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Considering emotions and contextual factors in music recommendation: a systematic literature review

***Willian G. Assuncao[1] · Lara S. G. Piccolo · Luciana A. M. Zaina[1]**

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Abstract In recent years, several music recommendation systems have been developed with the aim of incorporating valuable information into the user's modeling and recommendation process. The inclusion of emotions and contextual information in music recommendation applications is increasingly becoming a relevant aspect to improve the listening experience. Thus, the main aim of this systematic literature review (SLR) is investigating the music recommendation approaches that considers emotions and/or context (research question 1) as well as to identify the main gaps and challenges that still remain and need to be addressed by future research (research question 2). After an extensive research, 64 publications were identified to answer the research questions. The studies were analyzed and evaluated for relevance. The main approaches that consider emotions and context were identified. The results of the review indicate that most studies in the field that combine multiple approach related to emotions or context factors have improved the user's hearing experience. The main contributions of this review are a set of aspects that we consider important to be addressed by the music recommendation systems, such as: user activity, satisfaction, feedback, cold-start problems, cognitive load, learning, personality, and user preference. In addition, we also present a broad discussion about the challenges, difficulties and limitations that exist in music recommendation systems that consider emotions and contextual factors.

Keywords Music recommendation · emotion · context · user experience

*Willian G. Assuncao
E-mail: willian.assuncao@ufscar.br

Lara S. G. Piccolo[2]
E-mail: lara.piccolo@open.ac.uk

Luciana A. M. Zaina[1]
E-mail: lzaina@ufscar.br

[1] Departament of Computer Science, Federal University of Sao Carlos, Sao Carlos, Brazil
[2] Knowledge Media Institute, The Open University, Milton Keynes, UK

1 Introduction

Over the past 20 years, new technologies have digitalized people's music listening experience, providing an ubiquitous access to unlimited amount of music [58, 18]. Spotify[1], SoundCloud[2], Last.fm[3], and Apple Music[4] are examples of digital platforms that have transformed the experience of listening to music in the last decades, facilitating the access to a plethora of tracks and the configuration of personal playlists. The myriad of options and flexibility to identify music can be an advantage but also a burden, suggesting the need of automated techniques to support users with some sort of recommendations [81].

Therefore, featuring an appropriate Recommender System (RS) is essential to improve the User Experience (UX) of a digital music platform [20]. Typically, recommender systems use standard information (i.e., artist's name, album, or music title) as seeds to select and suggest songs. Although this set of information is still essential for the algorithms, it has limitations in many music-related applications. For example, Peer-to-Peer (P2P) applications, which do not have vocabulary control in music representation [71]. In this situation, the user retrieves the music using the title of the music, authors, or album, without the system recommendation intervention. This situation causes redundancy, difficulty, and confusion in the the retrieval of musical information, because music has a cultural and linguistic aspect [71, 89].

Other applications of music recommendation can be found in the literature. For example, TagFlip, MeDJ, ContextPlay, Moodplay, SAfeDJ, MPlist, and m-Motion [63, 52, 62, 5, 51, 85, 37, 7]. TagFlip enables active music discovery based on social music tags. Each song is played for the user using the most popular tags on the Last.fm platform. MeDJ aims to help teens improve emotional management and prevent depression. On the other hand, ContextPlay is a music recommendation system that gives the user control over the contextual features that the platform uses. MPlist also uses contextual features and dynamically creates playlists for music lovers using data from the mobile device's sensors. An interactive recommendation application that addresses emotions is presented in the MoodPlay application. Similarly, SAfeDJ also considers emotions, however, the application aims to help drivers decrease fatigue. The m-Motion application, on the other hand, aims to help the user achieve a desired emotional state from the songs in the user's playlist.

A traditional RS is able to make high quality recommendations when modeling users' preferences in the recommendation process [54]. A user model consists of knowledge about the user that is encoded either explicitly or implicitly and is used by an RS to improve users' interactions with the system [72]. However, user modeling techniques used in traditional RS lack contextual information. Context data plays an important role when making recommendations, since users' behaviors are greatly affected by their current situation(s).

To enrich the user experience with a recommender system, we focus on merging two different approaches: context and emotions. Together, they have the potential to help the user achieve a desired emotional state. Exploring the emotional power of music is one way to improve the music recommendation process. Emotion is in the essence of music and music can express various emotions [131]. Lonsdale and North [83] showed that music is the most preferred leisure activity

[1] https://www.spotify.com/
[2] https://soundcloud.com/
[3] https://www.last.fm/
[4] https://www.apple.com/apple-music/

among people and that it is used to regulate emotions. Furthermore, music may match or evoke a particular emotional response [58].

This research focuses on bringing two additional users' aspects to improve music recommender systems, emotions and contextual data. Regarding context, daily activities circumstances involving music listeners influence their choices. Dey and Abowd [31] defined context in computing systems more formally as "any information that can characterize the situation of an entity. An entity is a person, place, or object considered relevant to the interaction between a user and an application, including the user and application themselves". In short, context is any information that influences the user's interaction with the system.

In the field of recommendation systems, context can be the user's situation when looking for recommendations (e.g., time, mood, current activity). Clearly, such information can influence the user's need for information, therefore, can enrich conventional knowledge such as user's preferences when providing recommendations [19]. In line with Magara's observations [85], users create music playlists manually for various contexts and activities in which they are interested. When their activity or context change, they have to update and reload a playlist based on a new search that fits the new situation.

In the recommender system literature for music listening applications, there is a lack of empirical studies on musical emotion and music listening contexts [123]. In music psychology, the usual focus is to understanding emotion in music and emotional responses to music [34, 76, 48]. Complementary, researchers in computer science are usually focusing on understanding emotion in music computing and building content-based models to solve issues such as identification, detection, recognition, and recommendation [112].

Aucouturier and Bigand [8] identified a series of "gaps" between these psychology and computing studies on music. They called for greater collaboration between psychologists and computer researchers. For Song [112], while psychologists can provide a deeper understanding of the theoretical background to emotion, computing researchers can provide valuable tools to help analyze data related to musical emotions. Furthermore, the need and potential to include context in music listening with the knowledge on musical emotions is acknowledged in both areas [10, 92, 53, 1, 116].

Within this scenario, this work presents a systematic literature review about music recommendation approaches including: (i) a broad discussion of approaches that consider emotions and contextual information to the music recommendation; (ii) an analysis of the challenges, difficulties and limitations that exist in music recommendation systems that considers emotions and contextual information; and (iii) a set of aspects that music recommendation systems should be addressed to improve the musical experience.

Our systematic review follow the guidelines by Kitchenham et al. [69] and considers primary studies published between January 2010 to July 2021. After carrying out the inclusion, exclusion and quality criteria, we got a set of 64 publications which are taken into account in our reviewing.

From this review, we conclude that: (a) considering the user's context and emotions, together with the perceived emotions in music, music recommender systems can improve the user's listening experience; (b) combining multiple recommendation approaches can make music recommendation systems increasingly intelligent. In this perspective, our SLR presents a set of aspects that influence music recommendation, such as: user activity, satisfaction, feedback, cold start problems, cognitive load, learning, personality, and user preferences; and (c) further research should better conceptualize and define the choice of model that describes emotions and context. As well as also presenting what contextual and emotional information is being captured so as not to infringe on the user's privacy.

The rest of the review is organized as follows: Section 2 provides the theoretical background and related work. Section 3 describes the systematic literature method. Section 4 provides an analysis of the extracted data, seeking to answer the research questions. Main challenges and limitations identified in recommendation systems that considers emotions and contextual information are discussed in in Section 5. Section 6 concludes the study and presents future research guidelines.

2 Theoretical Background

This section presents the two main research fields related to this article: music recommendation systems that considers emotions and contextual information.

2.1 Musical emotion and contextual information

One of the most relevant challenges in music research is understanding how music has such strong control over listeners [33], which includes both aspects of the *perception* of emotions and how exactly music *evokes* such emotions.

The perceived emotion in music concerns the emotional expression without changing the listener's emotional state. In other words, music is perceived as sad, but that does not necessarily affect who listens. On the other hand, the emotion evoked by music is the listeners' emotional response provoked by the music. A more in-depth discussion about the distinction between these two reactions can be found in [129, 114]. Wood and Semwal [129] explore the connection between music rating and emotion evocation. Song et al. [114] examine the difference between perceived and induced emotion for music using categorical and dimensional models of emotion.

Several emotional models conceptualize the emotions, and the most adopted by the researchers are the categorical (discrete models)[35] and dimensional (continuous models)[102] models. In the categorical model or discrete model, the emotions are seen as a sum of categories that can be separated to obtain more refined and smaller subcategories. For example, Plutchik and Kellerman [98], proposed a categorical model that considers eight emotions (joy/ sadness, confidence/ anger, fear/rage, surprise/anticipation). In the dimensional model or continuous model, emotion are seen as dimensional scales. Two dimensions emerge from most dimensional models: valence and arousal [102, 11, 108]. Valence corresponds to a pleasure/displeasure scale, whereas arousal corresponds to a sleepiness/excitation scale. These scales define a circumflex space where it is possible to locate any "popular psychology" [108].

The need for a deeper understanding of how music exerts strong control over listeners goes beyond emotions. Users' immediate preferences can be strongly influenced by a range of different factors and characteristics called context [122].

Different classifications for contextual information have proposed in the literature [4, 3]. For Adomavicius and Tuzhilin [4], three types of contexts in recommendation systems: completely observable context, partially observable context, and not observed context. In the completely observable context, the relevant contextual factors (or information) for the application are explicitly known when the recommendation is made. In the partially observable context, only some of the information about the contextual factors is known explicitly. In the not observed context, no information on contextual factors is explicitly available for the recommendation system. For this kind of context, recommendations are usually made using only implicit latent knowledge of the context.

Differently, Abowd et al. [3] suggest a classification distinguishing between primary and secondary contexts. The primary context is defined by the location, identity, activity, and time of the user, the four most important factors when characterizing a user's situation. The secondary context is defined as additional information that derives from the factors of the primary context. For example, current weather derives from the user's location and time.

2.2 Music recommendation systems

According to Srikanth and Nagalakshmi [115], an ideal music recommendation system should be ready to automatically recommend personalized music to your listeners. Unlike other systems that recommend books or movies, music takes up less space and can be heard several times anywhere and on several occasions [113]. Many music playback platforms (e.g. Spotify[5], Last.fm[6], Apple Music[7], Deezer[8]) have substantially increased the amount of active users[9] in recent years. The increase in users using music playback platforms has increasingly provided new studies that take into account factors that may influence user choices or preferences. The most common approaches used in these studies are: metadata information retrieval, collaborative filtering and content-based information retrieval.

2.2.1 Metadata Information Retrieval

Music recommendation based on metadata is the simplest method and that provide the easiest mechanism of searching music because the recovery of information uses textual methods, that is, the information provided by the creators, such as the title of the song, name of the artist and lyrics of the music [13]. Although this method is fast, it presents some limitations regarding with the need of users inform many details about the music to thus the searching mechanism suggest similar music [113].

2.2.2 Collaborative Filtering

Collaborative filtering systems suggest the most appropriate music based on user behavior of a group of users [110]. This approach's idea is that whether a user X and Y similarly classify n items or have similar behavior, they will classify or act on other items in a similar way. In this method, rather than calculating the similarity from the songs' data, it uses information of users with similar tastes. Collaborative filtering mechanism presents a good performance, however, it has a cold-start problem. The cold-start problem is divided into two categories: cold-start items and cold-start users [24]. The cold-start problem happens because little information is known about this user or the system has a new user. In collaborative filtering, the cold-start problem is caused when there is a new user presented with few opinions.

[5] https://www.spotify.com/
[6] https://www.last.fm
[7] https://www.apple.com/apple-music/
[8] https://www.deezer.com/en/
[9] https://www.statista.com/statistics/669113/number-music-streaming-subscribers/

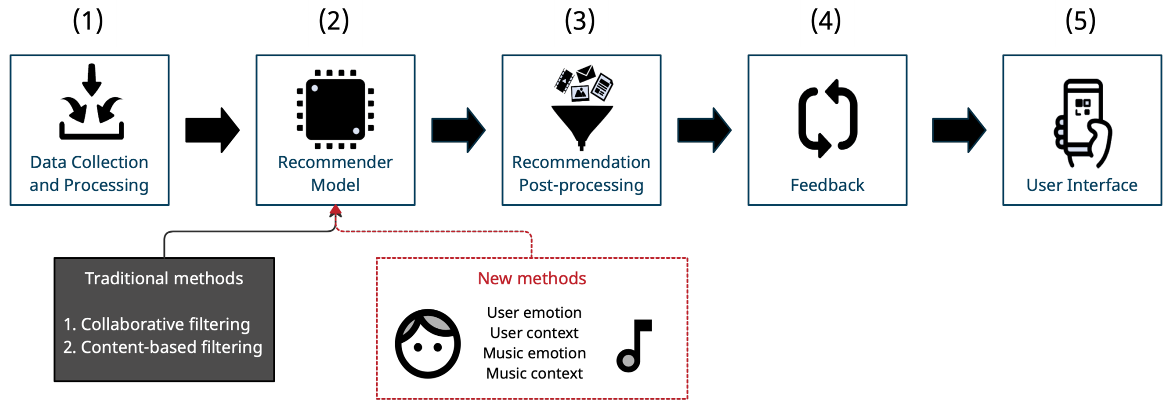

Fig. 1: Recommender system components and data flow [9].

2.2.3 Content based information retrieval

Differently of collaborative filtering technique, the content-based approach focuses on analyzing the content of musical items to make the suggestions to users [38]. The method's objective is to look for music similar to the ones the user liked. For this, the algorithm analyzes the acoustic characteristics of the music. Thus, based on the extracted features, the degree of similarity between each music is calculated and recommends the songs with lesser degree or distance. Although the content-based model can solve the cold-start problem, the method based on similarity has not been fully investigated in terms of the listeners' preference. Yet, no research has demonstrated that similar behavior leads to the same music's choice [113, 27, 28].

2.2.4 Recommendations that considers emotions and contextual information.

Many of the methods presented above make satisfactory recommendations after a long period of listening. However, users' listening preferences are usually immediate and can be strongly influenced by a range of different factors and features, for example, context factors and emotions.

Figure 1 describes the usual components of a recommender system and the order in which they work. The data collection and processing unit (DCPU) in step (1), provides a suitable tool for data collection involving users and items. The DCPU sends the data to the Recommendation Model (step 2), where the recommendation algorithms are executed. The Recommendation Post Processing module (step 3), makes the recommendations ready to be shown to users after filtering and sorting. The feedback module (step 4) used to track system usage and the user interface component (step 5) defines what users see and how they can interact with the recommender [9]. The figure also shows the collaborative filtering algorithms and the content-based filtering that make up the recommendation model.

New approaches that are proposed in the literature involving emotions and context are generally also included in step (2) of the recommender model (see the block with red dashed lines), since it is in the recommender module that the proposed approaches act to improve the performance of recommender systems and provide music suggestions suitable to the users' preferences.

The emotion has attracted attention of researchers and has become the primary trend for the discovery and recommendation of music [130, 55]. Identifying the music-expressed emotion or the user's emotion has been a valuable information for music recommendation systems. That allows users to retrieve music from the emotion which best fits to their current emotional state. Similar to the content-based model, the perception of music emotion is associated with different acoustic signal patterns. Besides, different perceptual characteristics, such as energy, rhythm, time, spectral, and harmony, have been widely used to recognize emotions [125].

In addition to that, the context-based music recommendation can use several information to improve a music suggestion, for example, public opinions, social networks, similarity, data mining, location, time, and even emotions [113]. In recent years, many studies have considered contextual or emotional information when making music recommendations [2, 32, 123, 134, 39, 62]. However, few of these studies include it simultaneously in the recommendation process. Although many studies in the literature deal with emotion as contextual information, in our literature review we highlight the importance of emotion, not treating it only as contextual information, but a more significant fundamental aspect of the Affective Computing area.

3 Method

We carried out a Systematic Review of the Literature (SRL) following the guidelines of Kitchenham et al. [69]. Our aim was to find out the music recommendation approaches that take into account the user's emotion and context. The systematic review process is clearly depicted in Figure 2. Four steps, i.e. study search, study selection, quality assessment and data extraction. In the first step (1), Figure 2, we conducted an initial search to identify the need for SLR (Section 3.1). On the sequence, we define the research questions (Section 3.2), the search string (Section 3.3) and search strategy (Section 3.4). In the second step (2), Figure 2, we selected the studies using the inclusion and exclusion criteria (Section 3.5). In step three (3), Figure 2, we proceed with the quality assessment (Section 3.6). Finally, data extraction (Section 3.7) occurred in step four (4).

3.1 Identification of the need for a review

According to Kitchenham et al. [69], before conducting a SRL, the authors should investigate the real demand for that SRL. Usually, the need for a review originates from the needed of understanding the state-of-the art in the area or from professionals who want to use empirical evidence in their strategic activities of decision-making or improvement. Considering this guideline, we first carried out an ad-hoc searching for SRLs connect our aim, i.e. music recommendation approaches that cover user emotions and context of use. We performed the search on the Google Scholar[10] platform with the following search term: "music recommendation systems: a systematic ("review" OR "mapping")". We filter the search to sort by relevance. However, the search brought up other studies that differ from review and mapping, but with research aim associated with music recommendations that consider emotions and contextual information. As result, we selected 15 publications, which helped us to understand the main characteristics of the literature in this area. In Table 1, we present an overview of these publications, i.e. authors and reference, their objective, and keywords.

The diagram in Figure 3 shows the relationship between related works indicating the main focus. Usually, the works are focused on music context, user context, music emotion, and user emotion. This preliminary analysis suggested that there are few investigations on music recommendation

[10] https://scholar.google.com

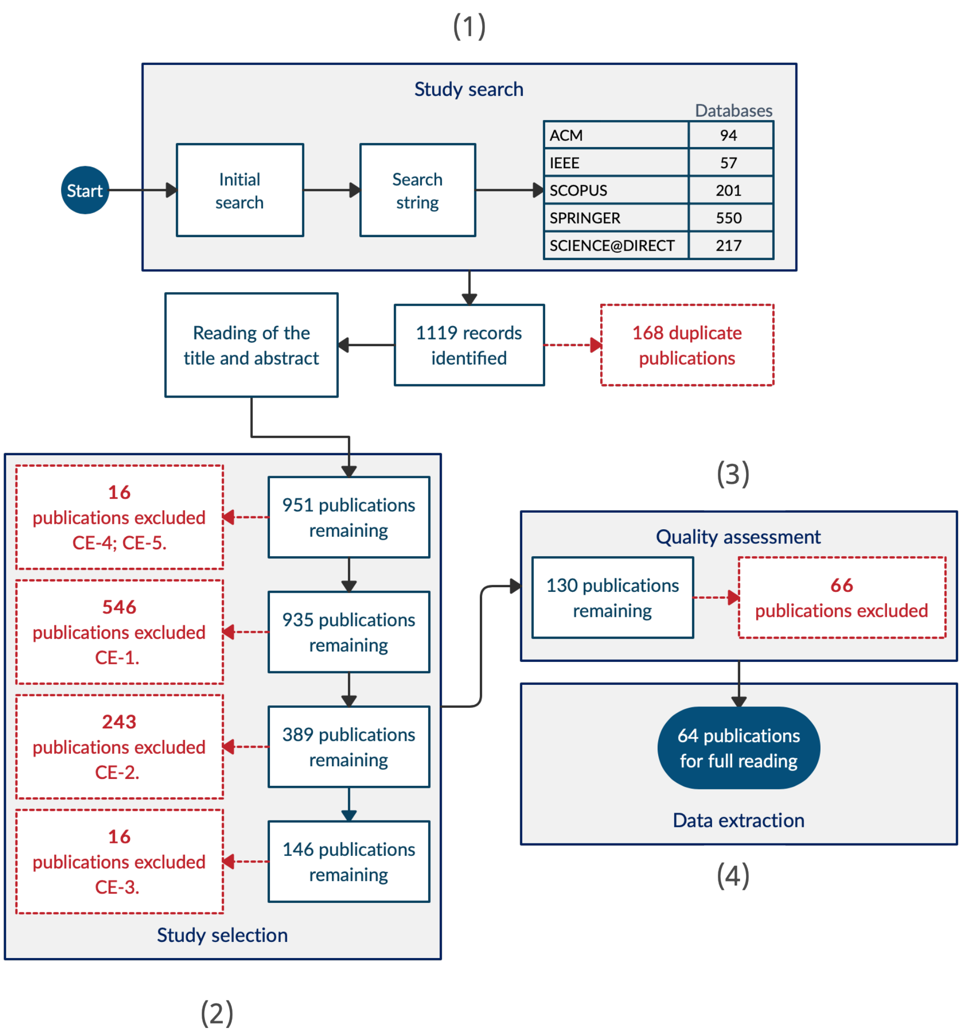

Fig. 2: Overview of the systematic review process.

approaches that handle user emotion and context of use together. The proposals consider only the emotions or only the user's context to perform the recommendation, and emotion is often take as a context factor. Furthermore, this analysis indicated that the SLR objective was viable and could present important contributions to the state-of-art. In addition to seeking approaches, we also identified limitations in the research of music recommendations by considering emotions or context factors.

3.2 Research questions

The first step in SLR planning is the research questions' definition since the entire review process is based on the questions' objectives. The method of defining the research questions took place in the face of the gaps discovered by the initial search presented in subsection 3.1. Based on our first exploration of the literature, we defined the following RQs:

Table 1: Related publications.

Author	Objective	keywords
Abdul et al. [2]	An emotion-aware personalized music recommendation system (EPMRS) that extract the correlation between the user data and the music.	convolutional neural networks; latent features; machine learning; music; user preference; weighted feature extraction.
Chiu and Ko [26]	An intelligent music selection system that help people identify and select appropriate music to improve their learning performance.	music recommendation; personalized music system; machine learning; heart rate variability (HRV); wearable device.
Deng and Leung [29]	An Personalized emotion-based music recommendation using Conditional Random Fields.	music emotion; music recommendation; conditional random fields, graph embedding, rank.
Dias et al. [32]	A personalized music recommendation solution for daily activities, whose approach associates music content (acoustic features) with activities (context).	user-centered; music recommendation; content; context; retrieval.
Gilda et al. [39]	An affective cross-platform music player, EMP, which recommends music based on the real-time mood of the user.	recommender systems; emotion recognition; music information retrieval.
Guo et al. [41]	A novel music system that using the EEG signal as a way of enhancing user's music experience in real-time.	music therapy; music listening; music recommendation; recommendation engine; sequential floating forward selection.
Han et al. [42]	A novel emotion state transition model (ESTM) to model human emotional states and their transitions by music.	emotion state transition model; music information retrieval; mood; emotion; classification; recommendation.
Han et al. [43]	A smart alarm sound recommendation system and an application that study how alarm sounds can impact human emotions.	context-aware; smart alarm sound recommendation; emotion.
Hsu et al. [50]	An evidence-based and personalized model for music emotion recognition.	music emotion recognition; EEG; personalization; emotion trail; affective analysis.
Jin et al. [62]	ContextPlay, a context-aware music recommender that enables user control for both contextual characteristics and music preferences.	context-aware recommendation; user control; music recommendation.
Mariappan et al. [86]	FaceFetch, a novel context-based multimedia content recommendation system that understands a user's current emotional state through facial expression recognition and recommends multimedia content to the user.	emotion recognition; facial expression recognition; context-based content recommendation; computer vision.
Schedl [105]	An intelligent mobile music player that automatically adapts the current playlist to the user context.	user-centric music retrieval; mobile music player; adaptive playlist generation; hybrid music recommendation.
Yang and Teng [133]	A quantitative study ofthe personal, situational, and musical factors of musical preference in a smartphone context.	music information retrieval; music emotion recognition; context-aware music recommendation; smartphone.
Wang et al. [123]	An integrated approach to enhance the prediction of a user's preference that incorporates context factors and emotion.	music recommendation; context; emotion; service-oriented architecture.
Yoon et al. [134]	A personalized music recommendation system that using selected features, context information and listening history.	using emotion triggering low-level features; low-level feature selection; emotion triggering low-level feature; personalized music recommendation system.

RQ-1: What approaches are used for the music recommendation?

RQ-1.1: What approaches are used to recommend music considering the context?

RQ-1.2: What approaches are used to recommend music considering the emotions?

RQ-1.3: What approaches are used to recommend music considering the emotions and context at the same time?

RQ-2: What aspects are desirable to be addressed in music recommendation systems?

The research questions developed to provide an overview of this study, providing guidance and setting limits. We developed the **RQ-1** and its auxiliaries to reveal which approaches the authors to use to perform the process of music recommendation so that the emotion and context are significant to this process. **RQ-1** and its sub-questions helped us to uncover which approaches are used in

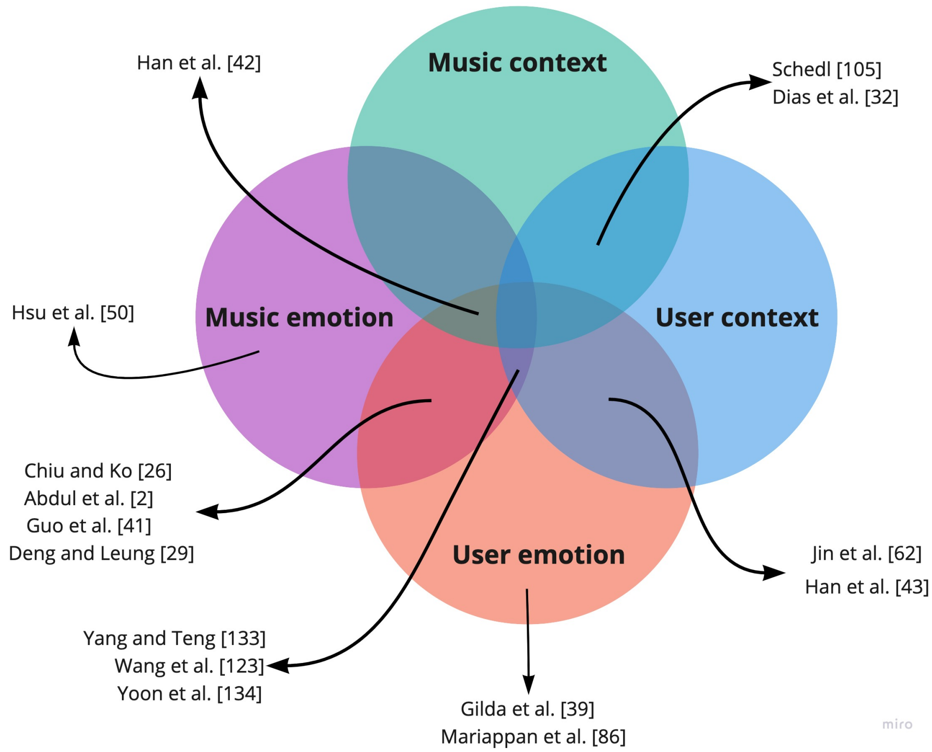

Fig. 3: Works related to emotions and context.

the music recommendation process where the emotion and context of use are meaningful aspects. **RQ-1.1** specifies that the approaches only consider emotion and can be related to the user or the music. Unlike **RQ-1.1**, **RQ-1.2** specifies that the approaches consider only the user's context or the music's context. After the initial study, we noted a shortage of studies considering emotion and context approaches simultaneously, so **RQ-1.3** was defined to cover this gap. Finally, we defined the **RQ-2** to provide insight into which aspects are significant for improving music recommendation approaches.

3.3 Defining the search string

The basis of our search string came from the 15 publications we arose in our first analysis of the literature (see Table 1). We use the keywords from the publications to start building the search string.

Considering that the keywords in Table 1 cover different aspects of our aim, we decided to create the search string from the most relevant keywords in the publications. We checked the frequency of the keywords in the Write Word[11] platform. The Write Word platform has a word frequency counter that allows counting each word's frequency of use in a text. With this, we were able to count incidences by a single word (single term) and by compound words (compound terms). Table 2a shows the number of occurrences for a single word, and Table 2b, the number of compound terms. We considered only words with at least three occurrences for constructing the search string.

[11] http://www.writewords.org.uk/

Table 2: Keyword frequency

(a) Single term

Words	Occurrences
music	21
recommendation	14
emotion	12
context	6
recognition	5
retrieval	5
user	4
low	3
level	3
feature	3
aware	3
information	3

(b) Compound term

Words	Occurrences
music recommendation	9
emotion recognition	4
context-aware	3
music information retrieval	3

In the next step, we found the terms “music” “recommendation” were the words with the highest number of occurrences, which formed the term composed most frequently. Therefore, the term “music recommendation” was the only one defined, and the others discarded. We also define the terms “emotion” and “context”, as they are directly linked to the aim of SLR. Other terms were considered optional for the search, being: “recognition”, “retrieval” and “user”. The terms “aware”, “low”, “level” and “feature” and “information” were discarded as they were part of the discarded compound terms or were present in only one work. After choosing the most relevant terms, we performed three tests to define the search string.

To support research, we chose scientific repositories with a broad scope, and well reputation in Computing area. These repositories were defined by Buchinger et al. [16], being: ACM Digital Library[12], IEEE Explorer[13], Scopus[14] and Science@Direct[15]. In addition to these repositories, we've also added Springer's[16] scientific repository.

Table 3: List of tested search strings in all the repositories.

#	Search strings	Publications
1	(“music recommendation”) AND (context AND emotion) OR (“recognition” OR “retrieval” OR “user”)	1,612,790
2	(“music recommendation”) AND (context OR emotion OR recognition OR retrieval OR user)	1,759
3	(“music recommendation”) AND (context OR emotion) AND (“recognition” OR “retrieval” OR “user”)	1,119

[12] https://dl.acm.org/
[13] https://ieeexplore.ieee.org/
[14] https://www.scopus.com/
[15] https://www.sciencedirect.com/
[16] https://link.springer.com/

Table 4: Inclusion criteria.

Criteria	Description
CI-1	The work is related to music recommendation.
CI-2	The work presents a music recommendation approach that considers the context or the emotions.
CI-3	The work is a primary study.
CI-4	The work was published in a scientific journal or conference.

All versions of the search string are described in Table 3. We execute each version of the search string on the scientific repositories and analyze the search result for the number of publications returned. The first version of the string was very generic and returned 1,612,790 because it did not correctly filter the searched contributions. We got the best result with the third search string returning 1119 publications. The formulation of the last string followed a pattern of three groups linked by the AND operator. The first group allows focusing on studies in the area of music recommendation. The second group makes a refinement allowing only studies that address emotion or context to be involved. Finally, including the third group in the string makes the results approach how to recover or recognize both context and emotion.

3.4 Search strategy

The period definition is crucial for the search strategy. To obtain concise and reliable answers to the questions, we define the search period between January 2010 and July 2021. As of 2010, there was an exponential increase in smartphones, tablets, and various custom applications for these devices [90]. This advance has allowed more and more musical applications to emerge over the years.

The first search took place between 13 and 17 January 2020, in which we applied the search string in all the repositories. The second search took place between July 8 and 9, 2021. In total, the search returned 1119 publications. We exported the search results to the Parisif[17] tool, which automatically identified 168 duplicate publications. We recovered and downloaded all the results manually for analysis.

3.5 Study selection

To reinforce the validity of our review, we identified the relevant studies based on the inclusion and exclusion criteria (see Table 4 and 5 respectively). We elaborated the inclusion and exclusion criteria considering our research question (see Section3.2).

The selection criteria were tested individually for each job. Figure 2.2 shows a flowchart detailing the selection process of the studies. We divided the analysis procedure into four steps. In the first step, we applied the exclusion criteria **CE-4** and **CE-5** to reduce the number of publications to read. In the second step, 515 publications were excluded by the **CE-1** criterion, because they are studies that do not include the music recommendation. Then, in the third stage, 148 publications were excluded by the **CE-2** criterion because the recommendation approach does not consider emotion or context. Finally, the **CE-3** criterion was applied, excluding 13 other publications. In total, we

[17] https://parsif.al/

Table 5: Exclusion Criteria.

Criteria	Description
CE-1	The aim of the work is not related to the music recommendation.
CE-2	The work does not propose a music recommendation approach based on emotion or context.
CE-3	The aim of the work is to propose a new emotion prediction model tied to the user or the music.
CE-4	The work has three pages or less.
CE-5	The work is not written in English.

have selected 110 publications according to the inclusion criteria for the next stage. Table 6 shows an overview of the publications accepted by each scientific repository.

Table 6: Publications accepted and rejected in each scientific repository.

	ACM	IEEE	Scopus	Springer	ScienceDirect	**Total**
	94	57	201	550	217	**1119**
Duplicates	3	5	116	42	2	**168**
Rejected	46	25	47	492	211	**821**
Accepted	45	27	38	16	4	**130**

3.6 Quality assessment checklist

To determine the methodological rigor and quality of the primary studies, we elaborated a set of quality questions, see Table 7. We created 10 quality question, 8 question from the aim of this review and 2 suggested by [69] (**Q1** and **Q10**). The questions' objective was to consider the importance of the individual studies selected when the results were being synthesized. The answers to the questions were classified as 1 (yes), 0 (no) and 0.5 (partially). A study could have a maximum score of 10 and a minimum score of 0.

Table 7: Quality questions

Question	Description
Q1	Are the objectives of the research clearly specified?
Q2	Is the user's emotional recovery process adequately detailed?
Q3	Is the process of emotional recovery of the music adequately detailed?
Q4	Is the process of identifying the user's context properly detailed?
Q5	Is the process of identifying the context of the music adequately detailed?
Q6	The user's emotion and context are considered together?
Q7	Is the music recommendation process properly detailed?
Q8	Is music recommendation approached using a mobile device?
Q9	Is the evaluation with real users properly detailed?
Q10	Are the data collection methods appropriately detailed?

When applying the inclusion and exclusion criteria, the 130 publications were individually evaluated as to quality issues and received scores between 0 and 10. Just like the study of Sagar and

Saha [104], we adopted the scoring interval: low, medium and high, but with the following ranges: low (0.0 ≤ points ≤ 3.0), medium (3.5 ≤ points ≤ 5.0) and high (5.5 ≤ points ≤ 10.0). For this review, we considered only studies in the high range (5.5 ≤ points ≤ 10.0). Thus, we considered 64 publications for full reading and data extraction. Table 8 shows the five publications with the highest score. The complete list of the 130 publications evaluated and the score assigned to each work are in an external appendix[18].

Table 8: List of publications evaluated.

Publications	**Quality Score**
Mood-Based On-Car Music Recommendations	9.5
Ameliorating Music Recommendation: Integrating Music Content, Music Context, and User Context for Improved Music Retrieval and Recommendation	9.5
SAfeDJ: A Crowd-Cloud Codesign Approach to Situation-Aware Music Delivery for Drivers	9.0
From sensors to songs: A learning-free novel music recommendation system using contextual sensor data	8.5
Quantitative Study of Music Listening Behavior in a Smartphone Context	8.5

3.7 Data extraction

After executing the quality assessment checklist, we proceeded with the data extraction phase. Table 9 shows the data extraction form used to record detailed information for each study. For each selected study, we filled out the data extraction form so that the questions could be answered and satisfied. This step aimed to record the relevant information for each study. For this, we used the Parisif[19] digital tool for data extraction. The tool allowed creating a form with defined questions and saving the extracted data into Microsoft Excel documents.

4 Results

In this section, based on the reviewed publications, we provide answers to the research questions presented in Section 3.2 regarding the approaches adopted in recommendation systems (**RQ-1**) and the desirable aspects (**RQ-2**) of these systems. Figure 4 shows the distribution of the 64 primary studies per year selected to answer the research questions. Each line allows the visualization of number of publications per year considering the topics of our SRL as follow described: (a) green line refers to works with music recommendation approaches focused only on context; (b) gray line to only emotions; (c) the yellow line are publications that addresses emotion and context together; and blue line points out the total distribution of publications over the years.

Looking at the line of total publications, we can see that before 2012, only 4 publications were identified. From 2012 on, there was a considerable and almost constant increase in publications that cover the music recommendation. In the years 2011 and 2015, this review's selection process did not qualify any publication with emphasis on context.

[18] Appendix - `https://appendix.herokuapp.com/`
[19] https://parsif.al/

Table 9: Set of questions from the data extraction form.

Questions	Descriptions
Q1	What is the objective of the work?
Q2	How is the user's emotion recovered?
Q3	How is the music emotion recovered?
Q4	What is the emotion classification model used? (Class/Dimensional/Not used)
Q5	How is the context (user and music) recovered?
Q6	How is the process of music recommendation?
Q7	Does the recommendation consider the user's emotion and context together?
Q8	Does the work show evidence for the use of sensors? Which sensors?
Q9	Does the work explore the recommendation in a mobile environment? (Yes/No)
Q10	How was the evaluation performed, and which methods were used?
Q11	Does the work show evidence of an evaluation with users? How many users?
Q12	What are the relevant aspects of the publication?
Q13	What are the limitations or evidence for future work?
Q14	What is the conclusion of the publication?

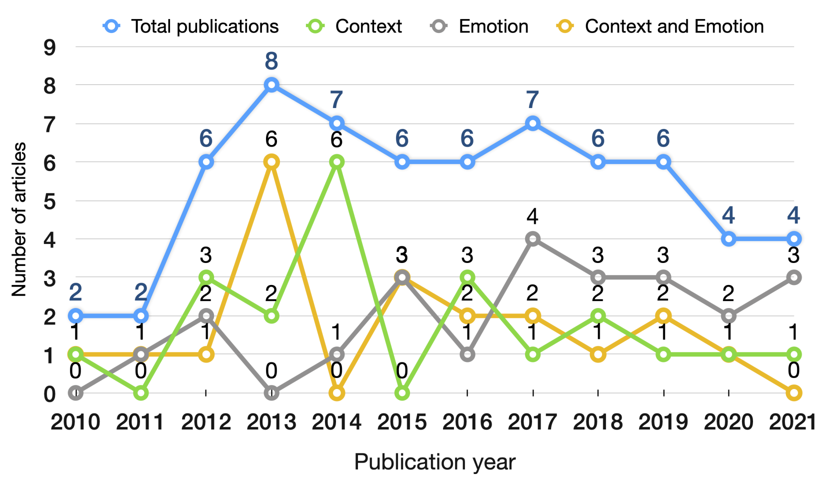

Fig. 4: Publications per year vs topics.

Similarly, in the years 2010 and 2013 for publications with emphasizing in emotions, as well as 2014 and 2021 for publications with emphasis on context and emotions. We also observed that the number of publications increased in 2013 (i.e. blue line) as well as the number of publications that approached the topics of emotion and context together (i.e. yellow line).

To explore the publications that answer the research questions, we understand and define **approaches** as all the methodologies, techniques, guidelines, frameworks, practices, or processes used by the authors during the proposal of the music recommendation that considers emotions and context.

The different types of approaches found in the literature are summarized in Table 10 with their acronyms and descriptions. These acronyms will be used to refer to approaches adopted by the studies found in the review. For example, the **UH** acronyms refer to works that use techniques or methods associated with recovering the user's history when recommending music to the user. This type of resource can generally be used in music recommendation approaches, emphasizing context, or emotion. The following subsections present the answers to the research questions defined and presented in Section 3.2.

Table 10: List of approaches.

Acronyms	Approaches
CCI	Common Context Information
CF	Collaborative filtering
DIM	Dimensional Emotion Model
DISC	Discrete Emotion Model
FE	Facial Expression
FEED	Feedback
MC	Music Context
MD	Musical Data
MDI	Mobile Device Information
ML	Machine Learning
MP	Musical Preferences
ON	Ontology
SEN	Sensors
SI	Subjective Information
SIM	Similarity
SN	Social Networks
UA	User Activity
UB	User Behavior
UH	User History

4.1 RQ-1: What approaches are used for the music recommendation?

To date, according to [119], human's perception of music is yet not fully understood. Therefore, there is no consensus on the best approach to provide music recommendation. In the literature,it has been influenced by several factors, such as age, gender, personality traits, socio-economic, cultural origin, and many other factors. To improve the performance of these system, different approaches have been found. In this review, we focus on the users' context and emotion, as reflected in **RQ-1**

The studies and approaches that respond to **RQ-1** are described in Table 11, along with the work's emphasis, whether is focused on a mobile platform or not and the acronym of the approaches adopted.

After summarizing the approaches of each publication, we realized that many of these approaches had a strong relation with contextual information or emotions. Given this relation, we present the Sankey diagram in Figure 5. The diagram shown in Figure 5 shows the relationship between the previously mentioned approaches with the emphasis on music recommendation. The diagram shows the approaches most used for each music recommendation scopes, besides identifying each approach's level of presence in one of the scopes by each line's size.

When we analyze the Sankey diagram, specifically the context approaches, we notice that the context is further explored by techniques that use standard contextual information (e.g., location, time, weather), historic, user activity, machine learning, among others music-related information (metadata and interaction). On the other hand, still in the diagram, we observed the user's context is still little explored, involving the following approaches: musical context, musical preferences, social networks, user behavior, and even the use of sensors.

Although many of these approaches are still little explored, many considered essential data sources to recover the user's context. An example of this is social networks with a massive flow of user interaction. Most of the time, users remain there, making several posts showing their feelings and daily routines [60, 93, 36]. Suppose researchers notice the importance of combining various contextual approaches. In that case, we may soon see increasingly intelligent music recommendation systems. A suggestive example of this would be a system capable of identifying the musical context related to the user's behavior. Mobile sensors or social networks could identify user behavior.

Table 11: Selected publications.

ID	Author	Related approaches	Focus	Mobile
1	Volokhin and Agichtein [121]	UA	Context	X
2	Bauer et al. [12]	ML		X
3	Lee et al. [78]	UA, ML, CF		X
4	Jiang and He [61]	ML, MD, FEED		X
5	Magara et al. [85]	CCI, MP, UH, MDI		X
6	Jenkins and Yang [60]	SN, UH, FEED		X
7	Schedl et al. [106]	IFFED, MD, MC		X
8	Lee and Cho [77]	CCI		X
9	Cheng and Shen [25]	UH,CCI		X
10	Helmholz et al. [46]	SEN, CCI		X
11	Hong et al. [49]	UH, CCI, FEED		X
12	Teng et al. [117]	MDI, UA, CCI, ML, CF		X
13	Okada et al. [96]	ML, UB, MD		X
14	Karlsson et al. [67]	UH, MDI		X
15	Nirjon et al. [95]	SEN, UA, MDI		X
16	Wang et al. [126]	MDI, UA, MD, ML		X
17	Miller et al. [88]	CCI, MD		X
18	Chang et al. [21]	MD, ML		-
19	Dias et al. [32]	UA, MD		-
20	Hansen et al. [44]	UH, CCI, ML		-
21	Wang et al. [124]	CF, MC, MD, UB		-
22	Assuncao and Neris [7]	DIM, SI, MD	Emotion	X
23	Kang and Seo [66]	DIM, MDI, CCI		X
24	Abdul et al. [2]	DISC, SI, SIM, ML		X
25	Chiu and Ko [26]	DISC, SEN, ML, SI		X
26	Iyer et al. [57]	SEN, FE		X
27	Rosa et al. [101]	DIM, SN		X
28	Guo et al. [41]	SEN, SIM		X
29	Lehtiniemi and Holm [79]	DIM, SI		X
30	Helmholz et al. [47]	SI, DIM, DISC		X
31	Andjelkovic et al. [5]	DIM, MD,SIM		-
32	Lopes et al. [84]	DISC, ML		-
33	Li and Liu [80]	UB, MP		-
34	Padovani et al. [97]	DISC, SI, ML		-
35	Gilda et al. [39]	DISC, FE, MD ML		-
36	Vateekul et al. [120]	DIM, CF, SIM		-
37	Narducci et al. [93]	DISC, SN		-

Table 11 continued from previous page

ID	Author	Related approaches	Focus	Mobile
38	Deng et al. [30]	DIM, UH, ML		-
39	Ferwerda and Schedl [36]	DISC, SN, MD		-
40	Le et al. [75]	DIM, SEN, FEED		-
41	Jazi et al. [59]	UB		-
42	Nair et al. [91]	SI, FEED		-
43	Polignano et al. [99]	SI, SN, UB		-
44	Kittimathaveenan et al. [70]	SIM, DISC		-
45	Jin et al. [62]	SI, MP, CCI	Context and Emotion	X
46	Kasinathan et al. [68]	UA, MP		X
47	Çano et al. [17]	DISC, DIM, SEN, MP, CCI		X
48	Hu et al. [51]	SEN, MD, ML		X
49	Sen and Larson [109]	DIM, MDI, CCI, MC		X
50	Yang and Teng [133]	DIM, SI, MDI, UA, MP		X
51	Schedl [105]	FEED, CCI, MD		X
52	Shen et al. [111]	UB, SN, CCI, MD		-
53	Wohlfahrt-Laymanna and Heimburgerh [128]	DIM, MD, SIM		-
54	Giri and Harjoko [40]	DISC, CCI, ML,		-
55	Yang et al. [130]	CCI, UH, MP		-
56	Braunhofer et al. [14]	CCI, MD, SIM,		-
57	Rho et al. [100]	DISC, MD, ON		-
58	Kaminskas et al. [65]	CCI, MD, SIM,		-
59	Chen et al. [23]	DIM, MD, CF, ML		-
60	Chen et al. [22]	SIM, ML		-
61	Yoon et al. [134]	DIM, SI, UH		-
62	Kaminskas and Ricci [64]	DISC, MC, CCI		-
63	Han et al. [42]	DISC, MD, ON		-
64	Wang et al. [123]	DIM, FEED, MD, CF		-

On the other hand, when analyzing the music recommendation approaches that consider emotion, we observed in Sankey's diagram that many of the studies that consider emotion intensely explore approaches that use facial expression to obtain emotion, as well as subjective information from users, social networks, sensors, similarity, musical information, and machine learning. Also, most of the studies adopt models that describe emotions in continuous and discrete ways. On the other hand, it is noticeable that the studies hardly involve approaches such as user activity and historic, feedback, behavior, and user preferences.

Music is the leisure activity most performed by people [83]. This is due to the significant proliferation of music transmission platforms that allow consumers to listen to music anywhere and anytime. Users of these systems spend much of their time interacting with these platforms and consuming music. Each interaction with these platforms results in a large amount of data that can improve the new recommendations that consider emotions. The music recommendation can be improved using the little-explored approaches in this review. For example, suppose that recommendation systems could combine several emotion-aware approaches. In that case, we could bring the user closer to a desired emotional state based only on their musical preferences, behavior, activity, history, and feedback.

Finally, proceeding with the Sankey diagram analysis and observing hybrid approaches that consider both emotion and context, we realize that hybrid studies tend to explore approaches more than studies that consider only context or just emotion. The most explored approaches involve musical data, musical preferences, common contextual information, and the discreet emotional

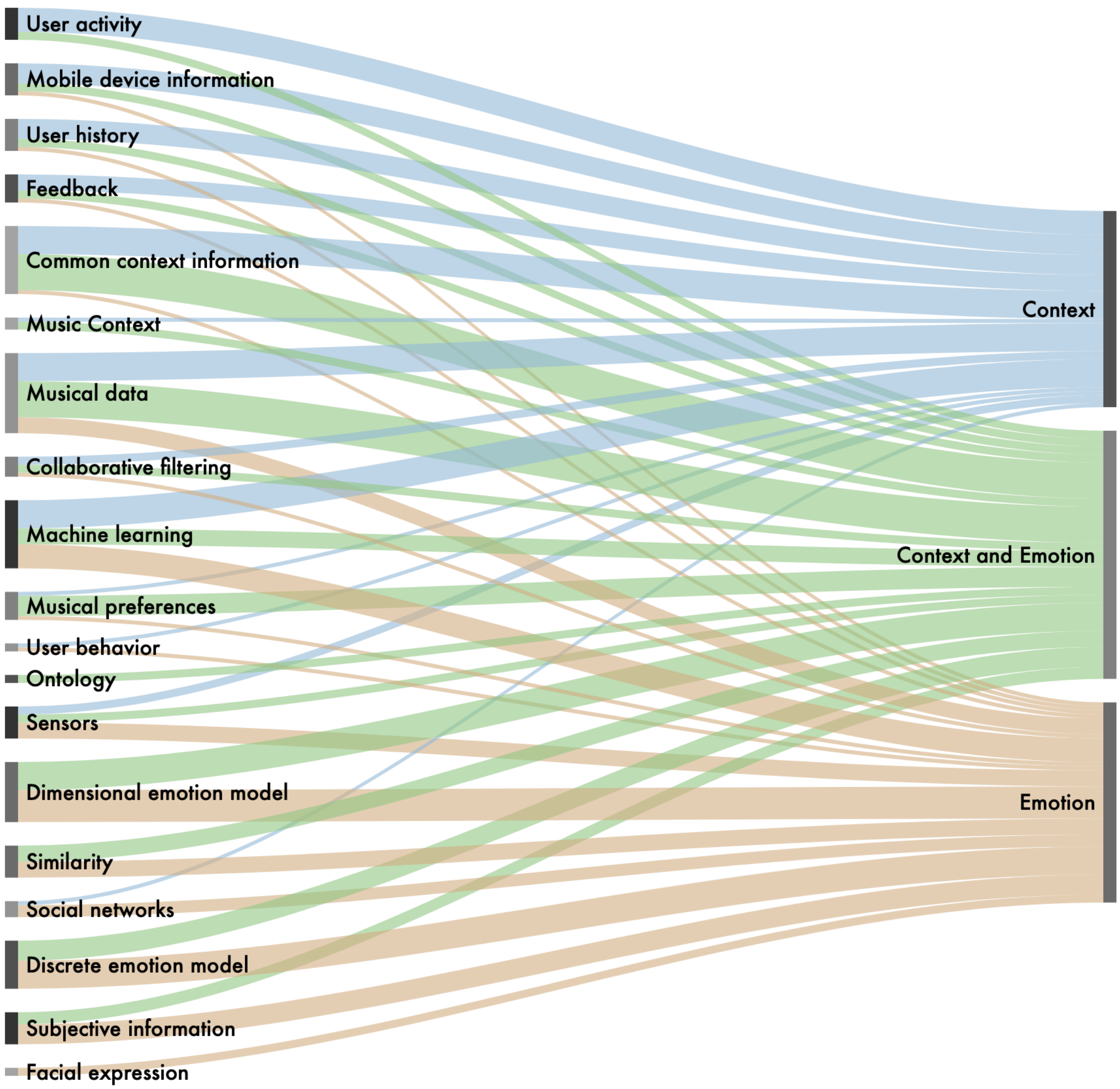

Fig. 5: Correlation between music recommendation approaches.

model. This review did not return any study exploring involving facial expression, social networks, and user behavior in the hybrid approaches. This fact indicates a possible opening for further research on recommendations specific to emotions and context. Next, we explore in more detail each of the approaches presented in the sections that answer the sub-questions RQ-1.1, R-1.2, and RQ-1.3.

4.1.1 RQ-1.1: What approaches are used to recommend music considering the context?

This section presents approaches to music recommendation that consider only the context, be of the music or the user. First, we perform a synthesis of the contextual information that the studies use and then discuss the music recommendation methods.

In recent years, there have been several attempts to incorporate contextual information to improve music recommendation [85, 77, 25, 46, 49, 117, 88]. In general, this information is composed of data such as location, time, date, and acceleration. Such data sets are called Common Context Information (CCI) because they often incorporate other contextual approaches and are widely used in literature. An example can be seen in the work of Miller et al. [88], which uses location to determine user's context through listening. In the work, the authors consider that automatically generated playlists' quality can be improved by taking into account available location data.

Wang et al. [126] present a probabilistic model to integrate contextual information with music content analysis. The contextual information is retrieved using data on user activity, with information coming from a mobile device, as in [12, 121]. User activity is inferred in real-time, and music is recommended based on the analysis of music content.

Karlsson et al. [67] present a system to collect contextual data to recommend music according to learned user-profiles and specific situations. The authors suggest a context with pre-defined songs and then use the first user interaction and their interaction response to shape another context.

In the proposal of Nirjon et al. [95], user activity is continuously inferred by monitoring the heart rate. To this end, they introduced a wearable detection platform called Septimu, which consists of a pair of headphones equipped with sensors that communicate with the smartphone through the audio connector. The smartphone periodically samples the accelerometer and microphone to determine a person's activity level and heart rate. Sensors were also used in the work of Helmholz et al. [46] to complement the study, in which the authors used GPS sensors, skin temperature and conductance, to analyze the effects of various types of music recommendations while driving a driver.

Another notable approach can be seen in the work of Teng et al. [117], the authors classify the user context in 10 pre-defined categories of activity (fooling around, waking up, exercising, in a vehicle, driving, walking, reading, at work, eating, going to sleep), for this they use information from sensors of a mobile device. After identifying the context, they implemented the factoring machine (FM) algorithm to use as a recommendation mechanism.

Dias et al. [32] also retrieve the situation context through the user's activity. For this, they use an approach associated with music content (acoustic resources) and activities (context), which allows analyzing which songs are more appropriate for each activity (based on the user's preferences). Okada et al. [96] have created an application that plays and recommends music to users following user-centred design processes. The following steps were followed: a) determine system objectives; b) identify user needs; c) outline a high-level product design; d) prototype; and e) iterate the project with evaluation results. The application recommends music based on user behavior and music metadata. For this, it has unsupervised learning of user profiles. The recommendations use the user's music with the possibility of discovering new music based on data from other people who listen to similar music or perform similar activities.

Contextual information that has gained much prominence in recent years has been the data of user interaction with social networks. Several recommendation systems have directly collected this data, which was not possible until some decades ago. Jenkins and Yang [60] proposed an algorithm that provides unique personalized recommendations based on users' Twitter posts and listening history. The system selects the lyrics and other fields to generate a list of similar songs and create the recommendation. The proposal is a hybrid approach that combines collaborative methods with user history. Cheng and Shen [25] did not use social network information, but in return, took advantage of the user's history in the music recommendation approach, as in [49, 85]. The authors present a system called "Just-for-Me" that considers contexts associated with the user's location and global trends in music popularity. The results presented showed that incorporating the popularity of music tracks can significantly improve performance.

Hong et al. [49] sought to recommend songs that corresponded to the user's context, considering the newly added songs and avoiding repeated songs. To do this, they analyze the user's feedback before recommending new music because they understand that whether a user likes a musical piece in a particular context, then he/she will listen to that musical piece; otherwise, he/she will skip the musical piece without listening to it until the end. Magara et al. [85] have proposed the MPlist that recovers the context via listening history. To do this, they use data from various sensors on a user's intelligent mobile device and use them to infer the context and user activity, generating a playlist based on contextual preferences.

Schedl et al. [106] say that a comprehensive set of resources derived from sensors, space-time information, and user interaction can be essential to learning what kind of music listeners prefer in a given context. The authors proposed creating a playlist in real-time in two ways: by the user's context and by the information of the songs using semantic tags (labels). Tag semantics is also used in Kaminskas and Ricci [64] to select a musical content that fits a place of interest. They used emotional tags assigned by the user to the musical tracks and points of interest. An online experiment was conducted by the authors to assess the suitability of the music selected by the system for the point of interest. The results show users tend to agree on the correspondence between the songs' emotional tags with the points of interest produced by the community users themselves.

On the other hand, some studies have used machine learning techniques in music recommendation [61, 78, 21]. Jiang and He [61] incorporate an evolutionary model called Incremental Regression Tree, which collects contextual data, musical data, and user feedback in an incremental way to characterize his/her personal taste for music. Lee et al. [78] present a mobile system that includes modules to recognize human activities. The recognition of user activities uses machine learning methods with smartphones signal resource selection techniques and collaborative filtering methods to estimate the user's musical preference. Other study that also incorporated machine learning methods for music recommendation was Chang et al. [21]. The authors used reinforcement learning algorithms to learn the user's preferences and then make the recommendations.

Hansen et al. [44] seek to predict at the beginning of the musical listening session what the user will hear during the session. To do this, the authors assume that they have access to the user's history and information about the current context. The context is defined by the time of day (morning, afternoon, etc.) and the device used to access the service (mobile, desktop, etc.). Finally, a neural network architecture is proposed, called CoSeRNN, which models user preferences as a sequence for each session.

Wang et al. [124] proposed a content and context-aware music recommendation model that can exploit heterogeneous information to make accurate music recommendations. For this, the authors drew inspiration from the collaborative filtering (CF) method based on matrix factorization. The content information includes music textual content such as metadata, tags, and lyrics. Context data incorporates user behaviors, including music listening logs, music playback sequences, and sessions. The music content and context embedding method (CAME) is proposed by the authors. CAME can learn the content and music context through network embedding and the works of convolutional neural network with attention mechanism and is able to accurately model the intrinsic characteristics of music pieces as well as their relevance and interactions.

In Polignano et al. [99] proposal, the authors investigated how to include emotional aspects in the recommendation process. The emotional state of the user is defined by a set of emotions (e.g., joy, surprise). The authors present an affective user profile in which preferences are modeled considering affective information. The affective profile was included in a recommendation process. For this, they implemented a system called emotion-sensitive RecSys and performed an evaluation in the music domain. The results showed higher recommendation accuracy compared to several baselines, including machine learning methods and content-based filtering methods that do not exploit any affective information to model user preferences.

4.1.2 RQ-1.2: What approaches are used to recommend music considering the emotions?

Most music recommendation systems use content-based or collaborative recommendation methods. However, the choice of a user's music depends not only on historical preferences or musical content but also on the user's emotions [9]. The analysis of human emotions after exposure to music is considered an essential direction because several studies have investigated the influence of emotions in decision-making and the recommendation process.

With the user's emotion recognized, the recommendation systems become capable of suggesting more good music to the user, as presented by Iyer et al. [57]. The authors' aim is to minimize the user's effort and suggest music based on current emotion. In the work, the emotion is identified through facial expressions using the Fisherfaces algorithm. When recognizing the emotion, the application sends the emotion to the music server and then suggests an appropriate playlist. Another work that uses facial expression is presented by Gilda et al. [39]. The authors present a music player that makes recommendations based on the emotion in real-time. The player is called EMP and incorporates the emotional context within the adaptive recommendation. The approach has an emotional recognition module that uses audio resources to classify the music into four different emotional classes. The user's face is captured and used in machine learning algorithms to identify the user's emotion. With this, the proposed application suggests music to the user, mapping the user's emotions with those of the music, besides considering the user's preferences.

In Chiu and Ko [26] publication, music is described in four categories: "Misery" and "Arousal" (I), "Pleasure" and "Arousal" (II), "Misery" and "Sleepiness" (III) and "Pleasure" and "Sleepiness" (IV). Songs of the same category are recommended to the user according to the emotional state detected. The emotion was recovered in two ways: by wearable devices that detect heart rate variability (CBV) and questionnaires of subjective feelings. The emotions were analyzed so that the appropriate music could be selected. Also, user preferences were recorded using machine learning algorithms.

Physiological signs have been studied for decades in psychophysiology to explain human behavior, and several physiological signs are available for measurement. Physiological signs are direct information of a human being and can tell health conditions, capture body actions, and even react with emotions [73]. Before, these signals were limited to capture only in the laboratory, but with the advancement of technology, the capture of physiological signals can be performed anywhere and at any time. Instead of bulky hospital instruments, mobile devices have become a trend for this capture in recent years [127, 73].

The recognition of emotions through physiological signals is one of the branches of affective computing, and many researchers use bio-signs to infer people's emotions [41, 75]. Guo et al. [41] use electroencephalogram (EEG) sensors to record the brain's electrical activities. Through the EEG signal, the user's emotion is recovered and associated with parts of the music that activate this emotion. Consequently, songs are suggested with the same characteristics. To monitor brain activity when listening to music and reflect emotional responses, the authors used the cell phone in cloud architecture to host the processing and recommendation algorithms.

The recommendation approach proposed by Le et al. [75] considers the emotion and feedback of users to suggest music. Le et al. [75] monitor small electrical changes in the body's skin using an electrocardiogram (ECG) sensor. In another way, Vateekul et al. [120] did a study using EEG signals to predict musical emotions. In this study, the authors present a new algorithm for predicting emotions applying collaborative filtering (FC) and similarity scores based on EEG signals. The results show the proposed method is superior to traditional FC and conventional classification techniques, including C4.5, SVM (Support Vector Regression), and MLP (Multilayer Perceptron).

A remarkable recommendation approach is presented in the works in [66, 5]. Kang and Seo [66] estimate a user's emotion based on the smartphone's texts and recommend music with the same emotions when the user returns home. Andjelkovic et al. [5] presents a new way of recommending songs based on the same artist's similarity of emotions. Also, the system brings a new way to visualize the emotion in a visual space that allows a better understanding of users' recommendations.

Another approach of music recommendation can be seen in the work of Abdul et al. [2]. The authors present a personalized music recommendation system that considers emotions and associates user data with music. Two approaches were combined to achieve this correlation: the convolutional neural network approach and the resource weighted extraction approach. Besides combining the two approaches, the user's emotion was considered and recovered subjectively, as in [79, 97, 7].

Lehtiniemi and Holm [79] used animated and emotionally defined images to identify the user's context and recommend music. On the other hand, Padovani et al. [97] presented Bardo, a system that automatically selects background music for table games. The system recognizes the user's speech and transforms into text everything that players say during a game session. Then, a supervised learning algorithm is used to sort the text into an emotion. Assuncao and Neris [7] present a mobile application that, when recommending music, considers the user's current and desired emotional state. The main objective of the work is to help the user achieve a desired emotional state. The study applies the Assuncao and Neris [6] algorithm that receives input three parameters: the current emotional state, the desired emotional state, and a set of songs with the emotions expressed in a dimensional model.

Although there are studies that classify emotions in dimensional models [30], generally, many studies describe emotions from a discrete perspective [93, 84]. In the discrete perspective, the emotions are seen as a sum of categories that can be separated to obtain more refined and smaller subcategories. Discrete models are quite popular because they are easily linked to "popular psychology" [82].

The proposal of Narducci et al. [93] is based on content filtering techniques to infer the user's emotions. The authors assume to extract the user's emotion from some user-generated text (e.g., a Facebook post, a tweet), using text analysis techniques, making the emotional information available to the recommendation algorithm. The same occurs in the works in [84, 36, 101].

Li and Liu [80] present a music recommendation approach based on the analysis of the user's behavior and the extraction of emotions from the user. To do so, it establishes a model of user interest through the analysis of musical preferences. The user's emotion is retrieved from social network messages using the Word2vec grouping method. The music recommendation combines the list recommended by the collaborative filtering method with the emotional analysis results to generate music recommendations according to the user's emotion.

Helmholz et al. [47] presented an emotional music player called Moosic that allows an immediate emotional change in music playback with one click. Context-based music playback. Moosic shows how music can be classified based on emotions. The system uses Spotify's API to create a playlist based on the user's emotional input. The music selection works through a circular avatar, which displays the Spotify user's profile image. Moving the avatar allows the user to select their emotional state. In addition, the user can select various genres as well as the popularity of the songs to further tailor the system's music selection to their personal preferences.

Jazi et al. [59] presented a music recommendation system that suggests music based on user keyboard and mouse click patterns. The music is recommended directly, without labeling the user's emotion, so that the error of estimating the user's emotion does not negatively affect the accuracy of the recommendation. This system is based on collaborative filtering.

Just like in the study of Helmholz et al. [47], the proposal by [91] uses the API of Spotify's platform for the generation and recommendation of the playlist. In the study, the authors developed a custom system, where the user's current emotion is analyzed with the help of the chatbot. The chatbot identifies the user's emotion by asking some general questions. Based on the input provided by the user, a score is generated for each answer, which adds up to a final score. The final score is used to generate the playlist.

Finally, in the study by Kittimathaveenan et al. [70], the proposed approach is based on the selection of music according to colors. The authors present an alternative way to choose music based on a selection of colors by applying color to music. The study presented three steps: the first step was the preparation of the music library of the association between color and emotion; and the association between music and emotion. The library data used to create the Hue, Saturation, and Value (HSV) color model were: Hue to represent musical instruments, Saturation referred to time, and Value was the key (tone). The second step was to create two types of graphical user interface (GUI) for color selection. The last step was to collect data from 120 participants who took part in the evaluations.

4.1.3 RQ-1.3: What approaches are used to recommend music considering the emotions and context at the same time?

Another recommendation approach that observes musical preferences was introduced by Kasinathan et al. [68] and is called HeartBeats. The HeartBeats uses a fuzzy inference mechanism that considers the user's activities (context) and emotion as part of the recommendation parameters. The recommendation system uses features of the user profile to recommend correct songs based on preferences. The results show it is possible to improve the user's music listening experience through recommendations that considers emotions and context.

Yang et al. [130] show the association of the climatic conditions with the observation of the user's emotional factors improves the music recommendation system. In the work, the authors present a method of emotion-aware music recommendation that proposes music and artists based on the emotion of each user. The authors have recovered the user's emotion from meteorological information in real-time. The recommendation process analyzes the user's listening history and classifies music and artists that are favourable in different weather conditions. The researchers discover the user's musical preference for the user's behavior and service consumption pattern.

Chen et al. [23, 22] present two approaches for the recommendation of music aware of context and emotion. In the first study, Chen et al. [23] proposed a contextual approach that recommends music to a user based on the emotional state predicted in the text he/she writes. The authors analyzed the association between text and music generated by the user, from a set of real-world data. Listening behavior shaped the user's emotion and context. For this, they adopted the factorization machine (MF) algorithm with a learning approach by the author himself. In the second study, Chen et al. [22] present a recommendation approach based on various similarity information via MF, including similarities based on content and context. Through text analysis performed on LiveJournal's[20] real-world data set were recovered, the user's context and emotion.

Yoon et al. [134] implemented a custom recommendation system using selected resources, context information and listening history. In the proposed recommendation system, after the user provides the emotional state by emojis, context information (temperature, humidity and lighting), the system creates a playlist. The user can select a song from the playlist and listen or get a recommendation list from the server. The recommendation module retrieves the listening history, low-level features, contextual information and then creates a playlist and suggests it to the user. In the work, the authors adopted the Thayer [118] model to classify emotions.

Wang et al. [123] say that few studies take into account both context of use and emotions simultaneously. Faced with this, the authors proposed an integrated approach to improve the prediction of user preference, an approach that incorporates context factors and emotions. First of all, the recommendation mechanism collects the location, the time of listening to the songs and the representative emotion. Next, it recommends a playlist that relates to users' emotions and contextual information.

A particular type of music recommendation is presented in [14, 65, 64]. The works are quite similar. The main task is to recommend a song that fits in a place of interest (POI). Therefore, emotional tags have been assigned to both the songs and the POIs. With this, the similarity of tag features was used to establish a correspondence between the songs and the points of interest. Seeking similarity as a way to detect context and emotion during music recommendation can also be seen in the work of Wohlfahrt-Laymanna and Heimburgerh [128]. The authors provide a solution that generates a playlist based on the emotion expressed by the lyrics and musical resources. With these values, the system measured the distance between other values and automatically searched for a similar playlist that is contextually significant.

In Han et al. [42], the authors proposed an ontology called COMUS to represent various user situations. Also, an emotional transition classification was proposed to map the emotional transition with low-level music resources. The COMUS ontology is also used in the work of Rho et al. [100]. The authors present a new scheme for a situation-aware/adaptable music recommendation service in the semantic web environment. The ontology is used to model the user's musical preferences and contexts and support the reasoning about the user's emotions and preferences.

Another approach can be seen in the work of Giri and Harjoko [40]. In this, users inform their desired activity and emotion to receive a music playlist based on their context. For this, the authors used case-based reasoning (CBR). CBR can be applied to various types of problems, and CBR can provide a solution using the accumulation of previous cases at the base of the case. music recommendations for a particular context can be determined based on music choices made previously so that CBR can give recommendations based on musical solicitation cases on radio stations that have happened.

[20] https://www.livejournal.com/

When a music recommendation approach is proposed for a mobile environment, it should consider the resource limitations that a mobile device imposes and the user experience aspects [61]. In particular, the user's contextual aspects should also be considered significant, since the consumption of music in an environment, the context changes a lot [78].

Sen and Larson [109]'s objective is to provide music recommendations based on contextual information recovered by sensors. The context is inferred by the mobile device's location and sensors, for example, the accelerometer. The authors used climatic factors to define the user's emotion. That is, they considered that the climatic condition affects people in a particular geographical area. The model of emotional classification used was that of Russell et al. [103]. The recommendation process joins the data from the sensors with information from the web passing through a cascade of Fuzzy Logic models to infer the user's context and then recommend music.

Besides climatic factors, Jin et al. [62] designed a system that allows the user to control which characteristic he/she wishes to consider during the music recommendation. Users can indicate the importance of six contextual characteristics: mood, location, climate, social aspects, current activity and time of day. The recommendation algorithm created was based on the Spotify API. Playlists are created for different contextual characteristics. The results of the work show emotion seems to be the most significant contextual characteristic.

From another perspective, Schedl [105] presents the MMG (Mobile Music Genius), a music player capable of generating a music playlist with user recognition and matching of places of interest. The MMG does not perform signal processing to recover the music emotion. The emotions of music are described by emotional tags annotated by the community of listeners. User emotion and activity are requested every time a new song is played. The authors presented some contextual information, for example, time, location, climate, environment, physical activity, telephone status, connectivity, among others that can be seen in the work. The MMG learns relationships between contextual data and implicit feedback from the user (play, pause, stop, skip events), that is, what type of music you prefer and in what situation.

Another proposed recommendation approach for smartphones is SAfeDJ [51]. The SAfeDJ is a music recommendation system designed to turn driving into a safe and enjoyable experience. The aim of the work is to help drivers to reduce fatigue and negative emotions. The design is based on interactive methods that allow the smartphones inside the car to orchestrate multiple sensing data sources and the drivers' social context. The proposed solution is fascinating because different smartphones can recommend music preferable to drivers according to each driver's specific situation.

Also, thinking about how to recommend music that can improve a driver's driving, Çano et al. [17] presented a contextual music recommendation project to bring positive influences in the driver's driving behavior. For this, they focus on the user's emotion. Also, they considered physiological information about the driver's heartbeat dynamics obtained from wearable sensors; musical preferences saved from the user to take into account his/her musical tastes; telemetry of the current unit to consider the user's current driving style; location and time information to adapt the chosen playlists to the driving context.

On the other hand, a quantitative study of personal, situational and musical preference factors in a smartphone context was presented by Yang and Teng [133]. In this work, an experiment with 48 participants subject to a music listening application was performed. The application asked each participant to write down their activities and emotions before starting to listen to music. The emotions were classified into ten emotional states: happy, blessed, animated, sad, melancholic,

Table 12: Desirable aspects of music recommendation.

Aspects to be addressed	Reference
User activity	[117, 61, 78]
User satisfaction	[26, 67], [123, 42], [96, 61]
Feedback	[126, 96, 85, 61, 80, 105, 123]
Cold-start	[126, 21, 60, 85, 41]
Cognitive load	[62]
Learning	[85, 21]
Personality and user preferences	[42, 36, 36, 111]

angry, peaceful, feared, restless, none. The user's activity could be one of the 13 activities classified by the authors (wake up, exercise, drive, walk, among others). The recommendation used in the experiment was that the user could choose any music. It was enough for the experiment participant to inform the activity and the emotional state before starting to play some music. Although the approach may seem simple, it is rich because it brings results that better explain how the listeners' manual recommendation is.

In Shen et al. [111] approach, the authors are concerned with music recommendation on social media platforms and proposed the Personality and Emotion Integrated Attention (PEIA) model. In the model, each user was analyzed comprehensively, extracting personality- and emotion-oriented characteristics involving demographic, textual, and social behavioral attributes. Finally, for each song, acoustic, metadata, lyrics, and emotion features were considered. The PEIA model employs hierarchical attention under a deep framework to learn the correlations between user personality, user emotion, and music, and achieves remarkable performance on a large real-world dataset.

4.2 RQ-2: What aspects are desirable to be addressed in music recommendation systems?

Although the music recommendation systems often support users to find the music that brings pleasing to them, there are still challenges that need to be explored by these systems. Especially when it comes to building, incorporating, and evaluating of strategies that goes beyond linking into the choices that users make or content-based descriptors. These challenges involve additional research on the needs, preferences and intentions of listeners [107].

The users' desire to hear a music depends on several factors, which are often not sufficiently considered by current approaches of music recommendations. Table 12 presents aspects that can be considered significant and desirable to be addressed by music recommendation systems. During the step 4 da SLR (see Section 3.7), we extracted these aspects which were identified from the approaches of the publications or mentioned as essential factors for music recommendation by the authors. Considering Table 12, we discuss each aspect as follow.

User activity

Teng et al. [117] identify the user's activity in 10 categories: "at work", "eating", "driving", "doing exercises", "playing", "in a vehicle", "reading", "sleeping", "walking" and "going up". Each user selected the activities before listening to a song. The authors conclude that context-aware music recommendation obtained a better performance when they used tags that described the user's activities. Another way to detect user activity is by using a mobile device [61, 78]. Jiang and He [61] recovered user activity using the linear magnitude of acceleration. Lee et al. [78] considered three activities in the study: taking public transport (transportation), going out shopping (shopping) and taking a relax. For this, they used resource selection techniques based on smartphone data (location, movement, time, noise level, among others) and inferred the user activity by using machine learning methods.

User satisfaction

The evaluation of the quality of a recommendation system is usually done by functional tests, recommendation algorithm output quality or usability evaluation. However, these methods do not always reflect user acceptance, and recently there has been a growing consensus that recommendation systems should focus less on the offline evaluation of algorithms and focus more on user-centred approaches [96]. Jiang and He [61] sought to preserve the user experience during listening by using machine learning algorithms to learn the musical preferences of users in different contexts by incorporating the explicit and implicit feeding of the user. Okada et al. [96] have chosen to focus more on a qualitative assessment based on UX tests. According to the authors, providing recommendations in a mobile context while learning user profiles is still a challenge., because they found out that users feel confused by the lack of control over which songs would be played.

Several proposed recommendation approaches are evaluated by measuring the accuracy of the correct recommendations. However, Karlsson et al. [67] conducted a usability test with active music listeners to collect preferences, needs and opinions on possible improvements to the proposed recommendation system. The preliminary test showed that users felt confused by the lack of direct control over which songs were played and were curious to know which song would be the next suggested.

Chiu and Ko [26] followed another approach and measured subjective user satisfaction through the System Usability Scale (SUS) usability questionnaire [15]. The average SUS score for all surveys was 75.94, showing that usability ranges from *Ok* to *Excellent*. However, when we analyzed the questions addressing negative aspects, we noticed that the question with the highest negative average indicates the need for technical support from other people to use the system, an important usability gap to be addressed.

According to ISO 9241 [56], satisfaction is considered an essential aspect of usability. Among the aspects of usability (effectiveness, efficiency and satisfaction), satisfaction is considered the most challenging attribute to measure and quantify since it is related to subjective factors. Satisfaction refers to the degree of comfort users feel when using a product [94]. Recent studies seek to investigate more and more user satisfaction in recommendation systems [123, 77, 42]. These studies point out that satisfaction in musical recommendation systems can be associated with each type of user interaction, (e.g. saving a song, adding a song to a playlist, viewing an artist page or album). In general, the studies identify the degree of satisfaction with the recommendations that are suggested from data collected in interviews and questionnaires.

Feedback

The current recommendation approaches ignore the rich and customized information that can be gathered from the user interaction with mobile devices [61]. To improve the accuracy of recommendation systems, user feedback can be inferred from the user's implicit actions with the system. For example, whether a listener hears a music, ultimately, the user probably give a like to that music, which can be considered positive feedback [126]. Wang et al. [126] explore feedback implicitly by analyzing users' interactions with music recommendation systems, such as in [96, 85, 105].

By receiving feedback, the recommendation systems can take several suggestions for improvement from information about context, emotion, user activity, and design [96]. Magara et al. [85] used implicit feedback from the listener for continuous learning, thus improving their forecasting accuracy. The implicit feedback is captured the user's action (e.g., selected music) and and sent to the server, so the user's playlist is updated based on the user's response and change in context. Li and Liu [80] proposed to analyze in-depth the user's behavior data from the user's records and displaying the feedback information to examine which music the user listens to most often. Wang et al. [123] used questionnaires to get feedback from participants during the experiments and improve the recommendation.

Cold-start

Most current recommendation systems employ the collaborative filtering model, and these systems are vulnerable to the cold-start problem [21]. The cold-start problem arises because when a recommendation system has a new user, little information is known about that user. The "new users" represent a particular group of users who have not yet generated much data. Usually, the recommendation system needs to extract its current preferences from their location [24]. Wang et al. [126] present a solution to the cold-start problem using users' location by searching the most played songs in the user's region and for each song it makes an audio analysis to check whether that music is suitable for a particular user task or emotional state. Jenkins and Yang [60] seek to solve the cold-start problem using context information collected on Twitter combined with a collaborative approach using the K-Nearest Neighbourhood (K-NN) algorithm. However, whether the user does not have Twitter account, the approach does not work. Magara et al. [85] have shown it solves the cold-start problem using data from sensors installed on mobile devices and uses it to infer the user's context and current activity. Guo et al. [41] only emphasize the importance of avoiding cold-start and leaves for future work to investigate how to avoid the cold-start problem with the content filtering method.

Cognitive load

According to Harrison et al. [45], cognitive load refers to the amount of cognitive processing required by the user to use the application. It refers to the use of people's psychological resources to stimulate their ability to apply their acquired knowledge and skills to solve problems. Jin et al. [62] presented ContextPlay, a context-recognized music recommender that allows the user to control contextual characteristics and music preferences. The study shows that providing control over contextual information increases the perceived recommendation quality without increasing the cognitive load. Lastly, the authors suggest the recommendation designers include context control to increase the perceived recommendations' quality.

Learning

One relevant supposition is whether recommendation systems made it possible to recognize, interpret, adapt, and learn the activities of users, in addition to the context and auditory preferences. In that case, users could reduce the effort in looking for a song among billions of other songs in recommendation systems [85]. A system that learns from data is an intelligent system that makes decisions automatically, just like the MPlist proposed by Magara et al. [85]. The learning of MPlist is constituted of machine learning algorithms and implicit feedback to improve accuracy in forecasting. In part, Chang et al. [21] used a machine learning method called booster learning, which makes a sequence of decisions to learn the user's preferences from the music playback record.

Personality and user's preferences

Users' preferences are essential and should be taken into account by music recommendation systems. For instance, we can imagine that a person who is in the habit of listening to classical music in the morning, when waking up, receives the suggestion of a song of the rock genre. This person will probably have a bad experience because the music suggested did not belong to their musical style. Besides the musical genre strongly linked to people's preferences, the popularity of a song is an important aspect that can influence the listener's choice of a song. Recommendation system designers should always consider user preferences. Many recommendation approaches seek to prioritize users' preferences [42, 36]. In the recommendation architecture proposed by Han et al. [42], the user preference includes personal information (e.g., age, gender, work) and musical properties (e.g., favorite genre, singer, detailed musical description). Unlike other works, Ferwerda and Schedl [36] do not report which contextual information is associated with user preference but demonstrate that personality can be an essential aspect to understand the user's preference to improve music recommendation.

Personality has proven to be a lasting factor influencing an individual's behavior, interest, and tastes [87]. An emerging interest exists in how personality relates to the preferences of the user Ferwerda and Schedl [36]. Ferwerda and Schedl [36] discuss initial ideas on improving recommendation systems, incorporating the user's personality and current emotional state. They also suggest that as social networks generate a constant communication flow, they can extract personality and emotional states. Shen et al. [111] proposed PEIA, an Integrated Personality and Emotion Attention model, the authors extracted personality- and emotion-oriented features involving demographic, textual, and social behavioral attributes. The work delves into learning the correlations between user personality, user emotion, and music, and achieves remarkable performance on a large real-world dataset.

5 Challenges

Our findings reveal some limitations and challenges regarding musical recommendation systems, as previously described. These challenges need to be overcome so that music recommendation systems can suggest songs that meet the user's perspectives and, consequently, enable a better musical experience. We present our challenges from context and emotions perspectives which are the two main topics of our research. For each perspective, we discuss two types of challenges, technical and user-centered ones.

5.1 Context perspective

The main aim of music recommendation systems that consider contextual information is to allow users to listen to the music that best suits their current usage context. However, for this to be achieved, recommendation systems should first identify the context information. Several contextual information has been proposed and applied to improve the user's listening experience (see publications 1-19 in Table 11). We see that in most of the publications, the context information is often found using machine learning techniques, smartphone data, user history, user activity, location, climate, location, temperature, and musical information. Although the music recommendation studies that consider contextual information presented so far have presented relevant results, studies still need to further explore the technical and user-centred challenges that exist during music recommendation.

5.1.1 Technical Challenges

Incorporating contextual information is very important in several application domains, including music recommendation systems, where the user opinion about suggested music is context-dependent. Currently, it is quite common for new music recommendation proposals often provide recommendations features for mobile devices since these devices such as smartphones allow to recover the context more easily. However, many of these systems running on mobile devices have resource limitations. A significant processing effort may be required to apply popular and robust recommendation techniques such as Support Vector Arrays or Deep Learning [61]. Besides, a concern exists with battery life and data traffic. Depending on the application, the system may be associated with constant context recognition.

Other recommendation approaches often apply the user's history to identify the context and suggest music. These approaches assume that the current context can be retrieved from similar listening patterns and, therefore, have achieved significant results in recommendations [85, 60, 25, 49, 67]. However, these approaches are only efficient when the user's history is composed of a series of variables (e.g., daily use of the system and constant evaluations of music) involving user interaction with the system or the surrounding environment.

Besides the user's history, the user's activity has been taken into account in many approaches during music recommendation considering the context [44, 121, 78, 117, 95, 126, 32]. In these approaches, the context is identified from the activity it performs, whether running, walking, or working. The biggest challenge of these approaches is identifying the current activity, which is a complex task because the diversity of possible activities is extensive. Because it is a complex task, many of these systems use a smaller set of pre-defined activities or find patterns during the interaction with the systems.

Many approaches that relate music to contextual conditions tend to use a mix of contextual aspects in a music recommendation algorithm. For example, in Magara et al. [85], the authors use a mobile device's information, recover the user's history, and consider musical preferences. Similarly, Teng et al. [117] take advantage of information from a mobile device, recovers user activity, and join to machine learning methods to suggest music considering the context. Although in both works the union of various contextual aspects seems interesting to improve music recommendations, the authors do not highlight the contextual conditions in which music is recommended.

5.1.2 User-centred challenges

Besides technological challenges, human factors can impact in the recommendations based on contextual information. Selecting a song to play typically requires the user's attention and several operations on the screen. Therefore, when the user is in motion, which is more challenging than standing still, the application is expected to provide a more engaging experience. However, few approaches that consider emotions and context presented by this review are concerned with the user experience [96, 61]. Typically, music recommendation systems evaluations use accuracy metrics and related quantitative measures such as accuracy, recall, or error averages (between the prediction and the actual rating) [117, 85, 22].

The evaluation of the accuracy of recommendations does not guarantee that the user will have an good musical experience. A growing consensus exists that recommendation systems should focus less on the offline evaluation of algorithms and focus more on user-centered approaches because aspects such as presentation and interaction significantly impact the user experience [74]. Konstan and Riedl [74] says that measuring user experience is a challenge for research on recommendation systems. It requires developing a system that includes algorithms and an interface to conduct field studies with long-term users of the system.

5.2 Emotion perspective

Music recommendation systems that consider emotions aim to suggest music that best suits users' emotions. Identifying and considering the emotion from both the users and the music is essential to achieve this aim. In this review, we presented several recommendation approaches that consider emotions (see the publications 20-37 listed in Table 11). In general, each approach associated with studies is related to mechanisms that use machine learning, subjective information, sensory data, social networks and musical information. Approaches cannot be limited to these mechanisms alone, as many have implementation limitations and there is much to be explored. For this reason, a discussion of the main technical and user-centered challenges associated with emotion-aware music recommendations follows.

5.2.1 Technical Challenges

Okada et al. [96] explore contextual information and analyze the user experience in recommendation systems. The authors identified that among the contextual factors, emotion could affect the user is listening to behavior. According to Scherer [108], emotion involves different components: an observable reaction, a physiological reaction, a cognitive interpretation, a motor expression, and a subjective experience. In general, recommendation approaches that consider emotions obtain the user's emotional state through physiological reaction [41, 75] or by asking the user [47, 99, 7, 2, 26, 79, 97]. The most common way to obtain this is by using sensors [26, 57, 41, 75] facial expressions [26, 39].

However, using only one input source to identify the user's emotion may not be very accurate, as the emotion involves different components. The user's emotion can be more precise when exists multiple inputs, for example, joining physiological sensors with data of subjective emotions or motor expression [7].

Besides considering the user's emotion, other approaches strive to discover the emotion that a song carries (intentional, perceived, or induced) [107]. The area that addresses this theme is called music emotion recognition (MER) [132]. The MER seeks to detect people's emotional expression from a song and is useful in musical understanding, recovery of music, and other applications related to music.

Several approaches presented so far consider extracting information from music [7, 5, 39, 36] to obtain music emotion, whether through audio signal processing, similarity, or emotional tags. Many of these works present a great effort to detect the music emotion. Researchers also use this effort to predict the user's emotion by relating the predicted music emotion to the user.

It is essential to emphasize that this type of application may become increasingly common in recent years with the significant proliferation of mobile device applications. Besides, due to the possible need to involve machine learning and signal processing methods, resource constraints will still be maintained on mobile devices [61]. Several music recommendation systems such as Spotify[21], Deezer[22], and Apple Music[23] do not perform the client-side signal processing step. However, with the growth of wearable devices and music consumption offline, a smaller set of operations on the user's device may be required.

5.2.2 User-centred challenges

For a long time, the user had to go through a massive set of music provided by traditional music players to find songs that best fit their emotions. Nowadays, this dilemma has been much researched in literature and already has several proposals that seek to recommend songs automatically considering emotions [39, 57, 97, 101]. This advance shows that researchers have been concerned with making music discovery more understandable and more casual for the user.

However, few approaches have sought to improve the user's causality, more precisely in approaches that use external sensors to detect the user's emotion. For example, Guo et al. [41] used an electroencephalographic sensor (EEG) that monitors brain activity when listening to music and reflects emotional responses. Although this type of sensor may improve the suggestion of music to the user, on the other hand, depending on the type of sensor used may not bring an excellent music experience, but may generate discomfort with the use of the sensor. Thus, future proposals for music recommendation systems should consider the ergonomic aspects of the user.

Identifying the user's emotion while recommending music is still a challenge. The most common among the proposals presented is to use subjective information of the user [7, 2, 26, 79, 97]. The recommendation systems initially ask the user himself his current emotional state and then suggest music according to the emotion informed. In general, two problems exist when obtaining the user's emotion in these systems. The first is that the user may not be sure which emotional state he/she is in, which can give the recommendation system a wrong emotion. The second is that whether the user is sad, probably sad songs will be suggested to him. The ideal would be to obtain the user's current and desired emotion from various input sources, besides constantly receiving the feedback [75] to improve the suggested songs' accuracy.

The music recommendation approaches that consider the emotions, besides being aware of the user's emotion, also direct the efforts to identify the emotions of the songs. Usually, the approaches recover the music's emotion by extracting information from the songs [7, 5, 39, 36], either by emotional tags, similarity, or audio signal processing accompanied by machine learning methods [2, 26, 84, 80, 120, 30]. Most of these approaches require the audio of the music and depend on the user/specialist's intervention during certain phases of recognizing the music emotion, making it an even more significant challenge for recognizing emotions.

[21] https://www.spotify.com/
[22] https://www.deezer.com/
[23] https://www.apple.com/apple-music/

On the other hand, several approaches have been concerned with the user's musical preferences [80, 68, 17, 133, 130]. However, designers of music recommendation systems should be aware that when suggesting music considering musical preferences should always take into account the user's musical style and relate them to emotions. Suppose a user has the intention to improve his/her state of mind so he/she can be more content and, in a determining moment, receive music that carries joyful emotions but does not belong to his/her favorite musical style. Consequently, the user will have a bad musical experience. Therefore, we suggest researchers embrace psychological theories and gather specific user characteristics to integrate and build recommendation systems more conscious of emotion [107].

6 Conclusion

This review showed that researchers are trying to establish an automatic system for recognizing emotions and context using various methods. Therefore, music recommendation systems have been increasingly benefiting and receiving more and more attention. This study reviewed music recommendation approaches in which they consider only the context, only the emotions, and hybrid approaches in which they consider both the emotion and the context during music recommendation. We held a broad discussion on the main challenges faced by the study of this review. Challenges are ranging from technical challenges to user-centered challenges, and music recommendation systems should overcome.

This review also suggests that researchers need to explore further other factors that affect music recommendation. These factors involve user activity, satisfaction, feedback, cold-start problems, cognitive load, learning, personality, and user preferences. We consider it extremely important that researchers value these factors separately or together in their future research.

In general, we observe that approaches that consider the context still lack more clarity in describing the context. Researchers need to inform the adopted context model and what type of contextual information they use. Besides, privacy should be maintained, and all information about the user should be informed. The same occurs with approaches that consider emotion. The concepts of emotion should be well defined. Researchers should point out whether they are working with the emotion expressed or perceived from music. Because several evaluation artifacts proposed in the literature have a different direction on emotion, the authors should be clear which emotional model they use in the research.

Another critical point is the human factor, which is a little present in music recommendation systems' evaluations. Many researchers perform evaluations on a dataset without actual user involvement. The user should cooperate in the system's creation design. However, we realize that the real user's participation in the experiments of music recommendation applications is still little explored.

All this is currently happening in a mobile environment, using mobile phones with little storage and processing capacity. The design of a recommendation system should consider these constraints. Many of these tasks occur on the user side and not on the server.

Finally, we expect future research will also consider the user's musical intention and preferred style, adopting psychological theories, and bringing together specific users' characteristics. Thus, novel approaches to recommendation will provide a better listening experience for listeners and consequently advance the state-of-the-art towards music recommendation systems aware of emotion and context.

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