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Better late than never (or early): Music training in late childhood is associated with enhanced decision-making

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Abstract

Decision-making is critical to everyday life. Here we ask: to what extent does music training benefit decision-making? Supported by strong associations between music training and enhanced cross-domain skills, we hypothesize that musicians may show decision-making advantages relative to non-musicians. Prior work has also argued for a "critical period" for cross-domain plasticity such that beginning music training early enhances sensorimotor brain regions that mature early in life. Given that brain regions supporting decision-making begin maturing late in childhood, we hypothesized that an advantage in decision-making may only be present in musicians who began music training later in childhood. To test this hypothesis, young adults who began music training before and after 8 years of age (early-trained musicians, ET; late-trained musicians, LT, respectively) and non-musicians (NM) performed a decision-making task. We found a decision-making advantage in LT relative to ET and NM. To better understand the mechanism of the LT advantage, we conducted computational modeling on participant responses and found that LT were less biased by recent outcomes and incorporated longer strings of outcomes when deciding among the choice options. These results tentatively suggest that music training may confer decision-making enhancements, and carry strong implications for the utility of music training in childhood.

Keywords

cognition, computational modeling, critical period, decision-making, music training

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Decision-making is a critical skill required for everyday functioning. We use it to make choices, guide our actions, and complete tasks throughout the day. We can choose options that are riskier or safer and those decisions may lead to positive or negative outcomes immediately or after some delay. Prior work has shown that decision-making relies heavily on the prefrontal cortex across species (Barraclough, Conroy, & Lee, 2004; Bechara, Damasio, Tranel, & Anderson, 1998; Broche-Pérez, Herrera Jiménez, & Omar-Martínez, 2016; Hare, O'Doherty, Camerer, Schultz, & Rangel, 2008; Li, Lu, D'Argembeau, Ng, & Bechara, 2009). More specifically, Hare and colleagues found that activity in the medial orbitofrontal cortex is associated with the predicted amount of reward each option will confer (i.e. goal values), while the central orbitofrontal region is associated with measuring the net reward of choosing an option (i.e., decision values; Hare et al., 2008). Goals and decision values are critical components of the decision-making process that guide the participant to actions that result in the largest net benefit. Additionally, animal studies suggest converging evidence implicating the orbitofrontal region in updating expected outcomes during a decision-making task (Sul, Kim, Huh, Lee, & Jung, 2010). A recent study also implicates the medial prefrontal cortex in tracking differences between a received reward and the expected reward on a trial-by-trial basis (Samanez-Larkin, Worthy, Mata, McClure, & Knutson, 2014). Lastly, prior studies have found that damage to the ventromedial prefrontal cortex (Bechara, Damasio, Damasio, & Anderson, 1994), dorsolateral and dorsomedial prefrontal cortex (Bechara et al., 1998; Manes et al., 2002) results in impaired decision-making ability. Together, these results suggest that while different subregions of the prefrontal cortex may be responsible for specific reward-based processes during a decision-making task, the prefrontal cortex as a whole is a critical brain region for successful decision-making.

The prefrontal cortex demonstrates protracted development through childhood (Gogtay et al., 2004), suggesting that as children age, and their prefrontal cortices develop, they should show enhanced decision-making abilities. Supporting this notion, prior work suggests that in a classic decision-making task, the Iowa Gambling Task (IGT), in which the participant must choose between decks that lead to net gains or net losses, the tendency to avoid disadvantageous deck choices increases from childhood through adolescence to adulthood (Hooper, Luciana, Conklin, & Yarger, 2004), and overall performance also increases throughout childhood (Crone & van der Molen, 2004). The IGT has also been used as a measure of incentive-based decision-making across a variety of populations including healthy adolescents (Hooper et al., 2004), healthy older adults (Wood, Busemeyer, Koling, Cox, & Davis, 2005), and clinical populations such as patients with schizophrenia (Shurman, Horan, & Nuechterlein, 2005), bipolar disorder (Ono et al., 2015), and damage to the ventromedial prefrontal cortex (Bechara et al., 1994).

Music training across the lifespan confers advantages in domains well beyond music (Herholz & Zatorre, 2012; Kraus & Chandrasekaran, 2010) such as speech perception (Kraus & Chandrasekaran, 2010; Parbery-Clark, Anderson, Hittner, & Kraus, 2012; Parbery-Clark, Skoe, Lam, & Kraus, 2009) and cognitive abilities (Costa-Giomi, 1999; Moreno et al., 2011; Schellenberg, 2005) and frontally-mediated cognitive abilities such as working memory (Bergman Nutley, Darki, & Klingberg, 2014; George & Coch, 2011; Kraus, Strait, & Parbery-Clark, 2012), processing speed (Bugos, 2010; Bugos & Mostafa, 2011), and cognitive control (Bialystok & DePape, 2009; Pallesen et al., 2010). Music training beginning before the age of seven relative to later in life, can enhance sensorimotor abilities that persist beyond childhood (Steele, Bailey, Zatorre, & Penhune, 2013). These findings support the concept of a "critical period," which suggests that introducing a novel skill that utilizes brain regions that are undergoing significant development will confer long-lasting cross-domain benefits (Hensch, 2005; Steele et al., 2013). Given that regions implicated in decision-making, namely the prefrontal cortex, do not develop until late childhood, we posit that beginning to play music in late childhood may provide an enduring enhancement in decision-making relative to beginning to play music earlier in childhood or never at all.

The goal of the current study is to examine the extent to which music training impacts decision-making, as measured by the Iowa Gambling Task. We hypothesize that musicians will show a performance advantage in decision-making relative to non-musicians, supported by the literature showing associations between music training and enhanced cognitive ability. We also hypothesize that if there is an advantage, it may only be present in musicians who began music training later in childhood, given that the brain regions supporting decision-making begin maturing later in childhood (Gogtay et al., 2004).

We examined decision-making performance using behavioral and computational modeling approaches in three groups: Adults who began playing music at or before the age of 8, classified as "early-trained" musicians (ET), adults who began playing music after the age of 8 classified as a "late-trained" (LT) musicians. Adults who never played an instrument were considered non-musicians (NM). We predicted that late-trained musicians would perform better than both early-trained musicians and non-musicians. Although accuracy data is informative for showing group differences, we fit computational models to response patterns to identify the mechanism behind any performance differences between groups. Lastly, we included data from a "many labs" collaboration as a Super Control group in our behavioral analyses. The purpose of including the Super Control group is to compare any group effect to a large, established well-studied sample that is representative of healthy young adult performers on the Iowa Gambling Task (Steingroever et al., 2015).

Method

Participants

A total of 69 participants (aged 18–35 years) were recruited from The University of Texas at Austin community and were part of a larger multi-day study, which was occurring at the same time as testing for the present study. Written consent was obtained from all participants and the Institutional Review Board of The University of Texas at Austin approved the experimental procedure. Participants were classified as non-musicians (NM), early-trained musicians (ET), or late-trained musicians (LT). Operationally, non-musicians had less than 2 years of music training and were not currently playing any instrument. ET had at least 8 years of music training beginning at or before age 8, while LT had at least 8 years of music training beginning after the age of 8. Several intervention studies examining neural indices of cross-domain enhacements from music training have used 8 years as the starting point of music training (Chobert, Francois, Velay, & Besson, 2014; Moreno et al., 2009). These studies consistently find evidence of music-training induced plasticity even past 8 years of age. We used 8 years as the cut-off to be consistent with prior literature examining early versus late training as well as accommodating for the work on brain plasticity induced by music training past the "so-called" sensorimotor critical period (Bailey & Penhune, 2012; Steele et al., 2013). Both ET and LT actively practiced instruments at the time of testing and did not significantly differ in the number of hours they currently played, $t(44) = 0.44$, $p = .66$, the number of instruments they played, $t(44) = 0.85$, $p = .40$, or their age, $t(44) = 1.11$, $p = .27$. Participant demographic details can be found in Table 1. Reported participant ages for the Super Control group from the "many labs" collaboration were not complete, but from the five studies that published age information, the mean age of participants is 25.6 years (datasets from Horstmann, 2012; Kjome et al., 2010; Premkumar et al., 2008; Steingroever, Šmíra, Lee, & Pachur, n.d.; Wood et al., 2005), and for the two studies which did not report ages, the samples included only undergraduates (Maia & McClelland,

Table 1. Demographic information of participants.

	n	Age Mean (*SD*)	Years playing music Mean (*SD*)	Age began playing Mean (*SD*)	Hours currently play Mean (*SD*)
Non-musicians	23	23.91 (4.47)	0.00 (0.00)	n/a	0.00 (0.00)
Early-trained musicians	23	23.70 (5.34)	16.91 (4.82)	5.61 (1.85)	7.42 (5.82)
Late-trained musicians	23	25.17 (3.50)	13.65 (3.72)	11.43 (2.11)	6.46 (8.78)

Table 2. Instrument counts across musician groups.

	Strings	Brass	Woodwind	Keys	Percussion	Voice	Other
Early-trained musicians	11	1	6	18	7	10	3
Late-trained musicians	17	2	4	12	3	7	2

2004; Worthy, Pang, & Byrne, 2013). No music experience metric was reported for any of the studies included in the "many labs" collaboration. Several participants across both early-trained and late-trained groups in the present study played multiple instruments, as represented in the instrument count in Table 2.

Procedure

The Iowa Gambling Task was run on PCs using Matlab with Psychtoolbox (version 2.5). Participants were seated at a computer and instructed that on each trial, they were to choose a card from one of four decks (A, B, C, D) by pressing "Z," "W," "P" or "/" on the keyboard. They were told that after each card choice, they would be shown the number of points gained or lost, and that their goal was to maximize the number of points gained. The participants were unaware that two of the decks (C and D) led to a net gain of points (and are therefore considered "good decks") while the other two led to a net loss of points (A and B; considered "bad decks"). In addition, the decks varied by magnitude and frequency of points won or lost such that choosing decks B or D resulted in large but infrequent losses, while choosing decks A or C led to more frequent and smaller-magnitude losses. The task consisted of five 20-trial blocks and was identical to the task in Worthy, Pang, et al. (2013).

Neuropsychological testing measure descriptions

Participants completed several neuropsychological tests. The Stroop Test was administered to assess selective attention and inhibitory control ability (Stroop, 1935). A "relative interference score" was calculated as the number of words read in the "incongruent" condition normalized by the average of the number of words read in the "color" and "word" conditions. Operation Span was used to assess complex working memory ability. At a computer, participants were asked to remember a string of letters while completing a secondary math problem between each letter presented in the sequence. After each sequence of letters was presented, participants were asked to recall the sequence of letters in the order they were presented. Additionally, participants were told to maintain an accuracy of 85% or higher on the math problems (Unsworth, Heitz, Schrock, & Engle, 2005; see also Xie, Maddox, Knopik, McGeary, & Chandrasekaran, 2015). Lastly, the WAIS-III Digit Span was administered to assess verbal working memory. For this task,

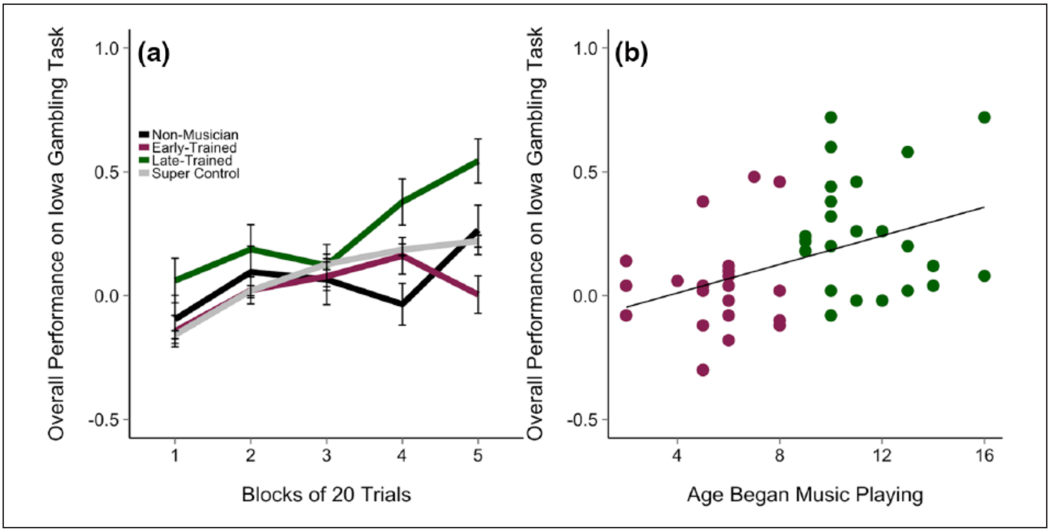

Figure 1. Overall performance on the IGT. Error bars represent standard error of the mean (a). Overall performance of musicians on the IGT plotted with the age they began playing music (b).

participants were required to repeat strings of numbers read aloud by the researcher; first exactly how the researcher read them, and then backwards (Wechsler, 1997).

Results

Iowa Gambling Task behavioral results

Overall performance on the IGT was our primary measure and was calculated as the proportion of good minus bad deck selections for each subject in five 20-trial blocks (C + D – A – B; Worthy, Pang, et al., 2013). A mixed ANOVA with group as a between-subjects variable (non-musician, early-trained, late-trained) and block as a within-subjects variable (1 through 5), revealed significant main effects of group, $F(2, 66) = 5.10$, $p < .01$, partial $\eta^2 = 0.13$, block, $F(4, 264) = 8.19$, $p < .001$, partial $\eta^2 = 0.11$, and an interaction between group and block, $F(8, 264) = 2.56$, $p < .05$, partial $\eta^2 = 0.07$. To decompose the significant interaction, we ran a series of one-way ANOVAs at each block comparing the effect of group on overall performance. We found a significant effect of group in blocks 4 and 5. Pairwise comparisons of overall performance between groups in blocks 4 and 5 suggest an LT advantage relative to NM in block 4, $t(44) = 3.29$, $p < .005$, and ET and NM in block 5, $t(44) = 4.61$, $p < .001$; $t(44) = 2.08$, $p < .05$, respectively. These results are displayed in Figure 1(a).

We also compared LT to a 441-participant "Super Control" group of young adults who performed the 100-trial IGT (shown in gray in Figure 1(a); Steingroever et al., 2015). To determine if the late-trained musicians performed significantly different from the Super Control group, we ran a mixed model ANOVA with group as a between-subjects variable (Super Control group, LT musician) and block as a within-subjects variable (1 through 5). We found significant main effects of group, $F(1, 462) = 6.96$ $p < .009$, partial $\eta^2 = 0.01$, and block, $F(4, 1848) = 83.67$, $p < .0001$, partial $\eta^2 = 0.15$, and interaction between group and block, $F(4, 1848) = 2.39$, $p = .05$, partial $\eta^2 = 0.005$. These results suggest that late-trained musicians perform significantly better than the Super Control group.

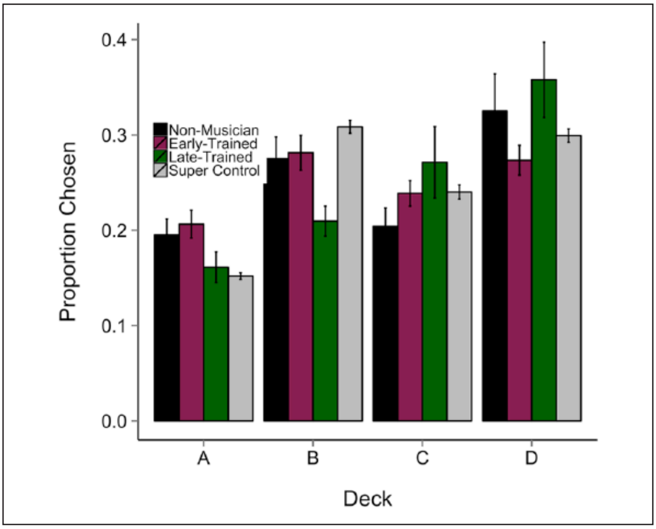

Figure 2. Proportion of decks chosen by non-musicians, early-trained musicians, late-trained musicians, and the Super Control group. Error bars represent standard error of the mean.

Within just the early- and late-trained musician groups, a linear regression of age of onset of music training as a predictor of overall performance suggests that the later an individual begins playing music in childhood, the greater the benefit to their decision-making skills as young adults, $F(1, 44) = 8.96$, $p < .01$, $R^2 = 0.17$, $b = 0.03$; displayed in Figure 1(b). Interestingly, although the two musician groups differed significantly in their years of playing music, LT: $M = 13.65$, ET: $M = 16.91$; $t(44) = 2.57$, $p < .05$, years of playing music was not a significant predictor of performance, $F(1, 44) = 1.90$, $p = .17$, $R^2 = 0.04$; $b = -0.01$.

Deck choice results

We also compared differences in deck choices between our four participant groups (late-trained musicians, early-trained musicians, non-musicians, and the Super Control group) in two steps. First, we compared deck choices between non-musicians, late-trained musicians, and early-trained musicians; and second, we compared deck choices between the late-trained musicians and the Super Control group. For our first analysis, we performed a two-way ANOVA on proportion of deck chosen with group (non-musicians, late-trained musicians, early-trained musicians) as a between-subjects variable and deck (A, B, C, D) as a within-subjects variable. We did not find a significant main effect of group, $F(2, 66) = 1.24$, $p = .300$, but we did find a significant effect of deck, $F(3, 198) = 11.14$, $p < .001$, partial $\eta^2 = 0.14$. There was no significant interaction of group and deck, $F(6, 198) = 2.14$, $p = 0.051$. Results are displayed in Figure 2 and suggest that Deck D was chosen most often ($M = 0.32$), then Decks B ($M = 0.26$) and C ($M = 0.24$), and Deck A was chosen the least often ($M = 0.19$). Post-hoc pairwise comparisons (with Holm correction) of selections in each deck suggest a group difference in only Deck B selection. Late-trained musicians selected Deck B significantly less ($M = 0.21$) than both early-trained musicians, $M = 0.28$; $t(44) = 2.97$, $p < .05$, and non-musicians, $M = 0.28$; $t(44) = 2.38$, $p < .05$.

To compare deck choices between late-trained musicians and the Super Control group, we ran a two-way ANOVA on proportion of deck chosen with group and deck (A, B, C, D) and found significant main effects of deck, $F(3, 1386) = 98.43$, $p < .001$, partial $\eta^2 = 0.18$, and group, $F(1, 462) = 14.91$, $p < .0002$, partial $\eta^2 = 0.03$, and a significant interaction of deck and group, $F(3, 1386) = 4.36$, $p < .006$, partial $\eta^2 = 0.5$. Post-hoc analyses at each deck suggest late-trained musicians and the Super Control group differ in the proportion they chose a deck in only Deck B, $F(1, 462) = 10.95$, $p < .002$, partial $\eta^2 = 0.02$. Results are displayed in Figure 2.

Neuropsychological testing results

To determine if there are any other differences between our participant groups that may mediate the late-musician advantage in the Iowa Gambling Task, we ran a series of planned pairwise t tests with Holm correction between the neuropsychological test scores of our three groups. Our results suggest there are no differences between groups with respect to Stroop Interference score [ET and LT: $t(44) = 0.50$, $p = 1.00$; ET and NM: $t(44) = 0.65$, $p = 1.00$; LT and NM: $t(44) = 0.25$, $p = 1.00$], Digit Span Total score [ET and LT: $t(44) = 0.50$, $p = .93$; ET and NM: $t(44) = 0.65$, $p = .91$; LT and NM: $t(44) = 1.08$, $p = 0.87$], and Operation Span score [ET and LT: $t(38) = 0.88$, $p = 1.00$; ET and NM: $t(41) = 0.88$, $p = 1.00$; LT and NM: $t(39) = 0.71$, $p = 1.00$].

Computational modeling results

To understand the mechanism involved in the LT performance advantage, we fit a series of computational models to the data (Worthy, Pang, et al., 2013). The full details of the models are provided in the online Supplementary Material. We fit a total of four reinforcement learning (RL) models: The Prospect Valence Learning Delta and Decay models (PVL2-Delta & PVL2-Decay), Valence-Plus-Perseveration (VPP) model, and the Expectancy-Frequency-Perseveration (EFP) model. These RL models all assume that participants track and update expected values for each action and then make decisions based on a relative comparison of the value of each deck. They differ in the ways that they account for specific processes like recency, loss aversion, frequency of gains versus losses, and perseveration. We also fit a win-stay-lose-shift model (WSLS; Worthy, Hawthorne, & Otto, 2013). This model fundamentally differs from the RL models because it makes no assumption about the expected value of alternatives, but instead assumes that participants stay with the same option or switch to a different option depending upon whether the outcome on the previous trial was a net gain or loss. Critically, in the IGT, the WSLS model assumes that participants will switch randomly between the three alternative decks on switch trials, rather than decks with higher expected values. Another critical assumption of the WSLS model is that it relies only on the outcome of the previous trial, and is thus heavily recency-biased. We also fit a Baseline or null model. Readers who are interested in a comprehensive account of each model beyond the basic mechanisms are directed to the online Supplementary Material.

We next used BIC or Schwarz weights to compare the relative fit of each model (Wagenmakers & Farrell, 2004). BIC weights are calculated from BIC to obtain a continuous measure of goodness-of-fit (see online Supplementary Material, section 1.2). These weights can be simply interpreted as the probability that the model is the best model given the data set and the set of candidate models (Wagenmakers & Farrell, 2004). We computed the BIC weights for each model for each participant. The average weights for participants in each group are shown in Table 3. Average weights for the WSLS model were nearly twice as high for participants in the NM and ET groups (both $M = 0.50$) compared to participants in the LT group ($M = 0.27$). This suggests that participants in the LT group relied on a simple WSLS strategy much less than

Table 3. BIC (Schwarz) weights for each model.

Model	PVL2-Delta	PVL2-Decay	VPP	EFP	WSLS	Baseline
Non-musician	0.06 (0.20)	0.37 (0.41)	0.00 (0.00)	0.05 (0.20)	0.50 (0.42)	0.02 (0.06)
Early-trained musician	0.06 (0.16)	0.22 (0.32)	0.10 (0.29)	0.09 (0.20)	0.50 (0.42)	0.03 (0.07)
Late-trained musician	0.18 (0.26)	0.22 (0.31)	0.14 (0.34)	0.15 (0.26)	0.27 (0.38)	0.04 (0.17)

Note. Standard deviations are listed in parentheses.

participants in the other groups and that they may have incorporated a more complex RL strategy by comparing the expected values of each action.

We also examined the best-fitting parameter estimates for each model across groups (Table 4) to compare specific decision-making sub-processes assumed by the models. For instance, the best-fitting recency or learning rate parameter (Φ) was lower for participants in the LT group than for NM and ET participants for both the PVL2-Delta and EFP models. Because the recency parameter represents how strongly someone weights recent trial outcomes in updating expected values, a lower recency parameter suggests that LT may have valued options based on a longer series of recent outcomes while NM and ET may have based decisions on only the most recent outcomes. Greater reliance on recent actions has been associated with WSLS strategy use in prior work as well (Otto, Taylor, & Markman, 2011; Worthy, Otto, & Maddox, 2012). Enhanced memory of more distant outcomes could account for LT participants' ability to avoid selecting Deck B, which yields very large but infrequent losses, less than NM and ET participants as well as the Super Control group.

Discussion

We examined the extent to which music training confers long-lasting decision-making benefits. Our results suggest that music training impacts decisional processes differently depending on the age at which the musician began his or her training. In particular, we showed that late-trained musicians (who began after age 8) show a performance advantage in the Iowa Gambling Task, a well-studied decision-making task, relative to early-trained musicians (who began playing at or before age 8) and non-musicians. The performance advantage is observed in the last two blocks of the task when the gains and losses associated with each deck have already been learned. Critically, "age of onset" but not "years playing" was a significant predictor of performance in the Iowa Gambling Task in musician groups. One possible explanation for these results is that music training beginning late in childhood capitalizes on the period of significant maturation in the prefrontal cortex, a region of the brain implicated in optimal performance on the IGT (Bechara et al., 1994; Hare et al., 2008; Samanez-Larkin et al., 2014). Per a critical period theory, taxing the neural regions implicated in decision-making during a period of significant growth can lead to long-lasting functional benefits in decision-making ability (Hensch, 2005). Because the prefrontral cortex does not begin a stage of rapid development until late childhood, introducing a novel skill that relies on the prefrontal cortex during this stage of rapid development can have a profound and positive impact on other functions that the area subserves.

Importantly, our results suggest that the *age* at which novel skill acquisition *begins*, and not necessarily the ages during which the skills are developed beyond initial training, may be an important metric for characterizing long-lasting impact on the brain regions the skill utilizes. This is because the process of learning a novel procedural skill can be decomposed into at least

Table 4. Average best-fitting parameter estimates for each model and group.

	Non-musician	Early-trained musician	Late-trained musician
IGT			
PVL2-Delta			
α	0.40 (0.34)	0.42 (0.32)	0.53 (0.35)
λ	3.00 (2.15)	2.16 (2.16)	3.09 (2.01)
Φ	0.56 (0.43)*	0.48 (0.43)†	0.21 (0.32)*†
c	0.24 (0.27)	0.21 (0.32)	0.32 (0.35)
p	25.10 (37.5)*†	−7.00 (36.0)‡	−8.70 (38.40)*
PVL2-Decay			
α	0.30 (0.35)	0.41 (0.28)	0.30 (0.32)
λ	1.34 (1.73)‡	2.93 (2.18)†‡	1.69 (2.00)†
Φ	0.43 (0.25)	0.55 (0.34)	0.58 (0.32)
c	0.56 (0.80)	0.23 (0.40)	0.46 (0.50)
VPP			
α	0.45 (0.29)	0.40 (0.37)	0.42 (0.35)
λ	2.40 (2.43)	1.95 (2.46)	2.68 (2.05)
Φ	0.30 (0.39)	0.32 (0.33)	0.18 (0.27)
c	1.84 (0.98)	2.08 (0.90)	2.51 (1.06)
w	0.53 (0.42)	0.63 (0.39)	0.69 (0.36)
k	0.42 (0.35)	0.52 (0.38)	0.43 (0.34)
ε_{pos}	0.30 (0.53)‡	−0.12 (0.58)‡	0.06 (0.57)
ε_{neg}	0.10 (0.83)‡	−0.41 (0.62)†‡	0.07 (0.78)†
EFP			
Λ	1.36 (2.04)*	1.71 (2.19)	2.88 (2.30)*
Φ	0.52 (0.40)*	0.57 (0.44)†	0.28 (0.33)*†
c	1.02 (1.13)	1.12 (1.02)	0.72 (0.52)
p	2.7 (6.40)	2.90 (15.9)	–2.30 (22.6)
ω	0.48 (0.36)	0.48 (0.38)	0.56 (0.41)
WSLS			
$P(stay \mid win)$	0.55 (0.20)‡	0.33 (0.24)‡	0.51 (0.32)
$P(shift \mid loss)$	0.59 (0.34)‡	0.80 (0.22)†‡	0.57 (0.34)†

Note. Standard deviations are listed in parentheses. All tests were two-tailed.
*Significant difference between Non-musician and Late groups at $p < .05$,
†Significant difference between Early and Late groups at $p < .05$,
‡Significant difference between Non-musician and Early groups at $p < .05$.

two stages (Karni et al., 1998; Miyachi, Hikosaka, & Lu, 2002; Yin et al., 2009). The first stage is characterized by rapid skill attainment at the onset of the learning process. Imaging research suggests that the initial fast learning of a procedural skill in the brain can characterized by first a reduction in activation in the primary motor cortex, followed by an increase in the area of activation in the primary motor cortex (Karni et al., 1998). Subcortically, initial fast learning is associated with increased activation in the association regions of the basal ganglia (Miyachi et al., 2002). The second stage is considered to be slower with neural changes occurring within the context of the template set up during the initial, fast stage of learning. The early learning changes to the motor cortex during procedural skill learning are thought to "set up" the motor cortex for a task-specific process and serve as a template for ongoing modification of the slower learning process (Karni et al., 1998; Miyachi et al., 2002).

The literature on the neural mechanisms of learning a procedural skill supports the results of the current study. As would be expected from the literature, we found that the best predictor of performance on the Iowa Gambling Task was *when* our participants began playing music, which corresponds to the initial (or fast learning) stage of procedural skill acquisition. Although the early-trained musicians played their instruments during late childhood, they were by that point beyond the initial stage of skill acquisition, and therefore may have received less cognitive benefit from taxing the decision-making regions of the brain with music-learning.

The findings of the current study are corroborated by a large literature supporting the notion that beginning music training at an age at when the underlying brain regions are undergoing significant development may grant long-term performance enhancements in other skills those brain regions serve. For instance, research suggests that beginning music training at an early age (before age 7 years) can produce significant structural and behavioral enhancements in perceptual-motor tasks and the associated regions because major neural development in perceptual-motor regions occur before the age of seven (Bailey & Penhune, 2012; Bailey, Zatorre, & Penhune, 2014; Steele et al., 2013).

Our computational modeling results suggest that late-trained musicians more successfully compared reward expectations of each option in order to perform well, the process of which has been associated with the medial prefrontal cortex (Samanez-Larkin et al., 2014). In addition, NM and ET participants were more likely to rely on the most recent outcomes and on recency-based WSLS strategies more than LT participants who may have avoided the disadvantageous Deck B more successfully by better retention of the infrequent, but very large, losses (−1,250 points) it provided. It is possible that late music training enhances individuals' ability to incorporate a longer series of events when engaging in complex cognitive processes like decision-making. Interestingly, the results of our linear regression also support this notion, as years of music-playing, was not a significant predictor of performance in the Iowa Gambling Task, but age of onset of playing was.

Our study design is similar to previous research that has examined the advantage of early music training, relative to late music training on brain plasticity (Bailey & Penhune, 2012; Steele et al., 2013). As in previous studies, a limitation is that our data are correlational in nature. We compared non-musicians and two types of musicians in a classic decision-making task, but this method does not allow us to draw a *causal* inference regarding the effects of age of onset of music-playing and decision-making later in life. Although additional analyses have ruled out a number of obvious alternative explanations, there may be other factors (e.g. personality; Corrigall, Schellenberg, & Misura, 2013) that influence when a person begins playing music that may mediate the intruiging relationship we find in the present study. Future work should seek to further refine this relationship using a longitudinal methodology to more directly test the effect of beginning music training earlier or later in life on decision-making ability.

The results of the current study have real-world implications: in addition to the rich sensorimotor benefits of early music playing may have on the developing brain, music training may also confer long-lasting benefits in complex cognitive functions like decision-making. To take a real-world example, the music classes offered during many children's elementary and high-school education in America (which correspond to the age of music-training onset in the present "late-trained musician" group) may result in improved decision-making ability as an adult. Understanding tools that can serve individuals who show profound decision-making deficits as young as 8 years old could have a dramatic effect on the rate of risky behaviors later in life. Specifically, our results lead to an exciting and testable hypothesis: learning to play music during elementary and high school may lead to dramatic enhancements on late-maturing brain regions that mediate decision-making abilities.

The results of the current study also suggest that music training should be added as a measure of individual differences for future studies in decision-making. The Super Control group data which came from a "many labs" collaboration is composed of young adults with a mean age of 25.6 years. Music experience was not reported for any of the studies included in the Super Control group; therefore, we cannot exclude the possibility that music training was a factor in any results presented. Our results suggest that music-training metrics may be easy and worthwhile measurements to obtain in future decision-making studies. Therefore, we recommend that future decision-making studies include measurements of music training to help elucidate any effects that might be otherwise obscured in a musically heterogeneous sample.

We also cannot completely rule out alternative explanations for our results. For instance, it can be argued that very few aspects about a child's environment throughout childhood are under the child's control. This means that the age at which a child begins playing music, or any other engaging activity, is most likely determined by the parents. It is possible that children who were introduced to music at an early age may have different motivations for pursuing music training than the children who began playing music later in childhood. It is reasonable to assume that parents may have had a larger influence in the decision to play music at an earlier age than later, suggesting that early-trained musicians would have a different motivation to play relative to the late-trained musician. Research also suggests that several factors such as self-regulation, deliberate practice strategies, and self-perception of competence all significantly influence musical achievement. These factors will likely differ in their relationship to musical achievement depending on what age the musician begins practicing (Bonneville-Roussy & Bouffard, 2015). For instance, a younger musician may practice a certain number of hours per week because of parental involvement, which shapes their practice schedule and influences how they self-regulate their practicing later in life. Although the current study was not equipped to measure the existence of such motivational differences, we cannot rule out that a difference in the primary contributor of motivation (i.e., parent or self) may have resulted in the current results.

A limitation of the current study is that our results are based on a group of young adults who had access to music education during childhood and may not generalize to the rest of the population. Factors such as socioeconomic status and race are important factors that can affect access to music education (Palmer, 2011). Because the participants in this study were among a cohort who had access to music education in schools or as an extracurricular activity and were later recruited in a university setting, our results are limited to such a cohort. Future studies should endeavor to include participants from diverse socioeconomic statuses, and races in order to better understand the ways in which music training may affect the developing brain.

"Future directions should also include a test for the existence of an upper age limit for beginning music training by which receiving music training after such an age would no longer provide the cognitive benefits explored in this paper. In our current sample, late-trained musicians began playing music between the ages of 9 and 16 years old." Because the neural regions supporting decision-making continue to develop into adulthood, it is plausible that beginning music training at any point between late childhood and adulthood might confer decision-making benefits (the correlational results displayed in Figure 1(b) suggests this may be the case). However, a study similar in recruitment methodology to Savion-Lemieux, Bailey, and Penhune (2009) including several age groups binned within a late-trained musician group, and an early-trained control group would be better suited to test such a phenomenon. Lastly, we encourage researchers to replicate the current study and publish both significant and non-significant findings in order to better understand the impact of music training in late childhood on decision-making abilities.

In conclusion, the goal of the present study was to test the extent to which the music training effects decision-making. Using the Iowa Gambling Task, we found that musicians who began training at age 8 or later showed improved decision-making ability relative to musicians who began training before the age of 8 or non-musicians. Using computational modeling, we found that the late-trained musician performance advantage was a result of using longer strings of trial outcomes to inform their current trial's strategy. Our results have important implications for science-based approaches to incorporating music education in school systems, cognitive development, and the development of ecologically valid tools to enhance individual deficits in decision-making.

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