Exploring the Hypothesis of the Region of Proximal Learning with Music

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Table of contents

List of tables

List of figures

Abstract

Recent developments in the psychology of learning, specifically, the hypothesis of the region of proximal learning (RPL), have proposed that curiosity, understood as a crucial element for information seeking behaviors and thus, for learning, is the antithesis of mind-wandering, a state that has been described as an obstacle to attention and information comprehension. Relatedly, recent research has also shown that music is able to elicit states of curiosity on listeners and therefore, it could be a useful tool to assess this hypothesized negative relationship. Since music-elicited curiosity has been seen to be predicted from theoretic measures that have been used to describe the relationship between musical expectancy and musical structure, such as information content and entropy values, it has been hypothesized that, if mind-wandering and curiosity are negatively correlated, then mind-wandering could also be predicted from these individual uncertainty measures. As such, this study proposed an experimental paradigm to assess if and to what extent curiosity and mind-wandering are mutually exclusive states, and if uncertainty measures, along with musical expertise, were meaningfully related to self-reported mind-wandering. 16 Individuals were exposed to two sets of stimuli that differed in their overall melodic uncertainty to assess their judgments of curiosity and mind-wandering while they listened to them. Results show a negative relationship between mind-wandering and curiosity, further informing the discussion about their hypothesized antithetical nature. On the other hand, other predictors, such as musical expertise and uncertainty measures did not show a reliable effect on mind-wandering. Implications and future directions stemming from these results are discussed.

Keywords: Musical expectancy, mind-wandering, curiosity, learning, musical expertise.

Introduction

Curiosity and its relationship with learning and musical expectancy

Learning is one of the most complex and remarkable psychological processes that occur in human and non-human animals. Therefore, multiple efforts have been made to understand how the learning process occurs and different perspectives have been proposed to explain its attributes. Different observations have led researchers to suggest that curiosity is one such key element that contributes to the learning process, guiding information seeking behaviors which motivate learning episodes (Gottlieb et al., 2013; Scacco & Muddiman, 2020; van Lieshout et al., 2020).

By studying curiosity, different researchers have proposed that not every stimulus with which individuals are presented elicit the same type of curiosity, thus suggesting the idea that different types may exist (Grossnickle, 2016; Loewenstein, 1994). One crucial type of curiosity is epistemic curiosity, which is considered to be opposed to perceptual curiosity, the drive to attain basic goals, such as obtaining food, being able to reproduce and feeling safe. Rather, epistemic curiosity is the drive to acquire precise or specific knowledge, thought to induce information seeking behaviors and to motivate how long and steadily an individual may engage with a stimulus (Hardy et al., 2017; Litman, 2008; Litman & Spielberger, 2003). Therein, thus, lies its relevance for learning: as individuals feel this type of curiosity with regards to a certain stimulus, they are more likely to engage in exploratory, information seeking behaviors and therefore will increase the probability that learning will occur (Hassan et al., 2015; Ligneul et al., 2018).

Interestingly, one type of stimulus that has been observed to cause curiosity is music. A recent study, conducted by Omigie and Ricci (2021), showed that music can produce feelings of curiosity by inducing perceived states of change and because listeners tend to be differently influenced by the salience of specific musical moments and features. This observation seems to imply that there is an expectation to hear specific musical features in given moments of a musical piece

Indeed, this interplay between what is expected to be heard, what actually is heard and the attentive state that happens in between has been termed as musical expectancy and has been described as one of the main sources of meaning in musical stimuli (Huron, 2008; Huron & Margulis, 2010; Krumhansl & Agres, 2008). In fact, this field of study has shown the importance of expectation violation during music listening by collecting neurophysiological and behavioral data, in children as well as in adults, showing consistently that musical expectations derived from the exposure to a specific musical context builds a framework in which violation is very strongly and unequivocally perceived (James et al., 2015; Pearce & Wiggins, 2012; Tervaniemi et al., 2003; Tillmann et al., 2014).

This attribute of music has motivated researchers to better understand the effects of manipulating of listeners' musical expectations. As such, to this date, the most useful account of how music is able to elicit curiosity has been information theory, which concerns itself specifically with quantifying how expected and/or uncertain a given sequence of events is. Indeed, information theory posits that information content (IC), a quantity that defines how probable is the occurrence of an event from a random variable, characterizes the unexpectedness of an event, and that entropy, the average amount of information that the possible outcomes of a random variable hold, characterizes the uncertainty of an event (Hansen & Pearce, 2014; Pearce, Ruiz, et al., 2010).

For instance, a recent study has shown that information content and entropy values (two information-theoretic measures of uncertainty) describing a melody predicted curiosity ratings of participants when exposed to it, reaffirming the hypothesis that unexpectedness and uncertainty have a relevant role in inducing feelings of curiosity (Omigie & Ricci, 2022). Another interesting observation made by this study is that musical background seems to have a differential influence on how curiosity is induced by the information-theoretic structure of the musical stimulus.

This evidence has several implications for the study of musical expectation, curiosity and learning in general. First, it shows that information-theoretic measures of uncertainty are able to predict uncertainty within musical stimuli, a fact that is useful to better understand individuals' expectations about a musical stimuli. It also suggests that, since music is able to elicit curiosity, it could be a useful tool to investigate how curiosity emerges and how it relates to learning. Finally, it implies that musical background may be an important individual difference to consider when assessing the possible effect that musical stimuli may have on listeners' perceived curiosity.

Mind-wandering: definitions, dynamics and its role on music research

Now, an important concept that sometimes is linked to learning is mind-wandering. Indeed, mind-wandering has been often described as an obstacle for learning episodes to occur (Pachai et al., 2016; Peterson & Wissman, 2020; Was et al., 2019). Thus, if epistemic curiosity motivates information seeking behaviors which then lead to learning, mind-wandering is described as the inability to focus attention and therefore lowers the likelihood of motivating learning episodes.

Research on mind-wandering has been informed by perhaps its most widespread characterization: Task-unrelated, stimulus-independent thought that individuals seem to report when trying to focus their attention on a specific stimulus (Irving & Glasser, 2020). However, recent observations in behavioral and neurophysiological studies have led researchers to rethink the idea of mind-wandering and therefore, have been used to redefine basic traits of mind-wandering.

For instance, Christoff et. al (2016) argue that "task-unrelated thought" is an insufficient feature to describe mind-wandering. They emphasize the fact that, defining the word "task" broadly, also including individuals' personal concerns, would lead to assume that mind-wandering is necessarily "task-related", because the content of mind-wandering is usually comprised of personal goals and individual concerns. Therefore, they have proposed that mind-wandering should best be described as one member of a wider family of phenomena characterized by spontaneous thought, similar to creative thought and dreaming. Accordingly, the authors define spontaneous thought as a set of mental states that arise freely and that are capable of constant fluctuation due to a lack of relevant constraints on whatever the content of each of those freely fluctuating states could be. They support their view by showing how the neural activity of the default network (DN), a group of brain areas in which reduced activity has been observed when individuals focus their attention in experimental tasks (Buckner et al., 2008; Raichle et al., 2001), has been linked with mental processes oriented towards self-reflection that arise freely and in an spontaneous fashion (Christoff et al., 2009), and by pointing to the network's role in the retrieval of contents from episodic memory and in future planning (Buckner & Carroll, 2007; Spreng et al., 2009). Crucially, spontaneous thought seems to be linked with activity on this network, especially with its mediotemporal lobe section, as recent research has shown that increased activity in the mediotemporal lobe during rest is correlated with spontaneous memories and mental simulations (Andrews-Hanna, 2012).

Relatedly, Seli et al. (2018) have proposed that given the heterogeneity of the descriptions that have been ascribed to mind-wandering, this phenomenon should be studied from a family-resemblances perspective, i.e., that mind-wandering is best understood as a category, to which many phenomena belong with graded membership, i.e., with some of them being more prototypical than others. Thus, to define the prototypical attributes, or characteristics, of mind-wandering, the authors propose to examine its most relevant definitions and determine the overlap in their characteristics. This, according to the authors, would lead to precise characterizations of the specific dimensions which tend to be associated with the content of the mind during mind-wandering in very precise contexts, and would therefore help build a better understanding of the causes and consequences, as well as the function of said thoughts, instead of assuming that all exemplars of the family should have exactly the same characteristics.

Interestingly, however, this heterogeneity of definitions has not been seen on research that has used music to study mind-wandering. In fact, the vast majority of the literature concerning the relationship between music and mind-wandering is motivated by the definition of mind-wandering as task-unrelated thought and has mainly focused on the relationship between mental wellness and mind-wandering, by describing how thoughts vary their valence with regards to a specific type of music (Taruffi et al., 2017). Another focus of research that links mind-wandering with music has examined how creativity and music performance is influenced by mind-wandering (Palhares et al., 2022). Finally, research aimed to study attention has also described mind-wandering as one of the consequences of listening to music while trying to attend to a task (Kiss & Linnell, 2021).

The hypothesis of the region of proximal learning

Despite all of the above, and although curiosity and mind-wandering would seem like the antithesis of one another, efforts to relate them in a theoretical way have only been proposed only recently. And in fact, one of the theoretical developments that has arisen as a framework that opposes both mental phenomena is the region of proximal learning hypothesis (Metcalfe et al., 2020).

This hypothesis is similar to previous work by Berlyne (Berlyne, 1954, 1966), who observed that individuals tend to be most curious when presented with stimuli that match their level of knowledge of those stimuli, i.e., when stimuli are neither too complicated nor too simple to grasp for the individual. As such, the RPL also builds upon the ideas of Piaget (Piaget, 1954), who described that ideal states for curiosity to arise tend to occur when individuals perceive that they "almost-know" the answer to a query regarding a stimulus. Consequently, the RPL hypothesis proposes a theoretical framework through which epistemic curiosity and mind wandering are thought to be part of an information seeking process and contribute to it in opposite ways.

More concretely, according to the RPL, the availability of "almost known" information about a stimulus to which an individual is being exposed can induce them to enter their RPL zone, a state in which learning is not only easier but also more enjoyable. The model put forward by this hypothesis predicts that, in such cases, individuals will choose to engage with the stimulus to which they are being presented, leading to an induced metacognitive state of curiosity and, consequentially, to learning. This model also predicts that, in contrast, if the information available to the individual is not enough to match the difficulty of the stimulus to which they are exposed, individuals will begin to mind wander and it is hypothesized that learning cannot occur in such state.

The present study

Accordingly, the present study aims to test the main assumption of the RPL hypothesis, i.e., that mind-wandering and curiosity are mutually exclusive, by assessing if, and to what extent, mind-wandering and curiosity are negatively correlated and exploring the role that information content and Entropy of musical stimuli play in explaining these phenomena.

Specifically, given the proposed mechanics of the information seeking process according to the RPL hypothesis, it would be justified to expect that being exposed to a musical stimulus with the appropriate information-theoretic structure as to engage an individual, could afford them the key information required in order to perceive themselves in their RPL. In these moderately predictable situations, individuals could be expected to engage actively with the listening activity, seeking to satisfy their curiosity by integrating the information available on the musical stream with their previous experience (in turn, leading to a learning episode).

Conversely, cases in which musical stimuli are highly entropic and unpredictable, information seeking states are unlikely to take place, given the lack of enough "almost known" information available to the listener. According to the RPL hypothesis, this could mean that no engagement in active listening will occur and mind wandering episodes may be elicited.

Considering all of this, then, it should be possible to assess the RPL hypothesis by accounting for the influence that information content and entropy can have on mind wandering and curiosity while attending to musical stimuli of heterogenous information content and entropy.

Hypotheses

First and foremost, based on the model proposed by Metcalfe et al. (2020), it is hypothesized that mind-wandering is negatively related to curiosity.

It is also hypothesized that the relationship between overall stimuli uncertainty and individuals' expertise should bear an influence on the presence of mind wandering episodes. Expertise has been shown to influence the experience of uncertainty in musical stimuli (Hansen et al., 2016) and as such, it is hypothesized that overall stimuli uncertainty, expertise, and their interaction can predict the frequency at which individuals mind wander.

Finally, as it has already been mentioned, recent research has shown that information content and entropy can indeed predict curiosity in a melodic excerpt (Omigie & Ricci, 2021). Therefore, it is hypothesized that, knowing the degree of uncertainty in the stimuli should offer an equally or even better gauge of Mind Wandering than curiosity. Thus, Information content, Entropy condition and expertise can predict whether Mind Wandering occurs or not during listening.

Methods

Participants

This experimental procedure was approved by Goldsmith's University Ethics Committee and every participant consented to take part on it.

16 participants (mean age = 27.5, SD = 6.72) from the community at Goldsmiths, University of London, as well as from other areas around London were recruited for this experiment. They all received a monetary compensation for their participation.

Stimuli

Participants were exposed to two sets of stimuli, one more unpredictable than the other.

Initially, 3 individual melodies were composed according to western tonal standards and using the open-source music notation software MuseScore. These melodic sequences comprised 80 bars of only quarter notes and every 16 bars a key change was introduced, which was aimed to a closely related key regarding the preceding one. Thus, melodies comprised 320 notes each and 5 key changes, as described in table 1.

Table 1

Description of the original stimuli

Melodic sequence	Timbre	Time signature	Number of bars	Number of pitches	Pitch duration (ms)	Total duration (minutes)	Key Changes
1	Violin	4/4	80	320	455	2:25	5
2	French Horn	4/4	80	320	910	4:50	5
3	Vibraphone	4/4	80	320	455	2:25	5

Subsequently, each melody was exported in MIDI format and then manipulated with the Python programming language using MidiFile, a library dedicated to managing MIDI files in Python. Then the order and the range of the notes of each individual melody was randomized, thus creating a randomized version of each sequence. This randomization was implemented by adapting the "choice" function, which is part of the "random" module in the standard library of the Python programming language and used to select random elements from a sequence. This selection was done without replacement.

Next, the tempo in each set of melodies was manipulated to create two fast-paced melodies and one slow-paced melody per set. To this end, the notes composing the fast-paced melodies were given a length of 455 ms, and notes of the slow-paced melodies were given a length of 910 ms. The reason to manipulate the tempo on the stimuli was to emulate how movements were written when used in the sonata genre (Peter et al., 2019) and thus attempt to give them more ecological validity.

Then, the uncertainty within each set of stimuli was quantified using IDyOM, a computational model based on the principle of statistical learning to extract their Information Content and Entropy values (Pearce, 2018). IDyOM supports a short-term and a long-term model to predict the uncertainty within the specified stimulus. The short-term model predicts the melodies as if it was the first melody it had seen, and as such, it emulates the experience of a naïve listener with no previous exposure to music. The long-term model, conversely, predicts the sequences by emulating the experience of a listener that has been familiarized with the musical context to which the sequence belongs. IDyOM also supports a configuration that uses both short-term and long-term models, emulating the experience of a listener who is exposed for the first time to a specific stimulus, but gradually learns about it, based on previously heard notes in the sequence but also based on their musical background. This compounded model was therefore used to score both sets of stimuli. To train the long-term model corpora of music that has been used elsewhere in the literature was used (Hedges & Wiggins, 2016; Omigie & Ricci, 2022; Pearce, 2005; Pearce, Müllensiefen, et al., 2010): 556 German folk songs, 185 Chorale melodies and 152 Canadian folk songs, ultimately adding up to 903 pieces, 60.867 in total. The distribution of the resulting entropy and information content values within both sets, as well as the probability of occurrence of each pitch are described in figures 1 to 4.

Figure 1

Aggregated distributions of entropy values in both sets of melodic sequences

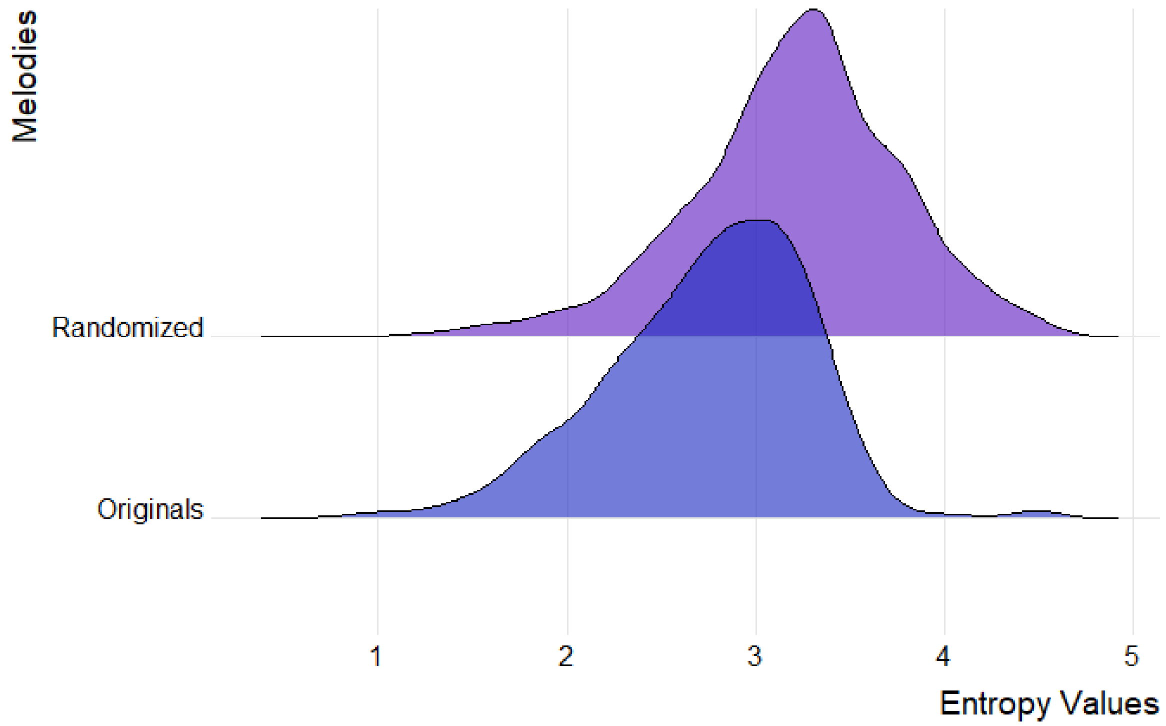


Figure 2

Aggregated distributions of Information Content values in both sets of melodic sequences

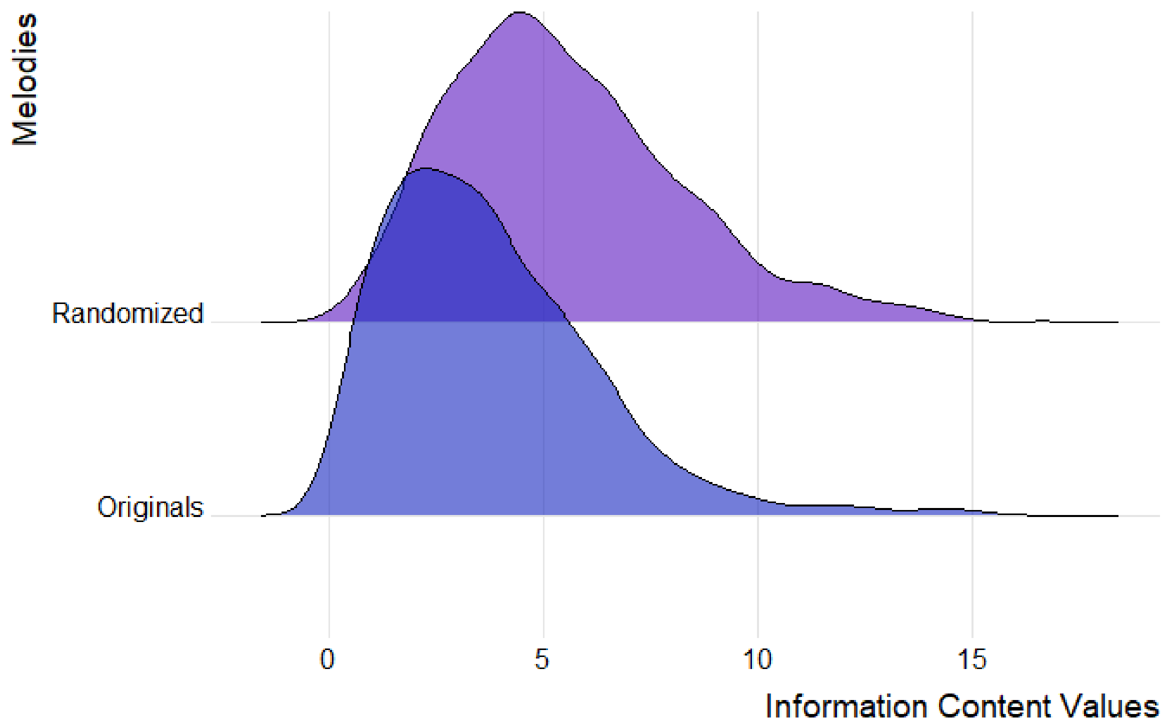


Figure 3

Probability of occurrence of pitches in original melodic sequences

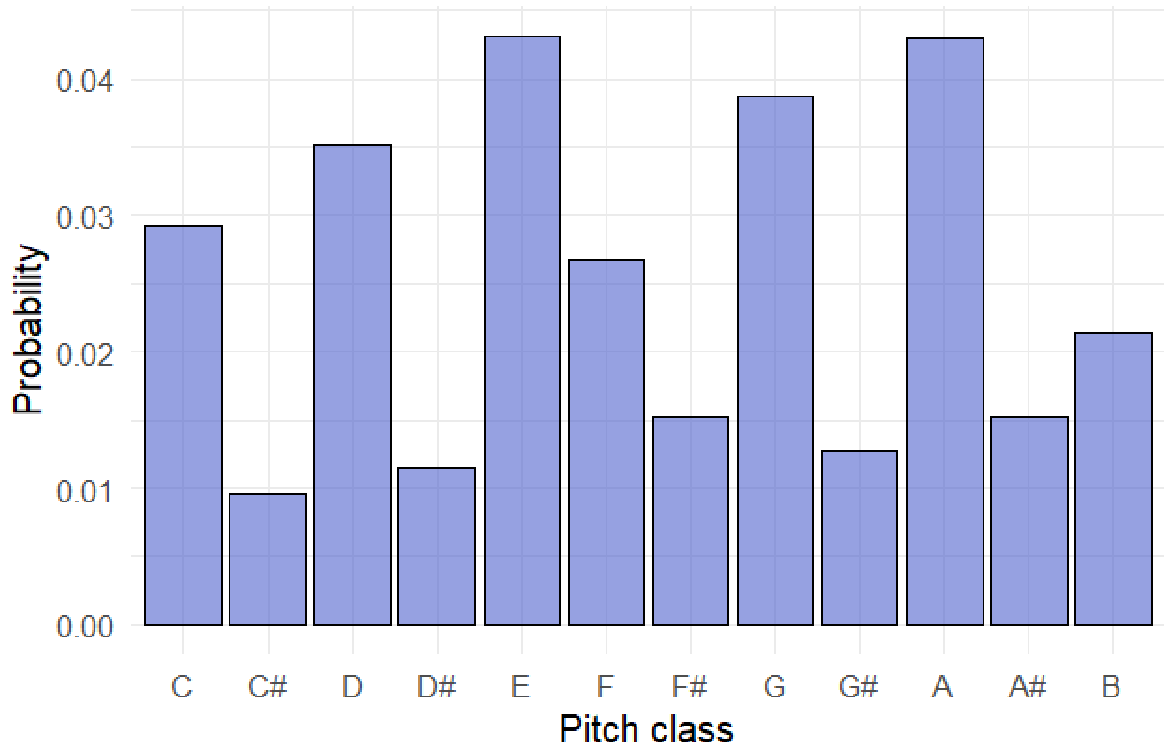
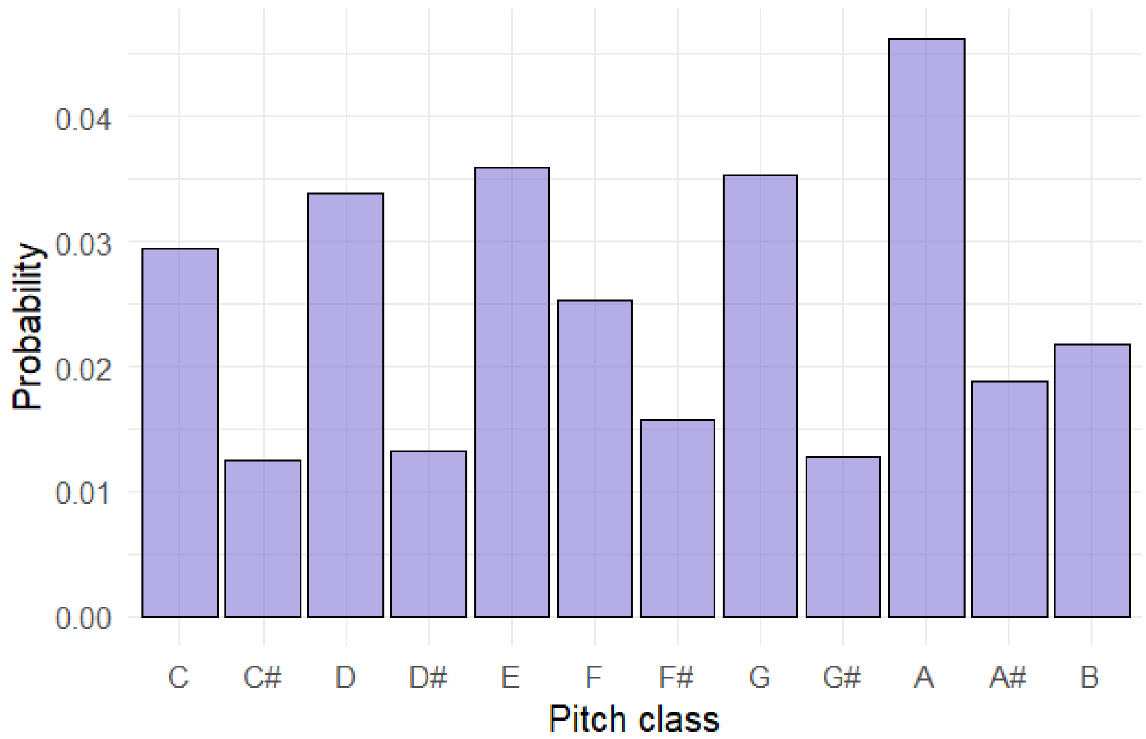


Figure 4

Probability of occurrence of pitches in randomized melodic sequences



Critically, pitch was the feature used to assess the uncertainty within each melodic sequence.

Finally, three different timbres were selected to play the melodies in both sets of stimuli. The first sequence in both sets was played with violin, the second with French horn and the last with vibraphone, all sounds from the standard sound library in MuseScore. This decision was made to improve the chances of participants engaging with the stimuli.

Equipment

Participants listened to the sequences using around-ear Behringer headphones and their responses were recorded using a keyboard and a mouse on a PC running Windows 10. Stimuli and data were presented and collected using the graphical experiment builder OpenSesame (Mathôt et al., 2012).

Procedure

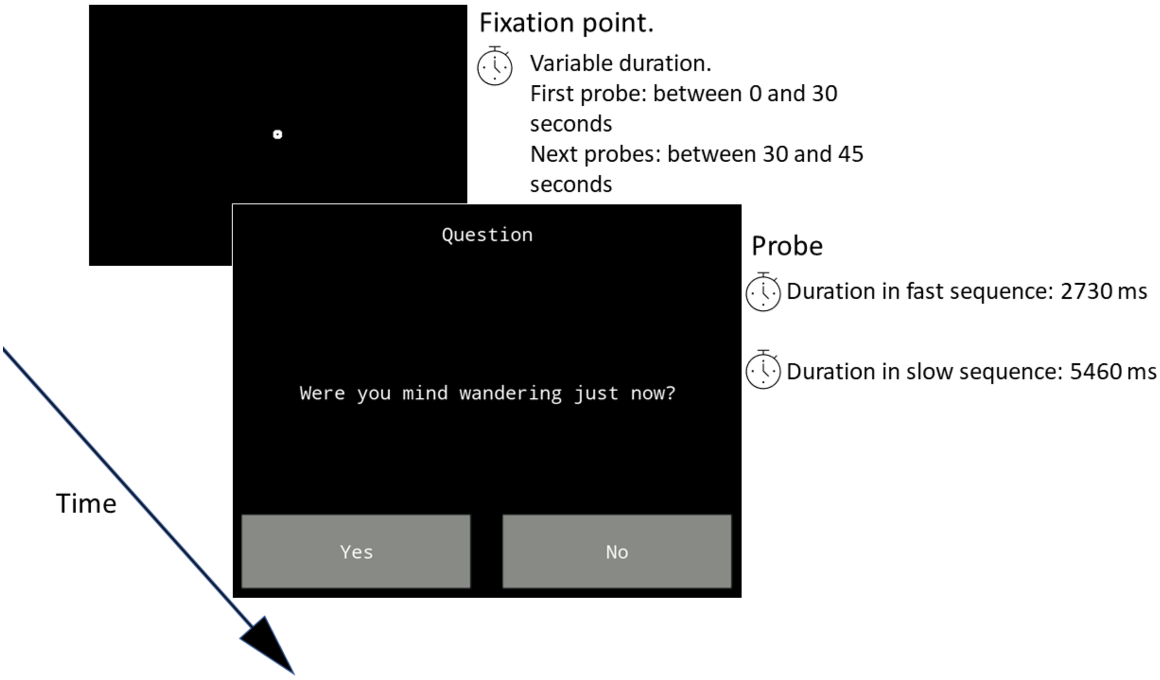
Participants were asked to perform two tasks to gather their mindwandering and curiosity ratings and were randomly allocated to first complete either of them.

In both tasks they listened to the original set of melodic sequences in one block and the randomized set in a subsequent block. However, the order in which these sequences were played was counterbalanced, randomly assigning participants to listen to one of them first.

In the mind-wandering task, participants were initially familiarized with the definition of mind-wandering that was used for this study, which was based on the task-unrelated thought that has been predominantly present in literature examining music-induced mind-wandering. Specifically, they were told that “mind-wandering is a state in which thoughts drift away from the material being presented. When you are mind-wandering, your thoughts may drift to memories of past events, friends or even concerns about an upcoming exam”. After this, they were given trial runs of the task, which required them to focus their sight on a white fixation dot in the middle of the screen until a probe appeared. The probes contained two buttons, “yes” or “no”, with which they were required to answer to the question “Were you mind-wandering right before the probe?”. This task is depicted in fig 5. After this task was completed, participants were asked to answer two questions about the order in which they had heard the instruments playing the sequences and if they were able to remember an excerpt of the sequences of the task. This was done to accommodate with the narrative that was used to describe the experiment to participants but it was not used as a relevant variable for analysis

Figure 5

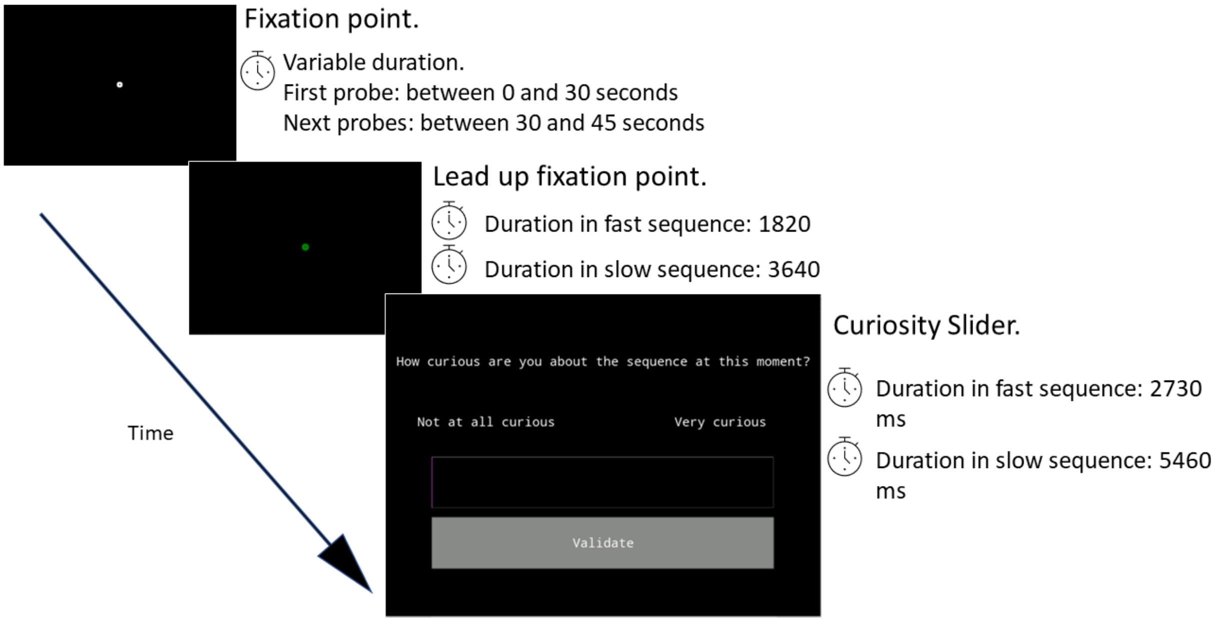
Schematic of the sequence during the mind-wandering task



During the curiosity task, participants were also familiarized with the experimental task by giving them trial runs previous to the actual experiment. In this task, participants were also required to focus on a white fixation dot on the screen. However, whenever a probe was about to appear on the screen, the white fixation dot changed its color and its size, after which the slider appeared. This was done to focus their attention on the sequence and give them enough time to answer the probe. The question on the probe this time read "How curious are you about the sequence right now?", and participants could answer in a range from "not at all curious" to "very curious", as described in fig 6.

Figure 6

Schematic of the sequence during the curiosity task



Participants were probed regularly while they listened to the sequences. Importantly, they were probed in intervals ranging from 30 to 45 seconds. However, the first probe they experienced was displayed at a random interval between 0 and 30 seconds. A unique sequence of intervals (including the interval between the beginning of the sequences and the first probe) was generated for each participant, which ensured that different parts of both sets of melodies were probed. Also, all probes were displayed at the same time across tasks and blocks of melodies, which allowed to compare individual participants' mind-wandering judgements with their curiosity judgements at the exact same moment across both sets of melodies.

In each task, participants saw 30 probes as they listened to the sequences, 16 of them occurred when they listened to the fast sequences and 14 when they listened to the slow ones.

Each probe remained on the screen for as long as 6 notes of the melodic sequences that they were listening were playing, time in which they had to answer the question in the probe. Thus, when participants were being probed during the fast sequences, the probe remained on the screen for 2730 ms. Conversely, the probe was displayed for 5460 ms when they listened to the slow sequence. An important difference between both tasks is that, when participants were on the curiosity task, the lead-up fixation point remained on the screen for 4 notes before the slider appeared, and as such, while participants were probed in the fast sequences, the lead-up point was displayed in the screen for 1820 ms, and when they were being probed in the slow sequences, it was displayed for 3640ms before the slider appeared.

Crucially, participants were told to answer as fast as they could when they saw the probes, but whether participants answered right after the probe appeared or did not answer at all, the question remained on the screen for as long as it was scheduled. This was to ensure that every probe was synchronized and was displayed when it was scheduled and during the time it was assigned.

At the end of the last task they performed, participants were asked to answer questions aimed to assess their degree of expertise in musical skills through the Music Training subscale of the Goldsmiths Musical Sophistication Index (Müllensiefen et al., 2014).

Analysis

Data was analyzed using the R statistical language, fitting the models to Stan with the rethinking package (McElreath, 2020; Stan Development Team, 2022).

Every hypothesis was assessed using multilevel logistic regression to model participants' mind-wandering frequency in response to the two sets of musical stimuli. Accordingly, to find the best performing model, PSIS cross-validation scores were computed and compared, along with their out of sample standard error and weights. PSIS scores offer an approximate gauge of the out of sample deviance of a model, and thus, estimates which one will perform better with future data. As such, lower values are better (Vehtari et al., 2017).

The Hamiltonian Monte Carlo algorithm was used to sample from the joint posterior distributions of each parameter assessed in the models, obtained by Bayesian updating. Furthermore, models were fitted with regularizing priors, allowing partial pooling to update estimates across clusters and inform those with few observations.

Accordingly, the first hypothesis, stating that mind-wandering would be negatively related to curiosity, was assessed by using curiosity ratings, a continuous range from 0 to 1, to predict mind-wandering frequency, a dichotomous variable.

Then, in order to test the second hypothesis, i.e., that mind wandering can be predicted from overall stimuli uncertainty and expertise, frequency of mind wandering was again the dependent variable, and stimuli uncertainty (randomized versus original melodies) and expertise, along with their interactions, were used as predictors. Importantly, expertise was assessed in a range from 1 to 7, according to the Gold-MSI subscale used to assess it.

Finally, the third hypothesis suggests that mind wandering can be predicted from entropy, information content and expertise. Therefore, entropy values, information content values, their interaction, and expertise, along with its interaction with entropy values and information content values, were used as parameters to predict mind-wandering frequency.

Results

Hypothesis 1

Initially, only the fixed effects of intercept and then curiosity were used to predict mind-wandering frequency. Then, in order to capture the variation within the sample, varying intercepts for participants was included. Subsequently, varying intercepts for melodic sequences were added in the next model. Finally, varying slopes for overall stimuli uncertainty, i.e., randomized and original melodies, were added and participant and melodic sequences were kept as varying intercepts.

As it can be observed in table 2, the deviance score estimated by the PSIS approximation of every model containing curiosity as a predictor is smaller than the model with only the intercept, which implies that the data is better explained considering curiosity ratings than only using the overall mind-wandering average frequency. However, it is also important to note that, although the model that only includes varying intercepts for participants seems to perform better than any other model, the PSIS scores of the top three models are very similar to each other, with very similar standard out of sample error, a fact also reflected by the weights calculated for each of these three models. This would suggest that any of these three models would perform very similarly in predicting out of sample mind-wandering frequency. As such, considering that the order in which both tasks were presented was counterbalanced, the major sources of variation in the experiment were participant and melodic sequences, and thus, the model that allowed intercepts of these two clusters to vary was used to analyze the data.

Table 2

Model comparison for hypothesis 1

Model Ranking	Fixed effects	Random effects	PSIS estimate	PSIS SE	Weight
1	Curiosity	Varying intercepts Participant	560	14.29	.37
2	Curiosity	Varying intercepts Participant melodic sequences	560.3	14.50	.32
3	Curiosity	Varying intercepts Participant, melodic sequences Overall stimuli uncertainty	560.9	14.65	.23
4	Curiosity	Varying intercepts Participant melodic sequences Varying Slopes Overall stimuli uncertainty	562.9	14.97	.09
5	Curiosity		601.9	9.27	0
6	Intercept only		635.5	.02	0

This model suggests that there is indeed a negative relationship between mind-wandering and curiosity, estimating a rather narrow posterior distribution for curiosity (β = -.80, SD = .35, 89% prediction interval (PI) = [-1.35, -.25]). This implies that, on the probability scale, for every positive change in curiosity rating, participants would be, at most, 20% less likely to be mind-wandering. Posterior distributions for both curiosity and mind-wandering frequencies estimated by the model can be seen in figure 7. The average effect of curiosity plotted against the raw data is displayed in figure 8. Statistics for the complete model can be seen on table 3.

Table 3

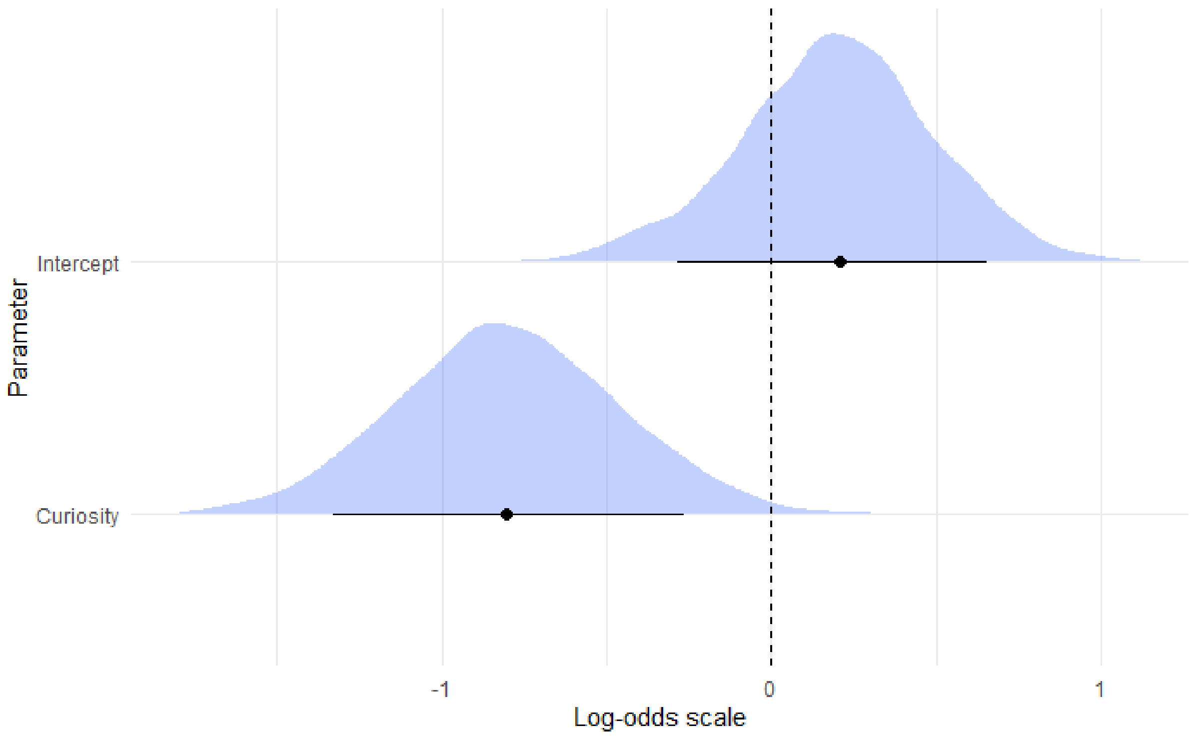
Statistics for the best performing model

Fixed Effects	Mean	SD	5.5% PD	94.5% PD	Effective samples
Intercept	.20	.29	-.28	.65	787
Curiosity	-.80	.33	-1.33	-.26	1762
Random Effects	**Mean**	**SD**	**5.5% PD**	**94.5% PD**	**Effective samples**
Participants	1.01	.26	.66	1.46	717
Melodic Sequences	.32	.23	.04	.71	726

Note: All values are given in the log-odds scale. PD = Posterior density

Figure 7

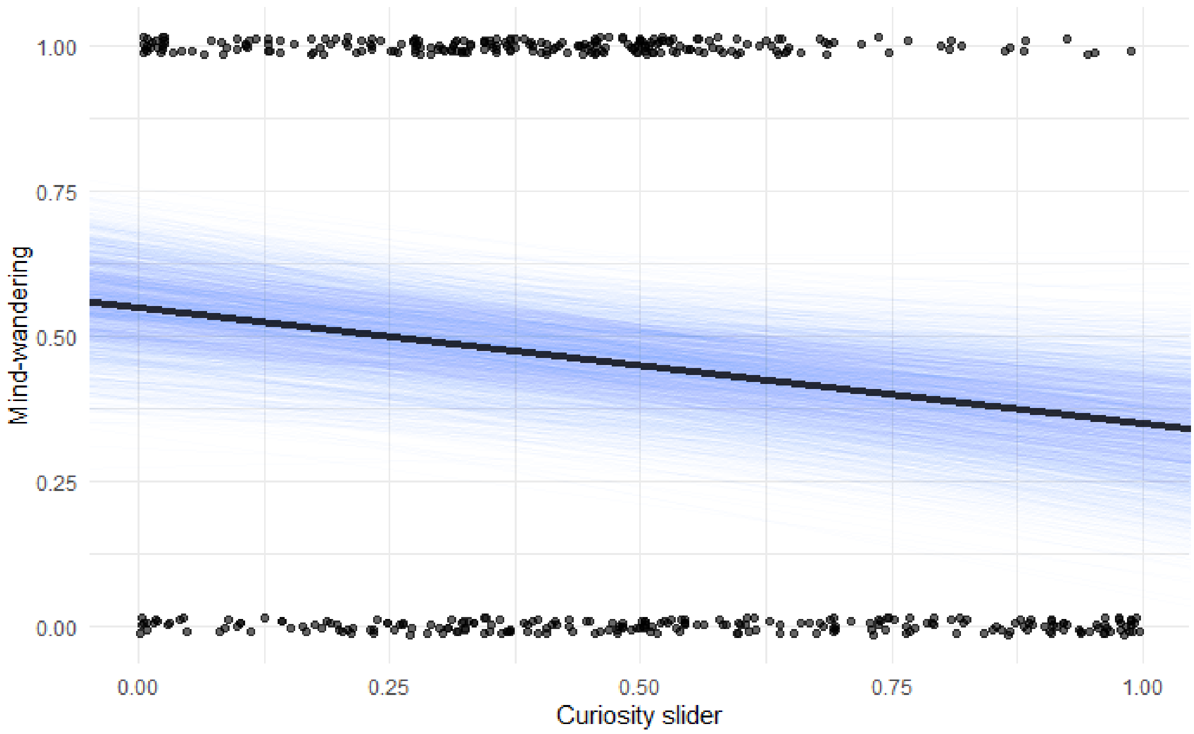
Posterior distributions of curiosity and intercept for the best model



Note. Posterior distributions (posterior median and 89% PI) estimated for the parameters in the model. An estimate is thought to have a meaningful inference when the majority of its density lies beyond or below 0.

Figure 8

Average tendency between curiosity and mind-wandering



Note. Dark black line reflects the average tendency between mind-wandering and curiosity estimated by the model. Light blue lines are draws from the joint posterior distribution.

Hypothesis 2

The random effects structure of the models to assess this hypothesis was also selected through model comparison. Importantly, a multilevel approach was used to assess the individual influence of variables over mind-wandering. To reflect this, initially, fixed effects of intercept, expertise and overall stimuli uncertainty were fitted separately. Later, considering that the two main sources of variation in the experiment were participants and melodic sequences, varying intercepts were used as the random effects structure and fixed effects were added gradually: first expertise, then overall stimuli uncertainty and finally the interaction between both. Lastly, the random effects structure was expanded to add varying slopes for overall stimuli uncertainty and participant and melodic sequences were kept as varying intercepts. Fixed effects were again added in the previous order: expertise, overall stimuli uncertainty and then their interaction.

Model comparison for hypothesis two can be found in Appendix A.

After comparison, the model with varying intercepts for participants and melodic sequences, and expertise as fixed effect is the one with less out of sample deviance. These results would suggest that participants were not influenced differently by any of the two uncertainty conditions that were represented by the original and randomized melodies, and that the relationship between mind-wandering and expertise did not vary according to the set of melodic sequences participants were listening.

The best model, however, and as displayed in figure 9, estimates that the posterior distribution of this effect is centered very close to 0 and is relatively narrow, suggesting that there is no discernible effect of expertise on mind-wandering ($\beta = -.06$, $SD = .17$, 89% PI = [-.34,.21]). Complete statistics for this model are displayed in table 4.

Table 4

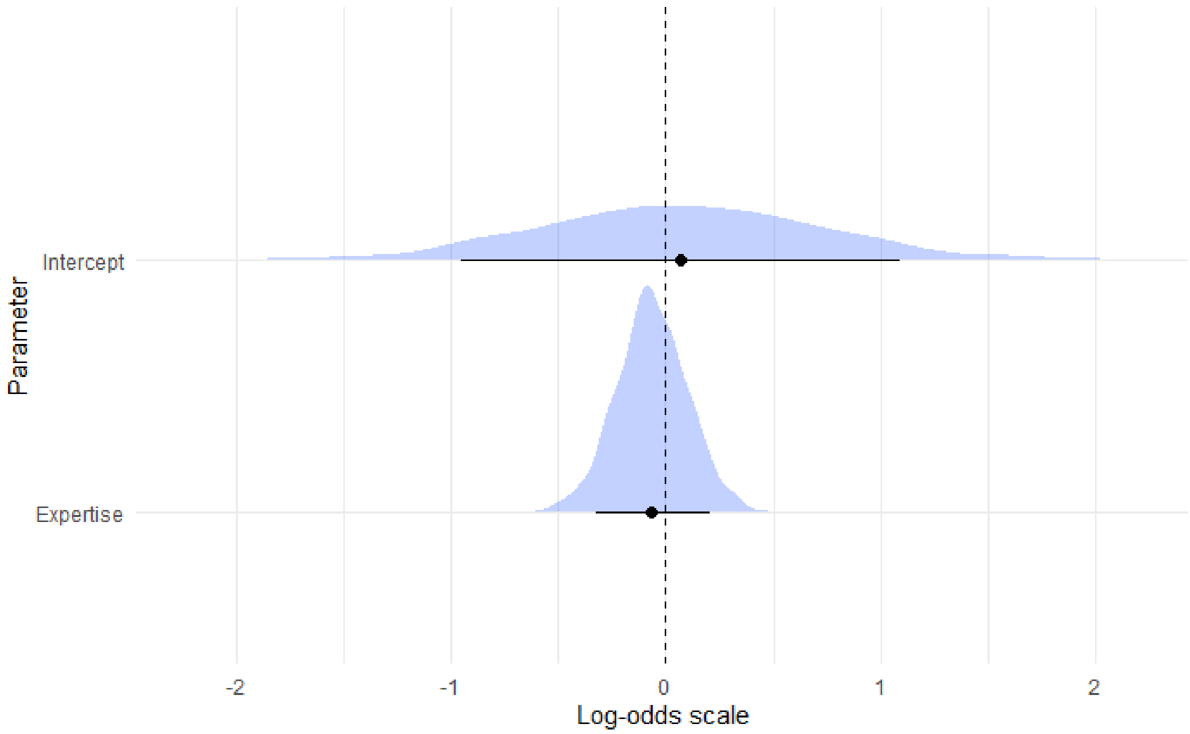
Statistics for the best performing model

Fixed Effects	Mean	SD	5.5% PD	94.5% PD	Effective samples
Intercept	.07	.65	-.95	1.09	470
Expertise	-.06	.17	-.32	.21	485
Random Effects	**Mean**	**SD**	**5.5% PD**	**94.5% PD**	**Effective samples**
Participants	1.52	.35	1.07	2.17	435
Melodic Sequences	.05	.05	0	.14	1197

Note: All values are given in the log-odds scale. PD = Posterior density

Figure 9

Posterior distributions of expertise and intercept for the best model

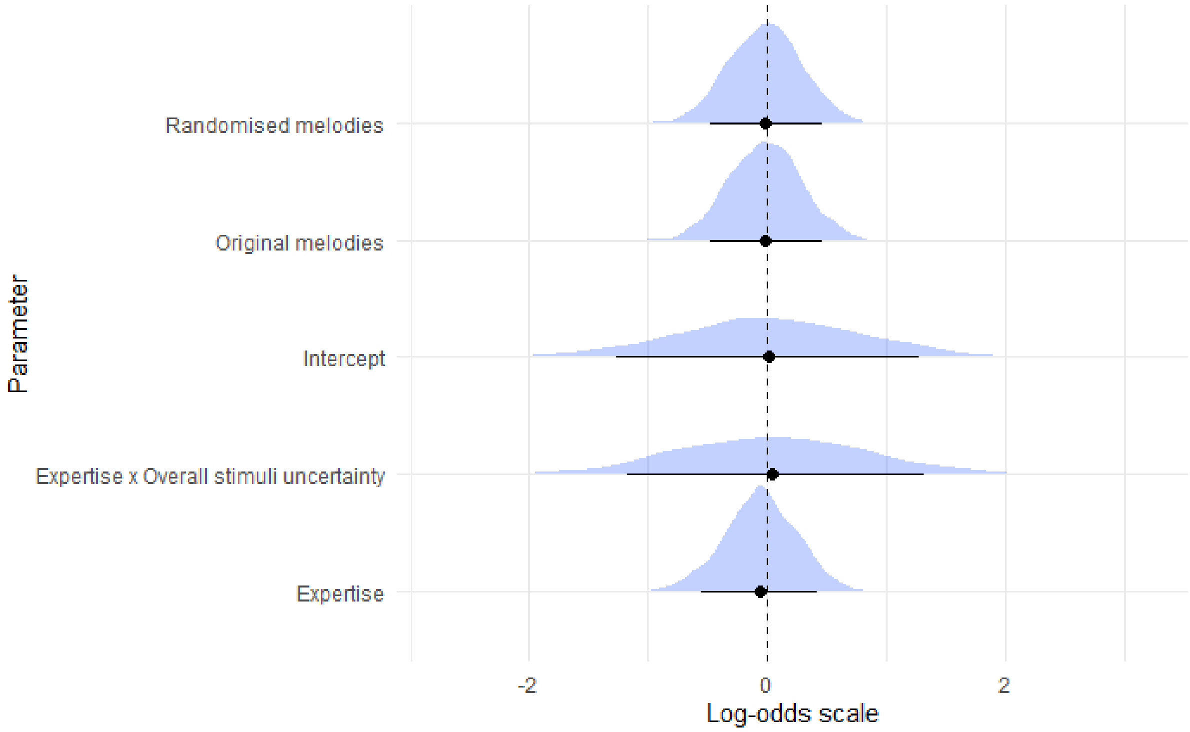


Note. Posterior distributions (posterior median and 89% PI) estimated for the parameters in the model. An estimate is thought to have a meaningful inference when the majority of its density lies beyond or below 0.

Now, as it was mentioned before, models including both overall uncertainty of the stimuli and the interaction term between expertise and overall uncertainty were not estimated to have as good out of sample accuracy as the model only including expertise. Nonetheless, considering that inspecting the posterior distribution for expertise revealed that it did not have a discernible effect neither, it could be inferred that choosing the best model or any of the three top models would not be too relevant for prediction. Therefore, and as displayed on figure 10, the best model including all of the predictors estimates that none of them has a relevant effect on predicting mind-wandering. Evidence of this is the fact that their posterior distributions are all centered around 0 and some are estimated with a very wide spread.

Figure 10

Posterior distributions in the best performing model including every parameter



Note. Posterior distributions (posterior median and 89% PI) estimated for the parameters in the model. An estimate is thought to have a meaningful inference when the majority of its density lies beyond or below 0.

Hypothesis 3

In order to instrumentalize the information content and entropy values for the analyses that this hypothesis required, the value of 3 notes previous to the moment at which the probe appeared, as well as the value of the note itself at which the probe appeared on the screen and the one after it, were averaged to obtain the overall uncertainty of the moments leading up to each probe which, it is hypothesized, are the moments that influenced participants' judgements of curiosity and mind-wandering when they answered any given probe.

A multilevel approach was also adopted to assess this hypothesis. Initially, individual fixed effects and interactions were fitted. Subsequently, varying intercepts for participant and melodic sequences were added to account for the variation among these two clusters. Finally, slopes of overall stimuli uncertainty were allowed to vary over participants, in addition to varying intercepts for participants and melodic sequences.

Model comparison for this hypothesis is displayed on Appendix B. PSIS scores for models with only fixed effects have the worst performance out of sample, repeating the pattern of the analysis in the last two hypotheses and implying that pooling information across clusters improves estimates significantly. Then, the model comparison suggests that the model including varying slopes for overall stimuli uncertainty, and varying intercepts for participants and melodic sequences as random effects, and expertise, entropy values and their interaction as fixed effects offers the best out of sample performance. This result would imply that the strength and direction of the effect that expertise may have on mind-wandering frequency depends on the strength and direction of the influence that entropy has on music training. Another relevant result is that the models including information content and its interactions with expertise and entropy are estimated to perform worse than using entropy values and expertise to predict mind-wandering. This could suggest that the melodic sequences were only perceived by participants as uncertain according to their individual musical expertise, but that they did not perceive the melodic sequences neither as expected nor unexpected, resulting in their mind-wandering frequencies not being influenced by information content values.

A relevant fact to note is that it is again the case that the difference between the best models allows to infer that any of them could be used to predict the data equally well, and that they would perform very similarly out of sample. This is reflected by the weights calculated for them. Thus, the best model, which includes varying slopes for overall uncertainty of the stimuli, varying intercepts for participants and melodic sequences, and with expertise, entropy values and their interaction as fixed effects, will be inspected to make inferences. Then, the model including every parameter will also be inspected.

The best model estimates that music training has a negative but small influence over mind-wandering frequency ($\beta = -.27$, $SD = .24$, 89% PI = [-.66,.10]), and although its posterior distribution does cross 0, it is important to note that 86.6% of its mass lies below it. This can be taken as evidence that there is, in fact, an effect of music training on mind-wandering frequency. It also implies that, for each negative change in one unit of the music training subscale, participants would be, at most, 6% more likely to mind-wander. With regards to the effect of entropy values, not only the model estimates a very small effect, but it also estimates it with a lot of uncertainty ($\beta = -0.07$, $SD = .32$, 89% PI = [-.59,.42]). This result implies that participants may have not been influenced by the uncertainty conveyed by individual notes in the sequences. Finally, the interaction term is estimated as having a small effect, barely above 0. In fact, although its posterior distribution is rather narrow, it is still too close to 0 to infer that it has a meaningful influence over mind-wandering frequency ($\beta = .09$, $SD = .08$, 89% PI = [-.03, .23]). However, as it was previously mentioned, the fact that 87.3% of its posterior distribution lies above 0 would suggest that the relationship between mind-wandering and expertise is dependent on the strength and direction of the influence that entropy has on expertise. In fact, the model would suggest that the highest the influence of entropy on expertise, the highest the likelihood of participants with a high score on expertise to experience mind-wandering. This result is interesting, as it would seem that only when both entropy values and expertise are considered in conjunction they have a positive influence on mind-wandering frequencies, opposite to what their individual estimates would suggest. Complete statistics of this model can be seen in table 5. Figure 11 shows posterior distributions estimated by this model.

Table 5

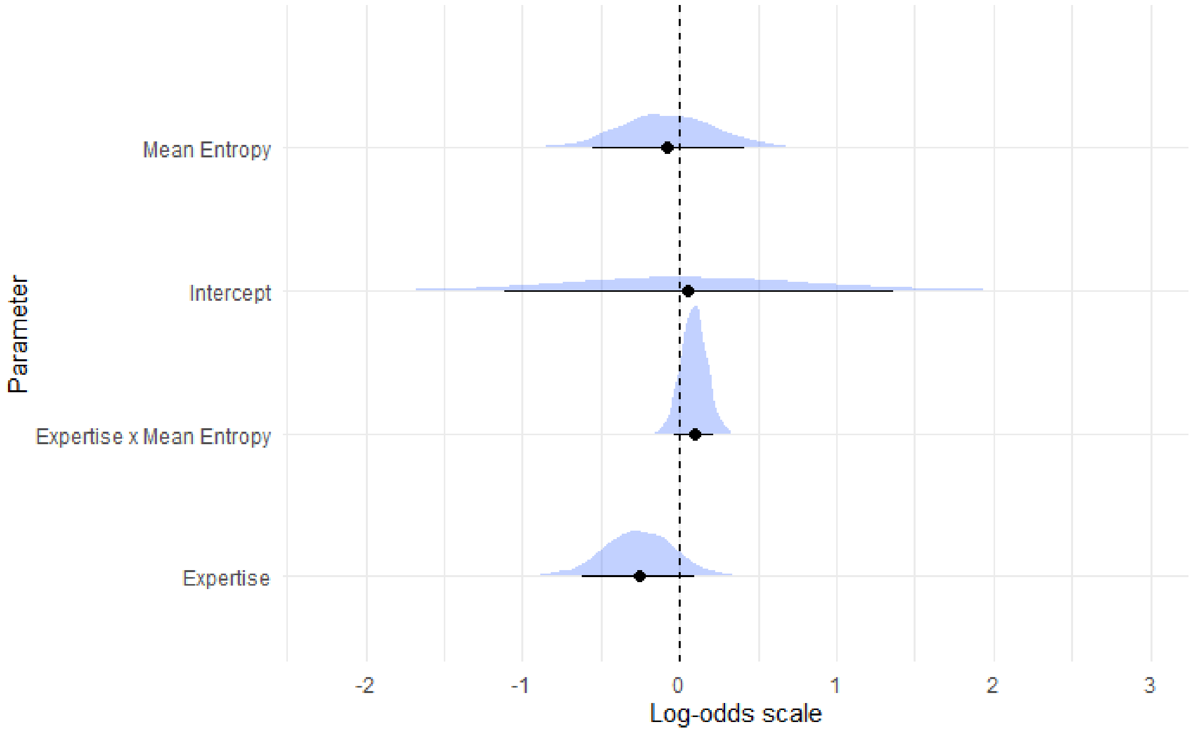
Statistics for the best performing model

Fixed Effects	Mean	SD	5.5% PD	94.5% PD	Effective samples
Intercept	.09	.82	-1.22	1.38	1652
Entropy	-.07	.32	-.59	.42	1505
Expertise	-.27	.24	-.66	.10	1316
Expertise x Entropy	.09	.08	-.03	.23	1393
Random Effects	**Mean**	**SD**	**5.5% PD**	**94.5% PD**	**Effective samples**
Participants	.79	.43	.11	1.48	341
Correlation between Participants and Overall stimuli uncertainty	.01	.45	-.71	.73	1432
Overall stimuli uncertainty					
Original melodies	1.07	.69	.10	2.20	410
Randomized melodies	.60	.44	.05	1.40	550
Melodic Sequences	.42	.24	.12	.86	747

Note: All values are given in the log-odds scale. PD = Posterior density

Figure 11

Posterior distributions for mean entropy, expertise and their interaction in the best performing model

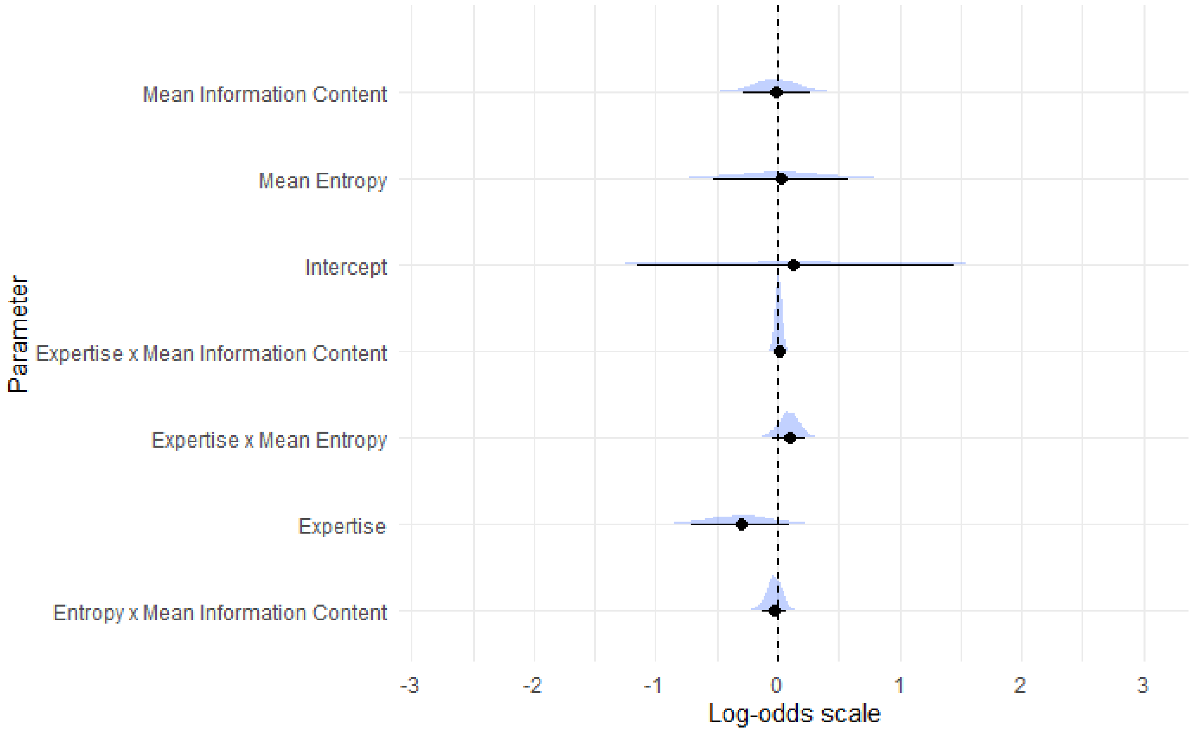


Note. Posterior distributions (posterior median and 89% PI) estimated for the parameters in the model. An estimate is thought to have a meaningful inference when the majority of its density lies beyond or below 0.

Lastly, the best model containing all of the parameters has a random structure of varying slopes for overall uncertainty of the stimuli and random intercepts for participants and melodic sequences. This model still estimates that expertise is negatively related to mind-wandering frequency, although its posterior distribution is wider than the one estimated on the best model (β = -.32, SD = .28, 89% PI = [-.79, .12]). Additionally, figure 12 shows that all other parameters estimated by this model are centered around 0 and their posterior distribution is quite wide, which would suggest that none of them has a relevant influence over mind-wandering frequency.

Figure 12

Posterior distributions in the best performing model including every parameter



Note. Posterior distributions (posterior median and 89% PI) estimated for the parameters in the model. An estimate is thought to have a meaningful inference when the majority of its density lies beyond or below 0.

Discussion

This study attempted to assess the hypothesis of the region of proximal learning (RPL) by studying its main theoretical proposition, i.e., that mind-wandering does not occur when curiosity is elicited. It also tried to assess if and how mind-wandering frequencies were influenced by different overall uncertainty conditions by exposing participants to two distinct sets of melodies and examining their mind-wandering frequencies in response to them, and by assessing if participants' individual musical expertise would moderate this hypothesized relationship. Finally, based on recent research, this study examined the possibility that mind-wandering frequency could be predicted from uncertainty measures adopted from information theory that describe the relationship between musical expectancy and musical structure. Thus, it assessed if and to what extent mind-wandering episodes could be predicted from information content and information entropy values, and if their interaction, first among themselves, and then with individuals' musical expertise, could also explain mind-wandering frequency.

Initially, the results showing that mind-wandering is indeed negatively correlated with curiosity further confirm the first hypothesis of this study and the observations made by Omigie and Ricci (2021) that music can indeed elicit curiosity. In fact, this result offers support to the idea that individuals do not experience both curiosity and mind-wandering states at the same time, which, in the framework proposed by the region of proximal learning hypothesis, can be interpreted as individuals displaying information seeking behaviors (Metcalfe et al., 2020). It could also lead to infer that music might indeed be a useful tool to explore the region of proximal learning. Future research could explore this relationship between mind-wandering and curiosity in the presence of music and assess the contents of the mind while participants mind-wander, which would be an interesting approach to inform the discussion about how mind-wandering is characterized. It would also be interesting to explore the contents of the mind when it wanders in response to music that has had its information-theoretic structure precisely manipulated.

Considering the second hypothesis of this study, which estimates that overall stimuli uncertainty and expertise would influence mind-wandering episodes, the RPL model also proposes that it would be expected to see individuals mind-wandering when they are out of their RPL zone and, indeed, results showing that expertise has a negative influence over mind-wandering support this view. As individuals acquire more knowledge about a topic it is easier for them to engage with harder, more complex stimuli from that topic (Metcalfe, 2002). Notwithstanding this observation, it is crucial to remember that the effect seen was rather small, and with the sample size used here it would be hard to make a generalizable claim about this relationship between expertise, uncertainty and mind-wandering. Future research could further investigate this observation by exposing participants to stimuli that are more different from each other than the ones used in this study, and by increasing the sample size used here.

In fact, the result showing that participants' mind-wandering frequencies did not differ when exposed to original versus randomized melodies could be attributed to the fact that the model of melodic expectancy estimated that both sets were fairly similar (Appendices C, and D). In that sense, it is not necessarily surprising that no difference was observed when the ratings elicited by both sets were contrasted. What is more, the fact that the relationship between mind-wandering and expertise was not moderated by the type of stimulus participants were listening would reaffirm the lack of difference between uncertainty in both sets of stimuli.

A very interesting observation was that none of the two measures of uncertainty that previous research has shown to describe the structure of the musical sequences predicted mind-wandering with certainty. As already mentioned, although both sets were very similar in information content and entropy values, the fact that curiosity was negatively correlated with mind-wandering allowed to hypothesize that any, if not both, of the uncertainty measures could predict mind-wandering. Indeed, according to recent research, if curiosity and mind-wandering are predictive of each other, and information content and entropy values have been observed to predict curiosity, it would have been expected that information content and entropy values showed a reverse trend when predicting mind-wandering (Omigie & Ricci, 2022).

However, although very weakly, entropy values were able to predict mind-wandering when considered as dependent on expertise. This observation would seem to contradict the hypothesized role that expertise has over mind-wandering and might be explained by considering a different definition of mind-wandering. For instance, if the episodes of mind-wandering that participants experienced were elicited by the uncertainty of the musical sequences they were listening, this could be taken as the uncertainty of the melodic sequences, estimated through entropy values of individual notes, eliciting stimulus-related mind-wandering. In fact, it has been reported that musicians tend to experience a flow state when they interpret and listen to music and that non-musicians experience this feeling of engagement too as they listen to music they prefer (Lange et al., 2017; Loepthien & Leipold, 2022). It has also been observed that episodes of flow tend to evoke mental imagery and thus, since musicians tend to experience more mental imagery episodes than non-musicians, this positive relationship could be explained as musical expertise positively influencing episodes of mind-wandering if musical stimuli are perceived to be uncertain (Talamini et al., 2022; Taruffi & Küssner, 2019). Crucially, this goes to show that it is important to consider that the definition of mind-wandering put forward by the RPL framework does not necessarily correspond to a definition for which there is clear consensus about the nature of this phenomenon.

Finally, this study is one of the firsts to explore the relationship between curiosity and mind-wandering using music and information theoretic measures, which offers a new perspective on the study of music-elicited mind-wandering episodes. Further research could investigate this relationship using neurophysiological measures to explore the hemodynamic and electrophysiological profile of the dynamics between curiosity and mind-wandering with regards to music listening.

Concluding remarks

To conclude, with the data available it is possible to assert that mind-wandering frequencies and curiosity ratings of participants were negatively correlated, and that this fact can be taken as evidence supporting the RPL hypothesis' framework. Accordingly, these results have important implications for the use of music as a tool to assess curiosity and mind-wandering as intimately related concepts to learning. Furthermore, the results of this study show that information theoretic measures of the stimuli to which participants were exposed did not predict mind-wandering frequencies, a fact that may have been influenced by the similarity between uncertainty contained within each stimuli and the overall small size of the sample used. As such, further research would still be needed to certainly assess the relationship between mind-wandering and uncertainty measures.

Supplementary materials

Supplementary materials, including raw data and stimuli are available online:

https://osf.io/7f9jm/?view_only=0f799edaf94d40099f0127f020eab3c2

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Appendices

Appendix A

Model comparison for hypothesis 2

Model Ranking	Fixed effects	Random effects	PSIS estimate	PSIS SE	Weight
1	Expertise	Varying intercepts Participant Melodic sequences	352.1	7.54	.30
2	Expertise Overall stimuli uncertainty	Varying intercepts Participant Melodic sequences	353.2	7.57	.18
3	Overall stimuli uncertainty	Varying intercepts Participant Melodic sequences	353.6	7.53	.15
4	Expertise Overall stimuli uncertainty Expertise X overall stimuli uncertainty	Varying intercepts Participant Melodic sequences	353.7	7.66	.14
5	Expertise	Varying intercepts Participant Melodic sequences Varying slopes: Overall stimuli uncertainty	354.7	7.60	.08
6	Overall stimuli uncertainty	Varying intercepts Participant Melodic sequences Varying slopes Overall stimuli uncertainty	355.3	7.68	.06
7	Expertise Overall stimuli uncertainty	Varying intercepts Participant	355.5	7.58	.06

		Melodic sequences Varying slopes: Overall stimuli uncertainty			
8	Expertise Overall stimuli uncertainty Expertise X overall stimuli uncertainty	Varying intercepts: Participant Melodic sequences Varying slopes: Overall stimuli uncertainty	356.5	7.71	.03
9	Intercept only		932.9	89.47	0
10	Expertise		935.2	87.61	0
11	Overall stimuli uncertainty		939.4	90.30	0
12	Expertise Overall stimuli uncertainty Expertise X Overall stimuli uncertainty		947.5	88.56	0

Appendix B

Model comparison for hypothesis 3

Model Ranking	Fixed Effects	Random Effects	PSIS estimate	PSIS SE	Weight
1	Expertise Entropy Values Expertise X Entropy Values	Varying intercepts: Participant Melodic Sequences Varying Slopes Overall stimuli uncertainty	563.6	15.45	.13
2	Expertise Entropy Values Expertise X Entropy Values	Varying intercepts Participant Melodic Sequences	563.8	15.32	.12
3	Entropy values	Varying intercepts Participant Melodic Sequences	564.1	14.94	.10
4	Expertise	Varying intercepts: Participant Melodic Sequences Varying Slopes Overall stimuli uncertainty	564.2	14.88	.10
5	Entropy values	Varying intercepts: Participant Melodic Sequences Varying Slopes Overall stimuli uncertainty	564.4	14.95	.09
6	Expertise	Varying intercepts	564.7	14.91	.07

		Participant Melodic Sequences			
7	Expertise Entropy values	Varying intercepts: Participant Melodic Sequences Varying Slopes Overall stimuli uncertainty	564.8	15.13	.07
8	Expertise Entropy values	Varying intercepts Participant Melodic Sequences	565.0	15.20	.06
9	Expertise Entropy values Information Content values	Varying intercepts: Participant Melodic Sequences Varying Slopes Overall stimuli uncertainty	565.1	15.55	.06
10	Expertise Entropy values Information Content values	Varying intercepts Participant Melodic Sequences	565.4	15.50	.05
11	Information Content values	Varying intercepts: Participant Melodic Sequences Varying Slopes Overall stimuli uncertainty	565.5	14.88	.05
12	Information Content values	Varying intercepts Participant Melodic Sequences	566.5	14.85	.03
13	Expertise	Varying intercepts:	567.0	15.66	.02

	Information Content values Expertise X Information Content values	Participant Melodic Sequences Varying Slopes Overall stimuli uncertainty			
14	Expertise Information content values Expertise X Information Content values	Varying intercepts Participant Melodic Sequences	567.1	15.58	.02
15	Entropy values Information Content values Entropy values X Information Content values	Varying intercepts: Participant Melodic Sequences Varying Slopes Overall stimuli uncertainty	569.6	15.70	.01
16	Entropy values Information Content values Entropy values X Information Content values	Varying intercepts Participant Melodic Sequences	569.8	15.61	.01
17	Intercept Only		635.6	.17	0
18	Information Content values		636.0	2.51	0
19	Entropy values		637.0	.32	0
20	Expertise		637.1	1.27	0
21	Expertise Entropy values Expertise X Entropy values		637.7	2.35	0

22	Expertise Entropy values Information Content values	638.0	3.40	0
23	Expertise Entropy values	638.6	1.39	0
24	Expertise Information Content values Expertise X Information Content values	640.5	3.54	0
25	Entropy values Information Content values Entropy values X Information Content values	641.4	4.04	0

Appendix C

Comparison of information content values predicted for both sets of stimuli

Parameter	Mean	SD	5.5% PD	94.5% PD	Effective samples
Original sequences	3.73	.08	3.60	3.85	2109
Randomized sequences	5.48	.04	5.35	5.61	1991
Contrast between sequences	Mean	SD	5.5% PD	94.5% PD	
Original sequences – Randomized sequences	-1.75	.11	-1.94	-1.58	

Note PD = Posterior density

Appendix D

Comparison of entropy values predicted for both sets of stimuli

Parameter	Mean	SD	5.5% PD	94.5% PD	Effective samples
Original sequences	2.75	.02	2.72	2.78	2132
Randomized sequences	3.20	.02	3.17	3.23	2016
Contrast between sequences	**Mean**	**SD**	**5.5% PD**	**94.5% PD**	
Original sequences – Randomized sequences	-.46	.03	-.5	-.41	

Note PD = Posterior density