The Computational Mechanism of How Music Influences Food Choices: A Drift-Diffusion Model Analysis

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Abstract

Food choices, as a type of value-based decision, are affected by environmental cues. We conducted three studies to investigate the computational mechanisms through which background music influences the food choice-making process. Hierarchical drift-diffusion modeling revealed that nature-related music led to higher drift rates than urban-related music, indicating faster evidence accumulation toward certain choices. Specifically, participants processed the value of vegetable-forward meals more efficiently when exposed to nature-related music compared to urban-related music. Moreover, the effect of music on the drift rate varied with the vividness of music-induced mental imagery and the perceived identity of performers (human or robot). Collectively, these findings reveal the computational mechanisms underlying the influence of environmental cues on value-based decision-making.

Keywords: mental imagery; music robot; computational model; drift rate

1 Introduction

The value-based choice model serves as a fundamental framework for deciphering decision-making processes, and food choices stand out as one of the most important value-based decisions in people's daily routines (Berkman, 2018; Krajbich et al., 2015). A variety of factors have been shown to influence food choices, spanning from the intrinsic attributes of food to extrinsic environmental cues (Chen & Antonelli, 2020). Many studies have investigated the computational underpinnings of how internal food attributes affect food-related decision-making (Maier et al., 2020; Krajbich et al., 2010). However, scant attention has been paid to the computational mechanisms through which environmental cues influence food-related decision-making. To address this issue, it is crucial to understand how environmental cues affect food choices, presumably as the ultimate food choices are direct manifestations of decision-making processes (Chen & Antonelli, 2020).

Among a diverse range of environmental cues, environmental music has been demonstrated to exert a significant impact on individuals' food selection preferences (Spence et al., 2019). For example, Qiu and Wan (2024) showed that environmental music could influence food choices by eliciting different types of mental imagery. In that study, participants were instructed to choose three dishes from two meat dishes and two vegetable dishes to form a three-dish combination. Consequently, they had to make a choice between a combination of one vegetable and two meat dishes (i.e., a meat-heavy meal), and one of one meat and two vegetable dishes (i.e., a vegetable-forward meal). Their results revealed that music depicting different scenes influenced participants' food choices. In comparison to urban-related music, nature-related music facilitated the participants' selection of vegetable-forward meals. This effect was more pronounced when the participants' mental imagery was enhanced, but it vanished when their imagery was suppressed.

Moreover, Qiu et al. (2025) showed that the perceived identity of the music performer (i.e., the perception of who was performing the music) modulated the impact of music on food choices. When participants believed that the music was played by humans, they exhibited a greater propensity to choose vegetable-forward meals while listening to nature-related music as opposed to urban-related music However, the disparity in choice outcomes between the two music conditions lessened when participants believed that the music was performed by robots.

These two studies, namely Qiu and Wan (2024) and Qiu et al. (2025), have focused mainly on probing into the direct effects of music on food choices. Expanding on this groundwork, we conducted the present study to investigate the mechanisms through which music might exert its influence on the processes of making food choices. The hierarchical drift-diffusion model (HDDM) employs four parameters to analyze the binary decision-making processes, namely the speed of evidence accumulation (drift rate, v), the level of caution in decision-making (boundary, a), the preparation time (non-decision time, t), and the prior preference (bias, z; Johnson et al., 2017). In brief, we conducted three studies and utilized the HDDM to gain a more profound understanding of how nature- and urban-related music influenced food choice-making processes (Garlasco et al., 2019). It should be noted that all the data used in this study were duly authorized by the authors of the two previous studies (Qiu & Wan, 2024; Qiu et al., 2025).

2 Study 1

Qiu and Wan (2024) showed that nature-related music inclined participants toward making healthier food choices in contrast to urban-related music. In this study, we adopted a hierarchical drift-diffusion model as a method to examine the influence exerted by both nature- and urban-related music on the food choice-making process.

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2.1 Methods

2.1.1 Data Source The dataset utilized in this study was sourced from the first experiment conducted by Qiu and Wan (2024). In the experiment, they recruited 40 participants and employed a between-participants design with a single factor featuring two levels (Music: nature or urban-related). The participants were instructed to complete a food choice task while being exposed to either nature-related or urban-related music. On each trial of the task, they had to make a choice between a vegetable-forward meal and a meat-heavy meal.

2.1.2 Data Analyses We applied a hierarchical drift-diffusion model (HDDM) to analyze the food choice outcomes and reaction time data of 40 participants. In the model, we designated "a vegetable-forward meal" as the upper threshold and "a meat-heavy meal" as the lower threshold. The initial bias (z) was assumed to remain constant across the nature- and urban-related music conditions, as the participants' initial choice preferences were stable. We set that the music had an effect on drift rate (v), boundary (a), and non-decision time (t) in the model. Moreover, this model exhibited the lowest Deviance Information Criterion (DIC) value (15660) compared with the alternative models, suggesting that it provided a better fit to the data.

In order to obtain the Bayesian posterior distributions, we used the Markov Chain Monte Carlo (MCMC) method for sampling. A total sample size of 10000 was set to ensure accurate model estimation. To mitigate the influence of early unstable samples, 1000 burn-in samples were applied. To further improve the reliability of the posterior distribution estimation and to verify the convergence of the model, we used four parallel chains to fit the model.

Bayesian methods are commonly employed in analyzing the HDDM as they provide more interpretable insights into decision-making processes (Boehm et al., 2024; Ju et al., 2024). Additionally, it is not appropriate to apply frequentist tests to the subject parameters of a hierarchical model, because the hierarchical models violate the independence assumption (Wiecki et al., 2013). Therefore, we first conducted Bayesian paired-sample t tests to compare the parameters under the two music conditions at the individual level. A Bayes factor (BF) greater than 10 indicates strong evidence for the alternative hypothesis (Jarosz & Wiley, 2014). Furthermore, we used Bayesian estimations to compare the posterior distributions of the parameters under the two conditions. The P_{Bayes} value represents the probability that parameters differ between the conditions. We also utilized the highest density interval (HDI) to evaluate the reliability of these differences. If the 95% HDI does not include zero, the difference in parameters between the two conditions is considered credible and statistically meaningful (Kruschke, 2018).

2.2 Results

In the present and following studies, we employed the Gelman-Rubin method to evaluate the convergence of the HDDM. The results showed that all the values approximated to 1, which indicated good convergence of the posterior distributions. Note that Bayesian methods yield results based on the level of support for a given hypothesis as opposed to relying on traditional statistical significance. Therefore, we present the results of the Bayesian analyses in line with the guidance provided by the literature (Van Doorn et al., 2021).

2.2.1 Drift Rate The results of the Bayesian paired-sample t test at the individual level revealed strong evidence that the nature-related music resulted in significantly higher drift rates than the urban-related music, BF_{10} = 5955.03. We also performed a Bayesian estimation to compare the posterior distributions of drift rates between nature- and urban-related music conditions (see Figure 1). The results provided strong evidence that the drift rate under the nature-related music condition was significantly higher than that under the urban-related music condition, P_{Bayes} = 99.5%, 95% HDI = [0.12, 0.90].

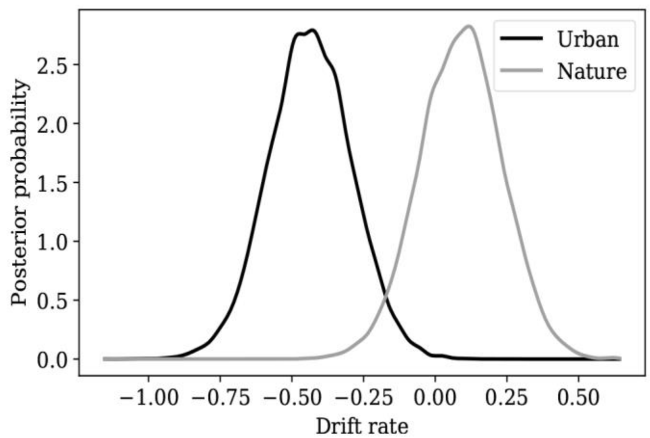

Figure 1: Drift rate distributions of two music conditions.

2.2.2 Boundary At the individual level, we found insufficient evidence to support a significant difference in boundaries between nature- and urban-related music, BF_{10} = 0.19. As for the posterior distributions of boundaries, we found insufficient evidence to support a significant difference between the two music conditions, P_{Bayes} = 59.1%, 95%HDI = [–0.34, 0.43].

2.2.3 Non-decision Time No sufficient evidence was found to support a significant difference in non-decision times between the nature- and urban-related music at the individual level, BF_{10} = 0.17. As for the posterior distributions of non-decision times, insufficient evidence was found to support a significant difference between the two music conditions, P_{Bayes} = 52.7%, 95%HDI = [–0.15, 0.17].

2.3 Discussion

In this study, our results revealed that the differential impact of nature- and urban-related music on the food choice-making process was manifested in the speed of evidence accumulation, as reflected by the drift rate. Notably, no significant effects were discerned with respect to the decision caution (boundary) or the preparation time before decision-making (non-decision time). These results suggest that nature-related music augmented the participants' pace of amassing evidence in favor of vegetable-forward meals, whereas leaving other facets of the decision-making process unaltered (Johnson et al., 2017). A higher drift rate indicates a faster extraction and processing of the overall value associated with a particular option (Garlasco et al., 2019). Consequently, when the participants were listening to nature-related music as opposed to urban-related music, they were able to extract and process the value of vegetable-forward meals more efficiently, culminating in the more straightforward selection of these meals (Garlasco et al., 2019). Qiu and Wan's (2024) study has shown that music-induced mental imagery exerts an influence on the effect of music on food choices (Qiu & Wan, 2024). Therefore, in order to further reveal how music influences food choice-making processes, we investigated the computational mechanism underlying such influence under varying prevalences of mental imagery in Study 2.

3 Study 2

3.1 Methods

3.1.1 Data Source This study was conducted by leveraging the dataset sourced from the second experiment of Qiu and Wan's (2024) study, which involved 72 participants. The experimental design was a 2 (Music: nature- or urban-related) × 3 (Imagery Manipulation: enhanced, moderately suppressed, or strongly suppressed) mixed design, with Music being treated as a within-subject variable and Imagery Manipulation being treated as a between-subject variable. The participants were randomly assigned to one of three groups, including an imagery-enhanced (IE) group whose music-induced mental imagery was amplified, an imagery-moderately-suppressed (IMS) group whose music-induced mental imagery was moderately curtailed, and an imagery-strongly-suppressed (ISS) group whose mental imagery was severely subdued. All participants across the three groups completed the food choice task while being exposed to both nature-related and urban-related music.

3.1.2 Data Analyses To analyze the data, we fitted a hierarchical drift-diffusion model using the food choice outcomes and reaction times of the 72 participants. The model was designed to account for the potential effects of both Music and Imagery Manipulation on drift rate (v), boundary (a), and non-decision time (t). All other procedures for constructing and analyzing the HDDM were consistent with those used in Study 1. We conducted 2 (Music: nature-related or urban-related) × 3 (Imagery Manipulation: enhanced, moderately suppressed, or strongly suppressed) Bayesian analyses of variance (ANOVAs) to compare the HDDM parameters at the individual level. Moreover, Bayesian estimation was performed to compare the differences in the posterior distributions of the parameters within the hierarchical drift-diffusion model.

3.2 Results

3.2.1 Drift Rate The Bayesian ANOVA results revealed strong evidence for a main effect of Music, BF_{incl} = 168825.65, indicating that Music significantly influenced drift rates. However, there was insufficient evidence to support the main effect of Imagery Manipulation, BF_{incl} = 3.18. Additionally, the analysis provided strong evidence for a significant interaction effect between Music and Imagery Manipulation, BF_{incl} = 12.35.

In order to interpret the interaction effect, we conducted Bayesian paired-sample t tests to compare the drift rates of the two music conditions across different Imagery Manipulation groups. The results revealed strong evidence that the drift rate for nature-related music was higher than that for urban-related music in the IE group, BF_{10} = 214.91, and in the IMS group, BF_{10} = 31.98. However, insufficient evidence was found to support a difference in drift rates between the nature- and urban-related music in the ISS group, BF_{10} = 1.18.

We also conducted Bayesian estimations on the posterior distributions of drift rates. As for the IE group (see Figure 2), there was strong evidence that the drift rate under the nature-related music condition was higher than that under the urban-related music condition, P_{Bayes} > 99.9%, 95%HDI = [0.40, 1.26].

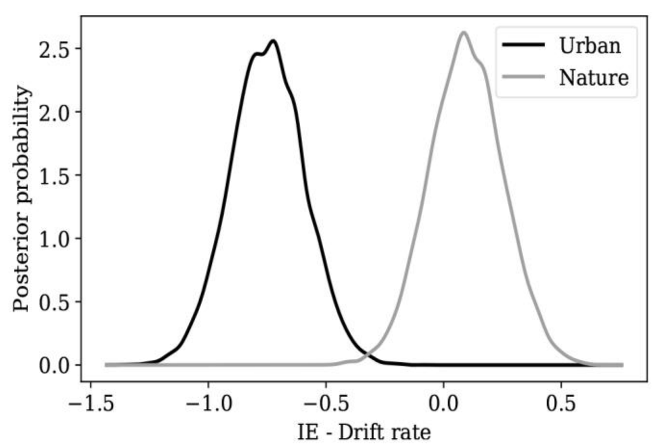

Figure 2: Drift rate distributions of two music conditions in the IE(Imagery Enhanced) group.

As shown in Figures 3 and 4, as for the IMS group, sufficient evidence was found to support that the drift rate under the nature-related music condition was higher than that under the urban-related music condition, P_{Bayes} = 96.6%, 95%HDI = [–0.03, 0.83]. However, since the 95%HDI contains zero, the probability of a significant difference in drift rates between the nature- and urban-related music conditions was relatively small for the IMS group. Regarding the ISS group, no sufficient evidence was found to support a significant difference in drift rates between the two music conditions, P_{Bayes} = 79.6%, 95%HDI = [–0.25, 0.61].

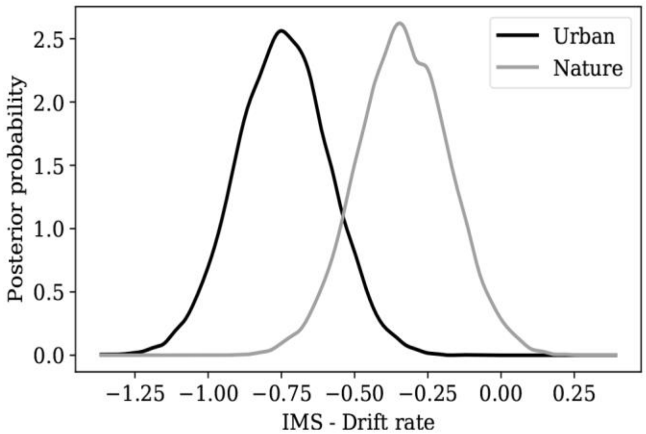

Figure 3: Drift rate distributions of two music conditions in the IMS(Imagery Moderately Suppressed) group.

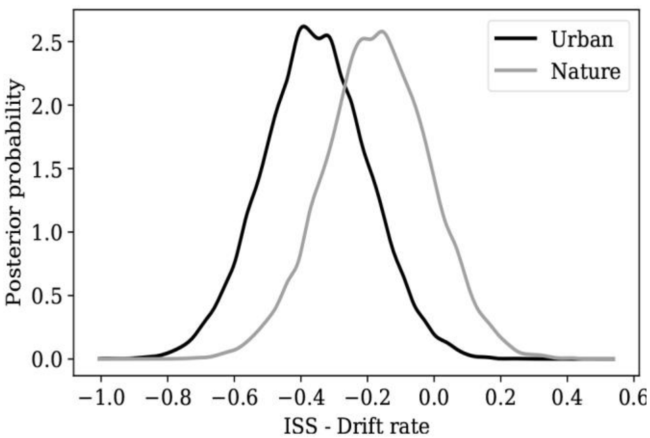

Figure 4: Drift rate distributions of two music conditions in the ISS(Imagery Strongly Suppressed) group.

3.2.2 Boundary Insufficient evidence was found for the main effect of Music, BF_{incl} = 0.19, the main effect of Imagery Manipulation, BF_{incl} = 7.57, as well as the interaction effect between the two factors, BF_{incl} = 0.35. The results of the Bayesian estimations on the posterior distributions showed insufficient evidence to support significant differences in boundary distributions for the IE group, P_{Bayes} = 55.0%, 95%HDI = [–0.48, 0.54], the IMS group, P_{Bayes} = 20.9%, 95%HDI = [–0.67, 0.28], or the ISS group, P_{Bayes} = 76.1%, 95%HDI = [–0.30, 0.65].

3.2.3 Non-decision Time We found insufficient evidence for the main effect of Music, BF_{incl} =0.23, the main effect of Imagery Manipulation, BF_{incl} = 0.28, and the interaction effect between the two factors, BF_{incl} = 0.06. Moreover, we found insufficient evidence to support a difference in the non-decision time distributions between the two music conditions in the IE group, P_{Bayes} = 66.4%, 95%HDI = [–0.19, 0.30], the IMS group, P_{Bayes} = 81.2%, 95%HDI = [–0.13, 0.34], or the ISS group, P_{Bayes} = 61.4%, 95%HDI = [–0.19, 0.26].

3.3 Discussion

Our results revealed that, depending on the varying degrees of prevalence of mental imagery, environmental music exerted its influence on the food choice-making process by modulating the drift rate. Specifically, when the music-induced mental imagery was amplified, participants amassed evidence at a notably faster pace under nature-related music in comparison to urban-related music. In contrast, when the mental imagery was subdued, evidence accumulation proceeded at comparable speeds under both music pieces (Garlasco et al., 2019; Myers et al., 2022).

These findings can potentially be ascribed to the possibility that the participants' perceived congruence between the music and the meals varied under different levels of mental imagery prevalence (Küssner & Eerola, 2019; Papies et al., 2022). When the mental imagery evoked by the music was intensified, participants discerned a more pronounced congruence between the music and the meals, presumably stemming from the alignment between the imagery and the meal. Consequently, nature-related music accelerated evidence accumulation for vegetable-forward meals, which were congruent with nature-related music. However, when mental imagery was suppressed, participants failed to detect any congruence between the music and the meals, resulting in similar evidence accumulation speeds across both music conditions (Krzemiński & Zhang, 2022; Roberts et al., 2024).

In addition to the prevalence of music-induced imagery, the content of such imagery also wields an influence over how music impacts food choices (Qiu et al., 2025). In that study, the perceived identity of the music performer influenced the content of music-induced imagery, thereby moderating the effect of music on food choices. Therefore, in Study 3, we probed into the manner in which environmental music influenced food choice-making processes when participants held diverse beliefs regarding the identities of the music performers.

4 Study 3

4.1 Methods

4.1.1 Data Source In this study, we utilized the dataset sourced from the second experiment of Qiu et al.'s (2025) study to fit a hierarchical drift-diffusion model. In that experiment, they recruited 52 participants and employed a 2 (Music: nature- or urban-related) × 2 (Perceived Performer: robots or humans) mixed design. Music was treated as a within-subject variable and Perceived Performer was treated as a between-subject variable. The participants were randomly assigned to one of two groups. One group of participants was presented with a video clip that depicted humans playing music, and they were subsequently informed that the music employed in the experiment was performed by humans. In the other group, the participants watched a video clip featuring robots playing music, and they were informed that the music they listened to was performed by robots. Following these procedures, all participants completed the food choice task while being exposed to either nature-related or urban-related music.

4.1.2 Data Analyses We used the food choice outcomes and reaction time data from the 52 participants to fit a hierarchical drift-diffusion model. In this model, we considered the potential effects of Music and Perceived Performer on the drift rate (*v*), boundary (*a*), and non-decision time (*t*). The methods for constructing and analyzing the HDDM were consistent with those used in Study 1. We then performed the 2 (Music: nature- or urban-related) × 2 (Perceived Performer: robots or humans) Bayesian ANOVAs to compare the HDDM parameters at the individual level. Moreover, we conducted Bayesian estimation to compare the differences in the posterior distributions of the parameters.

4.2 Results

4.2.1 Drift Rate The results of the Bayesian ANOVA on the drift rates showed strong evidence for the main effect of Music, BF_{incl} = 1231.90. However, we found insufficient evidence for the main effect of Perceived Performer, BF_{incl} = 1.17, and the interaction effect between Music and Perceived Performer, BF_{incl} = 1.99.

Considering the previous study found that the interaction effect between Music and Perceived Performer on food choices was significant (Qiu et al., 2025), we still conducted planned Bayesian paired-sample *t* tests to compare the differences in drift rates between the two music conditions for the participants who believed the music was performed by humans or robots. The results revealed strong evidence that the drift rate for nature-related music was higher than that for urban-related music among the participants who believed the music was performed by humans, BF_{10} = 84.49. However, insufficient evidence was found to support a difference in drift rates between the two music conditions for the participants who believed the music was performed by robots, BF_{10} = 4.36.

We conducted Bayesian estimations on the posterior distributions of drift rates for different music conditions under varying performance beliefs (see Figures 5 and 6). The results revealed that when the participants believed the music was performed by humans, there was strong evidence that the drift rate under the nature-related music condition was significantly higher than that under the urban-related music condition, P_{Bayes} = 98.8%, 95%HDI = [0.058, 0.82]. However, when the participants believed the music was performed by robots, there was insufficient evidence to support a difference in drift rates between the nature-related and urban-related music conditions, P_{Bayes} = 84.1%, 95%HDI = [–0.19, 0.58].

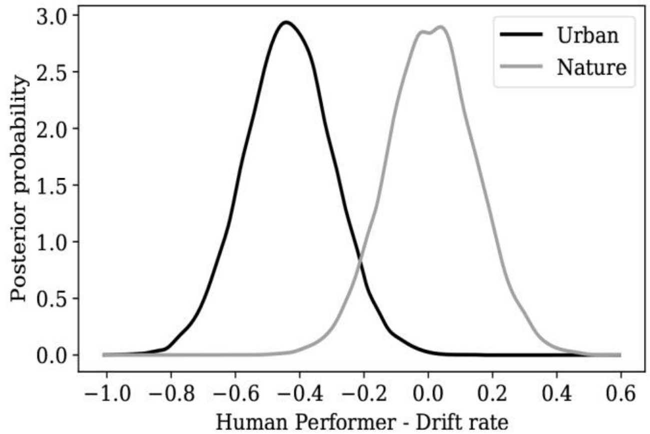

Figure 5: Drift rate distributions of two music conditions in the Human Performer group.

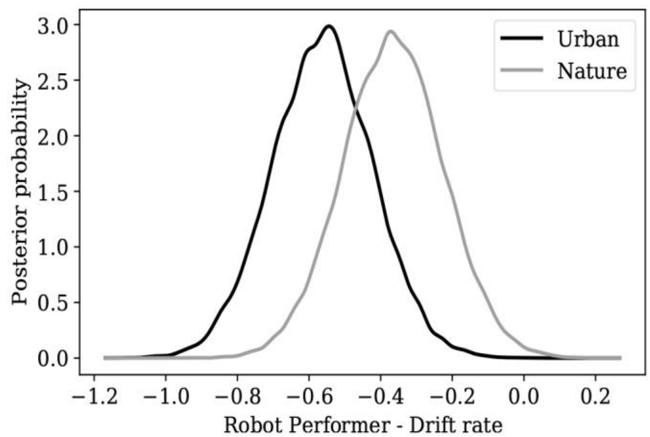

Figure 6: Drift rate distributions of two music conditions in the Robot Performer group.

4.2.2 Boundary The results of the Bayesian ANOVA on the boundaries showed insufficient evidence for the main effect of Music, BF_{incl} = 0.31, the main effect of Perceived Performer, BF_{incl} = 0.32, as well as the interaction effect between Music and Perceived Performer, BF_{incl} = 0.11. The results of the Bayesian estimations showed insufficient evidence to support significant differences in boundary distributions for the participants who believed the music was performed by humans, P_{Bayes} = 18.3%, 95%HDI = [–0.79, 0.30], as well as for the participants who believed the music was performed by robots, P_{Bayes} = 21.0%, 95%HDI = [–0.75, 0.31].

4.2.3 Non-decision Time The results of the Bayesian ANOVA revealed that insufficient evidence was found on non-decision times for the main effect of Music, BF_{incl} = 0.22, the main effect of Perceived Performer, BF_{incl} = 0.39, and the interaction effect between Music and Perceived Performer, BF_{incl} = 0.29. Insufficient evidence was found to support significant differences in non-decision time distributions, both for the participants who believed the music was performed by humans, P_{Bayes} = 91.2%, 95%HDI = [–0.067, 0.37], and for those who believed the music was performed by robots, P_{Bayes} = 14.3%, 95%HDI = [–0.32, 0.097].

4.3 Discussion

The results of the hierarchical drift-diffusion model revealed that the perceived identity of music performers exerted a moderating influence on the impact of music on the drift rate throughout the food choice-making process. Specifically, when the participants believed that the music was performed by humans, the drift rate was higher for nature-related music compared to urban-related music, indicating a faster evidence accumulation in favor of vegetable-forward meals within the context of nature-related music as opposed to urban-related music. In contrast, when participants believed that the music was performed by robots, the drift rates for both musical pieces were comparable, reflecting equivalent speeds of evidence accumulation for vegetable-forward meals in both music conditions (Johnson et al., 2017).

These findings can potentially be ascribed to the possibility that participants' beliefs had a profound impact on the content of music-induced imagery. When participants were convinced that the music was being performed by humans, they conjured up more vivid and elaborate mental imagery associated with the music, which engendered a stronger perceived congruence between the music and the meals (Küssner & Eerola, 2019). Consequently, they were able to amass evidence in favor of vegetable-forward meals that were congruent with nature-related music at a more accelerated pace. Conversely, when participants believed that the music was being performed by robots, the music-induced mental imagery was comparatively less distinct and detailed, thereby diminishing the participants' perceived congruence between the music and the meals. The diminished perceived congruence resulted in similar evidence accumulation speeds for the vegetable-forward meals across both music pieces.

5 General Discussion

In summary, through the application of the hierarchical drift-diffusion model, we uncovered the computational mechanisms underlying how environmental music exerts its influence on food choice-making processes. Specifically, music depicting different scenes was found to have an impact on the rate at which evidence accumulated during the process of making food choices. The impact of music on this evidence accumulation rate was not static; rather, it fluctuated in accordance with the prevalence of music-induced imagery. Moreover, the perceived identity of the music performers served as a moderating factor, modulating the effect of music on the speed of evidence accumulation throughout the food choice-making process.

These results align with the findings of the two previous studies, which focused on exploring how music influenced food choices (Qiu & Wan, 2024; Qiu et al., 2025). Building on the established influence of music on food choice, our results indicated that during the food choice-making process, participants were able to extract and process the subjective value of vegetable-forward meals more quickly while listening to nature-related music compared to urban-related music (Ozkan & Zhang, 2024). It should be noted that no sufficient evidence was unearthed to support the claim that music had an impact on the boundary and non-decision time within this context. These findings suggest that music did not alter the caution threshold set by participants when they were making food choices, or the perceptual processing and response preparation that preceded the decision-making stage (Lee & Usher, 2023). This phenomenon can potentially be ascribed to the congruence between the music and the meals (Motoki et al., 2023). Specifically, the congruence between meals and music-induced imagery might contribute to a higher-level congruence between music and meals. Congruent information has been shown to influence the drift rate during decision-making, with consistent cues resulting in a higher drift rate compared to inconsistent cues (Krzemiński & Zhang, 2022; Roberts et al., 2024). However, there is a paucity of robust evidence suggesting that congruence between information can affect boundary and non-decision time (Ozkan & Zhang, 2024; Pirrone et al., 2017). Consequently, when participants perceived the congruence between the music and the meals, they exhibited heightened sensitivity to the value of meals that were congruent with the music, which in turn influenced the drift rate but left the boundary and non-decision time unaffected (Ozkan & Zhang, 2024).

It should be noted that Krajbich et al. (2015) proposed a universal computational framework for value-based decision-making, positing that the model governing food choice-making could be extrapolated to other value-based choices, such as reward and social decision-making. From this perspective, the influence of environmental music on the food choice-making process may provide valuable insights into how environmental music affects value-based decision-making more broadly. Specifically, if the environmental music is congruent with a particular option in a binary value-based choice, individuals may amass evidence for that option more rapidly than for its counterpart, culminating in a more decisive selection in its favor (Krzemiński & Zhang, 2022; Roberts et al., 2024).

As with any study, there are certain limitations as far as the interpretation and generalizability of the present study are concerned. In addition to influencing food choices by inducing varying mental imagery, environmental music can also affect decision-making by evoking distinct emotions (Mathiesen et al., 2022). Future research may be conducted to explore how music-induced emotions impinge on the parameters of the HDDM during the food choice-making process (Roberts & Hutcherson, 2019).

In conclusion, the results of the three hierarchical drift-diffusion models consistently demonstrate that music influences the food choice-making process primarily through the speed of evidence accumulation, with music-induced mental imagery and performance beliefs modulating this speed. These findings also highlight the influence of physical environmental cues on the process of making value-based choices.

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