Measuring the Influences of Musical Parameters on Cognitive and Behavioral Responses to Audio Notifications Using EEG and Large-scale Online Studies

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ABSTRACT

Prior studies have evaluated various designs for audio notifications. However, calls for more in-depth research on how such notifications work, especially at the level of users' cognitive states, have gone unanswered; and studies evaluating audio notifications with large numbers of participants in multiple environments have been rare. This study conducted an electroencephalography study (N=20) and an online study (N=967) to enhance understandings of how three musical parameters – melody (simple, complex), pitch (high, low), and tempo (fast, slow) – influenced users' cognition and behaviors. There are eight different notifications with different combinations of these parameters. The online study analyzed the effects of user-specific and environmental information on users' behaviors while they listened to these notifications. The results revealed that tempo and pitch have the main effect on the speed and strength (accuracy) of users' cognition and behaviors. The users' characteristics and environments influenced the effects of these musical parameters.

CCS CONCEPTS

• **Human-centered computing → Empirical studies in HCI**;

KEYWORDS

Audio notifications; brain-computer interface; neuroergonomics

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1 INTRODUCTION

In an era characterized by visual-information overload, people receive massive quantities of information each day. A growing body of research indicates that this surfeit of visual information is increasingly likely to cloud people's understanding of issues and inhibit good decision-making [34, 43]. Unsurprisingly, audio notifications have emerged as popular alternatives to visual ones [12].

However, this wider usage of audio notifications has given rise to new design problems: notably, how to tailor them to varied tasks with widely divergent levels of urgency across a range of real-world scenarios. The perceived urgency, apparent emotional content and notifying effect of an audio notification can all be heavily influenced through manipulation of its musical parameters such as pitch, rhythm, and timbre [6, 12, 23, 24]. Accordingly, researchers have proposed several sets of guidelines on how to modify such parameters to obtain optimal notifying effects in particular scenarios [9, 22, 28, 36]. However, such studies have generally relied on indirect methods such as questionnaires and behavioral-response experiments to measure how changes of musical parameters influence user cognition, and have measured covert cognitive processes only indirectly [25, 37, 44]. In any case, prior studies have made it clear that the design of audio notifications is worthy of deeper investigation, and particularly emphasized the need to integrate cognitive properties into the evaluation of such notifications, to obtain direct information about users' cognitive states [26, 28]. Frauenberger et al. [9] indicated that the cognitive properties of the human auditory system are especially likely to provide useful information for the audio-notification design space.

Studies evaluating audio notifications in a broad range of environments and/or with large numbers of participants have been rare. They have reported that users' characteristics (e.g., demographics and experiences) [14], the experimental setting [9, 28], and task-oriented factors [4] could all change how manipulations of audio notifications' musical parameters affected their detectability. It is hoped that extending the findings derived from an initial electroencephalography (EEG) study via a large-scale online study would produce a more comprehensive understanding of how audio-notification design choices influence different people across different environments.

Because melody, pitch, and tempo have frequently and effectively been used by designers to modify the effects of their audio notifications [6, 19, 21, 28], the present researchers chose to investigate these three musical parameters, and in particular, how they influenced users' auditory perceptual response, attention-shifting and behavioral responses (i.e., reaction time and accuracy). The EEG study adopted the methodology proposed by previous studies [5, 25, 35] that evaluated audio notifications by measuring users' auditory perceptual response (mismatch negativity, MMN) and attention-shifting (P3a): two important cognitive functions related to the notifying effect. More specifically, MMN allows researchers to determine, unobtrusively, whether a user heard a notification; and once the user's brain has detected the notification, his/her level of attention-shifting to the notification can be measured via P3a. The latter variable is critical to the usability of audio notifications: for instance, if a notification causes too much attention-shifting, users could find it overly annoying, but if it causes too little, they could miss relevant information. Direct measurement of the influence of musical parameters on these two processes should yield much better clues for designers seeking to optimize notifying effects; and new data on user cognition may help to validate and refine existing audio-notification design guidelines.

Having used EEG to examine how their participants' auditory perception and attention-shifting was influenced by musical parameters in a laboratory environment, the present researchers conducted an online study with 967 participants using Amazon's Mechanical Turk. A dual-task paradigm was used in the online study to simulate a scenario in which the participants' attention was shifted away from a visual task by audio notifications. As well as comparing MMN, P3a and behavioral results, the researchers divided the behavioral data into subgroups based on user-specific factors and environments, to facilitate observation of the relationships between human responses and specific audio notifications in various contexts. So that the findings would be easier for designers or other researchers to make use of, comparison matrices of the findings of the EEG and online studies were created. The paper also provides a discussion of how these findings and matrices could benefit future exploration of the audio-notifications design space.

The intended contributions of the present work are: (1) to provide a better general understanding of the relationship between changes in audio notifications' musical parameters and changes in humans' auditory perception and attention-shifting; (2) by conducting a large-scale online study, to reveal how that relationship varies across individual users and with changes in environmental conditions; and (3) through the creation of comparison matrices, to improve understanding of the relationships among changes in musical parameters, human cognition, and specific behaviors.

2 RELATED WORK AND BACKGROUND

Audio-notification Design

In the fields of sonification, auditory display and auditory neurophysiology, several studies have proposed design guidelines for audio notifications based on investigations of their usability [6, 11, 12, 22, 24]. The term usability, in this context, includes effectiveness at attracting users' attention and whether these sounds annoy users or others [6, 29].

In the design of earcons, Brewster et al. [3] suggested that using timbres with multiple harmonics could help users perceive notifications more easily; while rising intensity, high pitch, and irregular harmonics are useful for grabbing users' attention. Edwrothy et al. [6] also found that increasing pitch of an auditory warning could cause high perceived urgency. Designers frequently use several musical parameters to manipulate the usability of audio notifications [6, 19, 28]. For example, prior research has indicated that tempo is highly correlated with emotional arousal, and thus influences users' behaviors [17, 23]. Much of the existing literature has focused on parameters that can directly correspond to sounds' physical features. However, Komatsu et al. [21] found that audio notifications with ascending melodies can increase users' willingness to follow their suggestions.

In addition to the characteristics of the audio notifications themselves, the environment where users hear them is a crucial usability factor. Several studies have included environmental dimensions such as visual complexity, auditory scene, and users' mental workload in their sound-design processes [9, 28]. For example, it has been shown that the masking of audio notifications by background noise can be avoided if their frequency is in a different bandwidth [33]. Users with different demographic characteristics have also been found to perceive the same audio notifications differently. Ghosh et al. [14] found that their older participants were less sensitive to sound-pressure levels used to convey a sense of urgency, as well as less likely to detect notifications of lower intensity regardless of the presence of ambient noise [42]. Based on EEG responses, gender differences in audio processing have also been reported [20].

It is also reasonably clear that human beings' processing of audio notifications, from perceiving them through to understanding the meanings of the sounds that are heard, involves a complex chain of cognitive operations [13, 27]. However, some studies have noted that the use of behavioral performance to assess cognitive states, being an indirect method, might lead to inconsistent or incorrect results [25, 37, 44]. As such, it is important not merely to consider, but to directly measure, the cognitive impacts of audio notifications when designing them.

EEG Measurements of Audio Notifications

With the aim of measuring users' cognition directly, several researchers in the fields of human-computer interface (HCI) and neuroergonomics have adopted brain-computer interface (BCI) techniques [30, 32]. In auditory neurophysiology and music cognition, several studies have used EEG to observe changes in human cognition that occur upon hearing different types or designs of audio notifications. Burt et al. [4] utilized EEG to measure people's arousal when listening to auditory warnings with varying levels of perceived urgency, and found that such levels had a significant effect on the participants' Alpha power. Glatz et al. [15], meanwhile, investigated their participants' behavioral and brain responses to auditory icons and recorded verbal commands, and found that – while the latter were more discriminable from background sound than the former – auditory icons were more easily updated to contextual working memory.

Two other forms of cognition, auditory perception and attention-shifting, are likewise critical to the usability of audio notifications [25]. Auditory perception refers to the ability of the human ear and auditory system to perceive sounds and detect changes in sound [41]; and attention-shifting is the effect whereby a perceived event redirects a person's attention away from his/her current task, and as such is the main purpose of notifications [18].

EEG has often been utilized in prior studies to measure auditory perception and attention-shifting. Two components of event-related potential are closely related to these two types of cognition: respectively, MMN and P3a [35]. MMN is a negative potential indicating how well a particular person's auditory system can detect and perceive changes in sound or musical parameters, including intensity and pitch [35]. MMN amplitude will be greater when the change in a sound is evident and easy to detect; and its latency refers to the period that a person needs to perceive changes in sound or musical parameters [35]. P3a, which often follows the occurrence of MMN, is a positive potential related to the re-orienting of a person's attention towards deviant stimuli [8]. P3a amplitude is higher when a deviant stimulus attracts a higher proportion of a person's attention, and its latency is the processing time between the moment of the stimulus' onset and the moment when attention-shifting occurs [38].

Lee et al.'s [25] method for evaluating users' levels of perception and attention-shifting by measuring their MMN and P3a has been used successfully to assess the impact of audio notifications in realistic scenarios. However, because Lee et al.'s goal was to measure cognition unobtrusively, they did not explore the influences of musical parameters in depth, instead focusing on changes in notifications' intensity. This paper, in contrast, utilizes the same method to investigate how three of the musical parameters most frequently used in audio-notification design influence people's cognition.

Large-scale Online Study

In the fields of HCI, social computing, and crowdsourcing, researchers now routinely assign various online tasks to users and/or collect massive datasets from them. Several prior large-scale studies have been conducted to gain a clearer understanding of how people behave in various environments, and of whether findings derived from lab-based studies were replicable online with much larger numbers of participants [7, 16, 39]. Reinecke et al. [39], for instance, collected 548 participants' ratings of the colorfulness, visual complexity, and visual appeal of 450 websites, and based on this dataset of ratings, built a computational model capable of predicting humans' aesthetic first impressions. The same authors found that the participants' demographic variables influenced their perceptions of visual complexity and colorfulness. Similarly, Eitz et al. [7] explored how people recognized sketches using a 20,000-sketch dataset collected using Amazon's Mechanical Turk. They designed a visual-feature descriptor for sketches, and based on the resulting features trained a computational model to recognize the objects in sketches.

3 RESEARCH GOAL AND QUESTIONS

The purpose of the present study is to clarify how the musical parameters melody, pitch, and tempo influence the cognition of people hearing audio notifications, and especially those cognitive functions related to auditory perceptual responses and attention-shifting. To achieve that goal, it will seek to answer the following research questions:

RQ1. How do the melody, pitch, and tempo influence EEG measures of auditory perception and attention-shifting, and are there interactions between these musical parameters?

RQ2. How do the melody, pitch, and tempo affect reaction time and accuracy, and are there interactions between these musical parameters?

RQ3. Do these musical parameters have similar effects

to the participants' behavioral responses and their auditory perception and attention-shifting?
RQ4. How are these interrelationships influenced by user-specific and environmental factors of the participants?

4 EEG STUDY

Participants and Device

Twenty participants (13 females; 20-28 years old) participated in the experiment. None of them had any history of hearing and vision problems. An LCD monitor (22 inches, 1920×1080 pixels) was used to show the film. Audio stimuli were presented via loudspeakers (Altec Lansing 2.0 ch, VS2620). A decibel meter was used to adjust the intensity of the stimuli to average 70dB before the experiment.

Material Preparation

To prepare experimental materials, a dataset of notifications from the websites Notification Sounds and Appraw were collected. Seven musically trained raters were recruited to determine the melody complexity of the 40 notifications. Each notification was rated on a 5-point scale (1 to 5: simplest to most complex melody). The notifications that were rated as 1 or 5 by all seven raters were selected as our set of notifications. Only one simple and one complex notifications emerged from this process. The absolute average pitch (AAP) of complex and simple melody is 204.13 and 342.39 Hz. Then, Garageband software was used to modify these two notifications by tempo (slow: 120 BPM; fast: 200 BPM) and pitch (low: original; high: add 500 cents to the original. The difference is almost half an octave so that the pitch manipulation is easily accessible to a broader audience). We obtained eight notifications as our stimuli (see Table 1).

Deviant	MelodyPitchTempo	Duration	MMN Time Range	P3a Time Range
Dev1	SimpleLowSlow	900 ms	300-400 ms	400-500 ms
Dev2	SimpleLowFast	562 ms	250-350 ms	350-450 ms
Dev3	SimpleHighSlow	900 ms	300-400 ms	400-500 ms
Dev4	SimpleHighFast	562 ms	250-350 ms	350-450 ms
Dev5	ComplexLowSlow	1400 ms	600-700 ms	700-800 ms
Dev6	ComplexLowFast	875 ms	600-700 ms	700-800 ms
Dev7	ComplexHighSlow	1400 ms	600-700 ms	700-800 ms
Dev8	ComplexHighFast	875 ms	400-500 ms	500-600 ms

Table 1: Audio stimuli used in this study and the temporal range for each stimulus used in EEG analysis (The stimuli can be downloaded at https://goo.gl/SnZrzG).

Methodology

The oddball paradigm [25, 35] was adopted to measure the EEG responses to the audio stimuli. The total time of all deviants appearing in each block was controlled so as to not exceed 30% according to the suggestion from the prior studies [25, 35]. In each block, all eight deviant stimuli were randomly scattered with an equal probability of occurrence and played as an overlay to the ambient noise. Sounds recorded in a coffee shop was selected as the ambient sounds. The intervals between each of the deviant stimuli were randomly varied from 3.4 to 6.8 seconds. The EEG data recorded between each pair of consecutive deviants were deemed the standard trials, and those recorded while each audio notification was playing were deemed the deviant trials. Each participant would hear each notification 40 times in the EEG study. Hence, 800 trials were collected for each notification.

We recorded the participants' EEG data during the entire EEG study. Once the experiment started, they watched a subtitled silent film, while continuously hearing the experimental stimuli. They were asked to concentrate on the film and ignore all auditory stimuli while their EEG data were being recorded. One advantage of this approach is that it allowed us to evaluate the effects of audio notifications in a condition of passive listening in which a person is not steadily listening out for audio notifications. This approach also incorporated the impact of realistic ambient sounds, a highly important consideration in audio-notification design.

EEG-data Recording and Processing

We used the equipment consisted of a non-invasive EEG cap, recorded using a NeuroScan system with 32 Ag-AgCl electrodes and a bandpass filter of 0.01-100 Hz. We synchronized a sound stimulus and its EEG recordings by using the software, Presentation (www.neurobs.com), to anchor and record the time markers of the onset time of each deviant in the EEG study. We used single-channel (Fz) event-related potential (ERP) information for analysis. EEG of many trials, which can average out the trivial brain activities and preserve the event-related waveform. Matlab toolbox, EEGLAB, was adopted to process EEG data, which was digitized with a 1000 Hz sampling rate and bandpass-filtered at 1-50 Hz off-line. After filtering, we applied Independent Component Analysis to remove ocular artifacts from the data [31]. The epochs used for computing ERPs were 1,100 milliseconds long, starting 100 ms before and ending 1,000 ms after the stimulus onset. The pre-stimulus period (100 ms) was set as a baseline. All epochs with voltage variations exceeding 80μV were rejected; then, all remaining epochs of the same standard/deviant stimuli were averaged.

For MMN and P3a analysis, the EEG response to the standard was subtracted from the the waveform of each deviant for each participant to reduce participants' individual differences. The peak amplitudes and latency of MMN and P3a were automatically measured from the most negative and most positive deflection respectively, that occurred at specific temporal ranges for each stimulus (Table 1). The latency of MMN and P3a were measured from the onset of each notification [25, 35]. We conducted analysis of covariance (ANCOVA) on the EEG data by treating the musical parameters as the independent variables, the peak amplitude and latency of MMN and P3a as the dependent variables, the participant as the random variable, and the duration of each notification as the covariate. Tukey's method for multiple comparisons was applied in post-hoc tests.

Results

The EEG results for deviants with simple and complex melody were analyzed separately. The first reason for doing this was that we found the ERP waveforms of the deviants with simple melody evoked more obvious MMN and P3a than the waveforms of those with complex melody. The second reason was that, Figure 1 reveals that the shapes of the waveforms of the deviants with simple and complex melody were different, which might indicate that melodically complex notifications do not have as obvious a notifying effect as simple ones.

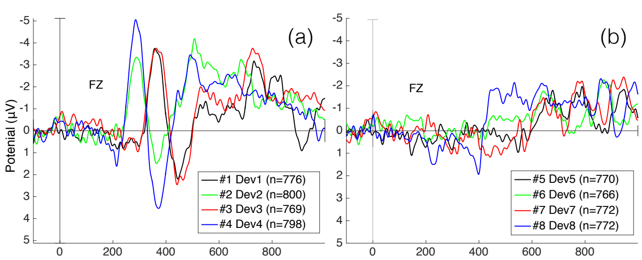

Figure 1: (a) and (b) are the MMN and P3a of all participants' brain response derived from a single electrode (Fz) to the audio notifications with simple and complex melody, respectively. Y-axis represents the value of potential (μV). Time 0 in the x-axis indicates the start of each notification. The time range of each deviant's MMN and P3a is listed in Table 1.

In the condition of simple melody, firstly, as can be seen in Figure 2(a), the high-pitch notifications evoked significantly larger MMN amplitude than the low-pitch ones (F=4.09, p=.048), indicating that raising the pitch of a notification can cause people to perceive it more easily. Secondly, Figure 2(c) shows that the slow-tempo notifications had significantly longer MMN latency than the fast-tempo ones (F=348.59, p<.0001). This result indicates that increasing the tempo of the notifications can shorten the period that users need to perceive them. Finally, there was a main effect of pitch on P3a amplitude (F=4.18, p=.0044), and interestingly, there was an interaction effect between pitch and tempo on P3a amplitude (F=4.88, p=.0313). Figure 2(b) shows that, in the fast-tempo condition, the high-pitch notifications evoked significantly larger P3a amplitude than the low-pitch notifications did (F=12.57, p=.0042). However, there was no significant difference between the high- and low-pitch notifications in the slow-tempo condition. This result implies that, if a designer wants to make users shift more attention from current tasks due to an audio notification, he/she should raise its pitch; but that if the designer slowed its tempo at the same time, the beneficial effect of having raised its pitch would disappear. Regarding P3a latency, as shown in Figure 2(d), the slow-tempo notifications had significantly longer P3a latency than the fast-tempo ones (F=318.58, p<.0001), suggesting that designers can shift users' attention sooner by increasing the tempo of audio notifications.

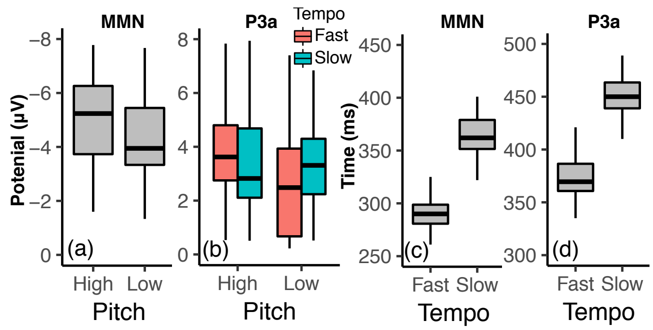

Figure 2: MMN and P3a results in the condition of simple melody, with (a) being the average amplitude of MMN associated with high and low pitch; (b), the interactive effect of pitch and tempo on the average amplitude of P3a; and (c) and (d), the average latency of MMN and P3a associated with fast and slow tempo, respectively.

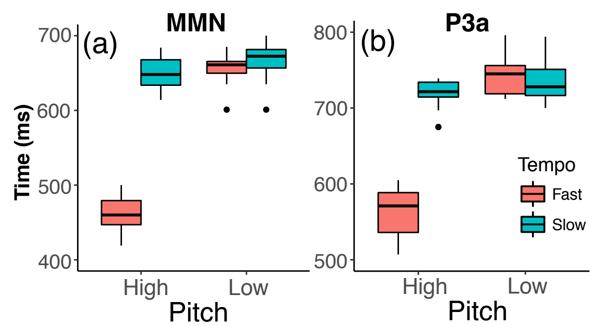

Figure 3: EEG results in the condition of complex melody, with (a) and (b) being the interactive effects of pitch and tempo on the average latency of MMN and P3a, respectively.

In the condition of complex melody, there were main effects of pitch and tempo (pitch: F=478.7, p<.0001; tempo: F=423.4, p<.0001) on MMN latency, and as can be seen in

Figure 3(a), there was an interaction between these two parameters (F=331.6, p<.0001). These results suggest that, in the condition of complex melody, the notifications' pitch and tempo should be increased at the same time to shorten the time users need to perceive them. Similarly, there were also main effects of pitch and tempo on P3a latency (pitch: F=267.9, p<.0001; tempo: F=157.9, p<.0001), and an interaction effect between two parameters (F=183.9, p<.0001). Figure 3(b) reveals that there were significant differences between the low- and high-pitch notifications in the fast-tempo condition (F=536.18; p<.0001) and between the fast- and slow-tempo notifications in the high-pitch condition (F=349.49; p<.0001). The results indicate that, in the case of melodically complex notifications, notifications' pitch and tempo need to be increased simultaneously in order to shift participants from their current focus more quickly.

Discussion of EEG Study

Above results reveal that audio notifications with different musical parameters were associated with differences in EEG responses, which confirms that changes in levels of melody, tempo, and pitch can evoke different auditory perception and attention-shifting. Tempo was found to be associated with the occurrence speed of the auditory perception and attention-shifting while the pitch was related to the strength of them. This finding is consistent with prior studies of MMN and P3a [35], and the common design guidelines also recommend using high-pitch notifications to grabbing users' attention [3] and playing sound at a faster tempo can effectively improve the response time of participants to the given tasks [1]. Our results empirically confirm the validity of this design guideline at a psychophysical level.

The MMN and P3a data revealed the interaction effects among the three musical parameters, which reflects that these parameters do not influence users independently of one another. For example, high-pitch and fast-tempo notifications had the maximal attention-shifting power among all the stimuli used in our experiment. However, if notifications had a low pitch, giving it a fast tempo did not increase the participants' level of attention-shifting. This result could explain the findings of a previous sound design study [28] in which users preferred high-pitch and fast-tempo sounds as notifications of emergency events. The complexity of the interactions that EEG revealed indicates that this technique, and particularly the cognitive measures we originally wanted to obtain, could allow for sensitive and delicate measurement of the influence of musical parameters on users.

We found that melodically complex notifications did not evoke very obvious MMN and P3a, in contrast to those that were melodically simple (See Figure 1). Melody is an arrangement of a series of musical notes that the listener perceives as a single entity, so the differences between the melodically simple and complex notifications may be compound differences in several factors (e.g., differences in rhythm pattern or pitch contour). The prior study also considered melody to be a higher-level musical parameter than tempo and pitch [10], which can both be objectively measured according to their physical differences, whereas determinations of melody are notoriously subjective. Although the melodic complexity of an audio notification may lower its effectiveness, it can offer unique design advantages with appropriate exploration. In line with our findings, previous studies have indicated that minimalist sound design leads to better user performance [29] and have recommended that audio notifications be designed with shorter durations [3]. Nevertheless, other prior studies have emphasized the importance of distinguishability between different audio notifications, and that such ability can be achieved via different melodies [3, 11]. Additionally, it is possible to make notifications more informative and intuitive by providing them with audio metaphors of the events they correspond to [11], and melodically complex notifications provide more flexibility for doing so. The notifications with the complex melody are also recommended for increasing the perceived urgency [14]. Therefore, the complex melody still has advantages in the design space of audio notifications, some of which cannot be achieved using the simple one.

Based on the results, a comparison matrix was created in the hope that the findings of EEG study can be readily applicable (Figure 4). In the matrix, the notation "Amplitude" indicates that the musical parameter in the column has a significant effect on the MMN or P3a amplitude, and "Latency" denotes that effect is on the MMN or P3a latency.

p<.0001; p<.05		*Pitch*	*Tempo*	*Pitch:Tempo*
Simple	**MMN**	Amplitude (F=4.09)	**Latency (F=348.59)**	
	P3a	Amplitude (F=4.18)	**Latency (F=318.58)**	Amplitude (F=4.88)
Complex	**MMN**	**Latency (F=478.7)**	**Latency (F=423.4)**	**Latency (F=331.6)**
	P3a	**Latency (F=267.9)**	**Latency (F=157.9)**	**Latency (F=183.9)**

Figure 4: Comparison matrix of the EEG study. The colon denotes the interaction between pitch and tempo.

5 LARGE-SCALE ONLINE STUDY

Having established the relationships between the changes in the musical parameters of audio notifications and listeners' cognitive responses via the EEG experiment, the researchers turned to the question of how these relationships would be reflected in a broader sample of participants with more diverse backgrounds and in various environments. Launching a study on a crowdsourcing platform is an effective way to recruit a large number of participants, including for studies of human perception [16]. The online component of the present research therefore collected individual-level and environmental data from a large number of participants, with the aim of confirming and extending the findings of the EEG with a larger, more diverse sample operating in a broader range of soundscapes.

Task

The online study's passive-listening scenario utilized a dual-task paradigm, in which the primary task was to watch a silent video and remember its visual content, as tested by the three post-video questions. Simultaneously, their secondary task was to press the Ctrl button on their keyboards when they heard an audio notification, i.e., any of the same set of ambient sounds and deviants that had also been used in the EEG study.

The researchers' intention was for each participant to assign priority to the primary task, yet still pay attention to the secondary task. Accordingly, they designed a scoring policy whereby the participants would receive 10 points when they correctly answered a primary-task question, and the same number of points whenever they successfully reacted to an audio notification. The participants were informed of this system (albeit not that the number of audio notifications was much larger than the number of questions) and instructed to garner as many points as possible.

Participants and Procedure

1093 workers from Amazon's Mechanical Turk crowdsourcing service completed the study and 126 of them who reported not having normal or corrected-to-normal vision and hearing or age less than ten were excluded. Eventually, 967 participants (478 female) with a mean age of 35.5 (SD=11.6) remained for the following analysis. Before conducting the tasks, The participants were asked to adjust their devices' volume levels until they were able to hear every audio notification in an example sound clip. Then, they were asked to read the instructions. Only those who successfully completed this practice task were able to continue the formal task. The average completion time for the whole experiment was 10 minutes, and we compensated the participants $0.50 for completing the formal task.

Behavioral-data Recording and Processing

We recorded each participant's average reaction time and accuracy for each deviant. Reaction time was defined as the period from a stimulus' onset to the Ctrl button being pressed. When average reaction times were computed, trials in which the participant did not press the button when the deviant was played were excluded. Accuracy was defined as the participants' hit rate when they heard the deviants. Each deviant appeared twice, randomly, in every online participant's experimental session. Although behavioral and EEG measures cannot be directly compared, prior studies [25, 35, 38] have reported a correlation between users' MMN and their behaviors (e.g., reaction time and accuracy) in experiments using the oddball paradigm. Based on those prior results, the present researchers expected that the accuracy of their participants' reactions to the notifications would approximate the influence of musical parameters on how well they detected and were distracted by these sounds (i.e., amplitudes of MMN and P3a), while their reaction times would be associated with their speed of cognition (i.e., latency of MMN and P3a).

In addition to the behavioral measures, self-reported information was collected, and can be subdivided into three categories: demographics, experience, and environment. In the first, each participant reported his or her gender and age level, i.e., teen (<20 years), adult (20 to 50), and elder (51 and older). In the category of environment, each participant reported whether he or she was in a public or private place at the time of completing the study, and whether the ambient sound in that place should be characterized as quiet or noisy. And in the category of experience, the participants were asked to report how often they used audio notifications, again on three levels (often, sometimes, and rarely). The factors in the demographics and experience categories were denoted user-specific, and those in the environment category, environmental factors. Figure 6 sets forth the complete sets of factors in each category, along with each one's label or level. For the factor of age level, due to the disproportionately small size of the teen participant group (N=14), teens were excluded from the Figure 6 and analyses related to age.

First, the entire dataset was analyzed to establish whether the influence of the manipulation of the musical parameters in the online study differed from that in the EEG study. Next, to examine whether such influence differed across the categories of user-specific and environmental factors, the dataset was divided into the groups based on the participants' self-report information. For example, to analyze the influence of gender, the dataset was divided into two groups, one containing all the female participants, and the other, all the males. Between-group analysis of the influence of musical parameters was then conducted. The "N" column in Figure 6 shows the number of participants in each group divided by each factor, separately. The survey for collecting self-report information and more descriptive statistics of collected dataset can be found in the supplemental materials.

Analysis of variance was conducted to test the effects of the user-specific and environmental factors on the behavioral measures. The factors were the independent variables and the behavioral measures were the dependent variables. ANCOVA was then conducted on the behavioral measures to test the effects of the musical parameters on each subgroup and on the group as a whole. The musical parameters were treated as the independent variables, the behavioral measures as the dependent variables, the worker ID as the random variable, and the duration of each notification as the covariate. Tukey's method for multiple comparisons was applied in post-hoc tests.

Results

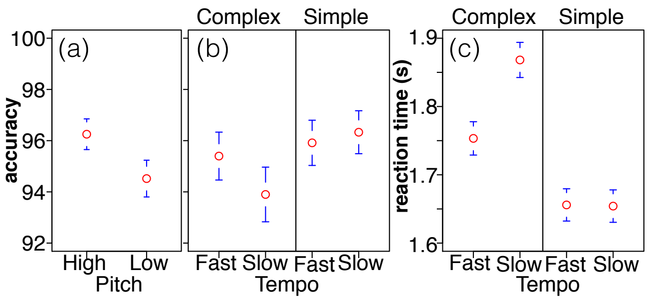

Figure 5: Behavioral results for the overall dataset, with (a) being the average accuracy associated with the high and low pitch, and (b) and (c), the interaction effect of melody and tempo on average accuracy and reaction time, respectively. The error bars represent the 95% confidence interval.

Effects on all participants. The overall rate of correct responses to the video questions was 77.5%, and the average hit rate for notifications was 95.2%. These results indicate that the participants were focusing on both the primary and secondary tasks. High-pitch notifications were associated with higher accuracy than low-pitch ones (F=13.22, p=.0002; Figure 5(a)); and fast-tempo notifications prompted shorter reaction times than those with slow tempo (F=20.53, p<.0001). Melodically complex notifications were found to have longer reaction times than melodically simple ones (F=156.44, p<.0001) and were also associated with lower accuracy (F=9.57, p=.002). Moreover, as shown in Figure 5(b) and (c), melody and tempo had interaction effects on both accuracy (F=4.09, p=.045) and reaction time (F=21.98, p<.0001): with fast-tempo notifications yielding shorter reaction times than slow-tempo ones only when their melodies were complex; and complex and simple melodies yielding similar accuracies if their tempos were both fast. Taken together, the online-experiment results broadly confirm those of the EEG study: with pitch being associated with how well a participant can detect a notification, and tempo with how fast he or she can react to it, while melodic complexity influences both reaction time and accuracy, and appears to cause variation in the effects of pitch and tempo on participants' behaviors.

The influence of the musical parameters, overall and in each group, are summarized in Figure 6. In the matrix, the notation "RT" indicates that the musical parameter in the column has a significant effect on the reaction time, and "Acc." denotes that effect is on the accuracy. Although the specifics of the effects of musical parameters can be seen to differ across groups, how changes in the parameters influenced behaviors was consistent across the groups. For example, raising the pitch of notifications always increased accuracy and increasing the tempo of notifications would shorten reaction time, irrespective of which user-specific or environmental factors were in play. A simplified comparison matrix is provided in the supplemental materials to offer an easier but readable view of the results.

Influence of Demographics. Interestingly, regardless of the influence of musical parameters, we found that the elders had significantly faster reactions than the adults (F=11.02, p<.0001), and equal accuracy. This result is somewhat surprising, as one might reasonably expect older participants to have lower hearing acuity and/or slower cognitive processes than their mid-life counterparts. A possible explanation for this unexpected result, based on the elders' markedly lower rate of correct answers to the video questions (72.9% vs. 81.3% for the adults), might be that the elders focused more on the secondary audio-notification task than on the primary task. If this was the case, their superior performance on the audio-notification task could have come at a price, i.e., lower performance on the video questions.

In terms of the effects of the musical parameters on the same two age groups, the major differences were that (1) the elders' accuracy was not influenced by melody or pitch; (2) there was no interaction effect of melody and tempo on elders' reaction time; and (3) there was no interaction effect of pitch and tempo on elders' accuracy. Prior studies had reported that older participants required more massive changes in intensity to perceive the cautionary and urgent nature of auditory warnings [2, 14]. Thus, the present results might also reflect that influencing the behavioral responses of people over age 50 using sound requires relatively greater differences in pitch and/or melody. Within the adult group, the interaction between pitch and tempo (F=4.03, p=.045) meant that raising pitch increased accuracy only in the slow-tempo condition.

As for gender difference, the female participants had faster reaction times (F=124.48, p<.0001) and higher accuracy (F=18.37, p<.0001) than the males. Within the female group, the notifications with high and low pitch were not associated with any significant differences in accuracy, which might have been caused by the female participants, whose mean accuracy was 96.4%, having achieved a ceiling effect [40] on accuracy. Within the male group, no interaction effect of melody and tempo on accuracy was found; i.e., the males' accuracy was higher for notifications with simple melodies regardless of whether the tempo was slow or fast.

Influence of Environments. The participants in private places had shorter reaction times (F=174.76, p<.0001) and higher accuracy (F=57.24, p<.0001) than those in public ones. Among the public-places group, there was no main effect of tempo on reaction time and no main effect of melody on accuracy. This result implies that the positive effects of this study's chosen musical parameters that were observed in private places would not necessarily operate in public places.

Although the ambient sound of a coffee shop was played along with the audio notifications in the online experiment, as it had been in the EEG experiment, the ambient sound of the place where the online participants were taking the study was treated as an environmental factor. Not unexpectedly, those participants who rated their current location as quiet had higher accuracy than those who said they were in noisy places (F=6.80, p=.0091). Interestingly, however, there was no significant difference in reaction time between these two groups; nor was there any main effect of pitch on accuracy in the quiet-places group. In the noisy-places group, on the other hand, raising the pitch of the notifications was associated with lower reaction times (F=4.35, p=.0037) and higher accuracy (F=13.78, p=.0002), which suggests that increasing pitch can effectively render audio notifications more distinguishable from ambient noise. There was also an interaction effect of melody and pitch on accuracy that only appeared in the noisy-places group (F=6.75, p=.0094). In the case of melodically simple notifications intended for use in noisy places, user accuracy can be increased by raising the pitch. Additionally, when pitch was not raised, the participants reacted to the notifications with a simple melody as accurately as they reacted to those with a complex one.

Influence of Experience. The participants who rarely used audio notifications in their day-to-day lives reacted to the experimental notifications faster than those who used them often or sometimes (F=97.47, p<.0001), with the 'often' group having the lowest accuracy of all three experience groups (F=32.11, p<.0001). A complex melody was only associated with higher accuracy for the 'often' group, whereas high pitch appeared to cause higher accuracy only in the 'sometimes' group. On the other hand, use of a simple melody significantly reduced the reaction times of all three groups. It is interesting to note that, the participants with the least experience of using audio notifications had shorter reaction time and higher accuracy than those who often used audio notifications. A potential explanation is that the participants in 'rarely' group experienced the novelty effect on reacting to audio notifications. Another reason might be that the rarely group were engaged in reacting audio notifications more due to the unfamiliarity with audio notifications. Further studies need to be conducted to confirm the speculations above.

6 GENERAL DISCUSSION

Connection between EEG and Online Studies. Looking at the results of the EEG and online studies together, the two strongest findings were (1) a confirmation of the positive effect of increases in tempo on the speed of the participants' cognitive responses (auditory perception and attention-shifting), and thus indirectly on the speed of their reaction to the notifications; and (2) a confirmation of the positive effect of increasing pitch on how strongly cognitive responses are evoked, which is in turn linked to accuracy.

p<.0001; *p<.05*		N	Melody	Pitch	Tempo	Melody:Pitch	Melody:Tempo	Pitch:Tempo
Overall		967	**RT (F=156)** Acc. (F=10)	Acc. (F=13)	**RT (F=21)**		**RT (F=22)** Acc. (F=4)	
Age	Adult	832	**RT (F=132)** Acc. (F=8)	**Acc. (F=15)**	**RT (F=17)**		**RT (F=20)**	Acc. (F=4)
	Elder	121	**RT (F=25)**		RT (F=4)			
Gender	Female	478	**RT (F=77)** Acc. (F=5)		RT (F=15)		RT (F=10) Acc. (F=4)	
	Male	489	**RT (F=82)** Acc. (F=5)	Acc. (F=13)	RT (F=7)		RT (F=20)	
Place	Private	885	**RT (F=138)** Acc. (F=15)	Acc. (F=7)	**RT (F=20)**		**RT (F=19)** Acc. (F=4)	
	Public	82	**RT (F=19)**	Acc. (F=9)			RT (F=4)	
Ambient Sound	Quiet	690	**RT (F=99)** Acc. (F=8)		**RT (F=16)**		**RT (F=15)**	
	Noisy	277	**RT (F=59)**	RT (F=4) Acc. (F=14)	RT (F=5)	Acc. (F=7)	RT (F=7)	
Using Audio Notifications	Often	367	**RT (F=56)** Acc. (F=5)		RT (F=7)		RT (F=10)	
	Someti-mes	438	**RT (F=77)**	Acc. (F=12)	RT (F=10)		RT (F=11)	
	Rarely	162	**RT (F=26)**					

Figure 6: Comparison matrix for the online study. Colons between two musical parameters indicate an interaction between them.

The universal operation of the melody effect across all subgroups can be seen in Figure 6. The strong influence of melody on participants' behaviors has already been noted based on the results of the EEG study: as shown in Figure 1(b), the less-obvious and later occurrence of MMN and P3a when notifications were melodically complex implied that such notifications would be associated with longer reaction times and lower accuracy than their melodically simple counterparts in online study. Figure 1 also shows that the notifications with complex and simple melodies elicited differently shaped ERPs waveforms, which could imply that the difference between complex and simple melody either impacts, or is impacted by, differences in other musical aspects that were not included in the present research. On the other hand, it is worth considering whether the universality of the melody effect in the online study could be due to its obvious influence on the participants' cognition.

Effect of User-specific and Environmental Factors. As shown in Figure 6, the effects of the musical parameters and the interactions between those parameters influenced the participants' reaction times and accuracy differently across different subgroups of user-specific and environmental conditions. For example, the female participants' accuracy was not significantly influenced by manipulations of notifications' pitch. The fact that the effects of changing the chosen musical parameters could not always be confirmed across conditions further highlights the importance of including contextual dimensions in the process of designing and evaluating audio notifications [9, 28]. Although the potential causes of these differences have been listed in the results section, validation via additional, more detailed investigations is still required.

Usage of Comparison Matrices. Audio-notification designers could use the comparison matrices provided by the present study to estimate how the notifications they create might influence users, both cognitively (Figure 4) and behaviorally (Figure 6). Moreover, the above findings, will enable designers to select the manipulations of these musical parameters that will most effectively induce specific desired effects on users, based on where and by whom their notifications will most likely be heard. For example, if a designer wants to design an audio notification that can be easily detected by users, Figure 4 suggests that he/she should use a simple melody and then increase its pitch to increase the strength of auditory perception (MMN) and attention-shifting (P3a). Moreover, if the notification is designed to notify users in noisy places, Figure 6 shows that a notification with high pitch and a simple melody can effectively make users react faster and more accurately.

7 LIMITATIONS AND FUTURE WORKS

First, in addition to some inherent drawbacks of EEG measurement such as low spatial resolution and extreme sensitivity to body movement, there are still some critical musical parameters (e.g., timbre), user-specific factors, and contextual factors worthy of deeper investigation via EEG study.

Second, the current study only investigated the influence of user-specific and environmental factors separately: not analyzing, for example, behavioral responses to, and effects of musical parameters on, elders who are in public, noisy environments. The reason this joint examination was not performed was that the numbers of participants in the groups formed based on more than one factor were not balanced enough to generate meaningful insights. In the future, a larger participant pool with an even distribution of user characteristics and environments should be used to arrive at a clearer understanding of how these factors jointly influence the usability of different audio notifications.

Third, although the duration of the audio notifications is treated as the covariate in the present study, it was not controlled as an independent variable. From the perspective of audio design, the duration of notifications is usually interdependent with other musical parameters, e.g., tempo and melody. Whether or not future research establishes that audio notifications' duration has any important effects on the key considerations of the present study, it will be useful to arrive at design guidelines that take account of the interdependence of musical parameters as commonly encountered in real design scenarios. In any case, better control of these potential confounding factors (e.g., repeating a short notification few more times to make its duration similar to those of other longer ones when adjusting the tempo) will be necessary if we are to obtain more definitive information on the effects of these and other musical parameters in the future.

Fourth, the present result did not take the equal-loudness contours into account, so the finding ignores the effect that the perceived loudness could vary with pitch. Future work considering the interdependence between pitch and perceived loudness are needed to complete the argument on the effect of raising the pitch.

8 CONCLUSION

The present EEG- and large-scale online study of how the musical parameters melody, pitch, and tempo influenced people's auditory perception, attention shifting, reaction time, and accuracy has established, based on EEG results, that the tempo of audio notifications had a main effect on how fast the participants noticed and reacted to them. Pitch, on the other hand, mainly influenced how easily the participants became aware of and shifted their attention to the notifications. There were also interaction effects between pairs of musical parameters, which the online study revealed as differing across participant characteristics and environments. Based on the combined results of the EEG and online studies, two comparison matrices were created to describe the relations between the changes in the chosen musical parameters and the participants' cognitive and behavioral responses. These matrices, coupled with the present study's other findings, can offer designers evidence-based guidance for adjustments to their notifications, and make it less likely that such adjustments will cause unexpected adverse effects. For researchers, the current study's findings help clarify the cognitive impact of design guidelines for audio notifications, and shed some light on how user-specific and environmental factors affect audio notifications' usability.

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