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Full Length Article

# Higher creativity is linked to increased association scores in an audiovisual task

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ABSTRACT

Human creativity is often studied in relation to idea-generation and problem-solving; yet a growing body of evidence suggests that creativity-related traits may also shape how we perceive and understand the world around us. In this study, we examined whether individual differences in creative disposition are associated with differences in crossmodal associations triggered by musical stimuli. A total of 97 healthy adult participants completed a crossmodal association task wherein they rated the extent to which short musical melodies could be associated with illustrations of everyday objects, followed by questionnaires assessing creative personal identity, creative self-efficacy, openness to experience, and creative activities. Using a Gaussian Mixture model-based clustering approach, we identified two participant profiles characterised by consistently high versus low creativity-related scores. By means of a Bayesian Zero-Inflated Beta-distributed Mixed Model, credible evidence was obtained that individuals from the former cluster, characterised by a broadly developed creative profile, gave higher association scores. Despite some uncertainty regarding its practical relevance, the effect showed a 95.82% probability of existence, suggesting that creativity-related traits may influence the crossmodal associations between musical and visual percepts.

## 1. Introduction

Creativity is a multidimensional construct that spans a wide range of domains, from individual thought to complex relational and cultural activities across the arts, sciences, and business innovation (Sawyer, 2006). As such, it is considered a fundamental psychological ability with both evolutionary and developmental significance (Csikszentmihalyi, 1999; Mithen, 2005). At a general level, creative cognition is assumed to involve mental processes that give rise to outputs (i.e., ideas or products) that are both novel and useful (Diedrich et al., 2015). Because of this, much research and theory on human creativity has traditionally focused on higher-order cognitive processes, including idea-generation and problem-solving (see Forgeard & Kaufman, 2016). This has led to a distinction between two complementary modes of thinking – which build on Guilford's (1967) structure of intellect model - that are commonly used to characterise and study creativity: *divergent* and *convergent* thinking. Put simply, divergent thinking refers to the generation of multiple potential responses to open-ended or ill-defined problems, which typically afford a large solution space (see Runco, 1991). Convergent thinking, in contrast, involves identifying a single appropriate solution to a problem that cannot be solved through routine or analytical strategies (see Cropley, 2006).

But while such modes of creative thinking can capture important aspects of creative cognition, they may be seen to represent only *one* component of a broader constellation of traits, processes, and modes of experience and engagement with the world associated with creativity (see Schiavio & Benedek, 2020). Indeed, more comprehensive models increasingly conceptualise human creativity as a multi-component phenomenon encompassing personality traits, self-related beliefs, intersubjectivity, motivation, bodily experience, and real-world

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engagement, alongside specific cognitive abilities (see Amabile, 1996; Glăveanu, 2014; Kaufman & Beghetto, 2009). Along these lines, consider how constructs such as openness to experience, creative self-efficacy, and creative personal identity have been shown to relate to creative achievement and persistence, often accounting for variance beyond divergent thinking alone (Abu Raya et al., 2023; Karwowski & Lebuda, 2016). These contributions suggest that creativity-related dispositions may shape not only how people think, but also how they feel, perceive, and experience the world. For example, it has recently been suggested that spontaneous thought elicited and shaped by music mirrors individual differences in creative disposition (e.g., see Kubit et al., 2025).

This is echoed, among others, in investment-based and systems-oriented models of creativity. For example, Sternberg and Lubart (1995) proposed that creativity emerges from the alignment of six interdependent resources: Motivation, intelligence, knowledge, personality, thinking styles, and environment. A prototypical creative profile, therefore, "might be someone who is intrinsically motivated, has relevant cognitive strengths and appropriate domain knowledge, is open to experiences (e.g., Feist, 1998), has a legislative (creative and self-directed) thinking style (Sternberg, 1999), and develops within a nurturing (or at least tolerant) environment" (Kaufman & Glăveanu, 2021, p. 7). Within this framework, creativity is not reducible to a single trait or skill; rather, it reflects the coordinated interaction of dispositional, cognitive, and contextual factors (see Benedek, 2024). Building on these perspectives, it may be argued that a multi-dimensional assessment of creativity offers a robust index of creative cognition. Indeed, capturing what can be defined as a *broad creative profile* requires the integration of both personality and behavioural dimensions of creativity: the personality-related dimension captures relatively stable dispositional tendencies, such as openness to experience, which may influence how individuals orient themselves toward novelty, complexity, and aesthetic exploration; the behavioural dimension reflects actual engagement with creative activities in everyday life, indexing the extent to which creative potential is translated into practice.[1] By integrating these two complementary components, we can move beyond narrow assessments of divergent thinking and model creativity as a more holistic disposition - one that encompasses how individuals construe themselves, engage with novelty, and express creativity in practice.

If creativity emerges from the dynamic interaction of multiple resources, its influence may extend to include more *foundational* modes of experiencing and engaging with the world. Because of this, recent scholarship has started to explore whether creativity-related traits are associated not only with idea- or product-generation, but also with more basic cognitive and perceptual processes that encompass associative thinking and broader organism-world synergies (e.g., Schiavio & Kimmel, 2021).

Recent embodied and process-oriented perspectives suggest that creativity is strongly supported by how individuals are meaningfully situated within a given (social, cultural) environment, and how they perceptually frame and actively engage with its situations and contexts (see Araújo et al., 2006, 2017; Hristovski et al., 2012). For example, Bellemare-Pepin and Jerbi (2024) propose that divergent thinking may reflect a form of *perceptual flexibility,* whereby individuals become attuned to alternative affordances and action possibilities rather than merely generating more ideas. Their work demonstrates that subtle manipulations of task framing can reorganise perceptual attention and systematically alter the structure and diversity of creative responses, even when task content is held constant. With this in mind, creative variability may be seen to emerge from dynamic perception–action couplings (Orth et al., 2017; van der Schyff et al., 2018), challenging strictly internalist accounts of creative cognition (see also Glăveanu et al., 2020; Sawyer, 2003). As such, perceptual organisation and embodied engagement with the environment can be conceived of as constitutive components of creative cognition (Schiavio & Benedek, 2020). Individuals continuously forge, reframe, and adapt their organism-world couplings, navigating uncertainty and taking risks, with curiosity, exploration, and novelty-seeking, further driving engagement with ambiguous or complex sensory information (e.g., Borgo, 2005; Daikoku, 2019). Despite growing research linking creativity to action and bodily experience across different domains (see Bertin-Renoux, 2024; Malinin, 2016; Schiavio et al., 2022, b, 2024), relatively little is known about how creativity-related dispositions shape perceptual experience and its associative mechanisms.

Creative individuals are known to form stronger connections between (semantic) concepts (Herault et al., 2024; Merten & Fischer, 1999; Rossmann & Fink, 2010), including non-verbal associations between concepts (Becker & Cabeza, 2023). These associative tendencies are thought to underpin their ability to combine disparate ideas in novel ways. Real-world creative achievements have been linked to differences in attentional filtering and heightened sensitivity to weak or ambiguous stimuli, although these effects appear to depend on the type of creativity assessed and the balance between associative and executive control processes (Carson et al., 2003; Volle, 2018; Zabelina et al., 2015). Neurocognitive accounts suggest that such differences may reflect altered balances between top-down executive control and bottom-up sensory processing, potentially allowing a wider range of information to enter conscious awareness (Beaty et al., 2016). From this perspective, creativity-related traits may be associated not only with downstream ideational processes but also with differences in how sensory information is integrated and experienced. Against this backdrop, a key unresolved question is whether creative individuals form more original associations because they perceive and attend to a broader range of sensory information ("leaky" attention), because they can generate more remote associations via flexible executive processes, or because of a combination of both mechanisms (Agnoli et al., 2015; Kasof, 1997; Vartanian, 2009; Zabelina et al., 2015, 2016; Zabelina & Robinson, 2010).

Despite growing scholarly interest in how multisensory integration and perceptual sensitivity are associated with creative cognition, research on auditory stimuli remains relatively limited. For example, Xiao et al. (2024) investigated how crossmodal audiovisual integration of emotional stimuli influences creativity, and showed that the bimodal audiovisual integration of positive emotions can enhance overall creativity and fluency, whereas visual-only stimuli were least effective. This last contribution highlights how the study of crossmodal associations can provide a promising and underexplored framework for investigating this, as it involves mapping features across the senses (e.g., sound, shape, texture) and can reveal individual differences in perceptual interpretation that are not confounded by explicit creative production demands (Parise, 2016; Spence, 2011). The present study addresses this gap by examining whether individuals with different creativity-related profiles exhibit systematic differences in self-reported crossmodal musical associations. Accordingly, our guiding research question was:

> Do individuals with different creativity-related profiles exhibit systematic differences in self-reported crossmodal musical associations?

The present work focuses on self-reported crossmodal associations between the auditory and visual domains, specifically examining the relationship between musical stimuli and images of everyday objects. Relatively complex and meaningful musical stimuli (e.g., short melodies or musical excerpts), as opposed to basic auditory inputs such as pure tones, have increasingly been used to study crossmodal perception over the past decades, especially in audiovisual contexts (Albertazzi et al., 2015; Di Stefano et al., 2024, 2025; Palmer et al., 2013; Wanke et al.,

[1] As will be seen later, the scales used in the present study were selected to reflect this structure. Measures of creative self-efficacy, creative personal identity, and openness to experience capture the personality-related dimension; and indices of creative activities represent the behavioural dimension.

2025). Neuroimaging studies show that music perception recruits distributed networks involved in emotion, imagery, and associative cognition (Koelsch, 2014); and when listeners are invited to match music to non-auditory stimuli, such as visual or object-based representations, their responses may reflect differences in how perceptual, affective, and conceptual information is integrated. In our study, participants completed an audiovisual task in which they rated the extent to which short musical excerpts were associated with everyday objects, followed by questionnaires assessing aspects of creative personality and behavioural traits. We anticipated that differences might emerge as a result of the combined influence of multiple creativity-related traits. We identified two groups – one scoring consistently higher and one scoring lower across creativity-related measures - and compared these groups' crossmodal association ratings. If creativity-related dispositions are indeed linked to enhanced crossmodal sensitivity, this would suggest that creative variability may partly arise from how sensory information is organised, explored, and imbued with meaning in everyday experience.

## 2. Methods

### 2.1. Participants

In total, 103 healthy adults were recruited via the online platform Prolific (www.prolific.co). Participants were required to be native English speakers. Due to a technical issue in the implementation of the experiment, data from four participants were lost. An additional two participants were excluded for failing an attention check (see Procedure). The final sample therefore consisted of 97 participants (44 females, 52 males, 1 non-binary / third gender; age: $M = 41.76$ years, $SD = 12.24$). Of the 97 participants, 30 identified as *non-musicians*, 47 as *music-loving non-musicians*, 13 as *amateur musicians*, and 7 as *serious amateur musicians*; no participants reported being semi-professional or professional musicians.

### 2.2. Ethics statement

All procedures were approved by the School of Arts and Creative Technologies Ethics Committee at the University of York and were conducted in accordance with the Declaration of Helsinki. All participants provided written informed consent.

### 2.3. Materials

Three questionnaires were administered to assess specific aspects of participant's creativity. Creative potential was measured using the Openness to Experience subscale of the Big Five Inventory (BFI-O) (John & Srivastava, 1999), as well as the "Short Scale of Creative Self" (SSCS) (Karwowski et al., 2018), which evaluates creative Self-Efficacy and creative Personal Identity. Creative activity was assessed using the "Short Inventory of Creative Activities" (S-ICA) (Steger et al., 2022). Musical training was determined using a single item asking participants "Which title describes you best?". Responses were given on a six-level ordinal scale: (i) *non-musician*, (ii) *music-loving non-musician*, (iii) *amateur musician*, (iv) *serious amateur musician*, (v) *semi-professional musician*, (vi) *professional musician* (Zhang & Schubert, 2019). The main task of the experiment aimed to explore the strength of individuals' crossmodal associations. In each trial, participants were presented with one melody and ten illustrations depicting everyday objects selected from a standardised set of drawings with norms for six European languages (MULTIPIC: Duñabeitia et al., 2018, see Fig. 1). Ten melodies were randomly generated using MIDIGEN 1.0 (www.midigen.app), an algorithmic MIDI composition tool. To ensure affective diversity across the stimulus set, five melodies were created in major keys (i.e., C, C#, D, D#, and E) and five in minor keys (harmonic scale: Cm, C#m, Dm, D#m, and Em). All stimuli consisted of four bars at a tempo of 68 BPM. The "dominant note duration" parameter was set to eighth notes. An example of melody used for the study is offered in Fig. 2. All of the melodies (scores and audio files) are provided in the Supplementary Materials and Open Science Framework (see Data Availability statement). All sequences were rendered using a realistic acoustic grand piano VST instrument[2] and saved as .wav files (44,1 kHz, 24 bits per sample, 15 s). For each trial, participants were instructed to listen to the melody and then rate the extent to which it was associated with each illustration. Ratings were provided on a continuous scale ranging from 0 ("Does not match at all") to 100 ("Complete match"). Each trial featured one distinct melody (in a randomised order), and participants provided one rating per everyday object, resulting in ten ratings per trial in total.

### 2.4. Procedure

After being informed about the aim of the experiment and receiving task instructions, participants provided informed consent and completed ten trials of the crossmodal association task. Following the experimental task, the participants completed the questionnaire battery. To ensure data quality, two attention checks were implemented. First, at the beginning of the experiment, participants were instructed to enter the word "modal" (in lower case) into a text box. Second, an attention check item was embedded in the BFI-O questionnaire instructing participants to respond by selecting "Agree a little" (Muszyński, 2023). The experimental procedure is depicted in Fig. 3. The average duration of the experiment was 16 min and 56 s ($SD = 7$ min and 45 s).

### 2.5. Statistical analysis

All analyses were conducted in JASP (i.e., reliability and correlational analyses) (JASP Team, 2026) and R (i.e., clustering and modelling) using a Bayesian approach. The specific packages used are detailed in the relevant sections below. As the statistical procedure comprises several sequential steps, these are presented separately for clarity.

#### 2.5.1. Reliability

MacDonald's ω was computed as an index of the internal consistency of the creativity indices (Dunn et al., 2014). For each computation, we ran three Monte Carlo chains with 5000 iterations and 1000 burn-in samples (Pfadt et al., 2022). R-hat index was always 1.00 and the Effective Sample Size always >8500, thus showing sampling adequacy (Vehtari et al., 2021).

#### 2.5.2. Correlations

As a first step, we inspected the correlations between the creativity indices and some centrality indices of the crossmodal ratings (CMR). Due to the high proportion of zeros in the participants' ratings ($M = 30.82\%$, $SD = 33.50$), we calculated Kendall's $\tau$ coefficient. As indices of centrality for the CMR, we calculated the overall median and the mean of the positive side of the distribution (i.e., $> 0$). Moreover, we computed the standard deviation under the expectation that more creative people would vary more in their CMR.

#### 2.5.3. Clustering the participants

Participants were grouped based on their z-transformed scores on the SSCS SE, SSCS PI, BFI-O, and S-ICA. To do so, a Gaussian Mixture Modelling for Model-Based Clustering using the *Mclust* package was used (Scrucca et al., 2016, 2023). This method assumes that the data arise from a mixture of $N$ underlying profiles, or latent subpopulations, each characterised by distinct patterns across the creativity indices

[2] NOIRE Pure samples the Yamaha CFX piano, further info about the sampling can be found here: https://www.native-instruments.com/fileadmin/ni_media/downloads/manuals/NOIRE_Manual.pdf

**Fig. 1.** Ten everyday objects which were used in the crossmodal association task.
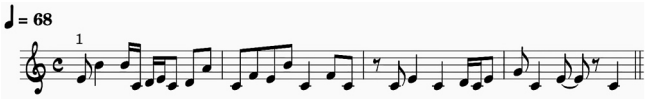
**Fig. 2.** One of the melodies used for the study.

(Fraley & Raftery, 2002–2003). In practice, we fitted different solutions varying in variance–covariance parameterisations (e.g., spherical, diagonal, ellipsoidal), each with one to nine clusters, and compared them using the Bayesian Information Criterion (BIC). As a robustness check, we used the *NbClust* package (Charrad et al., 2014) to calculate 24 different indices for computing the number of clusters (e.g., KL, Silhouette, Gap statistic, etc.). In the Results section, the frequencies of the proposed solutions are reported. Finally, the best-performing model assigns each participant a probability of belonging to each cluster. We used the highest probability to define membership, but we commented on such probabilities as a robustness check for the clustering. As an

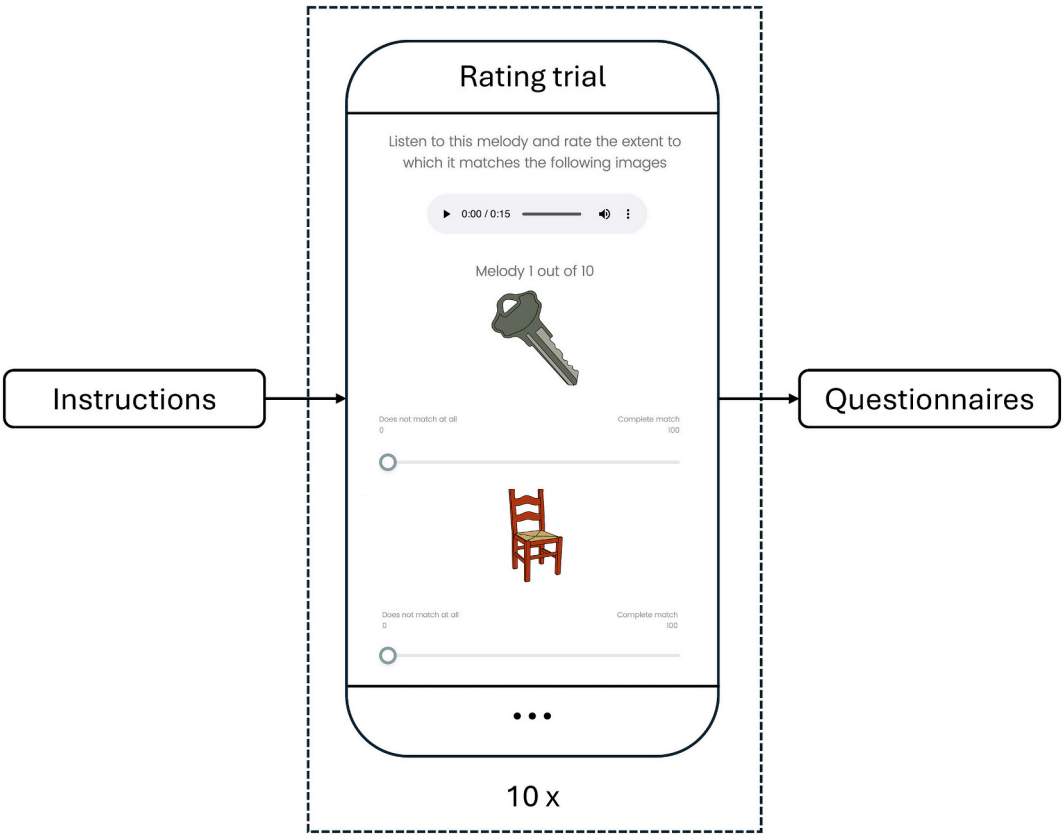


**Fig. 3.** Experimental procedure. After receiving the experimental instructions, participants completed 10 trials of the crossmodal rating task before filling out the questionnaires.

additional robustness check, we assessed clustering stability via nonparametric bootstrap, i.e., we refitted the model and at each iteration ($B = 1000$ resamples) quantified agreement with the original solution using the Adjusted Rand Index (ARI) and its standard deviation.[3]

#### 2.5.4. Modelling and model comparison

Once the number of clusters had been determined, we fitted a model to investigate whether the clusters differed in their CMR. Due to the high proportion of zeros in the data (i.e., 30.83%), we divided the CMR by 100 and fitted a Bayesian Zero-Inflated Beta-distributed Mixed Model (Bürkner, 2023; Heiss, 2021; Ospina & Ferrari, 2012) with a logit link function through *brms* (Bürkner, 2017). This approach allowed us to treat the CMRs appropriately as a bounded variable while explicitly modelling zero inflation. Such a model includes two submodels with separate formulas: one to predict the mean ($\mu$) and one to predict the probability of a zero ($\pi$). To account for the repeated-measure nature of the data and achieve partial pooling (McElreath, 2020), we included three random intercepts – for participants, tracks, and objects - in both submodels. In sum, the following formulas were used:

$$logit(\mu_i) = \alpha + \beta_{cl} c_{(i)} + u_{p(i)} + v_{t(i)} + w_{o(i)}$$

$$logit(\pi_i) = \gamma + \delta_{cl} c_{(i)} + u^{(zi)}_{p(i)} + v^{(zi)}_{p(i)} + w^{(zi)}_{p(i)}$$

In Wilkinson notation, these translate as:

$$\text{CMR} \sim 1 + \text{cluster} + (1 \mid \text{participant}) + (1 \mid \text{track}) + (1 \mid \text{object}),$$

$$\text{Zi} \sim 1 + \text{cluster} + (1 \mid \text{participant}) + (1 \mid \text{track}) + (1 \mid \text{object})$$

The estimation was based on six Monte Carlo chains with 10,000 iterations each, 3000 of which were warmup. The total number of post-warmup draws was then 42,000. An R-hat index of 1.00 was successfully reached for all model parameters. Bulk and Tail Effective Sample Sizes of the population-level and auxiliary parameters were above 2036 and 4299 (the statistics for all group-level parameters (i.e., random effects) are reported in the Supplementary Materials together with model diagnostics, prior and posterior predictive checks, and a comparison with the corresponding frequentist version of the same model). Taken together, these diagnostics show that the model converged satisfactorily and that the posterior estimates can be considered reliable (Vehtari et al., 2021). After fitting the model, we based our inference on the conditional posterior distribution of the cluster contrast to address our research question. Specifically, we extracted posterior draws of the contrast between the cluster levels while setting all random offsets to zero[4] (i.e., re_formula = NA, see Heiss, 2022). This approach provides an estimate of the expected difference in CMR between clusters (i.e., population-level effect). This was necessary because, due to the zero-inflated mixture structure and the inclusion of multiple random intercepts, the model parameters are not directly interpretable. Put differently, since the data are assumed to be generated by two joint processes ($\mu$ and $\pi$), the model primarily serves as a generative tool to achieve partial pooling and strike an optimal balance between underfitting and overfitting (McElreath, 2020).

In addition to creativity, we tentatively explored the role of musical expertise; namely, whether some familiarity with musical structure could impact CMR in a meaningful way. As a preliminary test to assess whether, as expected, musical expertise was not evenly distributed across the two clusters, a Bayesian contingency table analysis was conducted, and the Bayes Factor in favour of our hypothesis was computed under a joint multinomial sampling scheme (see Jamil et al., 2017). Subsequently, a model comparison technique was applied by comparing the main model with two alternative models: one with musical expertise as the only predictor (i.e., Model 2) and another more complex model in which musical expertise was added as a control variable in conjunction with the cluster (i.e., Model 3). The models were compared via a bridgesampling Bayes Factor (Gronau et al., 2017–2020), which represents a measure of the relative evidence (i.e., marginal likelihood) for one model over the other; in other terms, it indicates under which model the data are more likely, i.e., $BF_{M1-M2} = \frac{P(D|M1)}{P(D|M2)}$.

Lastly, the role of music mode (i.e., major vs minor melodies) was explored via another Bayesian Zero-Inflated Beta-distributed Mixed Model with mode and cluster as interacting predictors.

#### 2.5.5. Priors and Bayesian indices

In the Bayesian framework, all parameters are treated as random variables; as such, prior distributions must be defined. For Kendall's correlations, we used a beta distribution stretched over the [−1,1] interval, with both α and β equal to 7. Such a distribution is fairly sceptical of very strong correlations and concentrates its standard deviation (i.e., 68% of its probability mass) between −0.26 and 0.26, i.e., a moderate correlation in terms of Kendall's τ (Schober et al., 2018; Wicklin, 2023). In probabilistic terms, this can be expressed as $P(-0.26 < \tau < 0.26 \mid data) = 68\%$. For the correlations, we report Kendall's τ estimate, 89% credible intervals, and a one-tailed Bayes Factor where $H_1$ is a positive correlation, as hypothesised. Regularising (or weakly informative) priors were applied to all the parameters of the Zero-Inflated Beta Mixed Model, and extensive prior predictive checks (PPC) were conducted before feeding the model with the data. In specifying the priors, our goal was to regularise the estimates while avoiding excessive shrinkage. A more detailed description of the model prior distributions and prior and posterior predictive checks is presented in the Supplementary Materials. In the model results, we first report the Maximum A Posteriori (or MAP, i.e., the mode for continuous variables) as the central tendency measure of the contrast, the 89% credible intervals. Furthermore, we report the probability of direction of the parameter (*pd*) as an index of the effect's existence and the percentage of the full posterior distribution in the Region Of Practical Equivalence (*inROPE%*) as an index of the effect's relevance (Makowski, Ben-Shachar, Chen, & Lüdecke, 2019). The former directly translates into the probability of the effect being different from a null: $P(\theta > 0 \mid data)$ or $P(\theta < 0 \mid data)$, whichever is the most likely. The latter clearly communicates the probability that the effect is so small that it can be considered negligible, or $P\left(-\frac{SD_{CMR}}{10} < \theta < \frac{SD_{CMR}}{10} \mid data\right)$. Finally, we also computed the probability that the difference in CMR between the clusters was larger than a negligible effect, or $P\left(\theta > \frac{SD_{CMR}}{10} \mid data\right)$. All indices were computed through *bayestestR* (Makowski, Ben-Shachar, & Lüdecke, 2019) and *modelbased* (Makowski et al., 2020).

## 3. Results

### 3.1. Internal consistency and descriptive statistics of the creativity indices

As a first step, we inspected the reliability of the creativity indices. The full SSCS scale showed a very satisfactory internal consistency (MacDonald's ω =.93, 89% CI [.92, .95]). When split into its two subcomponents, both the Personal Identity and Self-Efficacy subscales had very high reliability (ω =.93, 89% CI [.92, .95] and ω =.87, 89% CI [.84, .90], respectively). The Openness to Experience subscale of the Big Five Inventory had very high internal consistency (ω =.89, 89% CI [.86,

[3] The ARI is a metric that measures the similarity between clustering results by correcting for chance agreement. It is bounded between −1 and 1, where 1 indicates perfect match, values close to 0 indicate performance similar to random assignment, and values below 0 signal less agreement than expected by chance (Hubert & Arabie, 1985; Steinley, 2004; Steinley et al., 2016).

[4] Note that setting the random offsets to zero does not mean the exclusion of the random effects from the focal inferential estimate. Conversely, the uncertainty of the REs is included in the model parameters and then propagated to the posterior distribution of the contrast.

.91]). S-ICA's reliability was acceptable (ω =.72, 89% CI [.66, .78]). SSCS Self-Efficacy and Personal Identity had average values in our sample ($M = 3.85$, $SD = 0.83$ and $M = 3.64$, $SD = 1.29$, respectively), similar to the BFI-O ($M = 3.61$, $SD = 0.49$). Comparatively, the S-ICA values were lower ($M = 2.49$, $SD = 0.81$).

### 3.2. Correlations

The results of the correlation analysis were not straightforward (see Table 1; see also *Table 5S* for the matrix format). Most of the *BF*s were inconclusive. However, moderate evidence was found for the relationship between SSCS Self-Efficacy and both the mean of the above-zero CMR ($\tau$ =.14, 89% CI [.02, .22], $BF_{+0} = 4.22$) and the SD, even though with weaker evidence ($\tau$ =.11, 89% CI [.01, .19], $BF_{+0} = 2.13$). The SSCS Personal Identity correlated with the CMR median ($\tau$ =.11, 89% CI [−.01, .19], $BF_{+0} = 2.21$), but also the mean of the above-zero CMR and SD, although more marginally. Trait Openness also showed some weak correlational evidence with the mean of the above-zero CMR ($\tau$ =.12, 89% CI [.00, .20], $BF_{+0} = 2.47$). S-ICA's correlation with the CMR SD was also anecdotally positive ($\tau$ =.09, 89% CI [−.02, .18], $BF_{+0} = 1.44$). Overall, most of the *BF*s were inconclusive, ranging between −0.19 and 0.99, although a few provided some evidence in the hypothesised direction.

### 3.3. Model-based clustering

In light of these inconclusive results, participants were grouped using a model-based clustering algorithm. This approach was motivated by the above mentioned hypothesis that increases in CMR might emerge from specific creativity patterns rather than from single indices alone. A 2-cluster model resulted in the highest performance. The best-performing model had ellipsoidal clusters with equal shape and orientation (Fig. 4). This suggested that the groups differed mainly in their mean profiles across the creativity indices rather than their response patterns or styles. The clustering proved to have strong classification certainty. More precisely, 91 out of 97 participants (i.e., 94%) had extreme posterior membership probabilities, i.e., $P(Cluster\ 1) \leq 5\%$ $or \geq 95\%$ = 94%. The nonparametric bootstrap resampling showed very good stability of classification (ARI: $M$ =.87, $SD$ =.21). The robustness check with the additional indices confirmed these results, with 14 indices supporting a 2-cluster solution, and 4 suggesting a 3-cluster solution. Solutions proposing more than 4 clusters were each supported by fewer than 2 indices. Therefore, we retained the 2-cluster solution as highly reliable.

Participants assigned to Cluster 1 ($N = 61$) scored high in all creativity indices, whereas the opposite was true for the participants who were assigned to Cluster 2 ($N = 36$). The clusters appear to be well differentiated, especially in terms of SSCS Personal Identity, whose mean difference between the clusters was slightly less than 2 *SD*, i.e., $\Delta = 1.78$, 89% CI [1.62, 1.93], $pd = 100\%$, *inROPE%* = 0. Even the smallest difference between the clusters, namely, the one in the S-ICA index, was above 1 *SD*, $\Delta = 1.19$, 89% CI [0.91, 1.45], $pd = 100\%$, *inROPE%* = 0 (Fig. 5, Table 2).[5]

### 3.4. Modelling the difference in CMR between the clusters

When examining the posterior distribution of the contrast (Fig. 6, lower panel), modest evidence was found that the cluster with the more creative participants had slightly higher CMRs. In greater detail, the High Creativity cluster yielded a CMR of 32.51 (MAP value), 89% CI [27.68, 37.90], whereas the Low Creativity cluster scored slightly lower, 25.04, 89% CI [17.72, 31.38]. The most likely difference in CMR between the two clusters was $\Delta = 8.40$, 89% CI [0.49, 15.93], approximately 0.30 pooled standard deviation units of the CMR outcome, which can be interpreted similarly to a small-to-moderate Cohen's *d* effect size. The probability of the parameter being positive was $pd = 95.82$, which directly translates to a 95.82% probability that a positive effect of creativity on CMRs exists. However, 11.61% of the posterior distribution of the contrast fell into the ROPE, signalling some uncertainty about the meaningfulness of the effect. If we consider the more stable 89% Highest Density Interval of the contrast distribution, 8.02% of it is contained in the ROPE. To give a more straightforward answer to our research question, the probability of the effect being positive and larger than negligible is 87.36%, i.e., the proportion of posterior draws with values larger than the upper bound of the ROPE.

As a supplementary analysis, to inspect the effect beyond the dichotomisation introduced by the cluster-based model, we fitted four univariate models, each with a different creativity index (z-scored) as the only predictor. The posterior distributions of the model predictors' slopes were analysed, but none of these yielded a meaningful result (Table 3). Moreover, we fitted a fifth model wherein the only predictor was a composite score derived by averaging the four creativity measures. Before computing the score, its unidimensional reliability was checked by merging all the items from the four scales. The reliability was very high: ω =.92, 89% CI [.90, .94]. The participants in the high creativity cluster had an average composite creativity z-score of 0.52, 89% CI [0.43, 0.63], whereas the low creativity group scored lower, $M = -0.91$, 89% CI [−1.02, −0.77], the difference being $\Delta = 1.43$, 89% CI [1.27, 1.59], $pd = 100\%$, *inROPE%* = 0). The slope estimated by this model was $b = 8.51$, 89% CI [−5.44, 21.57], $pd = 84.52\%$, *inROPE%* = 55.21%. However, as such a slope represents the most likely increase in CMR for a 1 SD increase in the composite creativity z-score, to have an estimate more comparable to the one of the cluster-based model, we scaled its posterior distribution by 1.43 (i.e., the most likely difference between the two clusters in terms of SDs). The adjusted estimate was therefore $b = 12.17$, 89% CI [−7.78, 30.85], $pd = 84.52\%$, *inROPE%* = 38.84%. Such an estimate is broadly consistent in magnitude and direction with the effect estimated in the cluster-based model, although it shows more uncertainty. This suggests that both operationalisations capture the same underlying signal. The cluster contrast does not reflect a distinct creativity profile, but the cluster-based model yields a more precise estimate because it focuses on the extremes of the general creativity distribution, whereas the continuous model estimates a global and thus more noisy linear trend across the full range of scores.

A more detailed representation of the object-melody associations is presented in Fig. 7 as a heatmap. To avoid any influence of the participants' response styles, the plotted values were z-scored within participants prior to creating the heatmap. Due to this procedure, the heatmap colours represent the extent to which the CMR of a given association was higher or lower than the participants' average CMR. As expected, due to the random nature of the task, none of the object-melody associations was systematically perceived as a good match.

#### 3.4.1. The role of musical expertise

As expected, we found strong evidence that the musical expertise was not uniformly distributed between the two clusters ($BF_{10} = 20.44$). More specifically, 76.62% of the amateur musicians ($N = 13$) and 100% of the serious amateur musicians ($N = 7$) were assigned to the High Creativity cluster, whereas 60% of the non-musicians ($N = 30$) and 31.91% of the music-loving non-musicians ($N = 47$) were assigned to the Low Creativity cluster. When comparing the main model with an alternative one having the musical expertise as the only predictor, the bridgesampling Bayes Factor strongly favoured the cluster-based model ($BF_{M1\text{-}M2} = 16.40$). Finally, when we compared the main model with the one

[5] These estimates are taken from a Bayesian Multivariate General Linear Model wherein the scores are predicted by the cluster membership alone. Regularising priors were used for the estimation (i.e., a zero-centred normal distribution with $SD = 1$ for the beta coefficients and intercepts, and an exponential distribution with $\lambda = 1$ for the sigma components (McElreath, 2020).

**Table 1**
Bayesian Kendall's τ correlation analysis.

| *Bayesian Kendall's τ correlations* | | | | | | |
|---|---|---|---|---|---|---|
| | | | Kendall's τ | Lower 89% CI | Upper 89% CI | $BF_{+0}$ |
| SSCS (SE) | – | SSCS (PI) | .636 | .426 | .613 | $4.081 \times 10^{+15}$ |
| SSCS (SE) | – | BFI-O | .561 | .368 | .559 | $1.590 \times 10^{+12}$ |
| SSCS (SE) | – | S-ICA | .325 | .175 | .374 | 11,070.651 |
| SSCS (SE) | – | CMR (Median) | .055 | −.054 | .148 | 0.748 |
| SSCS (SE) | – | CMR (Mean+) | .141 | .018 | .221 | 4.224 |
| SSCS (SE) | – | CMR (SD) | .111 | −.006 | .195 | 2.129 |
| SSCS (PI) | – | BFI-O | .582 | .384 | .574 | $1.261 \times 10^{+13}$ |
| SSCS (PI) | – | S-ICA | .306 | .159 | .358 | 3692.781 |
| SSCS (PI) | – | CMR (Median) | .113 | −.005 | .197 | 2.218 |
| SSCS (PI) | – | CMR (Mean+) | .097 | −.020 | .184 | 1.546 |
| SSCS (PI) | – | CMR (SD) | .100 | −.016 | .186 | 1.669 |
| BFI-O | – | S-ICA | .348 | .194 | .392 | 43,961.998 |
| BFI-O | – | CMR (Median) | .064 | −.046 | .155 | 0.868 |
| BFI-O | – | CMR (Mean+) | .119 | −.001 | .202 | 2.478 |
| BFI-O | – | CMR (SD) | .067 | −.044 | .158 | 0.904 |
| S-ICA | – | CMR (Median) | .046 | −.062 | .140 | 0.653 |
| S-ICA | – | CMR (Mean+) | −.011 | −.112 | .092 | 0.330 |
| S-ICA | – | CMR (SD) | .093 | −.022 | .179 | 1.439 |
| CMR (Median) | – | CMR (Mean+) | .524 | .336 | .530 | $2.344 \times 10^{+10}$ |
| CMR (Median) | – | CMR (SD) | .387 | .227 | .424 | 617,230.284 |
| CMR (Mean+) | – | CMR (SD) | .575 | .376 | .569 | $3.051 \times 10^{+12}$ |

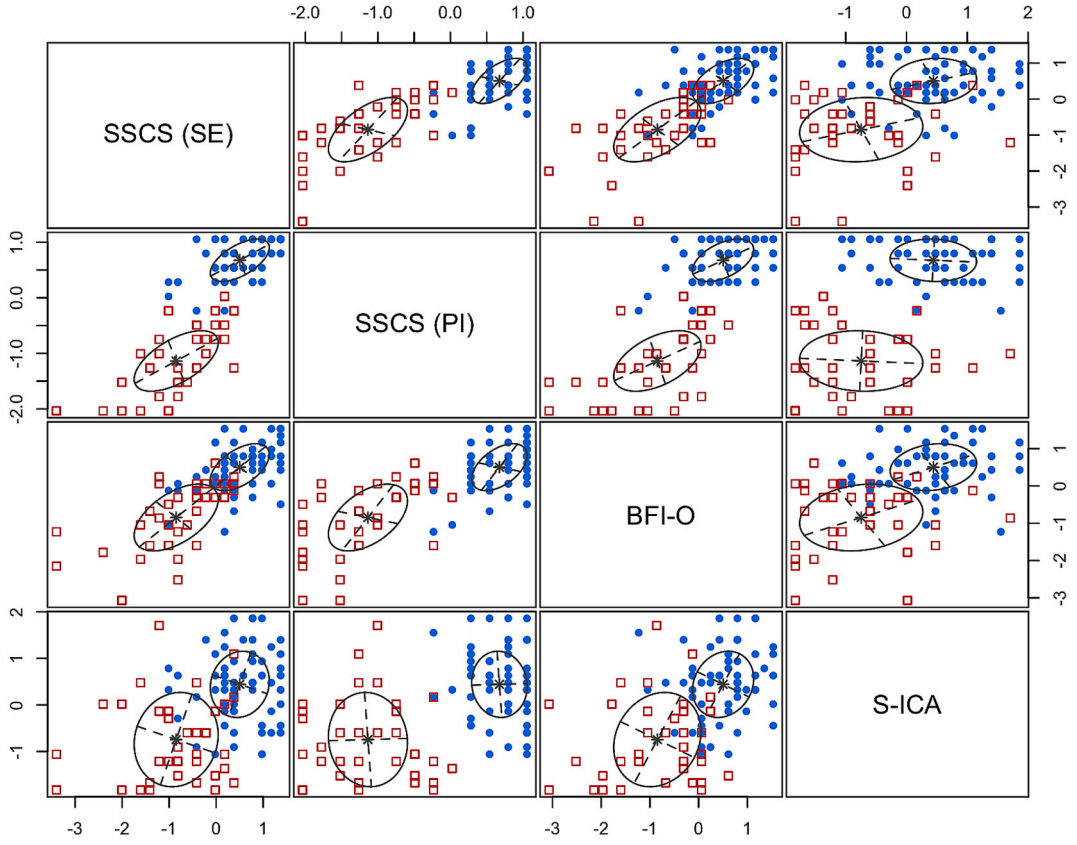


**Fig. 4.** Pairs plot of the 2-cluster solution. Points represent individual observations and are coloured based on the cluster membership identified by the best-performing model. The participants assigned to cluster 1 (i.e., High Creativity) are shown as blue circles; those assigned to cluster 2 (i.e., Low Creativity) are shown as red squares. The ellipses indicate the estimated Gaussian distributions for each cluster, with centroids marked by an asterisk. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

including cluster and musical expertise as a covariate, the model comparison favoured the main model with very strong evidence ($BF_{M1\text{-}M3} = 90.91$). Importantly, these results should be interpreted cautiously: the fact that Model 1 explained the data better than Models 2 and 3 does not imply the absence of a musical expertise effect. What the model comparison reveals is that the most parsimonious way to explain CMR is knowing the cluster membership of the participants. Once cluster membership is known, the degree of musical expertise provides little-to-no additional information to explain CMR. Furthermore, the inspection of the posterior distributions of the CMR's estimated conditional means

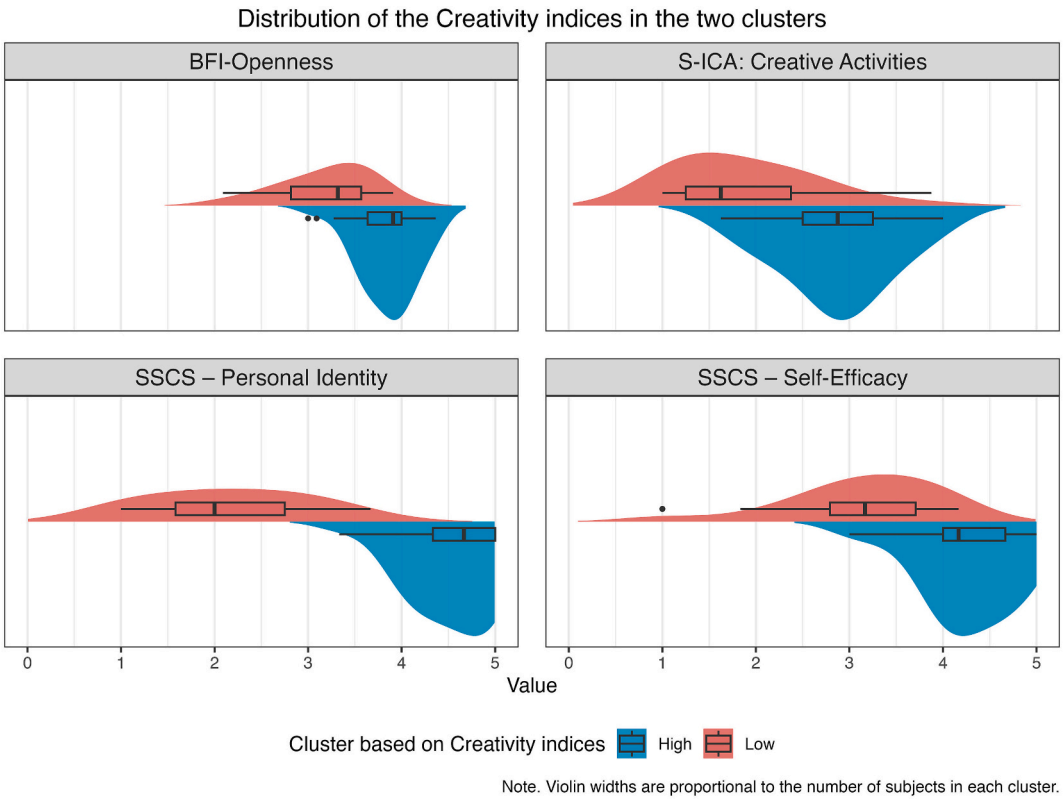


**Fig. 5.** Distribution of the observed creativity indices across the clusters.

**Table 2**
Creativity scores difference between the clusters.

| | $\beta$ | Lower 89% CI | Upper 89% CI | *pd* | *inROPE%* |
|---|---|---|---|---|---|
| BFI-O | 1.28 | 1.01 | 1.52 | 100 | 0 |
| S-ICA | 1.19 | 0.91 | 1.45 | 100 | 0 |
| SSCS (PI) | 1.78 | 1.62 | 1.93 | 100 | 0 |
| SSCS (SE) | 1.28 | 1.02 | 1.53 | 100 | 0 |

*Note.* The $\beta$ is expressed in terms of Standard Deviation.

across the levels of musical expertise of Model 2 (Fig. 8) revealed no clear upwards trend, with substantial overlap between groups and a non-linear pattern of central values. Notably, as the sampling did not include a balanced composition in terms of musical expertise, the uncertainty of the higher expertise categories is substantially large, thus discouraging strong claims about the role of musical expertise.

### 3.4.2. *The role of mode*

An alternative model was fitted to check the difference in CMR between the melodies in major and minor mode. Major melodies reported anecdotally higher CMR than minor ones, $\Delta = 1.62$, 89% CI [0.05, 3.13], *pd* = 94.84%, *inROPE%* = 89.18. Even though the probability of the difference being larger than a null was close to 95%, almost 90% of the posterior lies in the ROPE, thus signalling a practically negligible effect size. This difference did not vary based on cluster, $\Delta_{HC} = 0.96$, 89% CI [0.70, 2.58], *pd* = 82.09%, *inROPE%* = 96.21; $\Delta_{LC} = 2.06$, 89% CI [−0.15, 4.39], *pd* = 96.06%, *inROPE%* = 66.44). The probability of such an interaction being larger than null was 84.15%, $b_{int} = 1.34$, 89% CI [−0.70, 3.44].

## 4. Discussion and conclusions

The present study examined whether creativity-related dispositions are associated with differences in crossmodal musical perception. Specifically, the question asked was: do individuals with different creativity-related profiles exhibit systematic differences in self-reported crossmodal musical associations? By adopting a clustering approach, we identified two distinct participant profiles characterised by consistently higher versus lower scores across multiple creativity-related indices. On average, individuals in the high-creativity cluster gave higher overall ratings of self-reported association between the presented melodies and everyday objects. Bayesian modelling indicated a 95.82% probability that the effect was positive, and an 87.36% probability that it exceeded a negligible magnitude. While these initial results require further confirmation and reflect modest certainty about the magnitude of the observed effect, they are nonetheless promising in suggesting that different creativity-related traits may be linked with variation in perceptual and associative responses across modalities. Indeed, our correlational analyses revealed very little evidence that any single creativity measure was strongly associated with crossmodal ratings on its own. Most Bayes Factors were inconclusive, and only weak-to-moderate associations emerged for selected indices (e.g., creative self-efficacy). This pattern suggests that the observed effect is unlikely to be driven by any isolated component of creativity, such as openness or creative activity alone. In other words, it may not be one single creative ability or trait that matters, but a broader, integrated creative disposition encompassing identity, efficacy beliefs, personality, and real-world engagement (see Amabile, 1996; Benedek & Fink, 2019; Boden, 2004; Schiavio & Benedek, 2020). Such an interpretation is consistent with the idea that a meaningful difference in CMR may arise from the alignment of multiple creativity traits or dimensions, as captured by the clustering approach.

These findings help address our central research question by suggesting that self-reported crossmodal musical associations vary as a function of one's *broad creativity profile* rather than isolated traits. Participants with a more highly developed and internally coherent creative disposition were more likely to report stronger correspondences between auditory and visual stimuli, leading to higher association scores in

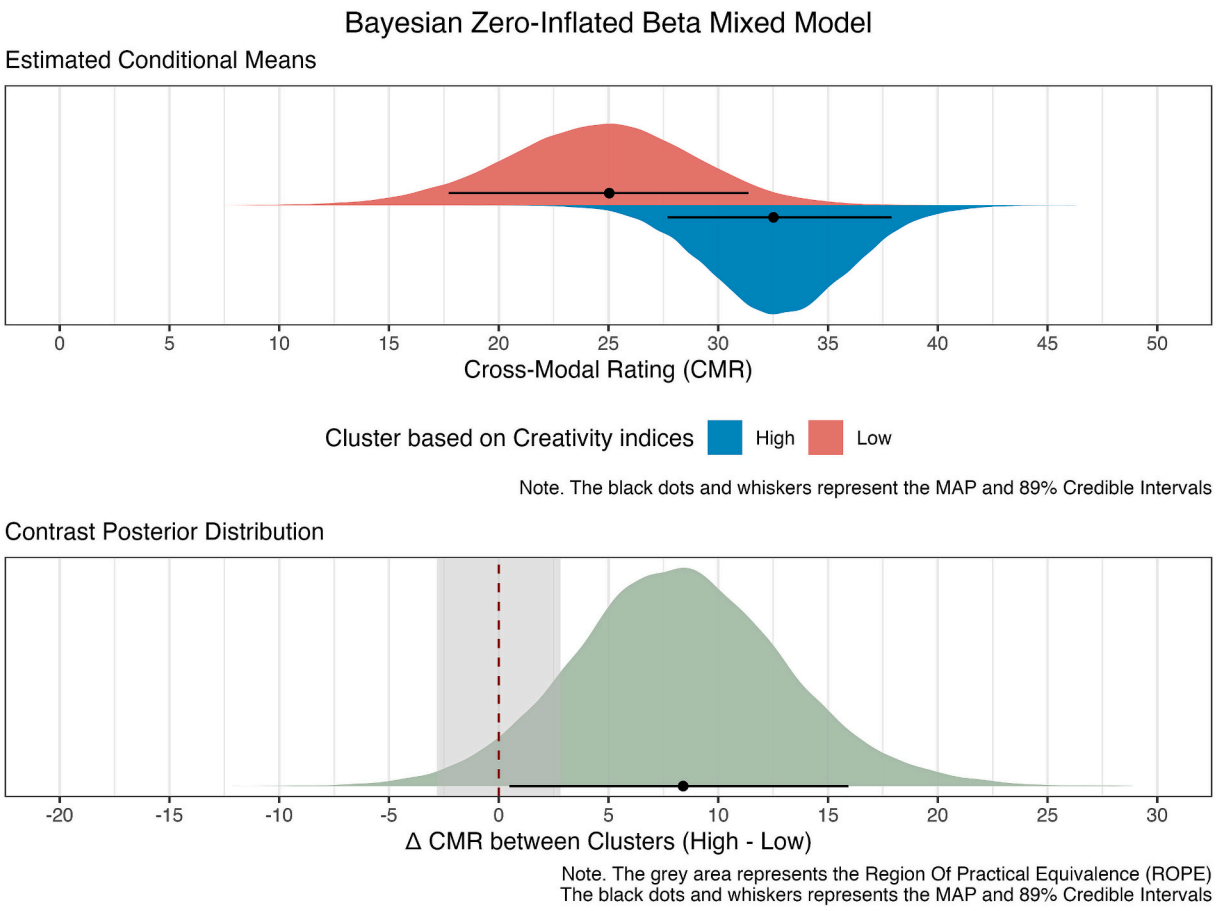


**Fig. 6.** Posterior distributions of the estimated conditional means and contrast.

**Table 3**
Supplementary analyses: estimates of the univariate models.

| Predictor | Estimate | Lower 89% CI | Upper 89% CI | pd | inROPE % |
|---|---|---|---|---|---|
| BFI-O | 0.36 | −3.56 | 4.20 | 56.93 | 74.43% |
| S-ICA | 1.48 | −2.69 | 5.06 | 72.80 | 67.70% |
| SSCS (PI) | 2.55 | −0.91 | 6.30 | 86.78 | 52.10% |
| SSCS (SE) | 0.36 | −3.91 | 4.40 | 57.18 | 70.93% |
| Cluster | 8.40 | 0.49 | 15.93 | 95.82 | 11.61% |
| Composite creativity score (adjusted estimate) | 12.17 | −7.78 | 30.85 | 84.52 | 38.84% |

the audiovisual task. Our interpretation relies on existing scholarship that frames music perception and cognition as an embodied process (Kozak, 2020; Schiavio, Moran, Antović, & van der Schyff, 2022), where bodily and creative factors may enable a range of *attentional drifts* through which listeners actively probe the possibilities for thought and action that a musical work affords (see also Antović et al., 2024; Dunn, 1997; Høffding & Schiavio, 2021; Kratus, 2017). On this basis, we advance the idea that crossmodal associations need not be reduced to low-level sensory or cognitive phenomena (see Spence, 2011; Stein & Meredith, 1993). Instead, such associations may be shaped by dispositional configurations and cognitive mechanisms that guide how individuals explore and attribute meaning across modalities. Put differently, for highly creative participants, a melodic pattern may function as a dynamic field of affordances rather than a static stimulus, inviting creative forms of interpretation and meaning-making (see Chemero, 2009; Glăveanu, 2014; van der Schyff et al., 2018). Visual stimuli can further scaffold these processes, providing additional cues that enrich conceptual mappings and associative forms of thinking. Participants in the creative cluster may thus exhibit more flexible cognitive boundaries, which would enable them to generate novel meanings by associating musical and visual properties in unexpected yet coherent ways. In light of embodied and sensorimotor approaches to musical understanding (Maes, 2016; Maes et al., 2014, b; van der Schyff et al., 2022), these participants may be especially attuned to the affordances inherent in musical motion or texture, e.g., mapping rhythmic jaggedness, melodic ascent, or dynamic contour onto visual or conceptual representations.[6] In such cases, the perceived "value" and "novelty" of an association – i.e., the core hallmarks of creativity (Diedrich et al., 2015) - may emerge dynamically during perceptual engagement (Kimmel et al., 2018; Steffensen, 2013). By contrast, less creative participants may rely on more conventional, literal, or habitual interpretations, reflecting narrower sensorimotor and conceptual scaffolds.

It is, however, important to stress that these interpretations remain necessarily speculative and extend beyond what can be directly inferred from the present data, which rely on self-reported associations. We therefore frame them as theoretically informed possibilities that align with broader trends in the literature, rather than as definitive claims about underlying cognitive mechanisms emerging from our data. In this sense, while we recognise the exploratory nature of the present

[6] A related consideration concerns creativity and synaesthesia. While our participants were not assessed for synaesthesia, richer crossmodal associations in creative individuals may reflect mechanisms similar to those underlying synaesthetic perception (Chun & Hupé, 2016; Ward et al., 2008). This suggests a broader link between crossmodal sensitivity and creative cognition, which could be explored in future research.

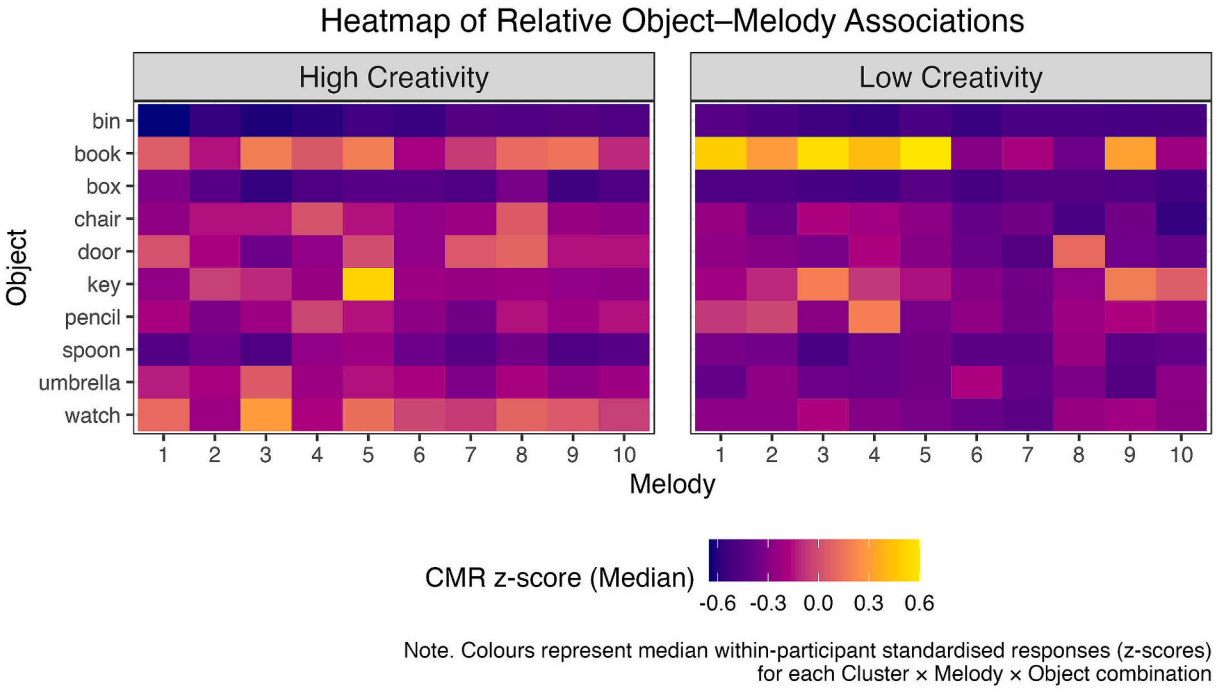


**Fig. 7.** Heatmap of relative object-melody associations.

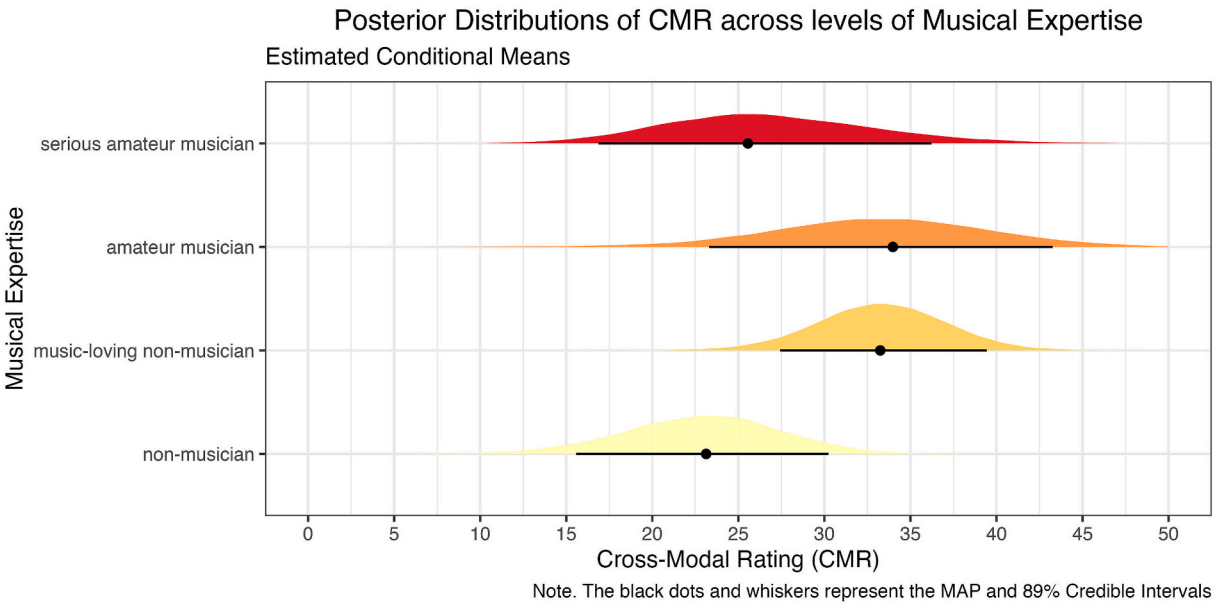


**Fig. 8.** Posterior distributions of the estimated conditional means and contrast.

investigation, we also note that our observations are consistent with perspectives in which creative cognition extends beyond idea generation to shape perceptual engagement and the flexible navigation of conceptual spaces (Boden, 2004). Specifically, they align with theoretical frameworks that situate creativity in active interaction with the environment, emphasising exploration, affordance sensitivity, and embodied meaning-making (Baber et al., 2019; Glăveanu, 2014; Lee & Lee, 2023; Torrents et al., 2021).

The findings also resonate with the literature on associative thinking and creativity (Beaty & Kenett, 2023) and, more specifically, studies on crossmodal associations conceptualised through multiplex networks (Samuel et al., 2023; Stella et al., 2024; Stella & Kenett, 2019). According to Beaty and Kenett (2023), associative theories of creativity suggest that highly creative individuals display an enhanced ability to form connections between ideas that are not obviously related. As such, creativity may be seen to depend on how information is organised in memory. This is also reflected by the fact that in less creative individuals associations between commonly paired concepts (e.g., pen-paper) tend to be strong, whereas links between more unusual pairings are relatively weak. As mentioned above, however, it currently remains unclear whether creative individuals generate more original associations because they perceive and attend to a broader range of sensory information ("leaky" attention), because they can form more remote associations via flexible executive processes, or because of a combination of both (Benedek, 2018; Benedek & Jauk, 2019; Chrysikou, 2019; Zabelina, 2018). Interpreting the present findings through the lenses of

embodied cognition and associative thinking suggests that these explanations need not be mutually exclusive. Rather than separating perception and association into distinct stages, creative engagement may arise from their dynamic interplay - where heightened perceptual sensitivity, crossmodal integration, and the active construction of novel links across conceptual and sensorimotor spaces mutually reinforce one another. It should be noted that this interpretation assumes a degree of continuity between perceptual and associative processes, which remains a heated topic of debate in contemporary research, particularly in discussions concerning the extent to which higher-level cognition penetrates perception (see Clarke & Beck, 2023; Firestone & Scholl, 2016). Indeed, within the present experimental paradigm, it is difficult to determine whether perceptual and associative processes can be cleanly disentangled; but more fundamentally, from an embodied cognition standpoint such a distinction may not be theoretically warranted beyond its potential analytical convenience, given the inherently intertwined nature of perception and meaning-making (see Gallagher, 2005, Noë, 2004; Varela et al., 1991).

The crossmodal association task used here may be seen as a first step toward operationalising perceptual variability in a domain that does not explicitly require creative production. However, the task also has limitations. The melodies were algorithmically generated and structurally constrained, and the visual stimuli consisted of static, everyday objects. While these choices ensure experimental control, they may have limited the richness and variability of possible crossmodal mappings. Everyday objects are readily recognisable and share broadly understood affordances, which enhances consistency across participants; however, this very familiarity and functional transparency may constrain more idiosyncratic or imaginative associations. As a result, the task may have privileged conventional correspondences over more exploratory or novel perceptual interpretations. A further important concern is that crossmodal associations were assessed exclusively via self-report. It has been shown that creative individuals tend to be highly open and receptive, and may therefore perceive, or at least report, a greater number of connections across modalities (Bellemare-Pepin et al., 2022). Thus, higher self-reported crossmodal associations could reflect differences in response style, perceived connectedness, or scale use rather than differences in underlying associative structure. This potential limitation is of course not unique to the present study as reliance on self-reported ratings characterises much of the existing literature - yet it remains an important methodological constraint. At the same time, the present paradigm is distinctive in extending investigation into new sensory modalities, which represents a meaningful step forward. Future research could address these limitations by incorporating more objective or indirect measures of association, such as implicit association paradigms, priming designs (e.g., facilitation effects of "related" musical stimuli), or behavioural indices embedded within creative performance tasks. Such approaches may help disentangle perceptual sensitivity from reporting tendencies and clarify whether crossmodal sensitivity translates into measurable differences in creative output. Additionally, given that participants might be driven toward specific associations based on the semantic properties rather than the appearance of the stimulus (i.e., drawings), future studies might be designed to distinguish between cognitive/semantic vs. perceptual factors.

More broadly, an overarching conceptual question concerns whether creative individuals generate more remote crossmodal links because of pre-existing differences in the structure of their semantic networks, or because they actively and strategically traverse or construct more distant connections. Contemporary cognitive network approaches offer useful frameworks for this issue. For example, entropy modulation accounts of creative exploration (Hills & Kenett, 2024) propose that creativity may involve dynamic shifts in exploratory patterns within semantic space, while broader discussions of network structure and process (Hills & Kenett, 2022) highlight the need to distinguish between static network properties and active search dynamics. Although the present cross-sectional design cannot adjudicate between these possibilities, situating crossmodal association within such network-based frameworks may provide a productive direction for future research. An additional limitation concerns the sample: participants were recruited through an online platform and consisted primarily of non-professional musicians, which may limit generalisability. Moreover, although we implemented attention checks and modelled zero inflation explicitly, the high proportion of zero responses suggests variability in engagement or interpretation of the task. Finally, the cross-sectional design precludes causal inference: it remains unclear to what extent creativity-related traits shape perceptual associations, whether richer perceptual engagement fosters creative development, or whether both reflect shared underlying mechanisms.

To conclude, the exploratory findings reported here resonate with contemporary embodied accounts of creative cognition and lend preliminary support to perspectives that locate creativity not only in idea generation, but also in modes of perceptual engagement with the environment (see e.g., Beaty & Kenett, 2023; Glăveanu, 2014; Schiavio, Biasutti, et al., 2024). Individuals characterised by a broad creative profile were more likely to perceive coherent correspondences across modalities, suggesting that creativity may shape how sensory information is integrated, explored, and endowed with meaning. At the same time, the effects observed here need further investigation to address important limitations related to the design of the study and to substantiate the interpretation of the results. Specifically, while we aimed for a broad assessment of individual differences in creativity capturing relevant core and surface personality traits as well as creative behaviour with established inventories, these measures relied on self-report which are known to be sensitive to cognitive biases such as self-serving bias or acquiescence bias. Future work thus should also include measures of creative performance such as divergent thinking tests to examine how the findings extend from creative personality, self-beliefs and behaviour to creative ability. Moreover, larger-scale studies, using refined crossmodal paradigms and multi-method approaches will be essential to determine the robustness, scope, and mechanisms of these associations. Nonetheless, we believe that the present work offers an initial step toward understanding creativity as a disposition that permeates not only what we think, but how we perceive and connect the world around us.

## CRediT authorship contribution statement

**Andrea Schiavio:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Conceptualization. **Alessandro Ansani:** Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Funding acquisition, Formal analysis, Data curation. **Nicola Di Stefano:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization. **Adrian Kempf:** Writing – review & editing, Writing – original draft, Software, Resources, Methodology, Investigation, Data curation. **Charles Spence:** Writing – review & editing, Writing – original draft, Validation, Supervision. **Mathias Benedek:** Writing – review & editing, Writing – original draft, Validation, Supervision.

## Ethics declaration

Written informed consent to take part in the study and to publish the article has been obtained from all participants or their legal representatives. The privacy rights of participants have been observed.

This study was performed in compliance with relevant laws, regulatory frameworks and guidelines where the research took place.

This study was approved by the School of Arts and Creative Technologies Ethics Committee (University of York) (Approval No. N/A).

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## Declaration of competing interest

The authors have no conflicts of interest to declare.

## Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.cognition.2026.106664.

## Data availability

The data that supports these findings, together with the audio and visual stimuli are available on the Open Science Framework via the following link: https://osf.io/aqs6b.

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