Effects of Music Listening upon online CS Students

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Abstract. *One of the challenges Computer Science (CS) tutors confront is applying methods to sustain their students' enthusiasm for learning topics perceived as complex, especially in online courses. The use of music has revealed several contributions in the educational context but is underutilized in the CS background. Hence, we conducted an exploratory case study on seven online groups of four different CS subjects to capture (using a survey) students' perspectives (N=97, 25% women, $Age_{avg} = 23$) on their experience listening to music before and after each lecture and demonstration. Our quantitative and qualitative analyses strongly indicated that music listening positively affected students' mood, energy, calmness, and attitude toward CS topics.*

1. Introduction

Teaching computer science (CS) topics face heterogeneous and vast challenges. As a tiny example, the CS's extensive curriculum comprises topics not "attractive" to all students. On the other hand, students may experience emotional obstacles (e.g., fear, anxiety) or lack fundamental concepts (e.g., mathematics) that cause them to drop out of the course. These and other challenges have encouraged computer science tutors to go deep into the science of learning, instruction, and assessment to help students pursue a career in CS.

Music is one of many resources (e.g., learning theories) that tutors have available to support them in teaching CS topics. In addition, several studies revealed that music is a medium to humanize, energize a learning environment, promote well-being, and reduce the subject's boredom, contributing to engaging students in knowledge construction [Schön et al. 2008, An et al. 2014, Lim and Bang 2018].

The CS literature has provided studies that embraced music thematic for developing CS learners. For example, several works revealed promising results in enthusiasm by integrating music-making activities in their interventions [Lavy 2021]. Similarly, other studies used music as a stimulus element for programming-related tasks [Lapidot and Hazzan 2005]. Some studies yet employ interdisciplinary approaches that congregate CS and Arts students to solve a common problem together [Sawyer et al. 2013]. Despite their contribution, this literature does not examine the potential benefits of music listening on the CS students' well-being and attitude when attending online courses.

Well-being is a suitable condition for promoting the learning of any topic [Pekrun and Linnenbrink-Garcia 2014]. Hence, knowing the effects of listening to music on students is paramount for CS tutors who intend to integrate it into their pedagogical intervention to promote a positive learning environment in the classroom.

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Encouraged by this relevance, the purpose of this exploratory case study is to describe and interpret the multiple learners' perspectives from seven real-life CS groups (including Software Engineering and Database) regarding their music listening experience before and after each lecture or demonstration. Hence, we used a survey with Likert and opened-end questions to facilitate students to express their perceptions. Next, we conducted quantitative (e.g., Wilcoxen Signed Rank, Power Analysis) and qualitative (e.g., Coding) analysis procedures. As a result, the present work states the following research questions:

> *What is the relation of the music listening experience before and after each lecture to the students' mood? What is the connection of this experience on the students' concentration and emotional state related to calmness and energy? Furthermore, what is the link of this experience to the students' attitude towards CS topics?*

This work has the following structure: We present the related works based on music initiatives in CS in Section 2. Next, we discuss the background and motivation that led us to use music listening in class (Section 3). Then, in Section 4, we describe our methodological approach, whose results we examine in Section 5. Finally, we indicate some threats to validity and conclude this work in Sections 6 and 7, respectively.

2. Related Works

Educational literature presents numerous studies that discuss the benefits of music for different knowledge areas (e.g., foreign language, math) and school terms (e.g., K12, high school) to act on cognitive (e.g., vocabulary acquisition [Schön et al. 2008]) or affective (e.g., anxiety reduction [An et al. 2014]) dimensions. However, the present work focus on computer science in higher education.

The use of music to introduce computer science topics provides some contributions to making them more appealing, especially to beginner students. A significant portion of the literature uses *music-making activities*, benefiting from the fact that composing a melody offers a concrete context to use the abstract concepts of programming structures [Lavy 2021]. Others use music as a *supportive resource* to "hook" students on discussing programming topics. In contrast, *performatics* refers to interesting initiatives that present CS topics availing the students' innate interest in performance and the arts. Finally, some studies focus on changing the learning environment by offering students the opportunity to *music listening*, which is the main interest of our work.

Regarding *music-making*, some studies provide specific tool environments that map programming concepts to music concepts and permit students to develop pieces of music by manipulating previous audios [Magerko et al. 2016] or a sequence of notes [Horn et al. 2020]. Likewise, others use songs or music theory as a basis to introduce programming concepts supported by the sound facilities of general-purpose environments (e.g., Scratch [Brown et al. 2020, Lavy 2021]) or programming language libraries (e.g., Gibber JavaScript [Allison et al. 2016]).

Original proposals add analogical resources to music-making activities. For example, Costa et al. [Costa et al. 2021] use tactile blocks of different meanings and textures to enable students with visual disabilities to represent some melodies. After that, these students use an application to capture the QR code of each block of their song that subsequently processes and converts them into sound. Similarly, an intervention oriented to unplugged computing activities requires students to fill incomplete pseudocode related to a melody and create a new rhythm (and its corresponding pseudocode) using plastic cups [Silva et al. 2019].

In terms of *supportive resources*, a study requires students to apply the debug process to eliminate program errors until it plays a melody correctly [Lapidot and Hazzan 2005]. Alternatively, Guzdial and Ericson [Guzdial and Ericson 2015] employ the idea of raw sound manipulation (e.g., adding effects, increasing volume, normalizing sound) to introduce programming structures.

Concern with interdisciplinarity, literature provides distinct approaches founded on *performatics* concept. For example, an interdisciplinary approach involves music and CS students in real-world projects [Heines et al. 2009]. First, the formers must create a composition based on household objects and devise their corresponding notation system. Subsequently, pairs of CS students build a visual application to permit writing a piece of music using each notation system. In this line, other performatics approaches introduce Design Patterns [Hamer 2004], programming and hardware (sensors) integration to design musical instruments [Sawyer et al. 2013], and game programming played through real instruments [Silla et al. 2016].

Best of our knowledge, we found no CS studies on *music listening* related to this work's focus. However, a pair of surveys on software developers practitioners revealed they listen to music *during* writing or testing code mainly to reduce office noise, increase focus, or change their mood [Barton et al. 2019].

3. Background and Motivation

3.1. Our students on pandemic

The pandemic event has impacted students' physical and mental health worldwide. For example, at our university, ad-hoc information (from students and tutors) revealed that students experienced time management stress to attending work and university demands. Messaging tools and online synchronous lectures were the only occasions to direct contact with colleagues and teachers. Moreover, the group concept at our university is somehow weak as students may opt to attend courses in a different order, impacting relationship strength. This situation also contributes to groups with varying heterogeneity levels.

3.2. Our Motivation

An extensive literature has demonstrated that music is wholesome to the human brain. Although usually related to social reward (e.g., family entertainment), several studies have indicated substantial evidence of cognitive, affective, and motor responses when humans perform or listen to music [Hodges 2000]. The latter (the main interest of this work) provides both reward and comfort (e.g., escaping from negative emotions) that can contribute to the listener's overall mental well-being and feelings, positively influencing their cognitive performance [Lim and Bang 2018].

The bidirectional influence of affective and cognition dimensions is well known, especially for knowledge-driven activities (e.g., problem-solving, knowledge organization). Indeed, the positive emotional state facilitates the processing of newly learned information and its organization in memory [Pekrun and Linnenbrink-Garcia 2014]. Furthermore, several studies highlight the contributions of such as state to students' persistence, creativity, and motivation. For instance, the CS literature provides studies' outcomes that corroborate the advantages of considering emotions and cognition in tandem in the classroom [Borovina Josko 2021a, Borovina Josko 2021b].

Considering human brains' predisposition toward music and our belief in the essential cognitive-affective interplay, we adopted music listening in our groups (Section 4.1). This adoption focused on contributing to an unwinding and enjoyable atmosphere to introduce the discussions of CS topics and reduce the social distance burden during the pandemic event.

4. Method

4.1. Selecting and Matching Songs to Lectures and Demos

We built a playlist without songs overlapping for seven CS groups: four database systems (DB) groups and one group for operating systems (OS), software engineering (SE), and introduction to programming (IP). The subjects are 12-week long at our university and have two lessons per week. As we reserved the last week for the final exam, each subject demanded around 28 songs: 22 lectures and six demos.

We followed a four-step process to build the seven playlists above: *song picking*, *playlist definition*, *song-lecture and song-demo matching*, and *song playing*. In the first step, we picked rock, pop, and miscellaneous songs from the 1950s to the 2000s, generating three strata with 200, 80 and 40 music. We considered representatives of different subgenres of rock (e.g., Blues-rock, Folk-rock), pop (e.g., New romantics, Synth-pop), and various genres like Boogie-woogie, Classic Music, and Bossa Nova. The main criteria for the picking procedure were their context representativeness, length (between 4 to 9 minutes long) and appropriate material (e.g., without profanities).

In the subsequent step, we applied the stratified sampling method with no replacement to distribute the songs among the playlists considering the number of instances available in each stratum. Having employed this method for each course, we obtained seven playlists (named $P_{DB1}, P_{DB2}, P_{DB3}, P_{DB4}, P_{SE}, P_{IP}, P_{OS}$) with eighteen rock songs, seven pop songs and three miscellaneous songs on average.

In the third step, we matched the playlist's songs with the sequence of lectures and demos in different ways to introduce variety. On the one hand, we considered the released date to match the melodies in ascending (P_{IP}, P_{DB2}) or descending (P_{SE}, P_{DB1}) order. On the other hand, we applied a random match of the songs to the remaining groups.

Finally, in the last step, we played each playlist song in the following manner: 50% at the beginning (part one) and 50% at the end (part two) of each lecture or demo. Moreover, to bring some musical culture, we offer three-minute information about each song's context (e.g., genre and when it emerged, the band or singer) just after listening to its part one. Nevertheless, it is worth mentioning that all demos and around 75% of lectures were asynchronous (videorecording), while the remaining lectures were synchronous.

4.2. The Data Collection Procedure

We designed a three-section survey with a front cover using a straightforward vocabulary. The first section comprises close-ended questions regarding students' demographic information, while the second one has questions about the influence of listening to music on students' emotional state and mood. The last section has one open-ended question, and the survey's front cover informs students about anonymising their data. For the second section, we opted for the Likert Scale because it is simple and permits students to respond to the questions according to a degree of agreement. In turn, we used an open-ended to allow students to express their experiences using their own words.

Considering our seven CS groups from the second semester of 2020 until the first semester of 2022, 271 students finished them. A total of 97 ($\approx 36\%$) students filled out the survey, of which 72 ($\approx 74\%$) were males, 24 ($\approx 25\%$) were females, and one preferred not to identify. Their age range has the following approximate distribution: 2% for 17 to 19, 42% for 20 to 22, 41% for 23 to 25, and 15% for 26 or more. A few participants ($\approx 5\%$) mentioned having some auditory disability, but it did not prevent them from listening to music. Moreover, 27 ($\approx 28\%$) participants indicated that they perform some musical instrument. As expected, students from database system classes had bigger participation in the survey (52%).

4.3. Analysis Process

We followed a four-step analysis process: *data arrangement*, *data reduction*, *data exploration*, and *analysis* per se. In the first step, we gathered all survey data into two interrelated repositories: one holding only the close-ended answers and the other containing the open-ended responses.

We used the Taguette tool to support our 4-round coding process in the data reduction step. In the first round, we decided on Emotion and Concept coding methods and defined a pre-list of likely coding items. The first method we used to capture feelings expressed by students, while the second determined the context or idea which students' emotions were anchoring. We applied both methods to all students' answers in the second round. Next, we used the third round to revise and align some new codings. Lastly, we solved differences confronting the coders' marks and performed the interrater reliability using the Cohen's Kappa coefficient [Landis and Koch 1977].

Having finished the reduction step, we explored the Likert answers to determine which statistical methods would be more appropriate: parametric or non-parametric. Finally, we applied the chosen methods to Likert answers and the analysis and reorganization of students' multiple perspectives about our intervention.

5. Results

5.1. The Likert Answers Analysis

Our data exploration (Section 4.3) revealed that not all the Likert answers resemble a normal distribution. As Table 1 illustrates, $\mathcal{Q}2$ to $\mathcal{Q}6$ held skewness or kurtosis z-values ($Skewness_z$ and $Kurtosis_z$) not between -2.575 and 2.575, the normality assumption for 99% confidence level (CL) [Ryan 2013]. Hence, as we can not presume the interval values between scales, only the median (mdn) is legitimate [Ryan 2013]. For this reason, we decided on a parametric method for $\mathcal{Q}1$ (t-test) and an equivalent non-parametric method for the remaining, named Wilcoxon Signed-Rank (WSR). We opted to use 99% of confidence level ($\alpha = .01$) on these methods for higher results accuracy.

Following, we applied the Cronbach's Alpha and obtained $.78$, indicating that Likert data had good internal consistency. Finally, we used the chosen statistical methods to analyse our two alternative hypotheses regarding our intervention:

H_0 : listening to music had a neutral effect, $\mu = 3$ for $Q1$ and $mdn = 3$ for the remaining.
H_1 : listening to music improved students' concentration, emotional state, mood, and interest, $mdn > 3$ for $Q1$ to $Q5$.
H_2 : listening to music did not degrade students' concentration, $mdn < 3$ for $Q6$.

Table 1. The Survey Likert Questions - Data Analysis (Source: The Authors)

Questions	$Skewness_z$	$Kurtosis_z$
$Q1$. Did listening to music enhance your concentration to follow the lectures/demos?	.13	.96
$Q2$. Did listening to music make you feel relaxed to follow the lectures/demos?	3.93	.84
$Q3$. Did listening to music energise you to follow the lectures/demos?	4.03	.16
$Q4$. Did listening to music enhance your mood?	5.53	1.99
$Q5$. Did listening to music improve your interest in the course topics?	3.30	.34
$Q6$. Did listening to music degrade your concentration to follow the lectures/demos?	13.49	18.41

Regarding contribution to concentration ($Q1$ in Table 2), the one-group $t - test$ revealed that listening to music ($\mu = 3.22$) did not differ from the null hypothesis ($\mu = 3$), $t(96) = 2.0061$, $p > .01$, ES = $small$ $(.204)$. Studies have shown that listening to music before cognitive tasks enhance concentration. However, this effect depends on students' mood and emotional state, which are impacted positively when the students listen to preferred songs [Shih et al. 2016]. The low knowledge level of playlist songs (less than 30%) among the students who reported a Likert scale of less than three may have prevented our result from reaching its plenitude. In other words, these students may not relish part of the playlist.

Table 2. $t - test$ analysis for $Q1$ (Source: The Authors)

t	df	$p - value$	Mean	Std. Deviation	Median	Effect Size (ES)	Power (CL=99%)
2.0061	96	0.02383	3.22	1.063	3	.204	.364

In contrast, students reported no adverse effects ($mdn = 1$) of music listening on their concentration ($Q6$ on Table 3). Hence, the alternative hypothesis (H_2) is statistically significant by the one-group WSR test, N=97, T=0, $p < .01$, ES = $large$ $(.96)$. This compelling result aligns with the previous works' results about the benefits of listening to music on concentration [Hodges 2000, Shih et al. 2016].

On the question of calmness ($Q2$ in Table 3), the one-group WSR test indicated that students noted the crucial contribution of listening to the playlist to change their emotional state to something more serene ($mdn = 5$), preparing them to follow the lectures or demos, N=97, T=3037, $p < .01$, ES = $fairly\ large$ $(.79)$. Such a result corroborates previous works that indicate music as a factor that initiates or induces a tranquillity state [Pekrun and Linnenbrink-Garcia 2014, An et al. 2014], including in music-making activities [Lavy 2021].

Table 3. WSR analysis for $\mathcal{Q}2$ to $\mathcal{Q}6$ (Source: The Authors)

Question	T	$p - value$	Median	z-score	Effect Size (ES)	Power (CL=99%)
$\mathcal{Q}2$	3037	1.979^{-15}	5	7.859	.79	.99
$\mathcal{Q}3$	2895.5	5.123^{-14}	5	7.44	.75	.99
$\mathcal{Q}4$	3242.5	1.103^{-15}	5	7.93	.80	.99
$\mathcal{Q}5$	2481	4.229^{-12}	4	6.83	.69	.99
$\mathcal{Q}6$	0	2.2^{-16}	1	-9.54	.96	1

Related to the previous question, listening to music also improved students' moods ($mdn = 5$), differing from the neutral hypothesis ($mdn = 3$). As illustrated $\mathcal{Q}4$ in Table 3, the one-group WSR test indicated this result as statistically significant, N = 97, T=3242.5, $p < .01$, ES = $large$ (.80). Indeed, improvements in both calmness and mood are foundations for a positive change in students' well-being, consequently implying better learning performance [Pekrun and Linnenbrink-Garcia 2014], even more in online settings [Lim and Bang 2018].

Another effective result ($\mathcal{Q}5$ in Table 3) revealed that music positively changed students' attitudes toward class topics ($mdn = 4$), differing from neutrality ($mdn = 3$). This difference is statistically significant, according to the one-group WSR test, N=97, T=2481, $p < .01$, ES = $medium$ (.69). Such result shows that students recognized that listening to music (and their stories) inspired them somehow to face the challenges (and possible boredom) of learning each course topic, enlarging previous CS literature focused only on computer programming [Horn et al. 2020, Allison et al. 2016, Lavy 2021].

Finally, on the question of energy ($\mathcal{Q}3$ in Table 3), our analysis revealed that students did not keep neutral ($mdn = 3$) but experienced energy level enhancement after listening to music ($mdn = 5$). The one-group WSR test indicated this result as statistically significant, N=97, T=2895.5, $p < .01$, ES = $medium$ (.75). This outcome widens previous CS programming-related studies that suggest music as one factor in enhancing students' attitudes around learning [Horn et al. 2020, Lavy 2021, Magerko et al. 2016].

5.2. Open-ended Answers Analysis

Figure 1 summarizes the 92 students' perspectives regarding our intervention, while five (5%) provided a single point. For each codings pair (context and emotion), Figure 1 shows the number of unique students and the number and percentual of absolute codings, respectively. These outcomes from the coding step had an interrater reliability coefficient (Cohen Kappa) of 0.49 with 70% of agreement, which is moderate [Landis and Koch 1977].

We identified a stimulating fact during coding: students perceived an environment or atmosphere in our intervention. As illustrated in Figure 1, students reported different terms to express the implications of such an environment on them as students and humans. Beyond impacts on calmness, energy, and engagement (corroborating other studies [Pekrun and Linnenbrink-Garcia 2014]), we were thrilled when students (22%) reported that our intervention created them a sense of belonging, even in online mode. Below we show some students' declarations regarding the implications.

> $\mathcal{S}10$*: I believe that the main benefit was humanising the student-teacher relationship. As many of the online lectures in this pandemic are recorded, it's happened to me not even to remember the faces of some tutors. The playlist and its stories*

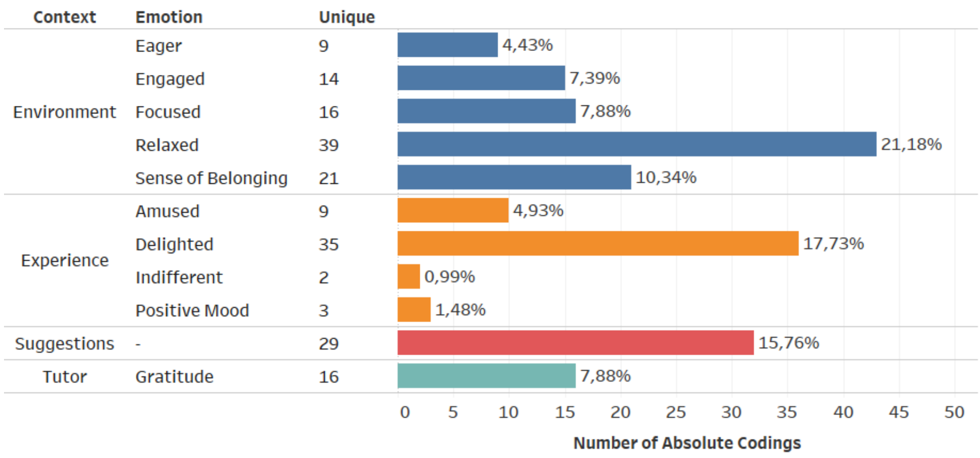

Figure 1. Codings pair summary (Source: The Authors)

> *helped to get to know you better as a teacher and person.*
>
> $\mathcal{S}27$*: I believe that the music helped to dictate the atmosphere of the classes, creating a more cosy moment in which we were more receptive to the content.*
>
> $\mathcal{S}40$*: In my opinion, arriving at class and listening to the genres of music played served as a shutdown of the thoughts I was in before class, making the lectures more relaxed.*

Likewise interesting, students used several feelings to express how happy and satisfied they felt because of the experience of listening to music before studying a lecture. Only two students ($\approx 2\%$) reported they were indifferent to listening to music without informing any reasons. We categorized their feelings as the *amused*, the *delighted*, and the *mood* (Figure 1), exemplified in the few excerpts below.

> $\mathcal{S}89$*: I loved it! The interesting was that sometimes when listening to the songs again, I remembered the material and the lecture content.*
>
> $\mathcal{S}90$*: I thought it was an exciting idea! Interesting enough to show my parents how fun and delicious the classroom can be.*

Corroborating their appreciation of our intervention, several students (31%) proposed enriching the playlist with songs from other genres (e.g., Brazilian Rock, Rap) or improving the song selection method. Finally, some students (17%) kindly left little passages thanking the tutor for the experience and recognizing his devotion to the class planning. The students' excerpts below are examples of a proposal ($\mathcal{S}21$) and recognition ($\mathcal{S}11$).

> $\mathcal{S}21$*: When we returned to the in-person class, there should be an interactive space where students could choose or vote on a song to play for the next classroom.*
>
> $\mathcal{S}11$*: I found the music very cool, for me, it gives the clear impression that you prepared the class with extra care.*

6. Threats to Validity

All our groups happened during the pandemic and before all students and tutors had conditions to returning to in-person classes. Hence, such an event may have induced some students to feel lonely, melancholic, or anguish, preventing music from touching their innermost. In contrast, the very same event may have enhanced the listening to music effect because of its humanization force [Pekrun and Linnenbrink-Garcia 2014]. Further, the tutor's preferences biased the song selections. Such a bias may have prevented a few students from enjoying music listening as they did not know them or did not like the playlist's genres or musicians.

7. Conclusion

This paper presented our approach to incorporating listening to music before and after lectures and demos (in asynchronous and synchronous modes) in seven online groups of different CS courses. Its quantitative results strongly indicate that listening to music positively affects students' well-being and attitude toward CS. Moreover, students' feedback ($N = 92$) highlighted the relevance of such an approach because it touched on humanization in the groups, while only two students were indifferent to it without providing any reason. In future works, we intend to conduct a controlled experiment to contrast students' emotional state and cognitive performance in three settings: traditional music, un-vocalized alpha waves, and no music.

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