

# Reexamining the Association between Aesthetic Sensitivity to Musical and Visual Complexity

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**ABSTRACT:** In a provocative recent study, Clemente et al. (2021) found that individual differences in aesthetic sensitivity to stimulus complexity in the musical domain were uncorrelated with those in the visual domain. This ostensibly contradicts existing theory and research pointing to a link between idiographic preferences for musical and visual complexity. However, a review of their methodology reveals that Clemente et al. (2021) inadvertently introduced confounds in the temporal dynamics of their experimental stimuli as well as in their operational definitions of complexity in each domain. To address these confounds, we conceptually replicated part of their procedure using musical and visual stimuli that were either very closely matched in their temporal dynamics and/or for which complexity was operationalized more similarly. With these modifications, reliable positive correlations indeed emerged between aesthetic sensitivities to complexity across domains, providing renewed evidence for cross-modal correspondence in evaluative responses to musical sounds and visual images.

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WHY is it that people find some musical or visual stimuli more appealing than others? In the decades-long search to understand the roots of such variation in “aesthetic pleasure” (Wassiliwizky & Menninghaus, 2021), several principles have been advanced to broadly account for people’s responses. For instance, it has been variously proposed that individuals prefer stimuli to which they have been exposed more frequently (Zajonc, 1968), those that are processed more fluently (Reber et al., 1998), or those that are intermediate in complexity (Berlyne, 1971). Whereas considerable efforts have been devoted to adjudicating between these and other propositions (see Palmer et al., 2013, for a review), if there is one thing that the available empirical findings convergently demonstrate, it is that there are substantial individual differences in how distinct stimulus features influence aesthetic judgments. For instance, Hunter and Schellenberg (2011) found that frequency of exposure was often positively associated with liking for music among individuals lower in Openness-to-Experience, whereas it tended to be negatively associated with liking for music among those higher in the same trait. Likewise, in a series of studies, Güçlütürk and colleagues (2016; Güçlütürk & van Lier, 2019) showed that results ostensibly revealing an inverse curvilinear relationship between complexity and preference may actually reflect a mixture of two groups of individuals, one with a preference for simpler stimuli and another with a preference for more complex stimuli. A common theme among these various proposals is that preferences can be driven by abstract stimulus attributes (e.g., familiarity, fluency, complexity) that can, at least in principle, apply to any stimulus regardless of whether they are in the musical or visual modality.

In a recent article, Clemente and colleagues (2021) put forward particularly comprehensive and compelling evidence that aesthetic preferences among individuals are driven not by modality-general stimulus attributes, but by the specific ways in which different attributes manifest in different modalities. In their study, participants were asked to rate their liking for visual stimuli that were systematically developed



to vary in their balance, whether their constituent elements (here, hexagons of different sizes) were spatially well-distributed versus clumped together; their contour, whether their constituent shapes featured smooth versus jagged vertices; their symmetry, whether they contained elements that mirrored one another across a dividing axis or featured different contents and/or arrangements of stimuli on different sides; and their complexity, whether they contained more or fewer constituent elements (here, geometrical shapes such as triangles or rectangles). Likewise, participants were asked to rate their liking for musical melodies that were designed to vary along analogous dimensions. Specifically, more balanced melodies featured a more homogeneous distribution of note onsets across the length of the musical line; “smoother” melodies featured smaller changes in pitch between adjacent notes and less abrupt rhythmic changes; more symmetrical melodies were more likely to involve the reversal of an initial sequence of notes (e.g., D-G-B-B-G-D) over the course of the melody; and simpler melodies contained fewer notes, with less variation in duration, pitch, and rhythm.

Using a novel analytic technique based on linear mixed modeling, Clemente et al. (2021) computed measures of how each participant’s liking ratings were associated with changes in stimulus features along each dimension, what they labeled the individual’s aesthetic sensitivity (AS) with respect to that dimension. Replicating their own earlier work (Corradi et al., 2020), Clemente et al. (2021) found that individuals showed considerable variability in their AS profiles. For instance, AS to visual symmetry was normally distributed with some participants showing a greater preference for symmetry and others for asymmetry. In addition, each visual feature—balance, contour, symmetry, and complexity—uniquely contributed to predicting individual liking ratings (see also Clemente, Friberg, & Holzapfel, 2023). Similar findings emerged for ratings of musical melodies, suggesting that participants also differed in terms of how each of the four stimulus dimensions affected their responses to the passages they heard (see also Clemente, Pearce, & Nadal, 2022). Together, these findings powerfully demonstrate the importance of taking AS into account in predicting and explaining aesthetic judgments of musical and visual stimuli, providing fertile ground for additional research, and potentially helping to account for past inconsistencies in the results of studies aimed at uncovering general principles of evaluative preference.

However, one of the most intriguing aspects of the work by Clemente et al. (2021) is what they did not find: Except for a single, moderate correlation between measures of AS to musical and visual contour, there were no reliable associations between stimulus features across sensory modalities. Based on this null finding, Clemente et al. (2021, p. 9) draw the provocative conclusion that “evaluative judgments of visual designs and melodies are not based on abstract representations of balance, symmetry, and complexity, but on visual- and auditory-specific instantiations of such attributes.” Yet, upon consideration, the absence of a significant association between AS measures in different modalities is puzzling, particularly with respect to the complexity dimension. Theoretically speaking, it has been proposed that individuals differ quite broadly in their receptivity to objects and events that require more or less cognitive processing to comprehend (Cacioppo & Petty, 1982) or that involve more or less uncertainty (Webster & Kruglanski, 1994), suggesting that they should respond to variations in informational complexity in a manner that is consistent across stimulus domains and over time. In addition, research by both Palmer and Griscom (2013) and by Song et al. (2022) has revealed strong positive correlations between individuals’ preferences for simplicity/harmoniousness versus complexity/inharmoniousness with respect to musical melodies/chords and combinations of colors. These empirical findings are difficult to square with the absence of any reliable cross-modal AS to stimulus complexity in the study by Clemente et al. (2021).

A close examination of the materials and measures used by Clemente et al. (2021) may help resolve this discrepancy. As alluded to by the authors themselves, the visual stimuli they used to test AS-to-complexity were static images made up of varying numbers and arrangements of geometric figures. However, melodies involve change over time, rendering the musical and visual stimuli in Clemente et al.’s study difficult to compare in terms of the amount of complexity they entail. Speculatively, this confound also opens the possibility that there may be distinct aesthetic sensitivities to stimuli that are static versus dynamic, a prospect that would be consistent with Clemente et al.’s overarching conclusion that individuals differ in their hedonic response to various attributes of a given stimulus.

It is also notable that Clemente et al. (2021) operationalized visual complexity via the number of elements contained in their static images. However, their operationalization of melodic complexity was itself more complex, involving a composite of event density and pitch-related entropy. Whereas the first component of the latter composite is akin to the number of elements in a visual figure in that it involves computing the number of notes per unit time, the second component captures the redundancy of the notes that appear within a given melody. This raises the possibility that a correlation between visual and musical

AS might emerge if they were both operationalized in terms of entropy rather than number of elements. If so, it would be well in line with Nadal et al.'s (2010) contention that inconsistencies between studies testing the relationship between complexity and aesthetic judgments may result from differences in how complexity is defined and measured (see also Van Geert & Wagemans, 2020).

To assess these possibilities, we conceptually replicated part of Clemente et al.'s (2021) procedure for assessing cross-modal AS by administering the same melodic complexity measure that they used and collecting liking ratings for two new types of visual stimuli. The first type involved a display of colored lights in which the number of lights and timing of light onsets directly corresponded to the number and timing of notes in the melodies employed by Clemente et al. (2021). In this way, both the musical and visual stimuli were characterized by the same dynamics. The second type of visual stimulus involved texture patterns in which squares could be programmed to appear or not in each cell of a 10 x 10 grid. This enabled computation of the number of constituent elements (i.e., clusters of squares) within a particular texture pattern as well as the first order information entropy (i.e., binary symbol redundancy) of each pattern. As such, the complexity of these (static) visual stimuli could be operationalized in terms of the number and variety of elements in the figure, analogous to how complexity is operationalized in musical melodies. If there is evidence for a cross-modal AS-to-complexity association with the first set of stimuli alone, it would suggest that this correlation depends on stimuli in each modality having comparable dynamics. If there is instead evidence for cross-modal AS with both sets of stimuli, it would suggest that the correlation depends more broadly on measuring complexity in an analogous fashion for both visual and musical stimuli. Finally, if there is no evidence of a cross-modal AS-to-complexity association in either set of stimuli, it would conceptually replicate the null result reported by Clemente et al. (2021).

## METHOD

### Participants

Participants were 486 undergraduate students at the University at Albany who completed the study online for course credit in an introductory psychology course. Thirty-two participants who completed fewer than 98% of the rating items were excluded from the analysis, leaving a total of 454 participants (Age:  $M = 18.93$ ;  $SD = 1.51$ ; Gender: 183 male, 262 female, 8 non-binary or unknown). Following these exclusions, the resultant sample for this replication study was still approximately ten times larger than that employed by Clemente et al. (2021). Research ethics committee approval for use of human subjects in this experiment was granted by the Institutional Review Board of the University at Albany.

### Materials

#### MUSICAL STIMULI

Replicating the procedure of Clemente et al. (2021), we asked participants to rate the 24 melodies included in the MUST abridged Complexity subset (Clemente et al., 2020). These 4-second monophonic melodies in the key of C major vary in their complexity within the same loosely "classical" genre. The melodies were played using a synthesized piano timbre (WAV files of the melodies were downloaded from the MUST repository available at <https://osf.io/bfxz7/>).

#### VISUAL STIMULI: LIGHT DISPLAYS

To manipulate the modality of the aesthetic stimuli while controlling for their dynamic qualities as closely as possible, we created 24 light displays, each corresponding to one of the 24 MUST melodies described above. Specifically, each musical note appearing in the MUST melodies was mapped to an approximately 1 x 1 in. PNG graphic of a colored light bulb (see Figure 1). To account for octave equivalence—the tendency for listeners to perceive notes representing a doubling of frequency as part of the same category—notes sharing the same pitch chroma (e.g., C4 and C5) were mapped to images with the same hue. Light bulbs appeared on the computer screen in one of five rows, each of which represented a different octave, with lower rows representing higher pitch registers. Bulbs in each of seven columns shared the same pitch chroma (C, D, E, F, G, A, or B moving left to right along the Western C major scale). For instance, the bulb representing the note C3 appeared in the first column of the second row, whereas the bulb representing the note D5

appeared in the second column of the fourth row. The timing with which bulbs came on and off for a given light display was matched to the onset/offset time of notes in a particular MUST melody. However, given that the sequence of musical notes was quite rapid in some melodies, to prevent the corresponding bulb onset/offsets from blurring together, we reduced the tempo of the visual “melodies” by 50% such that each light display was stretched out to 8 s in length. This modification preserved the relative duration of each event in the sequence.

To ensure that participants with color vision deficiencies could adequately perceive the visual stimuli, musical notes were mapped to light bulb images using colors selected from the Okabe-Ito color-blind accessible palette available within the R programming environment (R Core Team, 2021). In addition, to ensure that our results were not dependent on a particular association between specific screen positions and specific colors, participants were randomly assigned to receive one of two pitch chroma to color mappings (see Table 1 for details). The first mapping was created arbitrarily by the authors and the second was created by randomly swapping colors originally assigned to appear on the left (e.g., D55E00) and right (e.g., CC79A7) sides of the screen. A video-recorded example of one of the light displays is available at: [https://osf.io/34zqd/?view\\_only=e6f3ba01783643b2a4196ef2bda7bd82](https://osf.io/34zqd/?view_only=e6f3ba01783643b2a4196ef2bda7bd82).



**Fig. 1.** Colored light bulb images used to create light displays paired to each melodic stimulus.

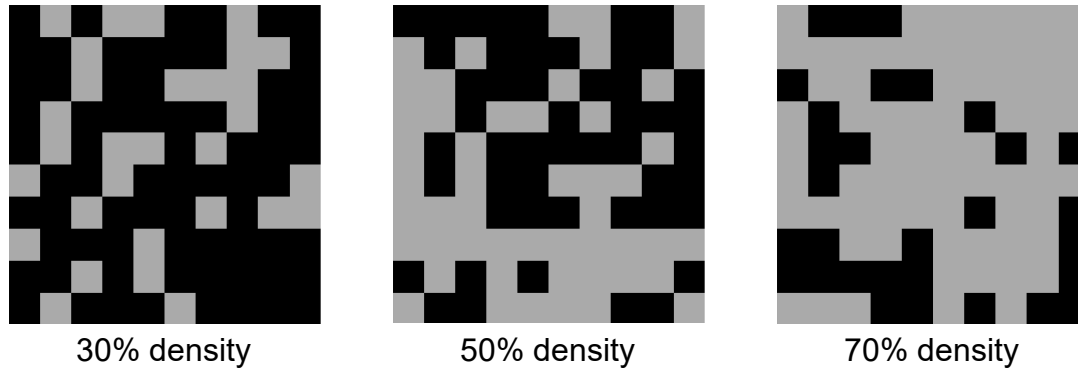
#### VISUAL STIMULI: TEXTURE PATTERNS

To enable computation of measures of visual complexity based on both number of elements and their entropy, we presented participants with texture patterns modeled after those recently designed by Friedenber and Liby (2016) to explore the association between visual complexity and aesthetic judgment. As alluded to above, each pattern involved presenting a set of gray squares within randomly selected cells of a 10 x 10 grid. Following Friedenber and Liby, patterns were created within each of ten density levels from 10% to 100% in increments of 10% (see Figure 2 for examples). Participants were presented with five patterns within each of the first nine density levels and with two exemplars of a 100% density pattern, for a total of 47 images. Each pattern was presented against a black-colored background. Building upon Friedenber and Liby’s work, Gauvrit et al. (2017) developed algorithms for computing the number of distinct parts within each texture pattern as well as the first order entropy of each pattern (see Results for additional details).

**Table 1.** Pitch Chroma to Color Mappings

Pitch Chroma	Hexidecimal Color Values	
	Mapping 1	Mapping 2
C	#D55E00	#CC79A7
D	#E69F00	#0072B2
E	#F0E442	#56B4E9
F	#009E73	#009E73
G	#56B4E9	#F0E442
A	#CC79A7	#D55E00
B	#0072B2	#E69F00

It should be noted that texture patterns with complementary density levels (e.g., 20% vs. 80%) shared the same entropy, avoiding any confound between entropy and the number of squares making up the pattern. Unlike the light display stimuli, these texture patterns were not systematically matched in their features with the melodies from the MUST set. However, this allowed us to assess whether AS-to-complexity would be positively correlated across modalities even when there was considerable variability in the specific, structural properties of the stimuli. As such, it enabled a stronger test of the role of modality-general representations of complexity in contributing to aesthetic preference.



**Fig. 2.** Examples of texture patterns at three density levels.

### Procedure

The study was programmed and hosted online using PsyToolkit (Stoet, 2010; 2017). Participants were initially administered informed consent, after which they were told that they would be asked to rate how much they liked each of a number of different types of audio or visual stimuli and that the stimuli would include musical melodies, colored light displays, and texture patterns. No mention was made of any connection between the different types of stimuli. Participants were presented with and rated their liking for each musical and visual stimulus, with different stimulus types (i.e., melodies, light displays, or texture patterns) presented in separate blocks, the order of which was selected at random. The order of presentation of stimuli within a given block was also randomized. Prior to beginning each block, participants were given a set of three practice trials using stimuli that were not included in the main stimulus sets. Adapting the procedure of Clemente et al. (2021), after hearing or viewing each stimulus, participants were asked to rate their liking for it (i.e., “How much did you like this [melody/light display/pattern of gray squares]?”) on a 5-point Likert scale anchored at 1 (*not at all*) and 5 (*very much*). Upon completing this procedure, participants were asked to complete demographic measures, after which they were fully debriefed regarding the aims and methods of the study.

## RESULTS

### Relations between Ratings of Dynamic Musical and Visual Stimuli

As a simple first step in the analysis, we computed correlations between ratings of liking for each melody and its paired light display to test whether individuals tended to rate dynamically analogous stimuli in a similar way across modalities. On average, this correlation was weakly, but reliably positive,  $r = .20$ ,  $p < .001$ , 95% CI [.18, .23], suggesting that this was the case.

Next, mirroring the analytical strategy of Clemente et al. (2021), we computed separate linear mixed-effects models of liking ratings for melodies and for light displays using the *lmer()* function of the ‘lme4’ package in the R programming environment (Bates et al., 2015). In both models, we included the metric of melodic complexity used by Clemente et al. (2021) as a fixed-effect predictor variable. This metric, labeled “KC1” by the authors, represents a composite of event density and pitch-related entropy (see Clemente et al., 2020, for details, including tabulations of KC1 values for each melody in the MUST set).[2] Our models also included varying intercepts and slopes for KC1. (A full tabular summary of the output of both linear mixed-effects models including fixed effect estimates and confidence intervals as well as  $R^2$  values is available at: [https://osf.io/34zqd/?view\\_only=e6f3ba01783643b2a4196ef2bda7bd82](https://osf.io/34zqd/?view_only=e6f3ba01783643b2a4196ef2bda7bd82)).[3]

Following Clemente et al. (2021), the individual slopes for the effect of KC1 computed for each participant based on this model structure were used to operationalize their AS-to-complexity for the melodies as well as their AS-to-complexity for the corresponding light displays. The resulting values quantify, for each participant, the degree to which their preference ratings are affected by stimulus complexity in each modality. The Spearman rank correlation between visual and melodic AS measures was again significantly positive,  $\rho = 0.37, p < .001$ , 95% CI [.29, .45].<sup>[4]</sup> Together, these results suggest that the influence of complexity on an individual's preference for musical stimuli is modestly but reliably associated with its influence on their preference for visual stimuli, at least when there is a close correspondence between the dynamic attributes of the stimuli in each modality.

## Relations between Ratings of Musical Stimuli and Texture Patterns

In the next part of the analysis, we examined the relationship between AS to melodic complexity and AS-to-complexity of static texture patterns instead of dynamic light displays. As alluded to earlier, we operationalized the complexity of texture patterns in two ways: First, we used the R function *nPart* developed by Gauvrit et al. (2017) to identify the number of distinct parts in each texture pattern. According to this method, a “part” is defined as a cluster of squares that share a side. For instance, four adjacent squares forming an “L” shape would constitute a single part, whereas four squares that only make contact at their corners (like the black squares on a checkerboard), would constitute four different parts (see Gauvrit et al., 2017, Appendix A, for additional examples). Texture patterns with more parts can be seen as more complex in that they contain a greater number of elements (cf. Clemente et al., 2021).

Second, as pointed out by Gauvrit et al., texture patterns in which elements are randomly selected to appear in the cells of a grid are essentially binary sources of information. As a result, their entropy ( $H$ ) may be computed as a mathematical function of their density according to the formula:

$$H = (-d * \log_2(d)) - ((1-d) * \log_2(1-d))$$

where  $d$  is the density of the texture, defined as the proportion of occupied grid cells. We therefore computed entropy in this way as a second measure of visual complexity. Here, texture patterns closer to 50% density exhibit greater information entropy, that is, less binary symbol redundancy, much as melodies with higher pitch-related entropy show less redundancy in their constituent musical tones.

To generate AS metrics for both visual complexity measures, we computed another linear model of liking ratings, entering the number of parts and entropy of the texture patterns as fixed-effect predictors and including random intercepts and slopes for both of these predictors, which were moderately correlated with one another using Spearman's method,  $\rho = .52, p < .001$ , 95% CI [.27, .70]. (A full tabular summary of the model output is available at: [https://osf.io/34zqd/?view\\_only=e6f3ba01783643b2a4196ef2bda7bd82](https://osf.io/34zqd/?view_only=e6f3ba01783643b2a4196ef2bda7bd82)). The individual slopes derived from the random-effects structure in this model were used to operationalize participants' AS to visual complexity based on number of parts ( $AS_{np}$ ) as well as their AS-to-complexity based on entropy ( $AS_H$ ). (VIF values for the predictors were less than 1.02, suggesting no risk of multicollinearity in estimating their effects.) Spearman rank correlations between these AS measures and measures of AS-to-complexity for both melodies and light displays are reported in Table 2. Most notably, this reveals that AS-to-complexity for melodies was modestly, albeit significantly correlated with  $AS_H$  for texture patterns,  $\rho = .19, p < .001$ , 95% CI [.10, .28], but not with  $AS_{np}$ . This suggests that AS-to-complexity for musical and visual stimuli are positively associated on average, provided that complexity is operationalized in a manner that takes the redundancy of elements into account and not merely their quantity. It also demonstrates that the existence of this association does not require similarity between the stimuli within each modality in terms of their temporal dynamics.

**Table 2.** Correlations between Measures of Aesthetic Sensitivity to Complexity

Stimulus Set	1	2	3	4
1. Light Displays (KC1)	–			
2. Melodies (KC1)	0.37**	–		
3. Texture Patterns (Entropy)	0.26**	0.19**	–	
4. Texture Patterns (Number of Parts)	0.13*	0.07	0.09	–

Note: \*\* =  $p < .01$ , \* =  $p < .05$



Although the abovementioned results implicate a role for modality-general representations in forming evaluative judgments, the relatively small size of the cross-modal correlation between AS-to-complexity scores might prompt the inference that this contribution is less than that of modality-specific representations (Clemente et al., 2021). However, as shown in Table 2, the *within-modality* correlation between AS-to-complexity for the two types of visual stimuli in our study, light displays and texture patterns, is similar in magnitude ( $\rho = .26$ ) to the between-modality correlation between AS-to-complexity for melodies and the very same texture patterns ( $\rho = .19$ )—a statistically nonsignificant difference ( $z = 1.37, p = .17$ ). That within- and between-modality correlations have roughly the same magnitude suggests that modality-general representations are not substantially less important than modality-specific representations for driving evaluative judgments. This comparison of within- and between-modality correlations was not possible in the original Clemente et al. (2021) study, as they used only a single task to compute AS-to-complexity in each modality. Notably, the positive correlation between AS-to-complexity for melodies and corresponding light displays ( $\rho = .37$ ), was greater in magnitude than either the within-modality correlation between AS-to-complexity for light displays and texture patterns ( $z = 1.99, p < .05$ ) or the between-modality correlation between AS-to-complexity for melodies and texture patterns ( $z = 3.37, p < .001$ ). This suggests that shared variance in AS-to-complexity across tasks may depend more upon whether complexity is operationalized similarly for those tasks than whether the tasks share the same modality.[5]

## DISCUSSION

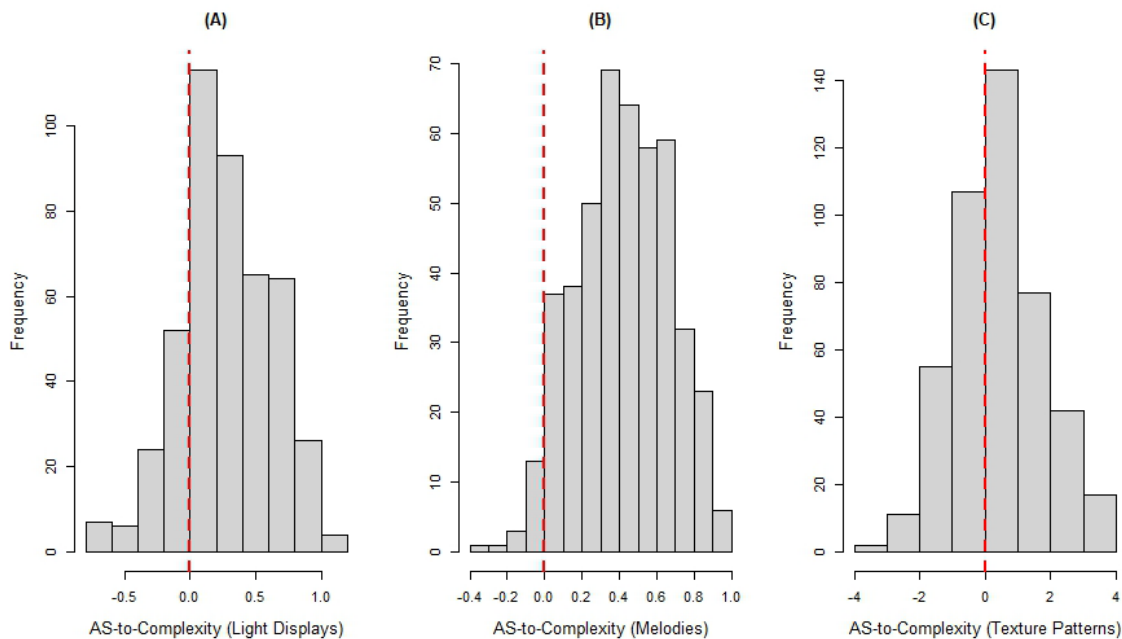
It has long been recognized that people differ in how their preferences for musical sounds or visual images are influenced by stimulus complexity. However, the extent of overlap between individual differences in AS-to-complexity across the musical and visual domains has remained unclear. In their important recent study, Clemente et al. (2021) put forth evidence suggesting that aesthetic sensitivities to complexity in the musical and visual domains are uncorrelated. This lack of reliable cross-modal associations between AS measures led them to conclude that evaluative judgments of aesthetic stimuli are not based on modality-general representations of complexity. However, we hypothesized that the inability of Clemente et al. (2021) to detect cross-modal associations between AS-to-complexity for musical versus visual stimuli may have at least partly resulted from a confound between modality and temporal dynamics in their experimental stimuli and/or a confound in their operationalization of complexity for stimuli in different modalities.

To test these possibilities, we conceptually replicated part of their procedure using visual images and musical melodies that were either very closely matched in their temporal dynamics and/or for which complexity was operationally defined in a very similar way (either in terms of number of elements or their information entropy). Our results revealed that there was indeed a reliable overall association between AS-to-complexity within the musical and visual domains, even when the stimuli differed in their temporal dynamics, so long as complexity was measured using similar metrics that account for entropy. This suggests that Clemente et al. (2021) underestimated the role of modality-general representations of complexity in evaluative judgment. More broadly, our results serve to reconcile Clemente et al.'s (2021) findings regarding AS-to-complexity with theories that posit modality-general individual differences in preference for information differing in complexity (e.g., Cacioppo & Petty, 1982), with theories of aesthetic preference that are based on domain-general cognitive mechanisms of prediction and processing fluency (e.g., Briellmann & Dayan, 2022), and with other recent empirical studies that appear to show quite robust cross-modal commonalities in preferences for complexity (e.g., Palmer & Griscom, 2013; Song et al., 2022).

It is important to note that the present findings are silent regarding why Clemente et al. (2021) did not show cross-modal aesthetic sensitivities for stimulus attributes other than complexity. As noted earlier, Clemente and colleagues found that AS to visual balance and symmetry were not reliably associated with AS to musical balance and symmetry. Although these null findings may point to the involvement of modality-specific representations of sensory information for the same attributes, it is also possible that the attributes described by the terms “balance” and “symmetry” are qualitatively different between visual and musical modalities. In other words, the senses of the terms “balance” and “symmetry” when used to describe the distribution of visual elements within a two-dimensional frame may be largely unrelated to the senses of those same terms when used to describe the distribution and ordering of musical notes in time. For instance, it is unclear whether individuals construe melodies in terms of isochronal sections, akin to spatial “sides”, over which they might cognitively represent the extent to which the melodic sequence in the first section has been reversed in the second. Detecting cross-modal commonalities in aesthetic preference may require ensuring that the materials and measures implemented to assess AS within each modality are closely aligned,

as we did in the present work concerning “complexity”. Future work may thus focus on how terms like “balance” and “symmetry” are applied to different types of materials, enabling the development of formal measures of these constructs that can be applied to stimuli from multiple modalities as we did when using entropy to operationalize “complexity”.

Although our results appear to be inconsistent with one of the conclusions drawn by Clemente et al. (2021), they resoundingly support another of their primary contentions: We find evidence of substantial variability in individuals’ aesthetic sensitivities to complexity. Histograms of AS for each of the three stimulus types in our study are shown in Figure 3. These show that scores on all three measures are roughly normally distributed with a considerable proportion of participants showing positive responses to increased complexity, others showing negative responses, and a great many showing relative indifference to this attribute (cf. Güçlütürk et al., 2016; Güçlütürk & van Lier, 2019). Likewise, it appears that even when stimuli in different modalities are matched very closely in terms of their objective complexity, individuals markedly vary in terms of the extent to which they assign these stimuli similar ratings. For instance, whereas the average correlation between liking ratings for melodies and matched light displays was significantly positive in the present study, correlations at the individual level ranged from  $-.58$  to  $.90$ . Considering such variability, it is possible that the conclusions of Clemente et al. (2021) were subject to sampling variability that we were able to characterize more fully using our comparatively larger sample. In addition, the modest overall correlations we report leave considerable room for modality-specific mechanisms to operate. However, the presence of only modest modality-general effects does not imply that the remaining variance in evaluative judgments must be due to modality-specific effects. As noted earlier, within-modality correlations in our study were also rather modest, opening the possibility that modality *per se* may not be as essential to evaluative judgments as Clemente et al. (2021) have argued.



**Fig 3.** Frequency distributions of AS-to-Complexity scores for (A) light displays; (B) melodies; and, (C) texture patterns. Vertical dashed lines represent insensitivity (i.e., indifference) toward a given aesthetic attribute.

In sum, the findings of our conceptual replication study stand to help resolve a theoretical and empirical conundrum posed by the intriguing results of Clemente et al. (2021), while validating their overall methodological approach to elucidating individual differences in AS across modalities (see also Clemente et al., 2020; Clemente, Pearce, & Nadal, 2022; Corradi et al., 2020). The study also introduces a novel paradigm for equating the temporal dynamics of musical and visual stimuli—involving light displays that constitute a form of “visual music”—and newly demonstrates the utility of random texture patterns (Friedenberg & Liby, 2016; Gauvrit et al., 2017) in equating measures of different forms of complexity across modalities. As such, we hope that the work will be of value to scholars of music and aesthetics, whose daunting challenge to



account for evaluative preferences is laid bare by the provocative recent contributions of Clemente and colleagues.

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## NOTES

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[2] Clemente et al. (2021) characterized the complexity of their musical stimuli using two components, KC1 and KC2, where KC2 represented rhythmic complexity (duration entropy). Because our texture pattern stimuli are static, the construct of rhythmic complexity does not apply to them. Moreover, even though our light displays were direct translations of Clemente et al.'s (2021) stimuli into the visual domain, durations of light events were twice those of the corresponding pitch events in the musical domain. As such, we were concerned that KC2 would not apply to our light displays either. Given our goal of employing comparable measures of complexity across all stimulus types, we therefore elected to focus only on KC1 in our analyses.

[3] Inclusion of color mapping (1 vs. 2; Table 1) as a factor when modeling ratings of light displays did not influence the results to be reported below and, as such, will not be discussed further. Full study data is available at: [https://osf.io/34zqd/?view\\_only=e6f3ba01783643b2a4196cf2bda7bd82](https://osf.io/34zqd/?view_only=e6f3ba01783643b2a4196cf2bda7bd82)

[4] As in the study by Clemente et al. (2021), Spearman's rank correlations were used in these analyses as Shapiro-Wilk tests revealed that AS-to-complexity measures were non-normally distributed. The pattern of findings was virtually identical using Pearson correlations.

[5] Since we computed correlations in terms of ranks, the impact of similarity of operationalization on the strength of this correlation cannot be attributed solely to the fact that the same operational definition involves use of the same measurement scale.

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