Auditory and visual category learning in musicians and non-musicians

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Abstract

Across three experiments, we compare the ability of amateur musicians and non-musicians in learning artificial auditory and visual categories that can be described as either rule-based (RB) or information-integration (II) category structures. RB categories are optimally learned using a reflective reasoning process, whereas II categories are optimally learned by integrating information from two stimulus dimensions at a reflexive, pre-decisional processing stage. We found that musicians have selective advantages for learning auditory RB categories, specifically when they are instructed about the dimensions that define the categories. In Experiment 1, musicians enrolled in a music college demonstrated advantages over non-musicians in learning auditory RB categories defined on frequency and duration dimensions but did not demonstrate differences in learning auditory II categories or either visual RB or II categories. In Experiment 2, a broader online sample of musicians who were not instructed about the dimensions did not demonstrate any advantage in auditory or visual learning. In Experiment 3, an online sample of musicians when given dimension instructions demonstrated early advantages over non-musicians for auditory RB but not visual RB categories. Musicians do not demonstrate a global categorization advantage. Musicians' category learning advantage is limited to their modality of expertise, is enhanced with dimension instructions, and is specific to categories that can be described with verbalizable rules.

Keywords: music experience; category learning; audition; vision

Musicians are auditory experts. Musicians demonstrate enhanced processing of acoustic features underlying music and non-musical sounds (Herholz & Zatorre, 2012; Meyer et al., 2012; Tervaniemi et al., 2001), better attention to (Jäncke, 2009; Patel, 2011, 2014), and memory for, auditory information (Tierney et al., 2008), and even enhanced speech categorization (Elmer, et al., 2012, 2013; Lee & Hung, 2008; Smayda et al., 2015).

The extent and specificity of the benefits of music training are highly debated. While some have argued that music training may confer domain-general benefits including enhanced IQ (Schellenberg, 2004, 2006), verbal intelligence (Bialystok & DePape, 2009; Moreno et al., 2011), inhibitory control (Bialystok & DePape, 2009), verbal memory (Chan et al., 1998), and working memory (George & Coch, 2011; Moreno et al., 2011; Weiss et al., 2014), others have argued that benefits are limited to the auditory modality (Odendaal et al., 2019; Schellenberg, 2008, 2016; Schellenberg & Peretz, 2008; Stoesz et al., 2007; Tierney et al., 2008, 2009).

To better understand whether musicians have domain-general or auditory-specific benefits, we examine auditory and visual category learning with tasks that have distinct cognitive demands. Participants learned *rule-based* (RB) categories (Figure 1, left), thought to rely extensively on working memory and selective attention processing (Ashby & Maddox, 2011; Maddox & Ashby, 2004; Poldrack & Packard, 2003) or *information-integration* (II) categories (Figure 1, right), thought to rely on procedural learning mechanisms (Ashby & Maddox, 2011).

If musicians experience *domain-general* cognitive benefits over non-musicians, we hypothesize that they will demonstrate a selective benefit in learning RB over II categories, regardless of modality, as successful RB learning is reliably related to higher working memory capacity (Filoteo et al., 2010; Kalish et al., 2017; Miles et al., 2014; Reetzke et al., 2016; Zeithamova & Maddox, 2006).

If instead, musicians experience *auditory-specific* perceptual benefits over non-musicians, we hypothesize that they will demonstrate a category learning benefit in the auditory modality, regardless of whether the categories are RB or II. To understand if musicians are able to flexibly use auditory information depending on what is required for learning, we examined categories defined by auditory dimensions that are familiar, salient¹, and verbalizable for musicians (frequency and duration).

A third possibility is that musicians may demonstrate a global categorization advantage, demonstrating benefits over non-musicians in learning any kind of category. We investigate learning by examining categorization accuracies. However, accuracies alone do not provide information about how participants use the sensory information to divide the categories. We assess participants' decision strategies using decision bound computational models to understand how participants learn to separate the categories based on the dimensions (Ashby, 1992; Ashby & Maddox, 1993).

In Experiment 1, we examined learning and decision strategies in musicians enrolled in a music college and non-musicians with categories defined by basic auditory (frequency and duration) and visual dimensions (line length and orientation) when participants were explicitly told that these dimensions defined the categories. In Experiments 2 and 3, we examined learning in a broader sample of musicians recruited online separately examining performance without these instructions (Experiment 2) and with instructions (Experiment 3).

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¹ By 'salient' we mean that these dimensions have specific meaning and relevance for musicians compared to non-musicians. Musicians are aware of what 'frequency' and 'duration' mean based on their experience and thus may be better prepared to attend to differences along those dimensions when cued.

Experiment 1

Methods

Participants

Twenty-four amateur musicians (M age = 24.1 years, sd = 3.75; 18 F) and 25 non-musicians (M age = 21.6 years, sd = 2.20; 17 F) from the University of Texas (UT) at Austin community participated in the study and were paid \$10 per hour. Musicians (M) were currently enrolled in the UT Butler School of Music and non-musicians (NM) were recruited from the general UT community. Participants completed a music history questionnaire (see Supplemental Materials). An additional two participants were run but excluded because they did not complete both tasks (one musician, one non-musician). The study was approved by the UT Institutional Review Board.

Each participant completed one auditory and one visual task. Within each modality, participants were randomly assigned to learn either an RB or II category. In the auditory modality, 23 participants (12 M, 11 NM) learned II categories and 26 participants (12 M, 14 NM) learned RB categories. In the visual modality, 26 participants (13 M, 13 NM) learned II categories and 24 participants (11 M, 13 NM) learned RB categories.

Stimuli

The auditory and visual categories had identical category structures, sampled from a bivariate normal distribution (Figure 1). After constructing the categories in a normalized space, the dimensions were transformed into auditory and visual dimensions (see Supplemental Materials). Auditory categories were defined by frequency (Hz) and duration (seconds) of a pure tone. Visual categories were defined by length (pixels) and orientation (degrees) of a line on the screen. Stimuli and data can be found at <https://osf.io/cp932/>.

Figure 1. Rule-Based (left) and Information-Integration (right) category structures for auditory and visual tasks across all experiments, shown in normalized space. Solid lines reflect optimal boundaries between categories and the different symbols denote stimuli from different categories.

Procedure

Across six 100-trial categorization blocks in both the auditory and visual tasks, participants were instructed to make their decisions based on the tone's frequency and duration in the auditory task and on the line's length and orientation in the visual task. Auditory stimuli were presented dichotically via headphones and varied in duration from 85-394 ms. Visual stimuli were presented on the screen for 1 sec at a viewing distance of approximately 45 cm at a height of 7 cm, with a visual angle of 8 degrees. Participants pressed one of four buttons (1, 2, 3, or 4) and received feedback ("Correct"/"Incorrect") for 1 sec followed by a 1 sec ITI.

Decision bound computational modeling

To understand participants' strategies during learning, we applied several classes of decision-bound computational models (Ashby, 1992; Maddox & Ashby, 1993; Supplemental Materials). These models assume that participants divide the categories in the two-dimensional space with decision boundaries that can rely on implicit or explicit learning processes. We fit several classes of models that make different assumptions: an implicit model, explicit conjunctive and unidimensional models, and a random responder model.

The implicit Striatal Pattern Classifier (SPC) model is a neurobiologically grounded model thought to reflect implicit procedural learning mechanisms (Ashby et al., 1998). The SPC model assumes that participants use feedback to learn stimulus-response associations instantiated within the striatum (Ashby & Waldron, 1999) and can be thought of as a complex implementation of an exemplar model (Ashby & Rosedahl, 2017). This model has nine free parameters: eight that determine the location of hypothetical striatal units in perceptual space and one that represents the noise associated with the placement of the striatal units. When a participant uses an SPC strategy, they combine information across both dimensions in a pre-decisional manner that is optimal for II categories.

The second class of models represents explicit, hypothesis-testing mechanisms and includes conjunctive and unidimensional rule models. Conjunctive models assume that the participant places two decision boundaries (one along each dimension) that are combined to determine category membership. When a participant uses a conjunctive strategy, they selectively attend to both dimensions in a manner that is optimal for the RB categories. The conjunctive model has three free parameters: two for the boundaries along the x and y-dimensions and one noise parameter. Unidimensional models assume that the participant sets three decision

boundaries along only one of the dimensions (x or y) and have four free parameters: three for boundaries along the relevant dimension and one noise parameter.

The random responder model that assumes that the participant guesses on each trial.

Model parameters were estimated using maximum likelihood procedures (Wickens, 1982) and model selection used the goodness-of-fit statistic Bayesian Information Criterion (BIC), which penalizes models with more free parameters: $BIC = r \cdot \ln N - 2 \ln L$, where r is the number of free parameters, N is the number of trials in a given block for a given subject, and L is the likelihood of the model given the data (Schwarz, 1978). Models were fit to each of the six 100-trial blocks for the auditory and visual tasks for each participant (6 blocks x 2 tasks x 49 participants = 588 total best-fit models). Within each block, the model with the lowest BIC value was selected as the best-fitting model. Overall, the models accurately captured participants' response patterns (M accuracy 68% vs. 25% chance).

Results

To evaluate the extent to which music training confers a domain-general or auditory-specific advantage in RB and II category learning, we compared musicians and non-musicians' auditory and visual category learning accuracy using mixed model ANOVAs (Figure 2A).

In the auditory modality, accuracy differed based on category and musician-status ($F(1, 45) = 10.2, p = .003, \eta_p^2 = 0.19$). Specifically, musicians outperformed non-musicians in auditory RB categorization ($t(24) = 4.92, p < .001, d = 2.01, 95\% \text{ CI } [0.14, 0.34]^2$) and were not different in auditory II categorization ($t(21) = 0.69, p = .50, d = 0.30, 95\% \text{ CI } [-0.06, 0.12]$). Additionally, the *pattern* of accuracy across blocks differed among musicians and non-musicians ($F(5, 225) = 2.39, p = .039, \eta_p^2 = 0.050$). Visual inspection of the learning curves indicates that musicians

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² Confidence intervals presented throughout always reflect proportions, rather than percentages.

improve rapidly from the first to second block for the RB task and non-musicians demonstrate a more gradual increase of accuracy across blocks. The pattern of accuracy across blocks was not influenced by category ($F(5, 225) = 1.53, p = .18, \eta_p^2 = 0.033$) or the interaction between musician-status and category ($F(5, 225) = 2.00, p = .080, \eta_p^2 = 0.043$).

In contrast, musicians and non-musicians did not differ in the visual modality ($F(1, 45) = 0.061, p = .81, \eta_p^2 = 0.001, 95\% \text{ CI } [-0.075, 0.059]$) and there were no differences between the II and RB categories ($F(1, 45) = 3.19, p = .081, \eta_p^2 = 0.066, 95\% \text{ CI } [-.13, 0.008]$). There was no interaction between musician-status and category ($F(1, 45) = 1.99, p = .17, \eta_p^2 = 0.042$). Participants learned the categories, as evidenced by a significant main effect of block ($F(5, 225) = 56.7, p < .001, \eta_p^2 = 0.56$), but performance across blocks did not differ between musicians and non-musicians ($F(5, 225) = 0.94, p = .56, \eta_p^2 = 0.020$), II or RB categories ($F(5, 225) = 0.74, p = .59, \eta_p^2 = 0.016$), or the interaction between category and musicianship ($F(2, 225) = 0.52, p = .76, \eta_p^2 = 0.011$).

For auditory II categories (Figure 2B), musicians and non-musicians used similar strategies across all blocks (Fisher's exact tests, all $ps > .34$). Participants gradually shifted from using suboptimal conjunctive and unidimensional strategies to using the optimal SPC strategy. For auditory RB categories (Figure 2B), musicians and non-musicians used different strategies in several blocks (Fisher's exact tests, blocks 3: $p < .001$, 4: $p = .025$, and 5: $p = .031$; no significant differences in blocks 1, 2, or 6: all $ps > .06$). While many musicians used an optimal conjunctive strategy throughout training, many non-musicians relied on suboptimal unidimensional strategies, separating the categories based on the frequency dimension.

Figure 2. A. Block-by-block accuracy for musicians and non-musicians in the auditory (top) and visual (bottom) category learning tasks, specifically for II (left) and RB (right) categories. The dashed line represents chance performance (25%). Individual data across participants as well as the individual group mean are shown. Error bars reflect *SEM*. B. Proportion of participants best-fit by each strategy type across the six blocks of the Auditory and Visual tasks. Musicians (left) and non-musicians (right) learning II (top) and RB (bottom) categories are shown separately.

For visual II and RB categories (Figure 2B), musicians and non-musicians used similar strategies across blocks (Fisher's exact tests, all $ps > 0.45$). For II learning, participants shifted from using suboptimal conjunctive and unidimensional strategies to optimal SPC strategies and for RB learning, participants generally applied an optimal conjunctive strategy throughout learning.

Musicians who used optimal conjunctive strategies during the final block of auditory RB categorization had higher accuracies than non-musicians using the same strategies (Musicians (M): 83%, Non-Musicians (NM): 70%, $t(9.36) = 2.52$, $p = .032$, $d = 1.26$, 95% CI [0.014, 0.25]). This pattern was specific to auditory RB categorization. For visual RB and II categorization and auditory II categorization, there were no differences in accuracies for musicians and non-musicians using optimal strategies (visual RB: M: 81%, NM: 80%, $t(13.5) = 0.58$, $p = .57$, $d = 0.25$, 95% CI [-0.052, 0.091]; visual II: M: 77%, NM: 80%, $t(12.4) = -0.89$, $p = .39$, $d = 0.42$, 95% CI [-0.10, 0.043]; auditory II: M: 77%, NM: 74%, $t(8.41) = 0.66$, $p = .53$, $d = 0.37$, 95% CI [-0.068, 0.12]). Musicians performed better than non-musicians at auditory RB categorization both because they were more likely to use the optimal strategy and they were more accurate than non-musicians who used the optimal strategy.

Experiment 2

In Experiment 1, formally trained musicians outperformed non-musicians during auditory RB, but not auditory II or visual category learning. However, with an appreciation that musicians may have a wide variety of music experience and training, in Experiment 2, we examined an online sample of musicians with a wider variety of music experience. Additionally, in Experiment 1, participants were told about the dimensions that defined the categories. Thus, participants did not need to discover the relevant dimensions and these instructions may have

helped the musicians find the optimal conjunctive rule to separate the auditory RB categories. Previous research has shown that instructing learners about the dimensions that define categories enhances learning and affects learners' strategies (Chandrasekaran et al., 2016). In Experiment 2, we removed these dimension instructions.

Method

Participants

Participants were recruited through Prolific (www.prolific.sc) and the experiment was administered using the online Gorilla Experiment Builder (www.gorilla.sc; Anwyl-Irvine et al., 2019). One hundred participants completed one session and 87 returned for a second session (13 did not return for a second session or failed to complete all tasks)³. Musicians and non-musicians were grouped based on their answers to the Ollen Musical Sophistication Index (OMSI, Ollen, 2006) musician rank item ("Which title best describes you?"), which is a single item measurement for measuring music experience (Zhang & Schubert, 2019). Participants were identified as musicians when they answered with 'musician' titles ($n = 36$; M age = 26.5 years, $sd = 4.60$; 19 F) and non-musicians answered with 'non-musician' titles ($n = 51$; M age = 26.8 years, $sd = 4.58$; 30 F).

Procedure

Participants completed two sessions, separated by one week and learned all four types of categories, with order counterbalanced across participants. Participants always completed one auditory and one visual task in each session to reduce potential carryover effects in learning within the same modality. Participants completed the same music history questionnaire as Experiment 1 (see Supplemental Materials). The stimuli were identical to Experiment 1.

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³ A power analysis indicated that to observe a medium-sized effect of musicianship on accuracy with a within-subjects design, we would need to recruit 32 participants in both groups.

The tasks were similar to Experiment 1, with two differences: participants completed three blocks instead of six⁴ and were not told about the dimensions that distinguished the categories.

Results

In this within-subjects study, without dimension instructions, musicians and non-musicians did not significantly differ in accuracies (Figure 3A; $F(1, 85) = 0.025, p = .88, \eta_p^2 = 0.0, 95\% \text{ CI } [-0.062, 0.053]$). Musicians and non-musicians were no different in auditory and visual categorization ($F(1, 85) = 1.37, p = .25, \eta_p^2 = 0.016$) or RB and II categorization ($F(1, 85) = 0.73, p = .40, \eta_p^2 = 0.008$). Performance was no different for II and RB categories ($F(1, 85) = 1.88, p = .18, \eta_p^2 = 0.022, 95\% \text{ CI } [-0.007, 0.038]$), but was better for visual compared to auditory categories ($F(1, 85) = 23.8, p < .001, \eta_p^2 = 0.22, 95\% \text{ CI } [0.035, 0.083]$). Unlike Experiment 1, musicians and non-musicians used similar strategies to learn the auditory RB categories (Figure 3B). The only difference in strategies was auditory II block 1 ($p = .043$). There were no differences in strategies across all other blocks of all tasks (Fisher's exact tests, all $ps > .19$). Participants used a mix of strategies, generally using optimal conjunctive strategies in the RB tasks and a mix of strategies in the II tasks.

Unlike Experiment 1, there were no differences in accuracies for musicians and non-musicians who used optimal conjunctive strategies during the final block of auditory RB categorization (M: 57%, NM: 61%, $t(38.3) = -0.77, p = .45, d = -0.22, 95\% \text{ CI } [-0.17, 0.076]$). There were also no differences in accuracies between musicians and non-musicians using

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⁴ In Experiment 1, the differences between musicians and non-musicians in auditory RB learning were present from the first block of training and much of the learning occurred within the first three blocks. Thus, with this fully within-subjects study, we decided to reduce the number of trials to lower the burden on participants who were completing four separate tasks and to reduce potential carryover effects across tasks.

optimal strategies for any other type of category (visual RB: M: 72%, NM: 67%, $t(48.9) = 0.95$, $p = .35$, $d = 0.26$, 95% CI [-0.053, 0.15]; visual II: M: 74%, NM: 74%, $t(14.8) = 0.017$, $p = .99$, $d = 0.01$, 95% CI [-0.11, 0.11]; auditory II: M: 69%, NM: 66%, $t(14.7) = 0.99$, $p = .34$, $d = 0.42$, 95% CI [-0.044, 0.12]).

Figure 3. A. Block-by-block accuracy for Experiment 2, error bars reflect *SEM*. B. Proportion of participants best-fit by each strategy type across blocks in Experiment 2.

Experiment 3

In Experiment 2, with a broader conceptualization of musician, within-subjects design, and lack of dimension instructions there were no musician benefits in any of the four types of category learning. To better understand whether this finding was due to the differences in the instructions, we ran Experiment 3. This experiment tests the hypothesis that the auditory RB musician benefit in Experiment 1 was driven by the presence of auditory dimension instructions, particularly benefitting musicians, for whom these dimensions are particularly salient. In Experiment 3, we examined auditory and visual RB learning in an online sample with dimension instructions.

Participants

Participants were recruited through Prolific and the experiment was administered using the Gorilla Experiment Builder. Sixty-four participants completed both tasks (one failed to complete all tasks)⁵. Musicians and non-musicians were grouped based on their answers to the OMSI musician rank question. Participants were identified as musicians when they answered with ‘musician’ titles ($n = 28$; M age = 27.3 years, $sd = 4.82$; 10 F) and non-musicians answered with ‘non-musician’ titles ($n = 36$; M age = 26.8 years, $sd = 4.14$; 27 F).

Procedure

In a single session, participants learned the auditory and visual RB categories, with order counterbalanced across participants. Participants completed the same music history questionnaire as Experiments 1 and 2 (see Supplemental Materials). The stimuli were identical to Experiments 1 and 2. Participants completed three blocks (as in Experiment 2) and were explicitly told about the dimensions that distinguished the categories (as in Experiment 1).

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⁵ A power analysis indicated that to observe a medium-sized effect of musicianship on accuracy with a within-subjects design, we would need to recruit at least 26 participants in both groups.

Results

In this within-subjects sample with dimension instructions, the pattern of performance across blocks, musicianship, and modality was marginally significant (Figure 4A; $F(2, 124) = 2.77, p = .067, \eta_p^2 = 0.043$). To investigate this further with exploratory analyses, we found that in block 1, musicians performed better than non-musicians in learning RB auditory categories ($t(62) = 2.13, p = .037, d = 0.54, 95\% \text{ CI } [0.0047, 0.15]$) but not RB visual categories ($t(62) = 0.99, p = .33, d = 0.25, 95\% \text{ CI } [-0.11, 0.036]$). Unlike Experiment 1, this advantage disappeared after the first block where musicians and non-musicians did not perform differently (all $ps > .39$). There were no differences between musicians and non-musicians in strategy across any block for either task (Figure 4B; Fisher's exact tests, all $ps > .12$).

As in Experiment 1, musicians who used optimal conjunctive strategies during the final block of auditory RB categorization had higher accuracies than non-musicians using the same strategies (M: 73%, NM: 57%, $t(30.5) = 2.64, p = .013, d = 0.85, 95\% \text{ CI } [0.036, 0.28]$). This pattern was specific to auditory RB categorization. There were no differences in accuracies for musicians and non-musicians using optimal strategies during visual RB categorization (M: 71%, NM: 69%, $t(34.1) = 0.67, p = .51, d = 0.19, 95\% \text{ CI } [-0.055, 0.11]$). Musicians performed better than non-musicians at auditory RB categorization when they used the same optimal strategy.

Figure 4. A. Block-by-block accuracy for Experiment 3, error bars reflect *SEM*. B. Proportion of participants best-fit by each strategy type across blocks in Experiment 3.

Discussion

Musicians have an *experience-specific* category learning benefit and demonstrate advantages when learning categories defined by acoustic dimensions that are directly relevant to music experience only when given instructions about the dimensions that define the categories.

In Experiments 1 and 3, musicians' advantage was limited to their modality of expertise and did not demonstrate a domain-general benefit. These results are aligned with prior research that suggests that musicians' advantages over non-musicians are predominantly in the auditory modality and may not extend to the visual modality (Chan et al., 1998; Cohen et al., 2011; Tierney et al., 2008). This is also supported by research demonstrating enhanced auditory processing in musicians (Barrett et al., 2013; Kraus & Chandrasekaran, 2010; Rammsayer & Altenmüller, 2006; Strait et al., 2012; White-Schwoch et al., 2013). Musicians also have processing advantages for visual information that is relevant to their musical experience (Maturi & Sheridan, 2020; Wong & Gauthier, 2012). Thus, the advantage that we observed may not be

auditory-specific per se, but rather due musicians' specific experience. It is possible that musicians may demonstrate benefits in learning categories that are defined by music-related visual dimensions.

Frequency and duration are fundamental dimensions in music. Musicians have experience with these simple, verbalizable dimensions that may make them very salient. Further, participants in Experiments 1 and 3 were told that these dimensions defined the categories. Musicians' real-world experience and the overt labeling enabled musicians to attend to and create relevant rules based on these dimensions, reflected in their optimal strategy use for RB categorization. Including instructions did not differentially benefit musicians during visual RB categorization, indicating that it is the combination of experience with the dimensions and explicit dimension instructions that supports superior learning. In Experiments 1 and 3, even when musicians and non-musicians were using the same optimal strategy during auditory RB categorization, musicians had better accuracies. This pattern was specific to auditory RB categorization.

Recent research has demonstrated that RB learning is enhanced when the dimensions are more verbalizable (Zetterston & Lupyan, 2020; Brashears & Minda, 2020). In contrast, II categories cannot be easily described using verbalizable rules. Thus, an enhanced ability to selectively attend to these verbalizable dimensions would not help musicians during II categorization. For frequency and duration, it seems that integrating the dimensions in a way that is optimal for II categorization is not benefitted by musical experience. This may be similar to the way in which it is difficult even for color experts to selectively attend to the perceptually integral dimensions of value and chroma (Burns & Shepp, 1988).

We also note that overall performance was poorer in our online follow-up Experiments 2 and 3 than in the in-person Experiment 1. To reduce potential carryover effects and the burden on participants, we trained participants on half as many trials. When comparing the first three blocks of Experiment 1, performance appears to be slightly lower on average in the online experiments (M block 3 accuracy: Exp 1: 67%, Exp 2: 55%, Exp 3: 57%). It is not the case that learning online is impossible; many participants learned the categories quite well. Critically, it is unlikely that an online testing environment would differentially impact musicians and non-musicians (see Supplementary Materials for information in the auditory equipment used by musicians and non-musicians in the online experiments).

Musicians are a heterogeneous group. Across experiments, music experience (Supplemental Materials; years of training, hours practiced per week, instruments played) varied widely across musicians. Differences in the nature of musicians' experiences may have contributed to the different effect sizes that we observed during auditory RB categorization (Experiment 1: $d = 2.01$; Experiment 3: $d = 0.54$). Musicians in Experiment 1 who completed the auditory RB task had an average of 16.4 years ($sd = 2.78$) of music training and were practicing music for 16.1 hours ($sd = 11.1$) per week. Musicians in Experiment 3 had 9.13 years ($sd = 6.10$) of music training and were practicing music for 5.80 ($sd = 5.47$) hours per week. It is common to treat musicians as a homogenous group even though they clearly have vast differences in their experience and how deeply they are currently engaging with music (Tervaniemi, 2009). Musicians in Experiment 1 were enrolled in a music school curriculum which, in addition to regular practice, places weekly emphasis on training for auditory acuity during ear-training, music theory, and other coursework. The immersive experience of a music school curriculum, both in playing and critical listening, may have led to the large accuracy differences in musicians

across Experiments 1 and 3. More research is required to understand the impact of individual differences within musicians on learning.

Together, these three experiments support the conclusion that musicians have an *experience-specific* advantage in category learning that is specific to rule-based categories and dependent on explicit instructions guiding their attention to the music-relevant dimensions.

Conclusion

As contribution to the debate of whether musicians demonstrate domain-general cognitive or auditory-specific benefits over non-musicians, our results support a musician advantage that is specific to their experience in the auditory domain, with category-specific advantages dependent on the presence of dimension instructions. By drawing attention to the dimensions of frequency and duration, which are salient and verbalizable dimensions relevant to music, musicians have an advantage in learning RB categories. The size of this advantage was much larger in formally trained musicians than in a population with a more general conceptualization of ‘musician.’ Musicians are heterogeneous and appreciation of this variability is important for putting their advantage into context.

Context of the Research

We have previously examined perceptual and cognitive processes supporting learning in musicians and the general population. Category learning presents an excellent testbed for understanding how music experience alters perception and cognition because it involves both elements. We designed experiments manipulating perceptual components (modality, dimensions) and cognitive demands of the categorization problem (II, RB). In the future, this research will be extended by comparing musicians and non-musicians with an expanded range of auditory and

visual dimensions and by examining these differences while appreciating the heterogeneity of musical experience within musicians.

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Supplemental Materials

Participant Information

Music history for musicians and non-musicians in Experiment 1 is reported in Table S1, Experiment 2 is reported in Table S2, and Experiment 3 is reported in Table S3.

Table S1

Experiment 1 Participants' music history

Subject ID	Years of training	Hours play per week	Instrument
Musicians			
1502	10	25	Piano, Voice, Organ
1503	10	15	Cello
1507	22	10.5	Voice
			Double bass, Piano, Bassoon,
1508	10	9	Violin, Horn
1509	15	3	Piano, Viola, Horn
1511	8	41	Flute, Piano
			Violin, Double bass, Electric
			bass, Viola, Oboe, Trumpet,
1512	13	25	Percussion, Piano
1513	10	25	Piano, Cello
1514	15	28	Recorder, Saxophone
1515	15	37	Violin, Piano
1517	20	9.5	Violin, Viola
1519	13	21	Piano, Voice, Viola
1521	16	11	Violin, Piano, Voice
1522	20	5	Violin
1523	15	16	Piano, Voice, Guitar, Flute
1524	7	23	Clarinet, Piano
1525	16	2	Violin
1526	11	8.5	Piano, Guitar, Bass
			Piano, Voice, Sitar, Saxophone,
1527	11	12	Guitar, Percussion
1528	14	26	Voice, Cello, Oboe, Piano
1529	12	7	Piano, Flute, Clarinet, Voice
1530	17	11	Piano, Violin, Voice
1532	15	36	Piano, Organ
1533	15	20	Flute
Mean	13.8	17.8	

Non-Musicians			
1402	0.5	0	Piano, Drums
1403	0	0	NA
1404	1	0	Violin, French Horn
1406	0	0	NA
1407	2	0	Violin
1408	1	0	Violin
1409	1.5	0	Did not report
1412	2	0	Trumpet
1413	2	0	Flute
1414	0	0	NA
1415	3	0	Piano, Guitar
1416	0	0	NA
1417	2	0	Recorder, Piano
1418	3	0	Saxophone
1419	0.5	1	Piano
1420	0.25	0	Piano
1421	0	0	NA
1422	0	0	NA
1424	1	1	Piano
1425	0	0	NA
1427	1	2.5	Did not report
1428	0	0	NA
1438	0	0	NA
1439	1	0	Voice
1441	1	0	Guitar, Piano
Mean	0.91	0.18	

Table S2*Experiment 2 Participants' music history*

Subject ID	Years of training	Hours play per week	Instrument
Musicians			
2566804	12	1	Flute, Piano
2566979	10	2	Trumpet, French horn, Piano, Voice
2567003	12	12	Flute, Electric bass, Piano
2567251	17	13	Voice, Piano, Guitar
2568008	12	3	Drums, Guitar, Trumpet, Piano
2568531	8	10	Guitar
2581259	15	20	Guitar, Voice, Piano
2581269	17	10	Clarinet
2581276	12	2	Violin, Piano
2581286	4	9	Guitar

2581267	10	5	Guitar
2581289	5	10	DJ mixing board
2581285	8	0	Triple harp
2581354	20	45	Violin, Harp
2581767	15	14	Flute, Keyboard, Guitar, Ukulele, Mandolin
2581788	3	3	Drums
			Guitar, Bass, Piano, Djembe, Drums, Mandolin,
2581795	9	27	Ukulele, Ocarina, Saxophone
2581806	7	1	Piano
2581805	13	1	Violin, Piano
2581818	9	4	Guitar, Voice, Piano
2581836	6	0.5	Guitar
2568024	10	1	Drums, Voice
2567987	0	0	N/A
2567953	7	15	Voice, Guitar, Piano
2567964	18	3	Guitar
2567955	12	6	Piano, Saxophone
2567942	20	7.5	Voice, Guitar, Keyboard
2567954	6	0	Guitar
2567626	15	50	Guitar, Bass, Voice
2567248	10	14	Piano, Flute, Clarinet, Violin
2567203	16	0	Trombone, Voice, Piano
2567234	11	0	Flute
2567078	4	10	Voice, Piano
2567065	13	20	Flute, Piano
2566939	13	9	Guitar, Piano, Bass Guitar, Drums
2566958	2	0	Keyboard

Mean 10.6 9.11

Non-Musicians

2567262	7	0	Guitar
2567304	0	10	Guitar
2581263	10	0	Piano
2581273	0	0	Bass guitar
2581747	0	0	N/A
2567966	0	0	N/A
2567971	3	1	Guitar
2567308	5	0	Piano, Trumpet
2566801	0	0	N/A
2566924	0	0	N/A
2566950	0	0	N/A
2566947	0	0	N/A
2566999	1	0	Keyboard, Clarinet
2567008	0	0	N/A
2567097	0	0	N/A
2567200	0	0	N/A
2567206	0	0	N/A

2567208	0	0	N/A
2567217	0	0	N/A
2567204	0	0	N/A
2567295	0	0	N/A
2567314	0	0	N/A
2567363	0	0	N/A
2567944	0	0	N/A
2567956	0	0	N/A
2567961	0	0	N/A
2567945	0	0	N/A
2567951	1	0	Clarinet
2568010	0	0	N/A
2567979	0	7	Piano
2568257	0	0	N/A
2581257	0	0	N/A
2581251	0	0	N/A
2581265	0	0	N/A
2581268	0	0	N/A
2581272	0	0	N/A
2581270	0	0	N/A
2581300	0	0	N/A
2581309	0	0	N/A
2581508	0	0	N/A
2581671	0	0	N/A
2581760	0	0	N/A
2581763	0	0	N/A
2581777	0	0	N/A
2581778	0	0	N/A
2581771	0	0	N/A
2581787	0	1	Recorder
2581789	0	0	N/A
2581802	0	0	N/A
2581803	0	0	N/A
2581769	0	0	N/A
Mean	0.53	0.37	

Note: Subject 2567987 identified as a musician, but reported no musical training, zero hours of music practiced per week, and no instrument. Removing this participant did not change the outcomes of any analyses.

Table S3*Experiment 3 Participants' music history*

Subject ID	Years of training	Hours play per week	Instrument
Musicians			
2855243	7	6	Voice, Viola, Guitar
2855293	11	6	Synthesizer, Guitar
2855430	0	10	Guitar, Bass, Drums
2855435	12	4	Bass guitar, Electric guitar
2855482	6	20	Voice, Guitar, Piano, Ukulele
2855499	10	5	Piano
2855552	15	3	Piano, Voice, Guitar
2855547	14	10	Guitar, Piano, Voice, Drums, Bass guitar
2855563	5	1	Keyboard, Guitar
2855586	8	3	Electric bass, Voice
2856439	17	2	Piano, Voice
2856445	6	1	Tuba
2856444	8	10	DJ mixing board, Guitar, Piano
2856453	8	15	Guitar, Bass, Violin, Piano
2856458	7	20	Euphonium, Baritone, Voice, Trumpet
2856485	5	2	Guitar
2856490	10	0	Piano, Guitar, Drums
2856476	5	8	Guitar, Piano, Voice
2856832	0.5	3	Guitar, Synthesizer
2857223	3	5	Guitar
2857225	3	10	Piano, Guitar
2857237	11	5	Drums, Keyboard
2857243	10	0	Drums, Saxophone, Electric guitar, Voice
2865813	22	6	Bass guitar, Guitar, Flute
2865815	10	0	Piano, Recorder, Voice
2869427	4	0.5	Violin
2855529	28	4	Voice
2856623	10	3	Piano
Mean	9.13	5.80	
Non-Musicians			
2855246	0	0	N/A
2855381	3	0	Violin, Keyboard
2855548	0	0	N/A
2855668	10	1	Clarinet, Tenor Saxophone, Alto Saxophone
2856479	4	0	Piano
2857313	4	10	Voice, Recorder, Violin
2865820	5	0	Voice, Flute, Bassoon, Xylophone
2865829	1	0	Drums
2855209	0	0	N/A

2855396	0	0	N/A
2855387	0	0	N/A
2855412	0	0	N/A
2855489	0	0	N/A
2855484	0	0	N/A
2855501	0	0	N/A
2855487	0	0	N/A
2855602	0	1	Guitar
2855626	0	0	N/A
2855637	0	0	N/A
2856153	0	0	N/A
2856428	0	0	N/A
2856432	0	0	N/A
2856461	0	0	N/A
2856466	0	0	N/A
2856465	0	0	N/A
2856498	0	0	N/A
2856651	0	0	N/A
2856658	0	0	N/A
2856984	0	0	N/A
2857176	0	0	N/A
2857214	0	0	N/A
2857228	0	0	N/A
2857311	0	0	N/A
2857384	0	0	N/A
2858100	0	0	N/A
2858207	0	0	N/A
Mean	0.75	0.33	

In Experiment 1, we assessed working memory differences between musicians and non-musicians using the digit span of the Weschler Adult Intelligence Scale, 4th edition (WAIS-IV, Weschler, 2008). Participants completed forward and backward digit span tasks, where numbers were read at a rate of one number per second with a monotone voice. Participants were instructed to repeat the string of numbers presented to them in the exact order they heard it (forward span) or in backwards order (backward span). The word span score was coded as the sum of the longest string of numbers that participants could correctly repeat across two repetitions. Musicians and non-musicians did not differ on the forward span score ($t(46.62) = 1.80, p =$

0.078, $d = 0.51$, 95% CI [-0.13 , 2.4]) or backward span score ($t(44.27) = 1.27$, $p = 0.21$, $d = 0.37$, 95% CI [-0.46 , 2.0]), indicating that any potential differences in learning may not be due to working memory differences between groups. Musicians had an average forward span score of 11.8 ($sd = 2.26$) and backward span score of 7.46 ($sd = 1.80$). Non-musicians had an average forward span score of 10.6 ($sd = 2.26$) and a backward span score of 6.68 ($sd = 2.42$)

In Experiment 2, we assessed working memory differences between musicians and non-musicians using an automated version of the operation span task (OSPAN, Unsworth et al., 2005). Participants were shown simple arithmetic problems (e.g., $(5 + 4) \times 1 = 12$), reported whether the solutions were correct or incorrect, and were shown a letter on the screen (e.g., A). Participants saw 15 letter sequences that spanned from three to seven letters. After a full sequence was presented, participants recalled the letters in the order they appeared. The OSPAN score was calculated as the sum of the length of all correctly recalled spans. For instance, if a participant correctly recalled a sequence of six letters, six points would be added to their score. We did not filter the scores on the basis of accuracy (Đokić et al., 2018). Musicians and non-musicians did not differ in their OSPAN scores ($t(85) = 1.96$, $p = 0.053$, $d = 0.43$, 95% CI [-0.090, 15.13]). Musicians had an average OSPAN score of 46.6 ($sd = 17.5$) and non-musicians had an average OSPAN score of 39.1 ($sd = 17.7$).

Summary of auditory equipment in online experiments

Collecting data for auditory experiments online raises important questions about how the experimental environment differs from highly controlled spaces typically used in laboratory experiments. The auditory and visual stimuli used across these experiments were designed intentionally to be above perceptual thresholds. That is, these stimuli do not require enhanced auditory or visual perception to be perceived and therefore, we do not believe that small

differences in auditory or visual equipment (i.e., natural variation in the types of headphones or computer monitors that participants use) would lead to differences in learning. However, it is important to confirm that our groups of interest (musicians and non-musicians) did not fundamentally differ on their at-home auditory equipment. In Table S4, we report the self-reported auditory equipment for musicians and non-musicians in Experiments 2 and 3. We note that there are no substantial differences between musicians and non-musicians in the types of headphones they used (in-ear vs. over-ear headphones), whether the headphones were noise-canceling, or in self-reported issues with the headphones.

Table S4

Auditory equipment information

Experiment 2			
<u>Group</u>	<u>% in-ear vs. over-ear</u>	<u>% noise-cancelling</u>	<u># self-report issues</u>
Musicians	44%	25%	2/36
Non-musicians	51%	29%	1/51
Experiment 3			
<u>Group</u>	<u>% in-ear vs. over-ear</u>	<u>% noise-cancelling</u>	<u># self-report issues</u>
Musicians	36%	43%	0/28
Non-musicians	44%	28%	0/36

Note: The self-reported issues with headphones were specifically that there were issues with sound in one of the ears. Because binaural sound presentation was not a critical component to the perception of our stimuli, we did not remove any of these participants from the analyses.

Stimulus Information

Auditory stimuli varying in frequency and duration were WAV files generated using Praat and were amplitude matched at 70dB. Visual stimuli were generated on-the-fly using a custom MATLAB script in Experiment 1. In Experiments 2 and 3, visual stimuli were PNG files generated using custom scripts in PsychoPy. Stimuli and scripts can be found at <https://osf.io/cp932/>. These pairs of dimensions were chosen because they have been used in studies before and found to have been in good alignment with assumptions about II and RB

category learning (Chandrasekaran et al., 2014; Edmunds et al., 2014; Ell et al., 2006). The distributions were created using probabilistic sampling from a bivariate Gaussian distribution in normalized space, with RB categories having boundaries orthogonal to the dimensions and II categories being rotated 45 degrees in space.

Distributional information for the categories in normalized space (Table S5), transformed visual space with length and orientation as dimensions (Table S6) and transformed auditory space with duration and frequency as dimensions (Table S7).

Equations used for transforming categories from normalized space to stimulus space (duration and frequency: equations 1 and 2; length and orientation: equations 3 and 4) are shown below:

$$\text{equation 1: } \textit{duration (sec)} = 0.103 + x * 0.29$$

$$\text{equation 2: } \textit{frequency (Hz)} = 523.46 + y * 482.47$$

$$\text{equation 3: } \textit{length (pixels)} = 51.03 + x * 96.72$$

$$\text{equation 4: } \textit{orientation (degrees)} = 54.69 + y * 96.49$$

Table S5

Category distributional information, normalized dimensions

Information-Integration					
Category	μ_x	μ_y	σ_x	σ_y	$\text{COV}_{x,y}$
A	0.217	0.470	0.103	0.104	0.00109
B	0.506	0.760	0.103	0.104	0.00095
C	0.506	0.180	0.103	0.104	0.00098
D	0.796	0.470	0.103	0.104	0.00093
Rule-Based					
Category	μ_x	μ_y	σ_x	σ_y	$\text{COV}_{x,y}$
A	0.349	0.330	0.0997	0.106	0.00105
B	0.349	0.753	0.0997	0.105	0.00097
C	0.747	0.330	0.0997	0.106	0.00092
D	0.747	0.753	0.0997	0.105	0.00096

Table S6*Category distributional information, length and orientation dimensions*

Information-Integration					
<u>Category</u>	<u>μ_{length}</u>	<u>μ_{orient}</u>	<u>σ_{length}</u>	<u>σ_{orient}</u>	<u>$COV_{len,ori}$</u>
A	72	100	10.0	10.00	10.1
B	100	128	10.0	9.99	8.85
C	100	72	10.0	9.99	9.12
D	128	100	10.0	9.99	8.72
Rule-Based					
<u>Category</u>	<u>μ_{length}</u>	<u>μ_{orient}</u>	<u>σ_{length}</u>	<u>σ_{orient}</u>	<u>$COV_{len,ori}$</u>
A	80	80	10.00	10.0	9.95
B	80	120	10.00	9.99	9.17
C	120	80	10.00	9.99	8.73
D	120	120	10.00	9.99	9.07

Table S7*Category distributional information, frequency and duration dimensions*

Information-Integration					
<u>Category</u>	<u>$\mu_{duration}$</u>	<u>$\mu_{frequency}$</u>	<u>$\sigma_{duration}$</u>	<u>$\sigma_{frequency}$</u>	<u>$COV_{dur,freq}$</u>
A	0.166	750	0.0300	50.0	0.152
B	0.250	890	0.0300	50.0	0.133
C	0.250	610	0.0300	50.0	0.137
D	0.334	750	0.0300	50.0	0.131
Rule-Based					
<u>Category</u>	<u>$\mu_{duration}$</u>	<u>$\mu_{frequency}$</u>	<u>$\sigma_{duration}$</u>	<u>$\sigma_{frequency}$</u>	<u>$COV_{dur,freq}$</u>
A	0.190	650	0.0300	50.0	0.149
B	0.190	850	0.0300	49.9	0.138
C	0.310	650	0.0300	50.0	0.131
D	0.310	850	0.0300	49.9	0.136

Computational Modeling Details

Decision bound computational models make different assumptions about how participants divide the stimuli into categories based on the dimensions that define the stimuli. As a demonstration of these models, the figure below shows a hypothetical response pattern for each model class. Importantly, these models are agnostic about the actual category identity of the stimuli and are based on the participant's response. To demonstrate, for a block of trials (100 trials in our case), we can plot all of the stimuli that the participant encountered in the two-

dimensional space (Figure S1). We then can divide that space using boundaries with models that have different assumptions with the goal of finding the best model to account for this particular participant's response pattern in this block of data. The key differences between the models is in the assumptions they make about how participants use the stimulus dimensions to separate the categories. In some instances, they use only one dimension (unidimensional-x and unidimensional-y). In other cases, they use both dimensions in a manner that is orthogonal to the dimension itself, consistent with selectively attending to that dimension (conjunctive models). Finally, in the case of the Striatal Pattern Classifier (SPC), they use both dimensions in a manner that is not orthogonal to the dimensions, but rather is a relationship that is harder to describe verbally and requires integration along the dimensions.

Figure S1. Hypothetical responses to each stimulus in the II category space. Each colored dot is a stimulus and the color corresponds to the theoretical response of this participant. Each panel reflects a different model with different decision boundaries. In each panel above, the stimuli are the same. It is only the mapping of stimulus to response label that is different across the panels.

In Experiment 1, across 49 participants, we fit models for each of the six blocks of data across the two tasks for a total of 588 blocks of data. In Experiment 2, across 87 participants, we fit models for each of the three blocks of data across the four tasks for a total of 1,044 blocks. In Experiment 3, across 64 participants, we fit models for each of the three blocks of data across the

two tasks for a total of 384 blocks. For each of those blocks of data, we fit each of our different models, which belong to one of the four general classes of models: SPC, conjunctive, unidimensional, and random responder. Within each of these classes, there are several different models fit that make different assumptions about which region of space is associated with which response. This allows us to capture variability due to valid application of a strategy, with varying category-response associations. Mathematical formulation of these models is outside of the scope of the current article and can be found elsewhere (Ashby, 1992; Maddox & Ashby, 1993). We applied 20 models to each block of data (Experiment 1: 588 blocks x 20 models = 11,760 model fits; Experiment 2: 1,044 blocks x 20 models = 20,880; Experiment 3: 384 blocks x 20 models = 7,680).

For each block of data, we selected the best-fit model on the basis of the goodness-of-fit statistic BIC. BIC penalizes more strongly against models with more free parameters. To understand how well the best-fit model for each participant (and each block) accounted for that participant's actual responses, we computed the proportion of participant's responses accurately predicted by the best-fit model (i.e., model accuracy) as a measure of goodness-of-fit. We computed the *predicted* response based on the best-fit model's fitted parameters. As these models are categorical models, the predicted response is the category response (i.e., 1, 2, 3, or 4) that the best-fitting model predicts that the participant would have made if they were applying this strategy consistently throughout that block. We compared the predicted response to the *observed* response made by the participant for each stimulus presented in a given block. For example, if the model predicted that for Stimulus-1, the participant would have responded 1 and the participant actually responded 1, this would be coded as a 'Correct' prediction. However, if the model predicted 1 and the participant actually responded 2, this would be coded as an

‘Incorrect’ prediction. For each participant and each block, we computed the model accuracy by comparing the model’s predicted response and the participant’s actual (observed) response.

The best-fit models accurately captured participants’ response patterns substantially better than chance (25%), with 68% average predicted vs. observed accuracy in Experiment 1, 48% accuracy in Experiment 2, and 51% accuracy in Experiment 3 (Figure S2). It is expected that accuracy would be lower than 100% as there is some variability in how consistently participants apply a given strategy within a block of 100 trials and these models fit behavior over an entire block. For instance, any lapses in attention or temporary switches in strategy cannot be captured. Instead, these models provide an estimate (with reasonable accuracy) of the strategy participants are using over the block of 100 trials. The assessment of goodness-of-fit tells us that the best-fit models provide a relatively accurate account of participants’ responses patterns.

Figure S2. Model accuracy as proportion (predicted response vs. observed response) for each participants’ best-fit model across all three experiments and blocks. The dashed line at 0.25 reflects chance performance.