). This phenomenon causes terminological confusion. In order to avoid this problem in this work, I follow the concepts (i.e., affect, emotion, mood, and feeling) defined in the book

Handbook of music and emotion: Theory, research, applications by Juslin and Sloboda (2010).

i *Affect*: This is used as an umbrella term that covers all evaluative - states (e.g., emotion, mood, and preference) or "valences" (positive/negative). The term denotes such phenomena in general. If that is not intended, a more precise term (e.g., mood, emotion, and preference) is used instead (p. 10);

ii *Emotion*: This term is used to refer to a quite brief but intense affective reaction that usually involves a number of sub-components: subjective feeling, physiological arousal, expression, action tendency, and regulation, that are more or less "synchronised". Emotions focus on specific "objects" and last minutes to a few hours (e.g., happiness, sadness) (p. 10);

iii *Mood*: This term is used to denote such affective states that are lower in intensity than emotions, that do not have a clear "object", and that are much longer lasting than emotions (i.e., several hours to days). Moods do not involve a synchronised response in components like expression and physiology (e.g., gloomy) (p. 10);

iv *Feeling*: This term is used to refer to the subjective experience of emotions or moods. Feeling is one component of an emotion that is typically measured via verbal self-report (p. 10).

This work focusses mainly on the *emotion* in music. Juslin and Sloboda (2010) define *musical emotions* as a short term for "emotions that were somehow induced by music", without any further implications about the precise nature of these emotions. In this work, I use the terms *emotion* and *musical emotion* to represent perceived and induced emotion interchangeably.

2.2 Perception and Induction of Musical Emotions

Music can both express and evoke emotions (Krumhansl, 2002). In the study of music and emotion, one of the challenges faced by psychologists is to compare the two forms of emotional processes in relation to music, namely perception and induction of musical emotions. Gabrielsson (2002) has stated that *induced emotion* (also known as *felt emotion*, or *internal locus*) is the emotion experienced by the listener, whereas the *perceived emotion* (also known as *expressed emotion*, or *external locus*) is the emotion recognised in the music. Schubert (2013) has summarised the terms used to describe these two forms of emotional processes in relation to music (see Table 2.1).

In the last ten years, research on emotions perceived in music and induced by music has gained increased attention (Eerola, 2013). The ways in which people recognise and experience emotion in music remain unclear. Generally, induced emotion is considered to be more subjective, and perceived emotion tends to be more objective (Västfjäll, 2002; Kallinen and Ravaja, 2006; Evans and Schubert, 2008). Other studies have also suggested that the rating level of induced emotion is higher than the level of perceived emotion in connection with positive valence, but lower in connection with arousal, positive activation, and negative activation (Kallinen and Ravaja, 2006).

TABLE 2.1
The terms used to describe the two forms of emotional processes in relation to music by grammatical subject (perspective).

Form	**Locus**	**Listener perspective**	**Music perspective**
Induction	Internal	Experienced, felt, own, reactivity, self	Conveys, induces, evokes, arouses, elicits, communicates
Perception	External	Noticed, perceived, recognised, sensed	Expresses, portrays, depicts, conveys, sounds, describes, has character, "is"

2.2.1 Perceived Musical Emotion

Music can express emotions (DeNora, 1999; Juslin and Laukka, 2004). Darwin (1872) demonstrated that emotional expression serves the vital function of externalising an individual's reaction and action propensity and of communicating this information to the social environment. This vocal communication of emotion has evolved in a phylogenetically continuous manner (Scherer, 1995). Ekman (1992, 1993) has shown that the ability to identify basic emotions (e.g., happiness, sadness, and anger) through facial expression seems to be universal among humans, and each of the basic emotions may also have associated vocal expression (Scherer and Oshinsky, 1977). Listeners judge vocal expression of emotion via acoustic cues such as pitch variation, pitch contour, and tempo. Similar to vocal expression (Wallbott and Scherer, 1986), music is also often regarded as an effective means of emotional communication (Gabrielsson and Juslin, 2003; Juslin and Laukka, 2003). For instance, children between age 3-12 have showed a reliable positive-major/negative-minor connotation of listening to music (Kastner and Crowder, 1990). Hunter et al. (2010) have suggested that people associate happiness with fast tempo and major key, and sadness with slow tempo and minor key. Juslin and Laukka (2003) have also compared the communication of emotion in acoustic cues between vocal expression and music performance, and have indicated that they (vocal expression and music performance) share similar cues such as intensity (i.e., loudness of speech, loudness) and attack (i.e., rapidity of voice/tone onset), and that music performance has specific cues such as articulation (i.e., the relative proportion of sound to silence in note values) and vibrato (i.e., periodic changes in the pitch of a tone).

Previously, research showed that happiness and sadness can be expressed well and identified easily in music (Vieillard et al., 2008; Mohn et al., 2010). However, fear and anger are harder to identify than happiness and sadness (Terwogt and Van Grinsven, 1991; Kallinen, 2005). As pointed out in some studies, certain genres such as classical and popular music may express specific emotions (Eerola, 2011), and other individual differences such as culture (Fritz et al., 2009; Zacharopoulou and Kyriakidou, 2009; Thompson and Laura-Lee, 2010; Hu and Lee, 2012; Kosta et al., 2013), age (Morrison et al., 2008), musical expertise (Castro and Lima, 2014), and personality (Vuoskoski and Eerola, 2011b) may also affect the perception of emotion in music.

2.2.2 Induced Musical Emotion

People in Western culture have reported that one of the main motivations to engage in musical activities is emotional responses (Juslin and Laukka, 2004; Schäfer et al., 2013). It is known that music can evoke strong emotions (Gabrielsson, 2010). Emotions induced by music are often accompanied with psychophysiological changes (e.g., heart rate, blood pressure, skin conductance, and temperature) (Nyklícek et al., 1997; Khalfa et al., 2002; Gomez and Danuser, 2004; Miu and Balte, 2012). For example, compared with emotional musical excerpts of sadness, fear, and tension, happy excerpts produce the largest changes in the measures of respiration and generate more zygomatic facial muscle activity and greater skin conductance (Krumhansl, 1997; Lundqvist et al., 2008).

Comparing with studies of perceived emotion in music, there is much less research concerning induced musical emotions. Questions such as "What emotions can be induced by music?" (Scherer, 2004) and "How does music induce emotions?" (Juslin and Västfjäll, 2008) remain unclear. Scherer and Zentner (2001) have suggested several production rules for emotion induction by music, including appraisal, memory, and empathy. In addition to cognitive appraisal (Scherer, 1999), Juslin and Västfjäll (2008) have proposed six additional underlying psychological mechanisms by which music might be expected to evoke emotions, (i) *brain stem reflexes*, (ii) *evaluative conditioning*, (iii) *emotional contagion*, (iv) *visual imagery*, (v) *episodic memory*, and (vi) *musical expectancy*. Later, a unified theoretical framework (BRECVEMA) is presented featuring two more mechanisms, namely *aesthetic judgment* and *rhythmic entrainment* (Juslin et al., 2010, 2014). Zentner et al. (2008) have reported some emotions (e.g., amazement, peacefulness) are more frequently felt in response to music than in everyday life. Also, generally, emotions induced by music tend to be more positive (Juslin and Laukka, 2004; Schellenberg et al., 2008). Meanwhile, individual factors such as personality (Kallinen and Ravaja, 2006; Vuoskoski et al., 2011), culture (Egermann et al., 2015), and current states (Vuoskoski and Eerola, 2011a) can also affect the musical emotion experience in response to music.

2.2.3 Relationship between Emotion Perception and Induction

People enjoy experiencing songs they perceive as sad (Vuoskoski et al., 2011), but they may also love songs which make them sad (Hunter et al., 2011; Schubert, 2012). Perceiving an expression of sadness in music without necessarily being affected oneself is mainly a perceptual-cognitive process, and it should be distinguished from listeners' emotional response to the music (Gabrielsson, 2002). In general, music seems to evoke emotions similar to the emotional quality perceived in music (Kallinen and Ravaja, 2006). Research has shown that ratings of perceived emotion are more consistent than ratings of induced emotion (Schubert, 2007a; Hunter et al., 2010).

Separating induced emotion from perceived emotion is not straightforward, and the distinction is not always observed (Eerola, 2011; Schubert, 2013; Egermann et al., 2013). Juslin and Laukka (2004) have distinguished the perception and induction of emotion in music from emotions induced in everyday life, yet the quantitative relationship between the two has not been examined (Evans and Schubert, 2008). Gabrielsson (2002) has proposed and given examples of four possible relationships between perceived and induced emotion (shown below), namely *positive relationship*, *negative relationship*, *no systematic relationship*, and *no relationship.* Those relationships have also been discussed by Kallinen and Ravaja (2006), and Evans and Schubert (2008).

- **Positive relationship** occurs when "the listener's emotional response is in agreement with the emotional expression in the music" (p. 131);
- **Negative relationship** occurs when the "listener reacts with an emotion opposite to that expressed in the music: positive emotion in the music elicits negative emotion in the response, or negative emotion in the music elicits positive emotion in the response" (p. 134);
- **No systematic relationship** occurs when the listener stays "emotionally neutral" regardless of the expression of the music, or experiences different emotions on different occasions (p. 136);

- **No relationship** occurs when there is not even a potential relationship, such as when a person feels an emotion that cannot be expressed in music (p. 136).

2.3 Musical Emotion Representation

During the past two decades, *categorical* (or *discrete*), *dimensional*, *miscellaneous* (McAdams et al., 2004; Ilie and Thompson, 2006), and *domain-specific* emotion models (e.g., Geneva Emotional Music Scale, which is only used for induced emotion) (Zentner et al., 2008) have been proposed and used in the study of music and emotion. The categorical model and dimensional model have received empirical support (Kreutz et al., 2007; Vieillard et al., 2008; Mion and Poli, 2008) and have been commonly used (Vieillard et al., 2008; Juslin et al., 2008; Truong et al., 2009; Vuoskoski and Eerola, 2011b). Recently, Eerola and Vuoskoski (2010, 2013) have compared the use of these two models and have suggested that the categorical emotion model is less reliable than the dimensional model at predicting the rating of excerpts that are ambiguous examples of an emotion category, but they both produce highly compatible ratings of perceived emotions. In addition, to model the mapping between the categorical and the dimensional models of emotion, a probabilistic framework utilising a Gaussian Mixture Model (GMM) has been discussed by Wang et al. (2012).

2.3.1 Categorical Model

The categorical model (CM) assumes that an independent neural system subserves every discrete basic emotion (Eerola and Vuoskoski, 2010) and it represents all emotions as being derived from a limited number of universal and innate basic emotions such as happiness, sadness, fear, and anger (Ekman, 1992; Panksepp, 1998). Empirical support for the categorical model can be found in the research on neuropsychological and functional brain imaging studies. For instance, researchers have found that recognition of facial expressions of fear may be associated with specific neural substrates (Morris et al., 1996; Phillips et al., 1998). Apart from the basic emotions such as happiness and sadness, the categorical model may also include emotions such as tragedy, aggressiveness, and sensation (Thayer, 1989; Schubert, 2003; Hu and Downie, 2007). Previous studies have suggested that musically inappropriate categories such as disgust should be replaced with more fitting categories such as tenderness or peacefulness (Gabrielsson and Juslin, 1996; Vieillard et al., 2008).

Previously, different researchers came up with different sets of emotions, and several emotion taxonomies have been used (Juslin and Laukka, 2003; Bischoff et al., 2009; Hu and Lee, 2012; Yang and Hu, 2012). For example, Hevner (1935) proposed eight clusters consisting of 68 words. Later, a combination of emotional words selected from Hevner (1935), Russell (1980), and Whissell (1989) was validated by 133 musically experienced people, and Schubert (2003) refined these into nine groups consisting of 46 words, as shown in Table 2.2. Thayer (1989) on the other hand classified emotions into four groups: high energy/high stress, high energy/low stress, low energy/high stress, and low energy/low stress (see Table 2.3). Recently, five mood clusters proposed by Hu and Downie (2007) have gained popularity in music information retrieval tasks such as music emotion recognition (MER), similarity, and music recommendation (Yang and Hu, 2012; Singhi and Brown, 2014). Table 2.4 presents the five mood clusters for audio mood classification (AMC) from the annual Music Information Retrieval Evaluation eXchange (MIREX)[1].

TABLE 2.2
Nine mood clusters proposed by Schubert (2003).

Cluster	Examples
1	bright, cheerful, happy, joyous
2	humorous, light, lyrical, merry, playful
3	calm, delicate, graceful, quiet, relaxed, serene, soothing, tender, tranquil
4	dreamy, sentimental
5	dark, depressing, gloomy, melancholy, mournful, sad, solemn
6	heavy, majestic, sacred, serious, spiritual, vigorous
7	tragic, yearning
8	agitated, angry, restless, tense
9	dramatic, exciting, exhilarated, passionate, sensational, soaring, triumphant

The categorical model provides people an easy way to select and categorise emotion (Juslin and Laukka, 2004), and it is most frequently used in the study of perceived emotion (Eerola and Vuoskoski, 2013). More importantly for recommending music, the emotion category can be easily incorporated into metadata-based retrieval systems (e.g., keyword and tag search) (Han et al., 2009; Laurier et al., 2009). Choosing from a set of emotions has shown an advantage for emotion recognition in music, and it can clearly differentiate one emotion to another (Lu et al., 2006, 2010). In my work, I select four basic emotion classes: "happy", "angry", "sad", and "relaxed", considering that these four emotions are widely used across different cultures and cover all four

[1] http://www.music-ir.org/mirex/wiki/MIREX_HOME

TABLE 2.3
Four mood categories proposed by Thayer (1989).

Energy	Stress	Examples
High	High	tense/anxious, angst-ridden, spooky, eerie, rowdy, fiery, angry, fierce, provocative, boisterous, hostile, aggressive, volatile, rebellious, confrontational, paranoid, outrageous, unsettling, brittle
High	Low	rollicking, exuberant, happy, sexy, exciting, energetic, party/celebratory, intense, gleeful, lively, cheerful, fun, rousing, freewheeling, carefree, passionate, playful, gritty, joyous
Low	Low	calm/peaceful, sentimental, cathartic, soft, romantic, springlike, warm, precious, laid-back/mellow, confident, hypnotic, naive, intimate, innocent, relaxed, soothing, dreamy, smooth, gentle
Low	High	sad, melancholy, detached, whimsical, gloomy, ironic, snide, somber, autumnal, wry, wintry, plaintive, yearning, austere, bittersweet, fractured, bleak, cynical/sarcastic, bitter, acerbic

TABLE 2.4
Five mood clusters used in the MIREX audio mood classification task proposed by Hu and Downie (2007).

Cluster	Examples
1	passionate, rousing, confident, boisterous, rowdy
2	rollicking, cheerful, fun, sweet, amiable/good natured
3	literate, poignant, wistful, bittersweet, autumnal, brooding
4	humorous, silly, campy, quirky, whimsical, witty, wry
5	aggressive, fiery, tense/anxious, intense, volatile, visceral

quadrants of the two-dimensional model of emotion (Laurier et al., 2008).

Although the categorical model has been dominantly used in the study of music and emotion, there exists some issues. Emotion is subjective in nature, and different people may use different words to describe the same emotions (Schuller et al., 2010). With few categories, the categorical model is inadequate to describe the richness of emotional effects of music (Yang and Chen, 2012); with many categories, the choice of emotion categories may overwhelm people (Yang and Chen, 2011).

2.3.2 Dimensional Model

The typical dimensional model (DM) represents emotions in an affective space with two dimensions: one related to valence (a pleasure-displeasure continuum), and the other to arousal (activation-deactivation) (Russell, 1980). Emotion dimensions are found by analysing the correlation between emotion terms. Factor analysis techniques are applied on a large number of rating scales of affective terms to obtain a small number of fundamental factors from the correlations between the scales (Yang and Chen, 2012). Studies have shown that valence and arousal may be the most fundamental, and most clearly communicated emotion dimensions among others (Yang and Chen, 2011). Research has shown that the two-dimensional model of emotion can adequately describe self-reported symptoms of depression (Killgore, 1999). The most well-known example is the circumplex model proposed by Russell (1980), who has applied four approaches to 28 emotion terms:

1. Ross's technique for a circular ordering of variables (see Figure 2.1);
2. A multidimensional scaling procedure based on perceived similarity among the terms;
3. A unidimensional scaling on hypothesised pleasure-displeasure and degree-of-arousal dimensions;
4. A principal component analysis of 343 subjects' self-reports of their current affective states.

Other studies have used a third dimension such as *dominance* (Pleasure-Arousal-Dominance, or PAD, Mehrabian and Russell, 1974), to explain the difference between dominant and submissive emotions (Ilie and Thompson, 2006; Schubert, 2007b; Collier, 2007), and *interest* (Leman et al., 2005), to contrast moving, exciting, pleasing, and passionate with indifferent, boring, annoying, and restrained. Participants, however, have found it difficult to rate on the *dominance* scale (Evans and Schubert, 2008). Likewise, the *interest* scale is sensitive to subject-related factors (Leman et al., 2005).

The typical dimensional model (Valence-Arousal, or VA) provides a reliable way for people to measure two distinct dimensions (Schuller et al., 2010; Yang and Chen, 2011; Schubert, 2014; Egermann et al., 2015). It allows representation of a more detailed range of emotion than what the categorical model can provide. These two core dimensions are often compared. For example, a study of emotion detection has suggested that arousal and valence (for high arousal states) can be differentiated using electrocardiogram (ECG). Previous research has also shown that the responses of arousal are more consistent than valence (Gomez and Danuser, 2004; Leman et al., 2005). Similarly, in the study of MER, arousal has been predicted from musical features better than valence (Schubert, 2007b; Yang et al., 2008; Huq et al., 2010).

Although the dimensional model has been widely used in the study of music and emotion (Leman et al., 2005; Ilie and Thompson, 2006), it is not free of criticism. For example, the dimensional model has been criticised for its lack of differentiation when it comes to emotions that

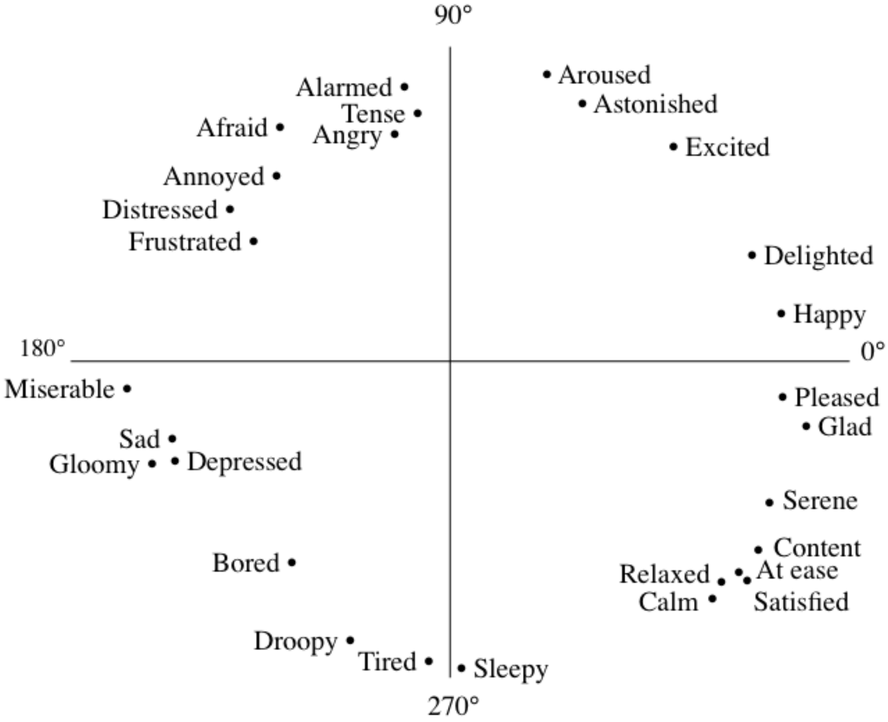


Figure 2.1: Russell's model using direct circular scaling coordinates for 28 affect words.

are close neighbours in the valence-activation space, which is one of the consequences of the low dimensionality of the model. Also, it has been reported that the two-dimensional model is not able to account for all the variance in music-mediated emotions (Bigand et al., 2005; Ilie and Thompson, 2006; Collier, 2007).

2.3.3 Domain-specific Model

Due to the fact that a large variety of emotions can be evoked by music (Scherer, 2004), a more sophisticated model of measuring music-induced emotion, the "Geneva Emotional Music Scale" (GEMS), has been developed by Zentner et al. (2008). The GEMS consists of 9-dimensional emotional scales - *wonder*, *transcendence*, *tenderness*, *nostalgia*, *peacefulness*, *power*, *joyful activation*, *tension*, and *sadness* (see Table 2.5, Zentner et al., 2008). Interesting results have been obtained using the GEMS, such as neurophysiological correlates (Trost et al., 2012; Miu and Balte, 2012) and emotion prediction by feelings of entrainment (Labbe and Grandjean, 2014). Though it has been suggested that the GEMS model outperforms categorical and dimensional emotion models in accounting for induced emotions in music (Juslin and Västfjäll, 2008; Zentner and Eerola, 2009), Eerola and Vuoskoski (2010) have pointed out that these studies are limited to only familiar classical music examples.

A comparison of these three models of emotion (i.e., the categorical, dimensional, and the GEMS) has shown that low-dimensional models often suffice to account for the main emotional experiences induced by music (Vuoskoski and Eerola, 2011a). Since the nine factors proposed in the GEMS consider only the emotion induced by music, and there exists no validated version in other languages, the use of the GEMS still needs further investigation.

TABLE 2.5
Geneva Emotional Music Scale (nine dimensions) proposed by Zentner et al. (2008).

Dimension	**Terms**
Wonder	filled with wonder, dazzled, moved
Transcendence	fascinated, overwhelmed, feelings of transcendence, spirituality
Power	strong, triumphant, energetic
Tenderness	tender, affectionate, in love
Nostalgia	nostalgic, dreamy, melancholic
Peacefulness	serene, calm, soothed
Joyful activation	joyful, amused, bouncy
Sadness	sad, sorrowful
Tension	tense, agitated, nervous

2.4 Related Work in Music and Emotion

Music provides a powerful means of communication and self-expression (DeNora, 2000). A study of recreational activities (i.e., watching television, listening to music, reading books, and watching movies) among undergraduates at University of Texas at Austin indicated that they listen to music more often than do any of the other activities (Rentfrow and Gosling, 2003). The powerful emotional effects in music have attracted significant research interest not only in fields such as neuroscience of music, music psychology, musicology, and music cognition, but also in signal processing, machine learning, and computer science (for reviews, see Juslin and Sloboda, 2010; Yang and Chen, 2011; Fu et al., 2011; Eerola and Vuoskoski, 2013). On the one hand, as for MIR researchers in computer science, researchers are interested in understanding emotion in music computationally and building content-based models to solve issues such as identification, detection, recognition, and recommendation (Casey et al., 2008). On the other hand, as for music psychologists, researchers are interested in the understanding of emotion in music such as emotional responses to music, and the role of music in everyday life (Hallam et al., 2008).

Therefore, this section covers studies in signal processing and machine learning (Section 2.4.1), and in music psychology (Section 2.4.2).

2.4.1 Research on Music and Emotion in Computer Science

The rapid growth in Internet technology and portable digital devices has made vast amounts of music available. In the past decade, MIR researchers have been developing methods to search, organise, and manage millions of songs (Casey et al., 2008). One of the applications is a music recommendation system, into which emotion can be easily incorporated. Musicovery, for example, has successfully used a two-dimensional model of emotion within its recommendation system. MIR techniques have also been developed to solve problems in the research of content-based models such as genre classification (Tzanetakis and Cook, 2002; Li et al., 2003; Fu et al., 2011; Laurier, 2011), cover song identification (Ellis and Poliner, 2007; Foster et al., 2015), and query by singing/humming (QBSH) (Jang and Lee, 2008; Wang et al., 2010a). Since 2007, the annual MIREX evaluation campaign for MIR algorithms facilitates finding solutions to the problems of music classification (Hu et al., 2008).

Research on music and emotion has attracted increasing attention in the MIR community, and has been widely discussed in the past ten years (for reviews, see Kim et al., 2010; Yang and Chen, 2011). In these studies of music and emotion, significant amount of research has been carried out on MER systems (Kim et al., 2010; Yang and Chen, 2011). A typical method for emotion recognition is to classify music into different emotion categories (e.g., happy, sad, angry, and relaxed) (Trohidis et al., 2008). For classifying musical audio signals, various feature extraction toolboxes have been developed to extract features such as dynamics, rhythm, timbre, and harmony (Beveridge and Knox, 2012). However, features provided in these toolboxes are different. For example, MIRtoolbox[2] provides a set of features from the statistics of frame-level features (Lartillot and Toiviainen, 2007), and Marsyas[3] computes features from audio, including melody and frequency spectrum (Tzanetakis and Cook, 2000). In addition, PsySound3[4] creates features based on psychoacoustic models, and the Sound Description Toolbox[5] gives a set of MPEG-7 standard descriptors. Classifiers are then trained using machine learning techniques (Yang and Chen, 2012). For instance, previous studies have successfully applied a regression approach to predict emotion categories and values of valence and arousal in music (Lu

[2] https://www.jyu.fi/music/coe/materials/mirtoolbox
[3] http://marsyas.info/
[4] http://psysound.wikidot.com/
[5] http://www.ifs.tuwien.ac.at/mir/muscle/del/audio_tools.html#SoundDescrToolbox

et al., 2006; Yang et al., 2008; Eerola et al., 2009). Other common classification algorithms used in MER systems include k-Nearest Neighbour (k-NN) (Saari et al., 2011), random forests (RF) (Eerola, 2011), support vector machines (SVMs) (Laurier et al., 2007; Schmidt et al., 2010; Schuller et al., 2010), and deep belief networks (Schmidt and Kim, 2011; Schmidt et al., 2012). Pachet and Roy (2009) have proposed feature generation to improve classification results, and it can outperform approaches based on standard features in some contexts. Recently, Serra (2011) criticised MIR for being Western-specific. To meet the needs of music users in different cultures and languages, MIR researchers have also investigated cross-cultural and multilingual music information seeking behaviours (Downie and Cunningham, 2005), cross-cultural emotion classification (Yang and Hu, 2012), and development of culture specific approaches in MIR (Serra, 2012).

Apart from the audio signal analysis mentioned above, studies in computer science have also considered the linguistic aspect of songs. In fact, lyrics contain semantically rich information, which is not taken into account in audio signal analysis. Also, lyrics can provide a more explicit and objective expression of emotion (Logan and Kositsky, 2004). Juslin and Laukka (2004) have reported in a questionnaire study of everyday listening that 29% of the sample choose lyrics as the basis of their judgements of emotional expression in music. Previous studies have extracted words and characteristics of sentences from lyrics, and each song has been represented by a vector of features. The most popular approaches to analysing lyric features are using Probabilistic Latent Semantic Analysis (PLSA) (Logan and Kositsky, 2004; Laurier et al., 2008; Saari and Eerola, 2014), Bag-of-Words (BOW) (Hu et al., 2009; Lu et al., 2010), and Term Frequency Inverse Document Frequency (TF-IDF) (Van Zaanen and Kanters, 2010; Wang et al., 2011; McVicar and De Bie, 2012). Moreover, several language packages are developed to provide semantic meanings in different aspects of emotion. For example, Affective Norms for English Words (ANEW) (Bradley and Lang, 1999), WordNet (Fellbaum, 1998), and Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2007) have been successfully applied in computing the emotion values of valence, arousal, and dominance (Alm et al., 2005; Pettijohn and Sacco, 2009; Hu and Downie, 2010).

Both audio-based and lyric-based approaches have achieved satisfying results. Although previous research has reported conflicting results for audio and lyrics (i.e., lyrics-based approach outperforms audio-based approach, or vice versa), multi-modal emotion classification integrating these two approaches has provided a better classification accuracy (Laurier et al., 2008; Hu and Downie, 2010; Lu et al., 2010; Serra, 2011; McVicar and De Bie, 2012).

With the emergence of music discovery and recommendation platforms such as Last.FM in the past decade, which supports tagging for music videos, online social tags (OST) have received increasing interest for the study of music and emotion (Eck et al., 2007; Levy and Sandler, 2009; Wang et al., 2010b). Social tags are words or groups of words supplied by a community of Internet users. They are more and more commonly used to aid navigation through large media collections (Wu et al., 2006), allowing users to get a sense of what qualities characterise a song at a glance (Hoffman et al., 2009). Compared with traditional expensive human annotation, or web mining that gives noisy results, semantic tags provide a large-scale, cost-efficient, rich, and easily accessible source of metadata (Hu and Downie, 2007; Turnbull et al., 2008a; Saari and Eerola, 2014). In addition, the information they provide is highly relevant to MIR, including genre, mood, and instrument, which together account for 70% of the tags (Lamere, 2008). Levy and Sandler (2007) have also shown that social tags give a high quality source of "ground truth" data and can be effective in capturing music similarity. Studies of social tags from Last.FM has confirmed the usability of emotion tags, which could help create "ground truth" for music research (Bischoff et al., 2009; Saari, 2015). Additionally, Laurier et al. (2009) have combined the use of emotion tags and audio signals to improve the emotion recognition systems. Although previous studies have suggested that tag features are more useful than audio content features for certain analyses such as artistic style clustering, and social tags have been widely used in areas of research such as classification, recognition, and identification, the reliability of emotion tags has rarely been evaluated (Lamere, 2008; Wang et al., 2010b).

2.4.2 Research on Music and Emotion in Psychology

In the past few decades, music psychologists have paid much attention to research on music and emotion (for reviews, see Eerola and Vuoskoski, 2013; Swaminathan and Schellenberg, 2015). Previous research has also reported that the primary motivation for people listening to music lies in its emotional functions, namely to express and induce emotion (Tarrant et al., 2000; North et al., 2000; Juslin and Laukka, 2004; Lonsdale and North, 2011). The ability to identify emotional content is established at a very early age (Dalla Bella et al., 2001), and people engage with music in different contexts (e.g., travelling, cooking, and driving) and for different purposes (e.g., distraction and emotion regulation) (DeNora, 2000; Sloboda et al., 2001; Juslin et al., 2008). A large body of research has focussed on fundamental questions such as "How does music evoke emotions and how do people perceive emotion in music?", "What factors (e.g., culture, music training, age, and personality) influence people's emotion experience in music?", and "In different situational contexts, which musical emotion typically occurs?".

Kreutz et al. (2007) noted that perceived emotion (see Section 2.2.1) refers to intellectual processing, such as the perception of an intended or expressed emotion, whereas induced emotions (see Section 2.2.2) reflect the introspective perception of psychophysiological changes, which are often associated with emotional self-regulation (Khalfa et al., 2002; Thayer and Faith, 2001). Schubert (2007a) has studied the distinction between induced and perceived emotion and suggested that induced emotional responses fluctuate more than perceived emotional responses. Understanding the similarities and differences between the two will provide a clearer view of the underlying psychological mechanisms involved in musical emotion (Scherer, 2004; Juslin and Västfjäll, 2008; Juslin et al., 2014).

The categorical model (see Section 2.3.1) and dimensional model (see Section 2.3.2), have received empirical support in studies of music and emotion (Kreutz et al., 2007; Vieillard et al., 2008). Owing to the nature of emotion, the categorical model tends to be applied for perceived emotion, whereas the dimensional model is frequently used for measuring induced emotion. A comparison of these two models has been presented by Eerola and Vuoskoski (2010), based only on film music excerpts. Therefore, a lack of studies in other musical genres still exists, which I address in Chapter 4.

Due to the subjective nature of emotion in music, the most common way to measure subjective emotional responses is still via a format of self-report (Gabrielsson, 2002). Although other approaches such as behavioural measurement and physiological reaction are becoming increasingly popular, there exist several issues. For instance, measuring behavioural responses to music including facial expression and body language (Frijda et al., 1986), and various physiological reactions such as heart rate, respiration, skin conductance response (SCR), and electroencephalograph (EEG) (Khalfa et al., 2002; Levenson, 2003; Baumgartner et al., 2006; Mas-Herrero et al., 2014) can provide us valuable evidence of emotion, but these behaviours do not always associate with specific emotions, and the relationships between emotions and physiological responses are still unclear (Juslin and Laukka, 2004; Eerola and Vuoskoski, 2013). Previously, the Experience Sampling Method (ESM) has been shown to be effective in study of music experience (e.g., emotion, and musical preference) in different situations of daily life (e.g., North and Hargreaves, 1996; Sloboda et al., 2001; North et al., 2004; Juslin et al., 2008; Greasley and Lamont, 2011). It provides a valuable tool to collect subjective responses in natural contexts. However, it is less appropriate when measuring the emotion in specific events such as cooking, studying, and clubbing (Randall and Rickard, 2013).

The emotional meaning of music always emerges from the interaction between a listener and a (real or imagined) sound object in some context. The listener plays an important role in the perception and recognition of emotion in music. Different individual factors such as one's personality, musical skills, age, and music culture, may affect how emotional meaning is elicited (Bigand et al., 2005; Kallinen and Ravaja, 2006; Schubert, 2007a; Sandstrom and Russo, 2011). Previous studies have suggested that age has negative correlation with music consumption (Chamorro-Premuzic et al., 2010). Also, older people reported fewer negative emotional experiences and greater emotion control (Gross et al., 1997; Mroczek and Kolarz, 1998; Novak and Mather, 2007). Additionally, Malatesta and Kalnok (1984) have shown that women consider emotion more important than men, and that women report more inhibition of emotion. Several studies have investigated the relationship between personality traits ("Big Five") (Gosling et al., 2003), musical judgements (Shiota et al., 2006; Vuoskoski and Eerola, 2011b; Vuoskoski et al., 2011), artistic interests (McAdams, 2006), and musical preferences (Rentfrow and Gosling, 2003; Chamorro-Premuzic and Furnham, 2007; North, 2010). Studies on classical music have claimed that emotional responses and intellectual responses tend not to occur together, and that musically experienced listeners are more likely to focus on intellectual properties, whereas less musically experienced listeners tend to focus on emotional properties (Gabrielsson, 2002).

A wealth of research focusses on the above themes in the context of Western musical culture (Kallinen, 2005; Eerola and Vuoskoski, 2010, 2013), assuming that generic models can be built independently from musical style, culture, genre, or listeners' acculturation. Although music is a cross-cultural universal (Fritz et al., 2009), Balkwill and Thompson (1999) found that emotion in music is communicated through a combination of universal and cultural clues. Cross-cultural studies in music have gained popularity considerably (Gregory and Varney, 1996; Tsai et al., 2006; Eerola et al., 2006; Morrison et al., 2008; Thompson and Laura-Lee, 2010; Kosta et al., 2013). For instance, several studies have attempted to explore the music emotion classification between Chinese and English songs (Yang and Hu, 2012), and perceived complexity of Western and African folk melodies by Western and African listeners (Eerola et al., 2006). Hu and Lee (2012) have explored the emotion perception of pop songs between American and Chinese listeners, and showed that people with the same cultural background tend to agree on what perceived emotions they recognise. Similar results were found by Egermann et al. (2015) between Canadian and Congolese Pygmies in music-related psychophysiological responses. Also, Singhi and Brown (2014) have revealed the consistency of music emotion judgement is reduced between Canadian and Chinese listeners with the presence of both lyrics and audio. A few studies have been performed that took into account only a specific culture such as Greek (Zacharopoulou and Kyriakidou, 2009; Kosta et al., 2013), Indian (Gregory and Varney, 1996; Gupta, 2005) and native African (Fritz et al., 2009).

2.5 Musical Stimuli

In recent years, psychologists have predominantly used excerpts of Western classical (Gomez and Danuser, 2004; Bigand et al., 2005), jazz music, film soundtracks (Vuoskoski and Eerola, 2011a; Eerola, 2011), and non-Western cross-cultural music in the study of music and emotion (Evans and Schubert, 2008; Mohn et al., 2010; Vuoskoski et al., 2011). Classical music (prevalence 48%) has been the most dominant genre in past studies, but listeners may not be familiar with the genre, and the results may not be applicable to other musical genres such as Western popular music (3%), which is generally well-understood by participants (Juslin and Laukka, 2003; Eerola and Vuoskoski, 2013). Musical preference influences perceived and induced emotion, and the emotional reactions may differ across genres due to their inherent musical differences (Kreutz et al., 2007; Zentner et al., 2008; Eerola, 2011). Among different experiments, the numbers of the stimuli used are normally less than 20 (60%); only a few studies have used more than 60 stimuli (Eerola and Vuoskoski, 2013).

Previous research of classifying different genres of music (i.e., classical, film, pop, and mixed) has shown that emotion can be better identified in classical music and film soundtracks (Saari et al., 2011; Eerola, 2011), whereas the recognition of pop music fails to reach a satisfactory level (see Yang and Chen, 2012, for a recent review).

One crucial problem of music research is a lack of "ground truth[6]". Most researchers compile their own databases (Yang and Lee, 2004). Due to copyright issues, only musical features (e.g., million song dataset, or MSD, McFee et al., 2012), ratings of emotion (Kim, 2008; Schmidt and Kim, 2010), and user posts (Liu et al., 2014) are made available, whereas the raw audio files cannot be distributed to reproduce the results for research and evaluation.

To investigate emotion in music, it is important to collect the "ground truth". Manual annotation is one of the most common ways to create a "ground truth" data set (Leman et al., 2005; Schuller et al., 2010; Yang and Chen, 2011; Saari, 2015). However, it is expensive in terms of financial cost and human labour. Additionally, terms used may differ between individuals leading to inconsistency and unreliability of the data. Turnbull et al. (2008a) mentioned that different

[6] "Ground truth" refers to a collection of objective data used in classification for supervised learning techniques.

emotions described using the same term by different people would result in poor prediction. With the help of social tags from music discovery web services such as Last.FM, it is possible to access rich human-annotated information (e.g., semantic tags) about music and fetch popular musical examples tagged with different emotional labels (Turnbull et al., 2008a; Levy and Sandler, 2009).

2.6 Discussion

In this chapter, I have provided definitions of relevant concepts in the research on music and emotion. Two forms of emotional processes in relation to music, perception and induction, are explained in Section 2.2. In addition, I have presented three models of emotion (i.e., the categorical, dimensional, and the GEMS) used in music research. However, due to the high-dimensionality and induced-emotion-only bias of the GEMS model, as well as the confusion caused by the *dominance* scale in the dimensional model of emotion, only the categorical model and the typical dimensional model with two core dimensions, *valence*, and *arousal*, are used in this work.

In Sections 2.4.1 and 2.4.2, I reviewed the related work in two different domains: computer science and psychology. I found that diverse attentions have been paid to research on music and emotion. For example, computer scientists have applied machine learning techniques to recognise different emotions, or to predict emotional ratings from audio recordings. In addition, much effort has been applied to combining other sources (e.g., lyrics and tags) to improve emotion classification and recommendation problems. Although machine learning techniques have been applied for genres such as classical music and film soundtracks, the study of emotion recognition for popular music is still limited. Moreover, the differences between two forms of emotional processes are often neglected, as well as the selection of models of emotion. Psychologists, however, have focussed on emotional responses to music and their underlying mechanisms, comparison of induced and perceived emotion, effects of individual factors (e.g., personality, age, gender, and musical training), cross-cultural studies of emotion perception in music, comparison of emotion models in music, and different approaches to measuring induced emotion such as behavioural measurement (facial expression and body language) and physiological reaction (e.g., heart rate, respiration, skin conductance, and electroencephalograph). However, the majority of those studies are limited only to classical music and film soundtracks, and their results may not be applicable to other musical genres such as Western popular music.

As we expected, there exists a “gap” between computer science and psychology (Aucouturier and Bigand, 2012). Aucouturier and Bigand (2013) identified a series of "misunderstandings" between these two disciplines, and called for greater collaboration between psychologists and MIR researchers. On the one hand, psychologists can provide a deeper understanding of theoretical background in emotion. On the other hand, music information retrieval researchers can provide valuable tools to help analyse data relating to musical emotions. In this thesis, I focus on the study of Western popular music. Due to the lack of a public dataset of Western popular music with "ground truth" annotations for emotion, I create a new dataset in Chapter 4, based on social tags. Although studies have successfully applied social tags in emotion related tasks, their reliability has not been examined.

In this work, I present studies of music and emotion spanning both computer science and psychology. Music emotions occur in complex interactions between the listener, the music, and the situation. Therefore, Chapter 3 covers the background in music-listening contexts, musical preference, emotional uses of music, and the functions of music listening.

Chapter 3

Music Listening: Function, Context, and Preference

This chapter covers background knowledge on the functions of music listening, musical preference, emotional uses of music, and music-listening context. First of all, Section 3.1 defines two concepts, *music-listening context* and *musical preference*, used for my work. Listening to music is a common activity in daily life. Various ways of categorising activities and situations have been proposed. These are presented in Section 3.2, where research on music-listening contexts in everyday life is reviewed. The study of emotion in music has received a lot attention in the past few decades (for reviews, see Chapter 2). Section 3.3 provides different examples of emotional uses of music listening (e.g., in the sporting context). In addition to the emotional use of music, other functional uses of music listening are explained in Section 3.4. The definitions of four recurring functions of listening to music extracted from previous studies, namely *distraction*, *energising*, *entrainment*, and *meaning enhancement*, are presented. Finally, Section 3.5 summarises background knowledge in musical preference, and a brief discussion in Section 3.6 concludes the chapter.

3.1 Terminology

According to Nielsen (2014), in the year of 2014, around 164 billion songs were streamed on-demand through audio and video platforms in the United States, which constitutes a 54.5% increase comparing to 2013. Also, a report from the International Federation of the Phonographic Industry (2014) showed that subscriptions of streaming services such as *Rdio*[1], *Spotify*, and *Google*

[1] `http://www.rdio.com/home/`

Play[2] have increased, whereas physical album sales have dropped by 11.2% (Nielsen, 2014). The rapid development of digital technology and social networks such as Twitter[3] and Facebook[4] has provided a convenient platform that enables people to listen to music, share music, and discover music everywhere (Lee and Waterman, 2012; Yang and Liu, 2013; Krause et al., 2014).

With the greater access to music, listening to it has become one of the main activities in everyday life (Juslin and Laukka, 2004; Juslin et al., 2008). Rentfrow and Gosling (2003) found that listening to music is more common than other activities such as watching television, reading books, and watching movies. According to recent surveys by UK Music (2014)[5] and Krause et al. (2015), mobile devices (such as mp3 players, radio, tablets (39%), and smartphones (44%)) are predominantly used for music listening in the United Kingdom.

The fact that people listen to music in diverse situations means that they choose music to accompany different non-musical activities (e.g., running, travelling, and commuting; see Sloboda et al., 2001). In previous studies of music in everyday life, different terms have been used to describe the contexts in which music is listened to. For example, North et al. (2004) examined various aspects of music listening, including when people listen to music (time of day or day of week), where they listen (e.g., restaurant, shopping mall, at home doing housework, pub/nightclub, and gym/exercising), and who they listen with (e.g., alone, with friends, with spouse/partner only, and with strangers). Research has also investigated other aspects of music-listening contexts such as listening conditions (group vs. solitary; Egermann et al., 2011), situational contexts (North and Hargreaves, 1996; Juslin et al., 2011; Krause et al., 2015), and activities (Sloboda et al., 2001; Greasley and Lamont, 2011). In this work, I focus on the activities during which music is listened to. I use the terms *activity*, *context*, and *situation* interchangeably.

Previously, Greasley and Lamont (2011) discussed the selection of certain styles of music used to accompany specific activities. The terms *musical taste* and *musical preference* have been commonly used in describing the liking for different types of music (Lamont and Greasley, 2009). Hargreaves et al. (2006) defined *musical preference* as “a person’s liking for one piece of music as compared with another at a given point in time”, and *musical taste* as “the overall patterning of an individual’s preferences over longer time periods”. Following these definitions, I investigate the liking of musical styles in particular activities, thus the term *musical preference* is selected and used throughout my work. I focus on general preference for a style rather than

[2]`https://play.google.com/music/`
[3]`https://twitter.com/`
[4]`https://www.facebook.com/`
[5]`http://www.ukmusic.org/`

specific preference for a piece or particular performance/recording.

3.2 Music-listening Contexts

The rapid growth in Internet technology and portable digital devices, has made music available almost everywhere. The nature of music experience has changed at a fundamental level, and traditional ways of exploring and listening to music from radio stations and record stores have been partially replaced by music discovery web sites such as Pandora, Spotify, and Youtube (Casey et al., 2008). Hence, music can be heard in far varied and diverse situations (Greasley and Lamont, 2011; Krause et al., 2015). Moreover, the idea of subjective music recommendation systems using emotion and context has raised considerable interest among researchers in recent years (Song et al., 2012a; Krause and North, 2014).

The majority of music and emotion studies (see Chapter 2) have focussed on emotional responses to music and their underlying mechanisms (Juslin and Västfjäll, 2008; Juslin et al., 2014), comparison of induced and perceived emotion (Gabrielsson, 2002), and emotion models (categorical and dimensional) in music (Eerola and Vuoskoski, 2010, 2013). It has been shown that emotional meaning in music is related to the context within which music is heard (Gabrielsson, 2010; Greasley and Lamont, 2011). Studies of music listening in daily life have focussed on the functions of music (Hargreaves and North, 1999; North et al., 2004) and the reasons for listening to music (Tarrant et al., 2000), where the situational factors are often neglected (Juslin et al., 2011).

The ESM and the mobile-ESM (or m-ESM) have been widely used in the study of music experience in different situations of daily life (North and Hargreaves, 1996; Sloboda et al., 2001; North et al., 2004; Juslin et al., 2008; Greasley and Lamont, 2011; Randall and Rickard, 2013). It presents the participant with brief questionnaires relating to their current subjective experience throughout everyday functioning (Csikszentmihalyi and LeFevre, 1989). The ESM can capture data in a spontaneous and natural context, as well as providing robustly interpretable results (Randall and Rickard, 2013). Sloboda et al. (2001) identified housework and travel as the most frequent activities involving music and showed that music listening was not randomly distributed over contexts, and that listeners' mood was changed based on different choices of music. Juslin et al. (2008) also used the ESM to investigate music listening in real situations (e.g., shopping, physical activity, and relaxation) and found that certain patterns such as anger-irritation occurred often during work, and happiness-elation usually occurred in social interaction.

TABLE 3.1
Situations designed by North and Hargreaves (1996).

Examples	**Factors**
At an end-of-term party with friends	A
At a nightclub	A
Jogging with your Walkman on	A
Doing the washing-up	A
Ironing some clothes	A
In the countryside	C
In a French restaurant	B
At a posh cocktail reception	B, D
Having just broken up with a boyfriend/girlfriend	D
On Christmas Day with your family	A, C
Your parents have come to visit	B
First thing on a Sunday morning	B
Last thing at night before going to bed	B
Making love	B
Trying to woo someone over a romantic candlelit dinner for two at home	B
In church	C
Driving on the motorway	A, C

Note. Factor A - activity, Factor B - localised subdued behaviour, Factor C - spirituality, and Factor D - social constraint.

Although the ESM and the m-ESM can provide vast amount of empirical data, and they allow an exploration of ways in which participants perceive their physical and social environments, they are not tied to specific events.

Music can be heard in diverse situations (Greasley and Lamont, 2011). Juslin et al. (2008) advocated that the study of music needs to take the context of music listening into consideration. Different categorisations of activities have been proposed. For example, to study the influence of the situation on musical preferences, North and Hargreaves (1996) identified seventeen music listening situations, and then factorised these situations into four categories: activity, localised subdued behaviour, spirituality, and social constraint (see Table 3.1). Sloboda et al. (2001) also classified music-listening activities into three main categories: *personal*, *leisure*, and *work* (see Table 3.2). Each category was further divided into subcategories based on purpose and engagement. For instance, the category *personal* consists of three levels, personal-being (e.g., sleeping and waking up), personal-maintenance (e.g., washing and getting dressed), and personal-travelling (e.g., walking and going home). Later, Greasley and Lamont (2011) used these categories and showed that people are likely to use music while travelling or engaging in active leisure. In addition, other research has also provided more refined categories of music-listening contexts including

TABLE 3.2
Categorisation of activities by Sloboda et al. (2001).

Category	Examples
Time fillers	doing nothing, waiting
Personal - being	states of being (e.g., sleeping, waking up, being ill, suffering from hangover)
Personal - maintenance	washing, getting dressed, cooking, eating at home, housework, shopping
Personal - travelling	leaving home, driving, walking, going home
Leisure - music	listening to music
Leisure - passive	watching TV/film, putting on radio, relaxing, reading for pleasure
Leisure - active	games, sport, socialising, eating out, chatting with friends
Work - self	writing, computing, marking/assessing, reading for study
Work - other	planning for meeting, in lecture/seminar, making appointment, in meeting

concert attendance, partying, and watching bands (see North et al., 2000, 2004; Juslin et al., 2008, 2011; Krause and North, 2014, in Table 3.3). Sloboda et al. (2009) summarised these into six main activities in which music may be present: travel, physical work, brain work, body work, emotional work, and attendance at a live music performance (as an audience member).

Previous research has suggested that different contexts should be considered for studies on emotional uses of music (see Section 3.3), functions of music listening (see Section 3.4), and musical preference (see Section 3.5) (Lamont and Greasley, 2009; Sloboda et al., 2009). In addition, the interactions among these factors (i.e., function of music listening, musical preference, emotion, and situation) and the reciprocal feedback that occurs between them are still unclear (Hargreaves et al., 2006; Hargreaves, 2012). Therefore in this work, I investigate the functions of music listening, musical preferences, and emotional uses of music in different situations (see Figure 3.1). Following previous studies, different activities are selected (see details in Chapters 5 and 6).

3.3 Emotional Uses of Music

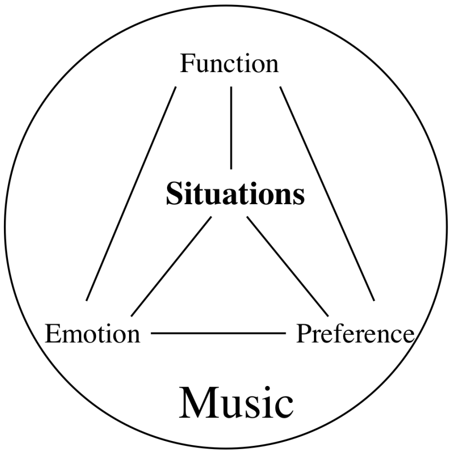
Previous studies have shown that listeners' primary motives for listening to music lie in its emotional regulation (see Chapter 2; Juslin and Laukka, 2004; Juslin et al., 2008). Saarikallio et al. (2012) analysed emotional uses of music, specifically associations between the affective response to music and the use of music for emotion regulation, and found that a tendency to react intensely to beauty and pleasantness in preferred music correlates with the personal use of music for inducing strong experiences.

The interactions of age and gender with emotional experience have been noted (Mroczek and Kolarz, 1998; Charles et al., 2001; Mather and Carstensen, 2005; Brody and Hall, 2008; Castro

TABLE 3.3
Examples of activities chosen in other studies.

North et al. (2004)	**Juslin et al. (2008)**
Restaurant	Work/study
Shop or shopping mall	Travel
Places of religious worship	Social interaction
At home doing housework	Housework
At home doing an intelligent demanding task	TV/movie watching
At home deliberately listening to music	Music listening
At home eating	Physical activity
At home doing something else	Shopping
Gym/exercising	Having a meal
Driving	Relaxation
Bus/train	Partying
Pub/nightclub	Gaming
Waiting room	Concert attendance
Friend's house	Other activity
Concert	
Other	
Juslin et al. (2011)	**Krause and North (2014)**
Alone	Posh cocktail reception
Music listening	House party
Travel	After a long day
Partying	While doing the washing/ironing
Ceremonies	At a wedding
Concerts	Before going to sleep
Relaxation	While commuting on public transportation
Dancing	While jogging with a mp3 player
Physical activities	
Housework	
Social interaction	
Intimate settings	
Movies	
At church	
Work/study	
Performing music	
Having a meal	

Figure 3.1: Interactions among musical emotions, functions of music listening, and musical preferences with different situations.



and Lima, 2014). For example, women reported more positive affect states while at work than they did while at home. However, men reported more positive affect states while at home (Larson et al., 1994). Other studies have suggested that as people get older, they focus more on self-control of their emotions and rate their emotion-regulation skills as better (Gross et al., 1997; Magai, 2008).

Music emotions arise in complex interactions between the listener, the music, and the situation (Juslin et al., 2011). Thus emotional experience in music is dependent on context. For instance, in the sporting contexts, Laukka and Quick (2011) presented a questionnaire of emotional uses of music to Swedish athletes, and found that athletes used music in purposeful ways. Additionally, athletes reported to experience positive affective states such as happiness, alertness, confidence, and relaxation in relation to music in sports. Similarly, Baldari et al. (2010) found that the presence of music significantly reduced people's anxiety after exercise.

In a study of music in everyday life, Sloboda et al. (2001) reported that participants' emotion was changed after listening to music. Research has also suggested that participants followed a "mood-optimisation" strategy when choosing music (Breckler et al., 1985; North et al., 2004). Later, Juslin et al. (2008) provided an overview of emotional experience in different situations and further revealed that the listener's activity was correlated with particular emotions (Juslin et al., 2011). Previously, research stated that music plays a major role in creating happiness and relaxation, and characterised the different ways music influences emotions i.e. to maintain, change, create, or to enhance an emotion (North and Hargreaves, 1996; DeNora, 1999; Van

Goethem and Sloboda, 2011). Moreover, Lonsdale and North (2011) argued emotional uses of music for "negative mood management". This means that music is used to alleviate negative feelings (e.g., anxiety and stress) and for mood enhancement. They also proposed the emotional use of music for "positive mood management", i.e., to achieve and optimise positive moods (e.g., to relax).

Although a few studies have examined emotional responses in different situations such as a posh cocktail reception, a house party, or a wedding (Juslin et al., 2011; Liljeström et al., 2012; Krause and North, 2014), yet the emotional changes (with and without the presence of music) within these contexts have rarely been studied.

Two forms of emotional processes in relation to music, namely perception and induction of musical emotions, and models of emotion (i.e., the categorical and the dimensional model) in music were discussed in Chapter 2. In my work, I am interested in the subjective emotional experience (induced emotion) across a wider range of situations. Additionally, previous research has shown the advantage of the dimensional model in measuring induced emotion (Eerola and Vuoskoski, 2013), thus I use the two-dimensional model of emotion (valence and arousal) in my study and focus only the emotions felt (or expected to be felt) in response to music.

3.4 Functions of Music Listening

Music provides a powerful means of conveying and evoking feelings (Eerola and Vuoskoski, 2013; Schubert, 2013), and it has been shown that "emotional regulation" is the primary reason for listening to music (Juslin and Laukka, 2004). In addition to this emotional use of music, researchers have also noted rational/cognitive and background uses of music (Chamorro-Premuzic and Furnham, 2007) and proposed that music can serve for different functions such as entertainment and communication (Merriam, 1964; Lamont and Greasley, 2009; Krause et al., 2014). For example, music is the most common topic in conversation among strangers given the task of getting acquainted (Rentfrow and Gosling, 2006).

People purposely choose to listen to music, and research has suggested that people listen to music for various reasons (North and Hargreaves, 1996; DeNora, 2000; Sloboda et al., 2001; Lamont and Greasley, 2009). Studies have shown that the presence of certain music can facilitate the first stages of language learning (Kang and Williamson, 2013), and even influence flavour perception in wine tasting (North, 2012). Additionally, Sloboda et al. (2009) revealed that music can serve various needs and functions, and the functions of listening to music are context-dependent (North and Hargreaves, 1996; Lamont and Webb, 2009). For example, Heye and Lamont (2010) reported that while travelling people used music to fulfil the functions of enjoyment, passing time, and enhancing emotional states. Moreover, Schäfer and Sedlmeier (2009) claimed that people tend to choose different musical styles for particular reasons based on a study of musical preference. Therefore, the study of music behaviour and the development and evaluation of music information retrieval systems should consider the listener and listening context (Sloboda et al., 2001; Schedl and Flexer, 2012).

Different functions of music listening have been identified by different researchers in the field (DeNora, 2000; Sloboda et al., 2001; Juslin et al., 2008; Schäfer and Sedlmeier, 2009). Merriam (1964) proposed ten functions as shown in Table 3.4, and the top three of them are “emotional expression”, “aesthetic enjoyment”, and “entertainment”. Hargreaves and North (1999) concluded that the social functions of music can be manifested in three principal ways for the individual, namely *self-identity*, *interpersonal relationships*, and *mood*. Later, Juslin and Laukka (2004) stated in a study of everyday listening that people predominantly engage with music “to express, release, and influence emotions”, “to relax and settle down”, and “for enjoyment, fun, and pleasure”. Likewise, Schäfer and Sedlmeier (2009) reported that in the case of people listening to their favourite music, the music is able to put them in a good mood, as well as help them “chill” and “tune out”. Other studies have also mentioned functions: “it helped to pass the time”, “it helped to create the right atmosphere”, “creating external impression”, and “social bonding through music” (Hargreaves and North, 1999; Tarrant et al., 2000; North et al., 2000, 2004; Juslin and Laukka, 2004; Rentfrow and Gosling, 2006). Chamorro-Premuzic and Furnham (2007) pointed out three underlying factors from the uses of music inventory (UMI): emotional (i.e., music for emotion regulation such as mood manipulation), cognitive/rational (i.e., rational musical appreciation or intellectual processing of music) and background (i.e., music as background for social events, work, or interpersonal interaction). However, functions such as social identity formation (North et al., 2000), and interpersonal exchange and communication (Rentfrow and Gosling, 2006) are missing in the study (Chamorro-Premuzic et al., 2010). Recently, Boer and Fischer (2011) have also proposed a model of functions of music listening based on a cross-cultural study containing seven functions (e.g., music as diversion and social bonding). In my work, I use four recurring functions summarised by Sloboda et al. (2009, p. 431, see below) in the use of self-chosen music.

i **Distraction:** A way of engaging unallocated attention and reducing boredom;

TABLE 3.4
Functions of music proposed by Merriam (1964).

Category
Emotional expression
Aesthetic enjoyment
Entertainment
Communication
Symbolic representation
Physical response
Enforcing conformity to social norms
Validation of social institutions and religious rituals
Contribution to the continuity and stability of culture
Contribution to the integration of society

ii **Energising:** A means of maintaining arousal and task attention;

iii **Entrainment:** The task movements are timed to coincide with the rhythmic pulses of the music, giving the task or activity elements of a dance;

iv **Meaning enhancement:** Where the music draws out and adds to the significance of the task or activity in some way.

According to Heye and Lamont (2010), different functions of music listening can occur simultaneously. Although functions overlap with emotion regulation strategies, I focus on the functions (the fourth of which is similar to emotion regulation) and contexts, one modifier (preferences) and one outcome (emotions). These four functions (distraction, energising, entrainment, and meaning enhancement) are used to categorise the purpose of listening to music in the different situations I consider.

3.5 Musical Preference

Preferred music serves an important role in our everyday life (Lamont and Greasley, 2009; Getz et al., 2010; Greasley and Lamont, 2011). Music has been ranked among the highest sources of pleasure, and liking for music has similar effects as food intake, sex, or drugs (Panksepp and Bernatzky, 2002; Salimpoor et al., 2011). Due to the prevalence of music listening in everyday life, the study of musical preference has had an increasingly important role in helping us answer questions such as *"Why do we like music?"* and *"How do we choose music?"* (Hargreaves et al., 2006; Lamont and Greasley, 2009). Studies have suggested that individual differences such as personality, intelligence, and musical skills could influence both musical preferences (Chamorro-Premuzic and Furnham, 2007) and emotional responses (Vuoskoski et al., 2011; Liljeström et al., 2012). For instance, individuals who listen to music in a rational/cognitive way tend to have higher IQ scores and be more open and intellectual (Chamorro-Premuzic and Furnham, 2007). Extraversion is correlated with musical preference for popular/rock music, whereas thinking-feeling is correlated with liking for country and Western music (Pearson and Dollinger, 2004). Moreover, individuals who enjoy energetic and rhythmic music tend to be talkative and full of energy (Gosling et al., 2003). However, the actual correlations are low (extraversion $r = .22$ and agreeableness $r = .08$, Rentfrow and Gosling, 2003).

Musical preference has also been shown to relate to properties of music such as tempo, rhythm, and pitch (Makris and Mullet, 2003). North and Hargreaves (1995) found a positive relationship between liking and familiarity, and an inverted-U relationship between liking and subjective complexity. They reported that repeated exposure to a given piece of music also increases its familiarity and reduces its subjective complexity (North and Hargreaves, 1995, 1997).

One important element of musical preference is musical genre. Rentfrow and Gosling (2003) factorised 14 musical genres into four music-preference dimensions: *Reflective and Complex*, *Intense and Rebellious*, *Upbeat and Conventional*, and *Energetic and Rhythmic*. Recently, Rentfrow et al. (2011a) proposed a five-factor model of musical preference related to emotional responses to music (i.e., mellow, unpretentious, sophisticated, intense, and contemporary). Various musical styles have been used in previous studies of musical preference. In my work, I use a genre-based method to explore participants' musical preferences and select the following 19 musical genres: *alternative*, *blues*, *classical*, *country*, *electronic*, *folk*, *hip-hop*, *jazz*, *light instrumental*, *metal*, *pop*, *RnB*, *rap*, *reggae*, *religious*, *rock*, *soul*, *soundtrack*, and *world*, combined from several past studies of musical preference (Rentfrow and Gosling, 2003; North et al., 2004; Ferrer et al., 2012).

Rentfrow et al. (2011b) reported that people may prefer a specific style of music in a given situation. Similar to the functions of music listening and emotions, musical preference is highly context-dependent (Lamont and Webb, 2009). For example, people reported to prefer arousal-polarising music over arousal-moderating music during relaxation and exercise. However, their preferences changed to arousal-moderating music over arousal-polarising music after exercise (North and Hargreaves, 2000). North and Hargreaves (2007a,b,c) also discussed the relationship between musical preference and life choices (e.g., travel, money, media, leisure time, relationships, and living arrangement), and suggested that different reasons can be found for liking different musical styles (North, 2010). On the one hand, certain music styles are related to functions (e.g., express identity, help meet people, and feel ecstatic; see Schäfer and Sedlmeier, 2009; Gardikiotis and Baltzis, 2011). On the other hand, musical genres are also associated with specific emotions (Eerola, 2011). The use of specific styles of music (musical preference) is used to accompany specific activities (Greasley and Lamont, 2011). At present, musical preference has not been extensively examined with other factors (e.g., musical emotion). Therefore, I investigate musical preferences within different situations in Chapters 5 and 6.

3.6 Discussion

In this chapter, I have explained the relevant concepts in the research on emotional and functional uses of music, musical preference, and music-listening context. Different music-listening contexts proposed and used in past studies were provided in Section 3.2. Change in emotional state, as an outcome of music listening, overlaps with functional uses of listening to music (Schäfer and Sedlmeier, 2009; Lonsdale and North, 2011; Chin and Rickard, 2013). Different examples for emotional uses of music were discussed in Section 3.3. In the past, few studies have explored the functions of and motives for listening to music in daily life (DeNora, 2000; Sloboda et al., 2001; Juslin et al., 2008; Schäfer and Sedlmeier, 2009), thus in Section 3.4, I have presented previous work on functions of music listening. Also, musical preference has become a topic of interest, the relevant background knowledge were given in Section 3.5.

In Chapter 4, the first element, musical emotion, is examined. I explain my collection of a Western popular music emotion dataset using social tags from Last.FM (see Section 4.1). Relevant musical features are extracted, and machine learning techniques are then applied to classify musical emotions. To have a better understanding of human responses to Western popular music and to evaluate the reliability of social tags, two models of emotions are used. Moreover, my MER system is trained with a user-suggested emotion dataset. The differences between the predictions of the MER system and responses from human beings are also provided.

Chapter 4

Music and Emotion

In the past decade, increasing attention has been paid to research on music and emotion. However, different approaches have been used by music information retrieval researchers and music psychologists to carry out their research. There exists a series of "misunderstandings" between these two fields, and it is important to bring their knowledge together. This chapter covers my work in automatic music emotion classification using machine learning techniques (MIR) and human's emotional responses to music (music psychology). First of all, Section 4.1 describes the collection of "ground truth" data using online social tags from the Last.FM web site. A total of 2094 Western popular musical excerpts in four emotion categories (i.e., happy, sad, relaxed, and angry) are collected. Next, audio features are extracted for the collected emotion dataset. In Section 4.2, machine learning techniques are applied to audio features, and I investigate the performance of my music emotion recognition system via four experiments. Eighty stimuli are randomly selected from those 2904 musical excerpts, and they are used in two listening experiments. The first listening experiment using the categorical model with four basic emotions is explained in Section 4.3, and the second experiment using the two-dimensional Valence-Arousal model of emotion is described in Section 4.4. Section 4.5 compares and summarises the results from the two listening experiments. To provide some insights into the performance of music emotion recognition systems, Section 4.6 presents the similarities and differences between listeners' emotional responses and predictions from a music emotion recognition system. At the end of this chapter, Section 4.7 concludes my work on music and emotion.

4.1 Emotion Data Collection for Western Popular Music

Although music emotion has been widely studied in music psychology and music information retrieval, there still exist problems of collecting ground truth on music emotion. As described in Section 2.5, classical, jazz, and film soundtracks have been frequently used, but the results may not be applicable to other musical genres, and existing music emotion recognition systems for popular music fail to produce satisfactory results (Yang and Chen, 2011). Most researchers have compiled their own databases (Yang and Lee, 2004; Law et al., 2007; Turnbull et al., 2008b; Kim, 2008), and those stimuli are typically annotated, selected, or manipulated by expert musicologists or researchers, which is expensive in terms of financial cost and human labour. Instead, I use social tags from the music discovery web site Last.FM, an approach that has been successfully used in previous MIR research (see Section 2.4.1 for background; Lamere, 2008; Levy and Sandler, 2009; Bischoff et al., 2009; Saari and Eerola, 2014). The emotion dataset is collected via the Application Program Interfaces (APIs) provided by Last.FM and 7Digital[1].

The five mood clusters (see Section 2.3.1) proposed by Hu et al. (2008) have been widely used in the MIR community, especially for the MIREX AMC task, however, emotion words such as *rollicking*, *literate*, and *poignant* are not popular in social tags. Therefore, I select four basic emotion classes: “happy”, “sad”, “relaxed”, and “angry”, considering that these four emotions are widely used across different cultures and cover all four quadrants of the two-dimensional model of emotion (Laurier et al., 2008).

4.1.1 Emotion Tags Provided by Last.FM

These four basic emotions (i.e., happy, sad, relaxed[2], and angry) are used as seeds to retrieve the top 30 tags from Last.FM[3] containing the emotion words as a substring. Table 4.1 presents an example of the retrieved tag results. Full lists of retrieved emotion tags can be found in Appendix A. I subsequently obtain the top 50 songs labelled with the retrieved emotion tags. Tables 4.2 - 4.5 show examples of the music metadata (i.e., artists’ names and titles) retrieved from emotion tags.

[1] `https://www.7digital.com/`

[2] The term *relax* was used in the data collection, which represented the emotion *relaxed*.

[3] I accessed the server in Feb, 2012.

TABLE 4.1
Top 5 emotion tags returned by Last.FM for four basic emotions.

Happy	**Angry**	**Sad**	**Relaxed**
happy	angry	sad	relax
happy hardcore	angry music	sad songs	relax trance
makes me happy	angry metal	*happysad*	relax music
happy music	angry pop music	sad song	jazz relax
happysad	angry rock	sad & beautiful	only relax

TABLE 4.2
Top 5 titles and artists' names returned with emotion tags from the "happy" category.

Artist	**Title**
Noah And The Whale	5 Years Time
Jason Mraz	I'm Yours
Rusted Root	Send Me On My Way
Royksopp	Happy Up Here
Karen O And The Kids	All Is Love

4.1.2 Musical Excerpts Collection

Given the retrieved titles and the names of the artists, I use a public API from 7Digital to get preview audio files. Each song excerpt is either 30 seconds or 60 seconds long (as provided by 7Digital), and in a standard mp3 format (bit rate: 128 *kbps* or 64 *kbps*; sample rate: 22050 *Hz* or 44100 *Hz*). The results cover different types of pop music, meaning that I avoid particular artist and genre effects (Kim et al., 2006). The purpose of this step is to find ground truth data, and I was using only the top 50 songs for each tag, which protects against issues such as cold start, noise, hacking, and bias (Celma, 2006; Lamere, 2008).

However, as shown in Table 4.1, there is some noise in the data such as confusing tags and repeated songs. I manually removed data with the tag "happysad" and "happy sad" which existed in both the happy and sad classes, and delete repeated songs, to make sure every song will only exist once in a single class. Most existing datasets on music emotion recognition are quite small (less than 1000 items), which indicates that 2904 songs (see Table 4.6) for four emotions retrieved by social tags is a good size for the current experiments. The dataset has been made available[4], to encourage other researchers to reproduce the results for research and evaluation.

[4]The dataset can be found at `https://code.soundsoftware.ac.uk/projects/emotion-recognition`

TABLE 4.3
Top 5 titles and artist's names returned with emotion tags from the "sad" category.

Artist	**Title**
Gary Jules	Mad World
The Smiths	Asleep
Counting Crows	Colorblind
Mayday Parade	Miserable At Best
Christina Perri	Jar Of Hearts

TABLE 4.4
Top 5 titles and artists' names returned with emotion tags from the "relaxed" category.

Artist	**Title**
Gorillaz	Hong Kong
Katy Perry	The One That Got Away
Seabear	Lost Watch
Little Joy	The Next Time Around
Jack Johnson	All At Once

Moreover, audio features are extracted from this emotion dataset of 2904 musical excerpts. Then machine learning techniques are applied to these audio features to classify emotions in music. Section 4.2 presents my work on music emotion classification.

4.2 Evaluation of Musical Features for Emotion Classification

A wealth of research has been performed on music emotion classification (refer to Section 2.4.1). Previous studies have shown that musical emotion is linked to features based on rhythm, timbre, spectral properties, and lyrics (Kim et al., 2010; Wang et al., 2011; Beveridge and Knox, 2012; McVicar and De Bie, 2012). For example, sad music correlates with slow tempo, while happy music is generally faster (Kastner and Crowder, 1990; Dalla Bella et al., 2001; Trainor et al., 2002; Hunter et al., 2010). Different classifiers have been attempted on audio features, but only limited success has been obtained in creating automatic classifiers of emotion in music. With the ground truth data set of 2904 musical excerpts that had been tagged with one of the four emotion words "happy", "sad", "relaxed", and "angry" on the Last.FM web site, I aim to

TABLE 4.5
Top 5 titles and artists' names returned with emotion tags from the "angry" category.

Artist	**Title**
Brand New	Seventy Times 7
Tech N9ne	Like Yeah
Jack Off Jill	Nazi Halo
Tyler, The Creator	Golden
The Smashing Pumpkins	An Ode To No One

TABLE 4.6
Summary of ground truth data collection.

Emotion	**No. of Songs**
Happy	753
Angry	639
Sad	763
Relaxed	749
Overall	2904

better explain and explore the relationship between musical emotions and audio features. In this section, I examine the following parameters: first, I compare four musical dimensions of audio features: *dynamic*, *spectral*, *rhythmic*, and *harmonic*; second, I evaluate an SVM associated with two kernels: polynomial (degree = 3) and radial basis functions (RBF); third, I compare the use of mean value versus standard deviation as features.

The experimental procedure consists of three stages: data preprocessing, feature extraction, and classification. Figure 4.1 illustrates these three stages as well as the data collection described in Section 4.1.

4.2.1 Data Preprocessing

The music excerpts I fetched are in mp3 format. In order to extract the musical features, I convert the dataset to standard wav format (22,050 *Hz* sampling rate, 16 bit precision, and mono channel). I normalise the excerpts by dividing by the highest amplitude to mitigate the *production effect*[5] of different recording levels (Yang and Chen, 2011).

[5]Some songs are recorded with a higher volume, while others are recorded with a lower volume.

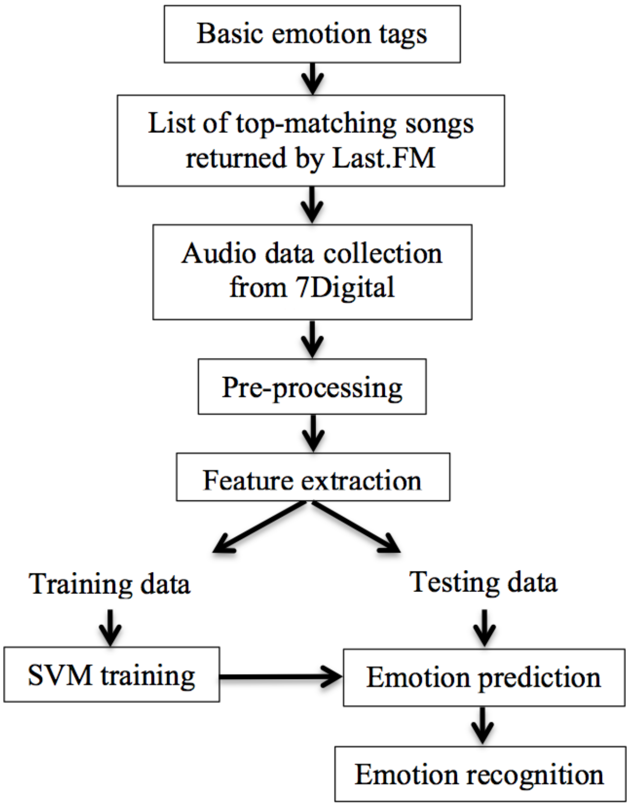


Figure 4.1: Stages of experimental procedure.

4.2.2 Musical Feature Extraction

Following the work of Saari et al. (2011), two different types of features (mean and standard deviation) with a total of 54 feature values are extracted using the MIRtoolbox[6] (Lartillot and Toiviainen, 2007, see Table 4.7). The features are categorised by the MIRtoolbox into the following four musical dimensions: *dynamics*, *rhythm*, *spectral properties*, and *harmony*.

4.2.3 Emotion Classification

The majority of music classification tasks such as genre classification (Tzanetakis and Cook, 2002; Tsunoo et al., 2011), artist identification (Mandel and Ellis, 2005; Tsai and Wang, 2006), and instrument recognition (Marques and Moreno, 1999; Hamel et al., 2009) have used k-nearest neighbour (Cover and Hart, 1967) and support vector machine (Boser et al., 1992) classifiers. In

[6]Version 1.3.3

the case of audio input features, the SVM has been shown to perform best (Bischoff et al., 2009).

TABLE 4.7
The feature set used in this music emotion classification experiment.

Dimension	No.	Feature names	Acronyms
Dynamics	1-2	RMS energy	RMSm, RMSsd
	3-4	Slope	Sm, Ssd
	5-6	Attack	Am, Asd
	7	Low energy	LEm
Rhythm	1-2	Tempo	Tm, Tsd
	3-4	Fluctuation peak (pos, mag)	FPm, FMm
	5	Fluctuation centroid	FCm
Spectral Properties	1-2	Spectrum centroid	SCm, SCsd
	3-4	Brightness	BRm, BRsd
	5-6	Spread	SPm, SPsd
	7-8	Skewness	SKm, SKsd
	9-10	Kurtosis	Km, Ksd
	11-12	Rolloff95	R95m, R95sd
	13-14	Rolloff85	R85m, R85sd
	15-16	Spectral entropy	SEm, SEsd
	17-18	Flatness	Fm, Fsd
	19-20	Roughness	Rm, Rsd
	21-22	Irregularity	IRm, IRsd
	23-24	Zero crossing rate	ZCRm, ZCRsd
	25-26	Spectral flux	SPm, SPsd
	27-28	MFCC	MFm, MFsd
	29-30	DMFCC	DMFm, DMFsd
	31-32	DDMFCC	DDm, DDsd
Harmony	1-2	Chromagram peak	CPm, CPsd
	3-4	Chromagram centroid	CCm, CCsd
	5-6	Key clarity	KCm, KCsd
	7-8	Key mode	KMm, KMsd
	9-10	HCDF	Hm, Hsd

Note. In the feature acronyms, m represents **mean** value, sd represents **standard deviation**. RMS = Root Mean Square, HCDF = Harmonic Change Detection Function, and MFCC = Mel-Frequency Cepstral Coefficients. DMFCC and DDMFCC represent first and second derivatives of MFCC.

In this experiment, therefore, I choose SVMs as the classifier, using the implementation of the sequential minimal optimisation algorithm in the Weka data mining toolkit[7]. SVMs are trained using polynomial and radial basis function kernels. I set the cost factor $C = 1.0$, and leave other

[7] `http://www.cs.waikato.ac.nz/ml/weka/`

parameters unchanged. A stratified 10-fold cross validation is applied. To better understand and compare features in the four musical dimensions, I divided the experiments into four tasks.

Experiment 1: I compare the performance of the two kernels (polynomial and RBF) using various features;

Experiment 2: four classes (musical dimensions) of features are tested separately, and I compare the results to find a dominant class;

Experiment 3: two types of feature descriptors, mean and standard deviation, are calculated. The purpose is to compare values for further feature selection and dimensionality reduction;

Experiment 4: different combinations of feature classes (e.g., spectral with dynamic) are evaluated in order to determine the best-performing model.

4.2.4 Classification Results

Experiment 1

In Experiment 1, SVMs trained with two different kernels are compared. Previous studies have found in the case of audio input that the SVM performs better than other classifiers (i.e., Logistic Regression, Random Forest, Gaussian Mixture Models, k-NN and Decision Trees) (Laurier et al., 2007). To my knowledge, no work has been reported explicitly comparing different kernels for SVMs. In MER tasks, the RBF kernel is a common choice because of its robustness and accuracy in other similar recognition tasks (Bischoff et al., 2009).

TABLE 4.8
Classification results of Experiment 1.

Feature class	**Polynomial kernel**		**RBF kernel**		**No.**
	Accuracy	**Time**	**Accuracy**	**Time**	
Dynamics	37.2	0.44	26.3	32.5	7
Rhythm	37.5	0.44	34.5	23.2	5
Harmony	47.5	0.41	36.6	27.4	10
Spectral properties	**51.9**	0.40	**48.1**	14.3	32

Note. Time represents model building time in seconds, and No. represents the number of features used in each class. The highest accuracy is shown in bold.

The results in Table 4.8 show however that regardless of the features used, the polynomial kernel (degree = 3) always achieves the higher accuracy. Moreover, the model construction times for each kernel are dramatically different. The average construction time for the polynomial kernel is 0.4 seconds, while the average time for the RBF kernel is 24.2 seconds, around 60 times more than the polynomial kernel. The following experiments reveal similar results. This shows that the polynomial kernel outperforms RBF kernel in the task of emotion classification at least for the parameter values used here.

Experiment 2

In Experiment 2, I compare the musical emotion prediction results for the following musical dimensions: *dynamic*, *rhythmic*, *harmonic*, and *spectral*. Results are shown in Figure 4.2. Dynamics and rhythm features yield similar results, with harmony features providing better results, but the spectral class with 32 features achieves the highest accuracy of 51.9%. This experiment provides a baseline model, and further exploration of multiple dimensions is performed in Experiment 4.

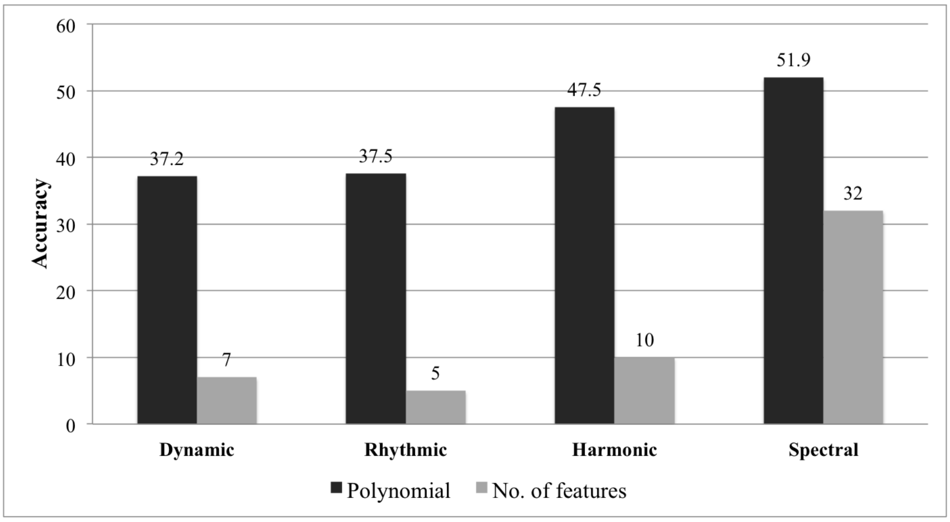


Figure 4.2: Comparison of classification results for the four classes of features.

Experiment 3

In this experiment, I evaluate different types of feature descriptors, mean value and standard deviation for each feature across all feature classes, for predicting the emotion in music. The results in Table 4.9 show that the use of both mean and standard deviation values gives the best results in each case. However, the processing time is increased, so choosing the optimal descriptor for each feature is highly desirable. For example, choosing only the mean value in the harmony class, the music emotion recognition system loses 2% of accuracy but increases the speed while the choice of standard deviation results in around 10% accuracy loss for the same increase in speed. As the number of features increases, I observe that the difference between using mean and standard deviation is reduced. However, more experiments on properties of the features are needed to explain why the mean values in harmonic and spectral features, and standard deviations of dynamic and rhythmic features have higher accuracy scores.

TABLE 4.9
Comparison of classification accuracy with mean (M) and standard deviation (SD) feature values.

Features class	**Polynomial**	**No. of features**
Dynamic all	**37.2**	7
Dynamic *M*	29.7	3
Dynamic *SD*	*33.8*	3
Rhythmic all	**37.5**	5
Rhythmic *M*	28.7	1
Rhythmic *SD*	*34.2*	1
Harmonic all	**47.5**	10
Harmonic *M*	*45.3*	5
Harmonic *SD*	38.3	5
Spectral all	**51.9**	32
Spectral *M*	*49.6*	16
Spectral *SD*	47.5	16
Spec+Dyn all	**52.3**	39
Spec+Dyn *M*	*50.5*	19
Spec+Dyn *SD*	48.7	19
Spec+Rhy all	**52.3**	37
Spec+Rhy *M*	*49.8*	17
Spec+Rhy *SD*	47.8	17
Spec+Har all	**53.3**	42
Spec+Har *M*	*51.3*	21
Spec+Har *SD*	50.3	21
Har+Rhy all	**49.1**	15
Har+Rhy *M*	*45.6*	6
Har+Rhy *SD*	41.2	6
Har+Dyn all	**48.8**	17
Har+Dyn *M*	*46.9*	8
Har+Dyn *SD*	42.4	8
Rhy+Dyn all	**41.7**	12
Rhy+Dyn *M*	32.0	4
Rhy+Dyn *SD*	*38.8*	4

Note. Only the features having both mean values and standard deviations are compared. The highest accuracy in each feature class is shown in bold, and the higher accuracy in mean and standard deviation of each feature class is shown in italics.

Experiment 4

In order to choose the best model, the final experiment fuses different musical features. As presented in Table 4.10, optimal accuracy is not produced by the combination of all features. Instead, the use of spectral, rhythmic, and harmonic (but **not** dynamic) features produces the highest accuracy.

TABLE 4.10
Classification results for combinations of feature sets.

Features	**Accuracy**	**No. of features**
Spec+Dyn	52.3	39
Spec+Rhy	52.3	37
Spec+Har	53.3	42
Har+Rhy	49.1	15
Har+Dyn	48.8	17
Rhy+Dyn	41.7	12
Spec+Dyn+Rhy	52.4	44
Spec+Dyn+Har	53.8	49
Spec+Rhy+Har	**54.0**	47
Dyn+Rhy+Har	49.7	22
All Features	53.6	54

Note. The highest accuracy is shown in bold.

4.2.5 Discussion

In this evaluation of audio features for music emotion classification, I used the "ground truth" emotion dataset of 2904 Western popular musical excerpts associated with one of the four emotion tags from Last.FM (i.e., happy, sad, angry, and relaxed). Musical features were extracted and grouped into four categories for training and validation. Four experiments were conducted to predict emotion labels. The results suggest that, instead of the conventional approach using SVMs trained with an RBF kernel, a polynomial kernel yields higher accuracy. Since no single dominant features have been found in emotion classification, I explored the performance of different musical classes of feature for predicting emotion in music. Experiment 3 found that dimensionality reduction can be achieved through removing either mean or standard deviation values, halving the number of features used, with, in some cases, only 2% accuracy loss. In Experiment 4, I found that inclusion of dynamics features with the other classes actually impaired the performance of the classifier while the combination of spectral, rhythmic, and harmonic features yielded optimal performance. The highest accuracy achieved by the MER system was 54% (baseline around 25%). Similar to other MER studies using popular music, the emotion classification accuracy failed to reach a satisfactory result. The confusion matrix showed that the proposed MER system collectively confused the emotions "sad" and "relaxed". Since only low-level features provided by the MIRtoolbox were used in this experiment, high-level features such as mode and genre could be considered in future studies.

One of the possible reasons for the low accuracy is the ground truth data collection using social tags. Though the use of social tags is a powerful tool which can assist searching and the exploration of music (Levy and Sandler, 2007), several issues with tags have been identified, such as the "cold start" problem (i.e., new or unknown music has no tags), noise, malicious tagging, and bias towards popular artists or genres (Lamere, 2008). Social tags have been successfully used in a variety of MIR studies, testing whether they are reliable is often neglected. There are a number of incentives and motivations for tagging, such as to aid memory, provide context for task organisation, social signalling, social contribution, play and competition, and opinion expression (Ames and Naaman, 2007). People annotate the emotional experience of music listening on the Last.FM web site, however, we know very little about the criteria on which tagging is based.

Music can both induce (more subjective) and express emotion (more objective) (Västfjäll, 2002; Kallinen and Ravaja, 2006; Schubert, 2007a; Evans and Schubert, 2008). Previous studies have suggested that music induces emotions similar to the emotional quality perceived in the music (Gabrielsson, 2002). To my knowledge, the two facets of emotion communication (perceived emotion and induced emotion) in music have rarely been studied in combination with emotion tags.

To describe musical emotions, two well-known and dominant models have arisen (see Section 2.3): the categorical model and the dimensional model. Sections 4.3 and 4.4 explore the association between human-annotated tags and emotional judgements in perceived emotion and induced emotion using both models of emotion. The data was collected through human-annotated social tags, which are categorical in nature (Ekman, 1992; Panksepp, 1998). Considering the difficulty in judging other proposed dimensions such as *dominance*, *intensity*, *tension*, or *interests* reported in previous studies (e.g., Leman et al., 2005; Ilie and Thompson, 2006; Schubert, 2007b; Collier, 2007), to find the mapping of emotion onto the dimensional model, only the two core dimensions valence and arousal are used. Similar to tempo (Repp, 1993; Dixon et al., 2006), emotion might be instantaneous, which can be recognised and experienced as soon as the music starts, or emotion may evolve and change continuously over time. Due to this dynamic nature of music, I measure the "dominant emotion" from a musical excerpt that participants perceive and feel, which might be considered as a central tendency (not an average, nor the median) of emotion in a certain range of exposure (e.g., 30 or 60 seconds). The following questions are examined,

i How do induced emotion and perceived emotion responses differ from each other, in the categorical and the dimensional models of emotion?

ii How well do semantic emotion tags reflect listeners' perceived emotion and induced emotion?

iii To what degree can the emotion tags be used to select stimuli for the study of music and emotion?

iv What are the influences of individual difference (i.e., musical training, music engagement, culture, age, and gender) on the attribution of emotion to music?

4.3 Listening Experiment 1 - The Categorical Model

4.3.1 Participants

Forty English-speaking students (20 male) participated in Experiment 1 using the categorical model. All the participants were recruited through university email lists, and had ages ranging from 18 to 44 years, with various educational backgrounds (from undergraduate to postgraduate) and levels of musical training. Among the participants, 50% attentively listened to music more than one hour per day, and 88% of the participants can play at least one instrument. Moreover, 68% of the participants preferred pop/rock music, 10% of them preferred jazz, and the rest preferred classical music. Full details of participants' information (i.e., age, gender and nationality) can be found in Appendix B.

4.3.2 Stimuli

The stimuli were selected from my collection of 2904 musical excerpts retrieved from Last.FM and 7Digital. Each excerpt had been tagged on Last.FM with one of the four words "happy", "sad", "angry", or "relaxed". I randomly chose a total of 80 excerpts from these four categories (20 tracks from each category). The excerpts ranged from recent releases back to 1960s, and covered a range of Western popular music styles such as pop, rock, country, metal, and instrumental. It is worth noting that emotion induction usually requires longer excerpts than emotion perception (e.g., 45-60s, Vuoskoski and Eerola, 2011a), but I wanted the length to be consistent for measuring both induced and perceived emotion. Each excerpt was either 30 seconds or 60 seconds long (as provided by 7Digital), and it was played from a standard mp3 format file (bit rate: 128 *kbps* or 64 *kbps*; sample rate: 22050 *Hz* or 44100 *Hz*). Although emotion can be perceived and felt from shorter excerpts, such emotions are liable to vary over time within a piece. I assume that the emotion tags correspond to the overall affect or most frequent emotion over the whole piece, so I took the full length of the excerpts that were available from the database, in order to smooth out short-term affects. This 80-excerpt dataset is described in Appendix C and is also available online[8], to enable further studies with this data and comparisons with the current work.

In order to minimise the effect of song order and condition order (perceived and induced emotion), four different list conditions were constructed. The order of presentation of the two rating conditions and two song lists (n=40, 10 for each emotion category) was counterbalanced across participants. The songs in each song list were presented in a different random order for each participant (Welch and Krantz, 1996). Therefore, the participants were divided into four groups as shown in Table 4.11.

TABLE 4.11
Group allocation among participants.

Group	**Song list 1**	**Song list 2**
Group 1	induced emotion	perceived emotion
Group 2	perceived emotion	induced emotion
	Song list 2	**Song list 1**
Group 3	induced emotion	perceived emotion
Group 4	perceived emotion	induced emotion

4.3.3 Procedure

In the study of music and emotion, the categorical model has been predominantly used, and over 75% of the studies used happiness, sadness, and anger. In order to cover all four quadrants of the two dimensional model, four basic emotion classes: "happy", "angry", "sad", and "relaxed" were

[8] `https://code.soundsoftware.ac.uk/projects/emotion-recognition`

used. Experiment 1 was conducted using the categorical model in a laboratory environment[9] in November 2012. The study was approved by the Queen Mary Research Ethics Committee (REF: QMREC1019). The only way to assess subjective emotional experience, is via a format of listening and self-report (Gabrielsson, 2002). First, the participants were asked to read the instruction page:

1. Listen to the songs (they will last either 30 or 60 seconds);
2. After listening, for each piece please choose one of the following: *happy*, *sad*, *relaxed*, *angry*, or *cannot tell/none of above*;
   Note: participants were asked to answer one of the two questions (condition *induced* and condition *perceived*).
3. For each track, you may click the "stop" button of the audio player if required;
4. Be careful, do not press too quickly, since you can only listen to each song once;
5. Please answer all the questions; the test will take about 40 mins to complete.

Participants were then asked to fill in a demographic form including name, age, gender, "type of music they are most familiar with", nationality, and "music culture they grew up with" as well as a selected subscale from the Goldsmiths Musical Sophistication Index (Gold-MSI v0.9[10]) questionnaire to measure participants' level of musical expertise and engagement (Müllensiefen et al., 2012). For Experiment 1, 32 questions regarding the importance of music in everyday life (importance), importance of music for psychological functions (emotion), and life history of formal musical training (music skills) were measured by the Gold-MSI. The listeners responded to each excerpt (10 excerpts per page) and rated them with a categorical model. Participants were reminded of the two different rating conditions (induced and perceived emotion). During the listening test, they were asked "How would you describe the emotional content of the music itself?" for the emotion perceived, and "What emotion do you feel in response to the music?" for the emotion induced. In order not to constrain people in the experiment to four basic emotion classes, I added the fifth option *cannot tell/none of above*. The whole test lasted about 40 minutes without any planned breaks. However, the participants were able to stop whenever they wanted and adjust volume to a comfortable level. At the end of the experiment, their opinions

[9] `http://isophonics.net/emotion/test/`
[10] `http://www.gold.ac.uk/music-mind-brain/gold-msi/`

and feedback were collected. Participants were also asked to provide examples of musical pieces for each perceived and induced emotion (see Appendix E), as well as the activities involved with music listening and its purposes (see Appendix D).

The statistical analyses were all conducted using the Matlab 2012 Statistics Toolbox. Responses were aggregated across participants for song-level analysis, or aggregated across items for individual-level analysis.

4.3.4 Results

4.3.4.1 Comparison of Responses for Perceived and Induced Emotion

The normality of participants' responses was checked via a Kolmogorov-Smirnov test (K-S test), and the results rejected the assumption of normality with $KS = 0.5$ ($p < .001$). To compare listeners' reports of induced and perceived emotion of music, a nonparametric Wilcoxon signed-rank test was used to analyse the results of the two conditions. Participants' responses were aggregated by their corresponding labels, and the agreement between responses and emotion tags for perceived emotion ($Mdn = 0.54$) was significantly higher than for induced emotion ($Mdn = 0.47$, $Z = -2.09$, and $p < .05$).

Participants' consistency of perceived and induced responses

Regardless of the emotion tags, to examine the differences in the consistency of participants' perceived and induced responses, one-way analysis of variance (ANOVA) was conducted on the category with the highest number of responses for each music excerpt. The analysis revealed that the consistency of participants' perceived emotional responses ($M = 0.61$) was significantly higher than of their induced emotional responses ($M = 0.52$, $F(1) = 10.27$, and $p < .01$). For each stimulus, I computed an uncertainty score, corresponding to the proportion of participants who indicated *cannot tell/none of the above*. Using this as a dependent variable, a Wilcoxon signed-rank test revealed a significant difference between the uncertainty for induced ($Mdn = 3$) and perceived emotion ($Mdn = 2$, $Z = 5.27$, and $p < .001$). The result is consistent with the literature in suggesting that a higher consistency can be found in the responses of perceived emotion (Gabrielsson and Juslin, 1996; Schubert, 2007a). One of the possible reasons for the lower uncertainty level in perceived responses could be explained by the previous findings that the basic emotions such as *happiness*, *sadness*, and *anger* are often expressed in music because of their distinct expressive characteristics (Juslin and Laukka, 2004). A different explanation may come from the fact that emotions induced by music are more sophisticated and context-dependent, and the categorical model is inadequate to describe the richness of subjective emotions (Zentner et al., 2008; Eerola and Vuoskoski, 2013).

The relationship between listening duration and emotional responses

Given that participants were free to stop whenever they wanted, the listening duration for each emotional response was studied. The duration of each musical stimulus is either 30 or 60 seconds, and the percentage of the length of each excerpt that a participant listened to was computed as the "listening duration". Therefore, the listening durations across four emotion categories were compared using the Kruskal-Wallis test. The results showed that the listening duration for emotional responses of *sad* and *relaxed* was significantly longer than responses of *happy* and *angry*, for both induced ($\chi^2(3) = 47.96$, $p < .001$) and perceived emotion ($\chi^2(3) = 57.64$, $p < .001$). However, no significant differences in listening duration were found between induced and perceived emotional responses. This agrees with previous studies that happiness can be easily identified in music, whereas sadness and relaxedness are often confounded (Vieillard et al., 2008).

The relationship between the responses for perceived and induced emotion

Since participants' perceived and induced responses were different, the relationships between these two emotional responses were investigated. Correlation analyses between perceived and induced emotional responses were performed on the number of responses for each emotion category with the results shown in Table 4.12. Positive correlations ($p < .001$) were found on corresponding emotions in perceived and induced emotion, and several negative correlations were shown such as induced happiness with both perceived and induced sadness and relaxedness, as well as perceived anger with perceived happiness, sadness, and relaxedness. Interestingly, a positive correlation was found between perceived sadness and induced relaxedness (Pearson's $r(78) = .29$, $p < .01$).

In order to categorise the relationships between responses for perceived and induced emotion, I used and adapted Gabrielsson's (2002) model (see Table 4.13). To distinguish between various types of "negative" relationships, the negative category was further divided into three cases: *valence and arousal* (negative valence and arousal in perceived emotion, but positive valence and arousal in induced emotion, etc.), *valence* (negative valence and arousal in perceived emotion, but positive valence and negative arousal in induced emotion, etc.) and *arousal* (negative valence

TABLE 4.12
Correlations between induced and perceived emotional responses.

		Induced responses (IR)				**Perceived responses (PR)**		
		Happiness	Sadness	Relaxedness	Anger	Happiness	Sadness	Relaxedness
IR	Sadness	-.57***						
	Relaxedness	-.40***	.17					
	Anger	-.09	-.36***	-.59***				
PR	Happiness	**.85*****	-.52***	-.20	-.26*			
	Sadness	-.56***	**.90*****	.29**	-.39***	-.54***		
	Relaxedness	-.26*	.01	**.75*****	-.51***	-.16	-.04	
	Anger	-.08	-.37***	-.56***	**.96*****	-.28*	-.40***	-.49***

Note. Pearson's r values between corresponding emotions in perceived and induced emotion are bold. *$p < .05$; **$p < .01$; ***$p < .001$.

and arousal in perceived emotion, but negative valence and positive arousal in induced emotion, etc.). To categorise the relationship between perceived and induced emotion for each excerpt, I assessed which emotion is dominant among participants' responses. I took the label with the greatest number of votes to be the dominant emotion, as long as it received more than 8 out of 20 votes; otherwise "undecided" was marked. I chose 8 votes, since this gave a p value $< .05$, given the null hypothesis that $p(\text{happy}) = p(\text{sad}) = p(\text{relaxed}) = p(\text{angry}) = 25\%$ and $p(\text{none}) = 0\%$. Therefore, eighty relationships were collected. Seventy-one excerpts had one of the following relationships: *positive relationship*, *negative relationship*, *no systematic relationship*, and *no relationship*. Among these relationships, forty-three songs had a "positive relationship" (the listener's emotional response is in accordance with the emotion expressed in the music), and seven songs had a "negative relationship" (listener reacts with an emotion 'opposite' to that expressed in the music in at least one domain), of which four had a negative valence relationship (only with relaxedness and sadness), and negative arousal relationship took three (only with happiness and relaxedness). No cases of negative relationships were found for both valence and arousal simultaneously.

Meanwhile, fourteen songs had "no systematic relationship" between perceived and induced emotion (*case 1*: the music evokes various[11] emotional responses in different listeners, or *case 2*: listener stays "emotionally neutral" regardless of the expression of the music), of which twelve of them belonged to case 1. The remaining six cases had "no relationship". However, there was one special case in which an equally perceived happy and angry song induced only happiness (song

[11] Various for different listeners and occasions.

TABLE 4.13
Possible relationships between perceived and induced emotions in the categorical model.

Relationship	**Level**	**Perceived emotion**	**Induced emotion**	**Percentage**
Undecided relationship	Valence & Arousal	undecided	undecided	11%
Positive relationship	Valence & Arousal	happy sad relaxed angry	happy sad relaxed angry	54%
Negative relationship	Valence & Arousal	happy sad relaxed angry	sad happy angry relaxed	0%
	Valence	happy sad relaxed angry	angry relaxed sad happy	5%
	Arousal	happy sad relaxed angry	relaxed angry happy sad	4%
No systematic relationship	Case 1	happy sad relaxed angry	various	15%
	Case 2	happy sad relaxed angry	neutral	3%
No relationship	Valence & Arousal	not perceived	happy sad relaxed angry	7%

Note. The special case in which an equally perceived happy and angry song induced only happiness is not shown (covers 1%).

title: Motown Junk and artist's name: Manic Street Preachers). The relationships for these 80 excerpts are shown in Table 4.13.

4.3.4.2 Correspondence between Tags and Emotional Responses

Figures 4.3 and 4.4 show the response distributions for excerpts for each emotion tag which was retrieved from the Last.FM web site. As expected, the tags predicted both perceived and induced emotional responses. In both perceived and induced cases, the excerpts labelled with "happy", "angry", and "relaxed" were very distinct. The induced responses for the tag "sad" were somewhat blurred between "sad" and "relaxed". However, for the songs labelled with "anger" and "sadness", induced emotional responses as seen in Figure 4.3 received more positive emotion responses (relaxedness and happiness) than perceived emotional responses as seen in Figure 4.4.

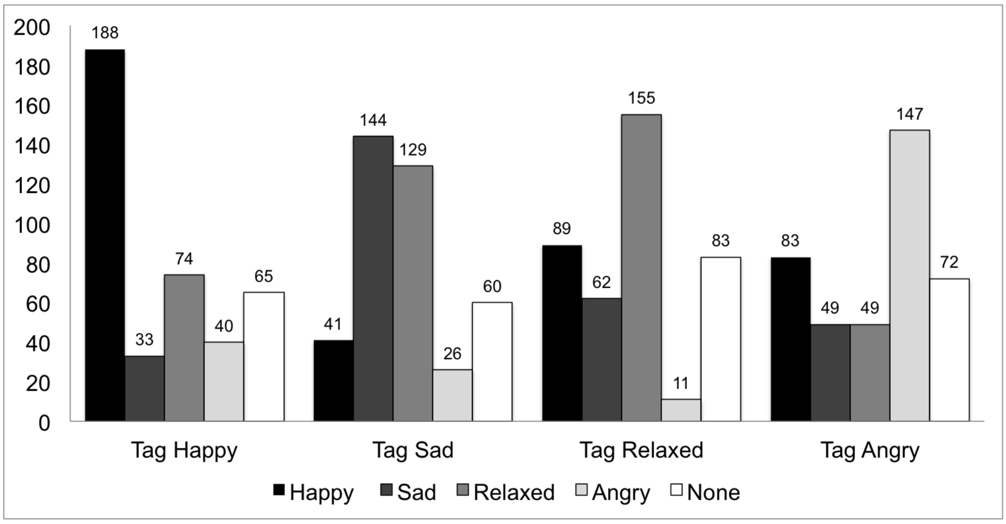


Figure 4.3: Induced emotional response distribution for each tag. The horizontal axis shows the five responses for each of the four emotion tags *happy*, *sad*, *relaxed*, and *angry*. The vertical axis shows the number of responses.

In order to evaluate the reliability of the emotion tags, Wilcoxon signed-rank tests were carried out for each emotion category. The analyses revealed that agreement between emotion tags and participant ratings was well above chance (for perceived emotion $Z = 4.67$, $p < .001$; for induced emotion $Z = 5.34$, $p < .001$). Though the overall agreement of the perceived emotional responses with emotion tags was ranked significantly higher than that for induced responses, in the case of happiness and relaxedness, the agreement of perceived and induced emotional

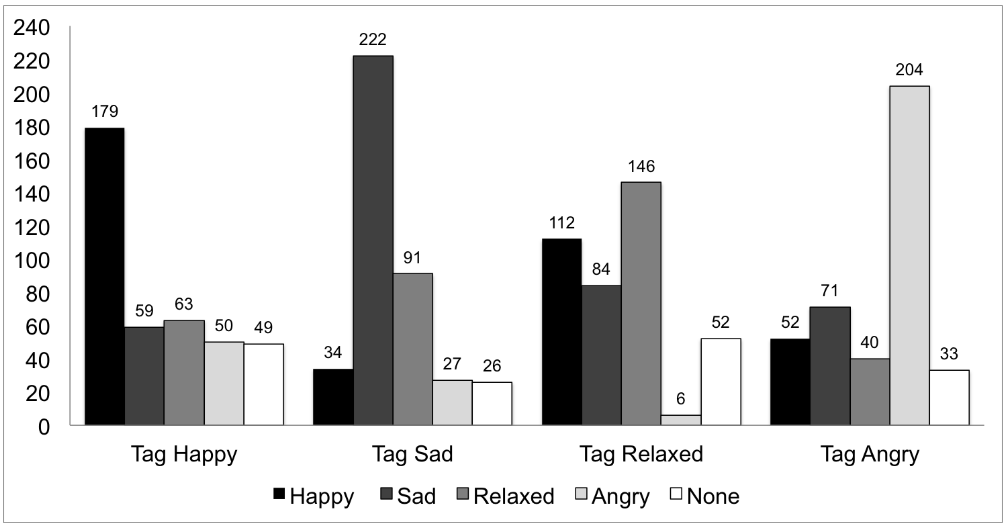


Figure 4.4: Perceived emotion response distribution for each tag. The horizontal axis shows the five responses for each of the four emotion tags *happy*, *sad*, *relaxed*, and *angry*. The vertical axis shows the number of responses.

responses showed no significant difference, as shown in Table 4.14. It suggests that when musical excerpts are labelled as "sad" or "angry", there is a greater chance that listeners supply these labels for perceived emotion than for induced emotion. In contrast, listeners who label excerpts "happy" or "relaxed" are about as likely to base these labels on perceived emotion as induced emotion.

TABLE 4.14
Proportion of responses agreeing with Last.FM tag data for the corresponding song.

	Happy	**Sad**	**Relaxed**	**Angry**
Induced responses	0.47	0.36	0.39	0.37
Perceived responses	0.45	0.56***	0.37	0.51***

Note. Columns represent the four emotion tags, rows the listener responses for induced and perceived emotion. *$p < .05$; **$p < .01$; ***$p < .001$ using Wilcoxon signed-rank test, for comparing the overall agreement of perceived and induced emotional responses with emotion tags.

4.3.4.3 Analysis of Individual Factors

In this experiment, the Gold-MSI v0.9 was used to assess participants' music expertise and engagement. The three factors measured were *importance* (importance of music in everyday life), *musical training* (life history of formal musical training), and *emotion* (importance of music for psychological, especially emotional functions). A summary of the responses can be found in Table 4.15, as well as statistics for a large BBC (British Broadcasting Corporation) Internet study ($n = 137,633$) using the Gold-MSI v1.0 (Müllensiefen et al., 2014). Comparing these three musical attributes in this study, a positive correlation was found for *importance* with both *musical training* (Pearson's $r(38) = .32$, $p < .05$) and *emotion* ($r(38) = .57$, $p < .001$).

TABLE 4.15
Summary of responses to 32 questions adapted from the Gold-MSI.

		Scale Min	*Scale Max*	*Mean*	*SD*
Experiment 1	**Importance**	15	105	72.5	18.1
	Musical training	9	63	37.4	15.0
	Emotions	8	56	45.5	6.7
BBC study	**Active engagement**	9	63	41.5	10.4
	Musical training	7	49	26.5	11.4
	Emotions	6	42	34.7	5.04

Note. For example, a musical training score of 26 using Gold-MSI v0.9 could mean that the participant can play one musical instrument, had one year of formal training, and practices the instrument for one hour daily.

To discover whether individual differences such as age, gender, musical training, and engagement influence emotion judgements, correlation analysis and Kruskal-Wallis one-way analysis of variance were carried out. However, no significant difference was found between responses of male and female participants, nor for age[12], on their agreement with emotion tags for perceived and induced emotion. I found that older participants were more likely to listen to music for its emotional functions ($r(38) = .57$, $p < .001$), and there was a tendency of participants to feel less "happy" from music with increasing age. Interestingly, the distribution of individual participant responses showed that some people perceived anger in the music but never became angry listening to the excerpts. Likewise, some people could be easily moved by music. Therefore, I examined the response distribution over the 80 musical excerpts for each participant, but no significant result was found. The reason for the random distribution among people might depend on other factors such as the participant's personality, taste, or current mood.

[12]Only age categories of 18-24 and 25-34 were compared, as there was not enough data for participants' age over 35.

4.3.5 Discussion

The aim of Experiment 1 was to examine the difference between perceived and induced responses using a categorical model, and to explore associations between participants' emotional judgements and emotion tags (happy, sad, relaxed, and angry), as well as the influence of individual differences. First, participants' responses for perceived emotion in popular music showed a higher level of consistency than induced emotion ratings, thus agreeing with a previous study (Gabrielsson and Juslin, 1996). In addition, I found a higher uncertainty level in induced compared to perceived responses, indicating that the basic emotions are often expressed in music and the categorical model may be inadequate to describe the richness of emotion induced by music. Though I found the listening duration for emotional responses of "sad" and "relaxed" were significantly longer than for the responses of "happy" and "angry" for both induced and perceived emotion, no significant differences in listening duration were found between perceived and induced emotional responses.

Secondly, the potential relationships between perceived and induced emotion were studied. The analyses showed the ratings of perceived and induced emotion were positively correlated. Nonetheless, a small but significant difference was found. It suggests most of the times a person feels the emotion that the music expresses. Some interesting correlations were also found such as a perceived sad song could induce relaxedness in listeners, but not the other way round. If a song is perceived as sad or relaxed, the song would be unlikely to induce happiness. The majority of the music excerpts used in the experiment were sung, and lyrics may add some semantic meaning for emotional responses, therefore it is also possible that emotional judgements could be related not to the elements of music structure itself but with the meaning expressed by the lyrics. The analyses showed the same results after removing the instrumental tracks[13]. However, the relationship between emotion perceived and induced is complex, as it may take various forms (Gabrielsson, 2002). Therefore, quantitative analyses were conducted between the two conditions. As reported in the literature, a positive relationship is the most frequent one (Gabrielsson, 2002; Evans and Schubert, 2008). A similar result was found in the experiment that a positive relationship occurred 54% of the time. Moreover, the only negative relationship on the valence level was between the emotions relaxedness and sadness, and the only negative relationship on the arousal level occurred between relaxedness and happiness. Other relationships

[13]There were not enough data points (4 in song list 1, and 6 in song list 2) to analyse instrumental tracks separately.

such as "no relationship" and "no systematic relationship" were found in 7% and 18% of the cases respectively.

Even though social tags have been widely used in recent literature, emotion tags are rarely explored. Therefore, it is important to evaluate the reliability of the emotion tags for predicting listeners' induced or perceived responses. The results showed that the participant agreement with emotion tags was well above chance for both perceived and induced emotion. For the cases of sadness and anger, perceived emotion showed a significantly higher agreement with tags than induced emotion showed. One of the explanations is that the user tagging behaviour is based on their perceived feelings, but other explanations could be the subjectivity of induced emotion and between-subject differences in music experience, culture, personality, situation, current mood, and preference. However, further studies need to be conducted with controlled environment and stimuli. Interestingly, the induced emotion distribution showed responses that were more positive than the emotion tags would have indicated. This agrees with findings that emotional functions of music are generally positive (Juslin and Laukka, 2004; Zentner et al., 2008).

Finally, the influence of individual differences in *age*, *gender*, *importance* (importance of music in everyday life), *musical training* (life history of formal musical training), and *emotion* (importance of music for psychological, especially emotional functions), on participants' emotion judgements was assessed. No significant differences were found between male and female participants' responses for either perceived or induced emotion, nor their agreement with emotion tags. Studies have suggested that as people get older, they focus more on self-control of their emotions and rate their emotion-regulation skills as better (Gross et al., 1997). Similar results could be found in this experiment that participants' ratings of importance of music for emotional functions increased with age. Previously, different findings on age and emotional experience have been reported (Mroczek and Kolarz, 1998; Charles et al., 2001; Mather and Carstensen, 2005). No significant relationships were found between age, participants' emotional responses and the agreement with emotion tags, but a tendency of older participants to choose "cannot tell/none of above" rather than "happy" of induced emotional responses was shown. In addition, the three musical attributes *importance*, *musical skills*, and *emotion* had no correlation with participants' emotion judgements. Positive correlations were found between *importance* and both *musical training* and *emotion*. Individual differences such as preference, personality traits, and listener's current mood are also known to be relevant to emotional judgement (Vuoskoski and Eerola, 2011a,b; Shiota et al., 2006), but they are beyond the scope of this study.

General comments from participants raised other issues which are worthy of further investigation, for example: participants' musical preferences may influence their emotion judgements ("*I really like heavy metal, so I think many of the metal songs, normally people would've felt angry, but I just felt happy and energised.*"); the responses for perceived and induced emotion in music may depend on lyrics and cultural factors ("*If I feel sad I will usually listen to songs in my mother tongue*", "*Sometimes, emotional content of the music itself is closely related to the lyrics. Considering that English is not my mother language, it is more difficult for me to get the insight*"). Feedback from participants reinforces the issue of the inadequacy of the categorical model, with comments such as: "*four emotional classes are not enough*", "*more options should be added*", "*many times I was feeling limited because of the small amount of feelings options I had to choose from*", and "*I could feel more than one emotion, or another emotion which was not included in options (like energetic, romantic, etc.)*". To address the limitations in the categorical model, Experiment 2 was conducted using a two-dimensional continuous model of emotion.

4.4 Listening Experiment 2 - The Dimensional Model

4.4.1 Participants

Fifty-four English-speaking participants (25 male) took part. They were recruited through professional and academic email lists and social media, and had ages ranging from 15 to 54 years, as well as various educational, cultural, and musical training backgrounds. Full details of participants' information (age, gender, and nationality) can be found in Appendix B.

4.4.2 Stimuli

The same 80 musical excerpts used in Experiment 1 were used in Experiment 2. Similar to the design in Experiment 1, four different list conditions were constructed to minimise the effect of song order and conditions (perceived and induced emotion). The order of presentation of the two rating conditions and two song lists (n=40, 10 for each emotion category) was counterbalanced across participants. The songs in each song list were also presented in a different random order for each participant.

4.4.3 Procedure

In the past two decades, about a third of music and emotion studies have used a dimensional model (Eerola and Vuoskoski, 2013). Two dimensions, *valence* (happy versus sad) and *arousal* (calm versus excited) which were proposed by Russell (1980), are the most typical ones. Later, a third dimension *dominance* was also utilised (Killgore, 1999). However, to keep a simple mapping of emotions, only two dimensions, *valence* and *arousal*, on an 11-point scale, were used in Experiment 2. In addition, to map the dimensional model of emotion with emotion tags, the same four basic emotions (*happy*, *sad*, *relaxed*, and *angry*) used in Experiment 1 are chosen such that each occupies a unique quadrant of the valence-arousal plane as shown in Figure 4.5.

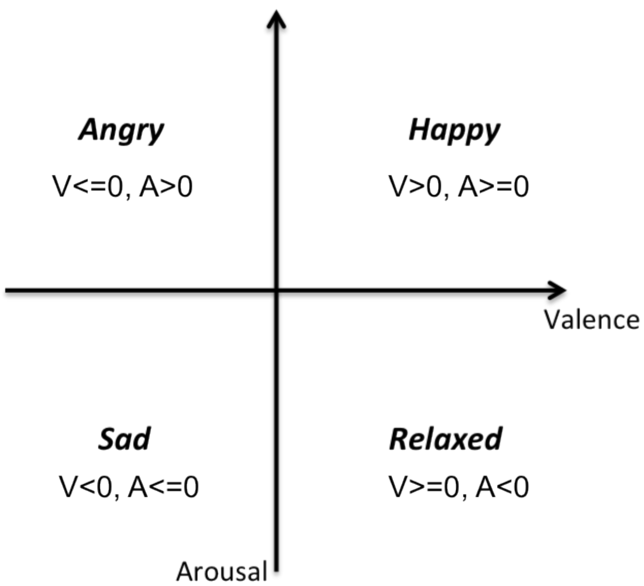


Figure 4.5: Valence-Arousal model showing the quadrants of the four emotion tags used in this experiment.

Experiment 2 was conducted using the dimensional model via an online platform[14] in May 2013. The study was approved by the Queen Mary Research Ethics Committee (REF: QM-REC1019). The participants were asked to read a similar instruction page as shown in Experiment 1 except that they rated each piece on the dimensional model: *valence* (happy-sad continuum) and *arousal* (excited-relaxed continuum).

[14] `http://isophonics.net/dimensional/test/`

Participants were asked to fill in a demographic form including name, age, gender, "type of music they are most familiar with", nationality, and "music culture they grew up with" as well as the musical training background from the Gold-MSI v0.9. The participants then responded to each excerpt (10 excerpts per page) and rated valence and arousal on an 11-point scale. Valence was rated from very positive to very negative; arousal from very calm to very excited. Participants were also reminded of two different rating conditions (*perceived* and *induced*) by an alert box when turning each page. During the listening test, they were asked "How would you describe the emotional content of the music itself?" for the perceived emotion, and "What emotion do you feel in response to the music?" for the induced emotion. The whole test lasted about 40 minutes without any planned breaks. At the end of the experiment, participants' feedback was collected via email.

The statistical analyses were all conducted using the Matlab 2012 Statistics Toolbox. Responses were aggregated across participants for song-level analysis, or aggregated across items for individual-level analysis.

4.4.4 Results

4.4.4.1 Comparison of Responses for Perceived and Induced Emotion

To check the normality of participants' ratings of valence and arousal, the Jarque-Bera test was carried out. The results showed that the ratings of valence were normally distributed, whereas the analysis rejected the assumption of normality for ratings of arousal. In the dimensional model of emotion, to assess the effects of rating conditions (perceived and induced emotion) and emotion tags (happy, sad, relaxed and angry), two-way ANOVA was conducted on the ratings of valence, and Friedman's test and a Wilcoxon signed-rank test were conducted on the ratings of arousal. I found that the four emotion labels differentially predicted the ratings of *valence* ($F(3) = 34.02$ and $p < .001$) and *arousal* ($\chi^2(3) = 51.52$ and $p < .001$). However, no significant difference was found between the two conditions for the ratings of valence and arousal.

Participants' consistency of perceived and induced responses

The tags associated with a song are not an absolute ground truth, but are also generated by users, under unknown conditions; I also looked at the consistency of rating quadrants among the participants. The level of participant agreement is defined as the proportion of participants whose ratings are in the quadrant with the highest number of participant ratings. This value has as a lower bound the agreement with the tag quadrant, but can be higher if a greater number of participants agree on a quadrant other than that of the tag. The consistency for the individual dimensions of valence and arousal was also computed. A Wilcoxon signed-rank test was used to compare the consistency between perceived and induced emotion. Results showed that consistency of perceived responses ($Mdn = 0.60$) was significantly higher than of induced responses ($Mdn = 0.52$, $Z = -3.06$, and $p < .01$), in both the ratings of valence ($Z = -2.54$, $p < .05$) and arousal ($Z = -3.83$, $p < .01$), which is also consistent with the literature. In addition, in comparing levels of consistency for the two dimensions *valence* and *arousal*, a higher consistency of responses for arousal can be found. The results are shown in Table 4.16.

TABLE 4.16
Consistency of participants' responses for valence and arousal.

	Dimension	*Mean*	*Standard deviation*
Perceived emotion	Valence and Arousal	0.59	0.14
Induced emotion		0.55	0.15
Perceived emotion	Valence	0.68	0.14
Induced emotion		0.65	0.15
Perceived emotion	Arousal	0.77	0.15
Induced emotion		0.72	0.16

Note. The consistency was calculated by the highest number of responses divided by the overall responses for each excerpt.

The relationship between listening duration and emotional responses

The listening time for each excerpt was recorded, and next I studied the listening duration for four emotional responses using the dimensional model. First of all, participants' ratings of valence and arousal were mapped to the four emotion categories (see Figure 4.5), and then the listening durations for each emotion were aggregated. To explore the differences between listening durations for four basic emotions (happy, sad, relaxed, and angry), a non-parametric analysis (Kruskal-Wallis test) was conducted. The analysis showed the listening durations of the four emotional responses were significantly different, for both induced ($\chi^2(3) = 50.54$, $p < .001$) and perceived emotion ($\chi^2(3) = 42.6$, $p < .001$). Additionally, significantly shorter listening durations were found for emotional responses of "happy" in perceived emotion, and both "happy" and "angry" in induced emotion, than the responses of "sad" and "relaxed". This result may suggest that it is easier to feel and recognise emotions in the region of high arousal (happy and angry), whereas it takes longer time to distinguish in the lower region of arousal such as relaxedness and sadness.

The relationship between the responses for perceived and induced emotion

The comparison of ratings for perceived and induced emotion showed that there was no significant difference between the sets of ratings for the two conditions. Furthermore, Pearson's correlation analyses were performed to study the relationship between perceived and induced emotion ratings of valence and arousal. The results showed that regardless of the emotion tag, the listeners' valence and arousal ratings were highly positively correlated between perceived and induced emotion (*valence*: $r(78) = .94$, $p < .001$; *arousal*: $r(78) = .97$, $p < .001$).

TABLE 4.17
Possible relationships between perceived and induced emotions in the dimensional model.

Relationship	**Level**	**Perceived emotion**		**Induced emotion**		**%**
		Valence	**Arousal**	**Valence**	**Arousal**	
Undecided relationship		undecided	undecided	undecided	undecided	14%
Positive relationship	Valence & Arousal	high	high	high	high	16%
		high	low	high	low	
		low	low	low	low	
		low	high	low	high	
	Valence	high		high		12.5%
		low		low		
		zero		zero		
	Arousal		high		high	45%
			low		low	
			zero		zero	
Negative relationship	Valence & Arousal	high	high	low	low	0%
		high	low	low	high	
		low	high	high	low	
		low	low	high	high	
	Valence	high		low		0%
		low		high		
	Arousal		high		low	0%
			low		high	
No systematic relationship	Case 1	decided	undecided	undecided	decided	2.5%
		undecided	decided	decided	undecided	
	Case 2	decided	undecided	undecided	undecided	6%
		undecided	decided	undecided	undecided	
No relationship		undecided	undecided	undecided	decided	4%
		undecided	undecided	decided	undecided	

I therefore quantitatively categorise the responses of perceived and induced emotion. Similar to the relationship I defined for the categorical model, I also added the relationship *undecided* in the dimensional model, for the case where both valence and arousal ratings are undefined among listeners. Both negative and positive relationships were further divided into three levels: *valence and arousal* (valence and arousal simultaneously), *valence* (only the response of valence) and *arousal* (only the response of arousal). Table 4.17 gives the possible relationships between perceived and induced emotion in the dimensional model. The terms "high" (greater than zero), "low" (less than zero) and "zero" were used to represent the values for valence and arousal to avoid confusion with the relationship names. The term (high, low and zero) with the highest number of responses was selected to give a small p value ($p < .05$), but only if the highest number was more than 18 out of 25 participants' responses, or 20 out of 29 responses; otherwise "undecided" was used. These numbers of responses were selected, given the null hypothesis that p(valence or arousal rating greater than zero) = p(valence or arousal rating less than zero) = 50% and p(zero) = 0. The relationships were calculated for each of the 80 songs, of which sixty-nine had the following relationships: *positive relationship*, *negative relationship*, *no systematic relationship*, and *no relationship*. Among these relationships, fifty-nine of them had a "positive relationship", of which thirteen were at the level of valence and arousal simultaneously, and thirty-six cases were only at the level of arousal. Three cases had "no relationship" and seven had "no systematic relationship". However, no "negative relationship" was found. The distribution of relationships is shown in Table 4.17.

4.4.4.2 Correspondence between Tags and Emotional Responses

Considering that these basic emotions are widely accepted across different cultures, I am able to assess the agreement between tags and participant ratings according to the extent that participants' ratings correspond with the quadrant belonging to the song's tag as shown in Figure 4.5. For each song, the averages of participants' valence and arousal ratings were calculated for both perceived and induced emotion, to give a centroid for each song. The quadrant of this song centroid was then compared with the expected quadrant based on the emotion tag associated with the song. The proportion of songs for which the centroid quadrant corresponded with that of the tag as well as the standard deviations of the valence and arousal ratings are shown in Table 4.18. The highest values are shown in bold. Apart from the excerpts tagged with "relaxed", more than 60% of the average valence and arousal ratings lay in the song's corresponding tag quadrant. Fewer than 20% of ratings for songs labelled "relaxed" were located in the correct quadrant. Moreover, the standard deviation of valence and arousal ratings for both perceived and induced emotion was high, indicating that the ratings of "relaxed" excerpts were not consistent across songs.

TABLE 4.18
Agreement of valence-arousal ratings with tag quadrants, and spread of per-song ratings (averaged over participants).

	Happy	**Sad**	**Relaxed**	**Angry**
Perceived emotion				
Rating=Tag	0.65	0.70	0.15	0.60
Valence *Mean*	1.56	-1.16	0.49	-0.73
Valence *SD*	1.05	1.33	**1.76**	1.21
Arousal *Mean*	1.74	-0.91	-0.14	2.11
Arousal *SD*	1.57	1.43	**2.42**	1.86
Induced emotion				
Rating=Tag	0.75	0.70	0.20	0.60
Valence *Mean*	1.66	-0.90	0.54	-0.50
Valence *SD*	1.10	1.26	**1.42**	1.03
Arousal *Mean*	1.58	-0.87	-0.15	1.90
Arousal *SD*	1.38	1.35	**2.03**	1.53

Note. The highest standard deviation values in valence and arousal are shown in bold.

However, this analysis and the results were based on ratings for each excerpt averaged across participants. To analyse the relationship between individual ratings and emotion tags, I computed the proportion of ratings that were in the same quadrant as the emotion tag for the song, and compared this with the baseline of 25% for random choice of quadrants. Wilcoxon signed-rank tests were used to test whether the agreement with the emotion tag was significantly above chance level. The results are shown in Table 4.19. It was found that the songs labelled with "happy" for perceived emotion had the highest agreement at 58% (Z = 4.64 and $p < .001$). Significant results were also found for tags "sad" (Z = 4.20 for perceived emotion, Z = 3.93 for induced emotion and $p < .001$) and "angry" (Z = 4.57 for perceived emotion, Z = 4.24 for induced emotion and $p < .001$). However, the agreement of participant ratings and the expected quadrant for songs labelled with "relaxed" was at the level of chance. In addition, as can be seen in Figures 4.6 and 4.7, showing the response distribution in each emotion category, excerpts labelled with "happy" are the most distinct, but other tags "sad" and "angry" also predict well for both perceived and induced emotion responses.

TABLE 4.19
Agreement of participant ratings with the quadrant of the emotion tag for each category.

	Happy	**Sad**	**Relaxed**	**Angry**
Perceived emotion	0.58***	0.48***	0.24	0.50***
Induced emotion	0.56***	0.43***	0.26	0.47***

Note. Values above chance level according to Wilcoxon signed-rank tests are shown for the following significance levels: *$p < .05$, **$p < .01$, ***$p < .001$.

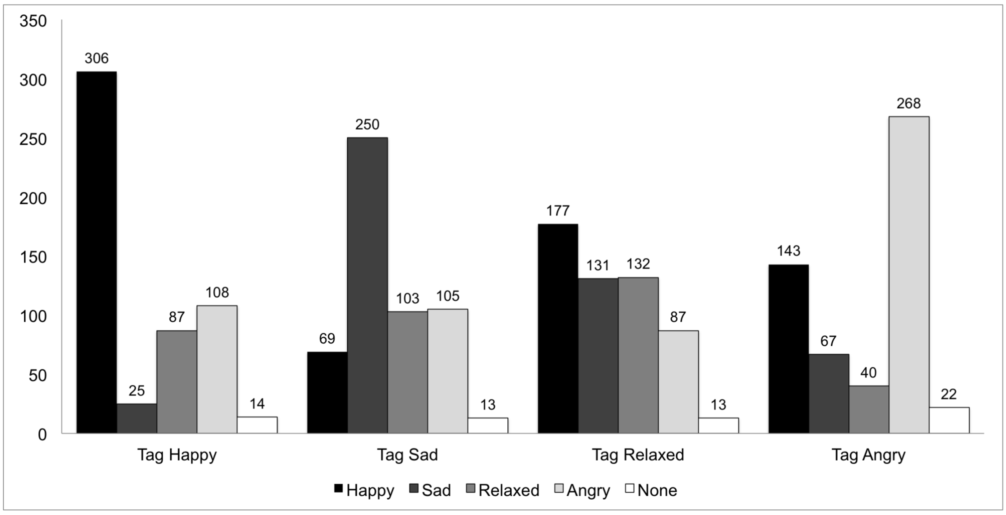


Figure 4.6: Perceived emotion response distribution for each tag. The horizontal axis shows the five responses for each of the four emotion tags *happy*, *sad*, *relaxed*, and *angry*. The vertical axis shows the number of responses.

4.4.4.3 Analysis of Individual Factors

Unlike Experiment 1, I only collected data on participants' musical training (*Scale Min* = 9, *Scale Max* = 63, M = 34.8, and SD = 13.98) via the Gold-MSI v0.9. For example, a musical training score of 26 could mean that the participant can play one musical instrument, had one year of formal training, and practices the instrument for one hour daily.

In the study using the dimensional model, I explored the influence of musical factors such as age, gender, and musical training, on the emotion judgements. Correlation analysis and Kruskal-Wallis one-way analysis of variance were used. However, the results showed no difference between male and female participants' ratings in perceived and induced responses, nor in the agreement with emotion tags. Also, no significant relationships were found between participants'

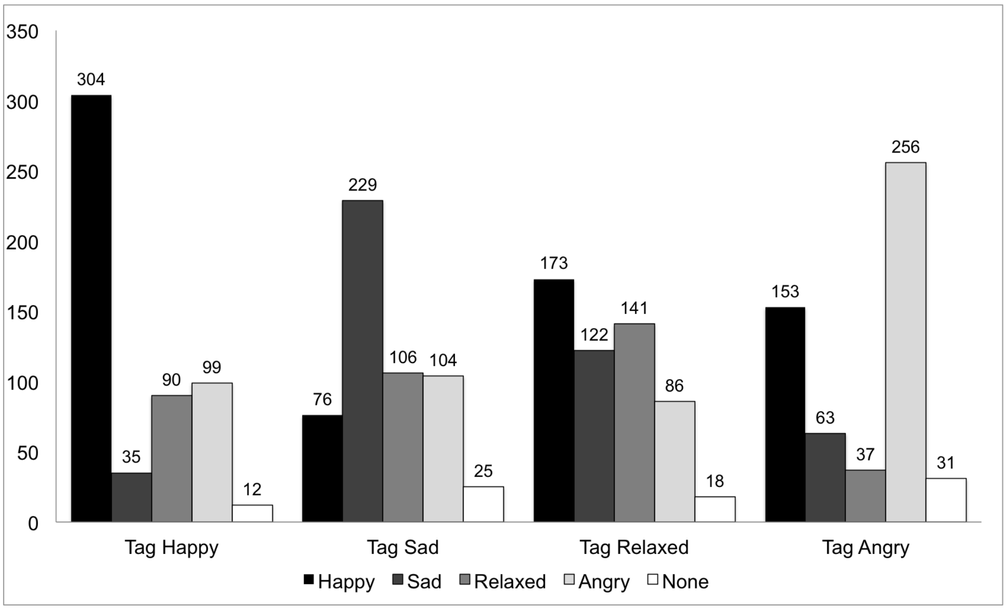


Figure 4.7: Induced emotion response distribution for each tag. The horizontal axis shows the five responses for each of the four emotion tags *happy*, *sad*, *relaxed*, and *angry*. The vertical axis shows the number of responses.

judgements, age, and musical training[15].

4.4.5 Discussion

Experiment 2 investigated the associations between emotion tags and judgements of perceived emotion and induced emotion using the *valence-arousal* two-dimensional model of emotion. No significant difference was found between the rating conditions, perceived and induced emotion. However, the four emotion tags differentially predicted the ratings of valence and arousal. The between-participant agreement on perceived and induced emotion was then measured by a Wilcoxon signed-rank test. The result showed a higher consistency among participants for perceived emotion. This agrees with previous studies on classical music using the dimensional model, which also suggested that consistency of arousal is higher than valence consistency. The same results were found in this study of Western popular music, whether instrumental tracks were included or excluded from consideration[16]. Additionally, the analyses between emotional

[15]Only age categories of "18-24" and "25-34" were considered, as the number of the participants aged over 35 was very small.

[16]There were not enough data points (4 in song list 1, and 6 in song list 2) to analyse instrumental tracks separately.

responses and listening duration showed that feeling and recognising emotion “happy” in music took significantly less time than experiencing emotions such as “relaxed” and “sad”. It also indicates that in the two dimensional model of emotion, emotions with high arousal are easier to identify and distinguish.

Furthermore, I studied the relationship between perceived and induced ratings. As expected, strong positive correlations between the two conditions for both ratings of valence and arousal were found. These results again suggest that listeners will typically feel the emotions expressed by the music. Due to the fact that perceived and induced emotion are often difficult to clearly delineate, a quantitative analysis was used to measure the possible relationships. The results showed that “positive relationship” dominates, covering 64% of the cases, and no cases of “negative relationship” were found. Due to the strict threshold, only the strongly consistent responses across participants were retained. Comparing Tables 4.16 and 4.19, the levels of participant agreement among themselves are higher than the agreement with the emotion tags, suggesting that at least some of the tags do not correspond either with participants’ perceived or induced emotion. It might also suggest that the controlled collection of responses creates more systematic results than data created for other purposes without specific instructions.

Thirdly, the reliability of emotion tags in the dimensional model was evaluated. A mapping between *valence*, *arousal*, and four emotion tags was created, so that each emotion occupies a unique quadrant of the two-dimensional plane. The analyses indicated that songs labelled with “happy”, “sad”, and “angry” had ratings in the corresponding quadrants of the valence-arousal plane at a level that was significantly above chance. For songs tagged “relaxed”, however, the agreement of ratings with the positive-valence, negative-arousal quadrant was at chance for both perceived and induced emotion. Comparing these four tags, regardless of song or person, the excerpts tagged with “happy” are most likely to produce responses in the corresponding quadrant of the valence-arousal plane.

Finally, I explored the influence of individual factors on the responses of perceived and induced emotion. Gender, age, and participants’ music training did not significantly mediate any relationships.

4.5 Summary of Experiments 1 and 2

4.5.1 Comparison of Two Models of Emotion

Although both Experiment 1 and 2 investigated the differences between induced and perceived emotion responses, two distinct models of emotion were used. Table 4.20 shows summaries of differences between the two experiments.

TABLE 4.20
Summary of design differences between the two experiments.

	Experiment 1	**Experiment 2**
Model	Categorical model	Dimensional model
Condition	Laboratory environment	Online environment
Equipment	Studio quality headphones	Any (Internet required)
Participants	40 (students)	54 (unknown)
Reminder of conditions	Yes (oral)	Yes (alert)
Practice page	Yes	No
Ratings	5 options	Two 11-point scales (-5 to 5)
Feedback	Paper	Email

To compare participants' responses for the categorical and dimensional models, their ratings were aggregated by label (for the categorical model: happy, sad, relaxed, and angry; for the dimensional model: valence and arousal). The ratings of valence and arousal in the dimensional model were mapped to the four basic emotions in the categorical model (see Figure 4.5). I calculated the inter-rater reliability (Fleiss's Kappa) for participants' ratings using the categorical ($\kappa = 0.31$) and dimensional ($\kappa = 0.25$) model. In addition, for each stimulus, I took the label with the greatest number of votes to be the dominant emotion in each model. If the same dominant emotion was found in both categorical and dimensional models, the song was marked as a "match", otherwise "no match".

In participants' perceived emotional responses, 53 cases had "match" and 27 cases were not matched. Among the 27 "no match" cases, 10 were collectively confused between the emotions "sad" and "relaxed". However, three responses using the categorical model and one response using the dimensional model received equal numbers of votes (e.g., angry with happy, happy with sad, and sad with relaxed), and they were considered as "no match". Similarly, in participants' responses of induced emotion, 45 cases were matched between two models of emotion, whereas the other 35 cases had "no match". As expected in the 35 "no match" cases, responses of induced emotion were more diverse, 9 of which were collectively confused between “sad” and “relaxed” and 11 of which had “none/none of above” in the categorical model.

The emotions from over half of the musical excerpts were matched for both models of emotion, yet the differences between “match” and “no match” cases in participants’ consistency (i.e., the greatest number of votes on the four emotions) are still unclear. Therefore, Kruskal-Wallis one-way analysis of variance tests were conducted on participants’ consistency between “match” and “no match” cases for the two models of emotion (shown in Table 4.21). For perceived emotion, significant higher consistencies can be found for “match” cases in both the categorical model (Mdn = 0.70) and the dimensional model (Mdn = 0.74) than “no match” cases (categorical model: Mdn = 0.50; dimensional model: Mdn = 0.68). Similarly, significant higher consistencies can be found for induced emotion in both the categorical model (“match” cases: Mdn = 0.55; “no match” cases: Mdn = 0.45) and the dimensional model (“match” cases: Mdn = 0.72; “no match” cases: Mdn = 0.67).

Two core dimensions (i.e., valence and arousal) were then investigated, and no significant differences were found in the responses of arousal between “match” and “no match” cases. However, a significant higher agreement was found in induced emotional responses of valence ($\chi^2(1, N = 80) = 19.36$, and $p < .001$) for “match” cases than “no match” cases, as well as a higher tendency in the agreement of valence ratings for perceived emotion ($\chi^2(1, N = 80) = 3.79$, and $p = .05$) for “match” cases than “no match” cases.

TABLE 4.21
The differences between “match” and “no match” cases in participants’ consistency.

	Dimensional				**Categorical**			
	Perception		Induction		Perception		Induction	
	match	no match	match	no match	match	no match	match	no match
Mdn	0.74	0.68	0.72	0.67	0.70	0.50	0.55	0.45
SD	0.09	0.10	0.11	0.09	0.19	0.13	0.14	0.11
$\chi^2(N = 80)$	4.91*		8.17**		8.79*		26.79***	

Note. *$p < .05$; **$p < .01$; ***$p < .001$.

4.5.2 General Discussion

These two listening experiments examined the relationship between perceived and induced emotion, and evaluated the reliability of emotion tags from music discovery websites as well as individual differences in emotion judgements. The majority of the previous studies on music and emotion deal with classical and film soundtracks, but as previous results may not be applicable to other genres, this work extends the study to Western popular music. In addition, two models of emotions, the *categorical* and *dimensional* models, were used in my experiments to structure the investigations and interpret my findings. Though the participants of the two experiments were recruited in different ways, the distribution of key variables (age and musical training score) did not differ significantly between experiments[17].

Results for both the categorical and the dimensional model showed that the four emotion labels “happy”, “sad”, “relaxed”, and “angry” did correlate with the perceived and induced emotional responses. The inter-participant consistency in perceived emotion was, however, significantly higher than the consistency in induced emotion. This supports the argument that perceived emotion refers to intellectual processing (objective), such as the perception of an intended or expressed emotional character, whereas felt emotions reflect the introspective perception of psychophysiological changes (subjective), which are often associated with emotional self-regulation. But also, it may be unreasonable to expect induced emotions to change so rapidly from moment to moment, and the results could be different in extended listening of a single piece. The excerpts used in these experiments were 30-60 seconds in duration. Since participants were able to stop whenever they wished, the listening time for each song was recorded. The analysis of listening duration and emotional responses showed that for both induced and perceived conditions, emotions such as “happy” and “angry” were easier to recognise and feel in music, whereas participants needed a significantly longer time to experience emotions such as “sad” and “relaxed”, which are located in the lower region of the dimensional model (low arousal). However, no significant differences in listening duration were found between induced and perceived emotion responses.

Similarly, a higher uncertainty level was found for induced emotional responses. To an extent, it suggests that these four basic emotions better capture the musical emotions which are expressed in music than those induced by music. The feedback from participants also implies that the categorical model is inadequate to describe the richness of emotions induced by music. In the analysis of the dimensional model, higher consistency was also found in the ratings of arousal than of valence, which is in accordance with previous results in music emotion prediction (Schubert, 2007b; Huq et al., 2010). The majority of music excerpts used in the experiment had lyrics, and the overall results remained the same after removing the instrumental tracks. However, it is

[17] The same participant could take part in both experiments.

possible that emotional judgements could be related not to the elements of music structure but to the meaning expressed by the lyrics.

In addition, positive correlations were found for corresponding emotions between perceived and induced emotion. This result is consistent with the finding that music evokes emotions similar to the emotions perceived in music. However, other correlations showed that a perceived sad song might induce relaxedness. Meanwhile, a perceived angry song is less likely to induce sadness and relaxedness. In addition, I tested for four possible relationships proposed by Gabrielsson (2002): *positive relationship*, *negative relationship*, *no systematic relationship*, and *no relationship*. I found that in both the categorical and dimensional models, a positive relationship is the most frequent one. Negative relationships were found in my analysis of the categorical model, but not in the dimensional model. This may be caused by the fundamental differences between the models, that one allows people to respond in a graded way whereas the other forces them into a small number of discrete categories; or this may be caused by the thresholding, that only the strongest response is retained in the dimensional model. "No systematic relationship" and "no relationship" also existed for a small minority of stimuli. My empirical results follow Gabrielsson's (2002) framework; however, the case in which both the perceived and induced emotions are disagreed by listeners was not included in this framework. I therefore expand Gabrielsson's framework with the relationship *undecided*. There are various underlying mechanisms involved in explaining the relationships between induced and perceived emotion. For example, Juslin and Västfjäll (2008) mentioned that the same perceived and induced emotional responses is due to the emotional contagion mechanism, whereas the negative relationship may involve the episodic memory mechanism. Details of underlying mechanisms are beyond the scope of this study, but for future studies it will be useful to consider all relevant mechanisms to provide an accurate understanding of the relationships between induced and perceived emotion.

The reliability of emotion tags was evaluated via the level of agreement between participants' responses and the tags. The results revealed that the agreement between social tags and participants' ratings was well above chance for both the categorical model and the dimensional model. However, the excerpts labelled with "relaxed" had the lowest agreement with tags in the categorical model and agreed with the tags only at the level of chance in the dimensional model. Moreover, the distribution of listeners' responses for the excerpts corresponding to each tag indicated that the emotion tags predicted both the perceived and induced emotional responses well. It is worth mentioning that with respect to valence, listeners often collectively confused sadness with relaxedness, and happiness with anger. Responses may vary because of individual factors such as current mood, music culture, and preference.

Finally, the analysis of individual differences showed that *age*, *gender*, and *musical training* were found not to mediate listeners' emotion judgements, nor their agreement with tags. One interpretation is that the excerpt selections are Western popular music which is generally well-understood by participants who are English speakers. However, a tendency was found that older participants were more likely to feel and experience less "happy", and use music more for its emotional functions. Also, positive correlations between three factors from the Gold-MSI v0.9, *importance* and *musical training*, *emotion* were found in Experiment 1.

I also need to acknowledge two potential limitations of collecting both perceived and felt emotion responses in a laboratory setting. First, it is likely that people do not feel as much in this setting as they would in a natural condition during which listeners are actively choosing music pieces for obtaining a given internal feeling (Altenmüller et al., 2002). However, I believe that whereas the setting might affect quantitative responses (how much is felt), it should not alter the qualitative responses (which emotion is felt). Second, it is possible that participants might confuse the two rating conditions. However, they were given very precise instructions and were reminded of the two different rating conditions (perceived and induced emotion) just prior to the ratings. Also, the obtained significant differences between the conditions show that, on the whole, the participants understood the tasks.

In summary, my study of the relationship between perceived and induced emotion showed similar results using both the categorical and dimensional models. This study supports the previous work on classical and film soundtracks, suggesting that the robustness of the models does not depend on the genre of music considered. Emotion, like music, is dynamic and it may change and evolve continuously. In my experiments, emotional response was measured by a static value. Future research should consider the dynamic emotional judgements in a more controlled environment (Egermann et al., 2013). In addition, a two-dimension model was used to map the categorical model. However, the third dimension "dominance" is worth investigating further. Musical emotional meaning can not only be influenced by subjective factors (taste, musical abilities, and personality), but also social factors (e.g., music culture and context). In further studies, I explore emotional association with and without the presence of music in various music-listening contexts (see Chapters 5 and 6). Also, more objective measurements such as behavioural and physiological reactions could be conducted in combination with a self-report approach to provide richer evidence of emotional responses. A greater understanding of these factors would be beneficial in the design of subjective music recommendation systems (Song et al., 2012a).

4.6 Human versus Machine Emotion Recognition

From two listening experiments using the categorical model in Section 4.3 and the dimensional model in Section 4.4, I noticed the ratings for perceived and induced emotions are positively correlated, and emotion tags can predict musical emotion well above chance. Interestingly, similar classification accuracy was achieved by my MER system as shown in Section 4.2.

In this experiment, I present a comparison of the results using MIR techniques and listeners' responses. In Section 4.3, I collected details of 207 musical pieces provided by participants for four basic emotion categories (happy, sad, relaxed, and angry). Assuming that these examples represent intense emotions, I used them to train musical features using SVMs with different kernels and with random forests. The goal of this section is to investigate how the emotion predicted using machine learning approaches (i.e., SVMs and random forest) differs from listeners' emotional responses.

4.6.1 Musical Example Collection Using Participants' Suggestions

Previously in Experiment 1 (see Section 4.3), forty participants were asked to provide examples of songs (song title and artist's name) that represent each of the four basic emotions (happy, sad, relaxed, and angry) in perceived and induced emotion. Given that music evokes emotions similar to the emotions perceived in music, the examples of musical excerpts for perceived and induced emotion are aggregated for this study. If the same excerpt is mentioned in both perceived and induced emotion categories, the song is only counted once. In some cases, participants mentioned only the artist's name (e.g., *Death Cab for Cutie*, *Mayday Parade*, and *Bandari*) or the album name (e.g., *The Dark Side of the Moon*), so this information is not considered for further analysis. Musical excerpts were then fetched via the 7Digital developer API or Amazon mp3 store[18]. A total of 207 songs (either 30 seconds or 60 seconds) are collected in this way (see Appendix E for the list of excerpts), with the distribution over emotion categories as shown in Table 4.22.

In contrast to the songs retrieved using emotion tags in Section 4.1, these examples are considered more likely to represent intense emotions. A music example from each emotion category is shown in Table 4.23. The dataset (i.e., song title, artist's name, and 7Digital ID) has been made available to encourage further research on music and emotion[19].

[18]Amazon Digital Music: `http://www.amazon.co.uk/Digital-Music/b?ie=UTF8&node=77197031`
[19]`https://code.soundsoftware.ac.uk/projects/emotion-recognition/repository`

TABLE 4.22
The distribution of musical examples provided by participants.

Emotion category	**No. of examples**
Happy	59
Sad	58
Relaxed	48
Angry	42
Total	207

TABLE 4.23
Musical excerpts examples for each emotion category provided by participants.

Emotion category	**Song title**	**Artist's name**
Happy	Wannabe	Spice Girls
Sad	Fix You	Coldplay
Relaxed	Eggplant	Michael Franks
Angry	Fighter	Christina Aguilera

4.6.2 Collection of Participants' Emotional Responses

Experiment 1 (in Section 4.3) and Experiment 2 (in Section 4.4) provided participants' (both induced and perceived emotion) emotional responses for 80 musical excerpts. These 80 musical excerpts are used for testing (see 4.6.3). Since a higher consistency in participants' perceived emotional responses was observed in previous research, only perceived emotional responses from participants in Experiment 1 and 2 are considered for this study.

4.6.3 Musical Feature Extraction

Two different emotion datasets, training and testing, are used in this experiment. The training dataset, which is provided by participants, contains 207 songs. The testing dataset contains 80 musical excerpts ($n = 20$ for each emotion category, as shown in Appendix C). Previous studies have suggested that emotion can be recognised within a second (Peretz, 2001; Bigand et al., 2005). Since each excerpt is either 30 seconds or 60 seconds (as provided by 7Digital and Amazon), I expand both the training and testing datasets by splitting each excerpt into 5-second clips with 2.5-second overlap. Musical features are then extracted using MIRtoolbox version 1.5 (Lartillot and Toiviainen, 2007)[20] for both the full 30/60-second excerpts and the 5-second clips. Similar to the features extracted in the music recognition experiment in Section 4.2, the musical features extracted are shown in Table 4.24.

TABLE 4.24
Audio features extracted from the musical excerpts.

Dimension	**Description**
Dynamics	RMS energy, slope, attack, low energy
Rhythm	tempo, fluctuation peak (pos, mag)
Spectral properties	spectrum centroid, brightness, spread, skewness, kurtosis, rolloff95, rolloff85, spectral energy, spectral entropy, flatness, roughness, irregularity, zero crossing rate, spectral flux, MFCC, DMFCC, DDMFCC
Harmony	chromagram peak, chromagram centroid, key clarity, key mode, HCDF

Note. The mean and standard deviation values were extracted, except for the feature "low energy", for which only the mean was calculated.

4.6.4 Results

4.6.4.1 Emotion Classification Using Machine Learning Approaches

207 excerpts provided by participants are used for training (see Section 4.6.1). However, a smaller training size may influence classification performance. To expand the data, each audio file was split into 5-second clips with 2.5-second overlap. Therefore, 207 (30/60 seconds) and 2990 (5 seconds) musical clips are collected, and trained separately.

Training

I adopted a 10 fold cross-validation approach, where for each song, all clips were placed in a single fold to avoid overfitting, and chose SVMs with different kernels (i.e., linear, radial basis function, and polynomial) and random forests as classifiers for training. I used the implementation of the sequential minimal optimisation algorithm in the Weka 3-7-11 data mining toolkit[21]. 54 musical features extracted from MIRtoolbox for both the 30/60-second ($n = 207$), and 5-second ($n = 2990$) datasets were used, with the classification results shown in Table 4.25.

The RF approach and SVMs with linear kernel both performed well, and classification accuracy using 5-second clips was 1% higher (but not significantly) than for the full excerpts.

[20] https://www.jyu.fi/hum/laitokset/musiikki/en/research/coe/materials/mirtoolbox/MIRtoolbox1.5Guide
[21] http://www.cs.waikato.ac.nz/ml/weka/

TABLE 4.25
Comparison of classification performance using support vector machines and random forest approaches.

Approaches	**Recognition accuracy**	
	30-second clips	5-second clips
SVM with linear kernel	**39.04%**	40.35%
SVM with RBF kernel	28.57%	26.89%
SVM with polynomial kernel	37.62%	29.16%
Random forests	38.57%	**40.75%**

Note. For the training of 5-second clips, the clips from the same song if used in training, were not used for testing. Due to the unbalanced ground truth data for training, the results might be biased.

Although RF using 5-second clips performed best, the classification accuracy is still very low. From the confusion matrix, I noticed that classification for the emotion "relaxed" was also collectively confused with "sad".

Testing

In training, RF gave the best classification accuracy using 5-second clips, and performed efficiently over time. Therefore, this approach (i.e., RF with 5-second clips) was also applied on the 80 popular musical excerpts. Similar to the data expansion for the training dataset, each audio clip in the testing dataset was also split into 5-second clips (n = 1292). Section 4.6.4.2 shows the classification results in comparison to participants' emotional responses.

4.6.4.2 Responses from Participants and the Recognition System

As each excerpt was split into 5-second chunks, each clip was recognised as expressing one emotion. The label with the greatest number of votes of the four emotions was chosen, and the greatest number of votes (consistency) for each excerpt was calculated as well. To compare the responses between outputs from the recognition system and participants for two models of emotion, Pearson's correlation analysis was conducted on the consistency for the 80 musical excerpts.

Table 4.26 shows that recognition consistency for each excerpt using the RF approach is positively correlated with participants' consistency in the categorical ($r(78) = .23$, and $p < .05$) and dimensional models ($r(78) = .36$, and $p < .01$). It tentatively suggests that regardless of the emotion, the consistency of the recognition system is similar to the consistency of participants' responses.

TABLE 4.26
Correlation between the song-wise consistency of the recognition system using the RF approach and participants' responses.

	Recognition	**Categorical**
Categorical	.23*	
Dimensional	.36**	.32**

Note. *$p < .05$, **$p < .01$.

To explore participants' responses for each emotion, correlation analyses were further conducted on the emotion vote distribution for each excerpt for the recognition system and participants' responses. Tables 4.27 and 4.28 show that no matter which emotion model is used, the emotion vote distributions from the recognition system and participants' responses are highly correlated (i.e., happy, relaxed, and angry). Interestingly, responses for relaxed from the categorical model are also correlated with sad from the recognition system. It suggests that both the MER system and people find it difficult to distinguish between *sadness* and *relaxedness*. The same results could be found in the results for the dimensional model, where significant correlations were shown in the ratings of arousal, whereas only weak correlations were found in the responses of valence (happy confused with angry, and relaxed with sad).

TABLE 4.27
Correlation between the responses from the MER system and participants using the categorical model.

		Participants (Categorical model)			
		Happy	Sad	Relaxed	Angry
MER	Happy	.42***	-.33**	-.32**	.13
	Sad	-.16	.18	.33**	-.30**
	Relaxed	-.07	.00	.46***	-.22
	Angry	.07	-.31**	-.39***	.52***

Note. *$p < .05$, **$p < .01$, and ***$p < .001$.

Finally, the dominant label(s) from each experiment (recognition system and responses from categorical and dimensional models of emotion) were compared. Considering the same dominant emotion label from both the dimensional and categorical models as the ground truth (53 cases, see Section 4.5.1), 32 responses out of 53 (accuracy = 60%) were classified correctly by the recognition system. However, if I consider the dominant emotion labels from either the categorical or dimensional models, 51 responses out of 80 (accuracy = 64%) are classified correctly.

TABLE 4.28
Correlation between the responses from the MER system and participants using the dimensional model.

		Participants (Dimensional model)			
		Pos V	Neg V	Pos A	Neg A
MER	Pos V	.33**	-.34**	.10	-.12
	Neg V	-.10	-.01	.15	-.16
	Pos A	.22	-.28*	.59***	-.64***
	Neg A	-.02	-.01	-.42***	.44***

Note. *$p < .05$, **$p < .01$, and ***$p < .001$.

To analyse classification error of the random forest approach, the incorrect classification results were compared with participants' responses. I found that the majority of songs given incorrect classifications had opposite signs for valence, confusing sad with relaxed and angry with happy. It indicates that compared with arousal, valence is more difficult to recognise. This also agrees with previous studies using regression models (Yang et al., 2008).

TABLE 4.29
Examples of emotion vote distribution for the recognition system and participants' ratings (categorical and dimensional models of emotion).

		Title			
		Creeks	**Requiem**	**Josephine**	**Blood**
Automatic Classification	Happy	1	0	5	3
	Sad	13	2	0	1
	Relaxed	9	9	8	6
	Angry	0	0	10	1
	Label	Sad	Relaxed	Angry	Relaxed
Human Ratings: Categorical	Happy	7	0	2	1
	Sad	3	16	5	1
	Relaxed	5	3	6	3
	Angry	0	0	5	13
	Label	Happy	Sad	Relaxed	Angry
Human Ratings: Dimensional	Pos valence	17	1	13	9
	Neg valence	8	24	10	13
	Pos arousal	16	4	7	24
	Neg arousal	8	23	14	0
	Label	Happy	Sad	Relaxed	Angry

Note. Creeks - If the Creeks Don't Rise by *Sunparlour Players*, Requiem - Love's Requiem by *HIM*, Josephine - Josephine by *Wu-Tang Clan*, Blood - Blood On the Ground by *Incubus*.

I noticed that if the recognition results were incorrect, it was likely that the emotion of a song itself was ambiguous. Examples for each emotion are provided in Table 4.29. For example, for the song "Josephine" by *Wu-Tang Clan*, the dominant emotion was chosen as relaxedness in both the categorical and dimensional models, whereas it was recognised as angry by the machine. The distribution, shows that 8 clips from the excerpt were classified as relaxed, whereas 10 clips were classified as angry. In addition, participants' responses for both models of emotion were also distributed across four emotions. Similarly, for the song "Blood On the Ground" by *Incubus*, participants mostly agreed on arousal level, but the responses for valence were ambivalent.

Interestingly, I found the song "Anger" by *Skinny Puppy* was recognised as angry by all participants, whereas the recognition system classified it as happy. Possible reasons could be the selection of clips, that different parts of the song may express different emotions. It is also reasonable to guess that the emotion perceived by human is genre-specific (e.g., metal as anger and pop music as happy) and cultural-dependent. Participants may also be influenced by lyrics.

4.6.5 Discussion

In this experiment, I presented an empirical study of music and emotion, comparing the results between a music emotion recognition system and participants' responses for two models of emotion. A total of 207 musical excerpts were collected from participants for four basic emotion categories (i.e., happy, sad, relaxed, and angry). My emotion recognition model was trained using support vector machines and random forest classifiers. Two different training datasets were compared, one using the entire 30/60-second audio files and the one using multiple 5-second segments with 2.5-second overlap from the same excerpt. Audio features were extracted using MIRtoolbox. The results showed that the support vector machine with linear kernel and random forest approaches performed best, and the use of 5-second clips increased the classification accuracy by only 1%. In addition, the recognition system did not classify emotions well for the emotions sadness and relaxedness. One of the possible reasons for the low accuracy of the music emotion recognition systems could be the participant-suggested dataset, that my MER system was trained using both perceived and induced emotion. Another explanation could be the subjective nature of emotion in music.

Finally, the time-efficient random forest with 5-second clips approach was applied to the 80 musical excerpts for testing. The analysis showed that responses from the recognition system were highly correlated with participants' responses for the categorical and dimensional models. Moreover, the distribution of responses for each emotion was also highly correlated. However, significant correlations between relaxedness and sadness in the categorical model suggest that listeners and emotion recognition systems have difficulty distinguishing valence (positive and negative emotions). Similarly, strong correlations were found for responses of arousal, whereas only weak correlations were shown in responses for valence. The comparison of emotion distribution also indicates that the performance of music emotion recognition systems is similar to participants' emotional responses for the two models of emotion. Additionally, the prediction accuracy is higher for songs where participants agreed more. This suggests that strongly consistent emotional responses are likely to be predicted by music emotion recognition systems.

In this study, only low-level audio features (e.g., MFCC and chromagram) were used for classifying emotions in music; future studies should consider incorporating high-level descriptors such as genres and instruments. Due to the dynamic nature of music, emotions may vary over time and the emotion classification accuracy may be affected by the selection of clips. Also more importantly, music emotion involves complex interactions between the listener, the music, and the situation. The perception of music is most likely influenced by individual differences such as age, music skills, culture, and musical preference (Malatesta and Kalnok, 1984; Rentfrow and Gosling, 2003; Shiota et al., 2006; Novak and Mather, 2007).

4.7 General Discussion

In this chapter, I described the collection of an emotion dataset via online social tags from the music discovery web site Last.FM. Each musical excerpt is associated with one of the four emotion categories, "happy", "sad", "relaxed", and "angry". With 2904 Western popular musical excerpts collected, an MER system was built using audio features for four musical dimensions. However, the fact that social tags are annotated by a wide range of internet users with different background (e.g., education and musical training), means that these tags may not be reliable. In addition, users' tagging behaviours are unclear. Therefore, I evaluated the reliability of emotion tags, and explored the agreement of emotion tags with participants' perceived and induced emotional responses.

Two popular models of emotion, the categorical and the two-dimensional model of emotion, were used with 80 stimuli randomly selected from the 2904 musical excerpts. The relationships between induced and perceived emotional responses were also systematically compared for those 80 stimuli. I found that the emotion tags can predict human emotional responses well above chance, and people tend to annotate emotion based on the emotion perceived rather than emotion felt. In addition, a participant-provided emotion dataset of 207 songs was collected. The MER system was trained again using these 207 musical excerpts, and tested on the previous 80 musical stimuli. Results from the MER system were highly correlated with participants' responses. The analysis showed that the MER system performs well in distinguishing the level of arousal (happy and angry versus sad and relaxed), which is similar to human responses. The results also suggest that consistent emotional responses are more likely to be correctly predicted by the music emotion recognition systems.

As mentioned in Chapter 3, listening context (the second element) should be considered in the study of music and emotion. Research has shown that the listener's emotion was changed based on different choices of music. In the next chapter, therefore, I explore the effects of context (twenty situations) on participants' expected emotional responses from the impact of music. A questionnaire containing various aspects of music listening is presented to participants. The interactions among emotion, musical preference, function of music listening, and context are investigated.

Chapter 5

Functions of Music Listening and Musical Preference in Everyday Situations

This chapter aims at exploring the functional uses of music, emotional responses to music, and musical preference in everyday situations. Music-listening contexts selected from previous studies, and the motivation of my work are presented in Section 5.1. The design of my experiment is then described in Section 5.2. Section 5.2.1 provides the details of forty-five participants recruited for this study, and Section 5.2.2 gives the instructions of my designed online experiment. Answers for the questions "What are the function of listening to music?", "What are the expected emotions from music in different situations?" and "How do individual differences relate to musical preference?" are shown in Section 5.3. At the end of this chapter, a discussion is provided (see Section 5.4).

5.1 Motivation

Chapter 3 gives the background knowledge for different aspects of music listening, namely contexts, emotions, functions, and musical preferences. People listen to music for various reasons, and listening context has a powerful influence on musical preference (Hargreaves and North, 1999; Hunter et al., 2011). The better the needs of a listener are served by a given music, the higher the degree of preference for that music should be (Behne, 1997). Similarly, Schäfer and Sedlmeier (2009) showed the functions of participants' favourite were highly related to the degree to which they preferred it. Sloboda et al. (2001) reported that music listening is not randomly

TABLE 5.1
Categorisation of situations used in the Experiment.

Category	**Examples**	**Abbr.**
	Waiting	W
Personal - being	Falling asleep	F
	Waking up	WU
Personal - maintenance	Doing housework	DH
	Eating at home	E
Personal - travelling	Commuting (public transport)	CO
	Travelling (holiday)	T
	Watching musical	WM
Leisure - music	Watching ballet	WB
	Playing music	PM
Leisure - passive	Reading for pleasure	RP
	Putting on the radio	P
Leisure - active	Chatting with friends	CF
	Clubbing	CL
	Reading for study	RS
Work - self	Working	WO
	Doing music research	D
Work - other	Planning for meeting	P
	In lectures/seminars	LS
Other	Background	BG

distributed over contexts, and later studies argued that music should be studied with situational variables (Lamont and Greasley, 2009). However, few studies have addressed the interactions among these closely related factors (i.e., functions, emotional responses, and musical preference) in different music-listening contexts (Juslin et al., 2011; Laukka and Quick, 2011; Sloboda, 2011; Krause and North, 2014). Therefore, the functions of music listening and emotional responses from the impact of music for different situational contexts, are explored in this study. In Section 4.3, different music-listening contexts such as “doing music research”, “watching bands”, and “hearing background music” were mentioned by participants (see Appendix D). Following existing studies, twenty typical situations are chosen for this work in Table 5.1.

These twenty music-listening contexts are used to investigate participants’ expected felt emotions, functions, and musical preferences. Previous research has shown that functions of music listening and emotional responses to music are often inconsistent due to individual differences (e.g., age, gender, and musical training) and situational variables, therefore I also explore the effects of individual differences in music listening behaviour given different situational contexts. I am interested in subjective experience in specific music listening situations, and I use a self-report approach to collect data for this study. Compared to conventional laboratory-based experimental settings, web-based experiments (or online experiments) have the advantage of efficiently allowing us to reach a wider participant demographic (for a recent overview, see Reips, 2012). I designed a web-based questionnaire measuring each of these factors (daily usage of music, musical preference, functions of music listening, expected felt emotional responses, and individual factors). This study is designed to be mainly exploratory, although based on previous studies I formed a few hypotheses. For example, previous research has demonstrated that the function of music listening is context-dependent, thus given a situation I hypothesise that significant differences in ratings of function (i.e., distraction, energising, entrainment, and meaning enhancement) can be found. Moreover in the sporting context, researchers found that athletes consciously selected music to fulfil certain functions and elicited various emotional states (Bishop et al., 2007; Laukka and Quick, 2011). I hypothesise that in the contexts of active pursuits (e.g., sport and housework), arousal will be higher than inactive/passive pursuits. I also hypothesise that positive relationships can be found between functions of music listening (i.e., energising and entrainment) and expected emotional responses to music (i.e., valence and arousal).

5.2 Method

This survey was conducted online[1] via self-report from October to November 2013, and approved by Queen Mary Research Ethics Committee (QMREC1255). No financial reward was offered for participation. The entire survey lasted about 25 minutes without any planned breaks.

5.2.1 Participants

A total of 45 participants took part in the survey. The participants were recruited through professional and academic mailing lists such as "ISMIR Community", "Auditory", and departmental mailing lists, as well as social media (i.e., Facebook and LinkedIn[2]). The participants all understood English. There were 18 male and 27 female participants, with ages ranging from 18 to 77 years (M = 37.6 and SD = 16.2). A selected subscale (9 items) from the Gold-MSI v0.9 questionnaire was used to measure participants' *musical training*. In version 1.0 of the Gold-MSI, 2 items of the factor musical training (i.e., "I can't read a musical score" and "I have played or sung in a group, band, choir, or orchestra for ___ years") were removed. I include my

[1] `http://www.isophonics.net/content/music-activity-survey`
[2] `https://uk.linkedin.com/`

results for both versions, and show for comparison the statistics of a large-scale (n = 137,633) study (Müllensiefen et al., 2014) in Table 5.2.

TABLE 5.2
Musical training score of participants.

	Scale maximum	*Scale minimum*	*Mean*	*SD*
MT (v0.9)	56	9	38.84	13.19
MT (v1.0)	49	7	28.71	9.97
BBC (v1.0)	49	7	26.52	11.44

Note. For example, a musical training (MT) score of 26 could mean that a participant can play one musical instrument, had one year of formal training, and practices the instrument for one hour daily. The v1.0 music training score of my study was calculated based on participants' ratings on v0.9 but with the two deprecated items removed.

Participants were also asked to select their preferred musical genres from a catalogue of 19 genres as shown in Table 5.3, and they were free to add other genres.

TABLE 5.3
Genre preferences of participants.

Genre	**Abbr.**	**No.**	**Genre**	**Abbr.**	**No.**	**Genre**	**Abbr.**	**No.**
Classical	C	32	Rock	RO	23	Jazz	J	19
Electronic	E	13	Folk	F	13	Metal	M	11
Alternative	A	10	Blues	B	10	Pop	P	9
World	W	9	Soundtrack	ST	8	Light-instr	L	6
Country	CO	5	RnB	RB	5	Reggae	REG	4
Hip-hop	H	4	Soul	S	2	Rap	RA	1
Religious	REL	1	None	N				

Note. The column *No.* represents the number of participants who chose the corresponding genre as one of their favourites.

5.2.2 Procedure

At the beginning of the experiment, participants were given instructions and asked to fill in some basic information (age, gender, and nationality), favourite musical genres, and 9 items from the Gold-MSI on factor *musical training* (life history of formal musical training). For each situation provided in the examples of Table 5.1, participants were asked the following questions:

1. How often do you listen to music in this activity?

2. How important is the music to you in this activity?

3. Which music genres would you like to listen to in this activity? [**see Table 5.3**];
4. Could you please provide us some examples of musical excerpts (artist and song title) that you would listen to while you are doing this activity? [**open question**];
5. Please rate each purpose for selecting music in this activity,
   - **Distraction**: A way of engaging unallocated attention and reducing boredom;
   - **Energising**: A means of maintaining arousal and task attention;
   - **Entrainment**: The task movements are timed to coincide with the rhythmic pulses of the music, giving the task or activity elements of a dance;
   - **Meaning enhancement**: Where the music draws out and adds to the significance of the task or activity in some way.
6. What emotional effect do you expect to feel in response to the music (**note: not from the action**), please click on the 2-D model (valence: sad to happy, arousal: relaxed to excited).

Question 1 was rated on a 5-point Likert scale (1 = *Never*, 3 = *Sometimes*, and 5 = *Always*) and Question 2 and 5 were rated on a 7-point Likert scale (1 = *Not at all*, 4 = *Neutral*, and 7 = *Extremely*). For Question 5, an explanation of each function was shown to participants. For Question 6, valence and arousal were rated from -0.5 to 0.5. There was also an additional free response field at the end of each page.

5.3 Results

Responses from forty-five participants were collected, as well as participants' comments for each response. I examined participants' free comments, and checked whether they understood the question correctly. However, the feedback for four situations showed disagreement in understanding among participants: "playing music", "doing music research", "watching ballet", and "watching musical". Therefore, to remove ambiguities, these four categories were discarded from further analysis so that responses for sixteen situations remained.

5.3.1 How Much Does Engagement with Music Vary Across Situations?

To investigate the question "How much does engagement with music vary across situations?", participants' ratings of frequency and importance of using music in various situations were collected. To summarise these, mean values of frequency and importance ratings were calculated (see Table 5.4). I noticed that participants frequently choose to listen to music while "travelling", "doing housework", and "waiting". Additionally, the highest average rating of importance was found for situation "waiting". The least common situations for listening to music are "planning for meeting" ($M = 1.69$) and "in lectures/seminars" ($M = 1.47$). Likewise, for these two situations music receives a low rating for importance.

TABLE 5.4
The mean (standard deviation) ratings for frequency (left) and importance (right), sorted in descending order.

Situation	**Frequency**	**Situation**	**Importance**
Travelling (holiday)	3.36 (1.17)	Waiting	4.71 (1.75)
Doing housework	3.24 (1.48)	Putting on the radio	4.58 (2.20)
Waiting	3.18 (1.25)	Travelling (holiday)	4.42 (1.90)
Background	3.11 (1.19)	Commuting (public transport)	4.18 (2.40)
Commuting (public transport)	3.00 (1.58)	Doing housework	4.16 (2.08)
Putting on the radio	3.00 (1.33)	Background	4.13 (2.08)
Working	3.00 (1.38)	Working	4.02 (2.17)
Clubbing	2.87 (1.83)	Clubbing	3.84 (2.75)
Waking up	2.38 (1.28)	Waking up	3.09 (2.00)
Chatting with friends	2.27 (1.12)	Reading for study	2.89 (2.24)
Eating at home	2.18 (1.07)	Reading for pleasure	2.71 (2.13)
Reading for pleasure	2.18 (1.17)	Eating at home	2.69 (1.72)
Reading for study	2.16 (1.41)	Chatting with friends	2.53 (1.67)
Falling asleep	1.87 (1.04)	Falling asleep	2.40 (1.79)
Planning for meeting	1.69 (1.10)	In lectures/seminars	2.20 (2.08)
In lectures/seminars	1.47 (1.01)	Planning for meeting	2.18 (1.76)

Note. Frequency was rated on a 5-point Likert scale (1. never, 2. rarely, 3. sometimes, 4. often, 5. always), and importance was rated on a 7-point Likert scale (1. not at all, 2. low, 3. slightly, 4. neutral, 5. moderately, 6. very, 7. extremely). The horizontal line divides the activities into two groups: high and low, by the mid-point on its rating scale.

Pearson's correlation analyses were then carried out for the frequency and importance ratings of each participant, and the mean correlation was computed across participants using Fisher's r-to-z transformation. The result reveals a strong positive correlation between the ratings of importance and frequency ($r(14) = .91$ and $p < .001$). The top seven situations whose mean values are above the mid-point on its rating scale, are the same for rankings of both importance and frequency, but with different order. Kendall's Tau was computed for each participant's frequency and importance rankings, and I obtained a correlation of .81. Yet, from participants' comments, it seems that responses for some situations are age and culture-dependent. For instance, with regard to the situation "clubbing", some people reported that they have never been clubbing, or it is not their scene.

5.3.2 What Are the Functions of Listening to Music?

Previously, Sloboda et al. (2009) showed how music accompanies non-musical activity and is often chosen to enhance the activity in some way. Thus, the functions of listening to music for each situation were studied. 720 ratings of sixteen situations were collected for four functions: *distraction* (a way of engaging unallocated attention and reducing boredom), *energising* (a means of maintaining arousal and task attention), *entrainment* (the task movements are timed to coincide with the rhythmic pulses of the music, giving the task or activity elements of a dance), and *meaning enhancement* (where the music draws out and adds to the significance of the task or activity in some way). The function ratings were considered if participants' frequency ratings were not marked as "never", and there was no explicit indication of ambiguity or misunderstanding in the comment such as *I have never been clubbing so all these answers are random* and *confusing.* 471 valid ratings were collected for analysis.

To assess the roles of the situation (16 levels) and the function dimension (4 levels) for participants' ratings of function, variance analyses were conducted using a non-parametric Kruskal-Wallis test, as the ratings were not normally distributed (Shapiro-Wilk normality test, $p < .001$). There were significant differences in ratings according to different situations ($\chi^2(3) = 19.37$, $p < .001$) and functions ($\chi^2(15) = 186.81$, $p < .001$).

A post-hoc multiple comparison analysis using Tukey's HSD test shows that some functions are significantly more important than the other functions for some situations as shown in Table 5.5. For example, for the situation "falling asleep", the ratings for function *meaning enhancement* are significantly higher than ratings for *energising* and *entrainment*. However, the analysis does not reveal the absolute level of importance of the functions. Therefore, the participants' responses for each function were categorised into two groups: important (5 = *moderately*, 6 = *very*, and 7 = *extremely*) and not important (1 = *not at all*, 2 = *low*, 3 = *slightly*, and 4 = *neutral*). Chi-square tests were applied for each situation on the four functions. In addition, participants' ratings for the four functions were ordered, and rankings were averaged across participant for each situation. The highest ranking was chosen as the predominant function (see

Table 5.6).

TABLE 5.5
Post-hoc analysis for functions of listening to music.

Situation	**Function**
Clubbing	**G>D, *T>D, *G>M
Commuting	**D>M
Doing housework	**D>M, **G>M
Falling asleep	**M>G, *M>T
Waiting	*D>T, *D>M
Waking up	*G>M

Note. The table shows all significant differences. D = Distraction, G = Energising, T = Entrainment, and M = Meaning Enhancement. ***$p < .001$; **$p < .01$; *$p < .05$.

For instance, listening to music while "waiting", "commuting", and "doing housework" is associated with the *distraction* function, and the main reason for using music while "falling asleep" lies in its *meaning enhancement* function. It is also worth mentioning that not all self-chosen music was used for one of these four purposes. For example, for the situations such as "reading for pleasure", people do not use music for its entrainment purpose, and when people are "eating at home", they do not use music to energise, entrain, or enhance the meaning. Meanwhile, as one would expect when people "fall asleep", they would not listen to music to maintain arousal. This can also be seen from participants' feedback. In the situation "falling asleep", a participant mentioned that she wants to maintain "low arousal" so she can sleep (for the question *energising*), and she wants to focus her attention on music, so that it clears her mind, stops her thinking about other things, which will keep her awake (for the question *distraction*). Also one participant reported that for "waking up", *as a teenager growing up, my mum somehow worked out the way to get me out of bed in the morning - by cranking up the CD player with my fav rock band! It still works on me!*. In the case of "working", a participant suggested that *the playlist provided above contains a lot of my favourite music from last decade, and I find having my favourite tracks on shuffle helps motivate me to do the work, though it does sometimes distract me from what I am meant to be doing.*

TABLE 5.6
Participants' ratings for the importance of functions of listening to music in various situations.

Situation	**Functions**				**No.**
	Distraction	**Energising**	**Entrainment**	**Enhancement**	
Waiting	**4.79**** (D)	3.69	3.59	3.69	39
Falling asleep	*2.65**	*2.17***	2.65	4.04 (D)	23
Waking up	3.67	**4.97***** (D)	3.67	3.63	30
Commuting	**5.26**** (D)	**4.77****	**4.52****	3.94	31
Travelling (holiday)	4.24 (D)	4.07	3.67	4.26	42
Doing housework	**4.97***** (D)	**5.06*****	4.03	3.23	35
Eating at home	2.97	*2.70***	*2.27****	*3.00** (D)	30
Putting on the radio	4.30 (D)	4.38	3.62	3.89	37
Reading for pleasure	3.00 (D)	3.15	*2.70**	3.15	27
Chatting with friends	*2.70****	3.63	3.40	3.63 (D)	30
Clubbing	4.22	**6.41***** (D)	**6.19*****	**5.04****	27
Reading for study	3.68	4.18 (D)	3.41	3.86	22
Working	3.74	**4.34**** (D)	3.26	3.69	35
In lectures/seminars	3.60	3.70	2.60	3.90 (D)	10
Planning for meeting	3.93	3.60 (D)	3.36	*2.79**	14
Background	3.92	**4.15*** (D)	3.54	3.59	39

Note. These four functions were rated on a 7-point scale for importance (1. not at all, 2. low, 3. slightly, 4. neutral, 5. moderately, 6. very, 7. extremely). Average ratings shown in italic and bold mean significantly less and more than the expected ratings respectively. p values were calculated according to the χ^2 test (df = 1) for the following significance levels ***$p < .001$, **$p < .01$, *$p < .05$. The predominant function is given by the highest ranking of four functions (not the highest ratings) for each situation, and is marked with (D).

5.3.3 What Are the Expected Emotions from Music in Different Situations?

To investigate the emotional effects of listening to music in various situations, participants' valence and arousal ratings (see Section 5.2.2, question 6) on a 2-dimensional model of emotion were collected. Similar to the data selection for the functions of listening to music, missing valence and arousal ratings, and the responses whose frequency values were marked as "never", were removed, leaving 447 entries retained. The normality of participants' responses on valence and arousal was checked via a Shapiro-Wilk normality test, and the results rejected the assumption of normality with $p < .001$ ($W = 0.96$ for arousal and $W = 0.97$ for valence). The mean values of valence and arousal ratings for each situation were computed (see Figure 5.1). A non-parametric Kruskal-Wallis one-way analysis of variance was performed on the ratings of valence and arousal separately. Significant differences were found in ratings of valence ($\chi^2(15) = 43.30$ and $p < .001$) and arousal ($\chi^2(15) = 128.03$ and $p < .001$) for different situations. In contrast to Juslin's recent study where "sad" was a commonly experienced negative emotion in connection with music (Juslin et al., 2011), my data contained no negative mean valence ratings. Hence, Figure 5.1 shows less than half of the valence space (-0.5 = *negative* to 0.5 = *positive*, 0 = *neutral*).

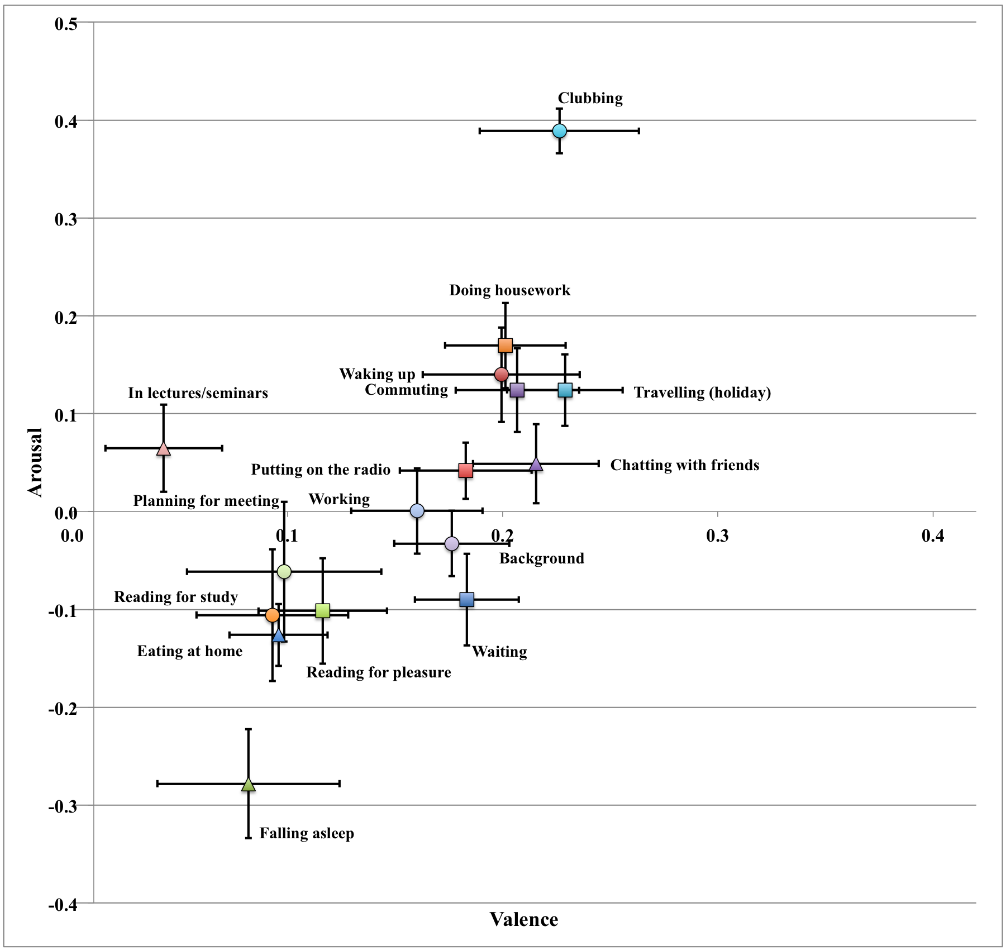


Figure 5.1: Expected felt emotion from music for each situation on a valence-arousal space. For each situation, the centroid is presented with standard error bars for both horizontal (valence) and vertical (arousal) axes. Note the difference in scale of axes. The predominant function shown in Table 5.6 is represented by circle = *energising*, square = *distraction*, and triangle = *meaning enhancement*.

Furthermore, to distinguish between different levels of valence and arousal, their scales were then divided into six subgroups (36 regions): very high (> 0.33), high (0.16 to 0.33), somewhat high (0 to 0.16), somewhat low (-0.16 to 0), low (-0.33 to -0.16), and very low (< -0.33). As shown in Figure 5.1, I noticed that there were no activities located at "somewhat low", "low", "very low", and "high" regions of the valence rating scale, and "very low" regions of the arousal rating scale. Figure 5.2 shows a summary of expected emotional effects from music on a valence-arousal space for each situation. Additionally, the responses for "working" lie in both low positive and negative arousal space, which may be influenced by other factors such as gender, musical training, types of job, and personality (see Section 5.3.5). Feedback from participants shows similar results. For instance, participants reported for "waiting", *during waiting I just like to listen to songs I like best (that are on my phone), and those will then make me happy and excited, depending on the song. During other activities other songs might be preferred, but also the same songs, but then with different results*, and for "waking up", a participant mentioned that music helps them to wake up and feel positive.

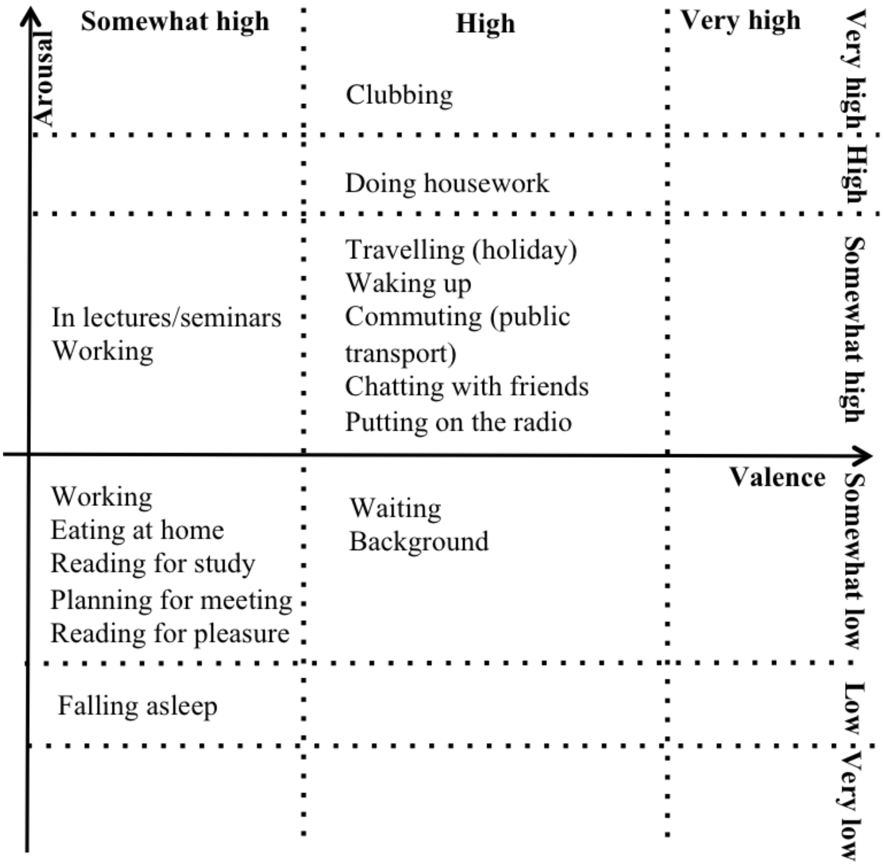


Figure 5.2: Summary of situations on a valence-arousal plane of emotion by dividing up the plane.

Although we know that the purposes of listening to music and expected felt emotions both differ with situation, the relationship between purpose and expected felt emotion to music is still unclear. Therefore, to investigate the relationship, correlation analysis was performed between mean ratings of each function (distraction, energising, entrainment, and meaning enhancement) and emotion ratings of valence and arousal. The results in Table 5.7 show that the expected felt emotional responses for arousal are highly correlated with responses for both purposes *energising* ($r(14) = .90$, $p < .001$) and *entrainment* ($r(14) = .80$, $p < .001$). It is also worth mentioning that ratings for the functions *entrainment* and *energising* are also highly positively correlated ($r(14) =$ $.89$, $p < .001$). Comparing with Table 5.6, under none of the situations is *entrainment* the primary function of music, and ratings for *energising* are always higher than ratings for *entrainment* except for "falling asleep". The overlap between functions *entrainment* and *energising* suggests that these two functions of listening to music could be merged in future studies or applications.

TABLE 5.7
Correlations between and within emotion responses to music and functions.

	Valence	**Arousal**	**Distraction**	**Energising**	**Entrainment**
Arousal	.67**	-	-	-	-
Distraction	.48	.50*	-	-	-
Energising	.63**	.90***	.62*	-	-
Entrainment	.69**	.80***	.59*	.89***	-
Meaning enhancement	.38	.53*	.23	.53*	.67**

Note. *$p < .05$; **$p < .01$; ***$p < .001$, and $df = 14$.

5.3.4 How Do Different Styles of Music Serve Different Situations?

To explore the question "Do different styles of music serve for different situations?", I collected participants' genre preferences in general (see Table 5.3) and for each situation. The counts of each genre are shown in Table 5.8. Table 5.3 shows that among these genres, classical, rock, and jazz were the most preferred choices. For genre preference for specific contexts, the two least frequent situations "planning for meeting" and "in lectures/seminars" were removed, as well as genres with small sample size. Chi-square tests were carried out to compare genre selections within each situation with participants' favourite music style selections. The results show that for situations such as "waiting", "travelling (holiday)", "putting on the radio", and "background", people tend to choose their favourite music styles. As classical music is the most preferred genre by participants, the selection of classical music dominates in most situations. However, for a case such as "clubbing", classical music is rarely preferred by participants ($\chi^2(5, N = 58) =$

59.23, $p < .001$). Likewise, in the situation "commuting (public transport)", rock music is typically preferred ($\chi^2(5, N = 72) = 6.71$, $p < .01$). Furthermore, other genres were mentioned by participants, including house, dance, indie, trance, dubstep, techno, trance, noise, glitch, postrock, soundscapes, funk, podcasts, musical, Indian classical, computer music, and 1960s pop. Interestingly, their choices did not necessarily only deal with music, but participants also preferred interviews, radio shows, and simply people talking. Participants also provided the reasons for choosing particular music styles. For example, for "travelling (holidays)", people reported that *I often travel very long distances (20-30 hours), at night, and usually in the middle of nowhere. This means the only features outside you can see, are the stars. My absolutely favourite thing to do on these journeys, is to play science fiction type classical music, and I can pretend I'm intergalactic travelling!*, and for "background", *I listen to background classical music at the end of the day to wind down, jazz and swing to do housework, pop and rock when driving and waking up in the morning.*

TABLE 5.8
Counts of genres selected for various situational contexts.

Situation	**Alternative**	**Classical**	**Electronic**	**Jazz**	**Pop**	**Rock**
Waiting	7	**25**	10	8	7	18
Falling asleep***	5	**22**	5	3	3	2
Waking up***	6	**15**	6	4	11	14
Commuting**	8	16	11	8	9	**20**
Travelling (holiday)	10	**26**	12	11	8	21
Doing housework***	7	**16**	6	8	11	12
Eating at home***	6	**16**	5	8	5	4
Putting on the radio	13	**23**	8	13	12	18
Reading for pleasure***	4	**16**	1	4	1	5
Chatting with friends***	9	**13**	9	9	11	8
Clubbing***	8	3	**18**	5	16	8
Reading for study***	5	**16**	6	4	2	4
Working***	5	**20**	6	8	6	10
Background	12	**26**	11	15	9	16
Favourite	10	32	13	19	9	23

Note. χ^2 tests ($df = 5$) are shown for the following significance levels: *$p < .05$; **$p < .01$; ***$p < .001$. The greatest number of genres for each situation is shown in bold.

5.3.5 How Do Individual Differences Relate to Musical Preference?

Given the individual factors such as age, gender, and musical training measured by the Gold-MSI v0.9, Welch's t-tests were carried out to investigate the relationships between three individual factors (i.e, age[3], gender, and musical training[4]) and three aspects of music listening preference (i.e., daily usage of music, four functions of music listening, and expected emotional responses to music, see Table 5.9). Regardless of the situation, I found that younger participants rated the four functions significantly higher than older participants, and likewise for their ratings of daily usage of music. However, no significant differences were found between gender and three aspects of music listening preference. Although no significant differences were shown between musical training and daily usage of music, ratings of function *energising* and expected emotional response *arousal* are significantly higher for participants with higher musical training scores.

Furthermore, for each of the 16 situations, Welch's t-tests and Pearson's correlation analyses were used to investigate the interactions among situational contexts, individual differences, and music listening preferences.

First, individual factors (i.e., age, gender, and musical training) were compared with daily usage of music[5] in different situations (shown in Table 5.10). Only one significant difference was found for situation "planning for meeting", where female participants use music more often than male participants. The frequency of listening to music for certain situations such as "doing housework" may be related to how often they are in these situations. People reported that they enjoy doing housework to music as a type of physical activity to music where the music is a good distraction from jobs that they hate to do. Moreover, results show that age is highly correlated with participants' reported frequency of listening, but only limited to certain situations such as "commuting", "chatting with friends", and "clubbing".

[3]Participants' ages were classified into two groups, younger group (23 participants, $\leq$ 30 years old) and older group (22 participants, $>$ 30 years old).

[4]Participants' musical training scores were categorised into two levels, high (25 participants, $>$ 40) and low (20 participants, $\leq$ 40).

[5]As ratings for importance and frequency were positively correlated, only ratings of frequency were used in this analysis.

TABLE 5.9
Correlations between three individual factors and three aspects of music listening preference.

		Music usage		**Functions of music listening**				**Expected emotions**	
		Frequency	**Importance**	**Distraction**	**Energising**	**Entrainment**	**Enhancement**	**Valence**	**Arousal**
Age	Old	2.38	3.20	2.89	2.88	2.42	2.62	0.48	0.38
	Young	2.72	3.63	3.33	3.54	3.22	3.21	0.51	0.43
	t	-3.24	-2.64	-2.69	-4.13	-5.08	-3.89	-1.39	-1.88
	df	716.96	714.73	715.22	715.80	715.48	715.78	701.52	716.95
	p	**	**	**	***	***	***	*ns*	*ns*
Gender	Female	2.53	3.44	3.14	3.27	2.91	2.88	0.51	0.41
	Male	2.59	3.39	3.08	3.14	2.72	2.99	0.48	0.40
	t	-0.55	0.31	0.32	0.81	1.17	-0.71	1.43	0.60
	df	594.86	614.64	621.14	628.24	642.71	604.17	600.48	619.32
	p	*ns*	*ns*	*ns*	*ns*	*ns*	*ns*	*ns*	*ns*
Musical training	High	2.56	3.47	3.17	3.43	2.95	3.03	0.50	0.43
	Low	2.55	3.36	3.04	2.96	2.68	2.80	0.49	0.37
	t	0.13	0.69	0.77	2.85	1.65	1.48	0.65	2.89
	df	670.01	676.76	655.79	666.59	684.78	659.46	645.46	640.09
	p	*ns*	*ns*	*ns*	**	*ns*	*ns*	*ns*	**

Note. *ns* represents not significant.

Second, individual differences and situations were compared with the ratings for the four functions. No significant differences were found between male and female participants in ratings of functions for different situations. However, I noticed that negative correlations exist between age (df = 43) and the ratings for the four functions in certain situations. For example, the analyses showed that younger participants listen to music more for function *distraction* while "commuting" ($r = -.36$, $p < .05$) and "clubbing" ($r = -.43$, $p < .01$). Participants' ratings of function *energising* decreased with age but increased for situations "chatting with friends" ($r = -.52$, $p < .001$). In addition, ratings of function *entrainment* for older participants were lower in situations such as "travelling" ($r = -.35$, $p < .05$), "commuting" ($r = -.41$, $p < .01$), and "chatting with friends" ($r = -.45$, $p < .01$). For function *meaning enhancement*, negative correlations with age were observed in situations "falling asleep" ($r = -.31$, $p < .05$), "travelling" ($r = -.39$, $p < .01$), "chatting with friends" ($r = -.31$, $p < .05$), and "clubbing" ($r = -.34$, $p < .05$). Although participants with higher musical training scores had higher importance ratings for function *energising* (refer to Table 5.9), the difference disappeared when considering context.

TABLE 5.10
Relationships between the frequency of listening to music in various situations between male and female, age, and musical training (MT).

Situation	**Gender**				**Age**	**MT**
	Female	**Male**	*t*	*df*	*r*	*r*
Waiting	2.93	3.56	-1.68	35.74	-.17	-.11
Falling asleep	1.78	2.00	-0.72	39.33	-.11	-.11
Waking up	2.48	2.22	0.65	34.58	-.00	.18
Commuting	2.78	3.33	-1.17	37.67	-.33*	-.08
Travelling	3.26	3.50	-0.65	32.28	-.30*	-.04
Doing housework	3.33	3.11	0.47	30.25	-.09	-.00
Eating at home	2.00	2.44	-1.30	29.07	.08	-.15
Putting on the radio	3.30	2.56	1.80	30.91	.39**	.13
Reading for pleasure	2.11	2.28	-0.47	38.53	-.10	.07
Chatting with friends	2.19	2.39	-0.57	31.99	-.41**	-.25
Clubbing	3.04	2.61	0.76	37.01	-.54***	.03
Reading for study	2.00	2.39	-0.93	40.05	-.15	-.19
Working	2.70	3.44	-1.81	36.88	.10	-.18
In lectures/seminars	1.48	1.44	0.11	31.34	.15	.30*
Planning for meeting	1.92	1.28	*2.20	39.77	.09	.21
Background	3.22	2.94	0.75	34.35	-.13	.16

Note. The significance value for the effect "gender" was computed by Welch's t-test, and correlation analyses were used for effects "age" and "musical training", df = 43, and *$p < .05$; **$p < .01$; ***$p < .001$.

Finally, the effects of individual differences on expected emotional responses to music were explored in different situations. Significant negative correlations between age and valence were found for situations "waiting" ($r = -.30$, $p < .05$) and "chatting with friends" ($r = -.38$, $< .05$). Additionally, ratings of arousal were negatively correlated with age for situations "commuting" ($r = -.52$, $p < .001$) and "clubbing" ($r = -.33$, $p < .05$).

5.4 Discussion

In this chapter, I explored functional uses of music in everyday situations, and their associations with emotions, particularly the expected felt emotion in response to music. Twenty situations were selected from past studies, and the ratings from forty-five participants were reported. Firstly, results for the study on the importance and frequency of music listening in everyday life revealed that regardless of situations, the frequency of using music is highly correlated with the perceived importance of listening to music. The least common and important situations for listening to music are "planning for meeting" and "in lectures/seminars". Reasons for these responses could be found from participants' comments such as *you don't listen to music during a lecture/seminar! Even if it's dead boring, that's not respectful!*, or *I usually leave planning a meeting until the last minute, which means I have a truck load of work to do, in very little time, therefore listening to music, is too distracting, and too fun, so I focus and punish myself for a short amount of time while I cram in the work.* The top seven mean ratings for situations "travelling (holiday)", "doing housework", "waiting", "background", "commuting (public transport)", "putting on the radio", and "working" were all above the mid-point for both frequency (sometimes) and importance (neutral). This is consistent with the literature that a greater frequency of listening to music can be found in music use for personal maintenance (e.g., doing housework) and personal travelling (e.g., travelling for holidays) than for other uses such as personal-being (e.g., waking up and falling asleep), work and leisure (Sloboda et al., 2001; North et al., 2004). It also supports studies showing that participants are likely to choose to listen to music "at home doing housework", "driving", and "travelling" (North et al., 2004). However, previous studies reported less frequent listening to music while "waiting", whereas participants tend to choose to listen to music in my study. This difference could be due to the popularity of portable devices such as iPod and smartphone, meaning that people can easily hear music everywhere.

Moreover, four recurring functions of using music, *distraction* (a way of engaging unallocated attention and reducing boredom), *energising* (a means of maintaining arousal and task attention), *entrainment* (the task movements are timed to coincide with the rhythmic pulses of the music, giving the task or activity elements of a dance), and *meaning enhancement* (where the music draws out and adds to the significance of the task or activity in some way) were compared in various situations. As expected, the ratings for these four functions showed that the choice of music is dependent on the situation. Among these functions, *energising* is the most common one, which can be found for situations such as "waking up", "commuting (public transport)", "doing housework", "clubbing", "working", and "background". I also noticed that music for "falling asleep" and "chatting with friends" was not chosen for *distraction*. These results support previous findings that motivations for music listening are context-dependent. My results agree with the statement that people listen to music for different reasons (Lamont and Greasley, 2009) but provide a more detailed account of functions of listening to music within different situations.

Though previous research suggested that listeners' primary motives for listening to music lie in its emotional functions, the emotional effects in everyday contexts are rarely studied. Therefore, the expected felt emotional responses to music were investigated given various situational contexts. My findings are consistent with others that regardless of various situational contexts, people tend to feel positive emotions in response to music (e.g., happy and relaxed), whereas the expected felt arousal level would differ with the situation (Schubert, 2007a; Eerola and Vuoskoski, 2013). This is also supported by Juslin et al. (2008) where the most frequent emotions connected with music were positive or neutral in valence. This supports the view that positive emotions such as *happy*, *relaxed*, and *moved* tend to be dominant in felt emotions as compared to perceived emotion (Juslin and Laukka, 2004; Zentner et al., 2008). This effect could also be because participants select music which they like. Situations such as "clubbing" and "falling asleep" received the strongest positive and negative arousal ratings respectively. However, ratings for the other situations were distributed over the middle region of the arousal space. Interestingly, "working" lies in both weak positive and negative arousal regions, and this may be caused by individual differences such as personality and types of job resulting in a relatively neutral average. Furthermore, correlation analyses revealed that the ratings for functions *energising* and *entrainment* are strongly positively correlated, and they also have a strong positive correlation with the ratings of valence and arousal. For future studies or applications, these two factors (i.e., energising and entrainment) could be merged. It is worth pointing out that the felt emotion data examined here pertain to self-report of what people expect to feel, but these expected emotional responses to music may differ slightly from how participants would actually feel in those situations. Additionally, participants suggested that the purpose of selecting music in various contexts seems to miss the point that the music might be enjoyable and absorbing in itself, and they raised some questions such as multiple emotional effects, the categories of situation and individual factors (e.g., occupation and culture).

With regard to the question "How do different styles of music serve different situations?", genre selection for each situation was compared with participants' favourite genres. My study supports previous results concerning musical preference in everyday life, and extends existing work to the association of preference with felt emotions and with various situational contexts. The analysis suggests that people tend to choose their favourite genres in most cases. However, for the cases such as "clubbing" and "commuting (public transport)" with high arousal expectations, "electronic" and "rock" were the most preferred genres respectively. This again supports the conclusion that people choose different types of music for different situations.

Finally, I studied the influence of individual differences in music use. Agreeing with Bonneville-Roussy et al. (2013), the analyses suggest that regardless of the situation, younger participants listen to music more often and consider the four functions of music listening more important. Individual differences (i.e., age, gender, and musical training) and situational variables were then studied with three aspects of music listening preference (i.e., music engagement, functions, and emotional responses to music). No strong correlation was found between the ratings of frequency with gender, but a weak correlation was found for the situation *in lectures/seminars* between frequency and musical training (life history of formal musical training) measured by the Gold-MSI v0.9. However, depending on the situation, age may influence daily use of music. One possible explanation is that music consumption behaviour has changed with recent technological and social development. The musical training effect may be explained by their profession, as some participants reported that as a teacher they use musical examples in lectures. The comments from participants also support my conclusions. Additionally, functions and expected emotional responses to music were also influenced by individual differences and situational factors. It appears that lifestyle variables (whether one commutes regularly, has hobbies relating to music, clubbing, etc.) that were only indirectly captured in the present study have an impact on music choices and functions. This calls for more study of the relationship between lifestyle variables and different aspects of music listening preference. However, the sample size is fairly small, and the results remain tentative. A larger amount of data and a more heterogeneous sample should be collected in future for more detailed individual analysis.

I also need to acknowledge three potential limitations of collecting participants' ratings in a web-based experimental setting. First, during a web-based experiment there is a lack of interaction with participants, and instructions might be misunderstood. However, I provided an additional free response field at the end of each page (Reips, 2002), and data was removed if misunderstandings were found in participants' responses. Second, it is possible that participants might have been unable to separate the expected felt emotion of the activity from the impact of the music. However, they were given very precise instructions "what emotional effect do you expect to feel in response to the music (note: not from the action)". As an example, "waiting" is generally considered to be a negative experience but the high positive emotional ratings obtained show that, on the whole, the participants understood the question. Finally, these analyses were provided by a sample of participants who like classical music. This bias in classical music could be affected by the recruitment of participants through professional mailing lists such as "ISMIR Community" and "Auditory" (e.g., people who are interested in classical music and music research). However, future research should examine whether the results generalise to participants with different stylistic preferences.

Although in this Chapter the function of music listening and musical preference in different situations were compared, situations "playing music", "doing music research", "watching ballet", and "watching musical" caused confusion in participants. Also, some music-listening situations ("planning for meeting" and "in lectures/seminar") were reported not to be very common. In this study, the question "what emotional effect do you expect to feel in response to the music (note: not from the action)" was asked to investigate only the expected felt emotional responses with the presence of music. However, the emotional changes due to the presence of music within these activities are neglected in this study. For instance, the question how emotion changes for situations such as "waiting" and "travelling (holidays)" remains unclear. Therefore, in the next chapter, based on the activities presented in this experiment, a refined category is selected. I focus on the emotional uses of music (e.g., to create, enhance, or to change), specially emotional changes after the presence of music in various contexts.

Chapter 6

Emotional and Functional Uses of Music in Various Contexts

The emotional responses to music, functions of music listening, and musical preference within different situations were examined in Chapter 5. However, participants reported only the expected felt emotion from the impact of music. The emotional association with the activity was missing, and emotion changes due to the presence of music was neglected in Chapter 5. Therefore in this chapter, I investigate the emotional associations with and without the presence of music, and further explore the relationships between emotional and functional uses of music. Based on the activities used in Section 5.1, Section 6.1 presents thirteen refined activities to avoid confusion, and explains the aims of the present study. The method of the experiment including participants, design of the questionnaires (an additional question concerning the emotional association without the presence of music is included), and procedure is explained in Section 6.2. Results are provided in Section 6.3. The emotional associations with (see Section 6.3.4) and without (see Section 6.3.3) the presence of music are compared in Section 6.3.5. Emotional and functional uses of music are further examined in Section 6.3.6. Finally, a summary of the study is provided in Section 6.4.

6.1 Aims

Previously in Chapter 5, twenty situations were considered and used. However, participants' responses for situations "playing music", "doing music research", "watching ballet", and "watching musical" were not consistent. Participants reported that they do not often listen to music in situations "planning for meeting" and "in lectures/seminar". Therefore, these activities are removed from the present study.

Some activities shared a similar purpose ("eating at home" and "reading for pleasure"), or are designed for different groups (student vs. professional, "reading for study" vs. "working"). For other activities "doing housework", "clubbing", "doing housework", and "chatting with friends", a more distinct categorisation is made for the present experiment. Additionally, I add two more activities "just listening to your selected music" and "exercising (e.g., running, cycling)" to cover a broader range of situations. Therefore, thirteen different music-listening contexts are selected in this study as shown in Table 6.1.

TABLE 6.1
Activities (situations, contexts) used in Chapter 5 and the present study.

Activities in Ch. 5	**Activities in the present study**	**Abbreviation**
Waiting	Waiting	Wait
Falling asleep	Falling asleep	Sleep
Waking up	Waking up	Wake up
Doing housework	Unpaid physical work (e.g., housework, gardening)	Physical work
Commuting	Commuting (public transport)	Commute
Travelling (holiday)	Travelling (holidays)	Travel
Chatting with friends	Talking with friends	Talk
Clubbing	Nightlife (e.g., dancing, clubbing) Night out (bars/bowling/pubs)	Nightlife Night out
Eating at home Reading for pleasure	Relaxing at home (e.g., eating, reading)	Relax
Reading for study Working	Studying/working	Study/work
	Just listening to your selected music Exercising (e.g., running, cycling)	Listen Exercise
Watching musical Watching ballet Playing music Putting on the radio Doing music research Planning for meeting In lectures/seminars Background	Removed from the present study	

Emotion experience in music is often reported with situations (Juslin et al., 2008, 2011). For instance, Liljeström et al. (2012) found that participants who listened to music together with a close friend or partner experienced more intense emotions than participants who listened alone. However, the study of emotional changes and situational factors received little attention (Juslin et al., 2008, 2011). Therefore, the aim of this chapter is to investigate the emotional changes due to the presence of music in different situations, and the relationships between emotional association (with and without the presence of music) and functions of music listening. Several hypotheses are formulated in this study. Firstly, I hypothesise that the emotional response to an activity is similar to the nature of the activity. Previous research has mentioned that people select music to follow a “mood-optimisation” strategy, and their emotions change after listening to music. As an extension to the previous study in Chapter 5, I examine the emotional changes for each given situation due to the presence of music. It is hypothesised that people’s “mood-optimisation” strategies vary across situations, but I expect a positive correlation between the emotional responses with and without the presence of music. Change in emotional state, as an outcome of music listening, overlaps with functional uses of music (Schäfer and Sedlmeier, 2009; Lonsdale and North, 2011; Chin and Rickard, 2013). Lastly, I hypothesise a positive correlation between participants’s ratings of valence and arousal with the ratings of functions of music listening.

Previous studies have shown that individual differences such as age and music-training also affect emotional experience (Malatesta and Kalnok, 1984; Novak and Mather, 2007; Castro and Lima, 2014). Kreutz et al. (2007) explained connections between emotional experience and musical preference. I also explore individual factors (age, gender, musical training, and musical preference) within different situations. Similar to the experiment in Chapter 5, I design a self-report format questionnaire to measure participants’ responses in this study.

6.2 Method

This study was conducted online[1] using a self-report approach. The data was collected from February to October 2014.

6.2.1 Participants

In the present study, ninety-four English-speaking participants (52 male and 42 female) took part in the experiment. All the participants were recruited through a variety of mailing lists such as “ISMIR Community”, “Auditory”, and the departmental mailing list, and social-media sites (i.e., LinkedIn and Facebook). Their ages ranged from 17 to 73 (M = 38.17, SD = 14.70 years, and 2 not reported) with various educational backgrounds. All participation was voluntary,

[1] http://www.isophonics.net/content/music-activity-survey-2

and participants were not paid to do the experiment. The participants consist of a mixture of musicians, students, and people from other professions.

A selected subscale (9 items) from the Gold-MSI v0.9 questionnaire was used to measure participants' musical training (Müllensiefen et al., 2012). Eighty-five participants reported that they can play at least one musical instrument, and nine participants can play more than five instruments. Also, seventy-five participants had at least half a year of formal training in music theory, and twenty-three participants considered themselves as a musician. I also show for comparison the statistics of a large-scale ($n = 137,633$) BBC Internet study in Table 6.2 (Müllensiefen et al., 2014).

TABLE 6.2
Participants' musical training scores.

	Scale maximum	*Scale minimum*	*Mean*	*SD*
MT v0.9	56	9	40.24	12.72
MT v1.0	49	7	29.68	9.61
BBC MT v1.0	49	7	26.52	11.44

Note. An example for a musical training (MT v1.0) score of 26, would be that a participant who considers themselves a musician, and was complimented for his/her talents as a musical performer. The participant can play one musical instrument, had two years of formal training on the instrument and in music theory, and practiced the instrument for one hour daily for two years. The v1.0 music training score of my study was calculated based on participants' ratings on v0.9, but with the two deprecated items removed.

Participants were asked to choose their musical preferences (unlimited number of favourite genres) from the same catalogue of musical styles as shown in Table 5.3. In this study, the most preferred three musical genres are classical, rock, and jazz (see Table 6.3). Participants also mentioned that they prefer other genres such as trip hop, ska, electroacoustic, electronica, shoegaze, experimental, Greek folk (rebetiko), and opera.

6.2.2 Questionnaires

The online questionnaire contains two parts: demographic questionnaire (1 page) and music-listening questionnaire (1 practice page + 13 pages).

Demographic questionnaire. First, participants were asked to fill in a demographic questionnaire including instructions, age, gender, nationality, and nine questions about musical training from the Gold-MSI v0.9. Participants were also asked to select their musical preferences from

TABLE 6.3
Musical genre preference of participants.

Genre	Abbr.	No.	Genre	Abbr.	No.	Genre	Abbr.	No.
Classical	C	71	Rock	RO	50	Jazz	J	42
Alternative	A	38	Electronic	E	35	Pop	P	34
Folk	F	29	Blues	B	28	World	W	24
Hip-hop	H	24	Soul	S	20	Rap	RA	19
Metal	M	17	Soundtrack	ST	17	RnB	RB	15
Light-instr	L	14	Country	CO	13	Reggae	REG	12
Religious	REL	5	None	N	-	Others	OT	41

Note. The column No. represents the number of participants who choose the corresponding genre as one of their favourites.

a catalogue of 19 musical genres and list other musical styles they like. For the question on musical preference, participants were asked to choose from Table 6.3.

Music-listening questionnaire. This 7-item questionnaire is designed to assess participants' expected "felt emotional responses" with and without the presence of music (optional, click on a two-dimensional valence-arousal model of emotion), daily usage of music (forced-choice, for frequency on a 5-point Likert scale; for importance on a 7-point Likert scale), functions of music listening (forced-choice for four functions on a 7-point Likert scale), and musical preference (multiple choice) for each given activity. The questions were asked as follows.

1. Please select your expected emotional association with this activity without music, and click on the two-dimensional space of emotion. (Do not click the space if you do not care about the emotional effects.)
   - Valence represents "sad" (-0.5) to "happy" (0.5).
   - Arousal represents "relaxed" (-0.5) to "excited" (0.5).
2. How often do you listen to music in this activity? (1 = *Never*, 3 = *Sometimes*, and 5 = *Always*)
3. How important is the music to you in this activity? (1 = *Not at all*, 4 = *Neutral*, and 7 = *Extremely*)
4. Which musical genres would you like to listen to in this activity? (music genres from Table 6.3 plus two additional items, "any genres from my preferred ones" and "I don't care about genres")

5. Please indicate your purpose of selecting music in this activity? (1 = *Not at all*, 4 = *Neutral*, and 7 = *Extremely*)
   - Distraction (a way of engaging unallocated attention and reducing boredom);
   - Energising (a means of maintaining arousal and task attention);
   - Entrainment (the task movements are timed to coincide with the rhythmic pulses of the music, giving the task or activity elements of a dance);
   - Meaning enhancement (where the music draws out and adds to the significance of the task or activity in some way).
6. If listening to music in this activity, select the emotional effect you expect to feel in response to the music (**NOT** from the activity), and click on the two-dimensional space of emotion. (Do not click the space if you do not care about the emotional effects.)

To increase the interaction with participants, an additional free response field was provided at the end of each page (Reips, 2012).

6.2.3 Procedure

The first page provided the instructions, and participants filled in the demographic questionnaire. Then a practice page of the music-listening questionnaire with activity "cooking at home" was shown to participants. For each question in the practice page, a detailed explanation was presented to participants. After the practice session, they completed a 13-page music-listening questionnaire with each activity provided in Table 6.1. Following the strategies proposed by Reips (2002), the activities were given in random order. The two-dimensional model of emotion (valence-arousal) is used to measure emotional responses. Ninety-four English-speaking participants completed the questionnaire. For the questionnaire, a 5-point Likert scale (1=*Never*, 5=*Always*) is used to measure the frequency of listening to music for each situation and a 7-point Likert scale (1=*Not at all*, 7=*Extremely*) used to measure the importance and the functions (distraction, energising, entrainment, and meaning enhancement) of listening to music. The whole experiment took 15 minutes to complete without any planned breaks, and participants were able to stop at any time.

6.3 Results

A total of 1222 participants' ratings (13 situations$\times$94 participants) was collected for data analysis. Firstly, I examined participants' feedback, and checked whether they understood the questions correctly. One participant mentioned that *It's not possible for me to make meaningful choices - because my response to, and association with music to, housework and gardening are *completely* different. So rather than choose one, I'm choosing "Not at all" for all answers. Please delete them as they are meaningless.* This entry was discarded, and only 1221 participants' ratings were retained for further analysis.

6.3.1 Usage of Music Varies Across Situations

To compare participants' usage of music across different activities, the mean ratings of frequency (1 = *Never* to 5 = *Always*) and importance (1 = *Not at all* to 7 = *Extremely*), as well as their standard deviations are shown in Table 6.4. The results revealed that the most frequent and important activity of using music is "just to listen to your selected music" ($M_{frequency}$ = 4.20 and $M_{importance}$ = 6.46). Other frequent and important situations which music is used to accompany include "travelling", "exercising", and "unpaid physical work". The top ten situations whose mean ratings were above the middle point of their rating scales are the same for both importance and frequency. A Spearman's rank correlation analysis between the ratings of frequency and importance was carried out for each participant. The Spearman's correlation coefficients were then aggregated over 94 participants using the Fisher z-transformation. The analysis shows a significant positive correlation between participants' ratings of frequency and importance ($r_s(11) = 0.86$, $p < .001$).

Although participants reported that they frequently listen to music during "nightlife", the standard deviations of participants' ratings on importance and frequency are also very high. These variations may be influenced by the individual differences in age, gender, and culture. Some participants pointed out that they used to do those activities a lot, but they no longer do so or they do not go to those kinds of places.

6.3.2 Functions of Music Vary Across Situations

To examine the question "How do the functions of listening to music vary across situations?", participants' ratings (1 = *Not at all*, 4 = *Neutral*, and 7 = *Extremely*) on four music-listening

TABLE 6.4
The mean (standard deviation) ratings of frequency and importance for music in different situations.

Situation	**Frequency**	**Situation**	**Importance**
Listen	4.20 (0.93)	Listen	6.46 (1.04)
Nightlife	3.85 (**1.43**)	Nightlife	5.40 (**2.11**)
Travel	3.65 (1.04)	Travel	4.90 (1.70)
Night out	3.45 (1.28)	Exercise	4.77 (2.07)
Physical work	3.42 (1.11)	Commute	4.60 (2.06)
Exercise	3.38 (1.38)	Physical work	4.58 (1.75)
Wait	3.33 (0.97)	Relax	4.52 (1.77)
Commute	3.31 (1.32)	Wait	4.38 (1.61)
Relax	3.27 (1.02)	Night out	4.28 (2.03)
Study/work	3.11 (1.19)	Study/work	4.11 (2.03)
Talk	2.47 (1.01)	Wake up	2.91 (1.94)
Wake up	2.18 (1.21)	Talk	2.88 (1.78)
Sleep	2.02 (1.03)	Sleep	2.52 (1.78)

Note. The horizontal line divides the ratings by its middle point 3 ("Sometimes") for frequency scale and 4 ("Neutral") for importance scale. The highest standard deviation of frequency and importance is shown in bold.

functions *distraction*, *energising*, *entrainment*, and *meaning enhancement* were compared. The function ratings were considered if participants' frequency ratings were not marked as "never". The mean values and standard deviations for the four functions were calculated across participants. Table 6.5 shows that the highest average ratings for the four functions are "waiting" (for *distraction*), "exercising" (for *energising*), "nightlife" (for *entrainment*), and "just listening to your selected music" (for *meaning enhancement*).

The Shapiro-Wilk test was then performed on the ratings of each function, and analyses rejected the assumption of normality for ratings of four functions, *distraction* ($W = 0.88$, $p < .001$), *energising* ($W = 0.89$, $p < .001$), *entrainment* ($W = 0.86$, $p < .001$), and *meaning enhancement* ($W = 0.89$, $p < .001$). A non-parametric Kruskal-Wallis analysis of variance was conducted to assess whether participants' ratings are different for functions (4 levels) and situations (13 levels). Significant main effects on ratings were found for situations ($\chi^2(12, 3984) = 410.68$, $p < .001$) and for functions ($\chi^2(3, 3984) = 134.89$, $p < .001$).

In order to compare the differences in each function across situations, post-hoc pair-wise comparisons using Tukey's HSD test were performed. Tables 6.6-6.9 show the differences between pairs of situations for the four functions of music listening. However, the tables do not indicate the level of the function per se. Therefore, a summary of pair-wise comparisons for the four

TABLE 6.5
Mean (standard deviation) ratings of importance of functions of music for each situation.

Situation	No.	Distraction	Energising	Entrainment	Enhancement
Commute	80	**5.87** (1.42)	4.01 (1.86)	3.19 (2.19)	3.84 (2.01)
Exercise	77	5.42 (1.83)	**5.84** (1.34)	5.29 (1.77)	4.47 (1.95)
Sleep	52	**3.88** (1.76)	2.37 (1.66)	2.58 (1.78)	3.02 (1.84)
Listen	92	4.45 (2.21)	4.92 (2.00)	3.87 (2.23)	**5.33** (1.85)
Night out	76	4.28 (1.58)	**4.79** (1.63)	4.36 (2.00)	4.45 (1.89)
Nightlife	81	4.80 (1.93)	5.56 (1.72)	**5.83** (1.71)	5.30 (1.58)
Relax	85	**4.31** (1.66)	3.93 (1.72)	3.06 (2.04)	3.89 (1.86)
Study/work	78	3.96 (2.07)	**4.81** (1.79)	2.47 (1.80)	3.54 (1.96)
Talk	60	3.20 (1.62)	3.73 (1.70)	2.93 (1.92)	**3.98** (1.79)
Travel	89	4.69 (1.86)	4.45 (1.90)	3.46 (2.24)	**4.55** (2.01)
Physical work	82	**5.76** (1.16)	5.51 (1.28)	4.17 (1.90)	3.66 (1.92)
Wait	88	**5.99** (1.30)	3.73 (1.82)	2.89 (2.04)	3.22 (2.06)
Wake up	56	3.75 (1.74)	**4.86** (1.69)	3.32 (2.07)	3.84 (1.94)

Note. No. represents the number of ratings used in the analysis. Highest average ranking are shown in bold.

functions across situations is shown in Table 6.10. The analyses show that people listen to music while "commuting" (M = 5.87, SD = 1.42), "exercising" (M = 5.42, SD = 1.83), "waiting" (M = 5.99, SD = 1.30), and "unpaid physical work" (M = 5.76, SD = 1.16) for its *distraction* function, during "exercising" (M = 5.84, SD = 1.34) for its *energising* function, during "nightlife" (M = 5.83, SD = 1.71) for its *entrainment* function, and while "just listening to selected music" (M = 5.33, SD = 1.85) and "nightlife" (M = 5.30, SD = 1.58) for its *meaning enhancement* function. In addition, the results also confirm that people do not use music for distraction while "talking with friends", and they do not want to be energised while "falling asleep". The same results can be found from participants' feedback such as *I am a dancer so doing exercise in time with music is normal for me and I find it easier to exercise for longer periods of time with music because there is a distraction from physical discomfort*, and *listen to a morning show on the radio where I do not choose the music but there are different musical selections. The variety of selections can be energising because new.*

Furthermore for each situation, to identify the main function, participants' ratings of four functions were ordered[2]. The highest average ranking is shown in bold (see Table 6.5). For most situations, the highest average rating for each function is the same as the highest ranking except for "travelling".

[2]If ratings are tied, I compute their average rankings.

TABLE 6.6
Results of pair-wise comparison of participants' ratings of importance for function "distraction" across situations.

Situations	Commute	Exercise	Listen	Night out	Nightlife	Physical	Relax	Sleep	Study/work	Talk	Travel	Wait
Exercise	*ns.*	-	-	-	-	-	-	-	-	-	-	-
Listen	***	*ns.*	-	-	-	-	-	-	-	-	-	-
Night out	***	***	*ns.*	-	-	-	-	-	-	-	-	-
Nightlife	**	*ns.*	*ns.*	*ns.*	-	-	-	-	-	-	-	-
Physical work	*ns.*	*ns.*	**	***	*ns.*	-	-	-	-	-	-	-
Relax	***	***	*ns.*	*ns.*	*ns.*	***	-	-	-	-	-	-
Sleep	***	***	*ns.*	*ns.*	*ns.*	***	*ns.*	-	-	-	-	-
Study/work	***	***	*ns.*	*ns.*	*ns.*	***	*ns.*	*ns.*	-	-	-	-
Talk	***	***	***	*ns.*	***	***	*ns.*	*ns.*	*ns.*	-	-	-
Travel	***	*ns.*	*ns.*	*ns.*	*ns.*	*	*ns.*	*ns.*	*ns.*	***	-	-
Wait	*ns.*	*ns.*	***	***	***	*ns.*	***	***	***	***	***	-
Wake up	***	***	*ns.*	*ns.*	*	***	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	***

Note. Significance level, $*p < .05$; $**p < .01$; $***p < .001$.

TABLE 6.7
Results of pair-wise comparison of participants' ratings of importance for function "energising" across situations.

Situations	Commute	Exercise	Listen	Night out	Nightlife	Physical	Relax	Sleep	Study/work	Talk	Travel	Wait
Exercise	***	-	-	-	-	-	-	-	-	-	-	-
Listen	*	*ns.*	-	-	-	-	-	-	-	-	-	-
Night out	*ns.*	**	*ns.*	-	-	-	-	-	-	-	-	-
Nightlife	***	*ns.*	*ns.*	*ns.*	-	-	-	-	-	-	-	-
Physical work	***	*ns.*	*ns.*	*ns.*	*ns.*	-	-	-	-	-	-	-
Relax	*ns.*	***	**	*ns.*	***	***	-	-	-	-	-	-
Sleep	**	***	***	***	***	***	*	-	-	-	-	-
Study/work	*ns.*	*	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	***	-	-	-	-
Talk	*ns.*	***	**	*	***	***	*ns.*	*ns.*	*	-	-	-
Travel	*ns.*	***	*ns.*	*ns.*	**	*	*ns.*	***	*ns.*	*ns.*	-	-
Wait	*ns.*	***	***	*	***	***	*ns.*	*ns.*	*	*ns.*	*ns.*	-
Wake up	*ns.*	*	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	***	*ns.*	*ns.*	*ns.*	*

Note. Significance level, $*p < .05$; $**p < .01$; $***p < .001$.

TABLE 6.8
Results of pair-wise comparison of participants' ratings of importance for function "entrainment" across situations.

Situations	Commute	Exercise	Listen	Night out	Nightlife	Physical	Relax	Sleep	Study/work	Talk	Travel	Wait
Exercise	***	-	-	-	-	-	-	-	-	-	-	-
Listen	*ns.*	**	-	-	-	-	-	-	-	-	-	-
Night out	*	*ns.*	*ns.*	-	-	-	-	-	-	-	-	-
Nightlife	***	*ns.*	***	**	-	-	-	-	-	-	-	-
Physical work	*ns.*	*ns.*	*ns.*	*ns.*	***	-	-	-	-	-	-	-
Relax	*ns.*	***	*ns.*	*	***	*ns.*	-	-	-	-	-	-
Sleep	*ns.*	***	*ns.*	**	***	**	*ns.*	-	-	-	-	-
Study/work	*ns.*	***	**	***	***	***	*ns.*	*ns.*	-	-	-	-
Talk	*ns.*	***	*ns.*	*	***	*ns.*	*ns.*	*ns.*	*ns.*	-	-	-
Travel	*ns.*	***	*ns.*	*ns.*	***	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	-	-
Wait	*ns.*	***	*ns.*	***	***	**	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	-
Wake up	*ns.*	***	*ns.*	*ns.*	***	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*

Note. Significance level, $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

TABLE 6.9
Results of pair-wise comparison of participants' ratings of importance for function "meaning enhancement" across situations.

Situations	Commute	Exercise	Listen	Night out	Nightlife	Physical	Relax	Sleep	Study/work	Talk	Travel	Wait
Exercise	*ns.*	-	-	-	-	-	-	-	-	-	-	-
Listen	***	*ns.*	-	-	-	-	-	-	-	-	-	-
Night out	*ns.*	*ns.*	*ns.*	-	-	-	-	-	-	-	-	-
Nightlife	***	*ns.*	*ns.*	*ns.*	-	-	-	-	-	-	-	-
Physical work	*ns.*	*ns.*	***	*ns.*	***	-	-	-	-	-	-	-
Relax	*ns.*	*ns.*	***	*ns.*	***	*ns.*	-	-	-	-	-	-
Sleep	*ns.*	**	***	**	***	*ns.*	*ns.*	-	-	-	-	-
Study/work	*ns.*	*ns.*	***	*ns.*	***	*ns.*	*ns.*	*ns.*	-	-	-	-
Talk	*ns.*	*ns.*	***	*ns.*	**	*ns.*	*ns.*	*ns.*	*ns.*	-	-	-
Travel	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	**	*	*ns.*	-	-
Wait	*ns.*	**	***	*	***	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	***	-
Wake up	*ns.*	*ns.*	***	*ns.*	**	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*	*ns.*

Note. Significance level, $^{*}p < .05$; $^{**}p < .01$; $^{***}p < .001$.

TABLE 6.10
Summary of pair-wise comparisons for four functions across situations.

Distraction		Energising		Entrainment		Enhancement	
Situation	**Group**	**Situation**	**Group**	**Situation**	**Group**	**Situation**	**Group**
Exercise	a	Exercise	a	Nightlife	a	Listen	a
Commute	a	Nightlife	ab	Exercise	ab	Nightlife	a
Wait	ab	Physical	ab	Night out	bc	Travel	ab
Physical	abc	Listen	abc	Physical	bcd	Exercise	abc
Nightlife	bc	Study/work	bcd	Listen	cde	Night out	abc
Travel	bcd	Night out	bcde	Travel	cdef	Talk	bcd
Listen	bcd	Wake up	bcde	Wake up	cdef	Relax	bcd
Relax	cd	Travel	cdef	Commute	def	Wake up	bcd
Night out	cd	Commute	def	Relax	def	Commute	bcd
Study/work	cde	Relax	ef	Talk	def	Physical	bcd
Sleep	cde	Talk	fg	Wait	ef	Study/work	cd
Wake up	de	Wait	fg	Sleep	ef	Wait	d
Talk	e	Sleep	g	Study/work	f	Sleep	d

Note. Each situation is ranked in descending order of participants' median ratings from high (a) to low (g), and significance level was calculated by $p = .05$. There exists a significant difference if no mutual letter is shown between two situations.

6.3.3 Emotional Associations with Situations

To establish a baseline for emotional effects of music in different situations, I first report the associations with situations, independent of music. The mean value and standard deviation of participants' ratings for valence (-0.5 = *negative* to 0.5 = *positive*) and arousal (-0.5 = *low* to 0.5 = *high*) were computed, as well as the number of *n/a* for participants who seek no emotional effects (see Table 6.11). Eighty percent of the ratings have values for valence and arousal. Situations "relaxing at home" and "talking with friends" received the highest (81) and the lowest number (69) of responses for emotional association respectively. Also, activities "talking with friends" and "exercising" were associated with the highest average levels of valence and arousal, respectively. However, participants were found to associate negative emotional experience (valence) with situations "commuting", "waiting", and "waking up".

Participants' ratings of emotion were then examined using the Shapiro-Wilk normality test, the analyses show that both ratings of valence ($W = 0.98$, $p < .001$) and arousal ($W = 0.98$, $p < .001$) do not follow a normal distribution. To investigate the emotional associations across situations (12 levels[3]), the Kruskal-Wallis one-way analysis of variance was performed. A significant main effect was found for situation on ratings of valence ($\chi^2(11) = 209.99$, $p < .001$) and arousal ($\chi^2(11) = 256.87$, $p < .001$).

TABLE 6.11
Mean (standard deviation) emotional ratings for different situations without music.

Situation	**No.**	**Valence**	**Arousal**
Commuting	76	-0.05 (0.18)	-0.07 (0.17)
Exercising	75	0.07 (0.18)	**0.16** (0.23)
Falling asleep	73	0.07 (0.15)	-0.28 (0.18)
Nightlife	71	0.04 (0.22)	0.11 (0.25)
Night out	74	0.13 (0.18)	0.11 (0.19)
Relaxing at home	81	0.15 (0.18)	-0.15 (0.20)
Studying/working	73	0.03 (0.16)	-0.05 (0.18)
Travelling	78	0.20 (0.20)	0.12 (0.22)
Talking with friends	69	**0.21** (0.16)	0.09 (0.18)
Unpaid physical work	76	0.01 (0.16)	-0.00 (0.17)
Waiting	77	-0.09 (0.16)	-0.06 (0.19)
Waking up	73	-0.00 (0.19)	-0.10 (0.21)

Note. The highest average ratings of valence and arousal are shown in bold.

6.3.4 Emotional Associations with Situations and Music

Similar to the analysis of emotional associations with situations, participants' emotional response to music and situations were investigated. Participants were asked to choose the emotional effects they expect to feel in response to music (not from the activity), and I found that more than 80% of the responses have emotional ratings, showing that participants have an intended emotional effect of listening to music. Table 6.12 presents the mean value and standard deviation of valence and arousal ratings with music. The effect of the situation on the ratings of valence and arousal with music was assessed using the Kruskal-Wallis test. The results show ratings of valence ($\chi^2(11) = 89.92$, $p < .001$) and arousal ($\chi^2(11) = 244.73$, $p < .001$) were significantly different across situations. In addition, I noticed that ratings of valence tend to be positive, whereas negative ratings of arousal were found only in situations such as "falling asleep", "relaxing at home", and "waiting". The highest mean ratings of valence and arousal were observed in

[3]As music is always present during the activity "just listening to your selected music", participants' ratings for this activity were not considered for further analysis of emotional associations with and without the presence of music.

situations "travelling" ($M = 0.27$) and "nightlife" ($M = 0.31$) respectively. Participants also provided the lowest average ratings for both valence and arousal while "falling asleep".

TABLE 6.12
Mean (standard deviation) emotional ratings for different situations with music.

Situation	**No.**	**Valence**	**Arousal**
Commuting	75	0.17 (0.16)	0.04 (0.19)
Exercising	77	0.17 (0.18)	0.26 (0.21)
Falling asleep	70	0.04 (0.20)	-0.15 (0.27)
Nightlife	76	0.22 (0.21)	**0.31** (0.16)
Night out	74	0.18 (0.18)	0.21 (0.19)
Relaxing at home	83	0.21 (0.16)	-0.04 (0.22)
Studying/working	78	0.12 (0.17)	0.03 (0.23)
Travelling	79	**0.27** (0.15)	0.15 (0.21)
Talking with friends	68	0.18 (0.17)	0.07 (0.21)
Unpaid physical work	78	0.15 (0.16)	0.14 (0.20)
Waiting	82	0.12 (0.15)	-0.03 (0.20)
Waking up	69	0.14 (0.16)	0.08 (0.21)

Note. The highest average ratings of valence and arousal are shown in bold.

6.3.5 Emotional Associations With and Without the Presence of Music

In the questionnaire, participants gave their expected emotional response to the activity (without the presence of music), and they reacted distinctively for different situations. Moreover, participants were asked to give their emotional responses due to the presence of music for each activity, and their expected emotional ratings on valence were found to be positive. To explore how emotion regulation strategies of listening to music change in different contexts, for each activity participants' ratings of expected felt emotion with and without the presence of music were compared. Since participants had the choice of not giving their emotional responses if they considered it to be irrelevant, 820 out of 1221 ratings containing emotional ratings were available for this analysis.

Firstly, I computed the Spearman's rank correlation coefficients between the ratings of valence (and arousal) for situations with and without the presence of music. The results show that regardless of the situation, the overall ratings of emotion with and without the presence of music are positively correlated for both valence ($r_s(818) = .30$, $p < .001$) and arousal ($r_s(818) = .48$, $p < .001$). Secondly, to examine the role of situation, correlation analyses were performed on the ratings of valence (and arousal) with and without the presence of music for each situation (see

TABLE 6.13
Results of Spearman's rank correlation analysis and Wilcoxon signed rank test between ratings of valence (and arousal) with and without the presence of music.

Situation	**V-coef**	**A-coef**	**DF**	**V-Zvalue**	**A-Zvalue**	**df**
Commuting	.24	.02	67	106.5***	564.5***	69
Exercising	.28*	.45***	68	486.0***	521.5***	70
Falling asleep	.07	.05	61	1016.5	544.5**	63
Nightlife	.14	.15	65	278.5***	252.0***	67
Night out	.26*	.35**	68	778.5*	580.0***	70
Relaxing at home	.47***	.48***	75	996.5*	706.0***	77
Studying/working	.27*	.32*	62	464.5***	638.0**	64
Travelling	.56***	.59***	72	792.0**	914.5*	74
Talking with friends	.33*	.52***	56	872.0	735.0	58
Unpaid physical work	.36**	.33**	69	260.0***	352.0***	71
Waiting	-.33**	.39***	72	222.0***	1108.0	74
Waking up	-.19	.29*	61	375.0***	195.0***	63

Note. V-coef (and A-coef) represent the correlation coefficients between the ratings of valence (and arousal) with and without the presence of music. V-Zvalue and A-Zvalue represent the statistics of Wilcoxon two-sample paired signed-rank test. df represents the degree of freedom. Significance level, *$p < .05$; **$p < .01$; ***$p < .001$.

Table 6.13, V-coef for valence and A-coef for arousal). Significant correlations were found for all of the situations except for "commuting", "falling asleep", and "nightlife". Significant positive correlations were found in situations such as "exercising" ($r_s = .45$) and "night out" ($r_s = .35$), and one significant negative correlation for ratings of valence during "waiting" ($r_s = -.33$).

To assess how emotions changed with situations, a non-parametric Wilcoxon two-sample paired signed-rank test was carried out on the ratings of valence (and arousal) with and without the presence of music for each situation, shown in Table 6.13 (V-Zvalue for valence, A-Zvalue for arousal). Figures 6.1 and 6.2 illustrate the changes of emotion (valence and arousal respectively) in each situation. I propose and define the following five different emotional uses of music which may apply to either or both dimensions (valence and arousal):

i **Maintain**: the expected emotion (valence and/or arousal) stays the same (i.e., negative/low, neutral, or positive/high), and no significant change is found in listeners' emotional responses whether or not music is present;

ii **Intensify**: when music is present, listeners' expected emotional responses (i.e. negative/low or positive/high) are significantly moved away from the neutral point;

iii **Diminish**: when music is present, listeners' expected emotional responses (i.e. negative/low or positive/high) are significantly moved towards the neutral point but do not cross the neutral point of the scale;

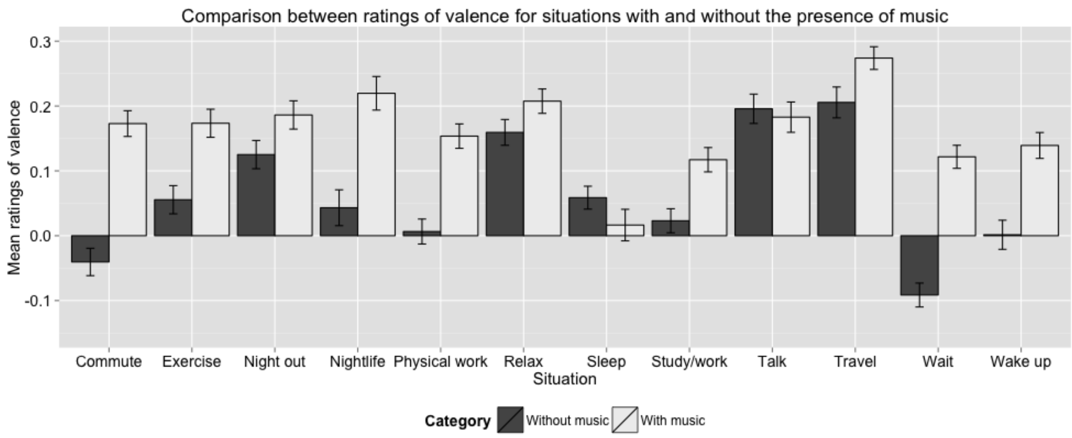
iv **Create**: listeners' expected emotional responses are neutral when music is not present, but significantly moved away from the neutral point when music is present (neutral to positive/negative valence, or neutral to high/low arousal).

v **Change**: listeners' expected emotional responses (i.e. negative/low or positive/high) are significantly changed to the opposite side of the scale (cross the neutral point of the scale). For instance, positive valence to negative valence or low arousal to high arousal;

For example, no significant difference was found for ratings of valence during "talking with friends" with and without the presence of music, and participants' ratings of valence remained positive. It suggests that music *maintains* the valence level. For situations "exercising", "night out", "nightlife", "relaxing at home", "studying/working", and "travelling", participants' ratings of valence were significantly increased to a higher absolute value. Although the increase of valence varies as per situation, it indicates that not only do people listen to music to *maintain* emotion but also to *intensify* their emotional experience. Participants' average ratings of valence with the presence of music were all positive. However, on the situation "falling asleep" ratings of valence were significantly *diminished* toward a neutral position. Additionally, music can help *create* an emotion. For example, participants' ratings of valence were significantly increased from neutral to the positive side of the scale after listening to music during "unpaid physical work" and while "waking up". Finally, participants reported negative emotional associations for situations "commuting" and "waiting", but their emotions were *changed* to be positive with the presence of music. In the present study, no cases of positive to negative emotional experience were found.

Similar changes were also found for participants' ratings of arousal. For instance, arousal was *maintained* low during "waiting" and high while "talking with friends". The level of arousal was *intensified* for situations "exercising", "night out", "nightlife", and "travel". Negative arousal was *diminished* towards neutral while "falling asleep" and "relaxing at home". Participants' ratings of arousal were changed from low to high for situations "commuting", "studying/working", and "waking up". Participants pointed out that *housework often needs music, gardening less so (to use your examples). When we were renovating and restoring our house, we had to have music on to keep us energised*. The same phenomenon can be found in the analysis where music is used to *create* a high-arousal environment for "unpaid physical work". A summary of emotional uses of music for valence and arousal is shown in Table 6.14. Additionally, Figure 6.3 shows a comparison between the changes of valence and arousal ratings for situations due to the presence of music.

Figure 6.1: Changes of participants' ratings of valence for situations with and without the presence of music.



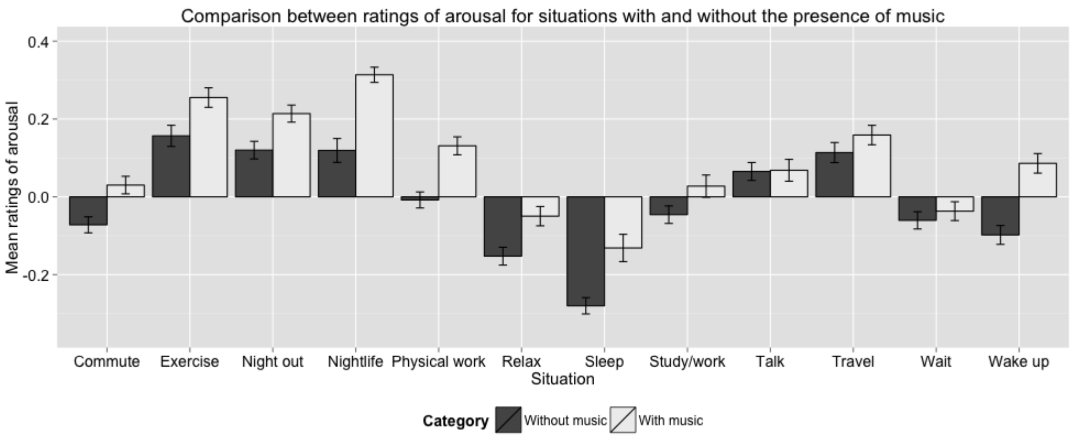
6.3.6 Emotional Responses and Functions of Music Listening

To explore the relationship between expected felt emotions with music and functions of listening to music, correlation analyses were performed between the ratings of emotion (i.e., valence and arousal) and four functions (i.e., distraction, energising, entrainment, and meaning enhancement). The results in Table 6.15 show that regardless of the situation, ratings of valence and arousal are significantly positively correlated with the four functions except distraction and valence. In addition, the ratings of all four functions are positively correlated. The strongest correlation was found for functions *entrainment* and *energising.*

6.3.7 Musical Preference Varies Across Situations

Next, I investigated the musical preferences for these thirteen activities. Table 6.16 presents the distribution of participants' preferred musical styles. As expected, participants often choose to listen to their preferred musical styles while "relaxing at home", "travelling", and "waiting". However, during "nightlife", participants preferred to listen to rock, electronic, and pop music. I also found that when "studying/working" participants tend to choose classical music, and this may be related to previous research showing that preference for classical music is linked to intelligence (Kanazawa and Perina, 2012). Other musical genres mentioned by participants include French chanson, merengue, opera, and vallenato.

Figure 6.2: Changes of participants' ratings of arousal for situations with and without the presence of music.



6.3.8 Individual Factors

To determine whether usage of music (importance and frequency), emotional responses (valence and arousal, with and without the presence of music), and functions of music listening (distraction, energising, entrainment, and meaning enhancement) were associated with participants' age, gender, and musical training, Spearman's rank correlation analysis and the Kruskal-Wallis one way analysis of variance were performed. The results in Table 6.17 show that participants' age is negatively correlated with usage of music (frequency $r_s = -.21$, importance $r_s = -.20$). Additionally, participants' emotional associations with situation without music are positively correlated with age. However, a negative correlation was shown between valence and age for emotional responses with music. It indicates that younger people enjoy the presence of music in everyday situations. Likewise, musical training is negatively correlated with ratings of valence with the presence of music. Moreover, younger participants were also shown to use music significantly more for distraction, energising, entrainment, and meaning enhancement. However, no significant effects of gender were found on participants' music-listening behaviour. Only significant correlations and differences were reported. It is worth noting that the analysis was based on a sample of participants who like classical, rock, and jazz music, other potential effects might be missed in the present study. Other individual factors such as personality and culture may also influence music-listening behaviour.

TABLE 6.14
Summary of emotional uses of music for valence and arousal.

Emotional use	Level	Emotional dimension: Valence	Arousal
Maintain	Positive (hi)	talking with friends	talking with friends
	Neutral	-	-
	Negative (lo)	-	waiting
Intensify	Positive (hi)	exercising, relaxing nightlife, travelling studying/working, night out	exercising, night out nightlife, travelling
	Negative (lo)	-	-
Diminish	Positive	falling asleep	-
	Negative	-	relaxing, falling asleep
Create	Neutral - Positive (hi)	unpaid physical work waking up	unpaid physical work
	Neutral - Negative (lo)	-	-
Change	Positive (hi) - Negative (lo)	-	-
	Negative (lo) - Positive (hi)	commuting, waiting -	commuting, waking up studying/working

TABLE 6.15
Results of Spearman's correlation analysis between the ratings for four functions and for two emotional dimensions.

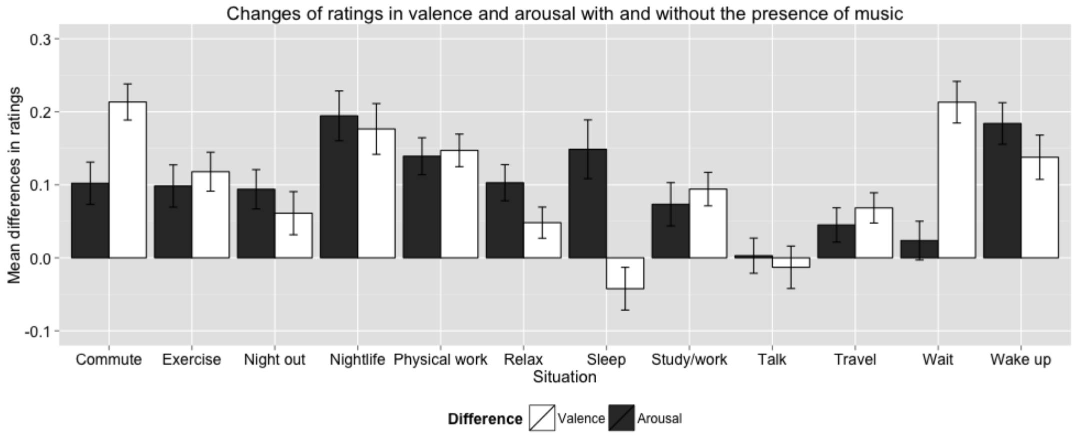
	Valence	**Arousal**	**Distraction**	**Energising**	**Entrainment**
Arousal	.24***	-	-	-	-
Distraction	.06	.09*	-	-	-
Energising	.20***	.44***	.33***	-	-
Entrainment	.21***	.41***	.18***	.52***	-
Meaning enhancement	.25***	.27***	.18***	.42***	.46***

Note. df=724. Significance level, *$p < .05$; **$p < .01$; ***$p < .001$.

6.4 Discussion

The aim of this chapter was to investigate how emotional and functional uses of music vary across daily activities, especially the emotional differences due to the presence of music. Participants' usage of music were compared. Consistent with recent findings of Juslin et al. (2011), the results showed that participants frequently choose to *just listen to their selected music* (attentive music listening) without any accompanying activities. In addition, agreeing with previous research, participants were found to be inclined to listen to music during "travelling", "unpaid physical work", and "nightlife". This also supports the statement that music is often used to accompany active leisure and maintenance activity (Sloboda et al., 2001; North et al., 2004; Juslin et al.,

Figure 6.3: Changes in valence and arousal ratings for situations due to the presence of music.



2011; Krause et al., 2015). The analyses of usage of music also suggest that the more important participants rate music to be, the more frequently they will listen to music.

Four functions of music listening summarised by Sloboda et al. (2009), namely *distraction*, *energising*, *entrainment*, and *meaning enhancement* were investigated in thirteen different situations. Significant differences were found for function and for situation, which supports the statement that music is used for different reasons and purposes (DeNora, 2000; Sloboda et al., 2001; Lamont and Greasley, 2009). Moreover, the analyses revealed the dominant function for each activity. For instance, the principal function of "just listening to your selected music" lies in the function of *meaning enhancement*, agreeing with previous research which suggests that listeners are inclined to experience emotions during attentive music listening (Juslin et al., 2011). My results of *entrainment* being considered important during "nightlife" were also supported by feedback, that one participant reported that *rhythm is more important than genre for this activity.*

Similar results were found when comparing each of the four functions across situations. I observed that music was dominantly used for *energising* while "exercising (e.g., running, cycling)". This is consistent with a recent study of young tennis players, which suggests that they consciously select music as a performance strategy to elicit various emotional states; Likewise, athletes often listen to music during pre-event preparation to help increase the level of activation, endurance, motivation, and performance (Bishop et al., 2007; Laukka and Quick, 2011). Heye and Lamont (2010) have reported that listeners create an "auditory bubble" in public places to pass

TABLE 6.16
Genre preference for each situation.

Situation	Fav.	No pref.	Classical	Rock	Jazz	Alt	Electro	Pop	Hip-Hop
Nightlife	22	11	4	23	17	11	**32**	**32**	20
Night out	**30**	12	7	20	17	14	17	16	12
Study/work	33	3	**35**	3	11	12	11	3	0
Relax	**46**	5	23	7	14	7	6	6	2
Listen	**52**	5	31	11	12	11	8	13	6
Sleep	17	4	**23**	2	9	3	7	4	0
Wake	**23**	2	18	6	7	4	5	8	3
Exercise	24	5	9	24	3	9	17	**26**	11
Wait	**51**	11	16	10	6	8	7	8	2
Talk	**29**	9	13	9	12	8	6	9	2
Physical work	**40**	7	15	18	9	13	6	19	5
Commute	**45**	6	17	16	6	10	13	13	7
Travel	**50**	10	18	15	7	12	7	8	3

Note. The highest number of votes for each activity is shown in bold.

time while “commuting”. Similar findings could be observed in the present study that music was frequently used for function *distraction* while “waiting” and “commuting (public transport)”. The ratings for functions *entrainment* and *energising* are positively correlated, and these two functions were mainly in activities such as “exercising”, “nightlife”, and “unpaid physical work”.

Previously, research has shown people’s emotional responses to music are context-dependent. In this study, the anticipated felt emotions were investigated and compared with and without the presence of music in different situations. Participants’ emotional reactions differed significantly in various situations. Participants associated negative emotions with activities “waking up”, “commuting”, and “waiting”, and the level of arousal were reported as low (below the mid-point of the scale) for situations “studying/working”, “waking up”, and “commuting”. Their emotional responses were related to the nature of the activity, as people pointed out that *I avoid waiting like the plague* and *I use music to maintain my happiness level during a vacation.* However, with the presence of music, participants’ ratings of valence and arousal are significantly different for many situations; ratings of valence tended to be positive and arousal to be higher. This is consistent with previous findings that people are more likely to feel positive emotion while listening to music (Juslin and Laukka, 2004; Zentner et al., 2008).

Eighty percent of the responses having emotional ratings for valence and arousal suggests that people have an intended emotional effect of listening to music. I also found that regardless of the situation, participants’ ratings of emotion (valence and arousal) with and without the presence of music were always strongly positively correlated.

TABLE 6.17
The effects of individual differences on music-listening behaviour.

	Dimension	Age	Gender	Musical training
Daily usage	Frequency ($N = 1221$)	-.21***	2.76	-.06
	Importance ($N = 1221$)	-.20***	0.37	-.05
Without music	Valence ($N = 895$)	.07*	0.56	-.04
	Arousal ($N = 895$)	.08*	0.84	-.03
With music	Valence ($N = 909$)	-.19***	2.04	-.07*
	Arousal ($N = 909$)	-.05	0.16	.00
Functions	Distraction ($N = 1221$)	-.14***	0.66	.02
	Energising ($N = 1221$)	-.14***	2.80	.00
	Entrainment ($N = 1221$)	-.19***	2.72	-.05
	Enhancement ($N = 1221$)	-.18***	0.34	.02

Note. Significance level, *$p < .05$; **$p < .01$; ***$p < .001$. Correlation analyses were performed on age and musical training, and the effect of gender was analysed using the Kruskal-Wallis one way analysis of variance.

Previous research has mentioned that people use music to change, create, maintain, or to enhance their emotions and moods (DeNora, 1999; Van Goethem and Sloboda, 2011). In the present work I further investigated the emotional uses of music in different situations. From the analysis of changes of participants' ratings of valence and arousal for situations with and without the presence of music, I propose that listening to music can influence our emotions in five different ways (i.e., maintain, intensify, diminish, change, and create). For instance, participants used music to *maintain* their level of valence and arousal in the activity "talking with friends". Also they listen to music during a "night out (bars/bowling/pubs)", "exercising (e.g., running, cycling)", and "travelling (holidays)" to *intensify* their level of valence and arousal. The most common use of music is to intensify emotional experience. Valence and arousal were increased to a higher level for situations "exercising", "night out", "nightlife", and "travelling" (Sloboda et al., 2001; Krause and North, 2014). However, the ratings of valence and arousal were *diminished* by the effect of music while "falling asleep" (North and Hargreaves, 1996). North et al. (2000) have found that individuals prefer "high-arousal music" during aerobic exercise activity but "low-arousal music" during guided relaxation. A similar result was found that participants' arousal was *diminished* by music while "relaxing at home". Furthermore, participants' valence (and arousal) were also *changed* from negative (low) to positive (high) for the activity "commuting (public transport)". A naturally negative activity such as "waiting" was also *changed* to a positive experience by listening to music. Similarly, the level of arousal was *changed* from low to high for situations such as "waking up" and "studying/working". No cases of positive-to-negative change were found. I have discussed in Chapter 5 that people associate high valence and arousal with doing housework with music. Although participants reported neutral with activity "unpaid physical work (e.g. housework, gardening)", a positive valence and high arousal was *created* by listening to music. A general increasing tendency for valence and arousal were observed with the presence of music, but the changes varied across situations.

The study of emotional and functional uses of music showed that ratings of valence and arousal were significantly correlated with four functions of music listening. Ratings of valence were most strongly correlated with function *meaning enhancement*, whereas ratings of arousal were most positively correlated with functions *energising* and *entrainment*. Musical preference was then investigated with situations. The results suggest that people generally choose to listen to their preferred music styles in most daily activities. However, people tended to listen to rock, electronic, pop, and hip-hop during "nightlife". People are also more likely to listen to classical music while "studying/working". Possible explanations could be that preference for classical music might be related to one's intelligence, and listening to classical music could help focus and increase performance (Schäfer and Sedlmeier, 2009; Kanazawa and Perina, 2012). Although the preference of music styles might be correlated with functions of music (North and Hargreaves, 2007a; Getz et al., 2010; Schäfer et al., 2013; Krause and North, 2014) and emotion (Rentfrow et al., 2011a; Eerola, 2011), it is beyond the scope of this study.

Lastly, individual analysis showed that participants' music-listening behaviour is not affected by gender or musical training. Similar to the findings in Chapter 5, younger participants are likely to use music more frequently, and they would react to music more positively. People's music-listening behaviour and emotional responses are also influenced by other factors such as personality, current mood, culture, and familiarity (Krohne, 2003; Schubert, 2007b; Delsing et al., 2008), therefore, future studies are encouraged to investigate these factors.

In summary, this Chapter investigated the emotional and functional uses of music, and extended the existing research to different contexts. This work agrees with and supports previous work on music in everyday life. Musical emotions arise in the interaction between the listener, the music, and the situation (Tarrant et al., 2000; Gabrielsson, 2002; Juslin and Laukka, 2004; Juslin et al., 2011). Therefore, future study of musical emotions, functions, and musical preference should consider music-listening contexts. It will also help the design of subjective context-based music recommendation systems in the future (Song et al., 2012a; Schedl, 2013; Kaminskas et al., 2013).

Chapter 7

Conclusion and Future Work

Musical emotion has been attentively examined by music psychologists in the past few decades. Music information retrieval researchers are concerned with computational tasks such as classification of music by its emotional content, and emotion- and context-based music recommendation systems that have emerged only in the last ten years. In this thesis, I have investigated two important roles in musical preference, namely musical emotion and music-listening context. Background knowledge on musical emotion and context was provided in Chapters 2 and 3 respectively. Chapter 4 presented my work on automatic emotion classification of music, the comparison between perception and induction of music, and the reliability of emotion tags. My work on musical preference, and emotional and functional uses of music in different music-listening contexts was then discussed in Chapters 5 and 6. Most of the work presented in this thesis has been published in or submitted to international peer-reviewed journals and conferences (see Section 1.4).

In this chapter, I summarise the experiments and my research contributions in Section 7.1. Finally, Section 7.2 proposes a few potential research questions for future studies.

7.1 Summary

This thesis investigated the role of emotion and context in musical preference. My work started with background knowledge of music and emotion for both psychology and music information retrieval, described in Chapter 2. Research efforts were discussed in detail to explore different aspects of musical emotion, and I identified the advantages of collaboration between these two fields. Psychologists provide a deeper understanding of theoretical background in emotion (e.g., forms of emotional processes in relation to music and models of emotion in music), whereas music information retrieval researchers provide valuable tools to help analyse data relating to musical emotions (e.g., machine learning techniques and musical feature extraction).

Previous research has suggested that emotional responses, functions of music listening, and musical preferences should be studied with their contexts (Juslin and Laukka, 2004; Juslin et al., 2008; Liljeström et al., 2012). Few studies have addressed the interactions among these closely related factors (i.e., functions, emotional responses, musical preferences, and individual differences) in different situations (Hargreaves et al., 2006; Hargreaves, 2012). In Chapter 3, research on emotional and functional uses of music was presented. In addition, musical preference and the music-listening context were discussed.

Chapter 4 presented my work on music and emotion. Emotion tags were collected using social tags, and musical excerpts were fetched. I provided an emotion data set containing 2904 musical excerpts. This data set has been used throughout my work, and each excerpt was tagged with one of the four emotions: "happy", "sad", "relaxed", and "angry". Musical features were then extracted for those 2904 musical excerpts, and SVMs were applied to classify emotion of music. The results, however, reached only the accuracy of about 53%. Compared with other classification tasks such as genre classification and instrument classification of music, emotion classification of music appears to be still very limited. Therefore, I investigated musical emotions and the reliability of social tags further using eighty excerpts (see Appendix C) that were randomly selected from emotion data set of the 2904 musical excerpts. The results of two listening experiments using the categorical model and dimensional model showed that four basic emotions (i.e., happy, sad, relaxed, and angry) better capture the emotions that are expressed in music than those induced by music. Emotions such as "happy" and "angry" were easier to recognise than "sad" and "relaxed". Additionally, a positive relationship between induced and perceived emotion was found to be the most frequent one. Although the agreement between social tags and participants' ratings was well above chance, the excerpts labelled with "relaxed" had the lowest agreement with tags. Moreover, I collected a participant-suggested emotion data set of 207 tracks covering four emotions of both perceived and induced emotion (see Appendix E). Assuming these 207 participant-suggested tracks represent people's emotional experience better, these tracks were used to train my MER system with SVMs and random forests. Then the 80 excerpts were tested by my MER system, and the classification results were compared with participants' responses. I found that consistent emotional responses were more likely to be correctly predicted by the music emotion recognition systems.

Musical emotion is known to be context-dependent. However, as I discovered in Chapter 3, existing research has paid little attention to the context, in which music is listened to. The emotional responses to music and functions of music listening were addressed in Chapter 5. A questionnaire was designed to measure three factors (i.e., emotional responses to music, functions, and musical preferences) in 20 different situations. Four recurring functions, *distraction*, *energising*, *entrainment*, and *meaning enhancement* were compared. The analyses suggest that reasons for listening to music vary with music-listening contexts. In addition, emotional responses were distributed widely across the full range of arousal on a two-dimensional model of emotion, whereas valence ratings tended to be positive.

Chapter 5 supported previous studies and extended the existing research to different contexts. Finally in Chapter 6, I further investigated the emotional responses with and without the presence of music in thirteen music-listening situations. Participants' emotional responses were found to relate to the nature of the activity. With the presence of music, I reported 5 different emotional uses of music, namely to maintain, intensify, diminish, change, and to create.

7.2 Future Directions

During the process of undertaking the research for this thesis, several research ideas for extensions and applications of this work arose. I propose seven potential directions for future research.

7.2.1 Continuous Emotion Prediction in Music

Emotion, like music, is dynamic and it may change and evolve continuously. The majority of emotion research in MIR is aimed at recognising emotion using 30/60-second audio previews, yet the changes of emotion in the whole piece are often neglected (Ogihara, 2004; Trohidis et al., 2008; Terrell et al., 2012; Flexer et al., 2012). For future study of emotion in music, it is recommended to use longer audio clips or the whole piece, to explore how emotion is formed and changed during music listening. Additionally, more research on building continuous music emotion prediction systems using the two models of emotion is also encouraged.

7.2.2 Cultural Dependence of Perception and Induction of Emotion in Music

The perception of music emotion is known to be culture-dependent. A wealth of research has focussed on cross-cultural studies in music and emotion (Fritz et al., 2009; Hu and Kando, 2012). In previous studies, research has suggested that individual differences such as culture may affect the perception of emotion in music. In this thesis, results from two listening experiments showed different relationships (i.e., positive, negative, no systematic, undecided, and no relationship) between the perception and induction of music. Over half of the musical excerpts had a positive relationship, but the reasons for these relationships were still unclear. One possible reason could be that the study was conducted using Western popular music; although all the participants understood English, they had a different cultural background. I suggest that future studies could investigate the effects of cultural differences on the perception and induction of music.

7.2.3 Genre-informed Music Emotion Recognition System

As pointed out in Chapter 2, certain genres such as classical and popular music may express specific emotions (Eerola, 2011). For example, blues is mostly sad and relaxed, whereas pop music tends to be happy (Laurier, 2011; Kosta et al., 2013). Progress in the development of emotion recognition systems is difficult. Additionally, how musical emotion is expressed is rarely empirically investigated. With the existing studies on genre classification, the differences in emotion and genre, and the selection of musical features could be further explored. In addition, music emotion recognition systems could incorporate genre information to test for an improvement in recognition accuracy.

7.2.4 Emotional Uses of Music and Musical Preference

In Chapters 5 and 6, the emotional uses of music were investigated. Given different music-listening activities, I proposed five different emotional uses of music (i.e., maintain, intensify, diminish, change, and create). However, the results were provided by a sample of participants who liked classical music. Participants with different stylistic preferences and cultural background could be selected to validate my results. For each emotional use of music, I also encourage other researchers to explore its underlying mechanisms.

In this thesis, I investigated musical preference for specific activities. Musical preference changes over time (Hargreaves et al., 2006; Lamont and Greasley, 2009), and it follows an inverted U-shaped function of exposure (North and Hargreaves, 1995; Schellenberg et al., 2008). For future studies, it would be interesting to explore how emotional uses of music can change with the exposure to music, and how short- and long-term musical preference affect the emotional uses of music.

7.2.5 Musical Emotions Using Psychophysiological Measurements

Because of the subjective experience of music, a self-report format is commonly used in the study of musical emotion. In recent years, with the development and availability of tools, we could reliably measure behavioural and physiological reactions such as facial expression, body language, heart rate, respiration, skin conductance response, and electroencephalograph. These objective measurements could be conducted in combination with the self-report approach to provide a deeper understanding and richer evidence of emotional responses.

7.2.6 Musical Feature Analysis of Musical Preferences

In this thesis, I have found that participants' emotional responses were distributed across the Valence-Arousal space for different situations. Musical emotions, genres, and instruments can all be classified into subcategories. Similarly, musical preferences for different situations can also be classified and categorised. Therefore, as a continuation of my work, it is worth investigating low-level audio features for modelling musical preferences. For example, studies could focus on whether people have certain preferences for musical features in different contexts, and how they are associated with emotional responses. More importantly, the study of contextual information may further improve accuracy of emotion classification of music.

7.2.7 The Design of Subjective Music Recommendation Systems

The development of music recommendation systems has gained increasing attention in the MIR community. Existing approaches such as metadata-based models (e.g., keywords, song title, and artist's name), collaborative filtering (CF), and content-based models (CBM) have achieved some success in music recommendation system technology. However, their drawbacks such as popularity bias and human effort seem to be obvious. For example, popular music can get more ratings. The music in "long tail"[1], however, can rarely get any (Celma, 2009; Schnitzer et al., 2011). As a result, collaborative filtering[2] mainly recommends popular music to listeners. Though giving popular items could meet some users' needs, it is still risky, since the user rarely gets pleasantly surprised. In addition, a perfect recommendation system should not involve too much human effort, since the users are not always willing to rate songs. The ratings may also

[1]The "long tail" includes unknown artists and songs where barely any information can be found.

[2]It assumes that if user X and Y rate items similarly or have similar behaviour, they will rate or act on other items similarly.

grow towards those who do rate, but it may not be representative of the overall population. Because of this absence of evenly distributed ratings, recommendation systems can either give users false negative or false positive results.

The experience of music is highly subjective. In recent years, there has been a tendency for music recommendation systems to have a more personalised design. Only considering the music itself, human ratings are no longer sufficient. Emotion and context, as two important factors in musical preference, have been proposed as ingredients of a human-centred approach to music recommendation. Due to the lack of empirical data, the research is still at an early stage. One future application would be focussing on the development of subjective design of music recommendation systems using affective (emotion-based music recommendation systems) and contextual information (context-based music recommendation systems). These two features can also be integrated directly into existing content-based models using musical features (Song et al., 2012a).

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Appendix A

Emotion Tags Retrieved from Last.FM

Happy tags	Sad tags	Relaxed tags	Angry tags
happy	sad	relax	angry
happy hardcore	sad songs	relax trance	angry music
makes me happy	happysad	relax music	angry metal
happy music	sad song	jazz relax	angry pop music
happysad	sad and beautiful	only relax	angry rock
happy metal	so sad	relax and cool	angry girl music
songs that make me happy	sad music	just relax	angry songs
happy songs	makes me sad	for relax	angry women
happy rock	sad but true	relax dance	angry love
happy punk	beautifully sad	relax jazz	angry girl
happy birthday	very sad	relax rock	angry angry angry
happy house	slow and sad	relax feelings	angry lyrics
happy grindcore	beautiful sad	to relax	angry chick music
happy pop	sad but beautiful	relax me	angry girl songs
die happy	sad mood	cool relax	angry samoans
happy song	sad and slow	relax song	angry punk
happy emo	songs for sad moods	rock relax	fucking angry
happy days	sad day	relax metal	angry hate music
happy happy joy joy	makes me smile in a sad way	chill relax	angry as fuck
happy happy	sad love	relax1	angry girls
happy feet	feeling sad	work relax	angry bitch
happy mondays	sad memories	aerobic relax	angry rap
happy sad	sad boys with guitars	relax baby relax	angry chick
get happy	happy sad	positive relax	mood: angry
music that makes me happy	sad love songs	no relax	angry mob
happy tunes	sad guitar	pop relax	angry pop
make me happy	sad lyrics	deep relax	angry song
happy dance	sad maniac	relax time	angry angry music
be happy	sad love song	music to relax by	angry woman
happy thoughts	sad bastard music	guitar relax	angry chair

Appendix B

Statistics of Participants in Two Listening Experiments

Participants	Category	No.s in Experiment 1	No.s in Experiment 2
Age	<18	0	2
	18-24	22	23
	25-34	14	25
	35-44	4	1
	45-54	0	3
Gender	Male	20	25
	Female	20	29
Nationality	Chinese	13	10
	British	6	4
	Greek	3	7
	Polish	2	2
	Italian	2	4
	French	0	2
	Slovenian	0	2
	Taiwanese	0	2
	American	0	2
	Argentinian	0	2
	Canadian/Romanian	1	1
	English/Australian	0	1
	British-Pakistani	1	0
	British-Indian	1	0
	Iranian	1	1
	Indian	1	1
	Canadian	1	1
	Belgian	1	1
	Pakistani	1	1
	Romanian	1	1
	Portuguese	1	1
	Australian	1	1

Lithuanian	1	0
Croatian	1	0
German	1	0
Cypriot	0	1
Moroccan	0	1
Spanish	0	1
Jamaican	0	1
Egyptian	0	1
Sri Lankan	0	1
Asian - other	0	1

Note. 40 participants took part in Experiment 1 using the categorical model, and 54 participants took part in Experiment 2 using the dimensional model.

Appendix C

List of Stimuli Used in Two Listening Experiments

Artist	**Song title**	**Emotion tag**
Mary J. Blige	Be Happy	Happy
The Busters	Skank Down	Happy
Muse	Starlight	Happy
Die Happy	Cry For More	Happy
Toploader	Dancing In The Moonlight	Happy
Louis Armstrong	Hello Dolly	Happy
Kakkmaddafakka	Restless	Happy
Al Green	Nothing Impossible With Love	Happy
Passion Pit	Make Light	Happy
Die Happy	Genuine Venus	Happy
Sunparlour Players	If The Creeks Don't Rise	Happy
Ezio	Steal Away	Happy
Dragonette	Get Lucky	Happy
Die Happy	Supersonic Speed	Happy
Uner	Labaneria	Happy
13th Floor Elevators	I'm Gonna Love You Too	Happy
Amy Winehouse	Valerie	Happy
MGMT	Kids	Happy
Hymns	St. Sebastian	Happy
The Go! Team	Ladyflash	Happy
Die Toten Hosen	Böser Wolf	Sad
James Taylor	Fire And Rain (LP Version)	Sad
Iliketrains	Death Is The End	Sad
TLC	Unpretty	Sad
In This Moment	World In Flames	Sad
Die Toten Hosen	Was Zählt	Sad
Santana Feat. Steven Tyler	Just Feel Better	Sad
Avantasia	Inside	Sad
The Veronicas	Heavily Broken (Live Version)	Sad

Wu-Tang Clan	Josephine	Sad
Fleetwood Mac	Dreams (LP Version)	Sad
Paul McCartney	Here Today	Sad
Tsunami	Fits And Starts	Sad
HIM	Love's Requiem	Sad
Birdy	Skinny Love	Sad
54.4	One Gun (Album Version)	Sad
The Secret Show	Old Blacktop	Sad
Richard Youngs	Broke Up By Night	Sad
Giorgia	Gocce Di Memoria	Sad
Shania Twain	It Only Hurts When I'm Breathing	Sad
Tok Tok Tok	Walk On The Wild Side	Relaxed
ATB	Mysterious Skies	Relaxed
Blur	Sweet Song	Relaxed
Carbon Based Lifeforms	Mos 6581	Relaxed
Kay Kyser	On A Slow Boat To China	Relaxed
The Mahotella Queens	Mbube	Relaxed
Chicane	Halcyon	Relaxed
Nightmares on Wax	The Sweetest	Relaxed
Future Sound of London	Papua New Guinea (12" Version)	Relaxed
Zwan	Honestly (Album Version)	Relaxed
Scorpions	Destiny	Relaxed
Seven Foot Wave	In The Ocean	Relaxed
Planet Funk	Chase The Sun	Relaxed
Free Planet Radio	Dhijaz	Relaxed
Mia Moi Todd	Digital	Relaxed
Bohren & Der Club of Gore	Karin	Relaxed
Tori Amos	Crucify (LP Version)	Relaxed
Joe Satriani	Come On Baby	Relaxed
Red Hot Chili Peppers	Tell Me Baby	Relaxed
Stephan Micus	Flowers In Chaos	Relaxed
Manic Street Preachers	Motown Junk	Angry
Wumpscut	Bunkertor 7 (German Texture)	Angry
Dido	Stan	Angry
Metric	Hustle Rose	Angry
Natalie Imbruglia	Want	Angry
Hole	Violet	Angry
Fear Factory	Edgecrusher (Urban Assault Mix)	Angry
Incubus	Blood On The Ground	Angry
Soulfly	Arise Again (Album Version)	Angry
Three Days Grace	I Hate Everything About You	Angry
The Distillers	Drain The Blood	Angry
Skinny Puppy	Anger	Angry
Savage Garden	Gunning Down Romance	Angry

Skinny Puppy	Scrapyard	Angry
Vanessa Carlton	Paint It Black	Angry
Kittie	Pain (Live Version)	Angry
Rilo Kiley	A Better Son/Daughter	Angry
Texas	Summer Son	Angry
4LYN	Incomplete	Angry
Stone Sour	Cold Reader	Angry

Appendix D

Activities Involving with Music Listening and Its Purposes

Activity	No.	Purposes	No.
Commuting/travelling (walking, tube, driving)	22	Relax	12
Exercising (gym)	20	Engage	2
Studying	13	Keep me awake	1
Dancing (club)	11	Motivate	1
Party	11	Synonym to music	1
Working	5	Feel excited	1
Sleeping	4	Help focus	1
Cooking	4	Make atmosphere	1
Chatting/talking with friends	4	Keep me company	1
Concerts/watching band	4	Feel happy	1
Surfing the Internet	3	Relax my brain	1
Reading	3		
Housework	3		
Eating	2		
Socialising	1		
Background	1		
Practicing instrument	1		
Making music	1		
Music research	1		
Mechanical work	1		
Sitting/waiting	1		
Dressing up	1		
Copying something	1		

Appendix E

Participant-Suggested Musical Emotion Excerpts

TABLE E.1
Examples for Induced Emotions.

Induced happiness		
Song title	**Artist**	**7Digital ID**
Baby	Justin Bieber	8497961
Best Of Me	Daniel Powter	19224050
Bouncing Off The Walls	Sugarcult	1170077
Call Me Maybe	Carly Rae Jepsen	18168224
Can Can	Bad Manners	7838548
Hall Of Fame	The Script	20177493
Heatwave	Wiley	19817103
I Got Rhythm	Yellowjackets	8440233
I Will Survive	Gloria Gaynor	11803402
Io Ho Mente In Te	Equipe 84	7543547
Kids	MGMT	3121833
KV 500 (Variation In B Flat)	Mozart	Amazon
Leaving On A Jet Plane	John Denver	14755986
Let It Go	Disney's Frozen	35008452
Love On Top	Beyoncè	29519839
On Fire	JJ Grey & Mofro	29616857
Play That Funky Music	Wild Cherry	3861425
Pork And Beans	Weezer	2991824
Pushing Onwards	Souleye	Amazon
Ran Kan Kan	Tito Puente	Amazon
Send Me On My Way	Rusted Root	4761642
Shake Your Coconuts	Junior Senior	3749465
She's A Rainbow	Rolling Stones	5119358
Sin Sin Sin	Robbie Williams	208646
Singin' In The Rain	Fred Astaire	9228217
Sometimes	Britney Spears	3379867

Strawberry Avalanche	Owl City	18610747
Sunsets	Powderfinger	5883636
Superman	Eminem	148206
Take On Me	A-ha	10297895
Tie A Yellow Ribbon Round The Ole Oak Tree	Dawn ft. Tony Orlando	18874861
Valerie	Amy Winehouse	16516898
Venus	Shocking Blue	23133986
What Makes You Beautiful	One Direction	15071300
Induced sadness		
A Gentleman's Excuse Me	Fish	3738956
Adagio In G Minor	Albiononi	Amazon
Bound To You	Christina Aguilera	11336479
Dance With My Father	Luther Vandross	3109264
Do I Have To Cry For You	Nick Carter	11464657
Dutty Love	Don Omar	17783701
Fade To Black	Metallica	416979
Farewell	Rihanna	16296046
For My Demons	Katatonia	Amazon
Für Elise	Beethoven	12850803
Here With Me	Dido	3849131
Invitation To The Blues	Tom Waits	3329132
Knives Out	Radiohead	Amazon
Let It Be	The Beatles	8897200
Lonesome Tears	Beck	164295
Moonlight Sonata	Mozart	32248672
My Heart Will Go On	Celine Dion	3721208
Nightmare	Avenged Sevenfold	10211513
Op. 13 Second Movement	Beethoven	Amazon
Proserpina	Martha Wainwright	30754945
River Flows In You	Yiruma	16674542
Sad	Maroon 5	19224928
Skyfall	Adele	21292798
Small Bump	Ed Sheeran	14756592
Someone Like You	Adele	11811836
Street Spirit (Fade Out)	Radiohead	9189532
The Real Her	Drake	Amazon
The World's Greatest	R. Kelly	9512054
Vanilla Twilight	Owl City	14563118
Vigil	Jack Wall	Amazon
When You Are Gone	Avril Lavigne	4276116
Wise Up	Aimee Mann	5223083
Induced relaxedness		
2/2	Brian Eno	Amazon
Anaesthesia	Maximiliam Hecker	4691028

Autumnsong	Manic Street Preachers	15417411
Baby It's Fact	Hellogoodbye	3532574
Born At The Right Time	Paul Simon	9985930
Byzantine Meditation	Antaeus	1802474
Canon In D	Johann Pachelbel	30815309
Don't Know Why	Norah Jones	4674
Don't Worry Be Happy	Bob Marley	906788
Dreaming My Dreams	The Cranberries	21327085
Emptiness Unobstructed	Nevermore	9566043
Every Teardrop Is A Waterfall	Coldplay	15845931
Fast Car	Tracy Chapman	Amazon
Fireflies	Owl City	7741108
Hold Tight London	Chemical Brothers	24798
I'm Yours	Jason Mraz	2876291
Lemon Tree	Fool's Garden	301307
Moonlight In Vermont	Ahmad Jamal	147388
Op. 68 First Movement	Beethoven	19631008
Red Red Wine	UB40	17743984
Round About Midnight	Miles Davis	12868415
Rubycon	Tangerine Dream	314620
Sometimes You Can't Make It On Your Own	U2	4129855
Somewhere Over The Rainbow	Israel K.	10242698
Wish You Were Here	Pink Floyd	15462697
Yellow Submarine	The Beatles	34464587
You Are Beautiful	James Blunt	2019812
Induced anger		
21 Guns	Green Day	4857590
Bad Romance	Lady Gaga	6876721
Beat It	Michael Jackson	6930066
Behind These Hazel Eyes	Kelly Clarkson	3428703
Diamonds	Rihanna	21150379
Duality	Slipknot	1397970
Fallen Leaves	Billy Talent	560339
Fighter	Christina Aguilera	4455043
Girlfriend	Avril Lavigne	3531232
Going Under	Evanescence	6521474
HYFR (Hell Ya Fucking Right)	Drake	18006271
I Am Afraid Of Americans	Davie Bowie	1171627
Just For	Nickelback	Amazon
Numb	Linkin Park	449745
Op. 67 First Movement	Beethoven	13570602
Paint It Black	Rolling Stones	5119347
Paralyzed	The Used	Amazon
Revelate	The Frames	12992757

Rolling In The Deep	Adele	13971198
Russians	Sting	166510
Stronger	Kanye West	Amazon
Wait And Bleed	Slipknot	1138547
We Are Your Friends	Justice VS Simian	3983544
Wedding Nails	Porcupine Tree	Amazon
Where Is The Love?	Black Eyed Peas	157958
Whiplash	Metallica	416969
You Slip She Grip	Pitbull ft. Tego Calderon	4501741

Note. The same excerpt mentioned in both examples of induced and perceived emotion for the same emotion category are shown in bold.

TABLE E.2

Examples for Perceived Emotions.

Perceived happiness		
Ali Farka Tourè E Toumani Diabatè	Hawa Dolo	31704122
All I Wanna Do	Sheryl Crow	1819590
All My Life	K-Ci & JoJo	150172
Big Girls Don't Cry	Frankie Valli	629500
Call Me Maybe	Carly Rae Jepsen	18168224
El Gato López	Ska-P	3334210
Firework	Kate Perry	17914166
God Is A Girl	Groove Coverage	15068568
Good Day Sunshine	The Beatles	19250585
Hurts Like Heaven	Coldplay	15845914
I Am Very Glad, Because I'm Finally Returning Back Home	Edward Khil	Amazon
I Can See Clearly Now	Johnny Nash	5046318
LDN	Lily Allen	4127828
Live While We Are Young	One Direction	20493393
Love Me Do	The Beatles	Amazon
Mamma Mia	ABBA	2853693
Murder On The Dance Floor	Sophie Ellis-Bextor	167431
New York, New York	Frank Sinatra	8032564
Shake Your Coconuts	Junior Senior	3749465
Soak Up The Sun	Sheryl Crow	1819592
Strawberry Avalanche	Owl City	18610747

Super Bass	Nicki Minaj	13221333
Viva La Vida	Coldplay	3824449
Waka Waka	Shakira	9082714
Wannabe	Spice Girls	533840
We Love You	Rolling Stones	5119356
Yellow Submarine	The Beatles	12321385
Perceived sadness		
Another Day In Paradise	Phil Collins	435077
Apologize	One Republic	2012173
As Tears Go By	Rolling Stones	5119647
Bai Mei Gui	Eason Chan	Amazon
Bakana Hito	Miyavi	1195190
Beautiful	Christina Aguilera	Amazon
Better Than We Break	Maroon 5	2991757
Bound To You	Christina Aguilera	11336479
Death and All His Friends	Coldplay	3824455
Disappear	Dream Theater	3043537
Don't Let Me Be Misunderstood	Nina Simone	596747
Fireflies	Owl City	7741108
Fix You	Coldplay	118130
Goodbye My Lover	James Blunt	1401859
Heal The World	Michael Jackson	3125937
I Fell In Love With A Dead Boy	Antony And The Johnsons	Amazon
Infinito	Raf	601833
Let It Be	The Beatles	8348639
Love Song	Bigbang	18423822
Make Me Wanna Die	The Pretty Reckless	9261679
Mocking Bird	Eminem	16765926
Nothing Last Forever	Maroon 5	2991752
OP272 No. 14 First Movement	Beethoven	Amazon
Proserpina	Martha Wainwright	30754945
Pyramid Song	Radiohead	2748245
Requiem K. 626 Dies Irae	Mozart	13024931
Someone Like You	Adele	11811836
Street Spirit (Fade Out)	Radiohead	9189532
Wait For Me	Motopony	31531505

What If I Was Nothing	All That Remains	21660485
White Flag	Dido	3849172
Perceived relaxedness		
Bad Day	Daniel Powter	11723187
Born At The Right Time	Paul Simon	9985930
Boxes & Angel	Peter Rehberg	Amazon
Can You Feel The Love Tonight	Elton John	15427770
Canon In D	Johann Pachelbel	30815309
D667 First Movement	Schubert	Amazon
Drive My Soul	Lights	9250781
Eggplant	Michael Franks	16704656
Gymnopédies	Érik Satie	886879
Hotel California	Eagles	1337516
Inion Daughter	Afro Celt Sound System	Amazon
Island In The Sun	Weezer	11465191
Kingston Town	UB4O	1860190
Moon River	Andy Williams	6656511
Secrets	One Republic	7001801
Seduto In Riva Al Fosso	Ligabue	5258629
Stairway To Heaven	Led Zeppelin	1829855
Take Care	Rihanna And Drake	18006237
Teardrop	Massive Attack	8481
The Mystic's Dream	Loreena Mckennitt	3213441
The Sacrament	HIM	3537397
When You Say Nothing At All	Ronan Keating	16057
Perceived anger		
All My Life	Foo Fighters	6788004
Angel Of Death	Slayer	23923091
Beast And The Harlot	Avenged Sevenfold	395111
Bullet With Butterfly Wings	The Smashing Pumpkins	104225
Call Me When You're Sober	Evanescence	6521505
Empty Souls	Manic Street Preachers	13064844
Fighter	Christina Aguilera	4455043
Fucking Hostile	Pantera	684698
Killing In The Name	Rage Against The Machine	5971578
Man Down	Rihanna	11297428

Payphone	Maroon 5	19039176
Secrets	One Republic	7001801
The Show Must Go On	Queen	11618646
The Wall	Pink Floyd	2677176
Them Bones	Alice In Chains	11984791
Where Is The Love?	Black Eye Peas	157958
Your Treachery Will Die With You	Dying Fetus	6782257

Note. The same excerpt mentioned in both examples of induced and perceived emotion for the same emotion category are shown in bold.