Psychology of Aesthetics, Creativity, and the Arts

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Online First Publication, February 10, 2025. https://dx.doi.org/10.1037/aca0000726

AMERICAN PSYCHOLOGICAL ASSOCIATION
DIVISION 10
Psychology of Aesthetics, Creativity, and the Arts

ISSN: 1931-3896
https://doi.org/10.1037/aca0000726

Dancing Through the Uncanny Valley: On the Likeability of Model-Generated Dance Movements

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The esthetic perception of model-generated dance movements was analyzed by varying the human likeness of the observed movements through the implementation of a model based on movement primitives. Likeability ratings and electrodermal activity in response to these model-generated movements varying in the number of underlying primitives were acquired for dancers and dance-novices. The results show that movements with a high degree of human likeness were generally associated with higher esthetic valuations. In dance experts, however, results show an uncanny valley effect in that likeability dropped for the most human-like model-generated kinematics. Additionally, the motion energy of the movement sequences also shows a remarkable association with esthetic responses, although to a lower degree for dancers than novices. Overall, these results not only extend the perceptual phenomenon known as the uncanny valley to the esthetic perception of model-generated movement kinematics, but also emphasize the relevance of sensorimotor experience for the esthetic perception of expressive movements.

Keywords: movement esthetics, motor experience, movement primitives, biological movement perception, uncanny valley

Supplemental materials: https://doi.org/10.1037/aca0000726.supp

It remains unclear what inspired René Descartes to construct an intricate automaton in the likeness of a young girl. However, it is documented that when he brought it aboard a ship in 1646 to journey to Sweden, the captain and crew, unnerved by its mechanical, seemingly soulless movements, shattered it and cast its remnants overboard (Kang, 2016). Replicating the refined control humans possess over their bodies continues to challenge today's roboticists. Studying the algorithms that drive the control of complex bodily movements, however, does not need to be postponed until the creation of biomimetic robots. Considering that Descartes passed away merely 4 years after the tragic fate of his humanoid creation, it might be prudent for movement science to develop computational methods for generating complex motor behavior even in the absence of perfect biomimetic robots and test them in advance in simulations involving virtual agents. This ensures that when the appropriate robots are ready, the algorithms to control their bodies in producing natural movements will be ready as well and no roboticist will have to endure a similar fate as René Descartes.

Within the development of such algorithms for controlling the many degrees of freedom of full-body movements, one approach is centered around the idea of modularity: complex movements are decomposed into simpler movement primitives (MPs) (D'Avella et al., 2015). These movement primitives are conceived as basic building blocks that can be flexibly combined to enable the central nervous system to generate complex movements according to different environmental constraints (for a review, see Giszter, 2015). With respect to studies on the perception of artificial movements, such a model-based approach offers the possibility to generate variations of the same movements, which is in contrast to a simple replay of the recorded motion. This allows the investigation of how different types of movement composition affect the perception of the generated movement. In comparison to neural networks used to generate complex movements (McCormick et al., 2015; Qi et al., 2019; Tang et al., 2018), the advantage of primitive-based generative models is that their parameters have a higher degree of meaningfulness, enabling a straightforward and target-oriented modulation of components used for movement production. We have recently reported a model based on temporal MPs that is able to generate dance movements that appear as natural as human-generated movements (Leh et al., 2023). For the artificial creation of expressive movement sequences such as used in

Eva Specker served as action editor.
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Source data and analysis code related to this article can be found at the institutional repository of the Justus Liebig University Giessen (https://dx.doi.org/10.22029/jlupub-17926). This work was funded by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation; SFB/TRR 135 TP B6 & C6) and the Hessian Ministry for Science and Arts (HMWK; Cluster Project The Adaptive Mind). We thank Ullrich Ott for providing the necessary hardware for the data acquisitions and Johannes Keyser and Jelena Müller for suggestions and support during hardware setup and testing. Many thanks to the professional dancer for his participation in the motion capture sessions.
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dance, naturalness, however, is only a starting point. As dance has unique esthetic qualities, it is yet to be demonstrated if such qualities can also be elicited through movements generated by a temporal MP model.

The esthetic experience that can be elicited by a dance performance is defined as a psychological state in the form of sensuous delights (Goldman, 2001), that is evoked by certain (not necessarily art-related) stimuli (Calvo-Merino et al., 2008). There are two main perspectives in the field of esthetics on what induces such an experience. The objective theory of esthetics holds that a universal impression of beauty is evoked by certain objective features, for example, the compositional arrangement of stimulus elements, and that the response evoked by these stimulus properties should, therefore, have some degree of generality, that is, be subject-independent (Jacobsen et al., 2004; Jacobsen & Höfel, 2002). In contrast, the subjective account of esthetics asserts that esthetic judgments depend on the beholder and focuses, for example, on the effect of prior experiences (Höfel & Jacobsen, 2007).

Although movements of experienced performers are perceived as being more esthetic than movements of less experienced performers (Bronner & Shippen, 2015; Zamparo et al., 2015), it is still unclear which objective movement features contribute to this increase in the perceived esthetic quality of movements. Findings from Bronner and Shippen (2015) suggest that an increase in movement esthetics is based on some sort of chunking or simplification of movement components. In detail, they found that the movement of expert dancers, when performing the dance sequence développé arabesque, could be represented with fewer principal components, that is, a reduced dimensionality, and was also given a higher esthetic proficiency rating by trained dancers than the movement of dancers with only an intermediate skill level. Additionally, there was an association between the number of principal components and the rated esthetic proficiency, suggesting, "that perceptual chunking could explain esthetic perception" (Bronner & Shippen, 2015). A similar understanding of subjective beauty has previously been put forth by Schmidhuber in a formal theory of creativity, fun and intrinsic motivation (Schmidhuber, 2009). Therein, he proposed that subjective beauty depends on the ability to compress the incoming sensory signals, that is, of several otherwise comparable patterns, the one with the simplest description (most compact representation) should be preferred. According to processing fluency theory (Reber et al., 2004), this preference may be due to the ease with which these types of stimuli can be processed, as high processing fluency should result in a positive subjective experience. Most interestingly, processing fluency has been suggested to depend on the interaction between the observer and the observed: beauty, on that account, arises from the processing experience of the observer (taking into account his or her sensorimotor, cognitive, and affective state) in combination with objective properties of the observed (such as goodness of form, symmetry, etc.). Analogously, it has also been suggested by Schmidhuber (2009) that perceived beauty should be modulated by the observer's prior knowledge, as experienced individuals can use previously learned compression encodings to better identify regularities in a novel movement. Generally, the mere repeated exposure to specific movement types might increase positive affective judgments (Zajonc, 1968), possibly due to an increase in perceptual fluency. With regard to the MP framework, a more compact representation with a lower dimensionality can be obtained by utilizing fewer primitives to generate the movement. As this represents a type of movement compression, the use of too few primitives will compress the movement considerably, reducing the human likeness of the generated movement.

In addition to compressibility, another important aspect regarding the generation of artificial human-like movements is the "uncanny valley" (Mori et al., 2012). This phenomenon describes an association between an artificial agent becoming increasingly human-like and the evoked response; an initial increase in likeability is postulated to be followed by a drastic decrease and a feeling of eeriness as human naturalness is approached, but not quite reached. Likeability only increases with a further increase in realism (Mori, 1970). Studies on the effect have mostly focused on static stimuli (see Kätsyri et al., 2015 for a review) or on the effect of a mismatch between sensory cues as a potential cause for the phenomenon (Saygin et al., 2012). Although movement was originally assumed to amplify the effect of agent appearance, that is, deepen the valley (Mori et al., 2012), the effect has actually been found to be diminished by movement (Piwek et al., 2014). Movement was originally only described as a moderator regarding the effect of character appearance. However, it has been proposed that the effect could also exist only within the movement dimension, that is, being driven solely by variations in how human-like the movements of the same character appear (Kätsyri et al., 2015). So far, there is no evidence for this. Rather, at least in the case of gait, an increasing human likeness of walking movements is accompanied by a monotonic decrease in eeriness (Thompson et al., 2011).

Besides objective movement features, several studies have also explored subjective features in regard to the esthetic perception of whole-body movement, in particular dance (see Christensen & Calvo-Merino, 2013 for a review). These studies have shown effects of visual and especially motor familiarity with an action (Kirsch et al., 2015, 2013). Accordingly, familiar movements that are represented in the motor repertoire of the observer should yield higher esthetic judgments than unfamiliar movements (Orgs et al., 2016). On the other hand, movements that are considered physically difficult to perform have been rated more esthetic as well (Cross et al., 2011). Stimulus familiarity also has an effect on implicit measures of arousal, based on the findings that the electrodermal activity (EDA) only differs between expressive dance movements for observers with art experience (Christensen et al., 2021) and for dancers only in the forward presentation, that is, the familiar presentation (Christensen et al., 2016). Similarly, the observation of affect-evoking stimuli only revealed a relationship between facial muscle activity and explicit affective judgments for dancers, but not for nondancers (Kirsch et al., 2016). Overall, the current state of the research suggests that familiarity with the observed action is a crucial factor for esthetic perception. Motor familiarity might modulate the ability to simulate the observed movement based on the present motor repertoire (Calvo-Merino et al., 2005, 2006). Observers with prior sensorimotor experience may also be able to use previously learned encodings to better compress the displayed movement, thereby leading to an increase in perceived subjective beauty (Schmidhuber, 2009).

The aims of this study were threefold: (a) we sought to test whether our model based on MP could also be used to not only generate dance movements that appear natural but also similarly likeable to human observers as the movements of a professional dancer; (b) furthermore, by experimentally modulating the human likeness of the movement, through the number of MPs used for movement generation, we sought to examine the effects of how human-like the generated movements were on their likeability; and (c) by including expert and nonexpert dancers, we aimed to elucidate the role of sensorimotor expertise in the perception of model-generated dance movements as such expertise has been shown to be a major determinant of esthetic perception. In order to obtain components for movement generation, we applied a temporal MP model to the motion capture data of a professional dancer, thereby ensuring a certain esthetic quality in the movement data used to train the model. Furthermore, we decided to extend the assessment of the esthetic perception of the observed model-generated movements beyond explicit subjective ratings by also assessing EDA as an indicator of implicit affective responses.

To our knowledge, the effect of human likeness of model-generated movements on esthetic perception and its modulation by the expertise of the observer has not yet been examined. Based on the previous findings, we expect the likeability judgements to differ with the experience of the observer (Kirsch et al., 2015, 2013) and to be higher for human-like movements (Orgs et al., 2016). For observers with no prior sensorimotor experience, the observed movements by a professional dancer might be low in familiarity and/or more difficult to compress (cf. Schmidhuber, 2009) irrespective of the degree of additional artificial decreases in human likeness. However, for observers that are generally familiar with the observed actions, also on a motor level, the effect of reducing human likeness through a reduction of movement components on perceptual esthetics might be much more pronounced. On the other hand, an uncanny valley effect could be observed instead of a monotonic increase in perceived likeability with increases in the number of MPs, in case model-generated movements that are highly human-like evoke a negative response.

Method

Participants

Thirty six individuals (six men) participated in the experiment after providing written, informed consent in accordance with the Declaration of Helsinki. Two participants were excluded, due to communication issues during the data acquisition. Of the remaining participants ($M_{\text{age}} = 24.4$ years, $SD = 4.1$), 18 participants had less than a year experience in formal dance training (group "novices") and 16 participants had at least 10 years of formal dance training in the styles contemporary, modern, or jazz (group "dancers"). Participants either received course credits or 8 /hr for taking part in the experiment. Exclusion criteria were disorders of the musculoskeletal system, abnormal vision or an age below 18 years. The study was approved by the local ethics committee.

Stimuli

The kinematic data of a professional dancer from the Staatsballett Berlin were captured at 240 Hz during improvised dancing with 17 inertial measurement units using the Xsens MVN Link-System (Xsens Technologies BV, Enschede, The Netherlands). Joint angles were computed, downsampled to 60 Hz and exported in the Euler angle representation with the software Xsens MVN Analyze (Version 2022.0.0; Schepers et al., 2018).

The joint angle trajectories (in axis-angle representation) were modeled with a temporal MP model. As a preprocessing step, the motion-capture data (overall duration of ∼9 min) were partitioned into segments with a minimum duration of 600 ms. The boundaries of the segments were determined by computing the minima (with a minimum prominence of 0.5 ms^{-1}) of the mean speed of the hands and feet. In cases were the resulting segments exceeded 3 s, additional minima were computed within these longer segments (minimum duration between minima of 1,000 ms and a minimum prominence of 0.05 ms^{-1}).

In the temporal MP model, the data X of a joint j over time t are a weighted sum of M movement primitives MPs, with additive Gaussian noise $\epsilon \sim \mathcal{N}(0, 0.03)$ (Equation 1). A Gaussian prior was used for the weights $W \sim \mathcal{N}(0, 1)$, which specify how much each MP is recruited for each joint. To facilitate smooth MP, a Gaussian process prior with a radial basis function (RBF) kernel (Equation 2) was used for the primitives, $\text{MP} \sim \mathcal{N}(\mu(t), k(t, t'))$.

$$X_{jt} = \sum_{m}^{M} W_{jm}\text{MP}_m(t) + \epsilon, \tag{1}$$

$$k(t, t') = \sigma^2 \exp[-\gamma(t - t')^2]. \tag{2}$$

The MP and weights were learned by optimizing the log joint probability of the data and the model parameters. We trained models with 3–23 MPs and estimated the model evidence via Laplace approximation (LAP) (Endres et al., 2013). The variance accounted for and model evidence of the trained models are displayed in Figure 1. The model with 15 MPs yielded the largest model evidence. See Figure 1c for the learned primitives of this model and an example of their weightings.

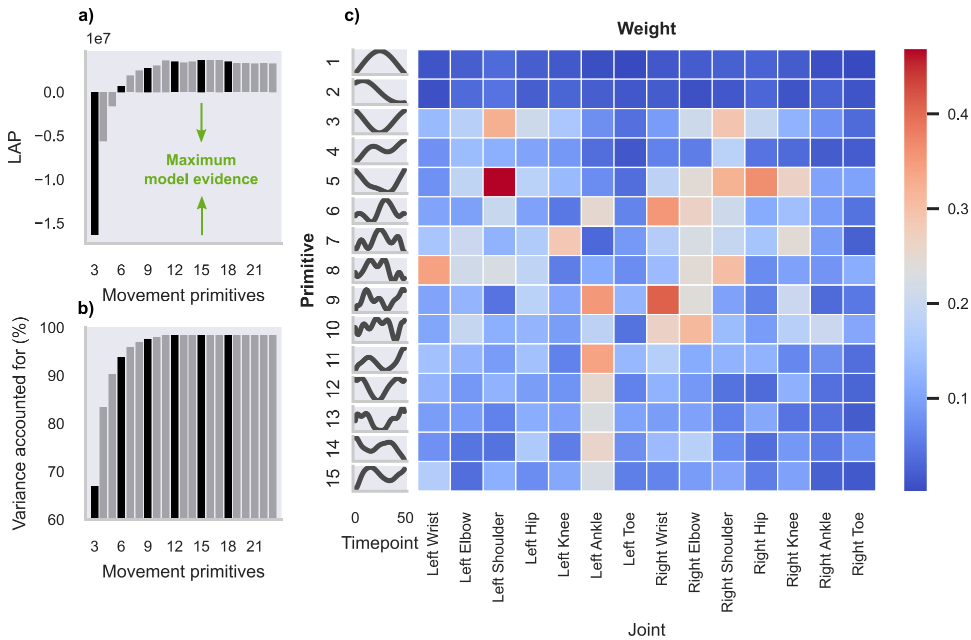
The segments were concatenated to obtain a minimum stimulus duration of 5 s. Of the resulting 96 movement sequences ($M_{\text{duration}} = 5.6$ s, $SD = 0.5$ s), 20 were randomly selected for the experiment in order to limit the duration of the experiment and prevent participant fatigue. Each movement sequence was displayed in its natural form (replay of the collected motion-capture data) as well as in six different MP representations (with three, six, nine, 12, 15, and 18 MPs). Examples of the stimuli can be found in the online supplemental materials. Furthermore, eight additional stimuli of dance sequences (not included in the main stimulus set and only displayed in its natural form) were randomly interspersed throughout the experiment to check participant attention (see the Procedure section). All movements were presented as stick-figures (covering a screen area of ∼7 cm in width and 10 cm in height). The stick-figures consisted of 27 lines that were rendered with openGL (glLineWidth set to 4) and displayed on a 27″-Monitor (BenQ ZOWIE XL2740, refresh rate 240 Hz; viewing distance ∼60 cm) at veridical speed using PsychoPy (Version 2022.2.4; Peirce et al., 2019).

Procedure

In order to measure EDA to assess an individual's arousal, participants were asked to wash their hands (without soap). Two Ag-AgCl electrodes (EL507A) were filled with isotonic electrode paste (GEL101A) and attached to the thenar and hypothenar eminence of the left hand. A minimum preparation period of 10 min was then set prior to recording the EDA signal in order for the electrode connection and the signal to stabilize.

During this preparation period, the participants filled out a questionnaire for a detailed assessment of their dance experience. To check the EDA signal, the participant was asked to take and hold

Figure 1
Model Evidences and Examples of Movement Primitives



Note. Model evidence, estimated via Laplace approximation (a), and variance explained (b) of all models trained. The models that were used to generate the stimuli for the experiment are marked in black. The primitives of the model with 15 primitives and an example of the corresponding weights of each primitive and joint of a movement sequence (c). LAP = Laplace approximation. See the online article for the color version of this figure.

a deep breath and to do an arithmetic task. The participant was instructed to minimize coughing, deep sighs, bodily movements and speaking throughout the measurements. A 2-min baseline was recorded while participants looked at a gray screen. Participants carried out a test trial to familiarize themselves with the task. Subsequently, the participants were asked to find a comfortable sitting position and to breath slowly and regularly for the recording of another baseline (1 min) directly prior to the start of the stimulus presentations.

Stimuli were presented in a random order. A white fixation cross (1.5 × 1.5 cm) was presented before (1,500 ms) and after (1,000 ms) each stimulus. To minimize surprise, the movement stimulus was faded in and out. After each stimulus presentation, the participant was asked to rate (self-paced) how much they liked the movement using a 7-point Likert-scale ranging from 1 (*liked very little*;in German: *Sehr wenig gefallen*) to 7 (*liked very much*; in German: *Sehr gut gefallen*). The response was given by pressing the corresponding key on the keyboard with the right hand. The elements of a trial are displayed in Figure 2. In the eight trials used to check attention, participants were asked a yes/no question regarding the movement in the displayed sequence (e.g., “Did the dancer raise his arms?”) and could respond with the keys three or five. The experiment consisted of 140 trials (20 sequences × 7 sequence presentations). The total duration of the experiment was ∼45 min.

Triggers were sent from the computer running the stimulus presentation software to the computer recording the EDA signal to mark the start and end of each movement stimulus in the EDA trace. The EDA signal was recorded with the software Biopac Student Lab (Version 4.1.1) at 2 kHz with a BIOPAC MP36 data acquisition unit (BIOPAC Systems, Inc., Goleta, CA) and a SS57LA lead set. The measurements took place in a soundproof room and the room temperature was kept constant at ∼22°.

Data Analysis

Behavioral Data

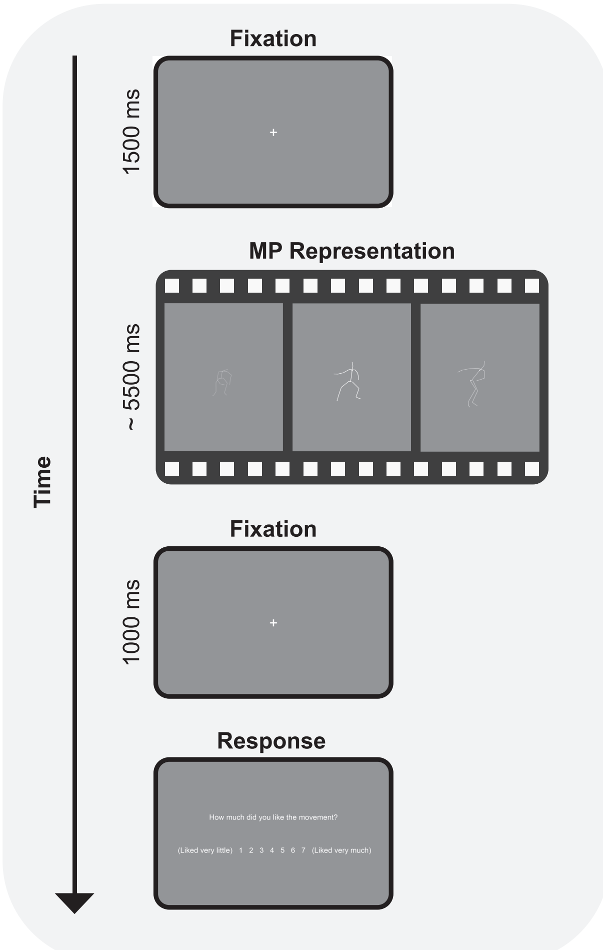
The data of one participant were excluded from the analysis due to the participant responding incorrectly in more than two of the eight attention check trials. The mean rating of each MP representation (across sequences) was computed for each participant. Likewise the mean rating of each sequence (across MP representations) was computed for each participant to analyze the effect of movement sequence.

Psychophysiological Data

The EDA signal was smoothed with a fourth-order Butterworth low-pass filter with a cutoff frequency of 3 Hz. Then, the phasic component of the signal was extracted using a second-order Butterworth high-pass filter (as in e.g., Biopacs AcqKnowledge Software) with a cutoff frequency of 0.05 Hz (Bach et al., 2013). The EDA signal was downsampled to 20 Hz and the signal trace of each trial was extracted. Specifically, the signal trace from stimulus onset to 1 s after stimulus offset was extracted, due to a typical latency of the EDA response of about 1–3 s (Lim et al., 2003).

The signal amplitude of each trial was obtained by first finding the peaks in the signal trace with a minimum width of 20 data

Figure 2
Elements of a Trial Including Representative Stimuli Used in the Experiment



Note. After a fixation cross the movement sequence was displayed in various movement primitive (MP) representations (3–18 primitives or natural representation). The stick-figure was faded in at the beginning and faded out at the end of the sequence, in order to minimize surprise. After another fixation cross following the movement stimuli, the participant was asked "How much did you like the movement?" and asked to rate the sequence from *Liked very little* to *Liked very much* on a scale from 1 to 7.

points (i.e., 1 s). In cases where only one peak was found in the signal trace of a trial (56.3% of trials), the amplitude was obtained by computing the minimum signal value between stimulus onset and that peak and subsequently the difference in the signal between the minimum and the peak. In cases where more than one peak was found (4.9% of trials), the minimum signal value between the first and the last peak was computed. Subsequently, the amplitude was obtained by computing the signal difference between the minimum and the last peak. The last peak was used due to the mentioned latency of the signal (see above). Lastly, if no peaks were found (38.8% of trials), the amplitude was obtained by computing the difference between the minimum value in the entire signal trace and the end value. In trials where the signal just decreased or remained stable, this last method would result in an amplitude close to zero. An example of EDA traces is shown in Figure 3.

To enable interindividual comparisons, the amplitudes of each participant were standardized by dividing the amplitudes of each participant with the median amplitude of that participant. Then, the amplitudes were normalized by applying a log transformation [log(amplitude + 1)]. To analyze the effects on EDA amplitudes, the median EDA amplitude of each MP representation and sequence was computed for each participant.

Statistical Analysis

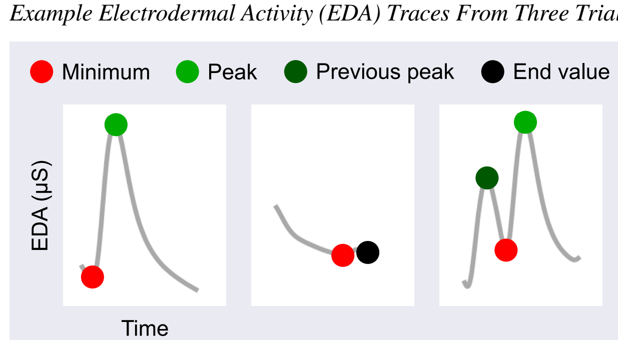
JASP (Version 0.17.1; JASP Team, 2023) was used for the statistical analysis of the data. Two 7 × 2 Bayesian mixed analysis of variances (ANOVAs) were performed to test the effect of movement representation (original + six MP representations) and group (dancers and novices) on ratings and EDA amplitudes. Similarly, Bayesian mixed ANOVAs were performed to test the effect of the factors sequence, repetitions (the repeated display of a sequence, but with a different MP representation) and group on ratings and EDA amplitudes.

Model Comparison

The data of both group were further analyzed with regard to an uncanny valley pattern (Mori et al., 2012), that is, showing an increase in ratings, followed by a dip and a subsequent increase close to the natural display. To this end, three models were fitted to the data of each group. Each individual's difference in rating between "neighboring" MP representations was computed, that is, the difference between representation with three and six MPs, six and nine MPs, and so on. According to the uncanny valley, a decrease in likeability should be observed with MP representations closely approaching but not reaching the natural human movement, which in this case would imply a negative difference value between 15 and 18 MPs followed by the positive difference value between 18 MPs and the original human movement stimulus.

The difference values of each contrasted MP representation *i* were assumed to be normally distributed (Equation 3), with Gaussian priors for μ_i and a half-student *t* distributed prior for σ_μ, which depended on the sample group size *N* (Equation 4). Different bounds and locations were implemented for $\boldsymbol{\mu}$ in the three models, however, all with $\sigma_\beta = 1$. The model "Increase" (Equation 8) only contained

Figure 3
Example Electrodermal Activity (EDA) Traces From Three Trials



Note. See the online article for the color version of this figure.

changes between MP representations that were bounded to be positive, β_+ (Equation 8). This was compared to a model, termed "Valley" (Equation 9), also containing positively constrained change parameters, however, with the second to the last change parameter bounded to be a negative, β_- (Equation 6), conforming to an uncanny valley pattern. Lastly, we compared these to a third model ("Unbound," Equation 10) with no bounds on the change parameter, β (Equation 7). The posteriors were computed with the No-U-Turn Sampler using the Python library PyMC (Version 5.6.0; Salvatier et al., 2016).

$$y_i \sim \mathcal{N}(\mu_i, \sigma_\mu), \tag{3}$$

$$\sigma_\mu \sim \text{Half Student}\, t(\sigma = 1, \nu = N - 1), \tag{4}$$

$$\beta_+ \sim \mathcal{N}(0.1, \sigma_\beta), \quad \beta_+ \in [0, \infty], \tag{5}$$

$$\beta_- \sim \mathcal{N}(-0.1, \sigma_\beta), \quad \beta_- \in [-\infty, 0], \tag{6}$$

$$\beta \sim \mathcal{N}(0.1, \sigma_\beta), \tag{7}$$

$$\boldsymbol{\mu}_{\mathbf{increase}} = [\beta_+\beta_+\beta_+\beta_+\beta_+\beta_+], \tag{8}$$

$$\boldsymbol{\mu}_{\mathbf{valley}} = [\beta_+\beta_+\beta_+\beta_+\beta_-\beta_+], \tag{9}$$

$$\boldsymbol{\mu}_{\mathbf{unbound}} = [\beta\ \beta\ \beta\ \beta\ \beta\ \beta]. \tag{10}$$

Results

Behavioral Responses

Overall, the likeability ratings of novices ($M = 3.73$, $SD = 0.40$) were lower than the ratings of dancers ($M = 4.06$, $SD = 0.59$). A 7 × 2 Bayesian mixed ANOVA with the factors movement representation (original + six MP representations) and group (dancers and novices) shows that the ratings (Figure 4a) are best represented by a model including the factors MP and group. The Bayes factor ($BF_{10} = 9.21 \times 10^{12}$) indicates decisive evidence in favor of this model compared to the null model. There is strong evidence ($BF_{10} = 18.3$) for the best model over the model that additionally includes the interaction effect. This means the data are 18.3 times more likely under the best model than the model that includes the interaction effect on top of the two main effects. Posthoc tests for the factor MP show decisive evidence for a difference in ratings between three MPs and more (range of BF_{10} : 548.0–15,189.9) and up to strong evidence between six MPs and more ($\max BF_{10} = 12.7$). Additionally, there is moderate evidence for a difference in ratings between 18 MPs and the natural representation ($BF_{10} = 3.1$).

A 7 × 2 Bayesian mixed ANOVA with likeability ratings as the dependent variable and the factors repetition and group shows no evidence for any model including repetition as a factor (all $BF_{10} < 1$; Figure 4b).

Regarding the effect of movement sequence on rating (Figure 4d), the best model includes the factors sequence and group, as well as the interaction effect. There is decisive evidence for this model over the null model ($BF_{10} = 9.3 \times 10^{50}$). The sequences that had a high mean rating were more dynamic (e.g., including turns and jumps) in comparison to the sequences with low ratings. To further elucidate the substantial rating differences between the sequences, we computed the motion energy of each sequence by computing the average of the summed interframe Euclidean displacements of each body segment. Group-wise Pearson correlations to test the association between the motion energy of the sequences and their mean rating (Figure 4c) shows decisive evidence ($BF_{10} = 2{,}982.1$) for a correlation between the ratings of novices and motion energy ($r = .82$, 95% CI = [0.55, 0.92]). Similarly, although to a lower degree, there is evidence ($BF_{10} = 74.3$) for an association between the ratings of the dancers and motion energy ($r = .70$, 95% CI = [0.34, 0.86]).

The difference in the likeability ratings of the dancers between MP representations, with model estimates of $\boldsymbol{\mu}$, is shown in Figure 5a. Of the models tested, the model valley is the best model according to the expected log pointwise predictive density (Figure 5b), which is a measure of a model's predictive accuracy for expected new data points, that is, higher values indicate a better out-of-sample predictive fit. This model receives a weight of 0.91, where the weight (ranging from 0 to 1) can be interpreted as the probability of the model being true among the models tested given the data. The other two models, unbound and increase, received weights of 0 and 0.09, respectively. For the novice data (Figure 5c), the difference in model weights (Figure 5d) is less pronounced, with the unbound model also receiving a weight of 0, while the increase and valley models receive weights of 0.39 and 0.61, respectively.

Psychophysiological Responses

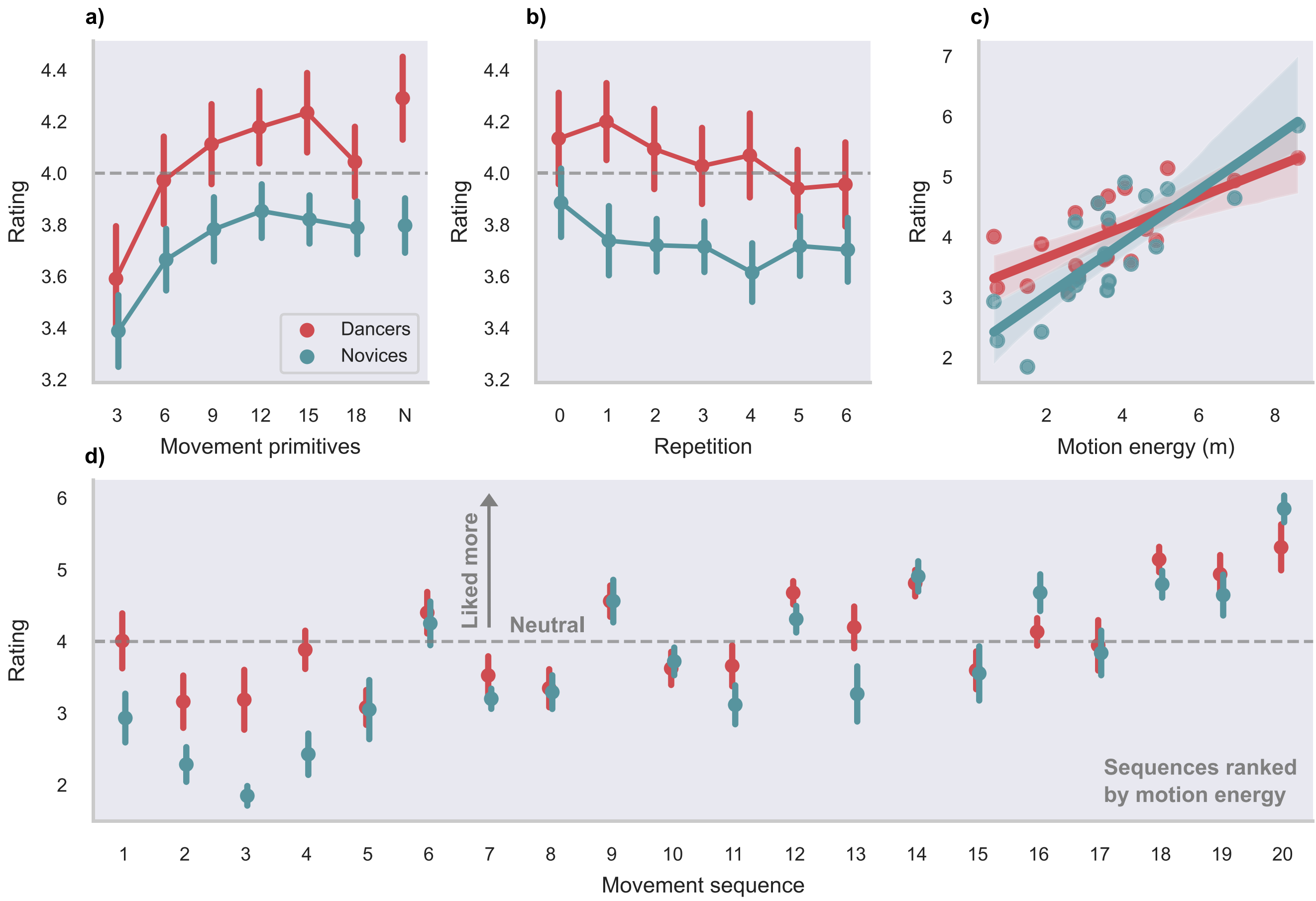
The EDA amplitudes elicited during the display of the MP representations are shown in Figure 6a. A 7 × 2 Bayesian mixed ANOVA with the factors movement representation and group shows moderate evidence for the null model, that is, the data are 5.4 times more likely under the null model than the second best model including the factor group. This suggests that the physiological arousal while observing the movement sequences was not influenced by the degree of human likeness of the observed movement.

A 7 × 2 Bayesian mixed ANOVA with the factors repetition and group shows that the amplitudes are best represented by a model including the factor repetition. The BF indicates decisive evidence in favor of this model compared to the null model ($BF_{10} = 2.21 \times 10^{12}$). Implicit affective responses to the same movement sequence were elevated on the first displays and then decreased as the sequence was repeated (Figure 6b). There is moderate evidence for the model including the factor repetition over the model additionally including the factor group ($BF_{01} = 3.4$).

Discussion

In this study, the explicit and implicit responses of dancers and nondancers to movements varying in human likeness were analyzed. Overall, results indicate that while model-generated dance movements can indeed evoke positive esthetic responses in human observers, both subjective and objective measures seem to be relevant for the esthetic perception of dance sequences generated by a temporal MPs model. Model-generated movements that contained fewer MP resulting in a less human-like appearance were found to elicit diminished likeability judgments. This was the case both for individuals with and without prior experience in dance. However, subjective likeability was overall higher for individuals that had prior experience in dance. The attenuated esthetic responses for observed movements with fewer MP and for individuals lacking skill-specific motor representations shows that esthetic responses are reduced when familiarity with the observed action is low.

Figure 4
Behavioral Responses to Movement Stimuli



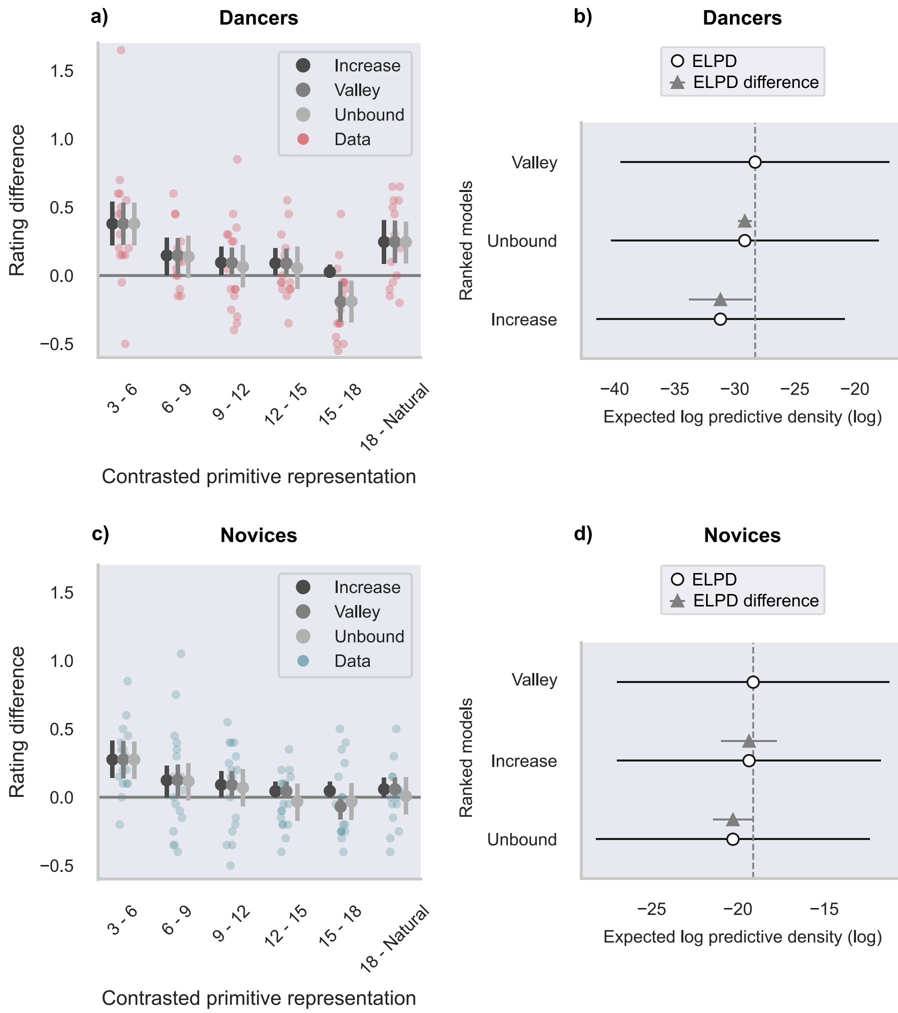
Note. Ratings of movement primitive representations (a; N: natural display) and repeatedly displayed sequences (b), as well as the association between sequence ratings and sequence motion energy (c) and the ratings of each movement sequence. (d) Error bars show standard errors. See the online article for the color version of this figure.

Thus, not only is the presence of corresponding action representations in the human observer relevant for esthetic perception, but additionally the degree to which these representations might be activated or utilized due to how human-like the observed movement is. This is in line with previous finding on the effects of sensorimotor familiarity on the esthetic perception of dance (Kirsch et al., 2015, 2013). Furthermore, the results corroborate the previous findings concerning other art-related skills. Chamberlain et al. (2022), for example, recently showed that human-like, computer-generated drawing movements were perceived as more esthetically pleasing than unnatural drawing actions, while this perception was, similar to the results of the present study, dependent on the observers' artistic expertise.

Interestingly, a deviation from the general pattern of greater likeability with more human-like movements emerged when dancers observed model-generated sequences approaching human likeness. For these individuals with prior motor experience, the highest likeability rating for the model-generated movements was found for the temporal MP model also deemed optimal by Bayesian model selection, that is the model with 15 MPs, whereas likeability dropped considerably for the movements generated by the model with 18 MPs. A subsequent comparison of three models used to assess the relationship between MP representations and likeability ratings showed that a model representing a valley pattern is the best one for the dancers' ratings. Conversely, the model displaying only an elevation in ratings with an increase in human likeness performs the worst. This can be taken to suggest that an uncanny valley effect can be found in the movement domain as well, that is, as a result of movement kinematics and irrespective of character appearance, which was the same for all presented stimuli. The underlying cause might be a better discrimination ability for observers with prior experience in producing the movement patterns displayed.

Although a previous study by Bronner and Shippen (2015) found that esthetic evaluations are higher for whole-body movements that are characterized by fewer principal components, our results do not suggest that esthetic perception could be based on a reduced dimensionality of components in the observed movement. Except for dancer's reduced esthetic evaluation of model-generated movements with 18 MPs, we did not find that evaluations differ in terms of the number of underlying movement building blocks given a similar quality of movement reconstruction, that is, variance accounted for. The model with for example nine primitives clearly offers a more

Figure 5
Comparison of Models Fitted to Rating Differences

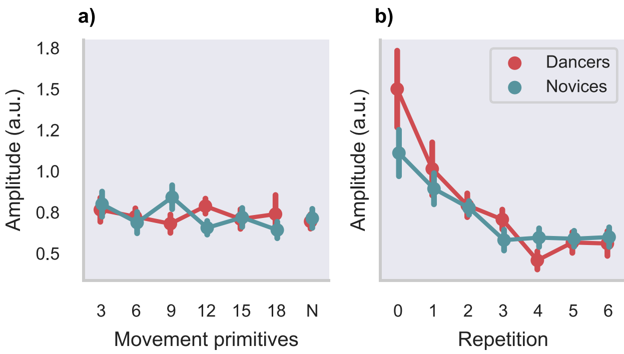


Note. Observed data and model estimates (**μ** with 95% HDIs) for the dancers (a) and novices (c). The leave-one-out ELPD as a measure of each model's predictive fit for the data of the dancers (b) and novices (d). The dotted line marks the ELPD of the best estimated model. HDI = highest density interval; ELPD = expected log pointwise predictive density. See the online article for the color version of this figure.

compact description of the movement than models with more primitives, while having a comparable reconstruction quality, but the movements generated with this model did not receive the highest esthetic ratings. Thus, the results obtained by varying the number of components underlying the movement do not support a compression account of beauty (Schmidhuber, 2009). However, the higher subjective ratings observed in the group with prior experience in dance would align with the proposed notion that experienced individuals can use previously acquired encodings to better compress incoming sensory signals, leading to an increased perception of beauty.

The movement sequence itself has a higher effect on perceived esthetics, than the representation regarding human likeness. The motion energy shows a strong association with behavioral responses, consistent with previous work showing that esthetic ratings are related to certain kinematic characteristics (Neave et al., 2011; Torrents et al., 2013, 2015). Interestingly, the association between ratings and this objective stimulus property is stronger for nondancers, indicating that simple objective kinematic features play a larger role in evoking esthetic responses in observers without specific prior motor experience in the skill displayed. Although individuals with prior motor experience are influenced by this kinematic feature to some degree as well, higher-level features, for example, related to pose configurations and multijoint movement dynamics, might be of more relevance for the esthetic perception of these individuals. This is supported by the finding that when "less is happening" in the sequence (low motion energy), the difference between the group ratings is largest, that is, dancers still gave these sequences a rating approaching a neutral liking, although they were less dynamic. This indicates that in assessing esthetic evaluations of dancers, factors other than standard kinematic metrics may be of greater importance.

Figure 6
Psychophysiological Responses to Movement Stimuli



Note. Amplitudes of the electrodermal activity for movement primitive representations (a; N: natural display) and repetitions (b). Error bars show standard errors. a.u. = arbitrary units. See the online article for the color version of this figure.

Our results confirm that stimulus familiarity has an effect on implicit measures of arousal. However, in contrast to previous studies finding a difference in skin conductance levels during stimulus observation due to long-term experience (Christensen et al., 2021, 2016), our results indicate a fairly short-term effect. On a psychophysiological level, the subconscious affective response to a movement sequence decreased and then plateaued within a couple of repeated displays of a sequence. This habituation effect has been observed for simpler stimuli as well, such as electrical stimuli and sound clicks (Lim et al., 2003). This shows that despite of the complexity of the stimuli and general interest in the skill displayed, evidenced by investing years in learning the skill, autonomic sympathetic arousal appears to still saturate quite rapidly when novelty is reduced.

The higher esthetic responses of dancers compared to novices that were observed in this study might be due to the presence of motor representations related to the observed actions for the dancers. On the other hand, they could also be due to visual familiarity with the stimuli displayed. An argument for the former is that increased esthetic preferences have primarily been observed due to the physical practice of a dance sequence (Kirsch et al., 2015, 2013). Obtaining motor experience in a skill might increase the ability to simulate observed movements, which has been postulated as an embodied simulation account of esthetics (Kirsch et al., 2015). Motor simulation has been associated with the activity of certain brain areas, therefore, termed action observation network (Buccino et al., 2001), which also is increased when observing dance actions that are part of the observer's own motor repertoire (Calvo-Merino et al., 2005, 2006; Cross et al., 2006). The increased activation of this network when observing certain actions has also been shown to be predominantly due to motor familiarity, and not visual familiarity with the observed movement (Calvo-Merino et al., 2006). Since also artificial movements of objects can activate this network of brain areas, although to a lesser degree than biological hand movements (Engel et al., 2008), it would be of interest to assess the activity of this network during the observation of model-generated movements varying in human likeness in future studies. Moreover, primitive-based models could offer an approach to test the extent of embodiment for movement esthetics, for example, by extracting MP from multiple subjects' movement data and assessing the esthetic evaluation of movements generated with self-based and other-based primitives by the same subjects.

Conclusion

In this study, we used a model-based approach relying on MPs to generate artificial dance movements. We find that higher explicit esthetic responses are elicited by movements with a high degree of human likeness and also for individuals with prior motor experience in dance. For the latter, however, the results suggest an uncanny valley effect, indicating that expert dancers are able to detect the artificial in the seemingly natural. Furthermore, we find that the motion energy of the movement sequences is positively associated with the likeability ratings, more so for novices than dancers, leading us to speculate that dance experts may be able to discover beauty in presumably less interesting movements. Such speculation aside, the findings clearly highlight the enhanced perceptual abilities associated with sensorimotor dance experience. In summary, the effects regarding human likeness support the role of familiarity for movement esthetics and show the relevance of both top-down and bottom-up processes for the esthetic perception of whole-body movement.

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Received May 27, 2024
Revision received August 10, 2024
Accepted September 2, 2024 ■