Revisiting the Stimulation-Rate-Dependent Pattern Mismatch Negativity

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Abstract

How does the brain process and represent successive sound in close temporal proximity? By investigating mismatch negativity (MMN) components, prior research (Sussman & Gumenyuk, 2005; Sussman, Ritter & Vaughan, 1998) has suggested that temporal proximity plays an important role in how sounds are represented in auditory memory. Here, we investigate how predictability affects the election of mismatch negativity components in auditory sequences consisting of two tones (frequent tone A = 440 Hz, rare tone B = 494 Hz, fixed SOA 100 ms). In the predictable condition, tones are presented in a fixed order whereas in the unpredictable condition, standards and deviants are presented in a pseudo-random order. We expect to find that B tones in the unpredictable condition will elicit a significant MMN while B tones in the predictable conditions will not. A repeating five-tone pattern was presented at several stimulus rates (200, 400, 600, and 00 ms onset-to-onset) to determine at what temporal proximity the five-tone repeating unit would be represented in memory. The mismatch negativity component of event-related brain potentials was used to index how the sounds were organized in memory when participants had no task with the sounds. Only at the 200-ms onset-to-onset pace was the five-tone sequence unitized in memory. At presentation rates of 400 ms and above, the regularity (a different frequency tone occurred every fifth tone) was not detected and mismatch negativity was elicited by these tones in the sequence. The results show that temporal proximity plays a role in unitizing successive sounds in auditory memory. These results also suggest that global relationships between successive sounds are represented at the level of auditory cortices.

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Introduction

Unraveling the mysteries of human perception might be one of the most fascinating and difficult challenges in cognitive sciences. Mostly unnoticed and at every moment in our lives, we achieve something outstanding: By forming a coherent representation from the tangled mess of external stimuli that reach our senses, we make sense of the outside world. Seemingly effortlessly, in doing so we solve complicated mathematical problems such as the inverse problem. Recent advances in fields like computer vision and machine hearing have provided a sense of how daunting these tasks can be - requiring complex models consuming vast amounts of computational resources and energy. What enables the brain to fulfill these functions with such ease while consuming no more than a lightbulb's power equivalent?

Overy the centruies, many theories have been broad forward attmepting to answer these qustions. Great philosophers like Plato, Kant and Locke had varyiing success in developing their own ideas on the inner workings of perception. Among the first who developed a consistent theory of the rules that perception follows, were the Gestalt psychologist of the early 20th century. Wertheimer, Koffka, and Kühler hypothesized that so-called Gestalt principles, rules on how indiivudal elements should be grosuped or seperated, would guide perception. Their conecpt was based on the the obersation that humans tend to perceive integrated patterns as opposed to just collection of individual elements.

Much later, auditory scientists faced the same challenge described earlier, but now in a very speific context. They were puzzled: How does the brain form meanignful peceptual experiences from what can only be desribed as a busy mess of sound waves that originate from a myriad of different sources differing in pitch, loudness, and spatal position. Known as the *cocktail party effect*, this problem is often compared to inferring the posiitons, shapes and movements of boats on a lake - just by observing how two nearby objects move up and down on the waves. Attempts to find answers to this perplexing question lead to the development of auditory scene anaylsis (ASA). Not unlike the concepts proposed by the Gestalt theorists some decades earlier, (**Bregman?**) suggested that the brain uses so-called *streaming* and *segregation* to form auditory objects from rich spectro-temporal infromation. Auditory scene analysis relies on two different categories of grouping, called sequential and simultaneous integration. Simultaneous or vertical integration refers to the grouping of concurent properties into one or more separable auditory objects, a process informed by temporal cues like common onset and offset, spectral and spatial characteristics among others. Sequential integration on the other hand describes how temporally distinct sounds are merged into one or multiple coherently perceived stream (contrary to simulatinous grouping, only one such stream can be activly perceived at any time). While vertical and horizontal grouping can come to different and therefore competing results (**needsref?**), sequential grouping often takes precedence over cues for simulatoius integration (**needsref?**),

As is so often the case, the key to understanding such complex phenomena seems to lie in learning about the most basic processing steps. In auditory research this steps usually come in the shape of simple stimuli, often consisting of nothing more than pure tones. The auditory oddball paradigm is a well-established and robust paradigm extensivly used in event related potential (ERP) studies. 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 larger neural activity over sensory areas - a finding that is known as the missmatch negativity (MMN) component, because when measured using EEG, a robust negative defelction can be observed obtained by subtracting the reponse to deviant events from the response to standard events. Negativity is strongest in the fronto-temporal area of the scalp with a peak latency ranging from 100 to 250 ms after stimulus onset. The eliction of MMN is not restricted to the reptition of physically identical stimuli but can also be observed when deviant events are of complex nature, e.g. when abstract auditory regularities are violated (Paavilainen, 2013). The regularities can come in the form of relationships between two (Saarinen et al., 1992) or multiple tones (Alain et al., 1994; Nordby et al., 1988; Schröger et al., 1996). Interestingly, this finding is also higly compatible with another prevalent theory of perception: The idea that prediction informs how humans percive the world. These kind of ideas have been around a long time and famously trace back to the remarkable physiologist Hermann von Helmholtz. In its most recent iteration, this theroy has been kown as (hirachical) predictive coding. These theories vary in how much reltive weight they assign to bottom-up processing and prediciton. But regardless of how one might interpret this relaton, the observation of MMN almost inevitably leads to an interpretation in which the processing of deviant signals can be reagrded as a violation of expectation. As such, these these error signals play an important role in understanding prediction, expectation and perception in the human brain.

But how does the brain handle situations in which concuretn but contradictory predictive clues exist? Follwing this idea, E. Sussman et al. (1998) presented participants with a sequency 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 1200 ms) stimulation rates. For the 100 ms SOA, they also included a control condition in which tone order was pseudo-random (e.g. A-A-A-B-A-B-A-A-A) without altering deviant probability ($p_B = 20\%$). When tones are presented randomly, only their relative frequency of occurance carries value for predicting the pitch of the next tone. This, we refer to as *proportional regularity*. In an ordered presentation however, a sequence of four standard tones is alsways followed by a deviant tone. Thus, understanding this relationship should allow for *perfect* precition in which all deviant tones are expected with near-absolute certainty. We call this regularity a *pattern regularity*. Provided the underlaying mechanism can incooperate such information, the processing of the pitch deviants should correspond with that of standard tones and therefore no MMN would be elicted. Interestingly, in the case of Sussman et al., MMNs were only elicted if tone presentation was slow and predcitable or fast and random, but not when precitable tones were presented in a rapid fashion. In a subsequent study, E. S. Sussman & Gumenyuk (2005) used the same pattern at different SOAs (200 ms, 400 ms, and 800 ms). Simmilarly to their prevous study, ordered presentation at 400 ms and 800 ms SOA elicted an MMN response, while at a stimulution rate of 200 ms evidence for such a deflection was absent. 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, tones could be integrated into a coherent representation allowing for accurate predictions of deviant tones. This, in turn, would explain the absence of MMNs in the fast presentation condition. Based on this, they argued that while true for fast presentation rates with SOAs up to 200 ms, for longer SOAs pattern durations would be too long and thus representatations would eceed sensory memory capacity.

In a recent in-class replication study, Scharf & Müller (in prep) presented participants with the same stimuli as Sussmann in a verry simmilar expeirmatnal setting. Their study only differed in that participants were given a simple task in whick they had to count visual targets instead of reading a book of their choice. Surprisingly, while descriptive results were compatible with those of Sussmann et al., pairwise comparison revealaed no significant effect when comparing deviant and standard tones fot both the *random* and the *predeictable* condition. Further Bayesian analysis remained largely inconclusive, providing only *andecdotal* evidece in favor of such an 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. It is clear that exact or quasi-exact replication studies that try to match experimental conditions of the original study as closely as possible are one kay to more reliable reasearch results (Popper, 1935). However, replications that extend, change or optimize materials or methods of the original work also offer valuable insight. These forms of replications are know as conceptal (Schmidt, 2009) and reffer to the use of different methods to repeat the test of a hypothesis or experimental result.

Design and Hypothesises

In this thesis, we try to answer the verry same question Sussman et al. posed: When first-order as well as higher-order relationships between auditory events can offer concurent but varying degrees of predcitve value, what information is used? We largly follow the procure layed out by E. S. Sussman & Gumenyuk (2005) though we deviate in some important aspects First, afforementioned five-tone patterns are not only presented in the *preictable* condition, but also in the *random* context. That is, pseudo-random order will be deberatly broken by occasionally presenting B-A-A-A-A-B-patterns. In particular, this will make sure that the local history of B-tones in the *random* condition is comparable to that in the *predictable* condition. Secondly, B tones are compared exclusively with their preceding A tones. And lastly, a small number of

A-A-A-A-B will be replaced by A-A-A-A-A sequences. The expected advantages of this design are discussed in more detail in the hypothesis section. A pre-registration coverng data collection, processing, and anaylis is avaible at https://osf.io/cg2zd/. Deviations from this pre-specified plan and further, exploratory analysisi will be clearly marked.

E. S. Sussman & Gumenyuk (2005) intepretation of the original results would suggests that at fast stimultion rates, pattern-based regulairites take precedence over proportion-based regularites. If this is indeed the case, B-tones in the *predictable* condtiion should not be considered a *missmatch* and thus should not elict an MMN. In contrast, since there is no way to reliably predict B-tones in the *random* condition, these tones would be still considered as *deviant* events and are therefore expcected to generate a MMN.

Specifically, the hypotheses are concerned with the ERPs elicted by the 5th tone in the five-tone sequence (A-A-A-A-**B** or A-A-A-A-**A**) compared to the 4th tone in that sequence (A-A-A-**A**-X, "X" marking either an A or an B tone).

We will also compare the repective difference waves (A-A-A-A-**B** vs. A-A-A-**A**-B) in the *precitable* condition with that in the *random* condition.

In summary, i) one expects negativity in the N1/MMN time domain (about 100-200 ms after the beginning of the tone) for deviations in the BAAAA*B* sequence in the *random* condition, since B tones violate the *proportioanl regularity*, ii) 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, and iii) the difference waves should differ significantly. If however no *pattern regularity* is extracted, B-tones should concotenly exlivt an MMN regardless of presentation context since the predictive value of the *proportional regularity* does not differ between conditions. In that case, difference waves should not differ. As a third possiblity, the brain might use *proportional regularities*and *pattern regularities* concurently, resulting in a negativity following B-tones in either condition. To further differentiate between these explainations, we also expect the comparison of 5th A tones to peceedin A tones (A-A-A-**A**-X vs. A-A-A-A-**A**) to elict a significant MMN for options i and iii, but not for option ii.

Methods and Materials

Data Acquisition

Participants

100 ms Presentation Rate Twenty-three psychology undergraduate students (2 males, average age 22.6 yrs., $SD = 5.57$, range 18 - 42 yrs.) were recruited at the Institute of Psychology at the University of Leipzig. All participants reported good general health, normal hearing and had normal or corrected-to-normal vision. Written informed consent was obtained before the experiment. One-third (34.8%) of participants spent time enaging in musical activities at time of survey, while 8.7% had no prior experience in music training. Handedness was asseced using a modified version of the Edinburgh Handedness Inventory (Oldfield, 1971, see appendix). A majoritiy (00%) of parcicipants favored the right hand. Particpants were blinded in respect to the purpose of the experiment and received course credit in compensation.

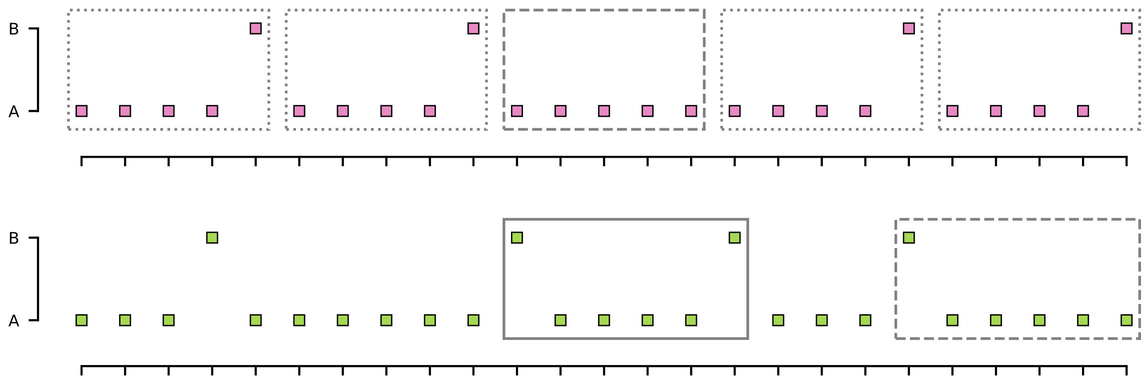
150 ms Presentation Rate Twenty healthy participants (0 males, average age 00.0 yrs., $SD = 0.00$, range 00 - 00 yrs.) were recruited. Particpants gave informed consent and reported normal hearing and corrected or corrected-to-normal vision. All participants were naive regarding the purpose of the experiment and were compensated in cource credit or money. 00 participants (00%) had received musical training in the last 5 years before the experiment while 00 (00%) reported no musical experiance. In addition, participants reported if streaming occured during the presentation of the tones.

Stimuli and Stimulis Delivery

Participants where seated in a comfortable chair in a sound-insulated cabin. The experimental setup was practically the same as the one used ny Sussman, but instead of reading a book, subjects were asked to focus their attention on a previously selected movie. Movies were presented with subtitles but without sound. 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.

Figure 1.

Tones of two different frequencies (A=440 Hz, B=449 Hz) were presented in two blocked conditions: In the "predictable" condition (top half), tones followed a simple pattern in which a single B-tone followed four A-tones. Some designated B-tones were replaced by A-tones ("pattern deviants"). In the "random" condition (lower half), tones were presented in a pseudo-random fashion ()



Stimuli consisted of pure sinusoidal tones with a duration of 50 ms (including a 10 ms cosine on/off ramp), presented isochronously at a stimulation onsets asynchrony (SOA) of 100 ms for study 1 and 150 ms for study 2. Overall, a total of 40 blocks containing a mixture of frequent 440 Hz tones ("A" tones) and infrequent 449 Hz tones ("B" tones) were delivered binaurally using Sennheiser HD-25-1 II headphones. In one half of the blocks, tones were presented in pseudo-random order (e.g. A-A-A-B-A-B-A}, "random" condition), while in the remaining block 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 accross participants. The ratio of frequent and infrequent tones was 10% for both conditions. Within the predictable condition, 10% of designated (infrequent) B tones were replaced by A tones, resulting in sporadic five-tone sequences consisting solely of A tones (i.e. A-A-A-A-A), thus violating the predictability rule. To assure comparability of local histories between tones in both conditions, randomly arranged tones were interspersed with sequences mimicking aforementioned patterns from the predictable condition (B-A-A-A-A-B and B-A-A-A-A-A) in the random condition. A grand total of 2000 tones in study 1 and 4000 tones in study 2 were delivered to each participant.

Data Acquisition

Electrophysiological data was recorded from active silver-silver-chloride (*Ag-AgCl*) electrodes using an ActiveTwo amplifier system (BioSemi B.V., Amsterdam, The Netherlands). Acquisition was monitored online to ensure optimal data quality. A total of 39 channels were obtained using a 32-electrode-cap and 7 external electrodes. Scalp electrode locations conformed to the international 10–20 system. Horizontal and vertical eye movement was obtained using two bipolar configurations with electrodes placed around the lateral canthi of the eyes and above and below the right eye. Additionally, electrodes were placed on the tip of the nose and at the left and right mastoid sites. Data was sampled at 512 Hz and on-line filtered at 1000 Hz.

Analysis Pipeline

Data prepossessing was implemented using a custom pipeline based on the *MNE Python* software package (Gramfort, 2013) using *Python 3.7*. All computations were carried out on a cluster operated by the University Computation Center of the University of Leipzig. Code used in thesis is publicly available at https://github.com/marcpabst/xmas-oddballmatch.

First, EEG data was 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 and subsequently interpolate bad channels. This specifically included the detection of channels thain contain prolonged segments with verry small values (i.e. flat channels), the exclusion of channels based on robust standard deviation (deviation criterion), unusualy 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). Electrode locations for interpolations were informed by the BESA Spherical Head Model.

For independant component anaylsis (ICA), a 1-Hz-high-pass filter (134th order hamming-windowed FIR) was applied prior to ICA (Winkler et al., 2015). To further reduce artifacts, Artifact Subspace Reconstruction (ASR, Mullen et al., 2015) was used to identify and remove parts of the data with unusual characteristics (bursts). ICA was then carried out using the *Picard* algorithm (Ablin et al., 2018, 2017) on PCA-whitened data. To avoid rank-deficiency when extracting components from data with one or more interpolated channels, PCA was also used for dimensionality reduction. 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 automatically classify estimated components. 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.

In line with recommendations from Widmann et al. (2015) and de Cheveigné & Nelken (2019), a ORDER finite impulse response (FIR) bandpass filter from 0.1 Hz to 40 Hz (Hamming window, 0.1 Hz lower bandwith, 4 Hz upper bandwidth, 0.0194 passband ripple, and 53 dB stopband attenuation). Continuous data was epoched into 400 ms long segments around stimulus onsets. Epochs included a 100 ms pre-stimulus interval. No baseline correction was applied. Segments exeeding a peak-to-peak voltage difference of 100 µV were removed. On average, NN epochs No data set meet the pre-registrated exclusion criterion stated of less than 100 trials per condition, thus data from all participants (20 for 100 ms presentation rate and 23 for 150 ms presentation rate) was analysed.

Statistical Analysis

Statistical Analyis was carried out using the R programming language (version 3.2). Dependent variables quantifying missmatch negativity response were calculated by averaging amplitudes in a time window strechting ±25 ms around the maximum negativity obtained by subtracting the mean ERP timecourse following the A tones from the mean ERP following B tones. 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 seperatly for both the *random* and the *predictable condition*. For the *random condition*, only tones that were part of a sequence matching the patterns in the *predictable* condition were included.

In accordance with the original analysis by E. S. Sussman & Gumenyuk (2005), mean amplitudes for frontocentral electrodes (FZ, F3, F4, FC1, and FC2) and the two mastoid positions (M1 and M2) were averaged separately. Then, for both SOAs, independant three-way repeated measures analyses of variance with factors *condition* (factors *predcitable* and *random*), *stimulus type* (factors *A tone* and *B tone*), *electrode locations* (levels *fronto-central* and *mastoids*), and all possible interactions were calculated. Following this, significant interactions effects were further investigated using post-hoc *t*-tests.

Besides the fact that p-values are frequently misinterpreted (Hubbard, 2011), traditional null hypothesis testing fails to explicitly quantify evidence in favor of $\mathcal{H}_0$ (e.g. Aczel et al., 2018; Goodman, 2008; Kirk, 1996; Meehl, 1978). Similarly, p-values can 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).[1] 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): $BF_{10} = \frac{Pr(data|\mathcal{H}_0)}{Pr(data|\mathcal{H}_1)}$. 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. Folowing this notion, 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).

Finally, the relationship between epoch number and the reliability analysis was analyzed by drawing random subsamples of different sizes from both our data sets and calculating split-half reliability employing the Spearman-Brown approach. For this, single trial responses for all A and B tones in the predictable condition were randomly shuffled. Then, $100, 200, ..., N_{max}$ ($N_{max,100ms} = 3000, N_{max,150ms} = 1500$) epoches were drawn, randomly assigned to one of two halfes, and afterwards averaged seperatly for bothtone types. Then, split-half realibility was calculated using the differences between A and B tones in the MMN

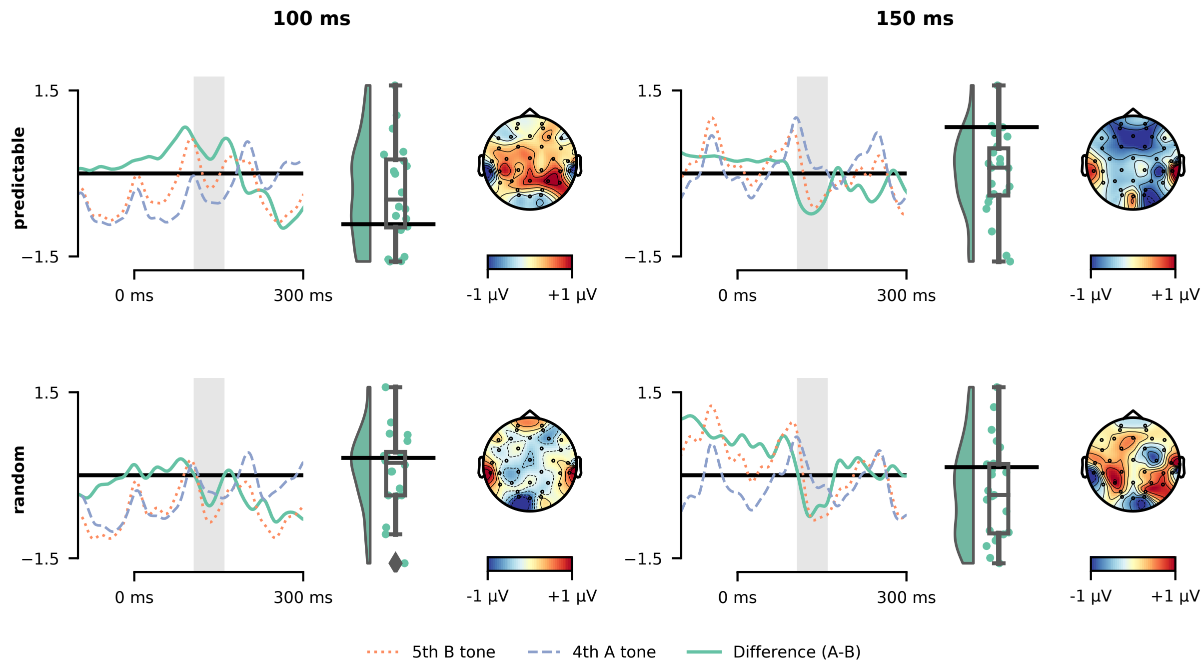
[1] it doesn't quantify evidence in favor of the $\mathcal{H}_1$, either

latency window using the Sprearman-Brown prophecy formula[2] (Brown, 1910; Spearman, 1910). This procedure was repeated 100 times for each N and split-half-relaibilites thus obtained were subsequently averaged.

[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.

Figure 2.

*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 predcitable pattern* (predcitable condition) *while lower panels show ERPs for tones presented in pseudo-random order* (random condition)*. Shaded area marks MMN latency window (110 ms to 160 ms) used to calculate the distribution of amplitude differences across particpants (middle of each panel) and the difference of topographic maps averaged over the same interval (right of each panel).*

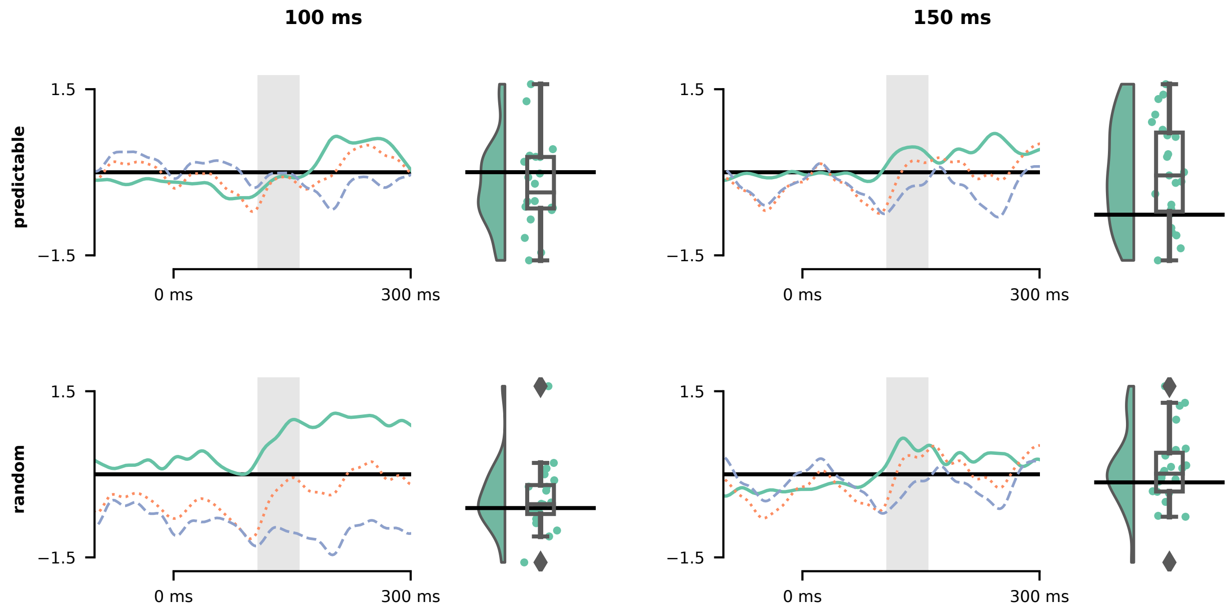


Results

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** tone minus **A** tone) are displayed in fig. 2 for both 100 ms (left panel) and 150 ms (right panel) stimulus onset asynchronies. The top half of each panel shows ERPs in the *predictable condition* while the lower half depicts ERPs in the *random condition*. For both presentation rates, clear rhythms matching the presentation frequency of 10 Hz (100 ms) and respectively 6.667 Hz (150 ms) are seen as a result of substantial overlap of neighbouring tones. Panels also show the distribution of mean amplitude differences in the MMN latency window (as defined above, 110 ms to 160 ms after

Figure 3.

*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, green solid line). Upper panels show ERPs for tones presented in a predcitable pattern* (predcitable condition) *while lower panels show ERPs for tones presented in pseudo-random order* (random condition)*. Shaded area marks MMN latency window (110 ms to 160 ms) used to calculate the distribution of amplitude differences across particpants.*



stimulus onset) across participants and the difference of scalp topographies averaged over the same interval. Similarly, waveforms and mean amplitude difference distributions at pooled mastoid sites are shown in fig. 3.

Evoked responses to A and B tones were compared by calculating mean amplitudes in the MMN latency window. Mean amplitudes in the MMN latency window and their standard deviations (SD) for all conditions are shown in Table X. Descriptively, mean amplitudes at pooled fronto-central electrode locations were more negative for randomly presented B tones than for randomly presented A tones, regardless of tone presentation rate (100 ms: $\Delta M = -0.358\ \mu V$; 150 ms: $\Delta M = -0.555\ \mu V$) This also held for tones presented predictably, but for the slower of the two presentation rates only ($\Delta M = -0.582\ \mu V$)). In contrast, when predictable tone patterns occurred at a faster 100 ms rate, B tones elicited descriptively more positive responses than A tones ($\Delta M = 0.383\ \mu V$). Descriptive comparison of evoked responses from pooled left and right mastoids revealed that pseudo-randomly presented B tones were more positive in the MMN latency window than A tones (100-ms-SOA: $\Delta M = 0.746\ \mu V$, 150-ms-SOA: $\Delta M = 0.510\ \mu V$). A similar observation could be made for predictable B tones compared to the preceding A tones at an SOA of 150 ms ($\Delta M = 0.399\ \mu V$)) but not for the faster presentation rate ($\Delta M = -0.132\ \mu V$).

Table 1

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

SOA	Condition	StimulusType	Mean	SD	Mean	SD
100	predictable	A	-0.431	1.23	-0.052	1.51
		B	-0.0477	1.22	-0.184	1.56
	random	A	-0.225	1.82	-1.04	2.64
		B	-0.583	2.16	-0.296	3.23
150	predictable	A	0.25	0.967	-0.349	1.19
		B	-0.331	1.09	0.0492	1.33
	random	A	0.0233	1.75	-0.292	1.64
		B	-0.531	1.82	0.218	2.38

Inference statistics provided support for these findings. For the 100 ms stimulation rate, the three-way ANOVA yielded a significant three-way interaction effect (*condition* x *stimulus type* x *electrode locations*; $F(1, 19) = 7.53$, $p = .013$) but failed to reveal main effects for factors *stimulus type* ($F(1, 19) = 1.05$, $p = .318$), *condition* ($F(1, 19) = 0.83$, $p = .373$), and *electrode locations* ($F(1, 19) = 0.04$, $p = .852$). In contrast, for tones presented at a SOA of 150 ms only the two-way interaction term *stimulus type* x *electrode locations* had a significant effect ($F(1, 22) = 20.76$, $p = 0.0002$). Mean amplitudes in the MMN latency window however did not differ for factors *stimulus type* ($F(1, 22) = 0.32$, $p = 0.5790$), *electrode locations* ($F(1, 22) = 0.04$, $p = 0.8540$) or *condition* ($F(1, 22) = 0.08$, $p = 0.7800$).

Two-way ANOVAs (*condition* x *stimulus type*) were carried out separately for pooled fronto-central and mastoid electrode locations. For 100 ms tone presentation rate, the *condition* x *stimulus type* interaction only resulted in a significant effect for the fronto-central electrode cluster ($F(1, 19) = 16.75, p = 0.0006$) but not for pooled mastoid sites ($F(1, 19) = 2.37$, $p = 0.1410$) indicating that the three-way interaction effect *condition* x *stimulus type* x *electrode* is indeed driven by the amplitude differences in the fronto-central electrode locations . Contrary to this, for the 150 ms presentation rate, main effects for *stimulus type* were significant for both fronto-central and mastoid sites, suggesting that there was both an MMN at fronto-central locations as well as a polarity-reversal at the mastoid electrodes.

Post-hoc tests between ERPs to A and B tones were carried out using two-tailed Student's t-tests complemenary Bayesian analysis.. P-values were corrected for multiple comparisons using the Benjamini–Hochberg step-up procedure. For the 100 ms SOA, results indicated a significant effect only for predictable tones at fronto-central electrodes ($t(19) = -2.77$, 0.0246, $CI_{.95} = [-0.67, -0.09]$). For the 150 ms SOA, B tones elicited significantly more negative ERPs than B tones at fronto-central electrode locations in both predictable ($t(22) = 5.20$, 0.0002584, $CI_{.95} = [0.35, 0.81]$) and random ($t(22) = 3.28$, 0.00909333333333333, $CI_{.95} = [0.20, 0.91]$) conditions. Significant polarity reversal effects at mastoid sites were only present for predictable ($t(22) = -3.95$, 0.002716, $CI_{.95} = [-0.61, -0.19]$) tones but not for randomly presented ($t(22) = -1.59$, 0.169333333333333, $CI_{.95} = [-1.18, 0.16]$) tones.

To investigate whether absence of evidence for an MMN might be due to low whin-participant sample sizes, the anaylsis was repeated for the *random* condition including not only B tone trials that occured within a five-tone sequence (as with the pregistrated analyis path), but all B tones and their immediately preceding A tone. Results from this comparison are shown in (**Fig?**):??.

Split-half reliabilities are displayed in fig. 5. Simulated values match the curve expected from the Spearman-Brown formula. In the context of classcial test theory, this method relates the length of a test (or *experiment*) to the number of items (or *trials*). The first derivitve of the Spearman-Brown function is monotonically decreasing, leading to two different observation: i) Adding additional epochs (extending the test length by an absolute value in classcial test theory terms) has a large effect when the number of already present epochs is low, but has only little

Figure 4.

Averaged voltages in the MMN latency window for pooled fronto-central and mastoid electrodes. Colored areas show sample probability density function for A tones (green) and B tones (red). White diamonds indicate estimated population mean, vertical bars represent 95%-conficence interval. Only Benjamini-Hochberg-corrected p-values < 0.05 *are shown.*

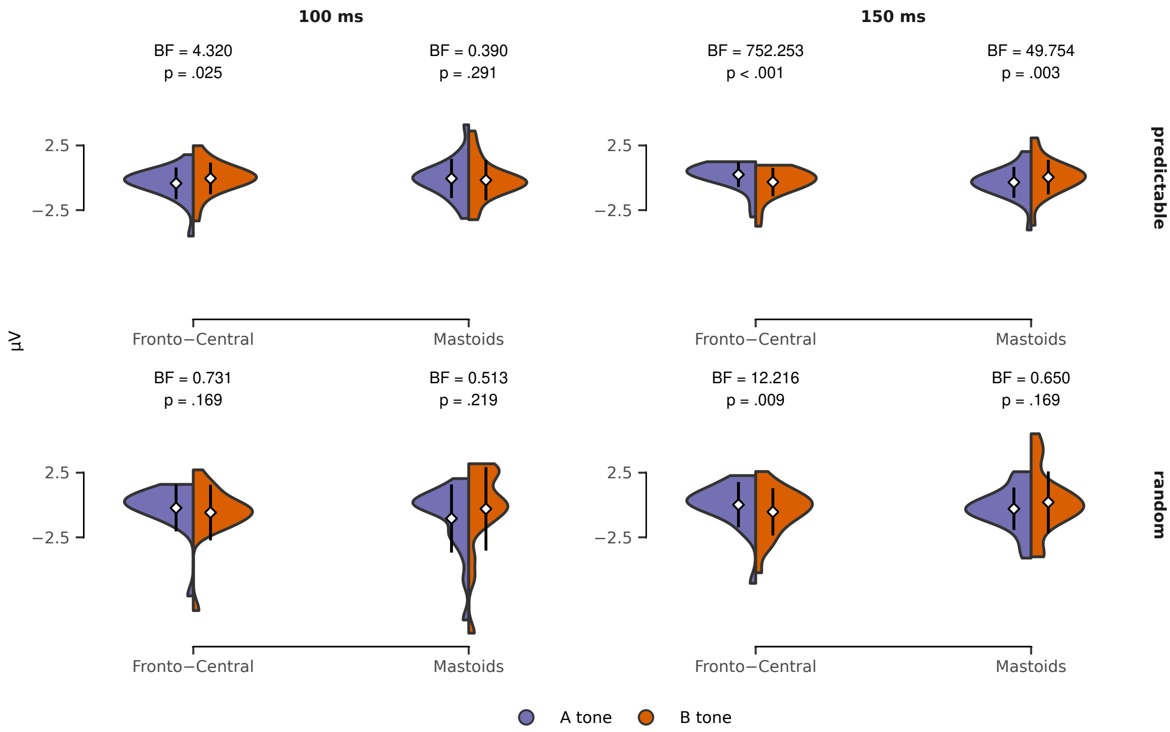
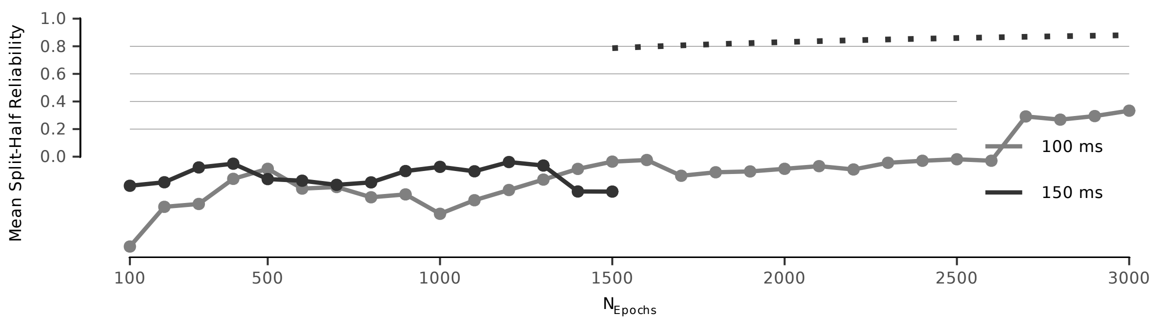


Figure 5.

EEG waveforms for five-tone sequences presented in an predictable context (dotted line) and pseudo-random condition (dashed line) for 100 ms presentation rate (top panel) and 150 ms presentation rate (lower pabel). Vertical lines indicate tone onset.



effect when already dealing with large numbers of epochs and ii) SOA and thus effect sized have a larger impact when epoch numbers are small compared to high epoch numbers. Graphed values also show that reliabilities for the 100 ms stimulation rate are considerably lower than for an SOA of 150 ms and that reliabilities are very low when using a relatively small number of epochs. There is no generally accepted rule as to the level above which the coefficient can be considered acceptable. Rather, reliabiliy should be evaluated based on the purpose of a study considering the cost-benefit trade-off (Nunnally et al., 1994). As laid out, inreased realibility comes at overproportionate cost, in that collecting more samples will not increase ralibility by the same factor. That said, many published articles deem reliability coefficients above .7 or .8 “acceptable” (Lance et al., 2006).

Table 2

Results of the 3-way ANOVA (condition x stimulus x electrode) for repeated measures conducted on the mean ERP-amplitudes (time window 111 - 161 ms) at electrode Fz (upper section). The significant interaction between the three factors included was further analyzed by 2-way ANOVAS (stimulus x electrode) conducted separately for the random condition (middle section) and the predictable condition (lower section).

	Effect	**DFn**	**DFd**	**F**	**p**	**p<.05**	**ges**
100 ms	Condition	1	19	0.831	0.373		0.008
	StimulusType	1	19	1.05	0.318		0.002
	Electrode	1	19	0.036	0.852		0.000331
	Condition x StimulusType	1	19	0.051	0.823		7.55e-05
	Condition x Electrode	1	19	0.763	0.393		0.002
	StimulusType x Electrode	1	19	0.797	0.383		0.001
	Condition x StimulusType x Electrode	1	19	7.53	0.013	*	0.01
150 ms	Condition	1	22	0.08	0.78		0.000263
	StimulusType	1	22	0.317	0.579		0.000339
	Electrode	1	22	0.035	0.854		0.000301
	Condition x StimulusType	1	22	0.16	0.693		0.000124
	Condition x Electrode	1	22	1.13	0.299		0.003
	StimulusType x Electrode	1	22	20.8	0.000155	*	0.026
	Condition x StimulusType x Electrode	1	22	0.053	0.819		4.63e-05

Table 3

Results of the 3-way ANOVA (condition x stimulus x electrode) for repeated measures conducted on the mean ERP-amplitudes (time window 111 - 161 ms) at electrode Fz (upper section). The significant interaction between the three factors included was further analyzed by 2-way ANOVAS (stimulus x electrode) conducted separately for the random condition (middle section) and the predictable condition (lower section).

		Effect	**DFn**	**DFd**	**F**	**p**	**p<.05**	**ges**
100 ms	Frontal	Condition	1	19	0.16	.694		0.003
		StimulusType	1	19	0.006	.938		1.5e-05
		Condition x StimulusType	1	19	16.7	< .001	*	0.013
	Mastoids	Condition	1	19	1.28	.272		0.014
		StimulusType	1	19	1.21	.285		0.004
		Condition x StimulusType	1	19	2.37	.141		0.009
150 ms	Frontal	Condition	1	22	0.947	.341		0.006
		StimulusType	1	22	22.7	< .001	*	0.038
		Condition x StimulusType	1	22	0.028	.868		2.2e-05
	Mastoids	Condition	1	22	0.206	.655		0.001
		StimulusType	1	22	6.56	.018	*	0.018
		Condition x StimulusType	1	22	0.122	.730		0.00028

Discussion

We did not replicate

For the 150 presentation, extreme evidence for an MMN and very strong evidence for an accopying polarity reversal at the mastoids was found in the *predcitable* condition, that is, when tones were presented in an repeated five-tone pattern. When tones were presented in random order, strong evidence was found for an MMN but Bayes factors suggested inconclusive evidence for mastoids. In light of the resuts by E. S. Sussman & Gumenyuk (2005), we would

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