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Encoding of Predictable Tone Deviance

in Recurrent Patterns

Thesis

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by

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I want to thank Dagmar Müller, who was always available to offer advice and encouragement.

Abstract

How does the brain process and represent patterns of tones? By investigating mismatch negativity (MMN) components, prior research (Sussman & Gumenyuk, 2005; Sussman, Ritter & Vaughan, 1998) has suggested that when presented in close temporal proximity, recurrent tone patterns are represented as single objects in auditory memory. In this study, Sussman et al.'s paradigm was replicated and extended, so that a five-tone pattern (A-A-A-A-B), consisting of pure standard (A) tone and pitch deviants (B), was presented in two distinct contexts. Contexts differed in that tone order was either predictable or pseudo-random. Data from two different samples were collected with stimulus-onset-asynchronies of 100 ms and 150 ms, respectively. Clear evidence for the elicitation of an MMN response to deviants, regardless of presentation mode, was obtained for tones presented with an SOA of 150 ms. However, results for faster presentation remained inconclusive. Although conflicting with the original authors' interpretation, the 150 ms SOA results are compatible with results from more recent studies and predictive coding accounts. Nevertheless, reliability analysis suggested that higher trial numbers might be required to obtain reasonably reliable effect estimates. Also, interpretation of ERPs from the 100 ms presentation rate proved difficult due to the overlap of ERP to subsequent tones. More sophisticated analysis methods and possible modifications to the stimulation protocol for future research are discussed.

Introduction

Unraveling the mysteries of human perception might be one of the most fascinating and difficult challenges in cognitive science. We usually have little regard for this, but at every single moment, we achieve something outstanding: By forming a coherent representation from the tangled mess of external stimuli that reach our sensory organs, we make sense of the outside world. In doing so and seemingly effortlessly, we overcome complicated mathematical and philosophical problems. Recent advances in emerging fields like computer vision and machine hearing have provided a sense of how daunting these tasks can be—requiring complex models that consume vast amounts of computational resources and energy. What enables the brain to fulfill these functions with such ease while consuming no more than the power equivalent of a lightbulb?

Over the centuries, many theories have been broad forward in an attempt to answer these questions. While early philosophers like Aristotle believed in the idea of direct or naïve realism (the idea that the outside world is perceived directly), early modern scholars like John Locke promoted the concept of indirect realism, which is highly compatible with the assumption of representationalism in cognitive science (perceptual experiences result from an internal representation rather than directly from external objects). Among the first who developed a consistent theory defining the rules followed by indirect perception were the Gestalt psychologists of the early 20th century. Wertheimer, Koffka, and Köhler hypothesized that Gestalt principles, self-organizing rules on how individual elements should be grouped or separated, guide perception. Intriguingly, they based their principle on the observation that humans perceive a global whole instead of just collections of individual parts.

Much later, auditory scientists faced the same challenges described in the first paragraph, but now in a very particular context: They were puzzled by the brain's ability to convert small air pressure fluctuations into actual auditory percepts. Somehow, the brain forms meaningful perceptual experiences from what can only be described as a busy mess of sound waves that originate from a plethora of different sources differing in pitch, loudness, and spatial position. Known as the *cocktail party effect* (Cherry, 1953), this problem was compared to inferring the positions, shapes, and movements of motorboats on a lake—just by observing how two nearby

objects move up and down the waves. Attempts to find answers to this perplexing question lead to the development of auditory scene analysis (ASA). Not unlike the concepts proposed by the Gestalt theorists six decades earlier, Bregman (1990) suggested that the brain uses so-called *streaming* and *segregation* to form auditory objects from rich spectro-temporal information. At its core, ASA relies on two different categories of grouping, namely *sequential* and *simultaneous* integration: Simultaneous integration (or vertical integration) refers to the grouping of concurrent properties into one or more separable auditory objects, a process informed by temporal cues like common onset and offset, spectral and spatial characteristics. Sequential integration (or horizontal integration), on the other hand, describes how temporally distinct sounds are merged into one or multiple coherently perceived streams (contrary to auditory objects in simultaneous grouping, only one such stream can be actively perceived at any time). While vertical and horizontal grouping can come to different and therefore competing results, sequential grouping often takes precedence over cues for simulations integration (Bendixen, 2014).

Often, the key to understanding such complex phenomena lies in learning about the most basic processing steps. In auditory research, these steps usually come in the shape of very simple stimuli, often consisting of nothing more than pure tones. Such stimuli were also the first to be used in the auditory oddball paradigm, a now well-established and robust paradigm extensively used in event-related potential (ERP) studies (Squires et al., 1975). In its basic form, participants are presented with a series of similar tones or sounds (so-called *standard* events), interrupted by rare tones or sounds that differ in at least one feature (*deviant* events) from the more frequent ones. Strikingly, deviant events elicit more extensive neural activity over sensory areas. This finding is known as the mismatch negativity (MMN) component because when measured using electroencephalography (EEG), a robust negative deflection can be observed in the difference wave obtained by subtracting the response to standard events from the response to deviant events. Negativity is strongest in the frontotemporal area of the scalp, with a peak latency ranging from 100 to 250 ms after stimulus onset. The MMN is not only elicited by individual rare deviant tones embedded in a stream of frequent tones but can also arise in the presence of complex rule violations, i.e. when abstract auditory regularities are violated (Paavilainen, 2013).

MMNs resulting from violations of regularities based on complex auditory regularities are referred to as *pattern MMN* from hereon. Complex auditory regularities can come, for example, in the form of the direction of frequency changes in tone pairs (e.g., Saarinen et al., 1992), infrequent shortenings of SOA (Ford & Hillyard, 1981), or rare breaks in an alternating sequence (Alain et al., 1994).

Interestingly, implications of observed MMN components are highly compatible with another prevalent theory of perception, namely the idea that perception is not exclusively a stimulus-driven bottom-up process but is informed by internal predictions. Despite their recent popularity, these ideas have been around for a long time and famously trace back to the physiologist Hermann von Helmholtz. Gregory's notion of "perception as hypotheses" is similarly well-known. Most recently, this notion has been introduced as a theory known as hierarchical predictive coding. Predictive coding specifically suggests that at every processing state, predictions from so-called *probabilistic generative models* and sensory input are compared continuously, and only their difference, termed *prediction error*, is propagated. MMN responses have been proposed as an index of prediction error (Wacongne et al., 2011). Although other interpretations exist (e.g., Bregman, 1990; May & Tiitinen, 2010), the MMN is frequently interpreted as a marker of expectation violations—a notion particularly emphasizing the role that predictions plays in perception (e.g., István Winkler, 2007).

An interesting situation arises when concurrent predictive clues exist. Following this idea, Sussman et al. (1998) presented participants with a sequence of frequent pure tones and rare pitch deviants while reading a book of their choice. Tones were arranged in a predictable five-tone pattern consisting of four standard tones and one deviant (i.e., A-A-A-A-B-A-A-A-A-B, "-" indicating silence between the tones). ERPs to A and B tones were compared for rapid (SOA of 100 ms) and slow (SOA of 1300 ms) stimulation rates. The 100 ms SOA presentation also included a control condition in which tone order was pseudo-random (e.g., A-A-A-B-A-B-A-A-A) but without altering deviant occurrence probability ($Pr(B) = .20$). When the tone presentation order is random, only the relative occurrence frequency of tones carries value for predicting the next tone. This, we refer to as *proportional regularity*. However, in an ordered presentation, a sequence

of four standard tones is always followed by one deviant tone. Thus, understanding this relationship should allow for *perfect prediction* in which all deviant tones can be expected with absolute certainty. We call this regularity a *pattern regularity*. Provided the underlying mechanism can incorporate such information, the pitch deviants' processing should now correspond to that of standard tones, and therefore no MMN should be elicited.

Interestingly, in Sussman et al., MMNs were only elicited if tone presentation was slow and predictable or fast and random, but not when predictable tones were presented rapidly. In a subsequent study, Sussman & Gumenyuk (2005) used the same pattern at different SOAs (200 ms, 400 ms, and 800 ms). Similar to their previous study, grouped presentation at 400 ms and 800 ms SOA elicited an MMN response, while no evidence for such a deflection was found at a stimulation rate of 200 ms. Sussman et al. attributed this observation to sensory memory limitations. That is, only when auditory memory can accommodate enough repetitions of the five-tone pattern can the brain integrate tones into a coherent representation allowing for accurate predictions of deviant tones. In turn, this would explain the absence of MMNs when the presentation was fast and ordered. They argued that while valid for fast presentation rates with SOAs up to 200 ms, for longer SOAs, pattern duration would be too long, thus exceeding sensory memory capacity.

In a recent in-class replication study, Scharf & Müller (in prep) presented participants with the same stimuli as Sussmann et al. in a very similar experimental setting. Their study only differed in that participants were assigned a simple task in which they had to count visual targets instead of reading a book of their choice. Surprisingly, while descriptive results were compatible with Sussmann et al., pairwise comparisons revealed no significant effect when comparing deviant and standard tones for both the *random* and the *predictable* condition. Further Bayesian analysis remained largely inconclusive, providing only *anecdotal* evidence in favor of the aforementioned effect for *random* presentation and *moderate* evidence for its absence in the *predictable* condition.

In the face of the replication crisis, many scientists have become painfully aware of the importance of replicability (Ioannidis, 2005). Exact or quasi-exact replication studies that try to match the original study's experimental conditions as closely as possible are often regarded as

the gold standard of science (Jasny et al., 2011; Popper, 1935). However, replications that extend, change, or optimize materials or methods of the original work also offer valuable insight. This kind of replication is known as *conceptual* (Schmidt, 2009) and refers to the usage of different methods to repeat the test of a hypothesis or experimental result.

Hypothesis, Aims, and Objectives   This thesis seeks to replicate Sussman et al.'s findings. It mainly follows the procedure laid out by Sussman & Gumenyuk (2005). However, it extends the original design in some critical aspects. First, the aforementioned five-tone patterns are presented in both the *predictable* condition and in the *random* condition. That is, pseudo-random order will be deliberately broken by occasionally presenting (B-)A-A-A-A-B-patterns. In particular, this will ensure that the local history of B tones in the *random* condition is comparable to that in the *predictable* condition. Also, B tones are compared exclusively to their preceding A tones. Lastly, a small number of A-A-A-A-B-sequences will be replaced by A-A-A-A-A sequences in both conditions, allowing for the comparison of physically identical tones in different contexts. The advantage of this design is discussed in more detail in the following paragraphs. A pre-registration covering data collection, processing, and analysis is available at https://osf.io/cg2zd/. Deviations from this pre-specified plan and further exploratory analyses are explicitly reported.

Sussman & Gumenyuk (2005) interpretation of the original results suggests that at fast stimulation rates (SOAs of 200 ms and faster), extracted pattern-based regularities take precedence over proportion-based regularities. If this is true, B tones in the *predictable* condition should not be considered a *mismatch* and should not elicit an MMN response. In contrast, since there is no way to predict B tones in the *random* condition reliably, these tones would still be considered *deviant* events and are therefore expected to generate an MMN. On the other hand, when an A tone replaces a predictable B tone, one would expect an MMN, despite tones beeing physically identical as *pattern regularity* is violated.

Specifically, hypotheses are formulated in regards to the ERPs elicited by the fifth tone in the five-tone sequence (A-A-A-A-**B** or A-A-A-A-**A**; boldface marks tone of interest) compared to the fourth tone in that sequence (A-A-A-**A**-X, "X" marking either an A or a B tone). Suppose

Sussman's interpretation holds, one expects negativity in the N1/MMN time range (about 100-200 ms after tone onset) for deviations in the B-A-A-A-A-B-sequence in the *random* condition since B tones violate the *proportional regularity* within the local context. This kind of response will hereinafter be referred to as a *local MMN*. Besides, one expects no evidence for such an effect (or evidence favoring $\mathcal{H}_0$, i.e., that there is no effect) in the *predictable* context since more informative higher-order predictions based on *pattern regularity* are not violated. Since MMNs should only be observed in one of the conditions, MMNs responses should also differ between conditions. Lastly, the comparison between the 5th A tone and the proceeding A tone (A-A-A-**A**-X vs. A-A-A-A-**A**) should be considered as a mismatch as the rare pattern (A-A-A-A-A) deviates from the more frequent pattern (A-A-A-A-B) and is therefore expected to elicit a significant *pattern MMN* response.

However, other results than those assumed by the original authors are conceivable. Here, two additional theoretical considerations that could explain divergent results will be briefly discussed. Of these, the first one is that the auditory system may not be able to extract complex patterns and therefore relies entirely on *proportional regularities*. In this case, no *pattern regularity* is extracted, and B tones should result in a *local MMN* response regardless of presentation context since the predictive value of the *proportional regularity* does not vary between conditions. Furthermore, this notion implies that local MMN responses would not differ between conditions. Similarly, when violating the pattern regularity by introducing rare A tones at the fifth place of the predictable sequence, no pattern MMN should be triggered since A tones do not constitute a mismatch under this premise.

As a another possibility, the brain might use *proportional regularities* and *pattern regularities* concurrently, resulting in a *local MMN* following B tones in either condition. Also, when violating the *pattern regularity* by presenting A tones at the fifth place, these tones should be detected as deviants and therefore result in a *pattern MMN*.

*Two different types of blocks were presented. In one, five-tone sequences of four standard tones and one deviant tone (A-A-A-A-B) were presented repetitively (*predcitable*condition, top half); in the other, the same sequences were embedded into a stream of random tones (*random *condition, lower half). Occurrence probability of deviants was 18% in both conditions. A small number of predictable B tones were replaced by A tones (A-A-A-A-A) so that the pattern itself was violated.*
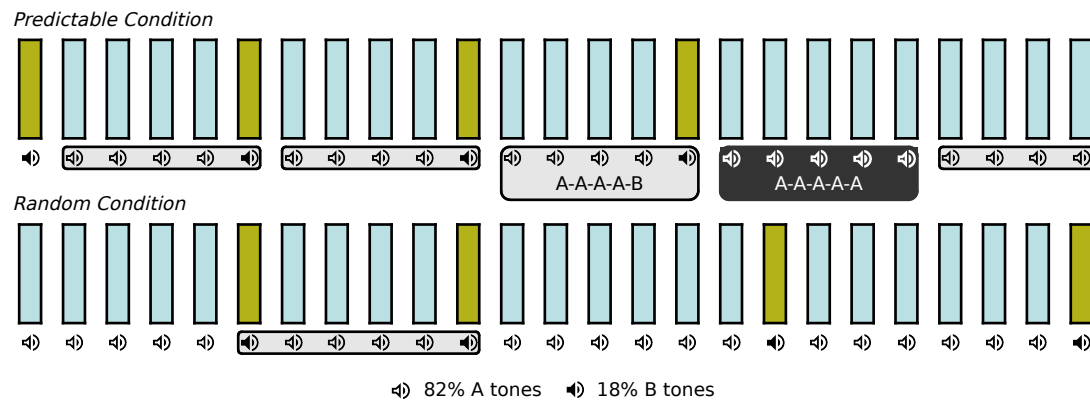
Method

Participants

All participants were recruited at the Institute of Psychology at the University of Leipzig and reported good general health, normal hearing, and normal or corrected-to-normal vision. Written informed consent was obtained before the experiment. Participants were blinded to the purpose of the experiment and received compensation in course credit or money.

For the 100 ms presentation rate, data were collected from twenty participants (2 males, average age 22.3 yrs., $SD = 6.46$, range 18 - 41 yrs.). The 150 ms presentation rate sample consisted of twenty-three psychology undergraduate students (2 males, average age 22.6 yrs., $SD = 5.57$, range 18 - 42 yrs.). Here, participants were also asked to provide information regarding their prior musical training: at the time of the survey, approximately one-third (34.8%) of participants engaged in musical activities, while 8.7% had no prior musical experience.

Procedure and Stimuli

Participants sat in a comfortable chair in a sound-insulated chamber. The experimental setup was practically identical to that of Sussman et al.; however, instead of reading a book, subjects were asked to direct their attention to a silenced but subtitled movie. Commercially available software (MATLAB R2014a; The MathWorks Inc, Natick, MA) in conjunction with the Psychophysics Toolbox extension (version 3.0.12, Brainard, 1997; Kleiner et al., 2007) was used to control stimulus presentation. Stimuli consisted of pure sinusoidal tones with a duration of 50 ms (including a 10 ms cosine on/off ramp), presented isochronously at an SOA of 100 ms or 150 ms, respectively. Presentation of tones was blocked, and participants had the option to take a break after each block. Blocks contained 820 frequent 440 Hz tones (A tones) and 180 infrequent 449 Hz tones (B tones), delivered binaurally using Sennheiser HD-25-1 II headphones at approximately 70 dB ($Pr(B) = .18$, fixed for both conditions). For the 100 ms condition, participants were presented with 40 blocks, while 20 blocks were presented in the 150 ms condition. In one-half of the blocks, tones occurred in pseudo-random order (e.g., A-A-A-B-A-B-A}, *random* condition) while in the other half, tone presentation followed a simple pattern in which a five-tone-sequence of four frequent tones and one infrequent tone (i.e., A-A-A-A-B) was repeated cyclically (*predictable* condition). Block order was counterbalanced across participants. Additionally, A tones replaced 10% of designated (infrequent) B tones in the *predictable* condition, resulting in sporadic five-tone sequences consisting solely of A tones (i.e., A-A-A-A-A), thus violating the *pattern regularity* but not the *proportional regularity*. To assure comparability of local histories between tones of interest in both conditions, pseudo-randomly arranged tones were interspersed with sequences matching those from the predictable condition (i.e., B-A-A-A-A-B-A and B-A-A-A-A-A-A). Care was taken that sequences in the *random condition* were always separated by at least five pseudo-random tones and that in the *predictable condition*, A-A-A-A-A-patterns were always separated by at least two A-A-A-A-B-patterns. A total of 20,000 tones at 150 ms SOA or 40,000 tones at 100 ms SOA were delivered to each participant resulting in a total duration (excluding potential breaks) of 1 hour and 7 minutes (100 ms SOA) and 50 minutes (150 ms SOA), respectively. For statistical analysis, the fifth B or A tone (A-A-A-A-**B** or A-A-A-A-**A**, **boldface** marks the tone of interest) was compared to the preceding

Number of presented tones and average number of epochs after preprocessing by presentation rate, condition and tone type.

	100 ms				150 ms			
	random		predictable		random		predictable	
	A tones	B tones	A tones	B tones	A tones	B tones	A tones	B tones
Total Number of Presented Tones								
	800	400	4000	4000	400	200	2000	2000
Average Number of Epochs after Preprocessing								
	719	360	3606	3241	368	185	1857	1670

A tone (A-A-A-**A**-X). Table 1 contains the number of tones presented as well as the number of remaining trials after preprocessing.

Data Acquisition

Electrophysiological data were recorded from active silver-silver-chloride (*Ag-AgCl*) electrodes using an ActiveTwo amplifier system (BioSemi B.V., Amsterdam, The Netherlands). A total of 39 channels were obtained using a 32-electrode-cap and seven external electrodes. Scalp electrode locations conformed to the international 10–20 system. Horizontal and vertical eye movement was measured using two bipolar configurations with electrodes placed around the lateral canthi of the eyes as well as above and below the right eye. Additionally, three electrodes were placed on the tip of the nose and at the left and right mastoid sites. Data were sampled at 512 Hz and on-line low-pass filtered at 1000 Hz.

Analysis Pipeline

Data preprocessing was implemented using a custom pipeline based on the *MNE Python* software package (Gramfort, 2013) using *Python 3.7.* Computations were partly carried out on a cluster operated by the University Computation Center of the University of Leipzig. Code used

in this thesis is publicly available at https://github.com/marcpabst/xmas-oddballmatch.

First, EEG data were subjected to the ZapLine procedure (de Cheveigné, 2020) to remove line noise contamination. A fivefold detection procedure, as described by Bigdely-Shamlo et al. (2015) was then used to detect bad channels. Namely, this included detecting channels that contained prolonged segments with very small values (i.e. flat channels), the exclusion of channels based on robust standard deviation (deviation criterion), unusually pronounced high-frequency noise (noisiness criterion), and the removal of channels that were poorly predicted by nearby channels (correlation criterion and predictability criterion). Channels considered bad by one or more of these methods were removed and interpolated using spherical splines (Perrin et al., 1989). The BESA Spherical Head Model informed electrode locations for interpolation.

For independent component analysis (ICA), a 1-Hz-high-pass filter (134th order hamming-windowed FIR) was applied (Irene Winkler et al., 2015). Artifact Subspace Reconstruction (ASR, Mullen et al., 2015) was used to identify and remove parts of the data with unusual noise characteristics. ICA was then carried out using the *Picard* algorithm (Ablin et al., 2018, 2017) on principal-component-analysis–whitened (PCA) data. PCA was also used for dimensionality reduction to avoid rank-deficiency when extracting components from data with one or more interpolated channels. The EEGLAB (version 2020.0, Delorme & Makeig, 2004) software package and the IClabel plugin (version 1.2.6, Pion-Tonachini et al., 2019) were used to classify estimated components automatically. Only components clearly classified (i.e., confidence above 50%) as resulting from either eye movement, muscular, or heartbeat activity were zeroed-out before applying the mixing matrix to unfiltered data[1].

In line with recommendations from Widmann et al. (2015) and de Cheveigné & Nelken (2019), a finite impulse response (FIR) bandpass filter from 0.1 Hz to 40 Hz (Hamming window, 0.1 Hz lower bandwidth, 5 Hz upper bandwidth, 0.0194 passband ripple, and 53 dB stopband attenuation) was applied. Continuous data were epoched into 400 ms long segments around stimulus onsets, including a 100 ms pre-stimulus interval. No baseline correction was applied,

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[1] It should be noted that this procedure deviated from the pre-registration in that it was fully automated. The pre-registration states that two experienced analysts should review ICA components.

and segments exceeding a peak-to-peak voltage difference of 100 μV were removed (see Table 1). No dataset met the pre-registered exclusion criterion of less than 100 valid trials per condition; thus, data from all participants (20 for 100 ms presentation rate and 23 for 150 ms presentation rate) were included in the analysis.

Statistical Analysis

Statistical analysis was carried out using the *R* programming language (version 3.2, The R Core Team) using the *rstatix* package (version 2.0, Kassambara, 2020).

Mismatch Negativity.   Calculation of the dependant variable followed the original study's procedure in averaging amplitudes in a time window extending ±25 ms around the expected peak of negativity. Specifically, this peak was obtained by subtracting the average ERP following the A tones from the average ERP following B tones in the *random* condition for both presentation rates separately. To compute mean amplitudes, ERPs to 4th position A tones (A-A-A-**A**-X, **boldface** indicates the tone of interest) and B tones (A-A-A-A-**B**) were averaged separately for both the *random* and the *predictable condition*. Notably, only tones presented as part of a sequence matching the discussed patterns were included in the analysis for the *random condition*,

In accordance with the original analysis by Sussman & Gumenyuk (2005), mean amplitudes for frontocentral electrodes (pooled FZ, F3, F4, FC1, and FC2) and the two mastoid positions (pooled M1 and M2) were averaged separately. Then, for both SOAs, independent two-way repeated-measures analyses of variance (ANOVA) with factors *condition* (levels *predictable* and *random*), *stimulus type* (levels *A tone* and *B tone*), and their interaction were calculated. Following this, significant interaction effects were further investigated using post-hoc *t*-tests.

Bayesian Analysis.   Going beyond the original study and extending the pre-registered procedure, Bayesian analysis was conducted for ANOVA posthoc comparisons. Traditional null hypothesis testing has some limitations that are often overlooked, leading to incorrect conclusions drawn from results. For example, not rejecting the null hypothesis

("non-significance") can usually not be interpreted as evidence in favor of the null hypothesis (e.g., Aczel et al., 2018; Goodman, 2008; Kirk, 1996; Meehl, 1978). Similarly, p-values might exaggerate evidence against $\mathcal{H}_0$ (that is, observed data might be more likely under $\mathcal{H}_0$ than under $\mathcal{H}_1$ even tough $\mathcal{H}_0$ is rejected, e.g., Hubbard & Lindsay, 2008; Rouder et al., 2009; Sellke et al., 2001; Wagenmakers et al., 2018). Conversely, Bayesian hypothesis testing using Bayes factors can provide an intuitive way to compare observed data's likelihood under the null hypothesis versus the alternative hypothesis (Wagenmakers, 2007), thereby making it possible to evaluate the null hypothesis: $BF_{10} = \frac{Pr(data|\mathcal{H}_0)}{Pr(data|\mathcal{H}_1)}$. Here, this approach was applied in agreement with the concept described by Rouder et al. (2009) as an alternative to classical frequentist paired t-tests. Following their sentiment, Bayes factors for within-participant differences y_i were computed assuming $\mathcal{H}_0 : y_i \sim Normal(0, \sigma^2)$ and $\mathcal{H}_1 : y_i \sim Normal(\delta, \sigma^2); \delta \sim Cauchy(0, 1/\sqrt{2})$. A Jeffreys prior was used for the variance σ^2 in both models: $p(\sigma^2) \propto 1/\sigma^2$. Calculations were performed using the Hamiltonian Monte Carlo method implemented in *Stan* (version 2.25, Carpenter et al., 2017) and *RStan* (Stan Development Team, 2020).

Reliability Analysis.   Finally, the relationship between epoch number and the estimate's reliability was analyzed by drawing random subsamples of different sizes from both data sets and calculating split-half reliability employing the Spearman–Brown approach. Thus, single-trial responses for all A and B tones in the *predictable* condition were randomly shuffled. Then, $100, 200, ..., N_{max}$ ($N_{max,100ms} = 2500, N_{max,150ms} = 1300$) epochs were drawn, randomly assigned to one of two halves, and averaged separately for A and B tones. Split-half reliability was calculated based on the mean amplitude in the MMN latency window as defined above. The Spearman–Brown prophecy formula[2] (Brown, 1910; Spearman, 1910) was used to obtain corrected reliability. This procedure was repeated 100 times for each *N*, and obtained split-half-reliabilities were averaged.

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[2] as given by $\rho_{xx'} = \frac{2\rho_{12}}{1+\rho_{12}}$, where ρ_{12} is the Pearson correlation coefficient between the two halfes.

*ERP grand averages (pooled FZ, F3, F4, FC1, and FC2 electrode locations) for an SOA of 100 ms (left) and 150 ms (right), for A tones (A-A-A-**A**-X, blue dashed lines) and B tones (A-A-A-A-**B**, orange dashed line) and their difference (B - A, green solid line). Upper panels show ERPs for tones presented in a predictable pattern (predictable condition) while lower panels show ERPs for tones presented in pseudo-random order (random condition). Shaded area marks MMN latency window used to calculate the distribution of amplitude differences across particpants (middle of each panel) and the difference in topographic maps (right of each panel).*
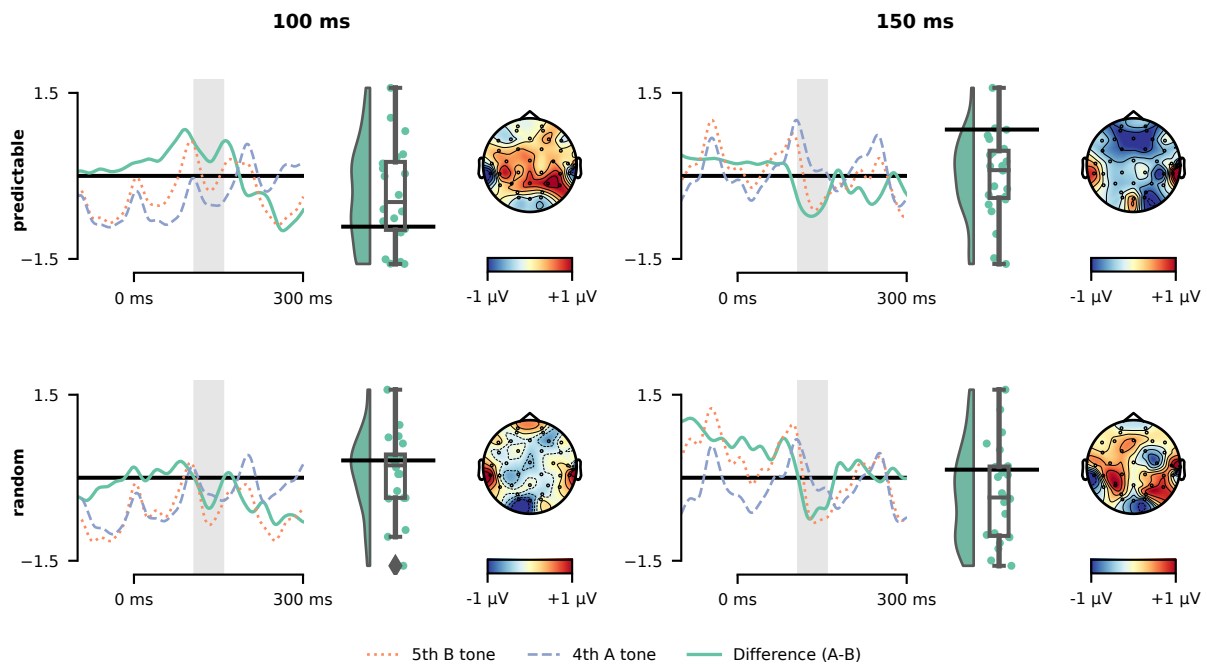

Results

Fig. 2 displays grand averages of event-related potentials (ERP) at pooled FZ, F3, F4, FC1, and FC2 electrode locations to A tones (A-A-A-**A**-X), B tones (A-A-A-A-**B**), and their difference (B tones minus A tones) for both 100 ms (left panel) and 150 ms (right panel) presentation rates. The top half of each panel shows ERPs in the *predictable condition* while the lower half depicts ERPs in the *random condition*. Clearly visible rhythms result from fast presentation frequencies and illustrate the considerable overlap between neighboring tones. Panels also show the distribution of mean amplitude differences in the MMN latency window across participants and the difference of scalp topographies. Similarly, waveforms and mean amplitude difference distributions at pooled mastoid sites are shown in Fig. 4. In the following, results are reported

FIGURE 3.

*ERP grand averages (pooled FZ, F3, F4, FC1, and FC2 electrode locations) for an SOA of 100 ms (left) and 150 ms (right), for 4th A tones (A-A-A-A-X, blue dashed lines) and 5th A tones (A-A-A-A-**A**, orange dashed line) and their difference (B - A, solid green line). Upper panels show ERPs for tones presented in a predictable pattern (*predictable condition*) while lower panels show ERPs for tones presented in pseudo-random order (*random condition). Shaded area marks MMN latency window used to calculate the distribution of amplitude differences across participants (middle of each panel) and the difference of topographic map (right of each panel).*
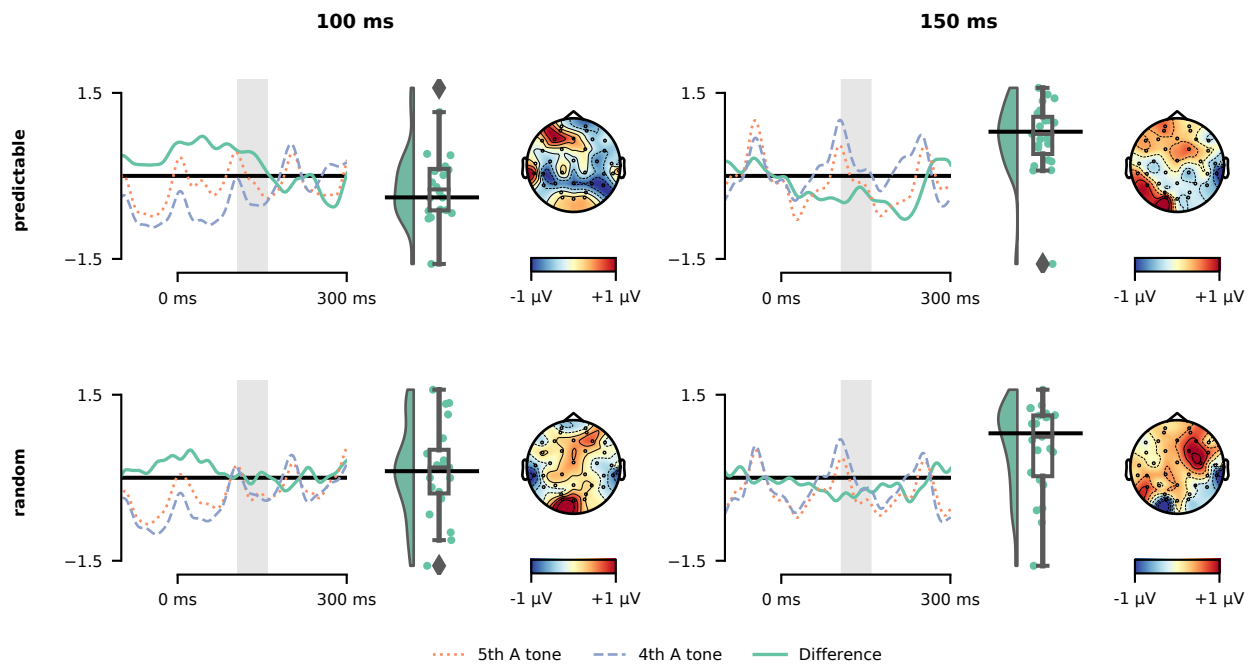

separately for both presentation rates. Table 2 provides an overview of descriptive statistics.

100 ms Presentation Rate.   The MMN latency window was determined to range from 108 ms to 158 ms after stimulus onset. Descriptively, mean amplitudes at pooled frontocentral electrode locations were more negative for randomly presented B tones than for randomly presented A tones ($\Delta M = -0.361\ \mu V$). Strikingly however, B tones in the *predictable* condition seemed to elicit more positive responses than associated A tones ($\Delta M = 0.379\ \mu V$).

ANOVA results for the frontocentral electrode cluster revealed a significant effect of the interaction term (*condition* x *stimulus type*; $F(1, 19) = 17.00, p < .001$) indicating that difference waves for A and B tones differed between condition. Analysis comparing the 4th A tone and the 5th A tone (A-A-A-**A**-X versus A-A-A-A-**A**; Table 5, see appendix) did not result in any

FIGURE 4.

ERP grand averages (pooled M1, M2 electrode locations) for an SOA of 100 ms (left) and 150 ms (right), for A

tones (A-A-A-A-X, blue dashed lines) and B tones (A-A-A-A-B, orange dashed line) and their difference (B - A, solid

*green line). Upper panels show ERPs for tones presented in a predictable pattern (*predictable condition*) while*

*lower panels show ERPs for tones presented in pseudo-random order (*random condition*). The shaded area*

marks the MMN latency window used to calculate the distribution of amplitude differences across participants.
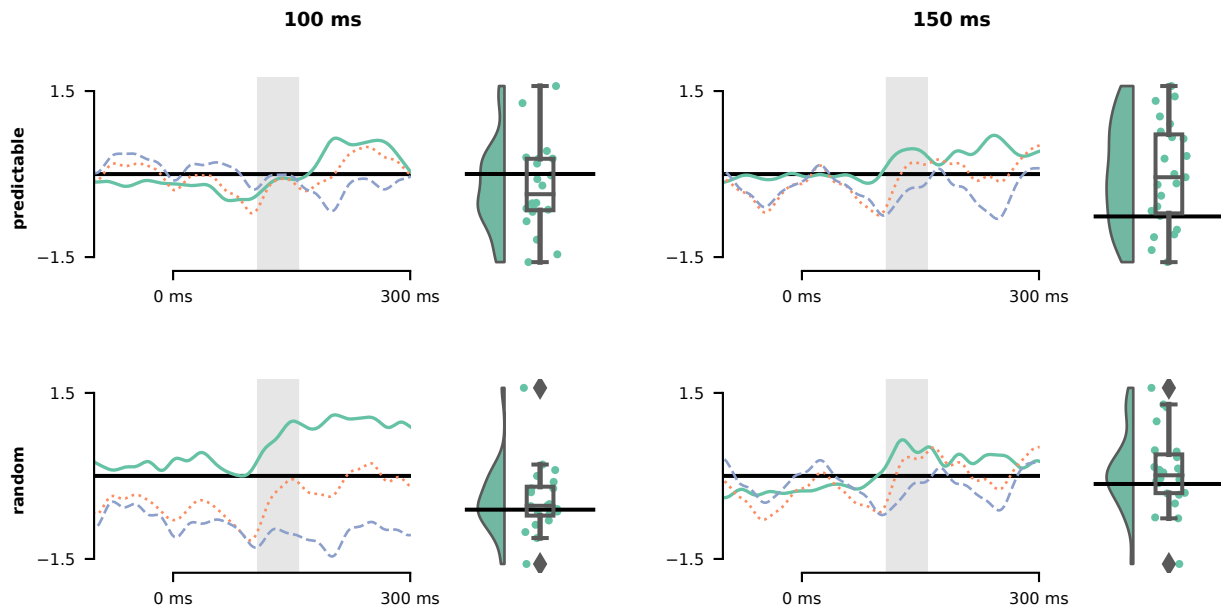
significant effects and therefore remained inconclusive.

Two-tailed Student's *t*-tests and complementary Bayesian analysis were used to test MMN

responses at the frontocentral electrode cluster for significance from zero. The

Benjamini–Hochberg step-up procedure was employed to correct p-values for multiple

comparisons. Results indicated that B tones eclicted more positive responses compared to A

tones when presented in a predictable context ($t(19) = -2.81, p = .022$,

$CI_{.95} = [-0.66, -0.10], BF_{10} = 4.65$). Although descriptive statistics suggested a contrary effect

for randomly presented tones, results remained inconclusive ($t(19) = 1.69, p = .108$,

$CI_{.95} = [-0.09, 0.81], BF_{10} = 0.77$).

150 ms Presentation Rate.   Calculation of MMN window of interest resulted in an interval

from 104 ms to 154 ms after stimulus onset. Descriptivly, B tones in that interval were more

TABLE 2.

Means and standard deviations for condition, stimulus type and electrodes.

SOA	Condition	StimulusType	Frontocentral		Mastoids	
			Mean	SD	Mean	SD
100	predictable	A	-0.40	1.22	-0.06	1.51
		B	-0.02	1.21	-0.21	1.57
	random	A	-0.18	1.83	-1.06	2.63
		B	-0.54	2.14	-0.36	3.24
150	predictable	A	0.32	0.98	-0.39	1.17
		B	-0.27	1.10	-0.01	1.31
	random	A	0.09	1.75	-0.34	1.64
		B	-0.43	1.83	0.15	2.36

negative than corresponding A tones for both *predcitable* ($\Delta M = -0.588 \ \mu V$) and *random* conditions ($\Delta M = -0.518 \ \mu V$). ANOVA results suggested a main effect of factor *stimulus type* for both frontocentral ($F(1, 22) = 21.62, p < .001$) and mastoid electrodes ($F(1, 22) = 6.26$, $p = 0.0200$). Since no significant interaction effect was present, no follow-up tests were performed.

Analysing Split-Half-Reliabilities. Graphed mean split-half reliabilities (Fig. 6) demonstrate that reliability can be characterized as a function of epoch number. Whereas a high number of epochs provided reasonable reliability, particularly small samples resulted in highly unreliable estimates. This observation might serve as a plausible explanation for the inconclusive result in the 100 ms condition, as epoch numbers for B tones ($N_{avg} = 360$) could simply be inadequately low to obtain a reliable estimate. In comparison, the inclusion of all B tones instead of only tones that were part of a five-tone pattern (akin to Sussman & Gumenyuk (2005)) on average led to an eightfold increase in epoch numbers ($N_{avg} = 2920$). Interestingly, statistical comparison for the extended sample was no longer inconclusive but indicated strong evidence in favor of more negative responses to B tones than to A tones ($t(19) = 3.31, p = .004,$

FIGURE 5.

Averaged voltages in the MMN latency window for pooled frontocentral and mastoid electrodes. The colored areas show sample probability density function for A tones (blue) and B tones (red). White diamonds indicate estimated population mean, vertical bars represent 95%-confidence interval. P-values are corrected for multiple comparisons with the Benjamnini-Hochberg procedure. Bayes factors are reported in favor of the alternative hypothesis.
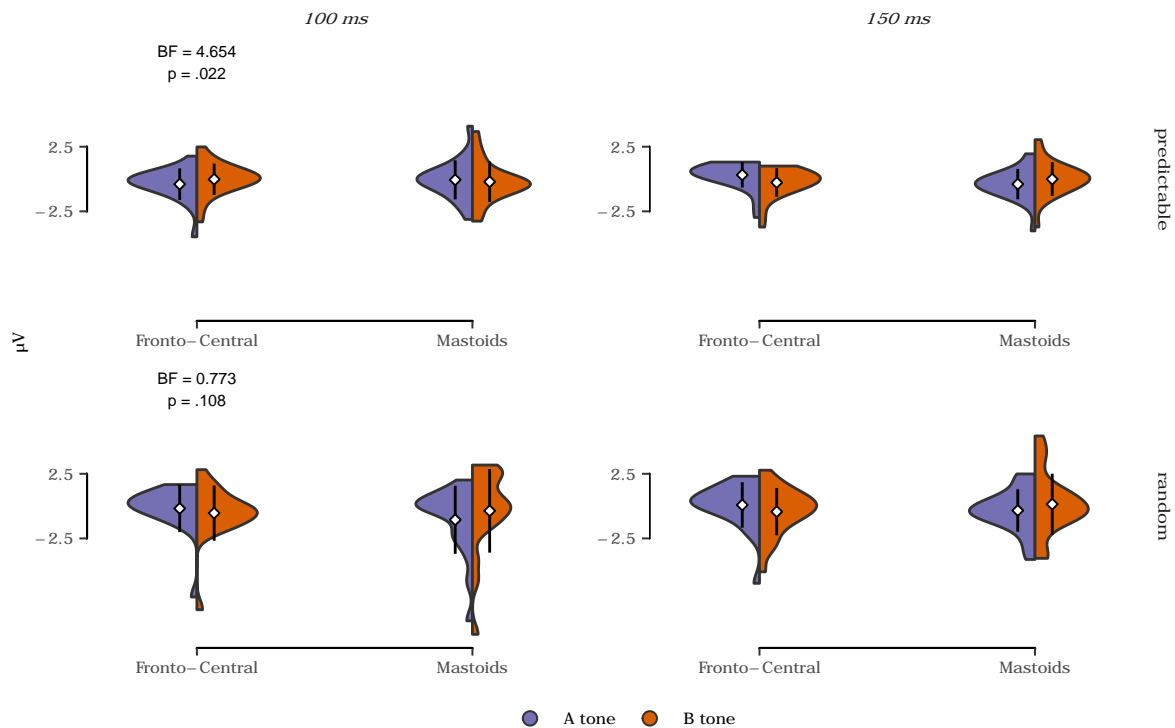

FIGURE 6.

Average split-half reliabilities for A and B tones in random and predictable conditions. Negative values might be interpreted as low or no reliability (Cronbach & Hartmann, 1954). Thin lines in the 150 ms condition indicate extrapolation using the Spearman-Brown formula.
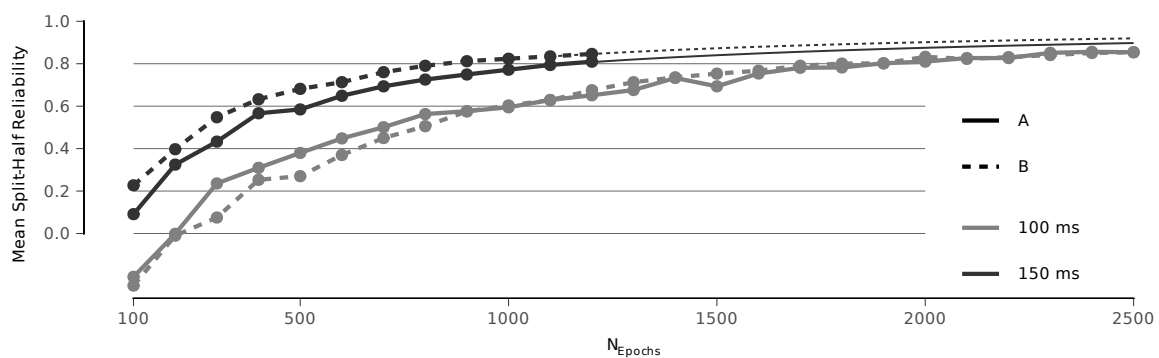
TABLE 3.

Results of the 2-way ANOVA (condition x stimulus type) for B and A tones..

		Effect	DFn	DFd	F	p	ges
100 ms	Frontal	Condition	1.0	19.0	0.137	.715	0.002
		StimulusType	1.0	19.0	0.004	.953	0.000
		Condition x StimulusType	1.0	19.0	16.998	< .001	0.013
	Mastoids	Condition	1.0	19.0	1.388	.253	0.015
		StimulusType	1.0	19.0	0.946	.343	0.003
		Condition x StimulusType	1.0	19.0	2.203	.154	0.008
150 ms	Frontal	Condition	1.0	22.0	0.775	.388	0.005
		StimulusType	1.0	22.0	21.623	< .001	0.036
		Condition x StimulusType	1.0	22.0	0.194	.664	0.000
	Mastoids	Condition	1.0	22.0	0.187	.670	0.001
		StimulusType	1.0	22.0	6.257	.020	0.017
		Condition x StimulusType	1.0	22.0	0.102	.753	0.000

$CI_{.95} = [0.20, 0.88], BF_{10} = 11.92)$.

Discussion

Summary and Interpretation of Results

When presenting rare deviant tones in a stream of frequent standard tones, deviant tones elicit more negative EEG potentials than standard tones. Known as the mismatch negativity (MMN), this finding is one of the most well-studied phenomena in auditory neuroscience. This thesis aimed to conceptually replicate findings reported by earlier studies suggesting that no MMN is generated if certain contextual information is available. Specifically, Sussman et al. (1998) and Sussman & Gumenyuk (2005) proposed that recurring tone sequences at fast SOAs would be processed as a single auditory object. That is, sequences of tones presented in close temporal proximity should be sequentially grouped, and both standard and deviant tones would be fully integrated into this representation. Thus, deviant tones presented as part of these sequences should not constitute a *mismatch* since tones may be fully predictable.

Indeed, the original authors found no MMN response for deviants that were predictable in that they were presented as part of a recurrent pattern (*predictable condition*) and presented at SOAs of 200 ms or faster. Conversely, a clear MMN response was elicited by deviants when presentation order followed no regular pattern (*random condition*) or presentation rate was slower.

This thesis extends Sussman et al.'s work by introducing the five-tone sequences (A-A-A-A-B) from the *predictable* condition–consisting of four standard tones (A) and one pitch deviant (B)–into the *random* condition, allowing for comparisons between both conditions unaffected by differences in local pre-stimulus history. Thus, diverging from the original analysis, only a subset of all presented deviant tones was analyzed in the *random* condition. For the *predictable condition*, the original authors' interpretation suggested that B tones presented as part of the recurrent pattern should not be processed as deviants, and therefore no MMN should be elicited. Extending Sussman et al., it was also hypothesized that rare violations of the pattern, created by replacing the deviant tone with a standard tone (i.e. A-A-A-A-A) would elicit an MMN response although consisting of five physically identical tones. Indexing violations of a more complex rule,

TABLE 4.

Summary of statistical hypotheses tested and their expected and actual outcomes.

	Predictable Presentation		Difference Wave
	$\mathcal{H}_0 : B_{5th} = A_{4th}$	$\mathcal{H}_0 : A_{5th} = A_{4th}$	$\mathcal{H}_0 : \Lambda_{rand} = \Lambda_{pred}$
Expected Outcomes if ...			
only pattern regularities used	×	✓	✓
only proportional regularities used	✓	×	×
both regularities used	✓	✓	
Actual Outcomes			
Results for 100 ms SOA	✓[1]	n.s.	✓[2]
Results for 150 ms SOA	✓	n.s.	n.s.

✓: $\mathcal{H}_1$ is expected to be true / $\mathcal{H}_0$ is rejected, ×: $\mathcal{H}_0$ is true, *n.s.*: inconclusive results   [1] The sign of the effect was different than expected.   [2] Effect might be driven by aforementioned positive effect.

this response was termed *pattern MMN* as opposed to *local MMN* elicited in response to local single-tone violations of the *proportional regularity*.

Several hypotheses were considered in this thesis. Specifically, local MMN were investigated for random and predictable presentation. Elicitation of local MMNs should be based on the extraction and usage of *proportional regularity*, i.e. standard tones are more frequent than deviant tones. Based on the account from Sussman et al. (1998) and Sussman & Gumenyuk (2005), local MMN should, however, not emerge when more informative *pattern regularities* are present, assuming the underlying neuronal mechanism can extract and use these more complex rules. Two alternative underlying explanations were proposed in the introduction section of this thesis. Table 5 gives an overview of the statistical hypotheses that were tested.

Local MMN in the Random Condition.   Deviant tones were expected to elicit more negative responses in the MMN latency range than standard tones when presented pseudo-randomly, mirroring he classical and well-proven auditory oddball paradigm. While this hypothesis held for the slower presentation rate at an SOA of 150 ms, surprisingly, results for faster presentation

(100 ms SOA) remained inconclusive when analyzing the originally defined subset of tones (360 epochs on average). Simulating reliability for different sample sizes by subsampling from all deviants and their directly preceding standard tones (in the *random* condition) revealed that epoch numbers used in the analysis above might only offer low to moderate reliablity. It is important to note, however, that power cannot be directly inferred from reliability, as realibility is inherantly a population-based measure (Humphreys & Drasgow, 1989). Nevertheless, increasing realibility (i.e, avoiding error of measurement) is an important aspect when increasing power (Zimmerman & Zumbo, 2015). Thus, this observation may be interpreted as an indication of low power, potentially explaining the absence of a significant effect. Interestingly, when the sample was expanded to include all deviant tones (2920 epochs on average)–therefore increasing the sample size at the cost of comparability with the *predictable* condition–strong evidence for an MMN was found. Taken together, small effect sizes, low reliability, and the fact that an MMN was found when including more deviant tone raise the question of whether power may have been simply too low to find a concluisive effect.

Local MMN in the Predictable Condition. It was hypothesized that if tones are presented as part of a repeated five-tone sequence with no change in occurrence probability, deviants should *not* elicit mismatch responses. While results remained inconclusive for faster presentation (100 ms SOA), contradictory evidence was found for data collected with an SOA of 150 ms. On the surface, results appeared to be inconsistent with outcomes and conclusions from Sussman & Gumenyuk (2005). as a clear MMN was found in the predictable condition but in Sussman et al. On closer inspection, however, it must be noted that Sussman & Gumenyuk (2005) interpreted the failure to find an effect as the absence of an effect. Therefore, results presented for the 150 ms SOA do not contradict the original findings but merely conflict with the authors' interpretation.

Moreover, although seemingly at odds with Sussman's account, the results parallel those of more recent EEG and MEG studies. For instance, Bekinschtein et al. (2009) and Wacongne et al. (2011) found MMN responses for spectral deviants when presenting five-tone patterns similar to those used in this thesis at an SOA of 150 ms. Analogous results using pure tones and magnetoencephalography were obtained by Recasens et al. (2014) with an SOA of 200 ms.

Surprisingly, in the 100 ms condition, responses to predictable deviants were more positive in the MMN latency range than responses to standard tones. Challenging one's expectations and contradicting the results from the 150 ms condition, this observation was unexpected. However, visual inspection of the ERP trace revealed a possible explanation for this finding: pre-stimulus intervals exhibited clear baseline differences that could have obscured real differences (or no differences) in responses. Thus, this result might have to be considered as an artifact of rapid stimulation and ERP overlap. Possible approaches that remedy this problem and may be used to disentangle evoked responses from subsequent tones will be discussed in a later paragraph.

Contrasting local MNNs between Conditions.   Based on the notion that *local MMNs* should only be elicited in the *random* and not in the *predictable* condition, *local MMNs* should differ between the two conditions. Statistical analysis provided support for this assumption only at the faster 100 ms presentation rate. However, this seems mainly to be driven by the more positive response to deviant tones in the *predictable* condition, as outlined above. Thus, this might not be taken as unconditional evidence in favor of the aforementioned hypothesis, and care must be taken when interpreting this effect.

Pattern-MMN.   No conclusive results were found regarding the hypothesis that violations of the regular five-tone pattern would trigger an MMN response. This assumption was based on the notion of higher-order MMNs that should be elicited when violating patterns of multiple tones that are represented as a single auditory object.

There are several avenues to explain the lack of a detectable effect. First, epoch numbers were relatively small, and therefore statistical power may have been very low. Secondly, mechanisms underlying MMNs for detection of simple local deviations might be different from those responsible for higher-order rule violations. An interesting line of research has suggested that pattern MMNs may involve different latencies than those explored in this study. For example, Bekinschtein et al. (2009) found that pattern deviations did not trigger MMNs at 150 ms SOA, but eclicited deflection at later latencies (>300 ms after stimulus onset). Recasens et al. (2014) reported no evidence for differences at earlier latencies but found that late MMNm responses

(approximately 160 ms after stimulus onset) indexed pattern violations. Based on source reconstruction, authors also argued that neuronal generators engaged in the encoding of *proportional regularities* might be distinct from those encoding *pattern regularities*.

This notion is consistent with computer simulations suggesting that the cortical mechanisms underlying the processing of sensory information as indexed by the MMN response may operate at several different hierarchical levels, spanning from the level of simple stimuli to more complex patterns (Kiebel et al., 2008). There is growing support for this theoretical notion of hierarchical predictive coding in the auditory domain from empirical work (e.g., Cornella et al., 2012). When following this line of reasoning, detection of simple feature deviations should occur at lower cortical levels and become apparent relatively early (i.e., within typical MMN latencies or earlier). In contrast, deviations from complex rules should be detected at higher cortical levels. Thus, effects in ERP would only become visible at later latencies.

In general, these findings might be better explained by a more general predictive coding framework than by the relatively narrow auditory integration-based account originally proposed by Sussman et al.. However, it remains unclear what the SOA's role would be. It is still very much conceivable that short SOAs facilitate pattern extraction compared to slower stimuli presentation. Also, if knowledge of complex regularities is constituted at higher cortical levels, backpropagation might inform mismatch detection at lower levels. While this, evidently, does not seem to result in a full suppression of MMNs to simple deviant tones, MMN responses might be partially diminished, thus explaining results from Sussman & Gumenyuk (2005).

Limitations and Future Research

In sum, results in the 150 ms condition contradict the interpretation of Sussman et al. An MMN response was found regardless of whether deviant tones occurred pseudo-randomly or in a predictable fashion, challenging the idea of a fully integrated representation of the five-tone sequences. However, data collected with tones presented at an SOA of 100 ms remained inconclusive to a large extent due to two likely problems. On the one hand, low epoch numbers might have reduced the reliability of results. On the other hand, the fast presentation rate made

it challenging to interpret responses to subsequent tones due to considerable overlap between ERPs. Several approaches to disentangle individual responses have been suggested (e.g., Plourde et al., 1988; Woldorff, 1993). Regrettably, these options often require specific stimulation patterns that predefine and limit experimental designs. However, more recently proposed methods include regressions ERPs (Ehinger & Dimigen, 2019; e.g., Smith & Kutas, 2015), that allow separating responses to different stimuli employing multiple regression models. Due to collinearity, however, they tend to work poorly on stimuli presented with a constant SOA. One method to deal with this is to add jitter to stimulus onsets, although it remains unclear if jittered presentation would still lead to the proposed grouping of tone patterns as proposed by Sussman et al.

It should also be noted that the original authors' filter parameters differed from those used in this thesis. In addition, the original study did not use ICA for artifact removal. However, it remains questionable whether this can fully account for the discrepancies found. Still, one might examine the impact of different preprocessing steps such as ICA and baselining to improve the interpretability of results. Recently introduced approaches such as multiverse analyses (Steegen et al., 2016) could provide additional transparency in reporting.

Conclusion

In conclusion, results from Sussman et al. (1998) were partially replicated but statistical analysis conflicted with the original authors' interpretation. Evidence was obtained for mismatch detection to simple proportional regularity violation even in the presence of a higher-order pattern. No *pattern MMN* was found at the latencies used by Sussman et al. (1998). Whilst the original hypothesis must be rejected for the slower SOA, no clear conclusions could be reached with respect to the other two possible explanations outlined in the introduction as several statistical tests remained inconclusive or hard to interpret. This was probably due to low reliability and ERPs considerably overlapping between subsequent tones. Larger sample sizes and more sophisticated analysis methods might offer more insight but may need modification to the presentation procedure. Finally, the presented results underline the need for replication studies and careful interpretation of statistical results.

References

Ablin, P., Cardoso, J.-F., & Gramfort, A. (2018). Faster independent component analysis by preconditioning with Hessian approximations. *IEEE Transactions on Signal Processing, 66*(15), 4040–4049. https://doi.org/10.1109/TSP.2018.2844203

Ablin, P., Cardoso, J.-F., & Gramfort, A. (2017). Faster ICA under orthogonal constraint. *arXiv:1711.10873 [Stat]*. http://arxiv.org/abs/1711.10873

Aczel, B., Palfi, B., Szollosi, A., Kovacs, M., Szaszi, B., Szecsi, P., Zrubka, M., Gronau, Q. F., Bergh, D. van den, & Wagenmakers, E.-J. (2018). Quantifying Support for the Null Hypothesis in Psychology: An Empirical Investigation: *Advances in Methods and Practices in Psychological Science.* https://doi.org/10.1177/2515245918773742

Alain, C., Woods, D. L., & Ogawa, K. H. (1994). Brain indices of automatic pattern processing: *NeuroReport, 6*(1), 140–144. https://doi.org/10.1097/00001756-199412300-00036

Bekinschtein, T. A., Dehaene, S., Rohaut, B., Tadel, F., Cohen, L., & Naccache, L. (2009). Neural signature of the conscious processing of auditory regularities. *Proceedings of the National Academy of Sciences of the United States of America, 106*(5), 1672–1677. https://doi.org/10.1073/pnas.0809667106

Bendixen, A. (2014). Predictability effects in auditory scene analysis: a review. *Frontiers in Neuroscience, 8.* https://doi.org/10.3389/fnins.2014.00060

Bigdely-Shamlo, N., Mullen, T., Kothe, C., Su, K.-M., & Robbins, K. A. (2015). The PREP pipeline: standardized preprocessing for large-scale EEG analysis. *Frontiers in Neuroinformatics, 9.* https://doi.org/10.3389/fninf.2015.00016

Brainard, D. H. (1997). The Psychophysics Toolbox. *Spatial Vision, 10*(4), 433–436. https://doi.org/10.1163/156856897X00357

Bregman, A. (1990). *Auditory scene analysis : the perceptual organization of sound.* MIT Press.

Brown, W. (1910). SOME EXPERIMENTAL RESULTS IN THE CORRELATION OF MENTAL ABILITIES1. *British Journal of Psychology, 1904-1920, 3*(3), 296–322. https://doi.org/10.1111/j.2044-8295.1910.tb00207.x

Carpenter, B., Gelman, A., Hoffman, M. D., Lee, D., Goodrich, B., Betancourt, M., Brubaker, M., Guo, J., Li, P., & Riddell, A. (2017). Stan: A Probabilistic Programming Language. *Journal of Statistical Software, 76*(1), 1–32. https://doi.org/10.18637/jss.v076.i01

Cherry, E. C. (1953). Some Experiments on the Recognition of Speech, with One and with Two Ears. *The Journal of the Acoustical Society of America, 25*(5), 975–979. https://doi.org/10.1121/1.1907229

Cornella, M., Leung, S., Grimm, S., & Escera, C. (2012). Detection of Simple and Pattern Regularity Violations Occurs at Different Levels of the Auditory Hierarchy. *PLOS ONE, 7*(8), e43604. https://doi.org/10.1371/journal.pone.0043604

Cronbach, L. J., & Hartmann, W. (1954). A Note On Negative Reliabilities: *Educational and Psychological Measurement*. https://doi.org/10.1177/001316445401400213

de Cheveigné, A. (2020). ZapLine: A simple and effective method to remove power line artifacts. *NeuroImage, 207*, 116356. https://doi.org/10.1016/j.neuroimage.2019.116356

de Cheveigné, A., & Nelken, I. (2019). Filters: When, Why, and How (Not) to Use Them. *Neuron, 102*(2), 280–293. https://doi.org/10.1016/j.neuron.2019.02.039

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods, 134*(1), 9–21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Ehinger, B. V., & Dimigen, O. (2019). Unfold: an integrated toolbox for overlap correction, non-linear modeling, and regression-based EEG analysis. *PeerJ, 7*, e7838. https://doi.org/10.7717/peerj.7838

Ford, J. M., & Hillyard, S. A. (1981). Event-Related Potentials (ERPs) to Interruptions of a Steady

Rhythm. *Psychophysiology*, *18*(3), 322–330.

https://doi.org/https://doi.org/10.1111/j.1469-8986.1981.tb03043.x

Goodman, S. (2008). A Dirty Dozen: Twelve P-Value Misconceptions. *Seminars in Hematology*,

45(3), 135–140. https://doi.org/10.1053/j.seminhematol.2008.04.003

Gramfort, A. (2013). MEG and EEG data analysis with MNE-Python. *Frontiers in Neuroscience*, *7*.

https://doi.org/10.3389/fnins.2013.00267

Hubbard, R., & Lindsay, R. M. (2008). Why P Values Are Not a Useful Measure of Evidence in

Statistical Significance Testing: *Theory & Psychology*.

https://doi.org/10.1177/0959354307086923

Humphreys, L. G., & Drasgow, F. (1989). Some Comments on the Relation Between Reliability

and Statistical Power. *Applied Psychological Measurement*, *13*(4), 419–425.

https://doi.org/10.1177/014662168901300407

Ioannidis, J. P. A. (2005). Why Most Published Research Findings Are False. *PLOS Medicine*, *2*(8),

e124. https://doi.org/10.1371/journal.pmed.0020124

Jasny, B. R., Chin, G., Chong, L., & Vignieri, S. (2011). Again, and Again, and Again …. *Science*,

334(6060), 1225–1225. https://doi.org/10.1126/science.334.6060.1225

Kassambara, A. (2020). *rstatix: Pipe-friendly framework for basic statistical tests* [Manual].

https://CRAN.R-project.org/package=rstatix

Kiebel, S. J., Daunizeau, J., & Friston, K. J. (2008). A Hierarchy of Time-Scales and the Brain.

PLOS Computational Biology, *4*(11), e1000209. https://doi.org/10.1371/journal.pcbi.1000209

Kirk, R. E. (1996). Practical Significance: A Concept Whose Time Has Come. *Educational and*

Psychological Measurement, *56*(5), 746–759. https://doi.org/10.1177/0013164496056005002

Kleiner, M., Brainard, D., Pelli, D., Ingling, A., Murray, R., & Broussard, C. (2007). What's new in psychtoolbox-3. *Perception*, *36*(14), 1–16. https://nyuscholars.nyu.edu/en/publications/whats-new-in-psychtoolbox-3

May, P. J. C., & Tiitinen, H. (2010). Mismatch negativity (MMN), the deviance-elicited auditory deflection, explained. *Psychophysiology*, *47*(1), 66–122. https://doi.org/https://doi.org/10.1111/j.1469-8986.2009.00856.x

Meehl, P. E. (1978). Theoretical risks and tabular asterisks: Sir Karl, Sir Ronald, and the slow progress of soft psychology. *Journal of Consulting and Clinical Psychology*, *46*(4), 806–834. https://doi.org/10.1037/0022-006X.46.4.806

Mullen, T. R., Kothe, C. A. E., Chi, Y. M., Ojeda, A., Kerth, T., Makeig, S., Jung, T.-P., & Cauwenberghs, G. (2015). Real-time neuroimaging and cognitive monitoring using wearable dry EEG. *IEEE Transactions on Biomedical Engineering*, *62*(11), 2553–2567. https://doi.org/10.1109/TBME.2015.2481482

Paavilainen, P. (2013). The mismatch-negativity (MMN) component of the auditory event-related potential to violations of abstract regularities: A review. *International Journal of Psychophysiology*, *88*(2), 109–123. https://doi.org/10.1016/j.ijpsycho.2013.03.015

Perrin, F., Pernier, J., Bertrand, O., & Echallier, J. F. (1989). Spherical splines for scalp potential and current density mapping. *Electroencephalography and Clinical Neurophysiology*, *72*(2), 184–187. https://doi.org/10.1016/0013-4694(89)90180-6

Pion-Tonachini, L., Kreutz-Delgado, K., & Makeig, S. (2019). ICLabel: An automated electroencephalographic independent component classifier, dataset, and website. *NeuroImage*, *198*, 181–197. https://doi.org/10.1016/j.neuroimage.2019.05.026

Plourde, G., Picton, T., & Kellett, A. (1988). Interweaving and overlapping of evoked potentials. *Electroencephalography and Clinical Neurophysiology/Evoked Potentials Section*, *71*(6), 405–414. https://doi.org/10.1016/0168-5597(88)90044-5

Popper, K. (1935). *Logik der Forschung: Zur Erkenntnistheorie der Modernen Naturwissenschaft.*
     Springer Vienna.

Recasens, M., Grimm, S., Wollbrink, A., Pantev, C., & Escera, C. (2014). Encoding of nested levels
     of acoustic regularity in hierarchically organized areas of the human auditory cortex. *Human
     Brain Mapping, 35*(11), 5701–5716. https://doi.org/10.1002/hbm.22582

Rouder, J. N., Speckman, P. L., Sun, D., Morey, R. D., & Iverson, G. (2009). Bayesian t tests for
     accepting and rejecting the null hypothesis. *Psychonomic Bulletin & Review, 16*(2), 225–237.
     https://doi.org/10.3758/PBR.16.2.225

Saarinen, J., Paavilainen, P., Schöger, E., Tervaniemi, M., & Näätänen, R. (1992). Representation
     of abstract attributes of auditory stimuli in the human brain: *NeuroReport, 3*(12), 1149–1151.
     https://doi.org/10.1097/00001756-199212000-00030

Scharf, F., & Müller, D. (in prep). *Predictable changes within fast-paced sound sequences do not elicit
     the mismatch negativity: An in-class replication study.*

Schmidt, S. (2009). Shall we Really do it Again? The Powerful Concept of Replication is Neglected
     in the Social Sciences: *Review of General Psychology.* https://doi.org/10.1037/a0015108

Sellke, T., Bayarri, M. J., & Berger, J. O. (2001). Calibration of p Values for Testing Precise Null
     Hypotheses. *The American Statistician, 55*(1), 62–71.
     https://doi.org/10.1198/000313001300339950

Smith, N. J., & Kutas, M. (2015). Regression-based estimation of ERP waveforms: II. Nonlinear
     effects, overlap correction, and practical considerations. *Psychophysiology, 52*(2), 169–181.
     https://doi.org/10.1111/psyp.12320

Spearman, C. (1910). Correlation calculated from faulty data. *British Journal of Psychology, 3,*
     271–295.

Squires, N. K., Squires, K. C., & Hillyard, S. A. (1975). Two varieties of long-latency positive
     waves evoked by unpredictable auditory stimuli in man. *Electroencephalography and Clinical*

Neurophysiology, 38(4), 387–401. https://doi.org/10.1016/0013-4694(75)90263-1

Stan Development Team. (2020). *RStan: the R interface to Stan.* http://mc-stan.org/

Steegen, S., Tuerlinckx, F., Gelman, A., & Vanpaemel, W. (2016). Increasing Transparency
Through a Multiverse Analysis. *Perspectives on Psychological Science: A Journal of the
Association for Psychological Science, 11*(5), 702–712.
https://doi.org/10.1177/1745691616658637

Sussman, E. S., & Gumenyuk, V. (2005). Organization of sequential sounds in auditory memory:
NeuroReport, 16(13), 1519–1523. https://doi.org/10.1097/01.wnr.0000177002.35193.4c

Sussman, E. S., Ritter, W., & Vaughan, H. G. (1998). Predictability of stimulus deviance and the
mismatch negativity: *NeuroReport, 9*(18), 4167–4170.
https://doi.org/10.1097/00001756-199812210-00031

Wacongne, C., Labyt, E., van Wassenhove, V., Bekinschtein, T., Naccache, L., & Dehaene, S. (2011).
Evidence for a hierarchy of predictions and prediction errors in human cortex. *Proceedings of
the National Academy of Sciences of the United States of America, 108*(51), 20754–20759.
https://doi.org/10.1073/pnas.1117807108

Wagenmakers, E.-J. (2007). A practical solution to the pervasive problems ofp values.
Psychonomic Bulletin & Review, 14(5), 779–804. https://doi.org/10.3758/BF03194105

Wagenmakers, E.-J., Marsman, M., Jamil, T., Ly, A., Verhagen, J., Love, J., Selker, R., Gronau, Q. F.,
Šmíra, M., Epskamp, S., Matzke, D., Rouder, J. N., & Morey, R. D. (2018). Bayesian inference
for psychology. Part I: Theoretical advantages and practical ramifications. *Psychonomic
Bulletin & Review, 25*(1), 35–57. https://doi.org/10.3758/s13423-017-1343-3

Widmann, A., Schröger, E., & Maess, B. (2015). Digital filter design for electrophysiological data –
a practical approach. *Journal of Neuroscience Methods, 250*, 34–46.
https://doi.org/10.1016/j.jneumeth.2014.08.002

Winkler, István. (2007). Interpreting the Mismatch Negativity. *Journal of Psychophysiology*, *21*(3-4), 147–163. https://doi.org/10.1027/0269-8803.21.34.147

Winkler, Irene, Debener, S., Müller, K.-R., & Tangermann, M. (2015). On the influence of high-pass filtering on ICA-based artifact reduction in EEG-ERP. *2015 37th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC)*, 4101–4105. https://doi.org/10.1109/EMBC.2015.7319296

Woldorff, M. G. (1993). Distortion of ERP averages due to overlap from temporally adjacent ERPs: Analysis and correction. *Psychophysiology*, *30*(1), 98–119. https://doi.org/https://doi.org/10.1111/j.1469-8986.1993.tb03209.x

Zimmerman, D., & Zumbo, B. (2015). Resolving the Issue of How Reliability is Related to Statistical Power: Adhering to Mathematical Definitions. *Journal of Modern Applied Statistical Methods*, *14*(2). https://doi.org/10.22237/jmasm/1446350640

Results for comparison of fifth-place and fourth-place A tones

TABLE A1.

Results of the 2-way ANOVA (condition x stimulus type) for fifth-place (A-A-A-A-A) and fourth-place A (A-A-A-A-X) tones.

		Effect	DFn	DFd	F	p	ges
100 ms	Frontal	Condition	1.0	19.0	0.026	.873	0.000
		StimulusType	1.0	19.0	0.938	.345	0.002
		Condition x StimulusType	1.0	19.0	0.961	.339	0.002
	Mastoids	Condition	1.0	19.0	3.593	.073	0.063
		StimulusType	1.0	19.0	1.001	.330	0.003
		Condition x StimulusType	1.0	19.0	0.822	.376	0.005
150 ms	Frontal	Condition	1.0	22.0	0.938	.343	0.003
		StimulusType	1.0	22.0	1.598	.219	0.008
		Condition x StimulusType	1.0	22.0	0.074	.789	0.000
	Mastoids	Condition	1.0	22.0	0.875	.360	0.005
		StimulusType	1.0	22.0	2.798	.109	0.009
		Condition x StimulusType	1.0	22.0	0.930	.345	0.003

Selbständigkeitserklärung

Hiermit erkläre ich, dass ich die vorliegende Arbeit selbständig verfasst habe und keine anderen als die angegebenen Quellen und Hilfsmittel benutzt habe. Alle Stellen der Arbeit, die wörtlich oder sinngemäß aus Veröffentlichungen oder aus anderweitigen Quellen entnommen wurden, sind als solche kenntlich gemacht. Diese Arbeit ist in gleicher oder ähnlicher Form noch bei keiner anderen Prüfungsbehörde eingereicht worden.

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- Alexandra Bendixen, Dagmar Müller, Florian Scharf: Experimentelles Design und Präregistrierung
- Dagmar Müller, Florian Scharf, Sophie Dreikopf, Christine Telle: Datenerhebung

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        Ort und Datum   Marc Pabst