Like It or Not: Exploring the Impact of (Dis)liked Background Music on Player Behavior and Experience

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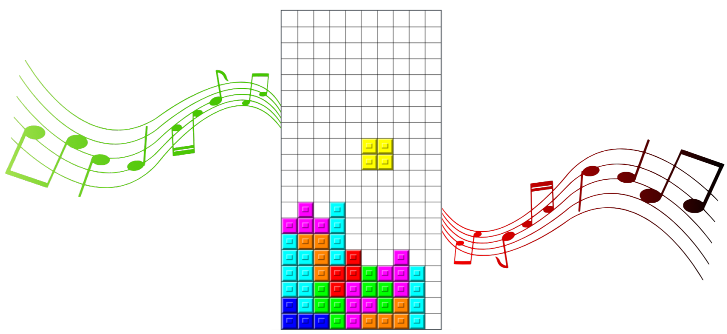

Fig. 1. Edited screenshot of our Tetris implementation accompanied by liked and disliked music.

Entertainment media, including video games, utilize background music (BGM) to enhance ambiance and gameplay, with a growing trend of players replacing in-game audio with personal music for potentially improved gameplay. Yet, research has not systematically investigated the connection between liked or disliked BGM and player behavior and experience. With our work, we make this step by letting users play the popular and well-researched game Tetris with BGM of their choice, and go one step further by adding music to the game that they specifically dislike, as this direction has been neglected thus far, but could prove interesting to target certain player behavior or experience. In our lab-study (N=31) we found that liked BGM increased engagement with the game and enhanced player experience, while disliked music reduced immersion. These findings suggest that music preferences should be taken into greater account in game design, e.g. by offering more options for BGM customization.

CCS Concepts: • **Human-centered computing** → **Empirical studies in HCI**.

Additional Key Words and Phrases: Audio, Music, Games, Play, User Experience Design

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1 Introduction

Music is a substantial part of today's entertainment media. Next to everyday listening, it is part of movies and games and serves different purposes: It can set the mood for a scene, create flow, or even be an integral part of the experience in music-games [29, 33].

Research on music in general has already shown that it can improve physical exercising, where faster music for example encourages a higher training intensity [41]. But also in reaction or cognitive tasks music has positively influenced user behavior, leading to improved reaction times [3] or memory recall [8]. In games specifically, research found similar effects on player experience, as well as player behavior. Certain factors, like for example the speed of music, i.e. beats-per-minute (BPM), can influence perceived game difficulty [19]. In racing games increased BPM have been shown to increase players' driving speed, while at the same time decreasing their accuracy [7].

A recent trend among gamers is to use their own custom-music instead of the game's provided in-game music [35]. One of the reasons to do so can be disliking the in-game music or perceiving it as distracting. Next to enabling players to listen to music of their own liking, studies looking at the usage of custom audio in games found that it can even improve player performance [33, 40], as well as factors like efficiency, focus and enjoyment [6].

However, research so far often focused on investigating high- or low-arousal music [34] and viewed "liking" music more as a by-product of their data and not as their core research [30, 37]. One aspect that has been neglected so far to our knowledge is looking at the effects of custom and liked music systematically, but also looking at effects of disliked music. This on the one hand complements the spectrum of effects induced by music on gamers, and on the other hand could proof useful for game designers to alter the player experience revolving around factors such as perceived mastery, challenge or meaning. A negative effect on player performance or perceived mastery for example could be utilized by game designers to spread out passages that intentionally alter the game to be subconsciously perceived as more difficult in the moment. In this work we aim to fill this gap by taking a closer look at player behavior and experience when utilizing liked or disliked background music in a game. More specifically, we investigated the following research questions:

RQ1 Does liked or disliked music influence player behavior?
RQ2 Does liked or disliked music influence player experience?

To this end, we implemented a study platform, which would allow participants to play the popular game *Tetris*, while at the same time allowing us to easily switch the background music individually on a per-participant and per-condition basis. In a lab-study (N=31) we used songs participants chose beforehand, indicating what they would like to listen to (or not) while playing Tetris. Additionally, playing without music served as a baseline. While we were not able to find effects on player performance between liked, disliked and not playing music at all, our results indicate that liked music increased the players' engagement with the game as they showed higher keypress-rates regarding the game's controls, as well as increased feelings of mastery and enjoyment. Disliked music on the other hand reduced immersion and significantly reduced the keypress-rate in comparison to liked music. Based on the knowledge gained from our study insights, we discuss implications of this work for researchers and game designers.

2 Related Work

Audio in games can be conveyed in different ways, such as individual sound effects or music. The prior is often used to create immersive environments, provide hints and communicate information to the player [12, 15, 16]. Music on the other hand can often be found in the form of background music (BGM), where it is used to evoke emotions, create flow, or complement the scenery [4, 21]. As we focus on the influence of liked and disliked music on player behavior and experience in this work, we will first take a look at the broader influence music has been shown to have on performance and user experience in related research. Afterwards, we will shed light on the use of music in games and, lastly, we point out how offering players to choose their music affected player performance and experience in the past.

2.1 Influence of Music on Performance and User Experience

In past research, music has been shown to affect user behavior in various contexts, such as e.g. during exercising [23] or cycling [41], where faster music increased training intensity. Less positive effects of music tempo were found in the context of driving, where increasing the tempo has been shown to increase heart rate, speed and virtual traffic violations in a driving simulation [5], hence, influencing the effects on the user and their actions.

Looking at how music influences task performance, we can find that tempo can influence e.g. visual selective attention. In their study, Amezuca et al. [3] let participants perform a reaction task with either no music, faster music or slower music. They found that faster music can lead to a faster response time, compared to slower music. Also related to music tempo, Silva et al. [38] found effects on perceived exertion and attentional focus in walking when playing either no music, normal music of faster music. They found that perceived exertion was higher with the latter and attentional focus better with any music condition compared to not playing music at all. Supporting this notion, music played at a specific tempo can also serve as a memory cue to improve user performance in a free recall memory task [8].

Another attribute of music next to tempo is loudness. Wolfe et al. [42] investigated how varying degrees of loudness can influence performance in a mathematical task. Participants were confronted with either no music or three types of increasing loudness. While there were no quantitative impacts on task performance in terms of solved mathematical problems, participants in the loudest condition reported being distracted by the loudness significantly more than in any of the other conditions.

Also investigating task performance, but in the context of liking or disliking music, Perham et al. [31] took a look at the impact of disliked music in comparison to liked music in a cognitive memory task. Their participants were asked to recall eight items from a list, either with no music, liked or disliked music playing simultaneously. Not listening to music at all lead to the best performance of their participants. Interestingly, disliked music lead to significantly worse performance and, against their expectations, listening to liked music was significantly worse than disliked music. They believe that liked music might have captured the participants' attention more than the disliked music, but at the same time acknowledge that they would have expected disliked music to capture more attention due to unfamiliarity as well.

2.2 Music in Gaming

Looking at the context of gaming, we can find similar effects on user experience and behavior induced by music itself or by varying parameters like tempo or choice of music, or even its presence or absence respectively. For example, Ribeiro et al. [33] found that thematic cohesion between auditory and visual perception is important for the perceived atmosphere of a game, but that a dissonance between the two can lead to more intense facial events, while at the same time not negatively affecting the self-reported player experience.

That the mere presence or absence of music can already influence player behavior was shown in a study by Rogers et al. [34], where background music decreased players' risk taking behavior, at least when playing the game for the first time. The effect diminished once players were acquainted with the game. Additionally, high arousal and low arousal music were shown to impact player immersion in terms of mastery and perceived challenge, where low arousal music showed a significantly higher mastery and lower challenge scores.

Klimmt et al. [24] furthermore found that the soundtrack of games can foster enjoyment through positive emotion and amplify the perception of emotions, such as horror. Similarly, Tafalla et al. [39] investigated gender differences in game performance and cardiovascular reactivity when playing the game "Doom" either with it's original soundtrack or without. The performance of male players, as well as their heart rate, notably increased with the soundtrack being present. Female players on the other hand showed greater signs of stress. While there were no performance improvements recorded for female players, both, men and women, reported that they perceived the game as more violent in the presence of the soundtrack. This study indicates that music can be used to directly impact player performance (even if not the case for all players here), as well as player experience. Tan et al. [40] similarly took a look at playing a game either in complete silence, with sounds from the controller, screen sounds and controller sounds and, lastly, unrelated music playing next to the setup. Unexpectedly, they found that the presence of game-unrelated music led to the least amount of re-trys and participants played the longest in this condition before failing for the first time. Although their study is limited to one game, it serves as an indication that music does not necessarily have to respond to the game events in order to support the player. In the context of a fighting game, Zhang and Fu [43] found that immersion was significantly higher for gamers with less experience when background music and sound effects were present compared to those playing with no background music and sound effects. However, background music was not investigated separately. In addition, Levy et al. [26] found that background music in a game increased mouse activity of players and their feeling of flow, compared to a silent version of the game. Regarding mouse activity, many participants stated that the music made them want to work faster.

Effects on physical activity through music as depicted in subsection 2.1 can be reproduced in gamelike systems. A mix of physical activity and gaming can be found in so called exergames, which are games promoting physical activity. Lilla et al. [27] found a significant difference in favor of the addition of music compared to playing their exergame without it. This complements the findings from [23] and [41] regarding physical exercise outside of the gaming context. They also investigated whether synchronizing or desynchronizing the music with the flow of the game influenced user performance, yet with no results.

Hufschmitt et al. [19] use different ways of music tempo manipulation to influence the difficulty of a game. They adapt the tempo of the BGM in the game *Tetris* by either increasing it gradually or stepwise, either synchronized to the gameplay, or desynchronized. Their results show that, depending on the desired outcome, music can be used to manipulate perceived game difficulty. Switching from a stepwise to a more gradual increase for example has a negative effect if both are synchronized to the gameplay, but can have a positive effect, if the same is applied in an asynchronous way. Hence, they showed that music tempo, and specifically the change of tempo, can influence user experience and performance. Also related to music tempo, Cassidy and MacDonald [7] use music to investigate the perception of time and performance in games. To this end, they let users play a racing game, either in complete silence, with participant-selected music, or experimenter selected high- or low-arousal music with either 70 or 130 beats per minute (BPM), while measuring time, accuracy, speed, among other variables. Experimenter-selected music with increased BPM led to faster driving, but also decreased accuracy, which is in line with Brodsky et al.'s driving simulation study [5]. Racing with self-selected music on the other hand led to participants overestimating elapsed time, i.e. the music supposedly changed the users time perception. Sanders & Cairns [37] also investigate the perception of time and game immersion and similarly find that both factors can vary through - and depend on - the actual choice of music and the degree to which it is liked. In their first experiment, the music was disliked leading to lower immersion scores, while the opposite happened in the follow-up experiment with a higher degree of likability. Unlike Perham et al. [31] outside of the gaming context, they did not investigate a connection between liking (or disliking) music and player performance specifically, it is also an area worthwhile investigating given the differences found in immersion.

That music preferences can influence player performance has also been found by North & Hargreaves [30]: They compared task performance and music preference in a racing game with either arousing, or less arousing music. Depending on the condition, participants were also asked to complete a backwards-counting task to increase their cognitive load, similar to [42]. Results indicate that the presence of music can limit one's cognitive capacities and that liking the music had a positive effect on the players' performance. Both, Sanders & Cairns [37], as well as North & Hargreaves [30], support the notion that the degree to which music is liked influences player performance and experience, but a look at disliked music specifically is missing in both, yet could prove interesting in shaping game experiences for players.

2.3 The Effect of Music Selection on Player Experience and Performance

With the insights from subsection 2.2, we also want to shed light on research investigating the choice of music selection in the context of games, as this factor is directly influenced by the player's own taste and their liking of, or aversion to, certain types of music. As indicated in a study by Rogers & Weber [35] targeted at players of infrastructure-building games (IBG) like *SimCity* or *Cities: Skylines*, 39% of their participants (n=737) reported not to listen to the in-game music, with 219 reporting to do so in favor of their own custom music, and another 132 indicating that they prefer to consume other media (e.g. *YouTube*) in parallel. Other reasons mentioned were disliking the provided in-game music or perceiving the music as distracting among other reasons. These statistics are interesting in the light of Tan et al.'s results [40], where game-unrelated music improved player performance. Although [35] focused on IBGs and [40] on one particular game, they indicate that deviating from the original game soundtrack can be beneficial, or even be wanted by players, including listening to their own playlist. Similar results have also been found by Ribeiro et al. [33]. In one of their study conditions, participants listened to a podcast while playing Bloodborne, instead of listening to the original soundtrack of the game. However, neither player experience nor immersion were negatively affected. This is further supported by Cassidy et al. [6], where players playing a racing game with self-selected music performed better in terms of efficiency, focus, enjoyment, liking and appropriateness. In addition, said players perceived less tension while racing. In contrast, pre-selected high-arousal music by the authors lead to the opposite, i.e. increased inaccuracy, distraction, aversion, displeasure and less appropriateness.

2.4 Summary

Taking these works into account we can see that music is not only highly relevant for games as a means of entertainment, but can also be used to actively influence and manipulate player performance and experience. Works outside of the gaming context, as depicted in subsection 2.1, support these notions. One work ([31]) already looked at the effects of and comparison between liked and disliked music. Hence, we want to shed light on the extent to which these results apply to the gaming context.

In subsection 2.2 and subsection 2.3, we highlighted the general influence music can have in gaming, as well as the benefits of allowing gamers to choose their own music, leading up to works indicating that liking music can positively influence performance. Yet, when taking [31] into account, there is a research gap in terms of considering both, liked and disliked music and comparing them systematically in the context of gaming. This could prove as a useful tool for practitioners and researchers alike in shaping the user experience of their applications and research in the future.

3 Tetris Study Platform

We followed the approach of [19] and used the puzzle game *Tetris*[1] as a means to investigate our research questions. Tetris is on the one hand among the most popular games of all time, and on the other hand comes with the advantage of being easy to learn for beginners, yet challenging to master for more experienced players.

3.1 Game Concept

At its core, Tetris consists of a 2D game field where the player navigates falling blocks, so called *Tetrominoes*, in the shape of the letters I, O, T, J, L, S and Z (see Figure 1). Goal for the player is to align the falling blocks in a way that they fill one to four lines on the game-field. Filled lines are then cleared and the player receives points. To control the Tetrominoes, the player can move them to the left and right and rotate them at 90 degree angles. Over time, the game will become faster, thus more challenging. The game continues until the Tetrominoes stack up to the top of the game-field, resulting in a game-over screen.

3.2 Implementation

Our study platform was implemented using web technologies and was separated into a frontend part, which would later be used by our participants, as well as a backend part, where we stored the respective data generated by our participants. The frontend was implemented using Angular[2] version 13.3.11. The backend is built on NodeJS[3] and a MongoDB[4] instance as a database.

As the idea of the platform was to provide not only the game, but also the possibility to instruct participants, prompt questionnaires etc., the frontend consists of several views, which we used to guide users through the study. The *landing page* for example could be used to inform users about the study purpose and terms of agreement, the *instruction view* allowed us to display text-instructions and the *end view* allowed us to inform participants that they reached the end of the study and to thank them for their participation. The core of the platform built the *questionnaire view* and the *game view*. The prior allowed us to define and prompt questionnaires, which would then be saved alongside the game data later. The latter provided the game instance, an overview over the game controls to the left of it as well as an indicator for the current score, level and upcoming Tetromino to the right. In order to implement Tetris itself, we built on the publicly available implementation "ng-tetris" for Angular on GitHub[5] and adapted it to our needs as described in the following. As we planned to have each participant play with their own BGM, we prepared the game in such a way, that allowed us to simply switch the music files in preparation of the study. No further sound effects were played during gameplay to ensure that no other auditory factors impact the auditory perception of the players.

[1] https://tetris.com/about-us, last accessed August 15, 2024
[2] https://angular.io/, last accessed on August 15, 2024
[3] https://nodejs.org/en, last accessed on August 15, 2024
[4] https://www.mongodb.com/, last accessed on August 15, 2024
[5] https://github.com/melcor76/ng-tetris/tree/master, last accessed on August 15, 2024

3.3 Performance Measurements and Gameplay

As the original GitHub version was not implemented for study contexts, we adapted it in ways that were aimed at improving comparability between participants, optimizing the game duration and allowing us to log and save data in addition to the plain score of each run.

3.3.1 Game Data. With the aim of this work being to compare players' performance and perception of the game under varying music conditions, we assessed specific gameplay attributes during each round of Tetris played. In order to gather and store gameplay related data we implemented additional key-loggers, which would log a users playing behavior next to their performance measures. Through this, we were able to capture the following data:

- score, cleared lines and level
- directional button presses (left, right, up, down)
- space button presses

While a user's score, number of cleared lines and reached levels on the one hand are used as direct performance measures, directional key presses and the space button on the other hand indicate how active a user is playing the game. While the left and right keys can be used to move a Tetromino horizontally, the up-key rotates it by 90 degrees and the down key increases the speed with which the Tetromino is falling. Using the space key would "hard drop" the Tetromino, i.e. instantaneously put it on the ground in a straight line from where it's currently floating. Higher key-press counts could be indicative of how engaged a user is with the game and have been means of measuring engagement in prior related works [18, 32].

3.3.2 Points, Levels & Speed. Users receive points for completing certain actions. Completing and clearing one row for example would be rewarded with 15 points. Clearing multiple rows with a single Tetromino is rewarded the respective amount of points x rows. For two rows a user would receive 30 points consequently, for three rows 45 points and for a maximum of four rows, they would receive 60 points. For every 3rd row cleared the player reaches a new level, i.e. the speed of the game increases. We adapted the speed increase per level such that one round would last approximately 3 to 4 minutes, which we evaluated with one self-reported beginner and one expert Tetris player outside of the group of the authors. We aimed at this time span in order to prevent long rounds where the chosen song would repeat too frequently, as well as fatigue effects through repeated play, as will be described in more detail in section 4.

3.3.3 Random Seeds . In the original version, Tetrominoes would spawn in an unpredictable random order, i.e. we had no control over the spawn-order between participants and conditions. This could have potentially led to entirely different experiences, ultimately harming comparability. Picking a set order of tetrominoes by hand as an alternative would be finite and repeat over and over, which might lead to participants recognizing said hand-picked order. To solve this we implemented so called *random seeds*, i.e. replicable random sequences instead of pure random sequences. This way, each participant received the same, infinitely long random sequence. The actual allocation of random seeds in the study procedure is described in more detail in section 4.

4 User Study

As outlined in section 2, we aim to investigate the link between liking or disliking background music and player performance, behavior and experience. To this end, we use the study platform described in section 3 and compare playing Tetris with no BGM to playing it with liked BGM or disliked BGM. We pose the following hypotheses:

H1 Background music that is liked by the player positively impacts player behavior (performance, engagement) compared to no music or disliked music

H2 Background music that is disliked by the player negatively impacts player behavior (performance, engagement) compared to no music or liked music

H3 Background music that is liked by the player positively impacts the player experience compared to no music or disliked music

H4 Background music that is disliked by the player negatively impacts the player experience compared to no music or liked music

H1 is derived from North & Hargreaves [30] where liking the played music had a positive impact on player performance. Since [30] did not specifically draw conclusions on disliked music, we hypothesize with **H2** that the impact contrasts H1, which then fits Perham's results on disliked music, as they found that it significantly reduced performance in their cognitive task in contrast to no music [31]. In order to measure the outcome of H1 and H2, we assess and compare each player's gameplay stats, i.e. reached score, cleared lines and level, as well as the player behavior, i.e. their engagement with the game in the form of relevant key presses. Similarly to H1 and H2, **H3** is derived from [37], where positive impacts on game immersion have been found based on the choice of music, as well as whether it was liked or not. Since game immersion is part of the player experience, we hypothesize that liked music will positively impact it, and analogous to H2, hypothesize that the opposite effect takes place when players listen to disliked BGM (**H4**). To assess player experience, we used the Player Experience Inventory (PXI) [1, 2], a validated instrument, specifically developed for this purpose and the Intrinsic Motivation Inventory (IMI) [28]. Lastly, we added custom questions, which are described in more detail in the following section.

4.1 Method and Procedure

The first step to conduct our user study was to consider each participant's individual music preferences. Hence, before participants actually took part in our study we asked them for one song that they would like to listen to when playing Tetris and one that they would not like to listen to while doing so. We would then use the responses provided by each participant to prepare the platform accordingly with their choice of songs.

During the study, participants would encounter three different conditions in counterbalanced order (within-subjects design): One with no BGM at all (*Baseline*), one with liked BGM (*Liked Music*) and one with disliked BGM (*Disliked Music*). After consenting to the data privacy conditions, we asked them to fill out a demographics questionnaire, containing information on age, gender and nationality, as well as a question on whether they played Tetris before and, if yes, how they estimate their experience on a scale from 1 ("Little Experience") to 7 ("Highly Experienced"). Since our setup required to play Tetris with a keyboard, we also assessed the input controls they were familiar with when playing the game prior to participating, namely "Keyboard", "Gamepad", "Touchscreen" and "Other" with the option to provide more details in a free-text field.

Afterwards, they were introduced to the concept of Tetris on an instruction page, where we would explain the goal of the game, its controls and that the game is over once the Tetrominoes stack to the top. They were also notified that they first go through a tutorial round, where they can get familiar with the game and their score would not be counted. Following said tutorial, each participant would face one of the three conditions (Baseline, Liked Music, Disliked Music) in counterbalanced order to prevent learning effects. Both music conditions would play either the liked or disliked music choice respectively. No further sound effects were played. Each condition was played twice, such that participants got the chance to even out failed play-throughs. Excluding the tutorial, this means that they played six rounds of Tetris in total. Regarding the spawn order of the Tetrominoes we used random seeds as explained in subsubsection 3.3.3. To prevent this fixed random sequence being noticed by participants (as they played the game 3x2 times), we decided to use two different sequences (A and B) for the first and second run of each condition respectively, meaning they would play in order: AB AB AB. This way, conditions stayed comparable to each other while hiding the fixed randomness in two different seeds at the same time.

After each condition, participants were asked to fill out questionnaires to assess player experience. The PXI [1, 2] can be divided into two groups of variables: Psychosocial Consequences and Functional Consequences. We decided to focus on the prior as we were more interested in psychological effects of the background music instead of functional consequences induced by the prototype itself. From the functional consequences we additionally included challenge. Consequently, from the PXI we assessed the subscales *Meaning*, *Mastery*, *Autonomy*, *Immersion* and *Challenge*, which had to be rated on a Likert scale ranging from 1 ("Strongly disagree") to 7 ("Strongly agree"). Additionally, we assessed the IMI [28] subscale for *Enjoyment* as the PXI does not contain a validated subscale on this item. Lastly, we added custom questions regarding the BGM ("I like the song that was played during the game", "I enjoyed listening to the background music", "The background music went well with the game") and perceived satisfaction ("I am satisfied with my overall experience in playing the game", "I am satisfied with my overall performance in playing the game") on an analogous Likert scale. Music-related questions were not prompted after the Baseline condition due to the absence of music. The study was approved by the Ethical Review Board of the Faculty of Mathematics and Computer Science at Saarland University (No. 22-08-3).

4.2 Participants

To determine a reasonable sample size, we ran a power analysis using G*Power [13]. As our main effects contain comparisons between three conditions, we calculated the power analysis for repeated measures and within factors. Due to the lack of a comparative study, we aimed for a medium sized effect, i.e. Cohen's f of 0.25 and a power of 80%, as recommended by Cohen [9]. A screenshot of all parameters used in the analysis can be found in Appendix A, Figure 4. This lead to an estimated sample size of 28. We recruited participants through the university network of the authors, mailing lists and via print-outs on the campus and ended up with 31 participants of which 23 identified as male, 7 as female and 1 as non-binary. 8 participants belonged to the age group 18-24, while 16 participants were between 25-31 years old and 7 participants between 32-38. In terms of nationality, 7 participants were German and Indian, respectively; 5 participants were Ukrainian and Pakistani, respectively; 2 Chinese and 1 each American, Moroccan, Iranian, Italian and Egyptian. Participants received sweets as compensation for their participation. While two participants indicated having no prior experience with Tetris, the remaining 29 responded with a 3.10 out of 7 on average (SD = 1.32) in terms of their prior experience level, indicating some familiarity with the game. Regarding the controls our participants used before, 13 participants were used to playing the game with the keyboard. Another 13 played the game with a gamepad beforehand, 4 on a touchscreen device and one on an older mobile phone with keys.

4.3 Results

In order to analyze our data, we used repeated measures analysis of variance (ANOVA), or the non-parametric Friedman's ANOVA in case of a violation of the assumption of normality as suggested by Field [14]. Post-Hoc tests were performed using the Tukey correction (p_{Tukey}), or Durbin-Conover correction (p_{Durbin}) in case of the non-parametric variant, respectively. For tests between only two conditions we ran Student's t-test, or the Wilcoxon signed-rank test as a non-parametric alternative wherever normality was not met within our sample. This was required for music-related questions which were not present in the Baseline condition as well as statistical tests run on the song selection

		Baseline			Liked Music			Disliked Music		
		M	SD	95% CI	M	SD	95% CI	M	SD	95% CI
Perf.	Score	179.27	92.44	144.63 - 213.91	182.90	89.20	150.19 - 215.62	159.68	78.26	130.97 - 188.38
	Lines	11.95	6.30	9.64 - 14.26	12.19	5.95	10.01 - 14.37	10.65	5.22	8.73 - 12.56
	Level	3.66	2.10	2.89 - 4.43	3.74	1.97	3.02 - 4.47	3.24	1.68	2.62 - 3.86
#Presses	Directional	225.79	78.17	197.12 - 254.47	243.71	72.17	217.24 - 270.18	221.89	77.60	193.42 - 250.35
	Down	49.29	77.10	21.01 - 77.57	46.03	58.44	24.60 - 67.47	43.48	62.75	20.47 - 66.50
	Spacebar	17.11	14.75	11.70 - 22.52	15.21	15.26	9.61 - 20.81	17.71	14.52	12.39 - 23.03
PXI & IMI	Meaning	4.20	1.17	3.78 - 4.63	4.34	1.12	3.93 - 4.75	3.97	1.30	3.49 - 4.44
	Mastery	4.31	1.13	3.90 - 4.72	4.69	1.01	4.32 - 5.06	4.05	1.31	3.37 - 4.53
	Autonomy	4.84	1.02	4.46 - 5.21	5.11	0.90	4.78 - 5.43	4.71	1.22	4.26 - 5.16
	Immersion	5.28	0.96	4.93 - 5.63	5.35	1.05	4.97 - 5.74	4.56	1.38	4.05 - 5.06
	Challenge	4.91	1.02	4.54 - 5.29	4.97	0.85	4.65 - 5.28	4.84	0.93	4.50 - 5.18
	Enjoyment	4.58	1.14	4.17 - 5.00	5.13	0.75	4.86 - 5.41	4.45	1.22	4.00 - 4.89
Sat.	Performance	3.81	1.58	3.23 - 4.39	4.55	1.59	3.97 - 5.13	3.65	1.84	2.97 - 4.32
	Experience	4.48	1.46	3.95 - 5.02	5.10	1.25	4.64 - 5.55	4.39	1.67	3.78 - 5.00
Music	Liking				6.45	0.77	6.17 - 6.73	2.32	1.72	1.69 - 2.95
	Impact				5.39	0.88	5.06 - 5.71	5.16	1.24	4.71 - 5.62
	Fit to Game				5.84	1.04	5.46 - 6.22	3.32	1.92	2.62 - 4.03
	Enjoyment				6.32	0.65	6.08 - 6.56	2.65	1.74	2.01 - 3.28

Table 1. Mean (M) Standard deviation (SD) and 95% Confidence Intervals (CI) of the player's performance measures, key presses, Player Experience Inventory (PXI) and Intrinsic Motivation Inventory (IMI) results, as well as the indicated feedback on satisfaction and the respective music.

Performance & Behavior

Dependent Variable	df	F	χ^2	p	η_p^2
Score	2	2.87	-	0.06	-
Lines	2	2.87	-	0.06	-
Levels	2	2.41	-	0.10	-
Directional presses	2	6.18	-	**< 0.01**	0.17
Down presses	2	-	1.22	0.54	-
Spacebar presses	2	-	3.11	0.21	-

Player Experience

Dependent Variable	df	F	χ^2	p	η_p^2
PXI Meaning	2	2.43	-	0.10	-
PXI Mastery	2	3.53	-	**0.04**	0.11
PXI Autonomy	2	-	3.51	0.17	-
PXI Immersion	2	6.26	-	**< 0.01**	0.17
PXI Challenge	2	-	2.65	0.27	-
IMI Enjoyment	2	5.16	-	**< 0.01**	0.15
Performance Satisfaction	2	-	4.34	0.11	-
Experience Satisfaction	2	-	2.88	0.24	-

Table 2. Results of the ANOVAs on the performance measurements (left) and player experience (right). Shown are the degrees of freedom (df), the test statistics for the repeated measures ANOVA (F), as well as Friedman's ANOVA (χ^2), the p-values and effect sizes (η_p^2) where significant effects were found.

data. Effect sizes are reported as either partial-η^2 for ANOVAs, or Cohen's d (d) for t-tests. In the following, we outline our results R1 through R7.

4.3.1 Performance & Behavior. Regarding player performance, we averaged all performance measures (score, lines, levels and key presses) of both runs for each player and referred to these values during our analysis. The mean and standard deviations can be found in Table 1 and are depicted as boxplots in Figure 2. Results of the ANOVAs on this data can be found in Table 2 in the "Performance & Behavior" column. As can be seen, neither score, lines nor levels show significant differences between the conditions. Consequently, we can neither say that liked music improves player performance nor that disliked music decreases it and pose **R1: Background music did not significantly influence player performance**.

In terms of player behavior, i.e. the number of key presses, we differentiate between directional key presses (up, left, right) and key presses influencing the fall-speed of the Tetrominoes (down,

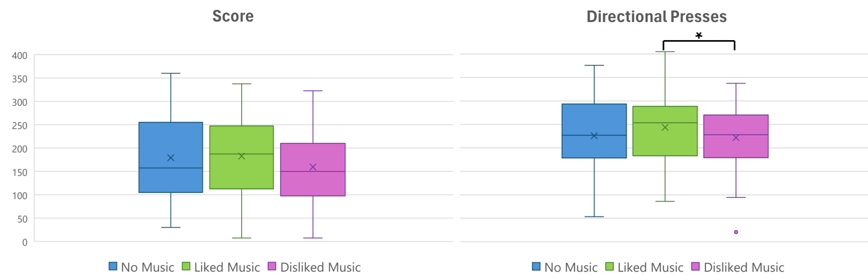

Fig. 2. Boxplots of the score and directional keypress data. *-signs indicate signiciant differences between conditions.

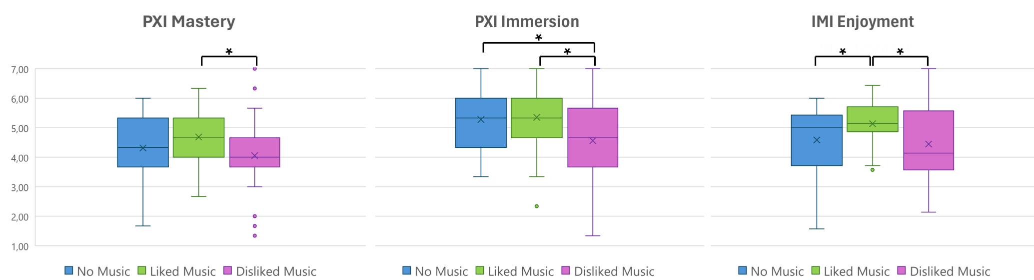

Fig. 3. Boxplots of the mastery, immersion and enjoyment data. *-signs indicate signiciant differences between conditions.

spacebar). For our analysis, the directional key presses were grouped as one variable since on the one hand all of them manipulate the position of the Tetrominoe and on the other hand differences between left and right or the rotation mechanic would likely be caused by chance and could not be derived by the use of varying BGM. We kept down and space presses seperated as their only purpose was to speed up the falling mechanic of the game, instead of navigating the Tetrominoe to the right position. Significant differences were found for the combined key presses (see Table 2), yet none for down presses nor spacebar. This indicates that the controls responsible for faster or instantaneous dropping of Tetrominoes were not used significantly different among all conditions. Post-hoc tests for the combined presses reveal that there is a significant difference between Baseline and Liked Music ($t = 2.57$, $p_{tukey} = 0.04$, $d = 0.46$) as well as Liked Music and Disliked Music ($t = 3.60$, $p_{Tukey} < 0.01$, $d = 0.65$), with Liked Music showing a higher number of key presses than both, Baseline and Disliked Music. Baseline and Disliked Music in comparison however did not differ significantly ($t = 0.57$, $p_{Tukey} = 0.83$). Hence, we pose **R2: Liked Music significantly increased the engagement rate with the game.**

4.3.2 User Experience. The ANOVA results on the PXI and IMI subscales, as well as the perceived satisfaction in terms of performance and experience while playing the game under all conditions can be found in Table 2 in the column "Player Experience". Figure 3 shows boxplots for all significant variables. While meaning, autonomy and challenge do not yield any significant results, mastery, immersion and enjoyment do. Again looking at post-hoc results reveals that for mastery, the Baseline showed no significant difference to Liked Music ($p_{Tukey} = 0.23$) and Disliked Music ($p_{Tukey} = 0.57$), yet Liked Music and Disliked Music differ significantly ($t = 2.60$, $p_{Tukey} = 0.04$, $d = 0.47$) in favor of Liked Music, resulting in **R3: Liked Music significantly increased the feeling of**

mastery compared to Disliked Music. Regarding immersion, the Baseline and Liked Music do not differ significantly (p_{Tukey} = 0.94), but Disliked Music reduced immersion significantly more when compared to both, Baseline (t = -2.58, p_{Tukey} = 0.04, d = -0.46) and Liked Music (t = -3.44, p_{Tukey} = < 0.01, d = -0.62). Hence, we pose **R4: Disliked Music generally decreased immersion**. Lastly, post-hoc tests on enjoyment show that Liked Music led to a more enjoyable experience in all cases, meaning that there is a significant difference between Baseline and Liked Music (t = 2.61, p_{Tukey} = 0.04, d = 0.47), as well as Liked Music and Disliked Music (t = 3.40, p_{Tukey} < 0.01, d = 0.61), but not between Baseline and Disliked Music (p_{Tukey} = 0.86) leading to **R5: Liked Music significantly increased enjoyment**.

No significant differences were found in terms of the self-reported satisfaction level regarding the players' own performance and player experience. With these results, we pose **R6: No significant impact was found in terms of meaning, autonomy and challenge, as well as perceived satisfaction with one's own performance and experience**.

4.3.3 Music Perception . Lastly, participants answered four custom questions aiming at assessing their perception of music in terms of how much they liked the BGM, whether they enjoyed listening to it, whether it had an impact on their gameplay and whether it went well with the game. Here, only both music conditions are compared, which is why we opted for t-tests in the analysis. Regarding how much they liked the songs, a significant difference was found in favor of the Liked Music condition (t = 11.82, p < 0.01, d = 2.12). Similarly, Liked Music was significantly perceived better in terms of fit to the game (t = 7.26, p < 0.01, d = 1.30) and player's enjoyment to listen to it (t = 10.21, p < 0.01, d = 1.83). Yet, no difference was found regarding the perceived impact on the players' gameplay performance (W = 113, p = 0.47). The latter was analyzed using a Wilcoxon test due to non-normally distributed data. This leads to **R7: Liked Music was more enjoyable during Tetris and perceived as a better fit, yet both Liked and Disliked Music had no perceived impact on gameplay performance**, which fits our objective performance results from section 4.3.1

4.3.4 Song Selection. Data on our participants' song choices can be found in Appendix B, Table 3. On average, songs in the Liked Music condition had 124.81 bpm (SD = 28.7, CI = $[114.28, 135.33]$) with an average loudness of -7.39 db (SD = 3.13, CI = $[-8.53, -6.24]$). Songs in the Disliked Music condition had on average 121.90 bpm (SD = 23.51, CI = $[113.28, 130.53]$) and a loudness of -6.71 db (SD = 2.27, CI = $[-7, 54, -5.88]$). In order to affirm that the song characteristics had no strong impact on our results, we ran additional t-tests on both variables. Regarding bpm, the t-test was non-significant (t = 0.41, p = 0.68). The same applies to loudness (t = -1.03, p = 0.31). While not finding significant effects does not exclude overlooking small effects, our data suggests that the aforementioned characteristics did not substantially differ between both conditions and, taking subsubsection 4.3.3 into account, that participants' preference or dislike towards their choices primarily impacted our results.

5 Discussion

In this section we discuss the results in light of our hypotheses, as well as how they fit into the body of existing empirical and theoretical research. Starting with **R1**, we were not able to find effects on player performance in terms of score, rows cleared or levels neither without music, nor with liked or disliked music. This could be caused by several reasons: First, the effects might be too small for the sample size that experienced our setup. Looking at related literature, we expected to find effects here, as [30] highlighted the positive impact of liking music on player performance and [31] found effects in a similar setup comparing liked and disliked music to no music outside of the gaming context. As can be seen in Table 1, the tendencies found in our descriptive results fit our expectations from H1: Disliked Music resulted in the lowest performance, no music was in-between and Liked Music resulted in the best performance. Our descriptive statistics support the conjecture that we may not have been able to find effects given the indication of effects in literature. Second, as stated by e.g. Amezuca et al. [3] or Chie et al. [8], music tempo, among others attributes, for example can influence performance. While bpm and loudness likely did not influence our results, other factors outside of these may have had an impact. Hence, the variety in music choices (liked and disliked) could have evened out the different conditions here.

Looking at how engaged players were with the game, we found with **R2** that the number of key presses got significantly influenced depending on the music condition. Liked music not only showed a significantly higher number of key presses compared to disliked music, but also in comparison to the Baseline condition. This partially complements the results from Levy et al. [26] where background music increased the mouse activity of players. As they compared one condition with music to one without, we support their results with ours. The significantly lower number of key presses in the disliked condition in comparison shows that while a positive effect can be achieved with music, it depends on the type and perception of the respective BGM choice.

Taking **R1** and **R2** together, we partially support our hypotheses **H1** and **H2**, background music that is liked / disliked by the player positively / negatively impacts player behavior. While we do not have evidence for impacts on performance directly, we were able to demonstrate differences in terms of player engagement in both directions between liked and disliked music and additionally found increased engagement between playing with liked music and without music.

In terms of player experience we also found mixed results, which are comprised by **R3 - R7**. **R4**, disliked music hurting immersion and **R5**, liked music increasing the player's enjoyment, fit our expectations, where liked music positively impacts the player experience and disliked music negatively impacts it. **R5** thereby also supports the findings of Cassidy et al. [6] in terms of self-selected music increasing players' enjoyment. Yet, given that disliked music was also "self-selected", we need to differentiate between the personal fit to one's own taste and a dissonance in that regard, to which we contribute important insights. Additionally, **R4** supports our initial assumption that disliked music negates the positive effects of liked music.

R3, liked music leading to a greater feeling of mastery compared to disliked music, again follows our expectations, but fails to establish this effect when compared to no music. While there is no clear explanation for this effect in research and when additionally considering the lack of effects on player performance, it could be that the increased enjoyment (**R5**) and engagement with the game (**R2**) also had an impact on perceived mastery as a direct comparison to earlier runs was only possible after the study was completed. Contrary, disliked music could have lowered the feeling of mastery similar to how it lowered the level of engagement. Thus, trying less hard to achieve a better result could be the root of estimating one's own level of mastery.

No effects were found on meaning, autonomy and challenge (**R6**), which could have been expected based on effects found by Rogers et al. [34]. They found significant differences at least in terms of challenge when comparing high arousal music to low arousal music. In our case, there may be no measurable outcome as players were able to choose their tracks freely, which means there was no clear distinction between both, high- and low-arousal music. Looking at e.g. Deci and Ryan's *Self-Determination Theory* [10, 36], autonomy is one of the basic psychological human needs. Autonomously choosing liked music and playing the game with it should have satisfied this need. In addition, the opposite should have happened with disliked music. While all players did get to choose their disliked song autonomously, they usually would not choose these songs voluntarily in a realistic scenario. Here, they were confronted with a setting where they were not able to change the music during the study on their own. In theory, this should have hurt the need for autonomy, consequently resulting in a lower score, which is also represented in the descriptive statistics in

Table 1, where Liked Music showed the highest, and Disliked Music the lowest autonomy scores. One potential explanation for this could be that the BGM is not a main gameplay element and plays passively while playing (and focusing on) the game. Participants also made their music choice before playing the game and had no active choice to change the music while playing it. Combining these factors could explain not finding an effect within our sample, as the focus regarding the autonomy questions was likely not on the BGM itself, but rather on what they could actively influence - the controls and gameplay, which were equal in all conditions. As part of **R6**, no effects were found for perceived performance, which fits in light of **R1** - not finding results on actual player performance. Consequently, liked and disliked music alike did not measurably influence how players perceive and estimate their own performance in our case.

Lastly, **R7** indicates that liked music was a better fit for the game in contrast to disliked music. While this was expected due to naturally liking the music more (6.45 out of 7 for Liked Music and 2.32 out of 7 for Disliked Music), it could have been that Liked Music receives similar scores in terms of fit to the game as it was not tailored to be played alongside Tetris. This complements the findings of Rogers et al. [35] in the context of custom music usage in the infrastructure-building games genre, where custom music was perceived as a better fit.

Taking **R3** to **R7** into account, we partially support **H3** and **H4** as we found positive impacts on player experience induced by liked music and negative effects induced by disliked music. In addition, none of the results indicate the opposite of what was expected, yet in some cases, not all variables that we measured benefited or suffered from the respective condition, which is why we cannot fully support both hypotheses.

Through a theoretical lens, our findings support existing theories: For instance, the Arousal-Mood Hypothesis ("AMH") states that "listening to music affects arousal and mood, which then influence performance on various cognitive skills" [20]. More specifically, according to AMH, mood has a positive impact on cognitive performance. Considering past research has demonstrated that listening to liked music has a positive impact on mood [25], our findings seem plausible: In line with AMH, the mood of participants listening to liked music while playing Tetris might have been positively affected, which in turn might have led to a better player experience and more engagement with the task. Another prominent theory on the relationship between attention, mental capacity and performance is Kahneman's Capacity Model of Attention [22]. It considers attentional capacity as a limited mental resource, which is dynamically allocated depending on the current demands on the attentional system. A core component of this theory is allocating enough attention, as a resource, to the task at hand. If this is not the case, task performance is hindered. Since disliked music might be more distracting than liked music, the attentional capacity of participants left for playing Tetris might have been diminished, potentially detrimentally affecting player experience and player behavior in the disliked music conditions.

6 Conclusion

In this work, we investigated the effects of liked and disliked music on player behavior and experience. To this end, we implemented a study platform containing the well-known puzzle game Tetris and invited participants to play with no music, liked music and disliked music. While we were not able to find effects on player performance induced by any of the conditions, significant effects were found in terms of player engagement, measured through the number of relevant key presses. While most of these differences appeared in direct comparison between liked and disliked music, with liked music outperforming disliked music, players also showed an increased engagement rate when it comes to rotating the Tetrominoes compared to no music. Regarding player experience we found that liked music can be perceived as more fitting to the game and improves the experience, disliked music on the other hand negatively impacts aspects such as mastery and immersion.

6.1 Implications for Research and Practice

Based on our findings, we generally recommend giving players the option to use their own custom music in games and researchers might want to consider this option if e.g. increased enjoyment is crucial to their study. Yet, offering this choice also comes with the drawback to lose control over confounding variables such as beats per minute and loudness among others, which is why the decision needs to be informed and sophisticated. These insights are also beneficial to practitioners in the gaming industry. We encourage making the option to select own, preferred background music easily available to players. Offering the possibility for custom music is not novel and has already been part of older games from different genres like *GTA: III*[6] or *The Sims*[7], where players could customize a radio station on the PC versions of the game. Yet, adding tracks to these games, was not part of the game's interface and had to be carried out manually on the system, which might discourage less tech-savy users.

Additionally, disliked music could be used to intentionally provoke certain behavior such as decreased engagement, or alter the player perception in terms of mastery. While we were able to simply ask our participants to provide music that they would not want to listen to while playing Tetris, providing this kind of music is harder in practice. Here, automated approaches to identify a user's taste in music could prove fruitful. First approaches in this direction already exist [11, 17].

6.2 Limitations & Future Work

We also faced some limitations while carrying out this work. First, while our sample size was big enough to find medium-sized effects, it could have been too small to find smaller effects related to performance or the other player experience measures. A larger sample size in the future could validate our results and allow to dive deeper into more fine grained effects. Second, as mentioned before, using entirely individual music on the one hand served the purpose of our study, but at the same time increased the variability in music tracks played within each condition on the other hand. To tackle this, pre-defined playlists featuring songs with similar attributes to choose from or focusing on certain genres could help reducing confounding factors. The latter could also prove interesting in terms of comparing BGM genres to game genres in terms of player behavior and experience, yet at the expense of giving players an entirely free choice. While music-characteristics such as bpm and loudness did not seem to significantly impact our findings, individual and less quantifiable attributes such as mood, arousal, or even memories connected to a song limit our expressiveness beyond the meta-characteristics of the used set of songs.

Building on our study, future work could try to replicate our results and at the same time focus on different aspects as well. For example we did not consider a comparison to the game's original background music in order to prevent inflating the study itself and as our main focus was comparing liked music to disliked music similar to [31]. Yet, the comparison to music tailored for the game could also prove interesting. Additionally, music has been shown to deepen the feeling of flow in the past [26], investigating in how far custom liked or disliked music supports or weakens a player's feeling of flow could give more valuable insights for researchers and practitioners.

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A Power Analysis

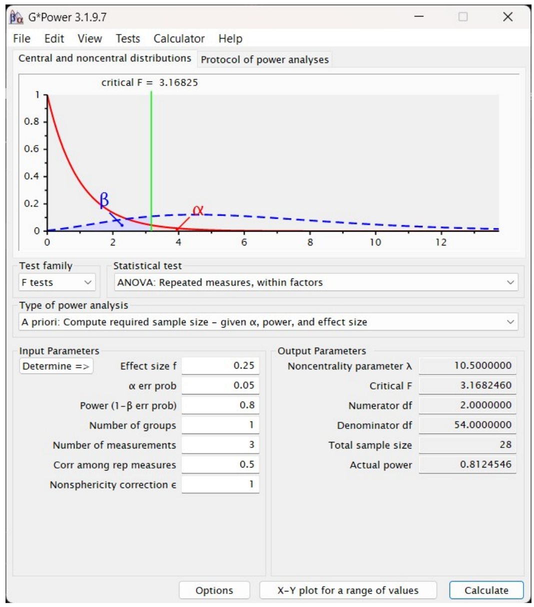

Fig. 4. Parameters and results of our power analysis using G*Power 3.1 [13]

B Song Choices

Table 3 shows the songs chosen by each participant for the liked and disliked music condition of our study. Data on beats-per-minute (bpm) and loudness (db) were taken from tunebat[8]. Bpm marked with * were estimated using beatsperminuteonline[9].

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[8]https://tunebat.com/, last accessed on August 15, 2024
[9]https://www.beatsperminuteonline.com/, last accesed on August 15, 2024

	Liked Music				Disliked Music			
pid	song	artist	bpm	db	song	artist	bpm	db
1	Wild Boys	Duran Duran	116	-8	Ding	Seeed	117	-6
2	Ramenez la Coupe a la Maison	Vegedream	108	-6	Savage Remix	Megan Thee Stallion	84	-5
3	Besharam Rang	Shilpa R., Visahal & Sheykar	116	-6	Iski Uski	Akriti Kakar & Shahid Mallya	135	-6
4	Tum Ho	Mohit C. & Kavita K.	94	-9	Prem Ratan Dhan Payo	Palak Muchhal	92	-6
5	Still Here	Fox Stevenson	174	-2	Stupid Hoe	Nicki Minaj	100	-6
6	Playing God	Polyphia	137	-7	I Love It	Icona Pop	126	-3
7	Mari Antaga	Sri Rama Chandra	117	-10	Orey Nuvvu Naaku Nachavura	Chitra & SP Charan	121	-11
8	Imagine Us There	Spring Gang	81	-9	Morbid Effigy	Frozen Soul	143	-9
9	Jee Karda	Divya Kumar	140	-8	Only God Can Judge Me	2Pac	90	-6
10	Unstoppable	Sia	174	-5	Kasih Sayang Kepada Orang Tua	Mawang	120	-6
11	Pasoori	Ali Sethi & Shae Gill	92	-6	Eye to Eye	Taher Shah	120*	-8*
12	Go Robot	Red Hot Chilli Peppers	131	-6	Swimming Pool	Marie Madeleine	120	-5
13	Demons	Imagine Dragons	90	-3	Pen Pineapple Apple Pen	Pikotaro	136	-6
14	Sanam Mennu	Sanam	98	-6	Someone You Loved	Lewis Capaldi	110	-6
15	Dice	Finley Quaye	111	-8	Last Christmas	Wham!	108	-12
16	Blue and White Porcelain	Jay Chou	118	-7	Lover	Kun	119	-7
17	Mystery of Love	Sufjan Stevens	132	-17	Cotton Eye Joe	Rednex	132	-8
18	Experience	Ludovico Einaudi	92	-11	Moves Like Jagger	Maroon 5	128	-4
19	Belgrade	Battle Tapes	130	-3	Sister	S!sters	142	-9
20	The Trooper	Iron Maiden	160	-5	Vom Selben Stern	Ich + Ich	140	-6
21	Sultans of Swing	Dire Straits	148	-7	I'm the Man	50 Cent	98	-8
22	Bella Ciao	Sound of Legend	128	-2	Squid Game: Pink Soldiers	Samuel Kim	116	-9
23	Zeit	Rammstein	123	-8	Dance Monkey	Tones and I	98	-6
24	Three Little Birds	Bob Marley	74	-10	Barbie Girl	Aqua	130	-11
25	Latexfauna	Kosatka	172	-7	What a Cossack You Are	Anna Trincher	130	-4
26	Falsafa	Tanzeel Khan	88	-12	Chemistry	Abeer Arora	180	-10
27	Panda	Desiigner	145	-6	Brown Munde	AP Dhillon, Gurinder & Shinda	100	-6
28	Eins Zwei Polizei	Mo-Do	145	-12	Taki Taki	Selena Gomez, Ozuna & Cardi B	96	-4
29	Fix You	Coldplay	138	-9	Low	Blaiz Fayah	190	-4
30	Lift Me Up	Rihanna	177	-6	Pen Pineapple Apple Pen	Pikotaro	136	-6
31	I Need a Miracle	ReMan & Taylor Mosley	120	-8	Belly Dancer x Temperature	Sean Paul, Imanbek & Byor	122	-5

Table 3. Participant id (pid), song, artist, beats per minute (bpm) and loudness (db) of the song choices made by each participant. Bpm and db marked with * were estimated.