# Rhythm perception and its mechanisms: Using neural resonance theory and predictive processing theory to explain human temporal expectations.

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## Abstract

Temporal expectations allow us to anticipate upcoming events and enhance the speed and accuracy of perceptual decisions. Within rhythm perception and cognition, there are two theoretical frameworks of temporal expectations that we take into account in our study. Neural resonance theory hypothesizes that people perceive a beat and rhythm due to resonance of neural oscillations to rhythmic stimuli and a connection between the motor and sensory system. This network tries to find periodicity in the input and we call these beat-based expectations. Predictive processing theory on the other hand argues that the brain uses statistical learning to acquire cognitive models of statistical regularities and then applies these models to make probabilistic predictions on the rhythmic input. This system thus searches for patterns and we call these pattern-based expectations. This study looks into the effect of beat-based expectations, pattern-based expectations and musical expertise on performance of an implicit, explicit and motor task. All tasks were performed on a set of 56 rhythms that were divided into four categories: periodic predictable, periodic unpredictable, aperiodic predictable and aperiodic unpredictable. We found that pattern-based expectations improved performance in all tasks, while beat-based expectations by themselves only increased performance in target detection in the implicit task. We also found interactions between beat-based and pattern-based expectations, in which the effect of periodicity was dependent on the predictability condition. Musical expertise as a main effect was significant for the hit rate in the implicit task and all measures of the motor task. In addition to this, we found interactions between musical expertise and both beat-based expectations and pattern-based expectations, in which the performance of participants with more musical expertise increased most for periodic and unpredictable rhythms. Overall, we cannot make definitive conclusions about the differences between beat-based and pattern-based expectations, as the computing of these expectations cannot be directly compared. Still, this study opens new avenues for research into the interplay between beat-based expectations, pattern-based expectations and musical expertise.

## Introduction

When you listen to music you will likely feel the urge to move your body to the rhythm, either through swinging, dancing or tapping. These temporal expectations are crucial for human beings in more areas than just music, since temporal expectations prepare us for perception and action. By forming expectations and anticipating upcoming events we can reduce cognitive load (Wilsch et al., 2015), enhance the speed and accuracy of perceptual decisions (Nobre & van Ede, 2018), and hence increase performance in tasks that rely on these perceptual decisions (Jin et al., 2020). Temporal expectations are also useful for cue-based or memory-based behavior (Ede et al., 2020; Jin et al., 2020). The consequences of these expectations are purpose dependent; the expectations are geared towards increasing the performance of the required behavior and not behavior in general (Ede et al., 2020). For example, if the required behavior is pressing a button on time, the temporal expectations will decrease the reaction time. Thus temporal expectations support humans in anticipating events and behaviors.

In music, temporal expectations relate to the timing of auditory events. While listening to music, the brain extracts certain elements and hierarchy from the stimulus (Kotz et al., 2018; Lenc et al., 2021). The elements that this paper focuses on are pulse and rhythm, which relate to the timing of music. *Pulse* refers to the periodicity underlying a rhythm with constant intervals, also called the beat. *Rhythm* is the pattern of sounds and silences in time on top of a beat. Figure 1 illustrates the difference between pulse and rhythm. Temporal expectations thus give rise to the perception of these elements in music.

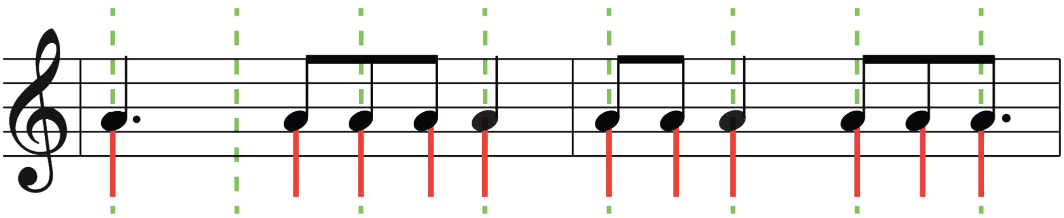

*Figure 1: Pulse and rhythm in music. The green dashed lines represent the pulse and the red lines represent the rhythm. The pulse lies under the rhythm and can, but does not have to be, accented by the rhythm.*

There are currently two established theoretical frameworks for overall rhythm perception, which includes the perception of the beat and rhythm. Both theories attempt to explain the formation of temporal expectations which give rise to rhythm perception, with their differences lying in the mechanisms used to make these expectations.

The first theory of temporal expectations is neural resonance theory (NRT), which is an entrainment theory. NRT hypothesizes that responses to rhythms are based on neural resonance to rhythmic stimuli (Lakatos et al., 2019; Large & Snyder, 2009). Neural oscillations resonate with the oscillations of the rhythmic stimuli, matching it in phase and amplitude. The perception of pulse and meter thus arise from entrainment of nonlinear neural oscillations to external stimuli.

Large et al. (2015) argue in NRT that the perception of pulse and meter is supported by an interaction between the sensory and motor system. This interaction takes the form of reciprocal plastic connections between the sensory and motor area in the brain. They argue that the sensory system, the auditory system in particular, extracts relevant temporal information from the rhythmic stimulus, such as the timing, duration and accent patterns in the sound. The motor system on the other hand generates predictions and expectations about future events in the rhythm, by internally simulating the timing and sequence of upcoming beats based on the information from the sensory system. The motor system then adjusts its predictions and timing expectations based on the input from the sensory system. The authors suggest that this interaction between the sensory and motor system enables the brain to dynamically track and anticipate the beat structure of a rhythm, allowing the body to synchronize motor actions with the perceived rhythm. These plastic connections also underly the capacity of humans to perceive a beat when there are no accents on this beat in the auditory input (Tal et al., 2017). One study by Tal et al. (2017) looked at this phenomenon. They presented the participants with four drum patterns with the pulse frequency of 2 Hz: one isochronous pattern (patterns with energy on the pulse frequency or "on the beat"), two syncopated patterns (patterns with no energy on the pulse frequency or "off the beat") and one random pattern. Their MEG recordings showed peaks at 2 Hz for both the isochronous and syncopated patterns, despite the absence of this frequency in the syncopated patterns. This shows that the brain can generate an internal representation of the pulse, even when it is missing from the stimulus. The interaction between the sensory and motor system is thus critical for beat perception within neural resonance theory.

The sensory system on its own can thus not detect a beat when it is not accented in the rhythm, it needs the input from the motor system to find this beat. There are multiple theories that try to explain this phenomenon. The Action Simulation for Auditory Perception (ASAP) hypothesis suggests that the perception of a beat relies on a simulation of body movement in the motor area of the brain (Patel & Iversen, 2014). The brain is planning on movement (without actually moving the body) and thereby entraining to the stimulus. Another explanation for the beat detection of the motor area is that the motor area tracks the progress between intervals by using the timing information from the auditory cortex and looks for consistent durations in these intervals (Cannon & Patel, 2021). In summary, while the exact workings remain debatable, the motor system is critical for pulse and rhythm perception in NRT.

The second theory of temporal expectations is the predictive processing theory, which relies on statistical learning and probabilistic prediction. Listeners acquire cognitive models of statistical and structural regularities in the music they are exposed to and make probabilistic predictions based on these cognitive models when listening to new music (Pearce, 2018; Rohrmeier & Koelsch, 2012). In addition to the prediction of *what* is coming next, the brain also assesses the precision of this prediction: how likely is it that the prediction is correct (Koelsch et al., 2019). This process is done by minimizing the prediction error, which is the difference between the cognitive prediction and the actual sensory input (Hohwy, 2020). The prediction error is calculated through Bayesian processes and added to the cognitive model (Hohwy, 2020). The predictions are then updates based on previous errors and auditory input (Vuust et al., 2022). In short, predictive processing theory predicts the event and precision based on previously obtained information.

Since the brain uses previously obtained information, aspects such as personal listening history, musical training, mood, listening situation, biology and culture can influence the temporal expectations within predictive processing theory (van der Weij et al., 2017; Vuust & Witek, 2014). Culture specifically has a big impact on the predictive processing. The brain is trained on the specific music cultures or genres that the listener is exposed to. This enculturation results in people being better at predicting rhythms that are culturally familiar (Kaplan et al., 2022). For example, scales, rhythms and meter can be completely different in music from other cultures, which explains how it can be hard for people to follow music from other cultures (Cameron et al., 2015). One study by Cameron et al. (2015) shows the effect of this enculturation by looking at the performance of a beat tapping test between two groups of participants: East-African participants and Northern-American participants. They presented both groups with rhythms from both cultures and asked them to perform a discrimination task, a reproduction task and a tapping task. The results from the tapping test showed that each group tapped more accurately to the beat of rhythms from their own culture. This shows that we actually train our brains with the musical culture we are exposed to, theoretically by learning statistical regularities in musical culture.

Although both the neural resonance theory and predictive processing theory explain temporal expectations, it is currently debated whether both of the underlying mechanisms are needed for temporal expectations (Bouwer et al., 2020, 2023; Nobre & van Ede, 2018; Palmer & Demos, 2022). Indeed, both theories rely on minimizing energy and differences between expected and observed outcomes (Palmer & Demos, 2022). Neural Resonance Theory attempts this by synchronizing neural oscillations with the beat, reducing the energy required for processing the rhythm (Large et al., 2015), while predictive processing theory focuses on minimizing the prediction errors and aligning internal models with the observed rhythm, reducing the mismatch between expectations and sensory inputs (Pearce, 2018). In addition to this, both mechanisms of predictions increase performance of rhythm related behaviors (Bouwer et al., 2023). However, the underlying processes and their performance in absence of input (i.e. perception of pulse without accents) are very different, suggesting that their underlying mechanisms may differ at least partly (Bouwer et al., 2020, 2023). Bouwer et al. (2020) looked at the different mechanisms underlying these expectations. They presented 16 different rhythms to their participants in which there were infrequent intensity decrement targets. Each rhythm consisted of a pattern that was repeated 128 times and 32 of these patterns had one event, the target, that was softer in volume than the other events. The participants were instructed to press a button as fast as possible when they heard a target. They used four types of rhythms: periodic predictable, periodic unpredictable, aperiodic predictable and aperiodic unpredictable. The periodic rhythms were used to stimulate entrainment, as entrainment looks for a beat or periodicity, and the predictable rhythms to stimulate predictive processing, as this looks for patterns in the stimulus. They found that pattern-based predictions (predictive processing theory) did improve the detection of targets, both in hit rate and reaction time. However, the effect of periodicity (neural resonance theory) was more complex. Beat-based expectations lead to a decrease in performance when targets were off-beat and only significantly increased performance when the rhythm was unpredictable based on predictive processing theory. They concluded that pattern-based and beat-based expectations share mechanisms and interact with each other, while they computation might be separate. In other words, more research is needed into the mechanisms and computation of temporal expectations according to both models to understand whether they are both needed.

One might argue that both theories are needed for temporal expectations and that the mechanism used changes according to the type of rhythmic input. The mechanisms of neural resonance theory are searching for a pulse, while the mechanisms of predictive processing theory are searching for patterns and statistical regularities (Large et al., 2015; Pearce, 2018). If a rhythm is highly periodic, NRT would have a better performance than predictive processing theory, while the opposite is true for aperiodic rhythms with clear patterns. Moreover, we can predict both periodic rhythms and pattern based rhythms, suggesting that both mechanisms are used. Therefore it seems that a combination of the two mechanisms are used for temporal expectations.

An additional factor to consider when researching temporal expectations is musical expertise. Within both theories, musical expertise has an effect on rhythm perception. Many studies have found an increase in performance on different tasks relating to music for musicians in comparison to non-musicians (Daikoku & Yumoto, 2020; Pesnot Lerousseau & Schön, 2021; Stupacher et al., 2017; Zhao et al., 2017). From the view of the predictive processing theory this makes sense, since the musical brain has gotten more input to base its predictions on. Studies show that statistical learning is in fact facilitated by musical expertise (Daikoku & Yumoto, 2020; Pesnot Lerousseau & Schön, 2021). Although stylistic specialization does affect the internal processing of music (Hansen et al., 2016), the instrument played by the musician does not have any effect (Matthews et al., 2016). Musicians in general are thus better at predicting rhythms than non-musicians, but we cannot differentiate between groups of musicians. Within the neural resonance theory there is also evidence pointing to an advantage for musicians. One study that looked at the processing of polyrhythms, which are rhythms that have at least two different beat levels (e.g. a 2:3 rhythm, that has one beat level that has two beats in one bar and one beat level that has three beats in one bar), found that neural entrainment during silent periods was stronger in musicians (Stupacher et al., 2017). In other words, musicians were better at keeping the beat of a polyrhythm in their head after the stimulus ended. They hypothesize that this is due to the top-down processes involved in neural entrainment. Another study looked at meter perception in musicians and non-musicians and found that music training experience modulates the neural processing of metrical structures (Zhao et al., 2017). The improved performance of musicians within the neural resonance theory is thus likely due to enhanced entrainment in the brain to rhythms. In summary, musical expertise has a positive effect on temporal expectations across both theories.

Although many studies have looked at one of these theories rhythm perception in isolation, there are only a few that looked at both beat-based and pattern-based expectations in the same study (e.g. Bouwer et al., 2020). In addition, studies that looked at the influence of musical expertise divide their participants in groups of 'musicians' and 'non-musicians', which ignores the great spectrum of musicality. Therefore, this study focuses on both theories of temporal expectations and how they explain rhythm-related behavior in combination with musical expertise. Specifically, we analyzed the performance on different tasks. To investigate how the two theoretical frameworks influence this performance, we selected rhythms that are either predictable or unpredictable based on each framework. To compute these predictabilities for each theory, we used computational models. Large et al. (2015) developed a computational model to represent neural resonance theory: the Gradient Frequency Neural Network (GrFNN) toolbox. Pearce (2018) developed a computational model for the predictive processing theory that works through statistical learning: Information Dynamics of Music (IDyOM). Using these models we selected rhythms that were either predictable according to both models, unpredictable according to both models or predictable according to one model and unpredictable according to the other model. This made it possible to investigate the different mechanisms behind temporal expectations and how they might work together.

These rhythms were then presented to participants who had to perform three tasks: an implicit, explicit, and motor task. We measured the musicality of the participants by using the musical training subscale of the Goldsmiths Musical Sophistication Index , which measures musicality as a continuous variable. This allowed us to take a broader spectrum of musicality into account instead of dividing the participants in groups of musicians and non-musicians. We predicted that a combination of both mechanisms was used to form temporal expectations, depending on the nature on the rhythmic stimulus, and that participants with higher musical expertise will be generally better in making these expectations. We studied this by analyzing the performance of participants on the tasks in relation to the predictability based on both models and the musical expertise of the participant to investigate how the neural resonance theory and the predictive processing theory explain human temporal expectations and how musicality plays a role in this.

# Methods

## Participants

132 participants (85 women), aged between 16 and 66 years old (M = 22.7, SD = 6.8), with no history of neurological disorders or hearing damage, took part in the experiment in exchange for course credit or monetary compensation. Ethical approval was obtained by the ethics review board of the Faculty of Social and Behavioral Sciences of the University of Amsterdam (March 13 2023, FMG-2079_2023) before we began recruiting participants. We recruited participants through the Behavioral Science Lab of the *University of Amsterdam* and by advertising at the *Conservatorium van Amsterdam* with posters and word of mouth. This way we tried to include participants with a variety of musical expertise.

## Materials

Rhythms

A set of 56 rhythms of all possible rhythms of 4000 ms with 8 events with intervals between 200 and 800 ms in 50 ms steps were selected for the experiment (see Figure 2 for a more detailed explanation). These parameters were chosen to be in line with what we know about human rhythm cognition. This resulted in roughly 30 million rhythms. We then removed circular duplicates, keeping the rhythms with the longest interval at the end. This resulted in about 3.7 million rhythms. These rhythms were all run through both GrFNN and IDyOM with one repetition, computing the predictability for the second repetition. In GrFNN we computed three indices of predictability from the output signal at the times of sound in the rhythmic pattern: amplitude, phase consistency and distance from 0 or pi phase. In IDyOM we computed entropy based on three features. The first feature is inter-onset interval (IOI), which is the absolute duration of the interval between two events. The second feature is the IOI-ratio, which is the ratio between an interval and the preceding interval. The last feature is contour, which describes whether the interval is longer, shorter of equal to the previous interval. This resulted in a total of 6 indicators of predictability per rhythm, 3 related to GrFNN and 3 related to IDyOM. Based on these 6 indicators, we selected rhythms to be predictable or unpredictable according to these two models.

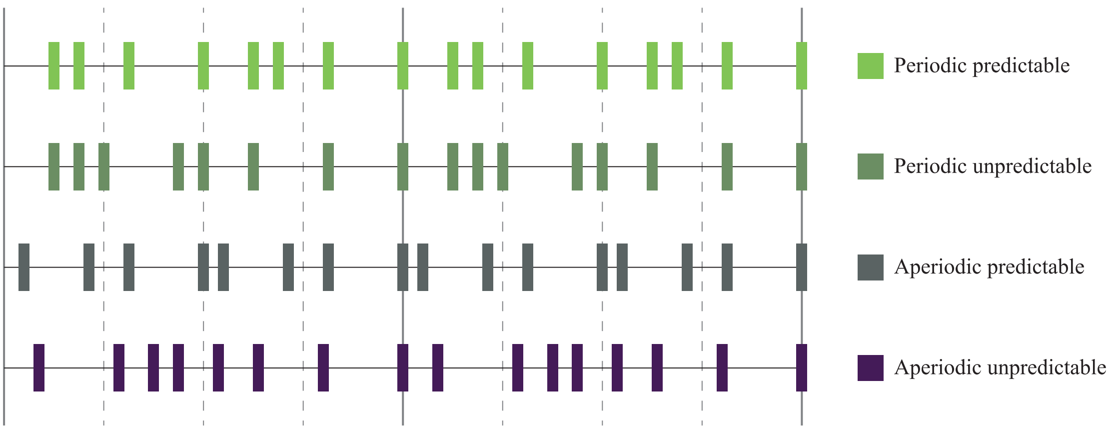


*Figure 2: Examples of the four different rhythm types selected for the experiment. The bold vertical lines represent the 4000 ms period and the dashed vertical lines represent the 1000 ms beats within this period. The periodic predictable rhythm (at the top) shows a clear pattern that repeats in one period and has accents on the beat or integer ratios to the beat (i.e. 1:2 and 1:4 ratios). The periodic unpredictable rhythm (second from the top) shows no patterns within one period, but has multiple accents on the beat and integer ratios to the beat (i.e. 1:2 and 1:4 ratios. The aperiodic predictable rhythm (third from the top) shows a clear pattern that repeats in one period, but has barely any accents on the beat and no accents on integer ratios to the beat. The aperiodic unpredictable rhythm (at the bottom) has no repeating pattern in one period and no accents on beats or integer ratios to the beat.*

We looked for rhythms that are predictable or unpredictable on all 3 indicators for each model, using a 6-dimensional space, with each indicator as a dimension and all indicators normalized between 0 (predictable) and 1 (unpredictable). To illustrate, in this space, we looked for rhythms that are predictable for both models and closest to [0,0,0,0,0,0], rhythms that are predictable for only one model and closest to [0,0,0,1,1,1] and [1,1,1,0,0,0], or rhythms that are unpredictable for both rhythms and closest to [1,1,1,1,1,1]. We selected a total of 56 rhythms, which is 14 rhythms per category.

Task 1: Implicit

In the implicit task, participants were asked to detect infrequent targets by pressing the space bar as quickly as possible. Infrequent targets were presented in the form of intensity decrements of volume to probe temporal expectations. The rhythms were presented as sequences of 10 patterns and 8 deviant per sequence. All deviants were at least 2 seconds apart and all positions in the pattern were probed once. One or two mock deviants were added in the first pattern to make the first deviant not overly predictable. These mock deviants were eliminated in the analysis. The measures of the implicit task were the reaction time per hit, the amount of hits per rhythm and the amount of false alarms per rhythm. At the start of the implicit task, participants had to perform two practice trials. After each practice trial and each block, the participant got informed on the percentage of targets they hit and how many times they pressed the spacebar when there was no target. The participants had to hit at least 50% of the targets and have less than 5 false alarms in the practice trials before they could start the task to ensure they understood the task. This task took between 45 and 60 minutes.

Task 2: Explicit

In the explicit task, participants were asked to rate the rhythms on a 1 to 7 Likert scale on complexity, liking and wanting to move to the rhythm by pressing the corresponding number on the keyboard. The rhythms were presented as a sequence of four patterns without any volume adjustments. The measures of the explicit task were the rating of complexity, liking and wanting to move on Likert scale ranging from 1 “Not complex at all” to 7 “Extremely complex” in the example of the complexity rating. The order of the questions was randomized. At the start of the explicit task, participants had to perform two practice trials with one non-complex rhythm and one complex rhythm. They were instructed to give these rhythms a score of 1 and 7, respectively. This was done to probe the participants to use the whole range of responses. This task took between 20 and 30 minutes.

Task 3: Motor

In the motor task, participants were asked to tap along to the rhythms. The rhythms were presented as sequences of six patterns without any volume adjustments. The tapping of the participants was recorded with a Soundcard (SSL 2 of Solid State Logic)  and microphone and transformed into csv data with Python code. The measures of the motor task were asynchrony and number of correctly tapped iterations. At the start of the motor task, participants had to perform two practice trails to get them acquainted with the task and check whether the tapping was recorded correctly. The participants could listen to two repetitions of the pattern before the word “TAP” appeared on the screen and they had to start tapping. The participants had two practice trials to get acquainted with the task. This task took between 20 and 30 minutes.

Musical expertise

The musical expertise of the participants was measured with the musical training subscale of the Goldsmiths Musical Sophistication Index (Gold-MSI), which is a self-report inventory consisting of 6 factors assessing musical sophistication (Müllensiefen et al., 2014). Age and gender were also recorded in this questionnaire. This questionnaire took between 2 and 5 minutes.

## Procedure

Participants were tested individually in a dedicated lab at the University of Amsterdam. Upon arrival, participants completed a consent form to be allowed to start the experiment. Before each task, the participants got an explanation from the researcher and had at least two practice trials. The researcher stayed with the participant to make sure the participant understood the task and was performing well enough. In all tasks, the 56 rhythms were divided into blocks of 8, allowing the participants to take small breaks between blocks. All participants started with the implicit task. The order of the explicit and tapping task were randomized. The GMSI questionnaire was filled in after the three tasks. All tasks and questionnaires were performed in PsychoPy 2022.2.5 (Peirce et al., 2019). In total, the experiment lasted about 2 hours.

## Analysis

We performed a linear mixed model on different dependent variables. The fixed factors were oscillator, which represents the predictability according to GrFNN, probabilistic, which represents the predictability according to IDyOM, and GMSI, which is the musicality score. We constructed our models by using a different combination of fixed factors, resulting in four models (see Table 1). Each model has a base of all fixed factors added as a main effect and an interaction between probabilistic and oscillator. We included the participant as a random factor in each analysis with a random intercept. For each dependent variable, we compared the models and selected the model that was the best fit for the data.

Table 1: Models for statistical analysis

| | |
|---|---|
| Model 1 | $Dep\ var \sim probabilistic + oscillator + GMSI + \ probabilistic \times oscillator + \ (1\vert PP)$ |
| Model 2 | $Dep\ var \sim probabilistic + oscillator + GMSI + probabilistic \times oscillator + probabilstic \times GMSI + \ (1\vert PP)$ |
| Model 3 | $Dep\ var \sim probabilistic + oscillator + GMSI + probabilistic \times oscillator + oscillator \times GMSI + \ (1\vert PP)$ |
| Model 4 | $Dep\ var \sim probabilistic + oscillator + GMSI + probabilistic \times oscillator + probabilistic \times GMSI + oscillator \times GMSI + \ (1\vert PP)$ |

We analyzed five different dependent variables. For the implicit task, we analyzed the ratio of targets the participants hit per rhythm, called hit rate, and the mean reaction time per participant per hit per rhythm. The hit rate was calculated by dividing the amount of hits by the amount of targets. For the explicit task, we analyzed at the complexity rating per participant per rhythm. For the motor task, we looked at the number of iterations they correctly tapped and the standard deviation of asynchrony per participant per rhythm. A larger standard deviation of asynchrony means more variability in asynchrony and thus a less good performance. For the reaction time analysis, we removed participants who had an average hit rate of 0.25 or lower, which would be an average of 2 hits or less per rhythm. Without removing these participants, the mean reaction time would not be balanced per trial. This resulted in excluding two participants from the analysis

A binomial generalized linear mixed model was used for the hit rate analyses. A standard linear mixed model was used for the reaction time analyses with a log-transformation on the reaction time to normalize the data. This transformation did not affect the outcome of the models. A mixed ordinal regression model was used for the complexity analyses to account for the ordinal nature of the Likert-scale responses. The statistical analysis was conducted in R version 2023.03.1 (R Core Team, 2022). The binomial generalized linear mixed model was implemented using the *glmer()* function from the lme4 package (Bates et al., 2023). The standard linear mixed model was implemented using the *lmer()*

function from the lme4 package (Bates et al., 2023). The mixed ordinal regression model was implemented using the *clmm()* function from the ordinal package (Christensen, 2022). The comparison between models was implemented using the *compare_performance()* function from the easystats package (Lüdecke et al., 2022).

## Results

We looked at the results per dependent variable. First, we analyzed the dependent variables of the implicit task: hit rate and reaction time. Second, we analyzed the dependent variable of the explicit task: complexity. Finally, we analyzed the dependent variables of the tapping task: number of correctly tapped iterations and standard deviation of asynchrony.

### Hit rate analysis

The first analysis looked at the hit rate of the implicit task as dependent variable. In general participants hit more targets in predictable rhythms than in unpredictable rhythms (see Table 2).

Table 2: Mean values of hit rate per condition

| | Periodic | Aperiodic |
|---|---|---|
| Predictable | 0.729 | 0.704 |
| Unpredictable | 0.643 | 0.643 |

Model 3 was the best fit for this analysis (see Appendix A for more information on the comparison). All fixed factors were significant, except for *oscillator* (see Table 3).

**Model 3 |** *Hit rate = probabilistic + oscillator + GMSI + probabilistic×oscillator + GMSI×oscillator*

These results suggest that *probabilistic* ($\beta = -0.479$, SE = 0.028, $p < 0.001$) had a negative effect on the hit rate in the implicit task, while *GMSI* ($\beta = 0.031$, SE = 0.009, $p < 0.001$) had a positive effect on the hit rate in the implicit task. The interaction between *probabilistic* and *oscillator* ($\beta = 0.152$, SE = 0.039, $p < 0.001$) suggests that periodicity only affected hit rate if the rhythm was predictable and that this effect was positive (see Figure 3). The interaction between *GMSI* and *oscillator* ($\beta = -0.004$, SE = 0.002, $p = 0.034$) suggests that effect of periodicity increased with the GMSI score (see Figure 4). Thus targets were easier to hit in predictable rhythms, while periodic rhythms only increased hit rate if the rhythm was predictable. In addition to this, musical expertise increased hit rate in general and especially for periodic rhythms.

Table 3: Statistics for the best fitting model for hit rate analysis. Significant factors are highlighted.

| | Model 3 | | | |
|---|---|---|---|---|
| | group / Est. | Est. | S.E. | P |
| (Intercept) | | 0.614 | 0.218 | 0.005 |
| probabilistic | | -0.479 | 0.028 | <0.001 |
| oscillator | | -0.070 | 0.047 | 0.139 |
| GMSI | | 0.031 | 0.009 | <0.001 |
| probabilistic × oscillator | | 0.152 | 0.039 | <0.001 |
| oscillator × GMSI | | -0.004 | 0.002 | 0.034 |

Table 3: Statistics for the best fitting model for hit rate analysis. Significant factors are highlighted.

| | | | | |
|---|---|---|---|---|
| | | **Model 3** | | |
| | group / Est. | Est. | S.E. | P |
| SD (Intercept PP) | PP | 1.102 | | |

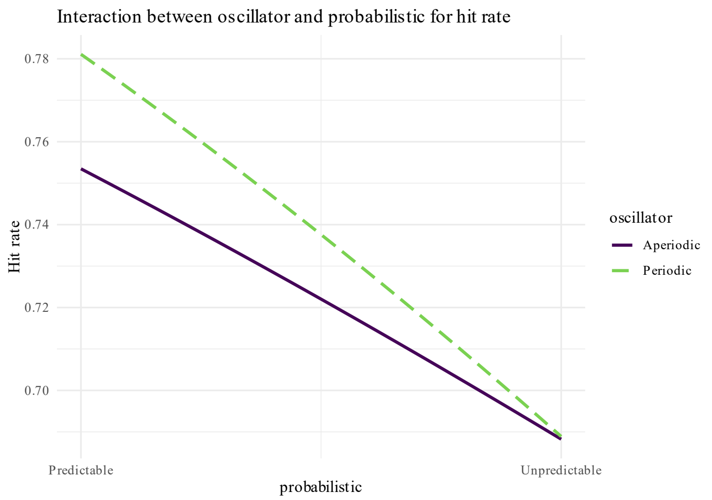


*Figure 3: Interaction plot of oscillator and probabilistic for hit rate. The effect of oscillator is only noticeable when probabilistic is predictable.*

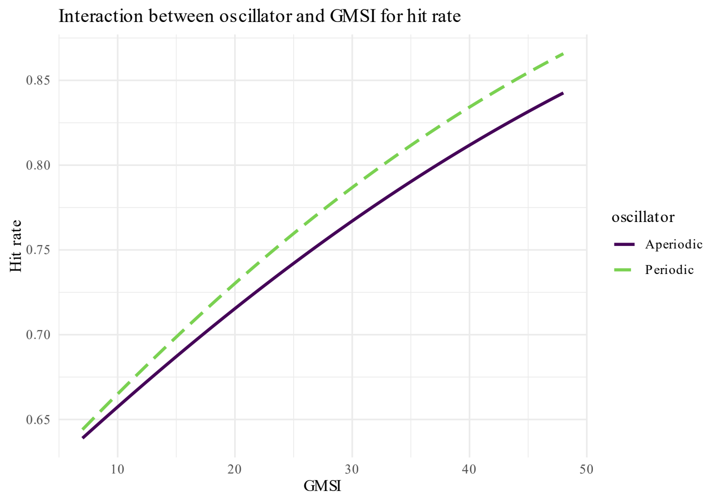


*Figure 4: Interaction plot of oscillator and GMSI for hit rate. The hit rate increases with GMSI and the difference in hit rate between periodic and aperiodic rhythms increases with GMSI.*

**Reaction time analysis**

The second analysis looked at the reaction time of a hit of the implicit task as dependent variable. In general, participants had a higher reaction time for unpredictable rhythms and aperiodic rhythms (see Table 4).

Table 4: Mean values of reaction time (s) per condition

| | Periodic | Aperiodic |
|---|---|---|
| Predictable | 0.496 | 0.503 |
| Unpredictable | 0.524 | 0.535 |

Model 1 was the best fit for this analysis (see Appendix A for more information on the comparison). All fixed factors had significant effects on the mean reaction time, except for the interaction between *probabilistic* and *oscillator* (see Table 5).

**Model 1** | *Reaction time = probabilistic + oscillator + GMSI + probabilistic×oscillator*

These results suggest that *probabilistic* ($\beta = 0.055$, SE = 0.006, $p < 0.001$) and *oscillator* ($\beta = 0.015$, SE = 0.006, $p = 0.011$) had a positive effect on the reaction time while *GMSI* had no effect on the reaction time. Thus both unpredictable and aperiodic rhythms had a longer reaction time, and musical expertise did not affect this reaction time.

Table 5: Statistics for the best fitting model for reaction time analysis. Significant factors are highlighted.

| Model 1 | | | | |
|---|---|---|---|---|
| | group / Est. | Est. | S.E. | P |
| (Intercept) | | -0.678 | 0.028 | <0.001 |
| probabilistic | | 0.055 | 0.006 | <0.001 |
| oscillator | | 0.015 | 0.006 | 0.011 |
| GMSI | | -0.002 | 0.001 | 0.057 |
| probabilistic × oscillator | | 0.004 | 0.008 | 0.603 |
| SD (Intercept PP) | PP | 0.141 | | |
| SD (Observations) | Residual | 0.175 | | |

**Complexity rating analysis**

The third analysis looked at the complexity rating in the explicit task as dependent variable. In general, participants rated unpredictable rhythms as more complex, with aperiodic unpredictable rhythms being the most complex (see Table 6).

Table 6: Mean values of complexity rating per condition

| | Periodic | Aperiodic |
|---|---|---|
| Predictable | 2.509 | 2.469 |
| Unpredictable | 4.835 | 5.207 |

Model 4 was the best fit for this analysis (see Appendix A for more information on the comparison). The significant fixed factors were *probabilistic* ($\beta = 3.028$, SE = 0.109, $p < 0.001$), *oscillator* ($\beta = -0.238$, SE = 0.102, $p < 0.001$), their interaction ($\beta = 0.545$, SE = 0.085, $p < 0.001$) and the interaction between *oscillator* and *GMSI* ($\beta = 0.010$, SE = 0.004, $p = 0.012$) (see Table 7).

**Model 4** | *Complexity* = *probabilistic* + *oscillator* + *GMSI* + *probabilistic*×*oscillator* + *GMSI*×*probabilistic* + *GMSI*×*oscillator*

These results suggest that *probabilistic* and *GMSI* had a positive effect on the complexity rating, while *oscillator* had a negative effect on the complexity rating. The interaction between *probabilistic* and *oscillator* (see Figure 5) suggests that unpredictable rhythms were evaluated as more complex when they were also aperiodic. The interaction between *oscillator* and *GMSI* (see Figure 6) suggests that the complexity score given to aperiodic rhythms increased with the GMSI score, while this did not happen for periodic rhythms. Thus participants found unpredictable rhythms more complex than predictable rhythms in general, while aperiodic rhythms were found more complex when the rhythm was also unpredictable and when the musicality of the participant was higher.

Table 7: Statistics for the best fitting model for complexity analysis. Significant factors are highlighted.

| **Model 4** | | | | |
|---|---|---|---|---|
| | group / Est. | Est. | S.E. | P |
| 1\|2 | | -0.876 | 0.197 | <0.001 |
| 2\|3 | | 0.297 | 0.197 | 0.132 |
| 3\|4 | | 1.382 | 0.198 | <0.001 |
| 4\|5 | | 2.404 | 0.199 | <0.001 |
| 5\|6 | | 3.454 | 0.201 | <0.001 |
| 6\|7 | | 4.743 | 0.204 | <0.001 |
| probabilistic | | 3.028 | 0.109 | <0.001 |
| oscillator | | -0.238 | 0.104 | 0.023 |
| GMSI | | -0.001 | 0.008 | 0.933 |

| Table 7: Statistics for the best fitting model for complexity analysis. Significant factors are highlighted. | | | | |
|---|---|---|---|---|
| **Model 4** | | | | |
| | group / Est. | Est. | S.E. | P |
| probabilistic × oscillator | | 0.545 | 0.085 | <0.001 |
| probabilistic × GMSI | | -0.006 | 0.004 | 0.130 |
| oscillator × GMSI | | 0.010 | 0.004 | 0.012 |
| SD (Intercept PP) | PP | 0.901 | | |

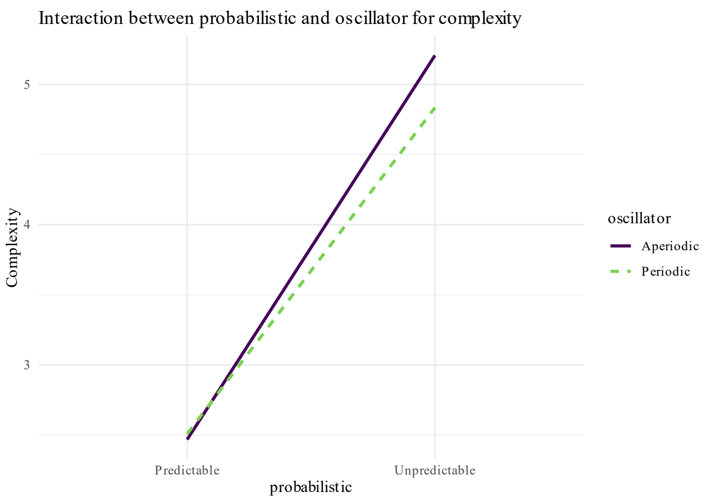


*Figure 5: Interaction plot of oscillator and probabilistic for complexity. The effect of periodicity is only noticeable when probabilistic is unpredictable.*

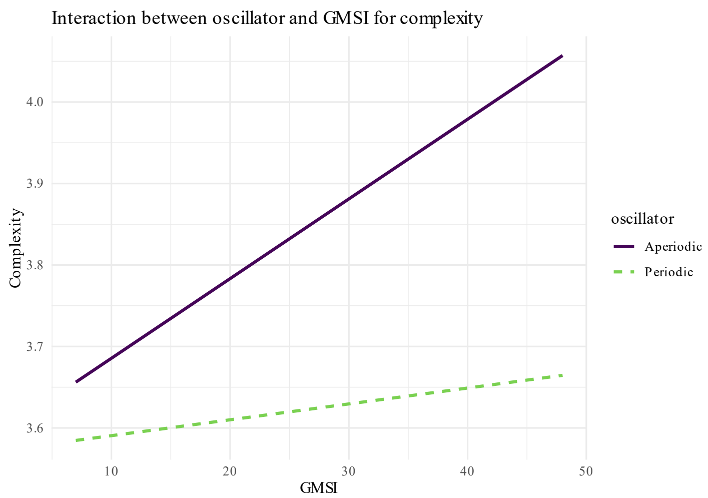


*Figure 6: Interaction plot of oscillator and GMSI for complexity. The complexity of aperiodic rhythms increases with GMSI, while the complexity of periodic rhythms only slightly increases for periodic rhythms.*

### Correctly tapped iterations analysis

The fourth analysis looked at the number of correctly tapped iterations in the tapping task as dependent variable. In general, participants tapped more correct iterations when rhythms were predictable (see Table 8).

Table 8: Mean values of correctly tapped iterations per condition

| | Periodic | Aperiodic |
|---|---|---|
| Predictable | 2.418 | 2.382 |
| Unpredictable | 1.477 | 1.403 |

Model 2 was the best fit for this analysis (see Appendix A for more information on the comparison). The only significant fixed factors were *probabilistic* ($\beta = -2.159$, SE = 0.086, $p < 0.001$), *GMSI* ($\beta = 0.022$, SE = 0.010, $p = 0.026$) and their interaction ($\beta = 0.016$, SE = 0.003, $p < 0.001$) (see Table 9).

**Model 2** | *Correct iterations = probabilistic + oscillator + GMSI + probabilistic×oscillator + GMSI×probabilistic*

These results suggest that *probabilistic* had a negative effect on correct iterations in the tapping task, while *GMSI* had a positive effect on the correct iterations. The interaction between *probabilistic* and *GMSI* (see Figure 7) suggests that participant with more musical expertise were better at tapping along to unpredictable rhythms than participants with less musical expertise, while this difference was smaller for predictable rhythms. Thus it was harder to correctly tap unpredictable rhythms, especially when musical expertise is low, and musical expertise made it easier to correctly tap rhythms in general.

Table 9: Statistics for the best fitting model for correctly tapped iterations analysis. Significant factors are highlighted.

| Model 2 | | | | |
|---|---|---|---|---|
| | group / Est. | Est. | S.E. | P |
| (Intercept) | | 1.253 | 0.241 | <0.001 |
| probabilistic | | -2.159 | 0.086 | <0.001 |
| oscillator | | -0.095 | 0.054 | 0.076 |
| GMSI | | 0.022 | 0.010 | 0.026 |
| probabilistic × oscillator | | -0.029 | 0.069 | 0.668 |
| probabilistic × GMSI | | 0.016 | 0.003 | <0.001 |
| SD (Intercept PP) | PP | 1.177 | | |

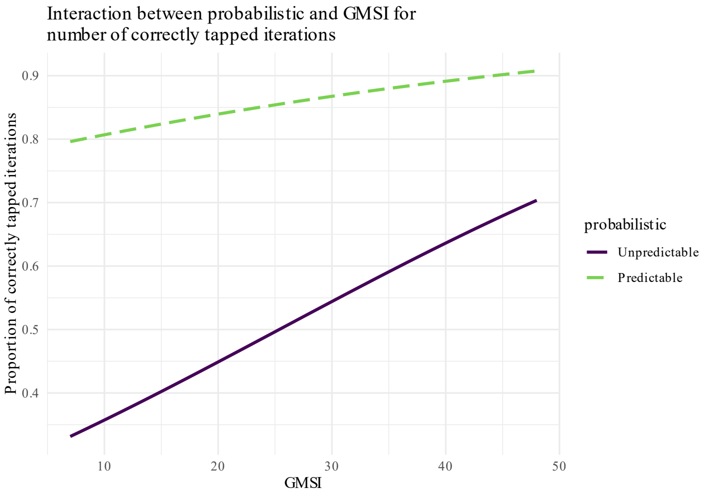


*Figure 7: Interaction plot of probabilistic and GMSI for number of correctly tapped iterations. The number of correctly tapped iterations for unpredictable rhythms increases with GMSI, while the number of correctly tapped iterations only slightly increases for predictable rhythms.*

**Standard Deviation of asynchrony tapping analysis**

The last analysis looked at the standard deviation of the asynchrony of the tapping task as dependent variable. In general, participants had a larger standard deviation of asynchrony when rhythms were predictable or aperiodic (see Table 10).

Table 10: Mean values of standard deviation of asynchrony per condition

| | Periodic | Aperiodic |
|---|---|---|
| Predictable | 0.046 | 0.052 |
| Unpredictable | 0.090 | 0.101 |

Model 4 was the best fit for this analysis (see Appendix A for more information on the comparison). All fixed factors and their interactions were significant, except for *oscillator* (see Table 11).

**Model 4 |** *SD Asynchrony = probabilistic + oscillator + GMSI + probabilistic×oscillator + GMSI×probabilistic + GMSI×oscillator*

These results suggest that *probabilistic* ($\beta = 0.063$, SE = 0.002, $p < 0.001$) had a positive effect on the standard deviation of asynchrony in the tapping task, while *GMSI* ($\beta = -0.001$, SE = 0.000, $p < 0.001$) had a negative effect. The interaction between *probabilistic* and *oscillator* ($\beta = 0.004$, SE = 0.002, $p = 0.014$) shows that the difference between the standard deviation of asynchrony between periodic and aperiodic rhythms was bigger when the rhythm was unpredictable (see Figure 8). The interaction between *probabilistic* and *GMSI* ($\beta = -0.001$, SE = 0.000, $p < 0.001$) suggests that the effect of musicality on the standard deviation of asynchrony was higher for unpredictable rhythms than for predictable rhythms (see Figure 9). On the other hand, the interaction between *oscillator* and *GMSI* ($\beta = 0.000$, SE = 0.000, $p < 0.001$) suggests that the effect of musicality on the standard deviation of asynchrony was higher for periodic rhythms than aperiodic rhythms (see Figure 10). Thus an unpredictable rhythm is harder to tap consistently, especially if it's also aperiodic. In addition to this, musical expertise makes it easier to tap consistently in general, but this effect is biggest for unpredictable and periodic rhythms.

Table 11: Statistics for the best fitting model for standard deviation of asynchrony analysis. Significant factors are highlighted.

| With GMSI: **Model 4** | | | | |
|---|---|---|---|---|
| | group / Est. | Est. | S.E. | P |
| (Intercept) | | 0.058 | 0.003 | <0.001 |
| probabilistic | | 0.063 | 0.002 | <0.001 |
| oscillator | | -0.001 | 0.002 | 0.701 |
| GMSI | | -0.001 | 0.000 | <0.001 |
| probabilistic × oscillator | | 0.004 | 0.002 | 0.014 |
| probabilistic × GMSI | | -0.001 | 0.000 | <0.001 |

Table 11: Statistics for the best fitting model for standard deviation of asynchrony analysis. Significant factors are highlighted.

| With GMSI: **Model 4** | | | | |
|---|---|---|---|---|
| | group / Est. | Est. | S.E. | P |
| oscillator × GMSI | | 0.000 | 0.000 | <0.001 |
| SD (Intercept PP) | PP | 0.011 | | |
| SD (Observations) | Residual | 0.029 | | |

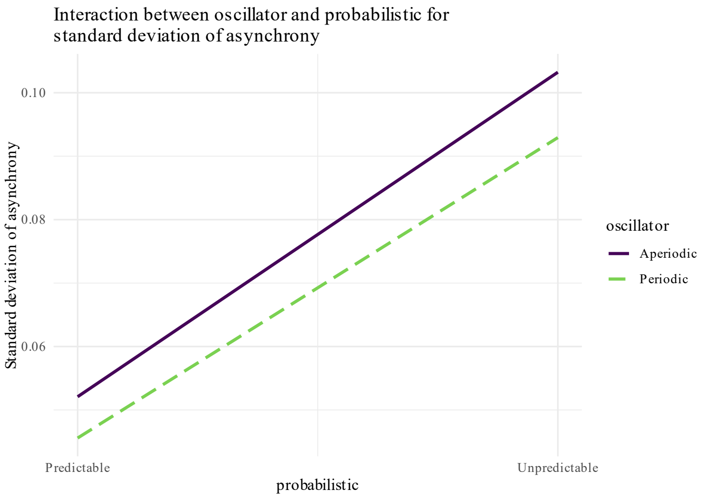


*Figure 8: Interaction plot of probabilistic and oscillator. The difference between standard deviation of asynchrony for aperiodic and periodic rhythms increases when rhythms are unpredictable.*

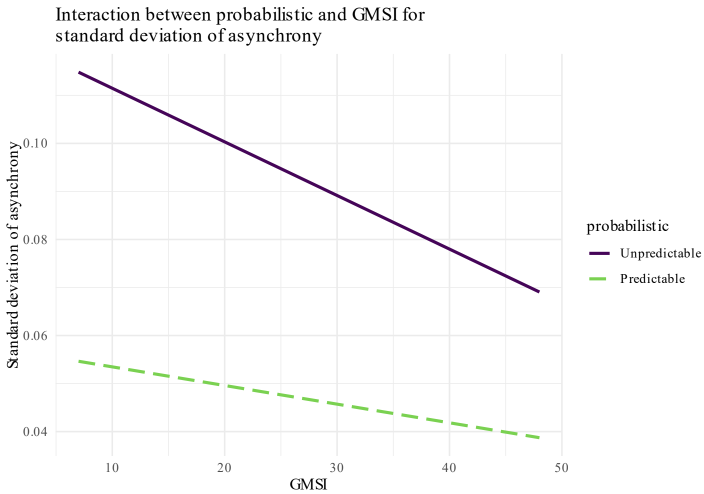


*Figure 9: Interaction plot of probabilistic and GMSI. The standard deviation of asynchrony for unpredictable rhythms decreases with GMSI, while the standard deviation of asynchrony for predictable rhythms only slightly decreases with GMSI.*

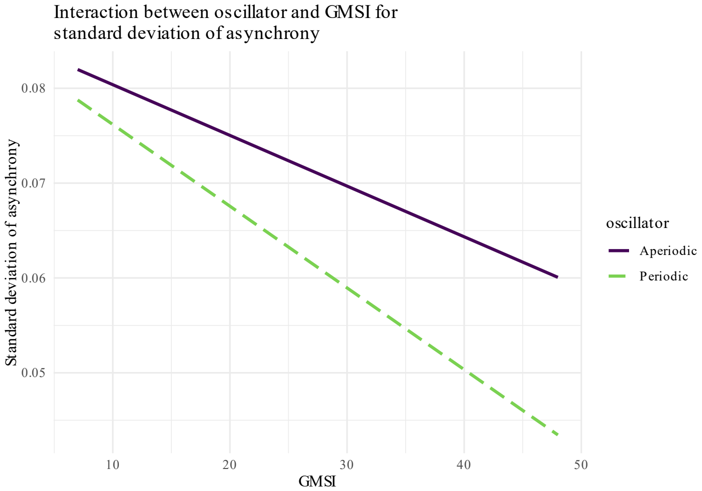


*Figure 10: Interaction plot of oscillator and GMSI. The standard deviation of asynchrony decreases with GMSI and the difference in standard deviation of asynchrony between periodic and aperiodic rhythms increases with GMSI.*

## Overview results

Table 12 shows an overview of the significant factors and their direction per analysis.

Table 12: The main findings per dependent variable. Grey highlighting means that this fixed factor was significant for this variable (with $p < 0.05$). The plus or minus sign represents the direction of the effect for the main effects. Note that a negative effect on reaction time and standard deviation of asynchrony means a better performance. Also note that the interaction effects can only be interpreted when looking at a visualization of the interaction (these can be found in the results section per analysis).

| | Implicit task | | Explicit task | Motor task | |
|---|---|---|---|---|---|
| | Hit rate | Reaction time | Complexity | Correct iterations | SD asynchrony |
| Best fitting model | Model 3 | Model 1 | Model 4 | Model 2 | Model 4 |
| probabilistic | – | + | + | – | + |
| oscillator | | + | – | | |
| GMSI | + | | | + | – |
| probabilistic × oscillator | + | | + | | + |
| probabilistic × GMSI | | | | + | - |
| oscillator × GMSI | - | | + | | - |

## Discussion

The purpose of this study is to gain a better understanding of how neural resonance theory (NRT) and predictive processing theory (PPT) explain temporal expectations and what role musical expertise plays in this, by examining performance on different tasks for rhythms that differ in predictability according to the two theories. To account for task-dependent expectations, we included three types of tasks in our experiment: an implicit task, in which participants had to detect infrequent targets in rhythms, an explicit task, in which participants had to evaluate the complexity of the rhythm, and a motor task, in which participants had to tap along to the rhythm. First, we found that pattern-based expectations, as operationalized by PPT, improved performance on all tasks. These expectations interacted with beat-based expectations, as operationalized by NRT, with larger behavioral effects of beat-based expectations in predictable rhythms for the implicit task and larger behavioral effects of beat-based expectations in unpredictable rhythms for the explicit and motor task. Pattern-based expectations also interacted with musical expertise in the motor task, with higher performance of musically trained participants, especially for unpredictable rhythms. Second, we found that beat-based expectations increased performance more for musically trained individuals. Beat-based expectations by themselves only increased performance in the reaction time of the implicit task. Third, musical expertise by itself only influenced performance in detection of targets in rhythms and reproduction of rhythms. This was illustrated by the positive effect of musical expertise on the hit rate in the implicit task and all measures of the motor task, but no effect on the reaction time of the implicit task and the complexity rating of the explicit task. It thus seems that pattern-based expectations are more accessible for everyone while beat-based expectations are strengthened by musical training, and that musical training facilitates performance differently depending on the type of task and rhythm.

We expected that both types of temporal expectations would increase performance on different tasks. However, only pattern-based expectations were significant in all tasks. Beat-based expectations as a main effect were only significant for the speed in the implicit task and the complexity rating in the explicit task. Interestingly, beat-based expectations sometimes had a negative effect on complexity rating; aperiodic but predictable rhythms were rated as less complex than periodic predictable rhythms. Moreover, the difference in reaction time and complexity between periodic and aperiodic rhythms was much smaller than the difference in these measures between predictable and unpredictable rhythms. It thus seems like pattern-based expectations are more prominent than beat-based expectations.

However, while our research shows some promising effects of different types of temporal expectations, the modeling and comparison of these expectations are not flawless yet. Our study used two computational models which each represented one of the theoretical frameworks and selected rhythms with extreme values for predictability. However, we cannot evaluate whether the extremes of these models are comparable. The difficulty of this lies in the difference in variables that are used per model to indicate the complexity of the rhythms. Since they are different and multiple variables per model, it is difficult to directly compare them to each other. Therefore nothing could be said about the effect size of the different models and the estimates of the fixed factors could not be compared to each other. In addition to this, our study only looked at the extreme values of predictability, while there are many types of rhythms that do not fall in these extremes. In short, we cannot conclude that pattern-based expectations are actually more prominent than beat-based expectations based solely on this research.

Nevertheless, we found an interaction between beat-based and pattern-based expectations, where the influence of beat-based expectations was dependent on the predictability condition. Bouwer et al. (2020) had similar findings where beat-based expectations only led to improved performance when there were no pattern-based expectations. However, in our study these interactions were different between tasks. For example, for the hit rate in the implicit task, the effect of periodicity was only noticeable in predictable rhythms, while for the complexity rating in the explicit task, the effect of periodicity was only noticeable in unpredictable rhythms. The effect of periodicity on performance might thus be rhythm and task dependent, as it does not affect all performances and the interactions varied between tasks. Interestingly, the response variables that showed a significant interaction between beat-based and pattern-based expectations were the same response variables that showed a significant interaction between beat-based expectations and musicality. Within all these interactions, the values of the response variable do not differ much between periodic and aperiodic rhythms for participants with low musical expertise. However, as musical expertise increased, the overall performance got better and the difference in performance between periodic and aperiodic rhythms got larger. Taking all this together, it suggests that beat-based expectations are context dependent, both internal context (e.g. musical expertise) and external context (e.g. pattern-based expectations and tasks).

Next we expected that musical expertise would increase performance in general, regardless of the type of temporal expectations that are formed. Our results suggest that this was partly correct, as musical expertise did have a main effect on three of the five response variables, namely hit rate in the implicit task and number of correct iterations and standard deviation of asynchrony in the tapping task. This is in line with previous research which shows that musicians are better at rhythm perception and production than non-musicians (Pesnot Lerousseau & Schön, 2021; Stupacher et al., 2017; Matthews et al., 2016; Chen et al., 2008). However, in our study, musicality also interacted with beat-based and pattern-based expectations in four of the five response variables, even in some cases when there was no main effect of musicality. For example, in the tapping task, participants with higher musicality were better at tapping the rhythms correctly and consistently than participants with lower musicality, but this difference was especially noticeable in unpredictable rhythms. The same kind of effect was observed between periodic and aperiodic rhythms. This suggests that the effect of musical expertise is not parallel in different rhythm conditions, but rather that musicians especially benefit from their expertise in more complex rhythms. Thus, while musicians are generally better in rhythm perception and production than non-musicians, musicians are especially better in dealing with complex rhythms.

Although musical expertise is a strong predictor of performance on rhythm related tasks, our results did not show any significant effect of musical expertise on the reaction time in the implicit task as either a main effect or interaction. This might be explained by the computation and analysis of the reaction time in the implicit task. Since the analysis was performed per participant per rhythm, an average of the reaction time was taken per participant per rhythm. Participants with lower musical expertise probably did less well on this task then participants with a higher musical expertise, leaving them with less reaction time data per rhythm. In addition to this, the targets that these participants had hit were most likely the easier targets, which will have a shorter reaction time than the more difficult targets. Therefore, the participants with low musicality only had a few reaction times which were probably on the easier targets, while participants with high musicality has more reaction times, including more difficult targets and thus longer reaction times. By taking the average reaction time per rhythm, the higher performance of the musically trained participants negatively affects the performance based on reaction time. The absence of a significant effect of musicality on the reaction time in the implicit task should thus not be seen as an argument to disprove the effects of musical expertise, but rather as an argument to analyze reaction times per target rather than per rhythm.

In summary, while we cannot base solid conclusions on our research, it shows some interesting findings that will open new avenues for research into types of temporal expectations and their effect on rhythm related performance. Indeed, future research should focus on developing a method to be able to directly compare computations of beat-based and pattern-based expectations. Moreover, research should look into the interplay between beat-based expectations, pattern-based expectations and musical expertise, as our study showed some interesting interactions. This will add a new dimension to the body of research that looks at rhythm perception and cognition.

# Appendix A: Figures of model comparisons

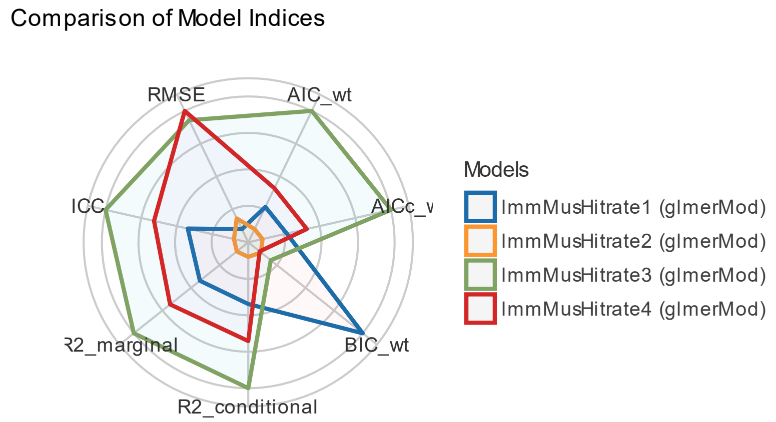


*Figure A1: Model comparisons of hit rate in the implicit task. Model 3 was chosen.*

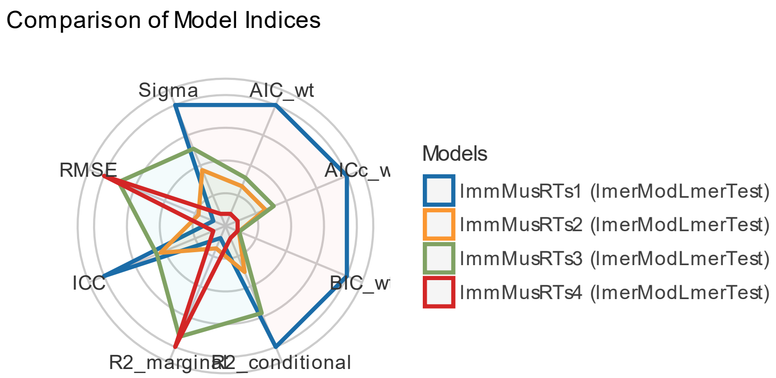


*Figure A2: Model comparisons of the reaction time in the implicit task. Model 1 was chosen.*

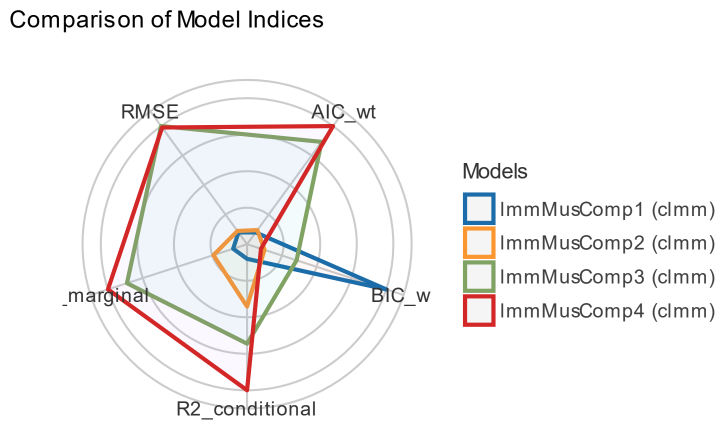


*Figure A3: Model comparisons of the complexity rating in the explicit task. Model 4 was chosen.*

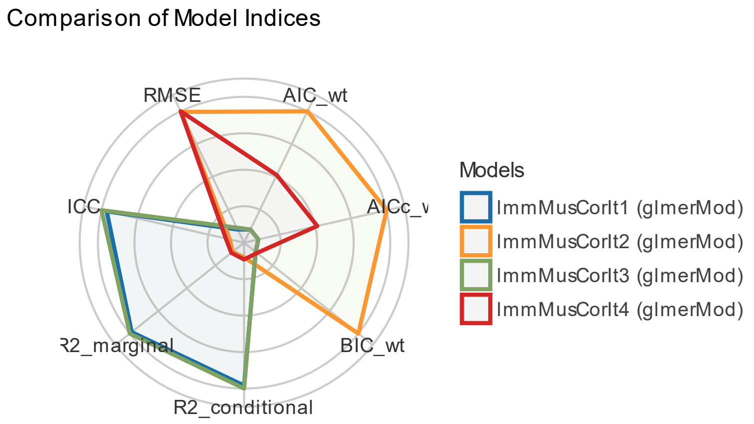


*Figure A4: Model comparisons of the number of correct iterations in the motor task. Model 2 was chosen.*

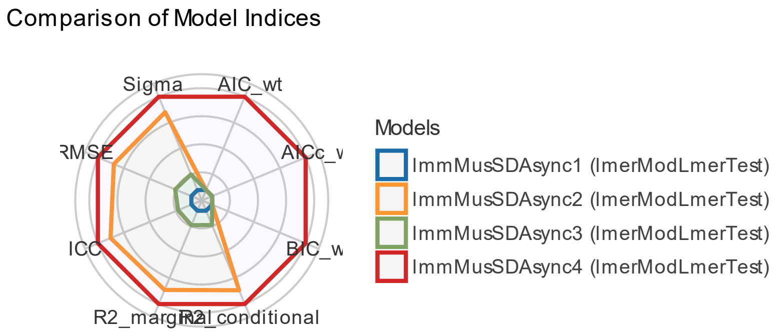


*Figure A5: Model comparisons of standard deviation of asynchrony in the motor task. Model 4 was chosen.*

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