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Socially Augmented Music Discovery with Collaborative Playlists and Mood Pictures

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This article describes the iterative design and user evaluation of a prototype, which enables collaborative music discovery by creating playlists and associating and expanding them with mood pictures. The concept was evaluated in two field trials by a total of 45 individual users, with both trials containing 30 users and 15 of the users attending both of the trials. The results from the two field trials are presented under three main themes: socially augmented music discovery, user-generated content enhancing music discovery and social usage patterns emerging from the usage of such a system. Users formed ways to facilitate social interaction and music discovery through the playlist content they shared. Social usage patterns reveal the social activities users performed with the service in the trials. The findings can be used as design implications for mood-based music service designers.

RESEARCH HIGHLIGHTS

- Results from the two field trials of social music discovery prototype use, both phases containing 30 users, 15 users participating in both phases of the study, thus the total amount of individual participants being 45.
- Description of the user evaluation findings of the service from the two study phases.
- Findings of user experience of socially augmented music discovery and user-generated content enhancing music discovery.
- Description of social usage patterns emerging from the usage of a music discovery system.
- The findings can be used as design implications for mood-based music service designers.

Keywords: Social music discovery; Social usage patterns; Playlists; Design; Social interaction; Music recommendation; User experience; Mood pictures

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1. INTRODUCTION

Music is one of the most enjoyed experiences regardless of age, gender or culture. Music can be used for various purposes such as general enjoyment, mood enhancement, sports, relaxation, and even therapy. There is a wide variety of different approaches to selecting music to listen to. Music selection can be highly focused on a specific song or artist, or it can be more exploratory without a clear goal in mind. Music subscription services have changed the way people search, play, and experience music. They provide the consumers with the ability to dynamically create and modify playlists in real time from vast online collections of music. Spotify (Spotify, 2016), as an example, is now present in a total of 58 markets with a song catalogue of over 30 million songs and over 1.5 billion playlists. As there is an almost endless selection of music available to consumers, the focus has now shifted from enabling instant access to massive music catalogues towards improving the music services' user experience. This has resulted in the emergence of music discovery services and recommendation systems that aim to provide new ways of finding relevant music from large catalogues, making music consumption a more enjoyable and serendipitous experience.

This work combines the fields of human–computer interaction (HCI), user experience (UX) and music information retrieval (MIR). The most commonly used approach in music discovery services today is collaborative filtering (Celma, 2008; Celma and Herrera, 2008). Collaborative filtering in the simplest form means recommending neighbours of a certain content item based on the calculated similarity. Although popular, collaborative filtering does not take into account any musical attributes of the songs but only relies on comparing user preferences in music listening, which heavily favours a small subset of the most popular songs. It also requires a large amount of listening history and transaction data to work properly. An alternative method of generating music recommendations is music signal analysis. This is based on algorithms that can be used to automatically process an entire catalogue of millions of songs and to recognize different characteristics of the songs, for example, the musical genre, the instruments, and the vocalist gender, as well as acoustical similarity between different songs. Music signal analysis is a powerful way of generating consistent metadata for a large catalogue of music, therefore avoiding potential gaps of missing or inconsistent metadata. It also avoids the cold-start problem, as it does not require any existing listening history data to function.

The work followed a design research approach (Hevner *et al.*, 2004), which usually includes building prototypes and evaluating them. Design research approach was selected to understand rather new way of social music discovery, and it was followed by studying the design and evaluation of a concept that enables creating musical playlists and associating them with mood pictures and thus collaboratively creating new mood-based playlists. The research goal was to provide insights and design implications for collaborative music discovery. Design research approach was natural choice to collect data on the social usage patterns that users form with the system. The implemented MoodPic prototypes were evaluated by 45 individual Finnish participants in two field trials. The set of features presented in the first and second prototype and two user trials of the prototypes are introduced in this paper. Lehtiniemi and Ojala (2013) described the applicability of using mood pictures for music discovery and the first prototype of MoodPic. The research involved three aspects of interaction design: understanding the users, prototype design and evaluation (Jones and Marsden, 2006). Based on the findings of the two trials, the design implications and social usage patterns were consolidated. Sorting music based on mood pictures instead of genres was found to be a natural way to classify and find music good, especially for the novice and inexperienced users. Based on the interview results, this paper proposes an extensive set of design criteria and further development ideas to take into account when designing music prototypes for new music discovery.

Associations of the songs to the mood pictures and the visual design of the mood pictures are out of scope of this paper. These aspects of using mood pictures for music discovery are presented in the Lehtiniemi *et al.* (2016). Lehtiniemi et al.'s work describes the iterative design of a set of mood pictures and results of the association tests with the users. Work also describes the iterative design of MoodPic and how users perceived the development between the two versions. This paper describes two trials of MoodPic, focusing on the design of social features and the social usage patterns that emerged in the trials. The contributing results of this work are divided into three themes: (1) socially augmented music discovery, (2) user-generated content enhancing music discovery and (3) the social usage patterns.

2. RELATED WORK

Currently, music listeners have more online music within their reach than ever. Portable music players allow the user to maintain a large collection of digital music files in a device that fits into a pocket (Reddy and Mascia, 2006). Smart Q3 phones include comprehensive music player functionality in addition to an Internet connection that allows users to discover music outside their own digital collection. Services that allow music streaming from their collections have grown in number. As services to purchase digital music have become a "status quo", users are transferring to personal collections of digital music (Sease and McDonald, 2009). A similar digitalization paradigm shift occurs amongst hobbyists as well as professionals (Ahmed *et al.*, 2012). As such an unlimited amount of music is reachable, and the prominent question seems to be: how can users retrieve the content they want easily? Music information retrieval (MIR) is a field of research that studies music categorization and retrieval methods (Casey *et al.*, 2008). The focus of many current music-related HCI and especially MIR studies is how to create easy and pleasurable solutions that easily offer music to the listeners.

2.1. Moods for music discovery

Genres are widely used as a classification method in the online music services. However, the harsh genre categorization seems to differ from the habits of how users classify their own collections. The variety of genres seems to be too limited within the services where they are created by the designers, and some classifications are even unusable for users since common listeners may not be aware of them (Vignoli, 2004).

Music listening may evoke strong emotions in people and can have an effect on their mood, facial expressions and physiological reactions (Juslin and Sloboda, 2001). As a consequence of its effectiveness, music is used for mood enhancement in many applications including sports, TV, relaxation, movies, and therapy. Virtually every brain region mapped by cognitive neuroscientists is activated by music. Music has access to regions involved in, for example, planning, motivation, forming expectations, memory, association, and attentional systems (Levitin, 2007). In addition to mental activity, music can have other physiological effects on a person including sweating, respiration, and changes in heart rate (Levitin, 2007). Most people are able to select the right type of music for their emotional goals, e.g., "people in a state of unpleasantly high arousal (for example, while driving in heavy traffic) generally prefer quiet, relaxing music, while people who are in a state of pleasantly high arousal (for example, exercising, working out) will prefer loud, energizing music" (Levitin, 2007). As music can play such a significant role in evoking, expressing, and communicating emotions in both listeners and performers (Juslin and Sloboda, 2001), it is natural for people to also categorize music based on emotions or moods.

Juslin and Sloboda (2001) describe the main differences between emotions and moods. Emotions last for a short while, have an identifiable stimulus and are complemented with distinct facial expressions. Moods may be experienced for a long period of time and cannot be directly expressed by a person. Any specific object or situation does not create a mood in a person. These terms are commonly mixed in MIR literature, as both moods and emotions are used for music categorization and discovery. Whereas emotions may have a clear focus and moods are more unfocused and have a longer duration, both are affective states that affect behaviour (Batson *et al.*, 1992; Blechman, 1990). Even there are differences in the intensity and arousal levels of moods and emotions, we see potential in simplifying both emotions and moods as one classifier of music. This is commonly used approach in MIR studies and solutions.

In MIR systems, emotions and moods are commonly classified using categorical or dimensional approaches, which have roots in psychological research. It remains a challenging problem to find a perfect set of emotion labels to be used as a base set for applications and algorithms (Kim *et al.*, 2010). A study by Skowronek *et al.* (2006) pursues a base data set by evaluating 470 music clips from 12 genres with nine bipolar mood scales. The results show only half of the clips receive strong judgements for the moods meaning that only half of the clips were easy to judge. Juslin and Sloboda (2001) explain the concept of basic emotions as "there is a limited number of innate and universal emotion categories from which all other emotional states can be derived". There is a big variation in different emotional categories depending on the case used and the application area. Ekman (2004) proposed six emotions including anger, disgust, fear, joy/happiness, sadness, and surprise. These basic categories are universally recognized. The number of emotional categories tends to be higher in automatic mood classification than in most psychological research (Ekman, 2004), although there are exceptions, such as a study by Zentner *et al.* (2008) with a significant number of mood classes.

Social tags of songs are commonly interpreted as determining different emotional categories as presented in, for example, Hu (2009). The later work by Hu (2010) extends Q4 the number of mood categories to 18, containing, in total, 135 mood tags. The All Music Guide (1991) features 179 distinct mood labels. However, the labels are partially related. In most of the music discovery services that are targeted at users, the number of mood labels is typically smaller. Music metadata or tags can be added to musical files in three ways: direct human annotation, indirect human annotation and content-based automated analysis (Kim *et al.*, 2010). The musical attributes described by the metadata can be added by the users or user communities, which is similar to collaborative filtering (Last.fm, 2016), by content-based and automatic signal detection and categorization (Dunker *et al.*, 2008), or by adding metadata or other additional information such as lyrics of the songs to the calculation (Hu, 2009; Hu and Downie, 2010).

An alternative way of modelling emotions focuses on "identifying emotions based on their placements on a small number of dimensions, such as valence, activity, and potency" (Juslin and Sloboda, 2001). The most commonly used dimensional scales for emotion are by Russell (1980) and Thayer (1989). Russell's circumplex model (Fig. 1) maps the *x*-axis to valence (pleasantness) and the *y*-axis to activation (arousal). The model is built in such a way that opposite emotions face each other.

Both moods and emotions are affective states that differ in the duration and depth (Batson *et al.*, 1992; Blechman, 1990). As Juslin and Sloboda (2001) point out: "[moods] denote such affective states that that are lower in intensity than emotions, that do not have clear "object" and that are much longer

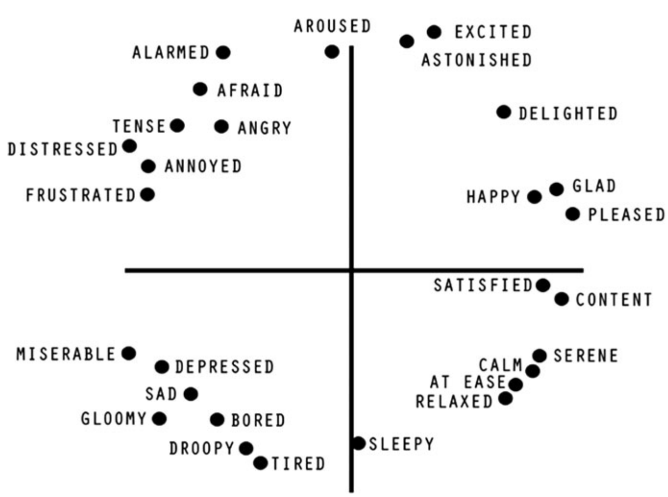

Figure 1. Russell's circumplex model of emotions. Adapted from Russell (1980).

lasting than emotions". Moods are more unfocused and do not have clear target or affect, which in some cases makes it easier to visually target towards emotions. Moods are more widely used as a term in MIR field and it was also decided to be used in the concept name of MoodPic. However, in the MoodPic categorization, the users are not required to make the effort of deciding if the visual cues in the system are moods or emotions. In the design of MoodPic, we conceptually condensed emotions and moods into the eight mood pictures.

Valence and arousal axes are also used in design of Emocards (Desmet *et al.*, 2001). Emocards are used for measuring emotional aspects in products in Desmet and others' work (Desmet *et al.*, 2001). Emocards are an example of a tool, where users select the moods that they relate to the product. However, automatic mood recognition using different sensors is a difficult task, and different measurement options are discussed in Desmet (2003). In MIR systems, the user typically selects the mood with specific user interface elements. These elements include, for example, buttons, emoticons, textual labels, or an interactive emotional space. Based on the user selection, the system commonly compares it with a database of mood metadata and returns a set of the best matching music.

2.2. Music discovery applications using moods and emotions

Musicovery (2011) is a music discovery application roughly following Thayer's model (Kim *et al.*, 2008), where the user can select music according to mood, artists, tags, and genre. The mood can be selected by clicking on an x–y space, where the y-axis has been mapped to energetic/calm music and the x-axis to dark/positive music. The mapping is automatic and does not require any effort from the user. When the user moves the cursor over the x–y space, preview clips of songs are played. When the user makes a selection, a playlist is automatically compiled and the user is able to change the playlist contents by changing decades and genres in a separate view. The changes are applied to the x–y space visualization. In addition to 2D spaces, moods and emotions have been visualized in various ways including discs, colour maps, icons, and vertical bars (Kim *et al.*, 2009), and also emoticons, and tag clouds.

TheSixtyOne (2008) focuses on full-screen album art and lets the user browse through popular and recent songs. The service also categorizes music based on moods (mellow, party, happy, trippy, crazy, smooth, sad, rocky, love, funny, remix, and covers). One special feature in the application is that while listening to a song and looking at the full-screen album cover, artists' comments and small facts appear on the screen. Songza (2007) combines mood and taste for music categorization and asks users questions while they are listening to music to learn more about when certain types of music are consumed. The service features user-curated playlists to match each mood and taste combination. Recently, Songza has included weather channel data as a new attribute for mood suggestions (Songza, 2007).

With the Moodagent (2001) application, the user is able to adjust the balance between five mood bars: sensual, tender, joy, aggressive, and tempo. The resulting playlist is automatically generated based on the mood bar balance. StereoMood (2012) represents mood tags with associated pictures with the user being able to make a selection for instant playback of music. StereoMood does not support collaboratively created playlists or associations with mood pictures. Approaches featuring colours representing moods include, e.g., the Colour Player application (Voong and Beale, 2007) which contains a manual assignment of coloured tracks based on their mood. Associating colours with musical genres has also been studied by Holm *et al.* (2009) and Julia and Jorda (2009).

Moody is a playlist generator, where users can create playlists for iTunes using moods (Moody, 2012). The iTunes music library can be manually tagged using a visual approach. The user can select the mood along axes representing happiness and intensity of the song and the selection grid is also colour-coded. There are also services to automatically retrieve compatible mood data for songs without the user having to categorize them manually. When the music library has been tagged the user is able to create new mood-based playlists by clicking the corresponding part of the screen. In Musicream colour represents the mood of the song in a way that songs with a similar mood are presented with the same colour in the prototype (Goto M. and Goto T, 2005; Kim *et al.*, 2009).

Using animated mood pictures in music recommendation is described in a previous work by Lehtiniemi and Holm (2012). Associating mood pictures with music has been studied by Holm *et al.* (2010). Automatically generating playlists (Lehtiniemi and Holm, 2011) and using mood pictures and collaborative playlists (Lehtiniemi and Holm, 2012; Lehtiniemi and Ojala, 2013) has been studied previously. The results show that accessing music through mood pictures is highly appreciated and is seen as a good way to discover music by the users. Earlier work has also described the design and user evaluation of the first version of MoodPic (Lehtiniemi and Ojala, 2013), and the visual design of mood pictures and associating songs to the pictures has been studied by Lehtiniemi *et al.* (2016). This work extends the research on using the mood pictures by revealing the activities with the user-generated playlists and the social usage patterns that occurred when users were using MoodPic to discover music together in the trials.

In the design of MoodPic, preset collection of moods and emotions were used. In the first prototype version, there were five mood pictures and in the second prototype the selection was expanded to eight mood pictures.

2.3. Retrieving and Discovering Musical Content

Genre classifications are widely used as a tool for categorizing music collections and for retrieval options for the music files (Kim and Belkin, 2002). However, genre classifications require some knowledge and experience of different music styles and they may not be the most intuitive way of classifying and searching for music. MIR studies offer some possible solutions for genre-based classifications. For example, automatically detecting the possible genre from the audio content (Kim *et al.*, 2010) or moods related to genres (Eerola, 2012). However, the whole idea of using genres as a music classificatory seems a bit outdated and its value has been questioned in current studies (McKay and Fujinaga, 2006). Instead of using "search terms" or genres in the process, more interactive and fun ways to discover new music are needed.

The problem with local digital music collections is the lack of dynamic content; besides the shuffle option and manual playlist composition, the library that is stored on the device stays the same and is played back in a similar way every time. The element of surprise is lacking. The current design trend uses the online connection and music streaming in order to expand the collection and bring variety to the user's local library. Some services even discard the idea of a local music library in the first place. A model of "satisficing" in media retrieval has been introduced by (Bentley *et al.*, 2006). People have an undefined need to listen to music but may not have a certain song or artist in mind. They choose a random set of songs and while listening change their minds, get bored, and skip songs (Bentley *et al.*, 2006). Eventually they "satisfice" by listening to music that matches their preferences well enough. The basic idea of "information need" does not fit well with music retrieval in most cases and novel solutions for combining the searching and browsing habits of the users are needed (Cunningham *et al.*, 2003). Retrieving content from users' own collections differs from retrieving content from services. The user has categorized/organized the music in their collection based on their own view, whereas music in different services is collaboratively categorized or categorized by the designers. A modern approach of recommending can rely on serendipity (Iaquinta *et al.*, 2008; Zhang *et al.*, 2012) on offering surprising recommendations. Serendipitous recommendations offer solution to "filter bubble" (Pariser, 2011), of never gaining recommendations from different genres. Serendipitous recommendations as a term means discovering content that user has a low chance of discovering autonomously, instead of recommending the close matches, that recommender systems usually compute based on similar artists or songs.

In a study by Brown *et al.* (2001) pleasurable digital music discovery was compared to the physical shopping experience of new music. Finding music that is new to the listener, namely music discovery was described in (Cunningham *et al.*, 2007), where encounters with new music were categorized into active and passive, depending on whether the users were purposefully trying to find new music. In this study, 62.3 % of all the encounters with new music were subjectively rated as positive experiences. The music lifecycle model that is introduced in a study by Brown and others (2001) gives six main phases in the music life cycle: finding out about music, copying and compiling, buying music, listening to music, choosing and organizing music, and collecting music. Similarly, in a work by Lehikoinen *et al.* (2007) a GEMS-model of personal content is introduced. GEMS consists of getting, enjoying, maintaining, and sharing. Arguably, managing personal music collections is not a novel paradigm, since many services allow online streaming. The need for local music collection is not relevant whenever a reasonable internet connection is available.

2.4. Social User Experience in Music Services

The social dimension of the user experience remains a less studied area as does social music discovery and related user experiences in online music services. A classical way to identify the factors that create the user experience is using Hassenzahl's (2003; 2008) pragmatic and hedonic division. Hassenzahl has identified that factors such as functionality, content, presentation, and interaction in combination create the user experience.

The social dimension of user experience has been brought up in a work by Battarbee (2004). Battarbee terms the social side of user experience "co-experience". A work by Väänänen-Vainio-Mattila and others (2010) opens the field of social user experience by introducing drivers and hindrances identified from a trial study of three social networking services (SNS). Self-expression, reciprocity, curiosity, and learning were stated as the most important drivers. Hindrances that were mentioned as mostly being negative factors in the experience were the suitability of content and functionality, completeness of user networks, as well as trust and privacy. On the positive side, the most important hedonic factors were self-expression, reciprocity, and curiosity.

A well-known challenge for services which are based on user-generated content is the uneven number of consumers and content creators (Lehtiniemi and Ojala, 2012). This seems to apply to the online music services, where users' roles as consumers and creators of content in digital music sharing are often mixed. In self-determination theory, Ryan and Deci (2000) introduce the categories of autonomy, relatedness, and competence as the bottom motivators. In other theories of motivation, intrinsic and extrinsic motivations have been separated from each other; extrinsic motivation refers to motivation that comes from external rewards and sanctions, whereas intrinsic motivation comes from inside an individual, from the pleasure of doing something, and satisfying the need for relatedness (Reeve, 2001). In particular, social rewards such as a good reputation, social status, and commitment and loyalty to the group seem to motivate users to contribute and create content (Blanchard and Markus, 2002; Tedjamulia *et al.*, 2005). Similar motivational structures can drive contributions in online music services.

2.5. Social Music Discovery

Music discovery in the social media services can rely on social navigation, collaborative filtering, and direct user recommendations as an addition to the automatic recommendations. Social music discovery is a term used in this work to describe the habit of collaboratively discovering new music. Social navigation means navigation towards where a cluster of people have looked, or in the case of online services towards content that others were interested in Dieberger (1997).

Peer-to-peer sharing of music was an extremely popular phenomenon, especially in the early 2000s. Services such as Napster, Kazaa and Gnutella offered ways to share files anonymously. These services have gained a controversial reputation because copyrights are ignored in some cases when the music is copied. The anonymity of sharers is a common thing in these peer-to-peer services, but on the other hand, the whole phenomenon relies heavily on the user communities. The development of the peer-to-peer services, however, created a community atmosphere and also a commercial solution that relied on music recommending and sharing.

Using social navigation in music services is proven to be effective, as Last.fm and similar services show. Social navigation can easily visualize the playlists and tracks that are most popular in the system. However, social navigation has a tendency to collect the user traffic of playlists that have already become popular, thus leaving the playlists with significant but lower traffic due to popularity. The surprise element and experience of discovering actual new music may not occur. An interesting finding was discovered in an "adaptive radio" study, where users' different tastes made adaptive radio play repetitive and conservative music selections, as it tried to please everyone (Chao *et al.*, 2005). UbiRockMachine (Kukka *et al.*, 2009) is an example mobile solution for urban and collaborative music consumption, where users are able to collaboratively select the music that is played in public locations. A problem of collaborative filtering is unwanted averages (Chao *et al.*, 2005). In addition, people want the extremes.

Collaborative filtering-based systems often rely on crowdsourcing the user base in order to collect the information from which the data is aggregated. For example, Kim *et al.* (2010) have introduced the Moodswings application thauup t aims to collect the collaboratively filtered data of moods in different music pieces by crowdsourcing people. Moodswings (Kim *et al.*, 2010), offers a motivating gaming solution where users compete with each other by linking moods to played music. As a more intuitive way to classify music, collaborative filtering and adding tags to music has been a method to add "folksonomy", subjective ratings, and intuitiveness to the classifications. However, describing musical pieces with words poses certain problems. Kim and Belkin (2002) asked users with no musical background to give vocal descriptions of the musical pieces that were played to them. In the study, the users gave optimal search phrases that they would use for retrieving these songs (Kim and Belkin, 2002).

As it is suggested personal preferences are one of the most important factors—if not the most important—subjective music associations should be taken into account. A study by Rentfrow and Gosling (2003) has identified relationships between the personality features of the users and their tendency to forecast what kind of music they prefer. For many people finding currently unknown music is a main motivator in using recommendation services online. Even though many services that support music discovery exist nowadays, many users still rely on traditional radio to find new music (Komulainen *et al.*, 2010). Mobile music listening and music discovery through mobile is a relatively old, but still growing phenomenon (Komulainen, 2012, Voida *et al.*, 2005). Q5

Despite there is a large amount of research specializing on various methods of discovering music, such as content-based MIR (Casey *et al.*, 2008; Dunker *et al.*, 2008) recommendations (Celma and Herrera, 2008; Vignoli, 2004), collaborative filtering (Dieberger, 1997; Kim *et al.*, 2010), serendipitous recommendations (Iaquinta *et al.*, 2008; Zhang *et al.*, 2012) and socially selecting and listening music (Chao *et al.*, 2005; Kukka *et al.*, 2009; Sease and MacDonald, 2009), research on socially augmenting the music discovery remains less studied. Moods and emotions on music discovery and classifications have been also studied (Kim and Belkin, 2002; Lehtiniemi and Holm, 2012; Skowronek *et al.*, 2006). Our work describes a novel implementation on the field of socially augmented music discovery and its user evaluation findings, which are further drawn into design implications. Social usage patterns that occurred during the use are presented. Social usage patterns can be used as design drivers in helping to drive design to support those practices.

3. DESIGN RATIONALE OF MOODPIC

The implemented web-based prototypes aim to support users in discovering and listening to music that matches their mood or a preferred mood. The prototypes help users to discover new music based on a collaborative playlist creation through mood pictures. MoodPic lets users create and listen to playlists that try to match the mood of a representative picture.

The prototype design is based on the idea of thinking beyond the commonly used genre classification of music. Instead of genres, MoodPic uses a preset set of mood pictures and users are able to add a cover mood picture to their playlists. The users are able to freely interpret the mood pictures and their meaning for music association and discovery because of the highly visual system design. The approach of using visual cues instead of words to describe the content is similar to the Moodboards method (Lucero, 2012), where the consensus of a design team is reached by a selected set of visual cues, instead of text descriptions. MoodPic is different from many other music services, e.g. StereoMood (2012) because of its focus on building collaborative playlists based on mood pictures and providing user-generated song recommendations. The prototype aims to add means for richer storytelling with a playlist and a mood picture associated to it. Similarly, as in Moodboards (Lucero, 2012), the consensus of the visual appearance of the product between design collaborators can be reached by using visual cues instead of word descriptions. In MoodPic collaborators are sharing the mood picture as a visual cue of the wanted content for the collaborative playlist. Mood categorization in TheSixtyOne (2008) was studied in the early stage of MoodPic design to inform the design of the preset mood pictures.

3.1. The First MoodPic prototype

After a successful login, a landing page is displayed (Fig. 2). The user is able to pin favourite or frequently used playlists to the landing page for direct access to preferred music. Each page in the system includes navigation links to other main features in the header row.

When using the system for the first time, five preset mood pictures are pinned to the landing page for quick access to different types of music (Fig. 2). The purpose of the initial preset mood pictures is to give the users an example regarding what type of images could be used in the system to represent different moods and enable a one-click access to a variety of music. These preset mood pictures were designed to visualize five emotions or moods: angry, happy, party, relaxed and sad (Fig. 3). The moods were selected in a way that there is, at least, one mood picture that relates to emotion from each section of Russell's circumplex model of emotions (Russell, 1980). In order to keep the design simple and avoid hierarchical organizing of playlists, the moods and emotions were simplified to preset mood pictures, which were presented to the users in the service without any textual cues. Using the simplified visual approach has promising results as work by Lehtiniemi *et al.* (2016) suggests. Preset mood pictures were mapped to the Russel circumplex's emotions (Russell, 1980), as described in the related work section.

In the playlist gallery (Fig. 3), the user is able to see all of the available playlists divided into preset mood picture playlists and user-generated playlists. Hovering over a playlist an enlarged version of the picture is automatically displayed.

The trial results from the first prototype show that the users wanted to know more details regarding the songs associated with the playlists without selecting the playlist for listening. The users were looking for ways to know a bit more about the playlist contents without having to listen to the whole list. It was said that some of the user-generated mood pictures were a bit difficult to interpret and it was slightly unclear with some pictures what type of music to anticipate.

Selecting a mood picture from the gallery opens a playlist view (Fig. 4) and the music from the associated playlist starts playing immediately. The selected mood picture is displayed as a full-size background image to emphasize the mood in the playlist view.

The automatic playback of the playlist was criticized by the users. In the current implementation leaving the playlist page stopped the music playback and the users were not able to browse through other content in the service while listening to a playlist. This was criticized by most of the users.

The playlist includes a list of all collaboratively added songs for the current mood picture. There is another tab for the playlist, which shows only the songs that the current user has associated with and added to the playlist. The current playlist can be added as a favourite or pinned to (or removed from) the landing page for quick access. New songs can be associated with any mood picture by any user in the system from the internal music catalogue or by uploading a new song

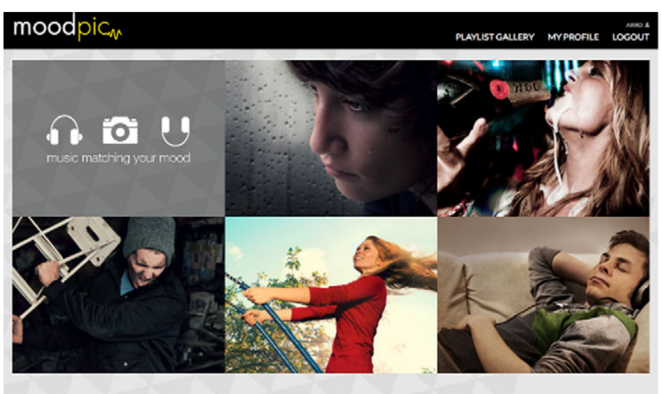

Figure 2. A landing page of the MoodPic service.

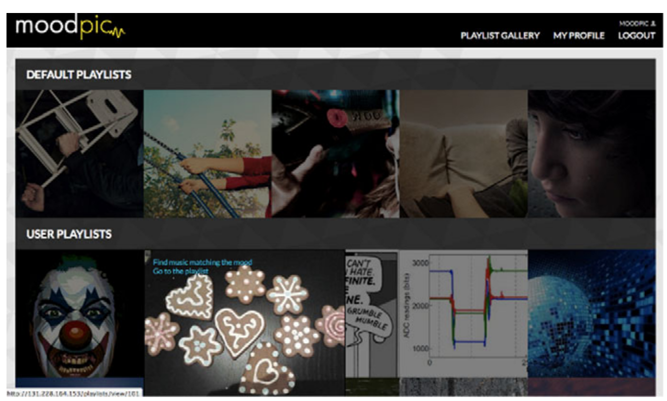

Figure 3. The gallery of preset and user-generated mood playlists.

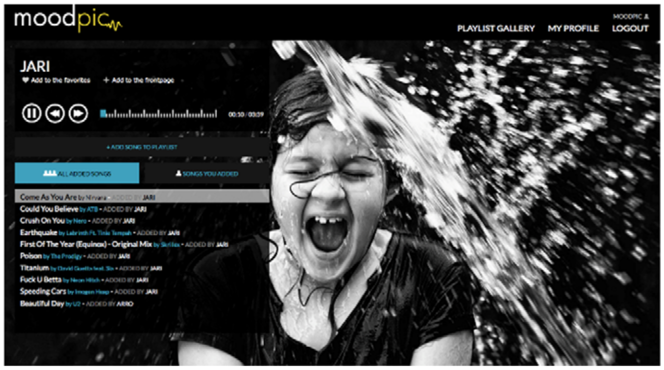

Figure 4. A playlist view of a selected mood.

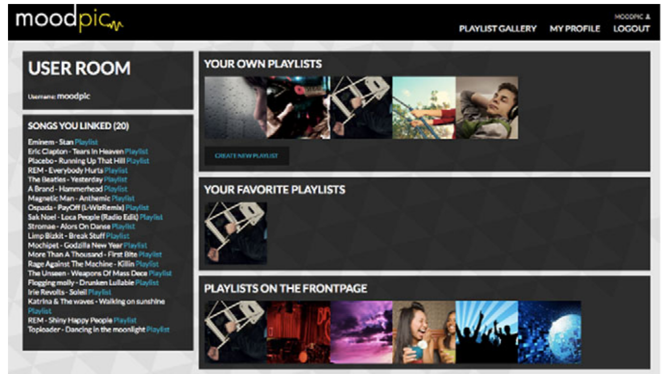

Figure 5. The user room for playlist management and recommended songs.

to the system from a user's local music library. The internal music catalogue includes different sorting and search features in addition to the ability to preview the songs. The song additions are displayed on the playlist followed by the username of the contributor e.g. "ADDED BY Paula".

Collaborative playlist creation encourages iteration of the playlist content over time and the creation of new playlists for the system. Users are able to interact within the system through new mood picture additions that work as a basis for new playlists and by adding music recommendation to existing playlists in the system i.e. adding new tracks to the playlists. Collaborative playlist creation was praised for its simplicity and novel experiences for music discovery by the users attending the interviews.

Many users were requesting ways to adjust the privacy for selected playlists in the system. The comments were mainly regarding being able to delete unsuitable song additions and making specific playlists only editable by the owner and a specific closed group. Some users were worried that the collaborative playlist creation could eventually result in many unwanted tracks on the playlists. Automatic recommendation of related mood playlists was brought up in the discussions in terms of not having to always make new selections from the playlist gallery when already listening to a preferred playlist.

Social interaction possibilities in the prototype are limited in this first implementation in a way that it encouraged users to interact through the music and playlists. The prototype intentionally does not include user manuals or other online documentation, in order to test how intuitive the proposed concept is to the users. The design is graphically oriented and the mood pictures do not contain any names in order that they are freely interpreted by the users. Free interpretation of the visual cues without textual descriptions gave positive on the Moodboards work to drive design (Lucero, 2012). That encouraged to use similar visual associations in MoodPic design. Many users commented that there could be more music related social interaction in the system to enhance the music discovery. They still wanted to keep the system specific to music and not compete with other social networking services.

User room (My Profile) is a place to manage playlists in the system (Fig. 5). Users are able to see their own playlists and create new playlists i.e. by uploading a new picture to the system as a basis for song additions and music recommendations. Additionally, deletion of own playlists can be done from the user room. Favourite playlists and landing page playlist content can be modified from this page as well. Information on recently recommended songs by the user is displayed with links to the corresponding playlists.

The users emphasized the possibility of seeing the user room—the type of profile information about other users in the system. It was said that having a way to see which of the users are active in the system would encourage other users to view more information about them and look at their recent playlist contributions. Seeing information regarding active users and their recent actions would make the system feel more reactive and lively.

3.2. Enhanced MoodPic Prototype based on User Trial Findings

Based on the findings of the first MoodPic prototype user evaluation, an enhanced prototype was created. The new prototype enhancements are introduced in this section and the user evaluation results for both of the prototype versions are described in the findings section.

The landing page of the new MoodPic prototype has an integrated music player in the header section. Integration enables users to always be able to see the player and it also enables music listening and using the basic playback controls while browsing through the service (Fig. 6).

The preset mood pictures were refined to the new version and the number was increased to eight based on user feedback. The new preset mood pictures illustrate (from top left to lower right, Fig. 6) eight emotions or moods: angry, energetic, happy, love, party, relaxed, sad and weird/unclassified. As mentioned before, these word descriptions are not visible

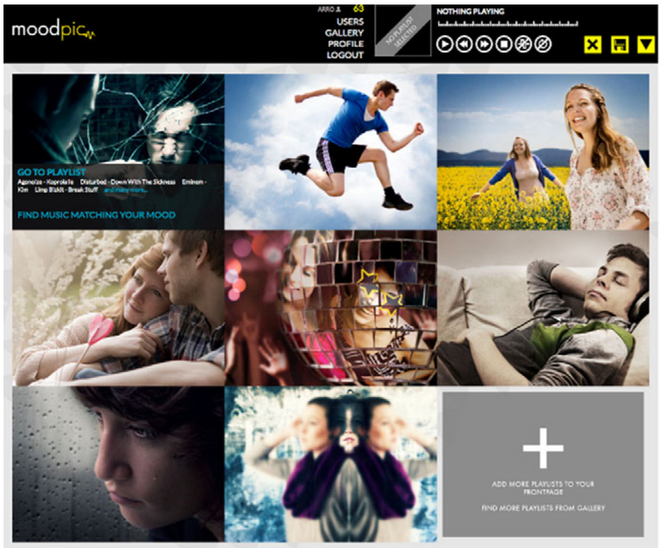

Figure 6. Enhanced landing page for MoodPic.

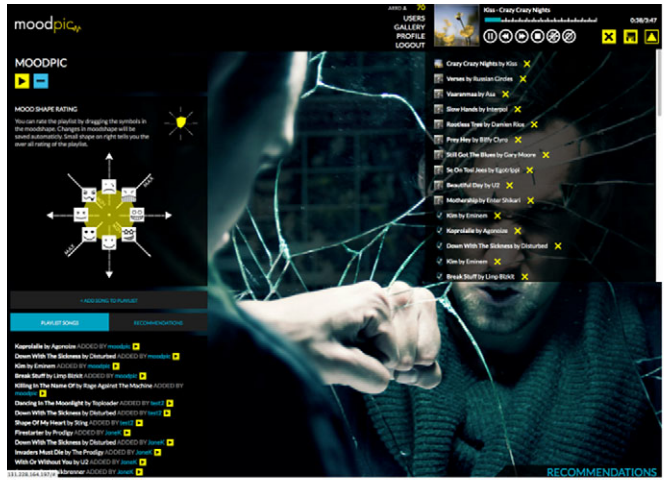

Figure 7. Playlist view of the enhanced MoodPic.

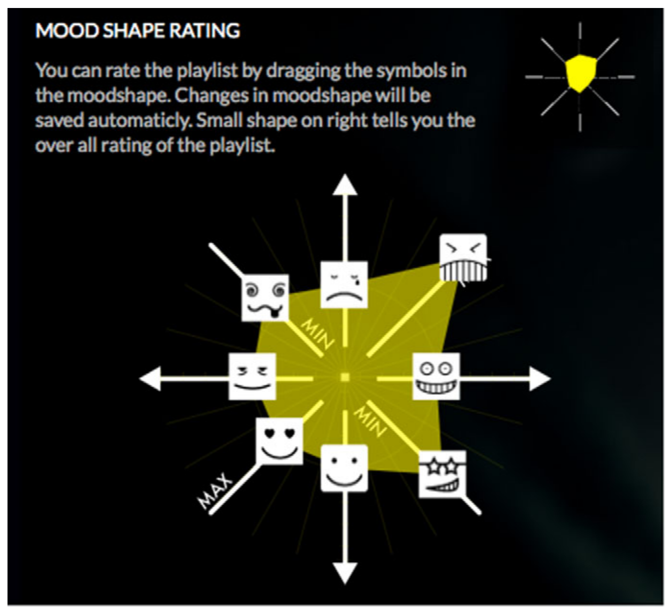

Figure 8. MoodShapes for playlist classification.

in the service and they are not given to the users in a text form so that users are able to make associations with the pictures freely. In the new implementation, users are able to see featured tracks from the playlists when hovering over the mood pictures as illustrated for the angry preset mood picture in Fig. 7. The new MoodPic features a scoring system for the users. Active usage and each action, e.g., recommending a song or creating a new mood playlist will increase the user activity score. Inactivity in the system will slowly decrease the score. The score is displayed in the header of each view next to the username.

The playlist view includes more significant changes to the original version (Fig. 7). Users are now able to play and remove individual songs directly from the playlist. The music player now includes a playlist queue where the user can add songs from different mood playlists or add full playlists to be played (visible in Fig. 7). The mood picture association with the tracks in the playlist queue is visualized with a small mood picture icon in front of the tracks. Users are able to remove tracks from the player queue. The whole playlist queue can be saved as a new mood playlist and a new picture can be associated with it.

The creator of the playlist will have an extra row above the playlist that can be used to set the privacy level of the playlist: public, shared and private. The privacy level describes who is able to directly add songs to the playlist. Song additions by other users will be shown in the recommendations tab. The recommendations are displayed on the recommendation tab followed by the username of the contributor e.g. “RECOMMENDED BY Paula”. The owner of the playlist can then approve selected recommendations to be visible on the actual playlist. Setting the playlist to public works as in the first prototype implementation, allowing everyone to add new songs to the playlist without moderation. Shared mode enables users that the playlist owner follows in the system to add songs directly to the playlist, and private will make all of the additions go through the owner’s moderation.

The most significant addition to the new MoodPic version is the introduction of a MoodShape concept (Fig. 8). The MoodShape allows users to classify the playlist contents by dragging the icons over the MoodShape.

The icons are made to represent the preset mood picture high-level moods. For example, if the playlist contains only angry songs, the user could drag the angry looking icon away from the centre (Fig. 8). The visual design of the emotion icons in the MoodShape is inspired by Emocards by Desmet

Figure 9. System generated recommendations.

and others (2001). MoodShape organizes the mood icons on a valence and arousal axes on a radar chart. Similar visual design of radar charts is used in a work by Nieminen (2015), where the radar charts are used for visualizing competencies of design teams. Many of the user-generated playlists tend to contain songs from slightly different moods and therefore users can classify the playlist mood balance by dragging suitable mood icons to annotate the playlist. The average of the user MoodShapes is calculated and presented with a MoodShape (top right corner, Fig. 8). The generated MoodShape helps users to find preferred types of music from the playlists in the system.

The lower right corner of the playlist view (Fig. 9) contains an automatic recommendation drawer for related playlists based on the MoodShape similarity and an ability to recommend the playlist to followed users in the system (Fig. 10).

The playlist gallery now integrates the MoodShape for searching playlists with certain types of music (Fig. 9). Users are now able to use the introduced MoodShape to filter the playlist collection. The MoodShape is displayed in the top right corner of every playlist to enable users to get a better understanding of the mood picture playlist contents. As on the landing page, hovering over the playlists will display featured songs from the playlists. In the new version, user-generated playlists are shown first and the default playlists at the bottom of the page. MoodShape sorting will apply for both preset and user-generated playlists (Fig. 10).

The user's view displays a list of all users in the system sorted by their activity score (Fig. 11). The activity scores are based on the earlier work by Montola *et al.* (2009) on the use of game achievement system in different contexts than gaming.

Basically, the view displays a high score list of the users in the system. Users are able to select other users, view their individual profile page and access their mood playlists (Fig. 12).

The user profile page now adds a personal MoodShape based on the consumed playlists in the system. A user's recent activity is shown as a graph with the X-axis representing time and Y-axis showing the score earned in the system.

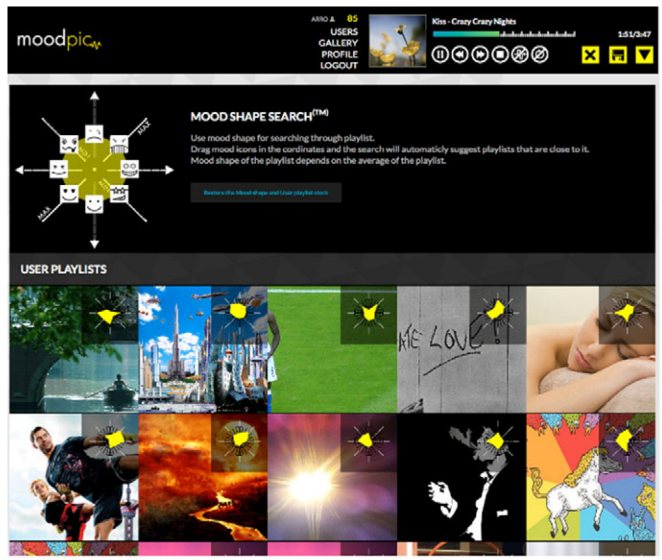

Figure 10. New playlist gallery enhanced with the MoodShape.

Users can follow others from their profile pages. The favourite playlists and playlists pinned to the landing page are now combined. Users are able to see which playlists each user has on their landing page. The information on who the user follows and which users are following you are displayed on the page.

4. METHOD

Two rounds of trial user studies were arranged in <BLINDED> with a total of 45 individual participants. User studies were organized in order to evaluate the web-based MoodPic concept. Both of the prototype versions were qualitatively evaluated by 30 users in each user trial. The methodology follows the design research approach (Hevner *et al.*, 2004). First, the design and implementation of a prototype was completed. The prototype was evaluated by the potential users.

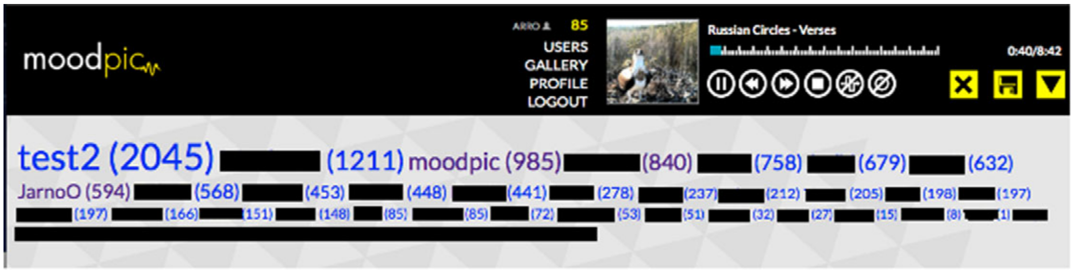

Figure 11. List of users in the system sorted by score, user names blinded.

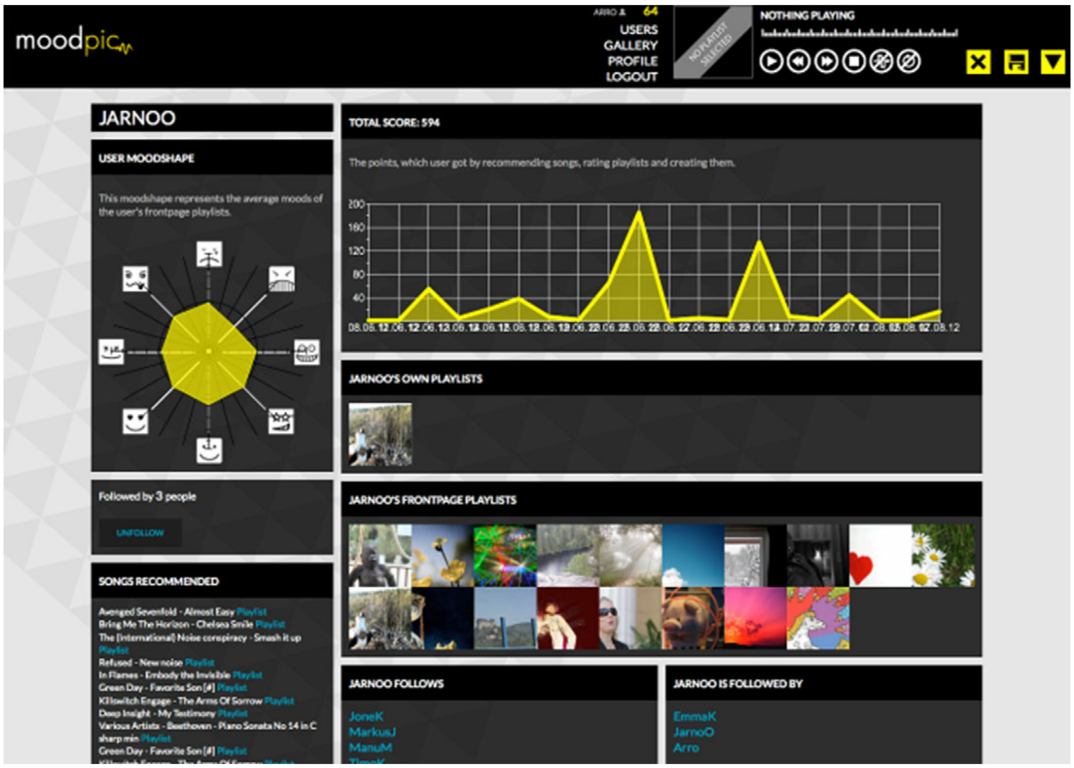

Figure 12. Enhanced user's profile page.

The evaluation of the first MoodPic prototype was organized in January-February 2012 with 30 participants. The study included 2-3 days of free prototype use and an interview session to collect feedback. The prototype and the preset mood pictures were refined as a new MoodPic prototype version and the trial study was repeated in June-August 2012 with 30 users. The trial was repeated with the new MoodPic implementation in <BLINDED> with 30 users. Totally 15 users were randomly selected from the first prototype trial group. This group was selected to collect insights in the interviews if the new implementation had been developed in the right direction. In the second prototype evaluation users had a longer time to test the service. The free use of the system in the trial was expanded due to requests in the first round. Also, in order to give time to ensure that there are enough users using the service at the same time, to make the social usage of the service possible. All of the users tested the service for a minimum of a week in the second trial, with the longer test period being 5 weeks, due to the summer holiday season. The users were able to test the application freely and complete structured tasks during the trial period. Interview sessions were held after the trial period, and included a UX questionnaire with 7-point Likert scale statements and a semi-structured interview about the service. In the first trial, UX questionnaire included 19 statements and in the second trial it was expanded to 25. Statements in the second trial investigated how users perceived the discovery and social features of the prototype. Examples of the statements: "Service helped me in finding new songs, artists or genres", "Service was easy to use", and "I liked the idea of organizing and searching music using the pictures".

Previous work on music discovery has focused on the music retrieval and developing the categorization of music (Kim et al. 2002) or recommendations (Celma, 2008; Celma and Herrera, 2008; Zhang *et al.*, 2012), as large part of the presented related work describes. There has been work on the music sharing (Voida *et al.*, 2005), collaboration around music collections (Sease et al., 2009) shared playlists and different services of selecting music together (Kukka *et al.*, 2009, Voida *et al.*, 2005). This work has a focus on improving the music discovery through social augmentation and identifying the practices users form with such features. The research topic was approached through three research questions.

> RQ1: How are the social features used in MoodPic for collaborative music discovery?
> RQ2: What kind of collaborative content do users create?
> RQ3: What kind of social usage patterns emerge from the use of such a service?

4.1. Data Gathering and Analysis

Users were given simple tasks to complete during both the trial periods. These tasks included creating their own playlist, adding songs to other user's playlist, uploading songs from their own personal library to the service and listening to the playlists freely during the trial period. These tasks were then discussed in the interview sessions in order to find the usability problems and social protocols related to these tasks.

In the interview sessions, participants were asked to give feedback regarding the current implementation of the concept and their music listening patterns in general. In addition, they were asked to generate ideas for further development. Interview sessions regarding the prototype evaluation were divided into three parts: (1) a walkthrough and evaluation of the system and participants' own content that they created in the trial, (2) an interview of social features and user experience and (3) the user experience (UX) survey. In the structured interview part, participants were asked questions about the current implementation of the system. In the walkthrough part, participants had a portable computer and they logged in to the service with their own username. Participants were instructed to present their own content (pictures and playlists) from the service. At the end of the session, participants filled in a survey of questions related to the overall user experiences from the trial. These sessions were similar in both of the trials.

The interview data from the two trials was analysed using grounded theory methodology, (Strauss and Corbin, 1994). Through bottom-up analysis of the research material, social usage patterns were identified from the activities users reported in the interviews. Finally, synthesis was drawn for generalisable results on social music discovery.

4.2. Participants' Background

Participants were recruited through <BLINDED> University's mailing lists of and researchers' social networks. Participants were selected according to their music listening practices, the only restriction being that they were relatively active digital music listeners. Music listening activity was confirmed from their answers to the screening questions.

In the first prototype evaluation the ages of the participants varied from 19 to 56, with the average being 29 years old. Of the participants, 19 were students and 11 were employed full-time, and 15 studied or worked in an ICT related field. Currently, the participants mainly found new music through their friends (77%), using radios or net radios (57%), and through magazines and website top lists or recommendation services (40%). In the first trial 16 of the participants were males and 14 females.

In the second prototype evaluation 15 users that had tested the MoodPic first prototype in the first round were selected for the study and as an additional 15 new users. Of these 15 users from the first phase, 9 were males and 6 females. The ages of the participants varied from 20 to 52, the average being 27 years old. Out of the participants, 22 were full-time students, 6 were employed and 2 were unemployed and 18 studied or worked in an ICT related field. They mainly found new music from their friends' recommendations (93%), recommendation services on the net (60%), from radio or net radios (63%), and through magazines and website top lists (50%). Of the new 15 users, 9 were male and 6 female, the total gender distribution in the second trial being 18 male and 12 female.

5. USER TRIAL FINDINGS

The results chapter discusses the main user study findings, starting with the general results regarding the overall user experience and the most appreciated features. The results are introduced by firstly revealing the user experience questionnaire ratings and then the qualitative findings from the user interviews, user-generated content, and from the trial period. In the last part, the section describes the social usage patterns which have been found.

In general, the MoodPic concept was well received amongst the users. Almost all of the users liked the idea of organizing and searching music using the pictures and considered the system offered a novel music listening and sharing experience. The general UX statements with numerical values support the interview findings (Fig. 13).

The users highly appreciated the collaboratively built playlists' personal touch. The MoodShape was stated as being

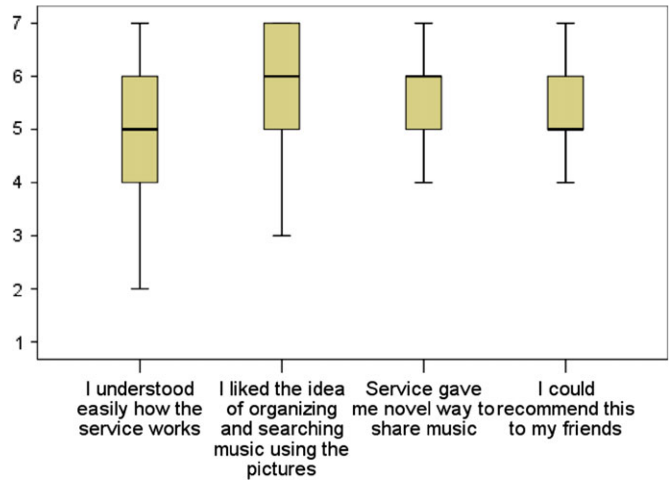

Figure 13. General user experience statements from the second version of MoodPic. 7-point Likert scale.

one of the key features of the concept, giving users a means for easily classifying playlist content and searching for suitable music from the playlist gallery faster. The new privacy options for the user playlists were found to be sufficient, and enabling new ways of managing the playlists (*privacy adjustments in the playlists were sufficient [public, shared, private])* gave an average of 5.8. The new MoodPic offered the users an even more unique music discovery experience. Their UX questionnaire ratings increased for all of the related topics from the first MoodPic evaluations.

The results in the following sections are presented in three themes: (1) socially augmented music discovery, (2) user-generated content enhancing music discovery and (3) the social usage patterns.

5.1. Socially Augmented Music Discovery in MoodPic

This section addresses RQ1: How are the social features used in MoodPic for collaborative music discovery? In our study, one of the most important tasks for many music listeners is finding new and interesting music. In the earlier studies, it was seen that users tend to keep somewhat static music collections on their personal music players (Lehtiniemi and Ojala, 2012). These collections can be large as the study by Sease and others (2009) shows. Even though one's own collection is valued, people are still eager to discover and be surprised by new music. As the study by Cunningham and others suggest, most encounters with new music are positive (Cunningham *et al.*, 2007).

Socially augmented music discovery in the second version of MoodPic affected the ways of using and experiencing the system. Users perceived the use of the service and especially discovering new music through recommendations of other users more pleasant. They thought more carefully about the content they added to the service since they were more socially aware of other users. All in all, the developed version gave a novel music discovery experience to the users. Comparison between the two versions of mood pictures and the iterative design process is presented in Lehtiniemi *et al.* (2016).

A design principle of the MoodPic prototype was that users do not need to know much about music or genres to be able to discover new songs to listen to. MoodPic supports music listening and discovery well as was also commented by a trial user: "To be able to use MoodPic you don't really need to know much about music and musical styles. In this service the styles mix nicely in the playlists and the service enables finding new and interesting tracks easily. If you only want to listen to a certain type of music, like heavy metal, this might now be the service for you." (P1).

Based on the user feedback, MoodShape feature (Fig. 8) was introduced in the second version of MoodPic to aid music discovery and to enable easier and faster ways to find wanted music. Some users commented that it was hard to imagine what type of music some pictures would contain and, therefore, the discovery time increased.

A feature supporting social music discovery especially designed for MoodPic is MoodShape. The MoodShape feature was created to give users the possibility of mixing many emotions and moods and ending up with a more complex and targeted way of searching. MoodShape enables the users to classify the playlists in a playful way by dragging individual mood icons. Mood pictures reinforced with the MoodShape feature were seen as an efficient and fun way to organize the playlists and was the most appreciated new feature in the second version of the MoodPic prototype. Sorting the playlist gallery with a MoodShape to find playlists including music mostly matching to a wanted mood was appreciated and was said to offer fast access to the preferred music and playlists. In the interviews, most of the users listed MoodShape as the most interesting idea of the service. It was said by some of the users that the MoodShape could be used for individual songs and then the MoodShape for a playlist could be calculated automatically.

During the trial, users explored the possibilities of the playlists, especially for new music discovery. Since all the playlists were public, users were able to find new music through others' playlists, but they also created certain usage patterns of the collaborative playlists to find new music. Fig. 14 presents the statements related to social music discovery.

In the interviews, most of the participants expressed that the most important content in a playlist-based service are the songs added to the playlists. Commenting and other ways to socially interact within the service was not seen as creating valuable content to aid music discovery. Most interesting and valuable contributions are the song additions to playlists that expand the playlists and provide positive surprises for music listeners and match music recommendations. Most of the users saw great value in the song recommendations, i.e.

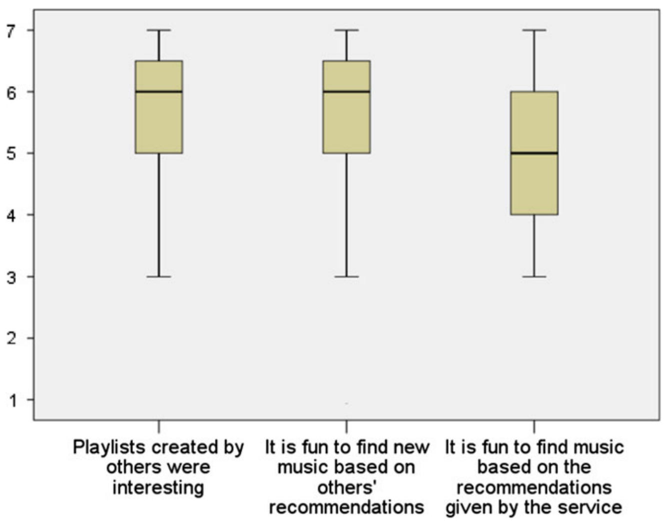

Figure 14. Statements related to social music discovery through playlists, using 7-point Likert scale.

additions to their playlists by other people. Direct recommendations were more valued than automatic recommendations from the service. For the computer generated recommendations many participants highlighted smart and dynamic recommendations that are recommended based on the user's actions in the system.

Participants wanted to have automatic recommendations based on songs they had added, songs they had listened to, songs that have been listened by other users with similar musical taste, and metadata or genre-based recommendations. Most of the participants said that they really appreciated the surprise element that was encountered when other users added songs to their playlists and that the automatic recommendations would work as an additional feature while the core was still personal recommendations.

5.2. User-Generated Content Enhancing Music Discovery

This section addresses RQ2: What kind of collaborative content do users create? Playlist creation is the main form of creating content in the MoodPic service. In the service, users are collaboratively creating unique playlists, which forms the content through crowdsourcing. During the interview sessions, participants were asked to show playlist content that they had created. Questions covered the creative process of the playlist making, including why they selected specific images to represent the playlist and the ownership of collaboratively created playlists. Playlist features in the system enabled user creativity in the selection of the mood picture to describe the content or the content they wanted others to add to the playlist. The playlists created during the user trials show that the users spent a lot of time and consideration

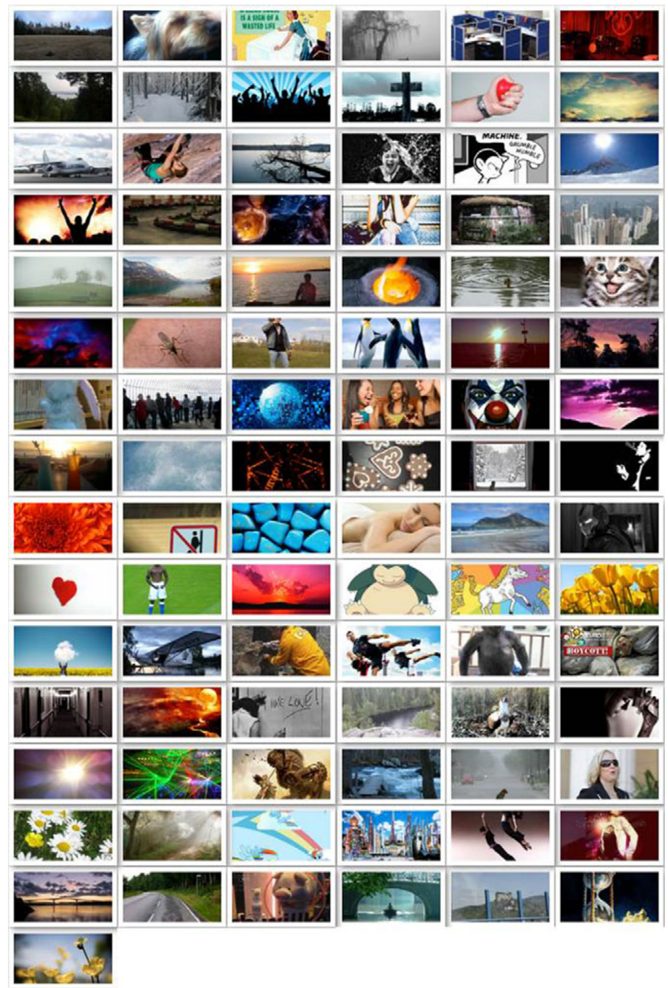

Figure 15. Thumbnail versions of mood pictures for user-generated playlists.

making their playlists interesting. Making the playlists look personal was essential for the participants.

The study results indicate that the motivation for playlist creation increases due to intrinsic motivation factors; users have a need for self-expression. Thus creating personal playlists and contributing to other user's playlists was seen as a good way of fulfilling that need. In addition to the eight preset mood pictures in the later version of Moodpic and associated playlists, users were able to expand the mood playlist collection by adding their own pictures as a basis for a playlist (Fig. 15). User-generated content in the prototype service shows that users have a tendency to be creative while making playlists. Enabling the users to visualize their playlist with a mood picture was seen as a good way of expressing the intended mood of a playlist, which then can be iterated collaboratively. The selected mood picture was also said to represent thoughts, opinions, and musical taste.

Figure 15 shows small thumbnail versions of the mood pictures for user-generated playlists. The playlist gallery images

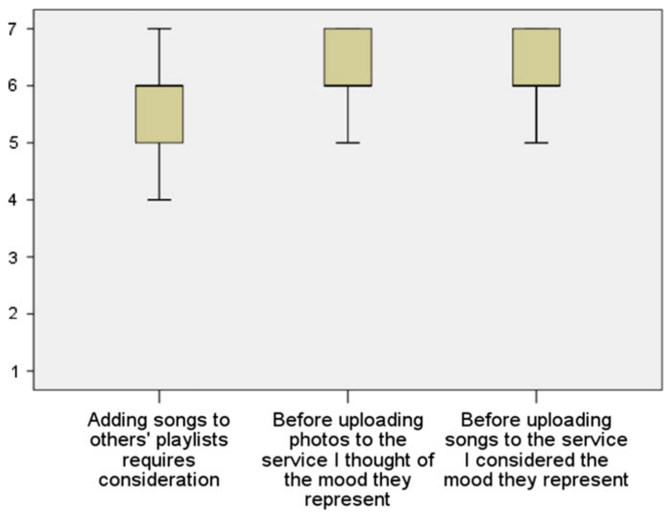

Figure 16. Added playlist picture content to the system, using 7-point Likert scale.

were significantly larger in the real prototype service (Fig. 15).

The themes of user-generated mood pictures can be categorized mainly into animals and fiction characters, people and facial expressions, landscape and nature, text and metaphors, situations and context.

Based on the results, users were focusing carefully on the pictures and the mood they represent before adding them to the system as a basis for mood playlists. The same applies to the song recommendations on others' playlists. The UX statements regarding these were ranked high in the evaluation of the second MoodPic prototype (Fig. 16).

As described earlier, there were 15 users that used both of the MoodPic versions. The increased social interaction in the iterated prototype implementation increased the time and effort that these users were putting in to create quality content for the system. The users were thinking even more carefully about what songs to add to the playlists and what type of pictures to use as a basis for a playlist. They emphasized that it was increasingly interesting to find new music based on recommendations from other system users.

5.3. Social Usage Patterns

This section addresses RQ3: What kind of social usage patterns emerge from the use of such a service? Social usage patterns are repeating or emerging ways of interacting/acting within the service in collaboration with other users. This section presents 19 usage patterns found through bottom-up analysis of the user data from the trials. Usage patterns are organized in four social user experience categories: *discovery and enjoyment, self-expression and presentation, connectedness,* and *competition and collaboration*.

Creativity and self-expression, as well as *music discovery and enjoyment,* are categories of an individual nature and they are mostly based on intrinsic motivations. *Connectedness* as well as *competition and collaboration* are of social or extrinsic nature and are mostly related to reciprocal interactions with other system users. The themes are similar to the ones drawn from the social user experience research previously (Väänänen-Vainio-Mattila *et al.*, 2010, Ojala 2013, Ojala et al 2013, 2014). *Self-expression* was also identified in a work by Väänänen-Vainio-Mattila *et al.* (2010). A previous work with the MyTerritory concept also identified the challenge in the balance between consuming and creating content Lehtiniemi and Ojala (2012). The *discovery and enjoyment* category is related to categories such as *suitability of content, and learning* (*curiosity*) (Väänänen-Vainio-Mattila *et al.*, 2010). *Connectedness* is related to *reciprocity, and curiosity* (Väänänen-Vainio-Mattila *et al.*, 2010). *Competition and collaboration* require design choices that make the activity of other users and their identities visible. In the work by (Väänänen-Vainio-Mattila *et al.*, 2010) reciprocity and learning were the factors that relate to collaboration.

5.3.1. *Discovery and Enjoyment*

Consuming others' playlists is a main method of music discovery. The main music discovery happened while listening to playlists created by other users of the system. Users are able to choose a suitable mood picture that matches their current mood and listen to the songs that are associated with that picture. Playlists can be filtered using the MoodShape feature. It also allows users to use others' playlists as cues for finding music. Users wanted the ability to discover new music without extensive musical knowledge or having to know too many artists or genre names. *"This is targeted at people like me who do not follow certain artists or music styles"* (P17, MoodPic 1).

Adding a mood picture is a way to receive recommendations. Users were experimenting with the system by adding an interesting picture that provokes people to view what type of music recommendations are associated with that image. This way of requesting music recommendations based on a mood image was received well making the use highly explorative. Users wanted to create the playlist as an initiative for other users to add certain types of music. Collaborative playlist editing adds a social layer to the playlist lifecycle thus enabling playlists to be a means to discover new music that is recommended or added by others. "Many people here have a great understanding of which songs match with each other or project certain situations. Finding new music is essential" (P10, MoodPic 1, male, 22).

Collaboration with the playlists creates positive inconsistency and makes playlists more interesting, which supports music *discovery.* Even though the additions may not always fit to their thinking of the mood for the playlist, the user-generated additions are more likely to be listened to and appreciated than computer-generated recommendations. *Positive inconsistency* occurs when users made new associations with pictures and music, by adding unexpected songs to the playlist. Playlists evolved into something that the creator did not think of in the first place, which provided both positive and negative experiences. Different interpretations of the mood pictures make the playlists rich from the content perspective and support music discovery.

Participants appreciated the surprise element that was encountered when other users added songs to their playlists and that the automatic recommendations would work as an additional feature while the core is still personal recommendations. In the interviews, users desired the possibility to just open the player and start a playback of interesting music, which is somehow targeted to them.

Users want to discover others with similar music tastes. Finding users with similar music tastes was highly interesting for the participants. It is a strong motivator to be socially active within the service. Participants did not want actual commenting within the service as it would, in the worst case, fill the whole service with irrelevant content. However, statistics of how many times their playlists are played and by whom were seen as very interesting and motivating. Instead of commenting, people were more interested in seeing others' music listening activities within the service. *"I want less words and more action. If then people comment, it will not bring here new music or expand the playlist. I like to still see the number of plays on my playlist and especially if people come back to the lists and listen to them again. That tells a lot"* (P2, MoodPic 2).

Users appreciated social music discovery; *"If you use this a lot, you can discover people that listen to similar music as you and discover new interesting music"* (P1, MoodPic 2).

5.3.2. Self-Expression and Self-Presentation

Own playlist is used as a visual and audial manifestation of self. Most of the users stated that a user-generated playlist is an instrument of self-expression. Some of the users saw the value of collaborative playlists as a tool for new music discovery. Additionally, the interview results show that the users had different ideas on what is the purpose of their playlists in the system and what they wanted to achieve with their lists. In MoodPic, users were building their identity within the service using playlists and mood pictures as the system intentionally didn't include detailed user profiles for the users. Creating a playlist and adding a picture to represent it is almost comparable to adding a cover photograph in Facebook in terms of being visible within a service. Interesting pictures draw a larger audience to view the playlists and encourage musical interaction within the service.

Combining pictures and a collection of songs allows users to be creative and create new types of playlists that are not restricted and guided by a genre classification. The playlist with a "cover picture" and a handful of example songs creates a basis where other users can easily contribute with their additions. "If I make the effort of creating the playlists, why not share them?" (P20, MoodPic 2).

Users were creating their "own albums" or "mixtapes" with the playlists. These can also be gifts to the other users. The idea that users themselves can be in charge of the visual content of the music service was gladly received. The service should be implemented in a way that users are given tools to create and they are able to invent new ways to interact with the content. Users' musical identity should be visible in the system. Musical identity reflects music related profile information e.g. listening history, preferred music, contributed musical content, and music related activity in the system.

The main usage patterns for image selection for a playlist were: (1) extending the selection of mood pictures in the system, (2) to express myself with a picture and a playlist, (3) the picture was meaningful to me and (4) the picture matched the visual look of the service well.

Reciprocity is a reason to share own playlists. Creating a personal mood picture related playlist with a lot of associated songs offers a potentially nice listening experience for others. Additionally, it gives a better means for other users to create matching song additions and thus enables the creator to receive more precise music recommendations. Matching music to pictures was said to be intuitive as an example quote describes, "I first found an interesting picture and then I started to seek matching songs from the music library. It was surprisingly easy to find matching songs!" (P1, MoodPic 2)

Playlists within a music service were seen as a way for sharing one's mood, music experience, and even musical taste with others. Other systems that use words or tags to describe playlists were seen as limited in the sense of storytelling. A comment from one of the users describes the overall opinion well: "It is hard to give a name to describe the content of a playlist" (P2, MoodPic v2).

Gaining listeners happens with interesting pictures and playlist combinations. Some users also commented that they would have wanted to see information on how many users have listened to their playlist. It was said to motivate playlist creation even more. Gaining popularity inside the user community was stated as being a reason for creating playlists. Following how many users listen to the playlist was stated to be a feature that can easily motivate more focused content creation between the users. Exclusiveness of the community or audience can be a motivator. "This is a closed community, which I like in a way. I would like to promote my favourite music to my friends!" (P2, MoodPic 1).

Some users are shy to share but are still interested in contributing—users want to control their playlists. Introverted users may not be comfortable with sharing their playlists. In the interviews the music sharing was an area which was different from other social media sharing habits; those who are active on Facebook for example may not be active music sharers and vice versa. Some users were uncomfortable about showing others what they really listen to. Keeping the image of a certain type of music listener can prevent particular people from using the service if their listening activity is shared automatically for example. "I would like to have recommendations from others. I would have recommended more myself, but I was a little bit shy because I did not know other users! On the other hand, you know what your friends are listening to, so their additions are not that interesting." (P1, MoodPic 2).

Users stated that they felt ownership of the playlists during the trial. Most wanted to have credit for their own lists and express themselves through their own lists. Some even wanted to have full control over their lists and felt that others' additions were intrusive. However, strongly associating the lists with specific users in the system works against the idea of shared content, such as lists and moods. The balance between self-expression and collaboration is hard to design. Users stated that author information could add value to the list. Mostly this was related to their viewpoint of the playlists in general. Some saw the lists as always being personal and some saw them as only being started by a certain user and then "released" or "published" on the service for collaborative use and editing.

People are willing to reveal to others what they listen to, but only to some extent. For embarrassing songs that they want to listen to in secret, there should also be a way to keep them safe. The musical identity that they want others to see may be somewhat different from what they really listen to. MoodPic answers this by showing abstract user MoodShapes, that give a general idea of what the user listens to, but without disclosing too much information.

Evidently, where the features of the playlists enabled users to be social and add songs to the playlists of others, users appreciated MoodPic especially as a way to share music with the people they know—their friends and loved ones. However, many stated that there is no point in limiting the music discovery possibilities to friends only—sharing with a bigger audience increases the possibilities of reciprocity in recommending.

5.3.3. Connectedness

Adding songs to others' playlists increases activity—encouraging others to be active content creators. Another way of discovering music was increasing the activity of the playlists that were seen as interesting. Adding new recommendations and thus steering the playlist style to a wanted direction often activated other users to add even more songs to the playlist and, therefore, provided new music recommendations for the mood picture. Results show that the users were critical with their song additions and were thinking carefully what to add to others' playlists. This also created a phenomenon where some of the users were too shy to add tracks freely to a playlist created by an unknown person, "I did one addition to someone's playlist and I would have done more but I didn't dare. I think it is because I didn't know the person or know his musical preferences. It might have been easier to make additions to a friend's playlist whose musical taste I know. Then again the additions might now have been so interesting" (P1, MoodPic 2).

On the other hand, if the other user makes the effort and gives recommendations, the playlist owner does not want to remove it, even it may not fit the playlist. Users stated that they did not want to remove the additions of others because they did not want to discourage interactions.

Openness creates an open atmosphere. Users emphasized the meaning of open atmosphere in the community. Creating playlists with other users they might not know can remove prejudices. Social presence and the feeling that the community is active is important. Users wanted to feel that the community is alive. Dynamic feel can be created by showing the latest activities of other users as well as offering the latest content. When users create something special, they want it to be seen and others to respond, by leaving evidence of their visit. Collecting history and thus visualizing the popularity of playlists was stated as adding a feeling of reciprocity. Openness in giving the recommendations and creating playlists evolves over time and requires some learning and critical mass of additions and recommendations made.

Playlists and pictures can be used as a provocation or discussion starter—playlists create connections between users. Connection with other users was a relatively high motivational factor for using online music services. Almost all of the users saw additional value in the fact that users can connect through the playlists and work in collaboration within the service. "I got the idea that the service is public by default. You can make your own private playlist with a desktop media player" (P4, MoodPic 1) "It would be extremely exciting to see if the interaction would work only by adding the songs to others' lists. Will there be any commitment to the reciprocity?" (P26, MoodPic 2).

Playlists were stated as working as a means of communicating within the system. The playlists can be seen as *social enablers* in the service. They were used as tools to promote one's favourite music by recommendations, as gifts to friends and loved ones, and as social playlists for a limited group.

The playlists socially augment the service outside music listening alone. Users also stated that they wanted to provoke discussion with their playlists. “I wanted that people would not be still but instead would move and do something when listening to my list!” (P2, MoodPic 2). “If you want to promote a cause that is important to you, why not do it by music and pictures? The whole idea is that you do not convey a ready-made message, but instead let others do their own interpretation. You can evoke thoughts” (P1, MoodPic 2).

Song additions can create a dialogue—a conversation through content. Song additions to the playlists seemed to be discussed in a reciprocal fashion and even formed dialogues. For example, additions generated more additions to the same topic and songs created conversation in relation to certain themes (Fig. 17). “The song additions created nice dialogue. The next song is a response to my addition!” (P3, MoodPic 2).

One example of such a dialogue: You are a knife (Veto), Yesterday (The Beatles), Wonderman (Tinie Tempah), The bitter end (Placebo), Du hast (Rammstein), Be quick or be dead (Iron Maiden), Lay down Sally (Eric Clapton). This list was related to Fig. 17.

5.3.4. Collaboration and Competition

Competition motivates content creation. People are willing to share the music they listen to with others, but in return, they want reciprocity and information on how many times their playlists are listened to: “The size of the playlist picture could represent the popularity, it could then build a nice jigsaw puzzle” (P2, MoodPic 1).

Competition can be a strong motivation for content creation. MoodPic included activity points in order to make it easy for the users to identify the lead-users and on the other hand to collect status and visibility in the community. Users stated that competition with the playlist popularity is motivating. The minority of the users wanted to collect the activity points and became the leader. During the trial, some unwanted point grinding also occurred.

Figure 17. Picture of the playlist in which the example discussion occurred.

Community creates positive pressure for content creation. There were social protocols that evolved around playlist creation in collaboration. Social “pressure” can make the recommendations more meaningful since users are aware that “bad recommendations” can be removed. Some thresholds in the additions to others’ playlists can work as a quality filter when users really consider what to add. “Creating it put me under pressure. The owner can remove my additions! I really had to focus and tried to think who the target audience is.” (P2, MoodPic 2).

However, certain boundaries exist in adding the songs to other users’ playlists. Users stated they would more probably give recommendations to other users they know. When adding a new music to others’ playlists or adding new images as a basis for a new playlist, the participants carefully considered the mood of the file. This indicated that the participants were very keen on expressing their moods and making an effort to create valuable playlist content within the service. This is a very positive driver for the further development of such systems.

Collaboration makes playlists more lively. The most appreciated social feature was creating playlists together and remixing own and others’ playlists. This feature gives collective dimension to the service’s music content and adds a sense of community and interaction to it. The most value was seen in interacting with friends and with those that have similar musical tastes (who have liked the same playlists and listened to similar music). The fact that in collaborative playlist editing the playlist evolves and changes over time was commented on as follows (male, 27 years); “There should be a possibility to develop the playlist in secret and launch it at a wanted moment. I also like the idea that nothing ever needs to be ready, the playlist develops over time” (P13, MoodPic 2). Subjective playlists make the service valuable and different from other “collaborative radios”, where the phenomenon of “unwanted average music” can occur. The inconsistency of the playlists is a problem that comes as a side-effect of collaboration. However, the inconsistency was stated by many users as being an aspect that generates interest in the playlists.

Users create playlists in collaboration for special events. In addition to the four main ways to discover music, it was said that the MoodPic could work well for collaborative playlist creation for a party or similar event where users could add their songs during the event. Users suggested social playlists for example to organize party playlists. “It would be very handy if you could ask the participants of your party to create the playlist to the party together. I like the idea of extending your own playlist and not hiding it!” (P2, MoodPic 2).

6. DISCUSSION AND CONCLUSIONS

Two rounds of iterative design and user studies of the MoodPic service show that the concept can offer novel experiences to music sharing. The concept was received well by the users in the field trials. Based on the UX questionnaire findings, the users carefully considered their picture and song additions to the playlists, and the findings suggest that users were willing to invest time in creating high-quality playlists. Collaboratively created playlists were perceived as of positive quality, even though their consistency was sometimes criticized.

The first theme in the findings was socially augmented music discovery, which was supported by added social features in MoodPic II. The new social features, which were implemented in Moodpic II were perceived positively by the users. The design of Moodpic leaned heavily towards music discovery without knowing genres or artists. Mood pictures reinforced with a MoodShape feature were seen as an efficient combination and fun way to organize playlists. The MoodShape feature aimed at combining music and playlists with eight moods that were based on Russell’s circumplex model (Russell, 1980). MoodShape itself was seen as an efficient way to sort the playlists. It might not be possible to achieve a set of moods that every user would relate to in the same way and always associate with the same songs and it might not even be desirable in many cases. Using mood pictures instead of words still expands the communication channel for expressing moods to others using the service.

Using mood pictures as a collaborative tool for music discovery was said to provide a way to easily create cross-genre playlists. In the second version, automatic recommendations, following friends, and new privacy levels were implemented. Statistics of how many times their playlists are played and by whom were seen as both interesting and motivating.

The second theme in the findings was user-generated content and how it enhanced the music discovery experience during the trial. Users had different perceptions of how the playlists can be used within the service. They wished to have variation and surprise elements in their playlists but the baseline of the content should somehow be categorized.

The findings on the user-generated content describe the 97 playlists users created during the trials and the related mood pictures they added. The playlist creation was clearly the activity that was the main role during the trials besides listening to music. Playlists using mood pictures to describe them were said to give a clear understanding of the atmosphere of the playlist and binding the set of songs together. Users carefully considered what music to add to the playlists of other users. This shows that the experience of constructing a collaborative playlist clearly has two phases: (1) an initiative playlist by the original creator, giving an idea to collaborators about the theme and (2) a collaborative phase where the playlist is collaboratively built. The meaning of the playlist will in some cases change and evolve when others contribute to it. User generated content evolves freely with the help of collaboration in MoodPic. Creating playlists and collaboratively improving them was a highly appreciated experience. User-generated picture-based playlists make the service valuable and different from other “collaborative radios”, where the phenomenon of “unwanted average music” can occur.

The third main theme of the results described 16 social usage patterns that emerged in the trials. Usage patterns can be divided into four main themes: self-expression and presentation, discovery and enjoyment, collaboration, and connectedness. Social usage patterns can be used by practitioners and researchers as design criteria for applications and services that enable social music discovery. Social usage patterns describe the habits of collaboration that occurred during the trials. They reveal the patterns that users adopted for collaborative music discovery during the trial. Most importantly, they can be used as design drivers for collaborative and social music service design.

The results further the knowledge of socially augmented music discovery by combining visually enhanced playlists, mood and emotion classifications and collaboratively created playlists into a new concept. This concept was evaluated by users in two trials. The results describe social usage patterns that users formed in the trial. The findings suggest, that augmenting music discovery applications and services with social features and collaboration can support new user experiences, discovering new music in a social way and involve users to use the system actively.

The main limitations of the study are related to the representativeness of the study population. As in many studies, the present study used a convenience sample of users. We targeted the study to the users that are interested in music listening and music discovery applications, which will be the most prominent user group for the service. The research in the future could be extended to users that have less interest in music discovery, to understand how MoodPic could motivate them. All of the users were from <COUNTRY>, and leaned towards highly educated population, which affects the generalizability of the results. For future research on the social music discovery, the effect of the cultural background should also be taken into consideration. In the second user trial gender division was uneven, but since the design was not gender-specific, no significant effect on the results was evident. In the second field trial, users had a longer period of using the system. Since no comparisons for the first and second trial were conducted, there was no significant effect on the duration of trials to the results.

Future development ideas include expanding the system to provide song based mood metadata that could contribute to

MIR research in the future when users associate songs with moods and rate them with MoodShape. Adding social commenting features to the system divided opinions dramatically. Some ways to comment on songs added to other user's playlists and a way of knowing more about other users' musical tastes and personalities could add collective value to the service. Comparing quantitatively the differences of using mood and emotions to classify On the other hand, too many interaction possibilities could reduce the main role of the music within the service. Our work gives a starting point to designing collaborative and socially augmented music discovery services and furthermore for the research of such services.

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