Distinct roles of cognitive and sensory information in musical expectancy

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Abstract

Expectation is crucial for our enjoyment of music, yet the underlying generative mechanism remains contested. While sensory–acoustic models derive predictions based on the short-term auditory input alone, cognitive models assume the use of abstract knowledge of music structure acquired over the long-term. To evaluate these two contrasting mechanisms, we compared simulations from computational models of musical expectancy against subjective surprise ratings of chords sampled from US Billboard pop songs in musicians and non-musicians. Bayesian model comparison revealed that probabilistic knowledge of music structure and auditory short-term memory both explained unique behavioural variance without mediation. However, probabilistic knowledge accounted for nearly four times as much variance in musicians, and over twice as much in non-musicians. Incorporating both probabilistic knowledge and auditory short-term memory together furthermore improved predictive accuracy over the individual models. Our findings thus motivate an alternative to the current debate by emphasising the distinct, albeit complementary, roles of cognitive and sensory information in forming expectations during music-listening in humans.

Keywords:

music; expectation; prediction; reward; harmony; Bayesian inference

1 Introduction

Most people enjoy listening to music (Dubé & Le Bel, 2003; Huron, 2019). How music evokes pleasure is strongly entwined with our ability to monitor and predict the sensory environment (Huron, 2006; Koelsch, Vuust, & Friston, 2019; Salimpoor, Zald, Zatorre, Dagher, & McIntosh, 2015). Recent work has shown that musical pleasure is modulated by the surprise elicited by unexpected chords and pitches in melodies (Cheung et al., 2019; Gold, Pearce, Mas-Herrero, Dagher, & Zatorre, 2019), and is related to brain activity in the mesolimbic reward network (Cheung et al., 2019; Gold, Mas-Herrero, et al., 2019; Kim, Mueller, Lepsien, Mildner, & Fritz, 2019; Salimpoor et al., 2013; Shany et al., 2019). However, the precise mechanisms explaining how listeners form these expectations remains intensely debated (Bigand, Delbé, Poulin-Charronnat, Leman, & Tillmann, 2014; Bigand, Tillmann, & Poulin-Charronnat, 2006; Collins, Tillmann, Barrett, Delbé, & Janata, 2014; Morgan, Fogel, Nair, & Patel, 2019).

1.1 Cognitive and sensory accounts of musical expectancy

Two contrasting accounts attempt to explain the source of musical expectancy. These accounts differ in whether expectations are mainly derived from abstractions such as chords, or from the auditory signal itself (Collins et al., 2014; Tillmann, Poulin-Charronnat, & Bigand, 2014). *Cognitive accounts* emphasise that listeners internalise the structure of a given musical style as probabilistic (Pearce, 2018) and syntactic (Rohrmeier & Koelsch, 2012) relationships that are held in long-term memory. In support of this, subjective expectations for tones and chords are modelled well by stylistic probabilities given the preceding context (Harrison & Pearce, 2018; Morgan et al., 2019; Pearce, Ruiz, Kapasi, Wiggins, & Bhattacharya, 2010; Sears, Pearce, Spitzer, Caplin, & McAdams, 2019), and listeners find chords that violate syntactic rules of Western tonal harmony unexpected (Koelsch et al., 2019). In contrast, *sensory accounts* argue that expectancy emerges as an epiphenomenon of how sounds are processed and then perceived

on the short-term sensory–acoustic level (Bigand et al., 2014, 2006; Craton, Lee, & Krahe, 2019; Parncutt, 1989). Many findings from existing behavioural and neurophysiological studies on harmonic expectations can be replicated using models that simulate the decay of auditory signals held in short-term memory (Bigand et al., 2014; Leman, 2000), or from the spectral similarity of pitches (Milne & Holland, 2016; Milne, Sethares, Laney, & Sharp, 2011) without resorting to syntactic principles or long-term stylistic probabilities. Whether, and to what extent, people form expectations directly based on acoustic features of the auditory input or learnt high-level representations of music structure thus remains unclear.

Reconciling cognitive and sensory accounts is challenging because the structural relationships between sounds in a music sequence are intrinsically constrained by their acoustic properties (Tillmann et al., 2014). For example, the tonic and the dominant are abstractions that represent the two most significant chords in Western tonal harmony (Berry, 1987), but also share highly overlapping harmonic spectra. As a result, many studies have resorted to carefully constructed artificial stimuli, which limits the comparison to few selected stimulus categories that may occur only seldomly in a musical style (Bigand et al., 2014; Harrison & Pearce, 2018). Dissociating the two accounts also limits the possibility of examining whether expectations are formed along a cognitive–sensory gradient (Collins et al., 2014), or whether predictions generated from high-level musical knowledge in fact depend on sensory–acoustic information. Identifying the roles of sensory and cognitive information in musical expectancy is crucial if we want to draw meaningful parallels with other domains such as language, where the distinction between grammatical and ungrammatical is more apparent (Bigand et al., 2014, 2006; Morgan et al., 2019), or to infer potential learning mechanisms that generalise across species (such as learnt vocalisation in songbirds (James, Sun, Wada, & Sakata, 2020; Woolley, 2012)).

We addressed these challenges by contrasting simulations from computational models of musical expectancy against subjective surprise judgements to chords taken from US Billboard pop songs in musicians and non-musicians. This allowed us to assess the importance of cognitive and sensory information in generating predictions during music-listening, as well as to directly test the underlying mechanisms assumed by each model using naturalistic stimuli that conformed to stylistic conventions. Comparisons across musicians and non-musicians further enabled us to verify cognitive accounts of expectancy given the increased stylistic knowledge in musicians.

1.2 Computational models of expectancy

As a cognitive model of musical expectancy, we employed the Information Dynamics of Music (IDyOM) model (Pearce, 2005, 2018; Pearce & Wiggins, 2012). IDyOM is a variable-order Markov model that simulates the acquisition and mental representation of probabilistic structure of a musical style through statistical learning. Statistical learning is a domain-general mechanism which posits that agents learn statistical regularities within sequences through long- and short-term exposure to music (Pearce, 2018). IDyOM returns the conditional probability for a chord given the preceding chords in a progression, constructed from statistics learnt both from a large pretraining corpus (intended to simulate the listener's prior musical exposure) and from the prior portion of the sequence (intended to simulate online learning during stimulus presentation). It simulates how surprising a chord is to the listener by computing its information content, which is given by the negative log-probability of the chord conditional on the preceding context (Figure 1; see also Section 2.3.1). Chords with higher information content are hypothesised to be rated as more surprising. Here, we trained IDyOM on all chords from the McGill Billboard dataset (Burgoyne, Wild, & Fujinaga, 2011) to simulate the long-term exposure of a listener to Western pop music.

As a sensory–acoustic model of musical expectancy, we used the Periodicity-Pitch (PP) model of auditory short-term memory (Bigand et al., 2014; Leman, 2000). This model operates on the level of the sound input and does not assume any representation of musical knowledge. Periodicity-pitch information in the auditory signal is first encoded as firing patterns of neurons in the peripheral auditory system. These patterns are then processed into ‘pitch images’ after bandpass-filtering and taking a windowed autocorrelation. To simulate memory decay, they are separately filtered with a long time constant (4 s) to represent contextual information held in echoic memory, and with a short time constant (0.1 s) to represent the instantaneous pitch percept. The two resulting pitch images are then correlated to generate a measure on their similarity referred to as tonal contextuality (Figure 1). A high tonal contextuality suggests that the immediate pitch percept is highly expected with respect to the context held in sensory memory. Chords with lower tonal contextuality are hypothesised to be rated as more surprising.

Figure 1. Evaluating cognitive and sensory contributions to chord expectancy. (A) Two contrasting computational models of music expectancy were employed to simulate the surprise of a listener to unexpected chords in a progression (here, “Ob-La-Di-Ob-La-Da” by The Beatles; refer to Audio S1). Information content is a measure of surprise premised on the assumption that listeners form probabilistic expectations based on long-term acquired knowledge of a musical style (simulated here by training IDyOM on chord sequences from 745 songs from the McGill Billboard dataset), whilst tonal contextuality is derived from the similarity of periodicity pitch information between the incoming chord and the sensory context held in short-term memory (for up to about 4 s). As shown in the grey bars, the same chord will have different information content and tonal contextuality values that depend on its preceding context. (B) Scatterplot and marginal densities of the information content and tonal contextuality of all chords ($n = 1,039$) in the presented stimuli.

2 Material and Methods

2.1 Subjects

Twenty-five healthy adults (13 musicians, 12 non-musicians) participated in this study. We reasoned that this sample size was sufficient because (1) substantially more observations were acquired from each subject compared to similar studies (e.g., 1,039 in the current study versus 80 in (Sears et al., 2019), 150 in (Harrison & Pearce, 2018), and 216 in (Hansen & Pearce, 2014)), and (2) we took a Bayesian approach to incorporate results from prior experiments, effectively constraining the outcome not by the current data alone, but by what is plausible given prior research (note that analyses were also repeated using models estimated with only weakly-informative priors to ensure robustness – see Section 2.5.3).

Musicians (mean age = 24.4 y, SD = 3.48) scored a mean of 40.5 (SD = 4.41) in the musical training subscale of Goldsmiths Musical Sophistication Index (Gold-MSI) (Müllensiefen, Gingras, Musil, & Stewart, 2014), whilst non-musicians (mean age = 26.1 y, SD = 4.56) scored a mean of 12.5 (SD = 5.64). These respectively corresponded to the 86th and 15th percentile scores from self-recruited participants for the online “How Musical are You” BBC study (Müllensiefen et al., 2014). The two groups thus showed differences in musical training (Wilcoxon’s rank sum: $W = 156$), but not in age (Welch’s t : $t(20.5) = -1.04$).

Inclusion criteria for musicians were musical training (in addition to music lessons at school) at or before age 10, at least seven continuous years of musical training, and actively practising their instruments on average at least once a week for the past three years. Inclusion criteria for non-musicians were no musical training before age 7, no musical training in the past 7 years, and less than 10 years of continuous musical training in total. An exclusion criterion for both groups was absolute-pitch, for which subjects were screened prior to the experiment using the absolute-pitch test devised in Kim & Knösche, 2016. Additional data from one non-musician were not analysed due to non-compliance with the experimental

procedure. All subjects reported right-handedness and normal hearing. The study was approved by the Ethical Committee of the Medical Faculty at Leipzig University and written informed consent was obtained from all subjects.

2.2 Stimuli

Subjects were auditorily presented with 30 isochronous chord progressions taken from commercially successful pop songs listed in the McGill Billboard dataset (Burgoyne et al., 2011). These stimuli were previously used to examine the effects of expectancy on musical pleasure and brain activity (Cheung et al., 2019). Each chord progression ranged between 30–38 chords inclusive (mean number of chords = 34.6, SD = 2.17) and the duration of each chord was 2.4 s. To mitigate confounding effects from interactions with other dimensions (such as timing and language) and familiarity, only the chord progression of the original song was retained and transposed to C major. Each chord was computer-generated with a timbre synthesised from a marimba, jazz guitar, and an acoustic guitar. All timbres played all pitches in each chord. Damping and reverb were adjusted to ensure no spill-over to the next chord. To give momentum to the stimuli, each chord progression was also accompanied by one of three background rhythms that repeated once per chord. The assignment of background rhythms to each stimulus was counterbalanced across subjects.

2.3 Computational models of expectancy

2.3.1 Information Dynamics of Music (IDyOM)

As our cognitive model of harmonic expectancy, we used the Information Dynamics of Music (IDyOM) model. IDyOM is a variable-order Markov model that learns statistical regularities in music from a given training dataset. IDyOM simulates the probabilistic predictions of a

listener who is assumed to acquire statistical knowledge in a particular musical style through exposure. Because we focus here on expectancy in tonal harmony, only chord symbols were included in IDyOM. In principle, IDyOM could be extended to also include surface features such as note duration and pitch interval. However, these multiple viewpoints are yet to be implemented in harmony (but see Hedges & Wiggins, 2016 for recent developments).

IDyOM generates the conditional probability of a chord given previous chords in a progression by combining its n -gram models of different orders (i.e., different values of n) using the PPM* algorithm (Bunton, 1997; Cleary, Teahan, & Witten, 1995; Moffat, 1990). Given a chord progression $\{e_1, \dots, e_i, \dots, e_j\}$, the n -gram probability of chord e_i is expressed as $p(e_i | e_{i-(n-1)}, \dots, e_{i-1})$. This enables us to calculate the information content (IC) of the chord, which is given by its negative log-probability conditional on the context of preceding chords, i.e.,

$$IC(e_i) = -\log_2 p(e_i | e_{i-(n-1)}, \dots, e_{i-1}).$$

IC is an information-theoretic measure that quantifies the amount of information transferred when a signal is sampled. Chords that appear rarely in a given context will have a high IC. There are two sub-components to IDyOM: In the long-term model (LTM), the conditional probability is estimated from all chord sub-sequences in the training set, whilst in the short-term model (STM), the conditional probability is estimated from all previously observed sub-sequences in the current song. The LTM and STM probabilities are then combined by taking the geometric mean. We trained IDyOM on all chords in the McGill Billboard dataset to simulate the long-term statistical knowledge of a listener exposed to Western pop music. This dataset contains over 80,000 chords from 745 pop songs listed on the US Billboard ‘Hot 100’ chart between 1958 and 1991. We applied ten-fold cross-validation when training the model to prevent overfitting to specific songs, and selected a maximum n -gram order of 10 in the LTM and unbounded in the STM.

1

2 2.3.2 *Periodicity Pitch*

3 As a contrasting model of harmonic expectancy, we used the periodicity-pitch model (Leman,
4 2000), which is a model of auditory short-term memory that computes the similarity of sound
5 representations in the memory trace based on the firing of neurons in the peripheral auditory
6 neural system. There are four components to this model: First, the auditory signal is
7 transformed into simulated neuronal firing probabilities; these probabilities are then taken as
8 codes of periodicity-pitch information. Firing codes are transformed and summarised into so-
9 called pitch images by bandpass filtering and taking a moving-window autocorrelation. Third,
10 the pitch images are then low pass filtered at two timescales to generate a global pitch image
11 (GPI) and a local pitch image (LPI). The GPI has a longer integration time and reflects the
12 accumulation of a pitch percept over a brief context. In contrast, the LPI has a shorter
13 integration time and reflects the perception of a novel pitch. Fourth, the similarity of GPI and
14 LPI is then evaluated using z-transformed Pearson's correlation. This measure of so-called
15 tonal contextuality quantifies the similarity between the immediate pitch and its pitch context
16 within the memory trace.

17 This model is parametrised by the time constants of the GPI and LPI. To match the span
18 of echoic memory, we used a GPI decay constant of 4 s (Darwin, Turvey, & Crowder, 1972;
19 Sears et al., 2019); LPI decay was kept at the default of 0.1 s.

20

21 2.4 *Procedure*

22 During stimulus presentation, subjects gave continuous ratings of their perceived surprise for
23 each chord using a 10-cm analogue slider similar to a previous experiment (Cheung et al.,
24 2019). This allowed us to acquire observations without restriction to a particular point in the

stimulus (see e.g., Aarden, 2003 on potential closure effects) and present stimuli with a much longer context (at least 30 chords in each progression compared to approximately 10 chords in previous studies (Bigand et al., 2014; Collins et al., 2014; Harrison & Pearce, 2018)) to closer-match actual music.

Subjects were asked to hold the slider with their left hand and to place it on their lap whilst controlling the slider pot with their right thumb. At the start of each trial, subjects moved the slider to the lowest position and stimulus presentation began 2 s later. They were asked to rate how surprised they were by each chord based on the chords they had heard so far in the stimulus by moving the slider pot to its appropriate position. A rating away from the body indicated higher surprise (with maxima indicating ‘Very surprised’) and closer to the body lower (with minima indicating ‘Not surprised at all’). They were prompted to use the entire length of the slider and to give at least five extremal ratings throughout the entire experiment. After each stimulus presentation, they rated their overall valence and arousal to the stimulus each within a 3-s time window using a 1–6 scale on the keyboard. The next trial then ensued as before.

The presentation of the 30 chord progressions (with 10 assigned to each of the three background rhythms) was pseudo-randomised. The experiment was conducted in a soundproof cabin and stimuli were delivered using supra-aural headphones (Beyerdynamic DT 770 PRO) at a comfortable volume using Psychtoolbox 3 (Brainard, 1997) in Octave 4.0.0 (Eaton, Bateman, Hauberg, & Wehbring, 2017). The slider interfaced with the computer using an Arduino Micro sampling at 20 Hz. Prior to the experiment, subjects practised on three trials with a stimulus set different from the actual stimuli. After the experiment, they were asked if the song and artist of our chord stimuli could be identified. No relevant artists or songs were named.

2.5 Statistical analysis

2.5.1 Preprocessing

We first examined the stationarity of the sequence of information content (IC) and tonal contextuality (TC) values for each chord progression using the augmented-Dickey-Fuller (ADF) and Kwiatkowski–Phillips–Schmidt–Shin (KPSS) tests, which together suggested that differencing was not necessary. Stationarity is a prerequisite for standard statistical analyses of time-series data (Jebb, Tay, Wang, & Huang, 2015). Next, a 5-sample symmetric median filter was applied to the slider responses for each subject to remove small signal fluctuations. The mode of the response was then sampled for each chord in the stimuli in the time window between 1 s after its onset and start of the subsequent chord. This time window was chosen to account for the delayed reaction in moving the slider when hearing a new chord. Ratings for the first chord of each stimulus were discarded as each trial began with the subject resetting the slider.

2.5.2 Bayesian multilevel modelling

We modelled the behavioural chord surprise ratings with Bayesian multilevel linear models. Ratings for each chord were averaged across subjects within musicians and non-musicians as model residuals otherwise became severely heteroscedastic. This resulted in 1,009 observations for each of the two groups (i.e., 2,018 chord surprise ratings in total), and were modelled with a Gaussian likelihood. To test the effects of information content (IC) and tonal contextuality (TC) in predicting chord surprise, we performed model comparison on the null (or baseline) model by including additional predictors (see Table 1) to assess the change in out-of-sample predictive accuracy, and made inferences from estimates of the posterior distribution. The null model comprised a varying intercept by song, and varying slopes for musicianship (binary-

coded), valence, and arousal. Varying intercepts and slopes account for differential effects across the stimuli and thus improve parameter estimation by partial pooling of information (McElreath, 2018). We imposed an AR(1) covariance structure on the chord order of each stimulus to account for temporal autocorrelations in the slider ratings. All variables were standardised to reduce collinearity and so that effect sizes were on a comparable scale.

2.5.3 Priors

An important advantage of Bayesian methods is the incorporation of prior knowledge when building statistical models to improve plausibility of parameter estimates (McElreath, 2018). We used a Normal(0.641,1) and Normal(−0.036,1) prior for the respective effect of IC and TC based on the observed correlations with surprise ratings in non-musicians (Harrison & Pearce, 2018). The increase in slope between musicians and non-musicians was captured using Normal(0.060,1) and Normal(−0.010,1) priors for IC and TC, respectively. These were based on correlations with fit ratings in cadences from Mozart piano sonatas in musicians and non-musicians (Sears et al., 2019). Findings from those studies were chosen as priors as their approach and paradigm most resembled the current study. For the remaining model parameters, we used as weakly-informative priors Normal(0,1) for parameter estimates, Half-Cauchy(0,1) for scale parameters, and LKJ(2) for the covariance matrix as previously suggested (McElreath, 2018) for regularisation. To ensure that our results were not biased by the choice of priors, models were also refitted and compared with only weakly-informative priors.

2.5.4 Model estimation and comparison

Models were compared using the expected log pointwise predictive density (ELPD) derived from Pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO)

(Vehtari, Gelman, & Gabry, 2016) using the loo package (version 2.2.0). This measure integrates over the posterior distribution of each model to estimate its out-of-sample predictive accuracy, so that models with a better fit to held-out data will have higher ELPD values. More precisely, for observations $\{y_1, \dots, y_N\}$, posterior samples $\{\theta^1, \dots, \theta^S\}$, and truncated Pareto-smoothed importance weights w_n^s on held-out data n and posterior draw s , the estimated ELPD is given by:

$$\widehat{ELPD} = \sum_{n=1}^N \log \left(\frac{\sum_{s=1}^S w_n^s p(y_n | \theta^s)}{\sum_{s=1}^S w_n^s} \right).$$

The joint posterior distribution of model parameters was sampled using adaptive Hamiltonian Monte Carlo in RStan 2.18.2 (Stan Development Team RStan) using brms 2.9.0 (Bürkner, 2017) in R 3.5.3 (R Foundation for Statistical Computing, Vienna, Austria) with four Markov chains (2,500 iterations for warm-up, 2,500 iterations for sampling) resulting in a total of 10,000 samples. Convergence of the Markov chains was examined by visual inspection of parameter trace plots and R-hat values, with no evidence of non-convergence. Model fit was further assessed by comparing simulated and actual responses through posterior predictive checks.

3 Results

3.1 Modelling expectancy

We used Bayesian multilevel linear models (Table 1) to evaluate the extent to which simulations from two contrasting computational models of expectancy—the Information Dynamics of Music (IDyOM) and Periodicity-Pitch (PP) models—predicted chord surprise. Figure 2 shows the predicted surprise ratings as given by each model compared to the actual behavioural ratings for one stimulus. As our null (or baseline) model (model 0), we included a varying intercept by song, a varying slope for musicianship, and varying slopes for valence and arousal ratings. This allowed us to estimate the mean surprise rating given by musicians and non-musicians across all stimuli, after controlling for effects of valence and arousal (Figure 3). On average, non-musicians tended to give higher chord surprise ratings than musicians (difference: $\beta = -0.279$, 95%-credible interval (CrI) = $[-0.425, -0.132]$, $\beta(\text{probability} < 0) = 0.999$). Increased arousal was also indicative of higher surprise, but no meaningful effect was detected for valence (Figure S1).

1 Table 1: Model comparison on cognitive and sensory contributions to chord surprise ratings

Model	Parameters	ELPD
0	Varying intercept: stimulus	−2,497.2
	Varying slope: musicianship, valence, and arousal	(37.0)
1	Varying intercept: stimulus	−2,090.4
	Varying slope: IC, IC*musicianship, musicianship, valence, and arousal	(34.7)
2	Varying intercept: stimulus	−2,444.0
	Varying slope: TC, TC*musicianship, musicianship, valence, and arousal	(36.1)
3	Varying intercept: stimulus	−2,038.8
	Varying slope: IC, IC*musicianship, TC, TC*musicianship, musicianship, valence, and arousal	(34.2)

2 Expected log pointwise predictive density (ELPD) of each model was compared to evaluate
3 the extent to which behavioural surprise ratings were predicted by chord information content
4 (IC), derived from probabilistic knowledge of music structure, and tonal contextuality (TC),
5 derived from auditory short-term memory. Models with higher ELPD show better estimated
6 out-of-sample predictive performance. Values inside each bracket denote standard error of the
7 estimate. Temporal autocorrelations in the slider rating were accounted for using an AR(1)
8 covariance structure in each model.

9

1 Figure 2. Comparing observed and predicted chord surprise ratings. Musicians and non-
2 musicians gave continuous ratings of how surprising they found 1,039 chords in 30 isochronous
3 chord progressions sampled from commercially successful pop songs. Bayesian multilevel
4 linear models (see Table 1) were fitted and compared to test the effects of information content
5 and tonal contextuality in predicting chord surprise. Solid lines indicate the mean predicted
6 response of each model to a chord progression taken from “Ob-La-Di-Ob-La-Da” by The
7 Beatles. Darker shaded regions show the 95%-credible interval of the mean. Lighter shaded

regions show the 95%-credible interval of predicted responses. Open circles indicate actual mean behavioural response averaged within the two groups. Error bars depict standard error of the mean.

Figure 3. Model posterior distributions. Posterior densities for the average chord surprise rating in musicians and non-musicians (model 0), as well as the standardised effect of information content (model 1), and tonal contextuality (model 2) on explaining the behavioural response. Solid line indicates posterior mean. Filled region denotes 95%-credible interval of the mean.

3.2 Cognitive contributions to expectancy

To test how chord surprise was influenced by acquired probabilistic knowledge of music structure, we modelled the standardised information content (IC) of each chord as simulated by IDyOM (model 1). This model revealed a substantial positive linear association between IC and surprise in both musicians and non-musicians (Figures 3 and 4; $\beta = 0.531$, 95%CrI = [0.470, 0.593], $\beta(\text{pr} > 0) = 1$; $\beta = 0.215$, 95%CrI = [0.158, 0.274], $\beta(\text{pr} > 0) = 1$, respectively). The strength of the association was also stronger in musicians (difference: $\beta = 0.317$, 95%CrI = [0.258, 0.374], $\beta(\text{pr} > 0) = 1$). This finding supports cognitive accounts of musical expectancy, and is consistent with the proposal that musicians possess a more accurate probabilistic

representation of music structure due to increased training and exposure (Pearce, 2015). It is furthermore in line with electrophysiology studies showing enhanced responses in musicians to surprising chord and pitch progressions compared to non-musicians (Di Liberto et al., 2020; Kim, Kim, & Chung, 2011; Koelsch, Schmidt, & Kansok, 2002; Park et al., 2018).

Figure 4. Explaining behavioural surprise ratings with information content and tonal contextuality. A positive linear relationship was found between chord surprise and information content (model 1) with a stronger association in musicians compared to non-musicians, which supports cognitive accounts of musical expectancy. However, a negative linear relationship between chord surprise and tonal contextuality (model 2) was observed with no meaningful difference between the two groups, suggesting that musical expectancy could also be driven by sensory mechanisms. Solid lines indicate the mean posterior estimate. Shaded regions depict the 95%-credible interval of the mean. Filled circles show mean behavioural ratings averaged within the two groups.

3.3 Sensory contributions to expectancy

Next, we modelled the standardised effects of tonal contextuality (TC) as simulated by PP (model 2) to examine how auditory short-term memory contributes to expectancy. We found a substantial negative relationship between TC and surprise ratings in musicians and non-musicians (Figures 3 and 4; $\beta = -0.145$, 95%CrI= $[-0.220, -0.0704]$, $\beta(\text{pr} < 0) = 1.00$; $\beta = -0.124$, 95%CrI= $[-0.195, -0.0494]$, $\beta(\text{pr} < 0) = 0.999$, respectively), consistent with sensory accounts. However, there was no meaningful difference in the slope between the two groups (difference: $\beta = -0.0210$, 95%CrI= $[-0.0880, 0.0463]$, $\beta(\text{pr} < 0) = 0.734$). This corroborates the proposal that larger evoked electrophysiological responses by chord deviants in musicians from the aforementioned studies is a result of implicit learning, and not enhanced sensitivity in general auditory processing (Koelsch et al., 2002).

3.4 Distinct contributions of cognitive and sensory information to expectancy

Importantly, when considering IC and TC simultaneously in the same model (model 3), we found that their effects were robust and remained virtually unchanged (Figure 5). This demonstrates that IC and TC each explained unique variation in the behavioural response, without mediation by the other variable. That is, the variance explained by IC or TC is not dependent on the other variable. Comparing the standardised parameter estimates further revealed that IC was a stronger predictor of chord surprise than TC, explaining 3.8 times (95%CrI = $[2.66, 5.73]$) more variance in musicians and 2.6 times (95%CrI = $[1.69, 4.13]$) in non-musicians. The separate contribution of IC and TC to chord surprise also implies that IC and TC are not meaningfully related (cf. Figure 1B). In other words, a chord that is regarded as surprising according to its statistical regularity could still be acoustically similar to its previous context held in auditory short-term memory.

1 Figure 5. Unique contributions of information content and tonal contextuality on chord surprise.
2 (A) Standardised effects of information content and tonal contextuality on predicting chord
3 surprise ratings when considered separately (models 1 and 2, respectively) and simultaneously
4 (model 3) across musicians and non-musicians. Values indicate mean posterior estimates.
5 Arrow width depicts relative magnitude of each effect. (B) Posterior estimates (mean and 95%-
6 credible interval) of each effect remained stable when considered individually or together,
7 indicating that information content and tonal contextuality each explained unique behavioural
8 variation.
9

3.5 Validation from model prediction

Our findings based on statistical inference so far suggest that cognitive and sensory mechanisms play distinct roles in determining chord expectancy. If that were the case, we would expect a model that incorporates both IC and TC to align more closely with behaviour. Notably, this model should not only fit the observed sample, but also accurately predict surprise ratings from chords it has not encountered before. We therefore compared the predictive accuracy of each model to held-out data using Pareto-smoothed importance sampling leave-one-out cross-validation (PSIS-LOO; see Section 2.5.4). Figure 6 shows the relative generalisation performance of each model, quantified by their change in expected log pointwise predictive density (ELPD). In line with the above, the model that considers both IC and TC (model 3) showed the highest expected predictive performance compared to the other models. Furthermore, the difference in ELPD between models 3 and 2 was 14.2 times its standard error ($d\text{ELPD} = -405.2$, $d\text{SE} = 28.5$), and 4.9 times between models 3 and 1 ($d\text{ELPD} = -51.6$, $d\text{SE} = 10.6$). These strongly indicate that incorporating IC and TC in the same model improves out-of-sample predictions for surprise ratings compared to the inclusion of IC or TC alone. Likewise, model predictions based on IC were substantially more accurate than TC ($d\text{ELPD} = -353.7$, $d\text{SE} = 29.3$), a finding which echoes the inference from comparing posterior estimates in the above.

3.6 Validation from weakly-informative priors

Finally, although our Bayesian approach enabled us to incorporate prior findings to improve the plausibility of parameter estimates (see Section 2.5.3), we further ensured the robustness of our results by re-estimating each model with only weakly-informative priors. This reanalysis yielded analogous findings as before (Figures S2 and S3).

1

2 Figure 6. Comparing predictive performance of models using leave-one-out cross-validation.
3 Model 3, which includes both information content and tonal contextuality, showed the highest
4 expected log pointwise predictive density (ELPD). Change in ELPD of each model (filled
5 circles) relative to model 3 was at least four times larger than the standard error of the change
6 (error bars). This indicates a substantial improvement in out-of-sample predictive accuracy for
7 model 3 compared to the remaining models, further suggesting unique cognitive and sensory
8 contributions to musical expectancy. Model 0: baseline; Model 1: information content; Model
9 2: tonal contextuality; Model 3: information content and tonal contextuality (refer to Table 1).

10

4 Discussion

Our results suggest distinct roles for cognitive and sensory mechanisms in generating musical expectations. We tested two computational models of musical expectancy—the Information Dynamics of Music (IDyOM) and Periodicity-Pitch (PP) models—against subjective surprise ratings of chords taken from commercially successful pop songs. Probabilistic knowledge of music structure simulated by IDyOM and auditory short-term memory simulated by PP explained unique variation in surprise judgements from musicians and non-musicians without mediation, although probabilistic knowledge accounted for over twice as much variance as auditory memory. A greater effect of probabilistic knowledge was also observed in musicians compared to non-musicians, consistent with greater stylistic musical knowledge, but not for auditory memory. Incorporating both probabilistic knowledge and auditory memory simultaneously further led to substantial improvements in predictive accuracy compared to relying on either predictor alone. We therefore contribute to the long-standing debate between cognitive and sensory accounts of musical expectancy (Bigand et al., 2014; Collins et al., 2014; Harrison & Pearce, 2018) by emphasising that the two are not mutually exclusive, but that each explains a complementary part of the variation in behaviour.

4.1 Dominant influence of cognitive over sensory information

Our findings support the view that musical expectancy is shaped by the combination of sensory and cognitive information, although with a greater influence from the latter. This view is paralleled in language, where the intonation and pitch of speech (Hellbernd & Sammler, 2016; Krocze & Gunter, 2017; Meyer, Henry, Gaston, Schmuck, & Friederici, 2017; Schafer, Speer, Warren, & White, 2000) facilitates the inference of syntax. It is also in line with previous attempts in quantifying the extent acoustic information and music structure explain priming effects in melodies and harmony (Collins et al., 2014; Eerola, 2004). However, those studies

employed relatively simple representations of learned stylistic structure, and used stepwise-regression methods that are prone to variable mis-selection and overfitting (Harrell, 2015; Thompson, 1995). In other words, the relative importance of cognitive and sensory information may not have been accurately determined. Here, we robustly demonstrate the dominant influence of probabilistic knowledge over auditory memory by comparing the standardised effect sizes of the two predictors within the same model, in addition to comparing the cross-validated predictive accuracy of either IDyOM or PP. Consistent with this result, a recent study found a larger effect size for probabilistic knowledge as compared to gestalt principles in explaining pitch continuations of melodies in musicians (Morgan et al., 2019). Nevertheless, it is important to note that our conclusion here is contingent upon the two computational models we tested. Further studies will need to test a variety of other models to verify the precise mechanisms and the relative importance of cognitive over sensory information in determining expectancy in music.

4.2 Distinct neural generators of expectancy

How might listeners combine cognitive and sensory information in generating predictions? Two possibilities have been proposed (Morgan et al., 2019): First, a single system learns and generates expectations based on both sources of information simultaneously. Second, two systems generate expectations based on sensory and cognitive information separately, which are then combined in a weighted fashion. Our data speaks in favour of the latter, as the absence of a mediation effect directly implies no meaningful association between the tonal contextuality and information content of a chord (Figure 1B). This means that cognitive and sensory knowledge could be represented along two orthogonal dimensions without the need for representing the covariation between them. An auditory-specific system could generate expectations based on low-level sensory–acoustic features, whilst mechanisms such as

1 statistical learning (Conway & Christiansen, 2005; Frost, Armstrong, Siegelman, &
2 Christiansen, 2015) or syntax processing (Fitch & Martins, 2014) could compute expectancy
3 as the auditory input is transformed into abstract representations such as chords (Morgan et al.,
4 2019).

5 Our view that expectancy is a function of both cognitive and sensory information is in
6 line with the modularity hypothesis of music perception, which argues that music is processed
7 in a distributed, parallel fashion (Fodor, 1983; Jackendoff, 1991). It is also consistent with
8 electrophysiological findings on musical expectancy. For example, a mismatch negativity
9 (MMN) elicited by infrequent acoustic oddballs within an auditory sequence is attenuated by
10 immediate changes in the environment (Koelsch et al., 2019). However, the early right anterior
11 negativity (ERAN) elicited by irregular chord progressions remains intact even after repeated
12 presentations (Guo & Koelsch, 2016). These point towards distinct neural mechanisms for
13 which expectancy is contingent upon real-time sensory–acoustic features of the auditory input
14 in the former, and long-term knowledge of a musical style in the latter. Predictions due to low-
15 level features in the sound signal likely originate from the primary auditory cortex, which is a
16 key contributor to the MMN (Koelsch, 2011). On the other hand, predictions based on acquired
17 probabilistic or syntactic knowledge likely involve higher-level regions: The inferior frontal
18 gyrus has been suggested to process music structure (Cheung, Meyer, Friederici, & Koelsch,
19 2018; Rohrmeier & Koelsch, 2012) as well as syntactic rules across different cognitive domains
20 such as language and mathematics (Jeon, 2014), whilst the hippocampus is associated with the
21 statistical learning of contingencies within the sensory environment (Frost et al., 2015).

22 23 *4.3 Cognitive and sensory information explain non-overlapping variance*

24 Our finding implies that sensory–acoustic models of expectancy argued to have reproduced
25 effects attributed to abstract knowledge of music structure (Bigand et al., 2014; Leman, 2000)

have in fact explained a different part of the observed behaviour. Here, we quantified cognitive information based on information content derived from transitional probabilities of chords in the training corpus with IDyOM. As each chord was represented symbolically, this means that the same chord could carry a different probability of occurrence conditional on the preceding context of chords. On the other hand, we quantified sensory information in terms of tonal contextuality using PP. This gives a measure of the similarity of auditory patterns undergoing short-term memory decay based solely on the harmonic and subharmonic features of the auditory input (Leman, 2000). The separate effects of these two models on surprise ratings and the improved predictive performance when incorporating predictions from both IDyOM and PP imply unique contributions of cognitive and sensory information, and speak directly against the proposal that abstract representations of music structure are not necessary for musical expectancy (Bigand et al., 2014; Craton et al., 2019).

4.4 Sensory effects on expectancy are comparatively small

The small, but non-negligible, effect of tonal contextuality (as given by PP) reported here could explain why some studies did not detect a significant relationship between auditory short-term memory and expectancy. Previous studies comparing tonal contextuality against surprise ratings of chords in 8-bar progressions randomly sampled from pop songs (Harrison & Pearce, 2018) or goodness-of-fit ratings to cadences in Mozart piano sonatas (Sears et al., 2019) collected a limited number of observations per subject (150 and 80, respectively, compared to 1,039 in the current study) and only compared few categories (e.g., five different cadences in Sears et al., 2019), which possibly resulted in low power. Another reason could be that the effect of tonal contextuality depends on the parameters chosen for the PP model relative to the stimuli. For example, if the time constant of the global pitch image is too short, then there may be insufficient contextual information for the model to integrate as there is no overlap between

the preceding and the actual chord. Here, the decay constant of the global pitch image was set to 4 seconds to correspond to the approximate duration of auditory echoic memory (Darwin et al., 1972). Since the duration of each chord was 2.4 seconds in our stimuli, auditory information from the preceding chord would have been incorporated when deriving the tonal contextuality of a given chord. However, this raises the question of how parameters in a computational model ought to be determined: Using parameters optimised to fit results from experimental data could risk overfitting as predictions may not generalise towards another study. On the other hand, choosing parameters a priori may be difficult if the dynamics of the underlying process is unknown. One approach could be to compare results using different parameter combinations (Bigand et al., 2014), although the problem persists as one would still need to decide on a reasonable range of values to test.

4.5 Relation to musical pleasure

Lastly, our findings provide important implications for the discussion of musical pleasure. Most people find music pleasing when there is a dynamic interplay between the confirmation and violation of expectations (Cheung et al., 2019; Gold, Pearce, et al., 2019; Huron, 2006, 2019; Levitin, Chordia, & Menon, 2012; Salimpoor et al., 2015). Given the predominant contribution of long-term probabilistic knowledge of music structure in determining expectancy, we suggest that whether a piece of music is regarded as particularly pleasing depends primarily on the stylistic enculturation of a listener. This is consistent with the view that musical preference is largely shaped by what a listener has been previously exposed to (Huron, 2019; Peretz, Gaudreau, & Bonnel, 1998). Notably, the lower average surprise ratings given by musicians in our data implies that increased exposure might lead to changes in musical preference. In line with this, musical training has been shown to influence receptivity and preference towards different musical styles (Ginocchio, 2009; Gregory, 1994). Nevertheless,

the effect of auditory short-term memory on expectancy shown in the present work also highlights how music perception, and consequently the affective responses elicited by music, is inherently constrained by the structure of the human sensory system. This echoes the parallel between observing $1/f$ power-law distributions in rhythm and pitch in music across all human societies (Mehr et al., 2019) and the increased sensitivity of sensory neurons towards signals that exhibit a $1/f$ structure (Levitin et al., 2012), which also affects musical pleasure (Teixeira Borges et al., 2019).

5 Conclusions

In summary, we compared simulations from computational models of expectancy against subjective surprise ratings of chords taken from commercially successful pop songs. Long-term probabilistic knowledge of a musical style and auditory short-term memory explained distinct behavioural variance, although probabilistic knowledge accounted for a larger part of the variation. Our findings therefore show that cognitive and sensory information play complementary roles in musical expectancy, and suggest that the affective appeal of music is a product of innate sensory processing and learning from our past musical encounters.

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Author Contributions

V.K.M.C., L.M., & S.K. conceived the study. V.K.M.C., L.M., P.M.C.H., M.T.P., & S.K. conceptualised the study. A.D.F. secured funding for the research. V.K.M.C. & L.M. developed the experimental paradigm. P.M.C.H. and M.T.P. prepared the computational model simulations. L.M., M.T.P., A.D.F. & S.K. supervised the research. V.K.M.C. collected and analysed the data, prepared the figures, and wrote the original draft of the manuscript. V.K.M.C., L.M., P.M.C.H., M.T.P., A.D.F. & S.K. reviewed and edited the manuscript.

Declarations of interest

None.

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1 Supplementary Information

2 Figure S1. Comparing posterior estimates across all models. Posterior mean and 95%-credible
3 intervals for all fixed effects estimated across all models. The intercept represents the average
4 chord surprise rating for non-musicians when all other effects are at 0. Musicianship is a binary
5 coded dummy variable (0 = non-musician; 1 = musician), and thus represents the change in
6 average chord surprise rating across the two groups. IC*Musicianship represents the change in
7 slope for the effect of information content (IC) between musicians and non-musicians.
8 Likewise, TC*Musicianship represents the change in slope for the effect of tonal contextuality
9 (TC) between the two groups.

Figure S2. Comparing posterior estimates across all models fitted with only weakly-informative priors. Posterior mean and 95%-credible intervals for all fixed effects estimated across all models. Highly similar parameter estimates between models using informative priors (refer to Figure S1 and Section 2.5.3) and only weakly-informed priors here indicate robustness of the current results.

Figure S3. Comparing predictive performance of models estimated using only weakly-informative priors. Analogous results were found compared to models estimated using informed priors (refer to Figure 6). As before, Model 3, which includes both information content and tonal contextuality, showed the highest expected log pointwise predictive density (ELPD). Model 0: baseline; Model 1: information content; Model 2: tonal contextuality; Model 3: information content and tonal contextuality (refer to Table 1).

- 1 Caption for Audio S1. Sample isochronous chord stimulus. Chord progression taken from “Ob-
- 2 La-Di-Ob-La-Da” by The Beatles. Each chord was 2.4 s long and featured a synthetic timbre
- 3 with a repeated background rhythm counterbalanced across subjects (see Section 2.4).