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Timing is everything: Dance aesthetics depend on the complexity of movement kinematics

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ABSTRACT

What constitutes a beautiful action? Research into dance aesthetics has largely focussed on subjective features like familiarity with the observed movement, but has rarely studied objective features like speed or acceleration. We manipulated the kinematic complexity of observed actions by creating dance sequences that varied in movement timing, but not in movement trajectory. Dance-naïve participants rated the dance videos on speed, effort, reproducibility, and enjoyment. Using linear mixed-effects modeling, we show that faster, more predictable movement sequences with varied velocity profiles are judged to be more effortful, less reproducible, and more aesthetically pleasing than slower sequences with more uniform velocity profiles. Accordingly, dance aesthetics depend not only on *which* movements are being performed but on *how* movements are executed and linked into sequences. The aesthetics of movement timing may apply across culturally-specific dance styles and predict both preference for and perceived difficulty of dance, consistent with information theory and effort heuristic accounts of aesthetic appreciation.

1. Introduction

What distinguishes a dance movement from an everyday action? In one of the few psychological approaches to dance aesthetics, Kreitler & Kreitler argue that dance movement is "remote from habitual movement" (Kreitler & Kreitler, 1972, p. 158). Everyday movements become dance through exaggeration or even caricature: Everybody can jump, but not everyone can jump as high or as elegantly as a dancer. Rudolf Laban, one of the pioneers of modern dance, argues that the primary purpose of dance training is to increase the range and clarity of bodily expression (Laban, 1950). Laban's ideas on dance anticipate evolutionary (Hagen & Bryant, 2003) and anthropological (Grau, 2015; Hanna, 1987) theories on the origins and societal functions of dance (and also music): as an intrinsically social art form, the aesthetics of dance should be fundamentally linked to effective non-verbal communication via observed movement (Hanna, 1987; Orgs et al., 2016). A dancer conveys feelings and intentions through the kinematics of their actions; the size and diversity of the movement vocabulary determine the range of potential emotional expressions and social signals that can be transmitted.

If aesthetic appreciation of dance is indeed linked to effective message passing between a performer and a spectator, then it should depend on the complexity of the movement message (Berlyne, 1974). In this study, we directly test whether the aesthetics of human movement are related to the non-verbal transmission of information, by manipulating the variability and predictability of objective kinematic features – velocity and acceleration – and assessing their effect on subjective judgments of speed, effort, enjoyment, and reproducibility.

Art appreciation depends on both objective features of an artwork and subjective characteristics of the observer (Leder et al., 2004; Leder & Nadal, 2014). The role of stimulus complexity has been studied extensively in the visual arts domain (Donderi, 2006; Makin, Helmy, & Bertamini, 2018) and in music (Brattico & Pearce, 2013). Nadal and colleagues (2010) argue that the relationship between complexity and liking depends on how complexity is defined and assessed. If measured as the number of elements that constitute an artwork, appreciation increases linearly with complexity. In contrast, if complexity is assessed as regularity of stimulus features, an inverted u-shaped relationship emerges. In music, complexity is often measured as entropy over time (Shannon & Weaver, 1949) and relates to the predictability of the

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unfolding sequence of sounds (Brattico et al., 2009; McDermott, 2012; Pearce & Wiggins, 2012; Proverbio et al., 2015). For instance, aesthetic preference is reported for an intermediate level of complexity of fractal melodies (Beauvois, 2007) and instrumental improvisations (jazz and bluegrass) in non-expert listeners (Orr & Ohlsson, 2005).

In contrast to the rich literature on stimulus complexity in visual aesthetics and music, a systematic investigation of the role of complexity for the aesthetics of human movement is still missing. Existing research into dance aesthetics has largely focussed on subjective or spectator-specific components, in particular the visual and motor expertise of the spectator (Cross et al., 2006; Cross et al., 2011; Kirsch et al., 2015; Kirsch et al., 2016; Orgs et al., 2008; Orgs et al., 2013; Orlandi et al., 2017; Orlandi & Proverbio, 2019) and their familiarity with the underlying movement vocabulary (Christensen, Gomila, et al., 2016) or the choreographic structure (Orgs et al., 2013). Yet, studies suggest that some movement features are more aesthetically pleasing than others. For example, Calvo-Merino and colleagues found a preference for dance steps involving the entire body, such as jumps with a large horizontal displacement (Calvo-Merino et al., 2008). Using motion capture, Torrents and colleagues showed that non-experts are attracted by basic features of dance performance, such as high turning speed, large movement amplitude, and balancing positions held for a long duration (Torrents et al., 2013). These results suggest a relationship between aesthetic appreciation and the overall *amount* of movement observed (Deinzer et al., 2017). Also, when observing groups of dancers, movement synchrony between individual dancers predicts an audience's engagement with a live dance performance (Vicary et al., 2017).

Whereas the link between movement kinematics and aesthetic appreciation remains largely unexplored, several studies have linked specific movement parameters to whole-body emotion expression and recognition (Camurri et al., 2004; Proverbio et al., 2014; Sawada et al., 2003; Vaessen et al., 2018). Although specific kinematic parameters are often complex and strongly dependent on the kind of movements being performed (i.e., walking, everyday actions, freestyle dancing, and ballet; Barliya et al., 2013; Dael et al., 2013; Keefe et al., 2014; Van Dyck et al., 2013), movement acceleration emerges as a strong predictor of emotional expressions. Sadness is typically associated with lower movement acceleration, whereas anger is associated with greater acceleration and longer traveled distance (Sawada et al., 2003). Despite a clear link between movement kinematics and whole-body emotion expression, recent studies on dance aesthetics suggest that movement expressivity in dance can not be reduced to differences in overall motion energy (Christensen et al., 2019; Christensen, Gomila, et al., 2016; Christensen, Pollick, et al., 2016). For example, expert dancers' emotion recognition and skin conductance differentiate between happy and sad ballet moves, but only if videos are presented in their correct forward playback direction (Christensen, Gomila, et al., 2016). Critically, forward and backward videos were identical for overall speed and acceleration, suggesting that differences in the overall amount of movement can not explain differences between happy and sad dance videos. Similarly, judgments of movement expressiveness across a library of contemporary and classical dance excerpts were unrelated to measures of movement quantity derived from the dance videos (Christensen et al., 2019). Yet, if the aesthetics of human action are indeed linked to movement expressivity and their respective kinematic signatures (i.e. sad/slow vs. happy/fast), then movements with greater variability in acceleration and velocity (range and clarity of movement expression, Laban, 1950) should be more enjoyable to watch than movements with less salient changes in movement timing.

The studies summarized above show that movement kinematics exert a strong influence on movement perception and recognition. Yet, it remains unclear whether this influence can be quantified as the structural complexity of kinematic information. In the case of human action, complexity might relate to (a) the number of potential changes in movement speed and acceleration and (b) the ease with which these changes can be predicted by a spectator. Changes in speed and velocity can be quantified as motion smoothness (Balasubramanian et al., 2015) to provide an index of the kinematic variability of action execution (Gulde & Hermsdörfer, 2017). Alternatively, kinematic complexity may be conceptualized as predictability over time, in lose analogy to musical expectations (Pearce & Wiggins, 2012), and quantified as entropy (Shannon & Weaver, 1949). Importantly, the kinematic complexity of *how* a given action (i.e., a jump or turn) is performed, is distinct from the complexity of the order of the movement sequence (Orgs et al., 2013), and the complexity of the movement elements and trajectories that compose a specific dance style such as ballet (Volchenkov & Bläsing, 2013).

Finally, the kinematic complexity of a movement sequence might be related to the perceived effort of movement execution. Perceived effort is an important predictor of appreciation in the visual and the performing arts. Cross and colleagues (Cross et al., 2011) presented dance-naïve volunteers with videos of dance movements and asked them to rate their enjoyment and ability to reproduce each movement. A negative correlation between the two factors emerged and indicated increased aesthetic appraisal as a function of decreasing capability to reproduce the dance actions. This “Cirque du Soleil” effect mirrors the effort heuristic (Kruger et al., 2004): artworks perceived as difficult to make are preferred to artworks that appear easy to make. Interestingly, the relationship between effort and liking reverses for actions without an aesthetic purpose, such as typing (Beilock & Holt, 2007), eye movements (Topolinski, 2010), and everyday interactions with objects (Hayes et al., 2008). In these latter examples, liking correlates positively with the fluent performance of a familiar action (Orgs et al., 2013; Reber et al., 2004).

In the present study, we focussed on the role of kinematic complexity for the aesthetic appreciation of human movement. We manipulated kinematic complexity by instructing a professional dancer to introduce subtle variations in movement timing for otherwise identical excerpts of the same choreography. We then quantified the effect of this manipulation on the objective kinematic features of the dance sequence and the subjective appraisal of the dance sequences by dance naïve observers. In line with an information theory account of aesthetic appreciation, we predict that spectators should prefer dance sequences with frequent, yet predictable changes in acceleration and velocity. Moreover, we hypothesized that dance excerpts judged as less reproducible would be preferred to ‘easier’ movements, consistent with the ‘Cirque du Soleil’ effect (Cross et al., 2011). Finally, the relative contribution of movement kinematics to movement appreciation might depend on the biomechanical constraints of the human body. For example, the kinematics of the arms and hands are less constrained by gravitational force and body weight than the kinematics of the legs and feet. Greater kinematic complexity may therefore be more difficult to achieve for lower than for upper limbs, with distinct effects on aesthetic appreciation and effort judgments.

2. Materials and methods

2.1. Open Science statement

Consistent with recent proposals (Simmons et al., 2011; Simmons et al., 2012), we report all data exclusions, all manipulations, and all measures in the study. In addition, following open science initiatives (Munafò et al., 2017), the data, stimuli, and analysis code associated with this study are freely available online (https://osf.io/ytrh3/?view_only=04060df1266948018d3419ab9f6355ac).

2.2. Participants

Forty-one volunteers took part in this study (31 females and 10 males). All participants were between 18 and 23 years old (mean 20 years) and reported no professional dance experience. Thirteen

participants reported some dance experience, mainly in the form of taking recreational dance classes for a short period (1.15 years, SD = 2.17). All volunteers were right-handed (Edinburgh Handedness Inventory; Oldfield, 1971) and had normal or corrected-to-normal vision. They also provided written informed consent before beginning any study procedures, and the study was approved by the Research Ethics Committee of Bangor University (approval number: 2017-16194). All participants received course credits or were paid £5 for taking part in the study.

2.3. Stimuli

We recorded 24 dance video clips, comprising 12 excerpts from the choreography *Duo* by William Forsythe (Waterhouse et al., 2014). Movement sequences were performed by a professional male dancer of The Forsythe Company in a neutral dance studio setting. Each sequence was recorded twice. For one set of videos, the dancer was instructed to perform each sequence in the correct order whilst maintaining a constant speed throughout the entire sequence (*uniform kinematics*). For the second set of videos, he was asked to perform the same sequences, but this time emphasize dynamic changes in movement speed (*varied kinematics)* to introduce more salient moments of acceleration and pause.

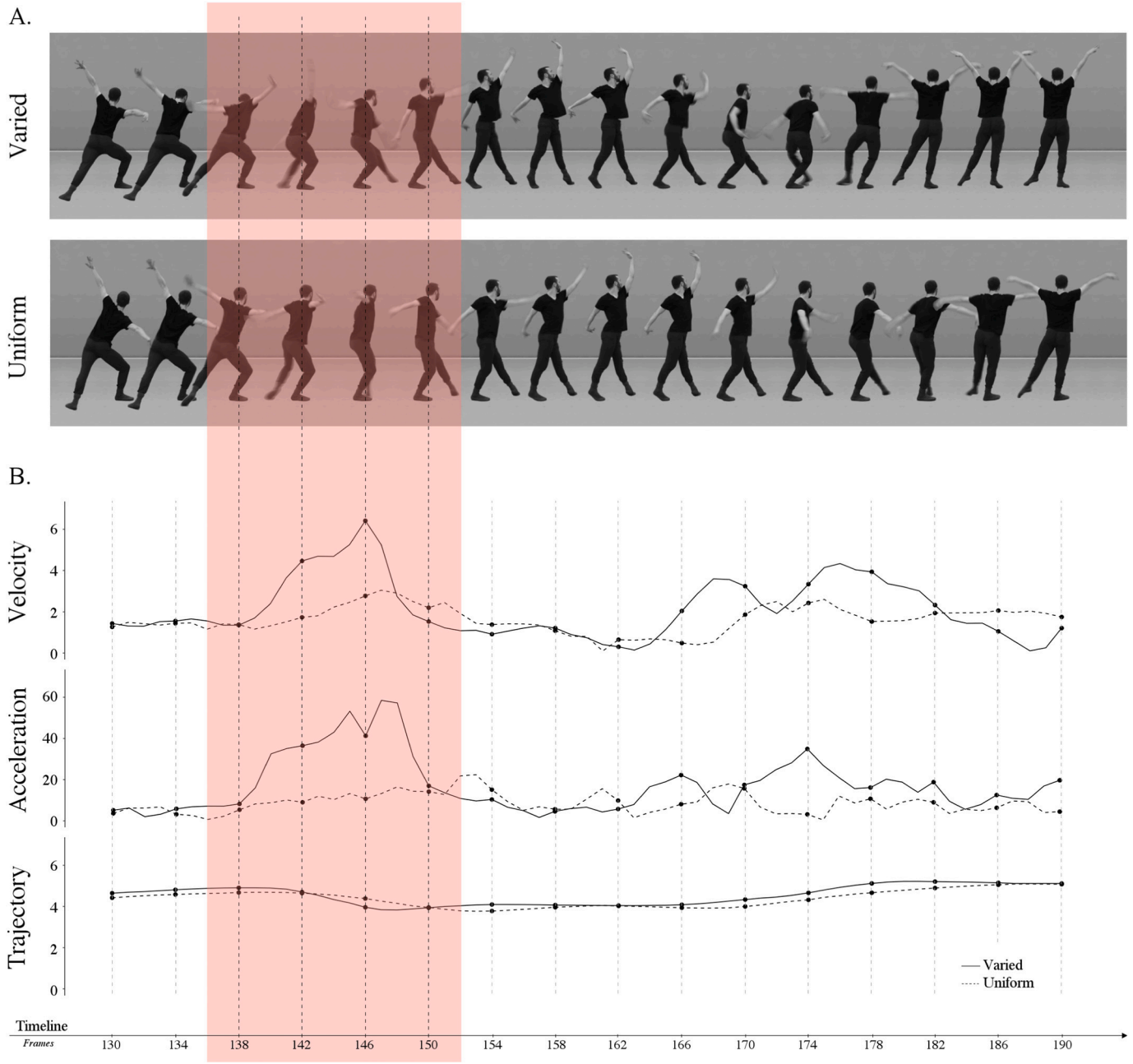

Fig. 1. Example of stimuli. A. To more clearly illustrate our dynamic stimuli in a static figure, pictured here are 16 static frames selected from a dance sequence at different time points (between 130° and 160° frame) and placed side by side to highlight the difference in kinematic complexity between the uniform (upper part) and varied (lower part) version of the same sequence. B. The three time-series represent examples of the velocity (m/s), acceleration (m/s^2), and trajectory (m) of the right hand of the dancer quantified by the offline motion capture. The timeline is visible in the lower part of the figure (number of frames). The light red area highlights an example of the different use of time dynamics by the dancer (e.g., larger velocity peaks) while performing the same chain of movements with almost no space-related changes. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

The final stimulus set thus consisted of 12 pairs of videos showing the same movement sequence but performed in two different ways (see Fig. 1 and Supplementary Video 1). For each video clip, the dancer started and ended the dance phrase in a relaxed standing position in the center of the scene. The videos were recorded using a Full HD format (1080i: 1920 × 1080 pixels) with a frame rate of 25 fps.

In subsequent editing, all videos were silenced and converted to grayscale. All videos started and ended with 12 frames of fade-in and fade-out (from and to black). The duration of the final version of the videos ranged from 8.64 to 15.68 s (mean: 11.78 s, SD = 2.00). Video duration differed significantly between uniform and varied kinematics versions of the videos, [$t(22) = 5.998$, $p < 0.0001$]. The uniform videos (13.32 s, SD = 1.15) lasted, on average, 3 s longer than the varied kinematics videos (10.24 s, SD = 1.38). Finally, 12 backward control video pairs were created by reversing the playback direction of the originally recorded clips, using *Adobe Premiere Pro CC 2015* (v. 9.0). The backward stimuli served as a control condition for the natural forward movements since each pair was characterized by the same low-level features (i.e., body kinematics) and duration (Christensen, Gomila, et al., 2016). Our study used a 2 × 2 within-subject design, with the two factors movement timing (uniform, varied) and playback direction (forward, backward). The total stimulus set comprised 48 video clips.

2.4. Motion energy

The overall motion energy (ME) for all dance videos was quantified using a MATLAB (version 2017b) algorithm (Bobick, 1997). A difference image for consecutive frames pairs was computed on each video so that any pixel with more than 10 units luminance change was classified as “moving”. The mean numbers of moving pixels per frame and movie were summed to give a ME index for that video (Cross et al., 2012). The video camera was placed in a fixed position during the recordings, so the body of the dancer was the only moving element in the scene. Hence, the ME index represents the overall visual displacement of the dancer's body. A 2 by 2 repeated measure ANOVA was performed on the ME values for both movement timing (uniform, varied) and playback direction (forward, backward) as within-subject factors.

2.5. Motion acceleration and velocity per limb

A more fine-grained measure of the action kinematics was obtained with offline motion capture (Jakubowski et al., 2017) using *Tracker* 5.0.2 software (https://physlets.org/tracker/). Each of the 24 original videos was manually processed by placing four markers on the wrists and ankles of the dancer in a frame-by-frame approach. The height of the dancer was used as the reference to calibrate the measurement system. Thus, velocity and acceleration profiles for hands and feet were computed for all the videos as a function of time, along with the trajectory of the body in 2D space (see Supplementary Table 1 for specific algorithms). Although the recognition of human motion from 3D-motion capture allows for greater precision (for a review see Aggarwal & Xia, 2014), 2D video analysis provides good reliability in kinematics quantification for whole-body movements (i.e., lower limbs kinematics during running or jumping; Hanley et al., 2018; Herrington et al., 2017).

The time series for velocity and acceleration were averaged for all four hands and feet of the dancer. We fitted a linear mixed-effects model (Winter, 2013) using the “lme4” toolbox in *R* (Bates et al., 2015). Several likelihood ratio tests (LRT) served to estimate the statistical model that best fitted the data for velocity and acceleration, including fixed effects and relative interaction one at a time. The results of this forward stepwise inclusion method are reported in Supplementary Table 2. Both models included the movement timing (varied, uniform) by limb (hands, feet) interaction and the limb by body side (left, right) interaction factor as fixed factors, and the by-stimulus intercept as a random factor. The “phia” *R* package was used to perform the post hoc tests (De Rosario-Martinez, 2015). The fixed effects estimates are reported together with standard errors.

2.6. Motion smoothness

In the varied kinematics condition, the dancer deliberately emphasized pauses and speed changes throughout the dance phrase. Kinematic complexity might be quantified as the number of alternations between movement accelerations and decelerations; a measure also referred to as motion smoothness (Balasubramanian et al., 2015). Specifically, we used the number of velocity peaks per meter (NoP) as an index of motion smoothness, since our stimuli met the criterion of an equal length of movement trajectories. Other measures of motion smoothness based on velocity, acceleration, arc-length, or log dimensionless jerk require equal speed and duration between conditions (Gulde & Hermsdörfer, 2018). NoP is a reliable measure of motion smoothness in the context of daily actions in both healthy (Gulde & Hermsdörfer, 2017) and clinical populations (Gulde et al., 2017). The NP was computed in R using a custom script. All velocity peaks greater than 0.05 m/s were counted in the velocity profile and divided by each limb's traveled path length. Path length was computed as the cumulative sum of the absolute values of the displacements along the x- and y-axes (Brooks et al., 1998). The resulting number was then inverted, so that higher NoP values indicate less kinematic variability and therefore, smoother movements (Gulde & Hermsdörfer, 2018). NoP values were then subjected to mixed-effect modeling. The final model (estimated with LRTs) included instructed kinematic variability (movement timing) in the dance videos (varied, uniform) and the interaction between the limb (hands, feet) by the body side (left, right) factors as fixed effects, and the by-stimulus intercept as a random effect (see Supplementary Table 2).

2.7. Motion entropy

To assess the predictability of all dance sequences, we computed Shannon entropy (Shannon & Weaver, 1949). Entropy has been previously used to assess the predictability of music (Pearce & Wiggins, 2012) and more generally as a measure of stimulus complexity and uncertainty (Boffetta et al., 2002; Da Silva et al., 2000). Importantly, greater entropy means lower predictability. An entropy package in R (Hausser & Strimmer, 2014) was used to compute the entropy of acceleration profiles for each limb of the dancer. The function used (entropy.ChaoShen) returns a non-parametric estimation of Shannon entropy using the method of Chao and Shen (2003). The resulting values were subjected to statistical analysis using mixed-effects modeling. The final model (estimated with LRTs) included the movement timing (varied, uniform) and limb factors (hands, feet) as fixed effects, and the by-stimulus intercept as a random effect (see Supplementary Table 2).

2.8. Procedure

All participants were tested in two experimental sessions, one week apart. In the first session, all videos were rated for perceived effort and speed – both descriptive judgments of dynamic features of the observed dance sequences (i.e., the varied stimuli were faster than the uniform stimuli). In the second session, all videos were rated for reproducibility and enjoyment, both evaluative judgments (I can't do it, but I enjoy it) previously associated with aesthetic appreciation of movement (Cross et al., 2011). The term *enjoyment* was selected (Jola & Grosbras, 2013) among different ways of defining aesthetics experience in movement literature (i.e., likability, enjoyment, interest, beauty/ugliness; Calvo-Merino et al., 2008; Jola et al., 2014; Marty et al., 2003; Torrents et al., 2013; Vicary et al., 2017) since the former has been used in relation to action timing and synchrony (e.g., variation in acceleration, collective stops) in the dance context (Vicary et al., 2017). The participants were

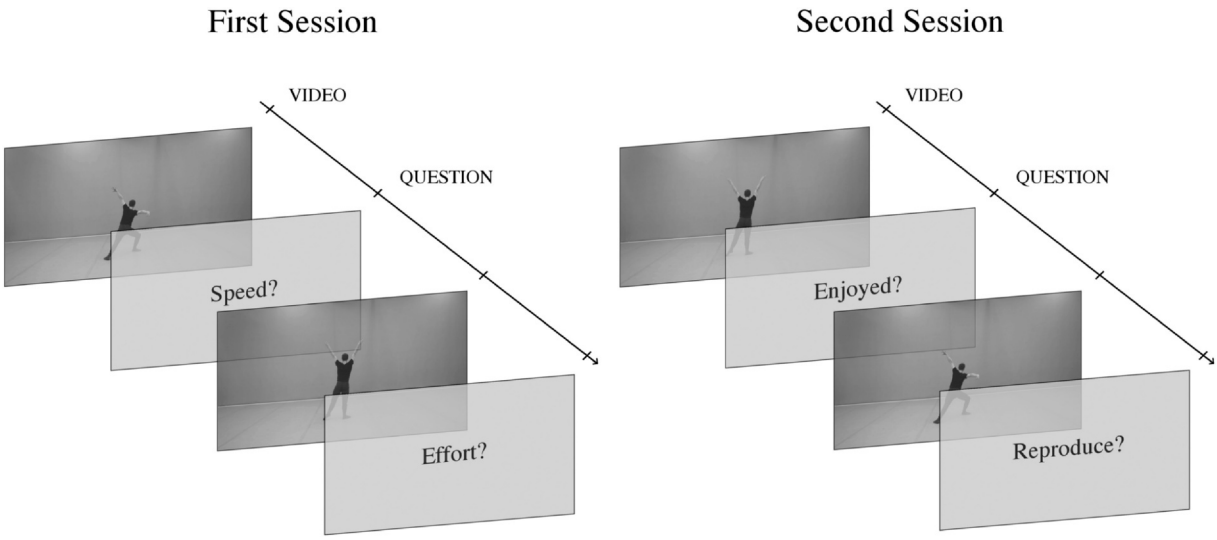

Fig. 2. Time scale of experimental design. Each trial consisted of a counterbalanced presentation of video stimuli representing the uniform or varied version of the same dance sequence in both forward or backward playback direction. The video offset was followed by one out of four prompts that remained on the screen until the next response. Data were collected in two separate sessions, one week apart. In the first session, participants rated each video for perceived speed and required effort using a 5-point Likert scale (1 = very little; 5 = very much). Enjoyment and reproducibility ratings were assessed in the second session.

comfortably seated in front of a high-resolution LCD computer screen where the written instructions for the study were initially presented. Videos were presented with *OpenSesame* software (version 3.1.9) and displayed at the center of the screen (1080i resolution), followed by one out of two black keywords/questions (Speed?, Effort?) on a light grey background. The keyword remained on the screen until a participant pressed a key. Participants were instructed to watch each video and rate the amount of speed (*Please rate the SPEED of the movements in this video*) or effort (*Please rate how much EFFORT is required to perform the movements in this video*) perceived in the dance sequence (see Fig. 2) on a 5-point Likert scale (1 = very little; 5 = very much). Videos were presented twice across four blocks of 24 clips in a pseudorandomized and counterbalanced order, 96 videos per session in total. In each block, the same video was presented once, and alternate questions followed different versions of the same dance sequence (i.e., video 1: uniform forward – Effort; varied backward – Speed). One week later, participants attended the second experimental session. For the second session, videos were shown in reversed order and again pseudorandomized and counterbalanced across experimental conditions. In the second session, participants rated movement reproducibility (*Please rate how well you could REPRODUCE the movements in this video*) and aesthetic pleasure (*Please rate how much you ENJOYED watching the movements in this video*) of each dance sequence. At the end of the experiment, they were debriefed and informed about the purposes of the study.

2.9. Data analysis

The subjective ratings for effort, speed, reproducibility, and enjoyment were analyzed separately. The volunteers that showed mean ratings and dance expertise (years) exceeding ± 2SD (standard deviation) were considered outliers and excluded from the analysis. Hence, the final data set comprised thirty-two participants. Also, only the ratings for 11 out of 12 sequences (44 out of 48 stimuli) were recorded due to technical issues, for a total of 1408 data point for each rating. The data were analyzed using linear mixed-effects modeling (Winter, 2013) using the "lme4" toolbox in *R* (Bates et al., 2015). The statistical model that best fitted the data for each DV was estimated by means of the LRT, by including fixed effects and relative interaction one at a time (see Supplementary Table 3 for the results of this forward stepwise inclusion method). The movement timing factor was tested as the only fixed factor in the statistical model relative to the speed, reproducibility, and enjoyment ratings. For effort ratings only, we included movement timing and interaction with the playback direction factor as fixed factors in the model. The by-subject intercept was included as a random factor in all 4 models. The fixed effects estimates are reported in the Results section, together with the standard errors.

Furthermore, Pearson's correlations were performed on the mean ratings for each dance clip to investigate relationships between the four rating scales. All clips were considered regardless of the playback direction or movement timing. Also, the intraclass correlation coefficient (ICC) was estimated for each DV as an index of agreement between the ratings express by the participants. The ICC function contained in "psych" *R* package was used (Revelle, 2018). The ICC(2,*k*) form was reported (two-way random effects, absolute agreement, multiple raters/measurements) with a 95% confidence interval.

Finally, the contribution of the dancer's kinematic parameters to the aesthetic experience of the participants was estimated by means of multiple regressions. For each video, subjective ratings were averaged to obtain a mean value for perceived effort, speed, enjoyment, and reproducibility, which served as dependent variables. The potential predictors consisted of the four kinematic parameters (acceleration, velocity, smoothness, and entropy) computed for all four limbs separately (IVs). Since some of the kinematic parameters showed a moderate correlation (see Supplementary Fig. 1), they were included in separate regression models: For each rating scale, four models were estimated with respect to the limb (hands, feet) and body side (right, left) factors as categorial IVs, and one out of the four kinematic parameters as a continuous IV. The goodness of fit of the models was estimated by means of AIC comparisons for each rating scale.

3. Results

3.1. Objective movement features

3.1.1. Motion energy

The main effect of movement timing [$F(1,11) = 200.562$, $p < 0.001$] confirmed that varied dance videos contained more movement than the uniform videos. As expected, motion energy was not affected by playback direction (main effect: $p = 0.41$, n.s., interaction, $p = 0.24$, n.s.).

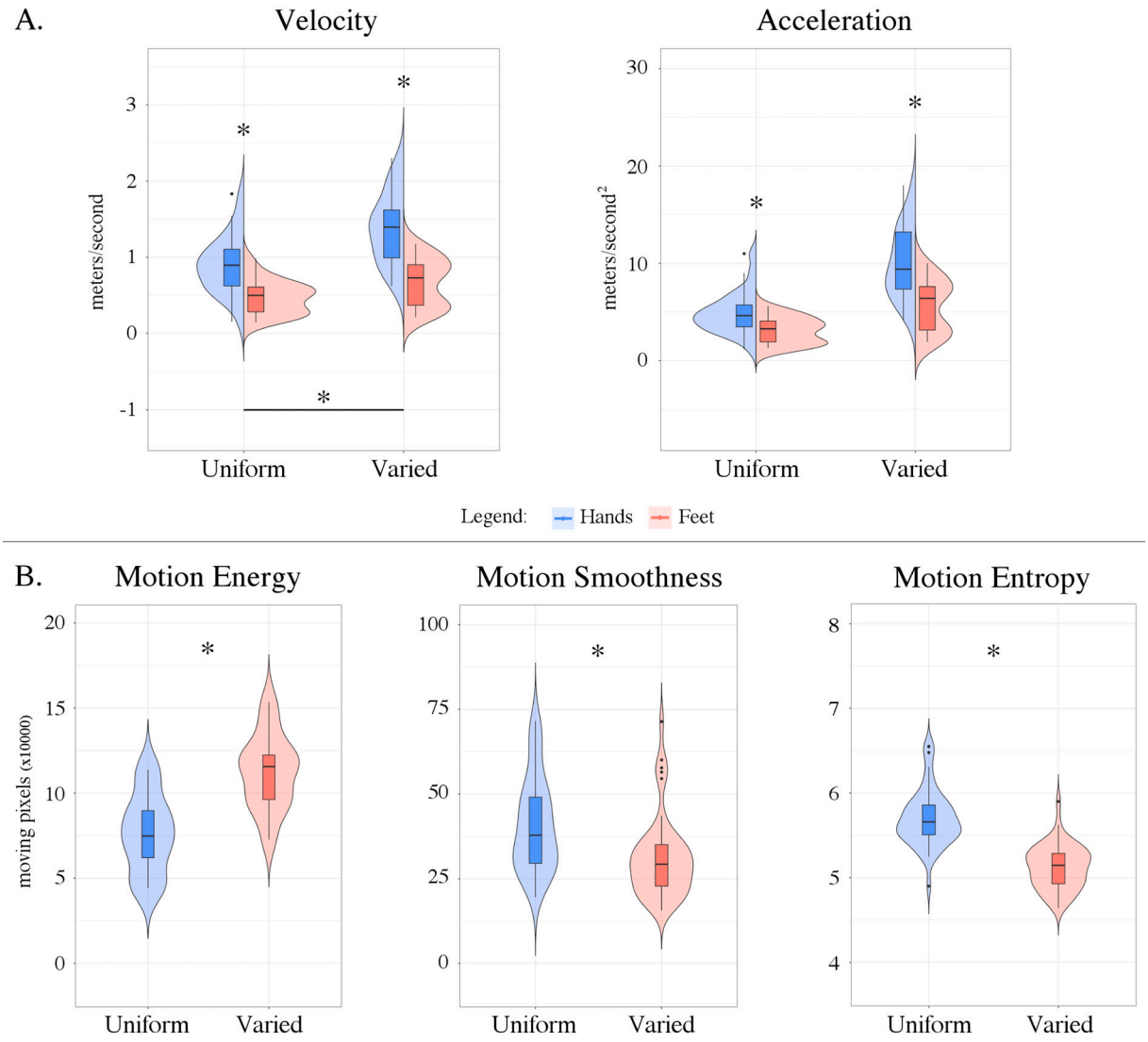

Fig. 3. Movement feature quantification. The plots in panel A illustrate the quantification of motion (mean velocity and acceleration) per limb obtained with offline motion capture. The plots in panel B illustrate the overall motion energy, motion smoothness, and motion entropy of the dance sequences. The videos with varied kinematics contain more motion energy, greater velocity and acceleration, and less smoothness and entropy (i.e., increased variability and predictability) than the uniform dance videos. Also, the dancer's hands show higher values of velocity and acceleration when compared with the feet.

3.1.2. Motion velocity and acceleration per limb

As shown in Fig. 3A, the varied (compared to uniform) kinematics stimuli were faster (0.33 *m/s m/s* ± 0.06) and contained more acceleration (3.81 m/s^2 m/s^2 ± 0.04). This effect was significant for both velocity ($\chi^2(1) = 32.21$, $p < 0.001$) and acceleration ($\chi^2(1) = 74.77$, $p < 0.001$). In particular, the hands displayed increased velocity (0.57 *m/s m/s* ± 0.06; $\chi^2(1) = 94.18$, $p < 0.001$) and acceleration (3.13 m/s^2 *m/s* ± 0.04; $\chi^2(1) = 50.45$, $p < 0.001$) compared to the feet. These results were confirmed by the significant interaction between movement timing and limb factors (Velocity: $\chi^2(1) = 5.83$ $p < 0.05$; Acceleration: $\chi^2(1) = 9.02$ $p < 0.01$). Also, greater velocity was shown for the right than the left limbs (Velocity: 0.12 *m/s* ± 0.06; $\chi^2(1) = 4.187$ $p < 0.05$). This body side difference was visible only for the hands (0.33 *m/s* ± 0.08) but not feet (interaction between limb by body side factors: $\chi^2(1) = 12.46$, $p < 0.001$), as well as in the acceleration ($\chi^2(1) = 6.28$, $p < 0.05$).

3.1.3. Motion smoothness

The uniform stimuli showed a higher smoothness value (0.85 ± 0.05) compared with the varied stimuli (see Fig. 3B), as shown by the significant main effect of movement timing ($\chi^2(1) = 18.95$, $p < 0.001$). Moreover, a significant interaction between the limb and body side factors ($\chi^2(1) = 9.43$, $p < 0.01$) indicated that the movements performed with the right foot were smoother compared with those performed with both the left foot (9.24 ± 3.20) and right hand (8.97 ± 3.20). Overall, the varied dance sequences were less smooth than the uniform videos.

3.1.4. Motion entropy

The uniform stimuli showed a higher entropy value (9.85 ± 2.26) compared with the varied stimuli (see Fig. 3B), as shown by the significant main effect of the movement timing factor ($\chi^2(1) = 120.31$, $p < 0.0001$). Moreover, the significant main effect of the limb factor ($\chi^2(1) = 13.05$, $p < 0.001$) indicated a higher entropy value for the movements performed with the hands (0.19 ± 0.05) compared with those performed the feet. Accordingly, the varied dance sequences were more predictable (i.e., conveying less information) than the uniform videos.

To sum up, the performer's deliberate emphasis on differences in movement timing produced dance sequences with greater visual displacement and more frequent changes in acceleration and velocity. As a result, dance sequences become less smooth but more predictable. The

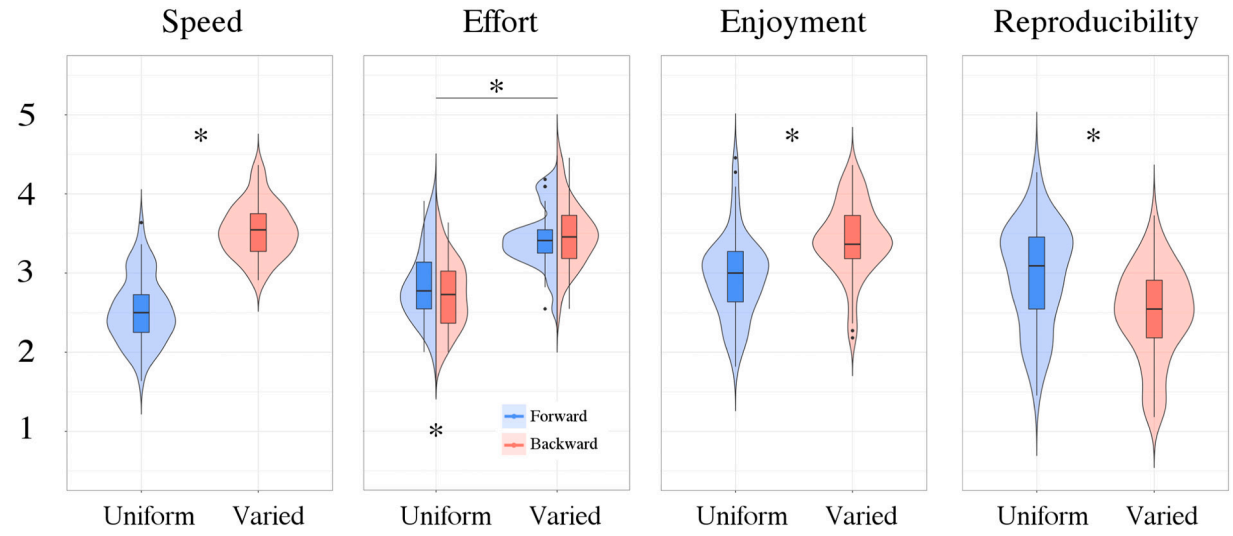

Fig. 4. The effect of movement timing on perceived speed, effort, enjoyment, and reproducibility. Dance sequences characterized by varied timing were perceived as faster, more effortful, enjoyable, and difficult to reproduce compared to the uniform versions of the same sequences. Additionally, uniform movement kinematics were perceived as more effortful when played back in the forward direction than in backward direction.

following section will assess how these differences in objective motion features translate to subjective appraisals of speed, effort, reproducibility, and enjoyment.

3.2. Subjective movement features

Linear mixed-effect models were used to assess the impact of movement timing and playback direction on the subjective evaluation of dance sequences. Movement variability significantly modulated enjoyment ($\chi^2(1) = 117.21$, $p < 0.001$), perceived reproducibility ($\chi^2(1) = 110.85$, $p < 0.001$), speed ($\chi^2(1) = 513.84$, $p < 0.001$), and effort ($\chi^2(1) = 219.69$, $p < 0.001$) ratings (see Fig. 4). Overall, dance clips with a more varied velocity profile were rated as more enjoyable to watch (0.48 ± 0.4), faster (1.02 ± 0.4), more effortful (0.66 ± 0.04), and less reproducible (−0.5 ± 0.05). However, the stimuli with uniform kinematics were perceived as more effortful (0.15 ± 0.06) when presented in the original/forward (than backward) playback direction (kinematics by direction interaction: $\chi^2(1) = 4.37$, $p < 0.04$).

The interclass correlation coefficient (ICC) was used to assess the consistency of the subjective judgments between participants. The ICCs were computed for each rating of interest suggested high reliability (standard range 0.90–1) between participants while judging the movements' speed (0.96) and the implied effort (0.92). A less (but still good) agreement was found between observers when reporting their aesthetic preference (0.83) or rating their ability to reproduce the movements (0.81).

We performed Pearson's correlations on the mean values for each condition to investigate the relationship between participants' ratings along the four factors (using; see Fig. 5). All the stimuli were considered together since no significant difference emerged as a function of movement timing or playback direction. The positive correlation between speed and effort ratings ($r = 0.8$, $p < 0.001$) indicated that faster speed was coupled with increased perceived effort. The negative correlation between reproducibility and both speed ($r = -0.33$, $p < 0.001$) and effort ($r = -0.38$, $p < 0.001$) ratings showed a decreased sense of being able to reproduce the movements with increasing speed and perceived muscular effort. Finally, enjoyment ratings were positively correlated with both effort ($r = 0.41$, $p < 0.001$) and speed ($r = 0.45$, $p < 0.001$) ratings and negatively correlated with reproducibility ($r = -0.25$, $p < 0.01$). Hence, the level of enjoyment of the participants increased with the perceived speed, effort, and difficulty of the dance sequences.

Finally, we used multiple linear regressions to link objective movement features for each limb separately to the subjective movement attributes of the dance sequences. Table 1 reports all estimated models, together with the explained variance (R^2), AIC, and beta values (β) for each IVs considered. The AIC comparison for each rating scale showed that the models that best fitted the data included acceleration as a continuous IV. These acceleration models explained 48% of the variance estimated for speed F[(4, 171) = 38.9, $p < 0.0001$], 39% for effort F[(4, 171) = 27.28, $p < 0.0001$], 38% for enjoyment F[(4, 171) = 26.18, $p < 0.0001$], and 35% for reproducibility F[(4, 171) = 22.63, $p < 0.0001$] ratings (see Fig. 6). As expected, greater acceleration ($1 m/s^2$) produced a linear enhancement in enjoyment (0.07 ± 0.01), speed (0.14 ± 0.01), and effort (0.1 ± 0.01) ratings, but a decrease in the judgment of reproducibility (−0.07 ± 0.01). Moreover, acceleration of the lower (compared with the upper) limbs was associated with increased enjoyment (0.3 ± 0.07), speed (0.6 ± 0.11), and effort (0.42 ± 0.1), but decreased reproducibility (−0.31 ± 0.08) ratings. Similar results were shown by velocity models, albeit with lower explained variance (R^2; see Table 1). Furthermore, decreasing both smoothness and entropy, that is, greater kinematic variability and predictability produced a linear enhancement in enjoyment (smoothness: 0.01 ± 0.01 entropy: 0.41 ± 0.06), speed (smoothness: 0.02 ± 0.01; entropy: 0.93 ± 0.01), and effort (smoothness: 0.01 ± 0.01; entropy: 0.6 ± 0.08) ratings, but a reduction in perceived reproducibility (smoothness: 0.01 ± 0.01; entropy: 0.44 ± 0.07). There were no limb-specific effects for smoothness and predictability, except for the speed ratings.

4. Discussion

Our aim was to evaluate how subtle changes in movement timing shape kinematic complexity and the aesthetic evaluation of human action. Specifically, we manipulated the movement timing of otherwise identical dance sequences and quantified the resulting objective changes in motion energy, smoothness, and entropy to predict subjective enjoyment, effort, and reproducibility. We found that information-based measures of stimulus complexity (Berlyne, 1974; Pearce & Wiggins, 2012) predict perceived effort and reproducibility, linking the aesthetics of human movement to both information theory and effort heuristic accounts of aesthetic perception.

Dance sequences with variable kinematic profiles were perceived as

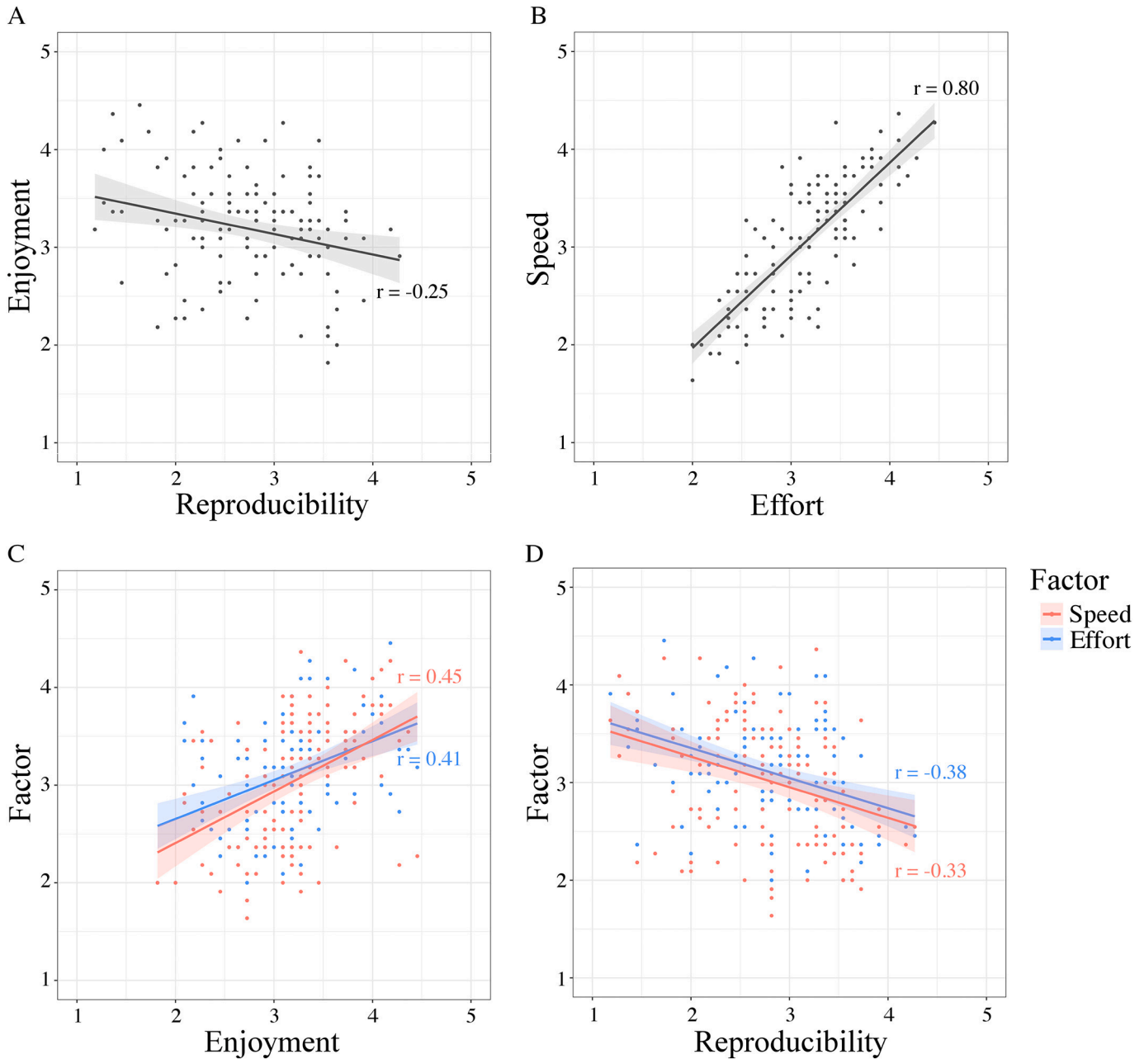

Fig. 5. Significant Pearson's r correlations between the subjective ratings (mean value for each stimulus condition) for all 4 DVs. The negative correlation between enjoyment and reproducibility ratings ($r = -0.25$) suggests enhanced aesthetic appreciation as a function of decreasing perceived ability to reproduce the dance sequences (A). The speed was positively ($r = 0.8$) correlated with the perceived effort required by the movements (B). Finally, both speed and effort had a positive impact (speed: $r = 0.45$; effort: $r = 0.41$) on the enjoyment judgments (C), but negatively affected (speed: $r = -0.33$; effort: $r = -0.38$) the reproducibility ratings (D).

more enjoyable than the same sequences performed with a more uniform kinematic profile (see Fig. 4), despite identical movement trajectories and movement elements. Increased enjoyment ratings can be attributed to the higher number of velocity changes and movement stops made by the performer, which resulted in greater kinematic variability and predictability of the varied dance clips. This result is consistent with the idea that the aesthetic appeal of dance involves effective nonverbal communication via movement (Grau, 2015; Hanna, 1987; Orgs et al., 2016). Variable movement timing emphasizes both the structure and the elements of the movement sequence, thereby enhancing the range of bodily expression (Laban, 1950). Our findings are also consistent with a preference for faster rather than slower dance movement (Christensen et al., 2019; Deinzer et al., 2017), and emphasize the role of pausing and stopping for the aesthetics of dance (Vicary et al., 2017).

Stimulus complexity plays an important role in the aesthetics of the visual arts (Donderi, 2006; Nadal et al., 2010) and in music (Beauvois, 2007; McDermott, 2012; Pearce & Wiggins, 2012). Our findings show that stimulus complexity is equally important for the aesthetics of human action. Moreover, the relationship between kinematic complexity and the observer's enjoyment depends on how kinematic complexity is quantified. If computed as the variability of velocity over time (motion smoothness), we observed a negative correlation between complexity and enjoyment. In other words, participants found less smooth dance sequences more enjoyable to watch than dance sequences that scored high in smoothness. In contrast, if kinematic complexity is

Table 1
Multiple regressions models. The table illustrates the multiple regressions for each rating scale (dependent variable, DV), which included the interaction between the limb and body side categorial independent variables (IVs) and one out of the four kinematic parameters as continuous IV. The variance explained by each model is reported (R^2) together with AIC used to estimate the goodness of fit. Each IV included in the regression models is reported with the relative β coefficients. The models that best fitted the data (for each rating scale) included the acceleration as continuous IV.

IVs	Relative contribution to DVs			
	Speed	Effort	Enjoyment	Reproducibility
Velocity	*AIC: 299***	*AIC: 215***	*AIC: 110***	*AIC: 141***
	R^2: 0.32	*R^2: 0.27*	*R^2: 0.27*	*R^2: 0.22*
	F(4, 171) = 19.98	*F(4, 171) = 15.87*	*F(4, 171) = 15.49*	*F(4, 171) = 12.37*
Limb	β: 0.48**	β: 0.53**	β: 0.53**	β: −0.48**
Side	β: 0.24	β: 0.22	β: 0.22	β: −0.20
Velocity	β: 0.73**	β: 0.68**	β: 0.67**	β: −0.62**
Limb:Side	β: −0.25*	β: −0.23*	β: −0.23*	β: 0.21
Acceleration	*AIC: 253***	*AIC: 184***	*AIC: 80***	*AIC: 111***
	R^2: 0.48	*R^2: 0.39*	*R^2: 0.38*	*R^2: 0.35*
	F(4, 171) = 38.9	*F(4, 171) = 27.28*	*F(4, 171) = 26.18*	*F(4, 171) = 22.63*
Limb	β: 0.46**	β: 0.41**	β: 0.41**	β: −0.39**
Side	β: 0.19	β: 0.17	β: 16.64	β: −0.16
Acceleration	β: 0.78**	β: 0.71**	β: 69.96**	β: −0.67**
Limb:Side	β: −0.19*	β: −0.17	β: −0.17	β: 0.16
Smoothness	*AIC: 330***	*AIC: 244***	*AIC: 141***	*AIC: 164***
	R^2: 0.19	*R^2: 0.14*	*R^2: 0.12*	*R^2: 0.12*
	F(4, 171) = 9.78	*F(4, 171) = 7.16*	*F(4, 171) = 6.11*	*F(4, 171) = 5.69*
Limb	β: 0.13	β: 0.11	β: 0.11	β: −0.10
Side	β: 0.08	β: 0.07	β: 0.06	β: −0.06
Smoothness	β: −0.44**	β: −0.39**	β: −0.36**	β: 0.35**
Limb:Side	β: −0.17	β: −0.15	β: −0.14	β: 0.14
Entropy	*AIC: 297***	*AIC: 224***	*AIC: 125***	*AIC: 147***
	R^2: 0.33	*R^2: 0.23*	*R^2: 0.20*	*R^2: 0.20*
	F(4, 171) = 20.65	*F(4, 171) = 12.9*	*F(4, 171) = 10.68*	*F(4, 171) = 10.69*
Limb	β: −0.07*	β: −0.06	β: −0.05	β: 0.05
Side	β: 0.03	β: 0.02	β: 0.02	β: −0.02
Entropy	β: −0.59**	β: −0.50**	β: −0.46**	β: 0.46**
Limb:Side	β: −0.11	β: −0.09	β: −0.08	β: 0.08

Legend: AIC-Akaike Information Criteria. (*p*-value significance: ** $p < 0.001$; * $p < 0.05$).

quantified as motion entropy (Delplanque et al., 2019; Volchenkov & Bläsing, 2013), more predictable dance sequences conveying less information produce greater enjoyment. Conceivably, kinematic predictability is linked to a more regular rhythmical structure of the dance sequences with varied movement timing, despite the absence of music in our dance sequences. Importantly, this pattern of results aligns with general aesthetic principles of unity in variety (Fechner, 1876; Phillips et al., 2011), or beauty as the ratio between order and complexity (i.e., symmetry and number of dots in static visual patterns; Makin et al., 2018). In our study, order corresponds to kinematic entropy, whereas complexity corresponds to kinematic variability. Future studies should aim to systematically disentangle the relative contributions of these two dimensions to the aesthetics of human action. Finally, the positive linear relationship between predictability and enjoyment is in line with predictive coding accounts of art evaluation (Kesner, 2014; Van de Cruys & Wagemans, 2011; Vuust & Witek, 2014). In sum, beautiful actions are characterized by *kinematic unity in variety*, that is frequent, yet predictable changes in movement acceleration and velocity.

We can think of at least two reasons why highly variable, yet predictable human movements should be aesthetically pleasing. First, the human repertoire of movement is characterized by distinct characteristics such as minimum jerk (Casile et al., 2009; Flash & Hogan, 1985). Varied dance sequences exaggerate these typically human kinematic properties in line with Kreitler and Kreitler's idea that dance movements are “remote from habitual movement” (Kreitler & Kreitler, 1972). Second, greater kinematic variability in combination with greater predictability might facilitate the recognition of emotions from human actions and therefore facilitate effective communication and social signaling (Orgs et al., 2016, Hagen & Bryant, 2003). Several studies report a direct relationship between movement kinematics and both aesthetic judgment (Chang et al., 2020; Torrents et al., 2013) and emotion recognition (Dael et al., 2013; Pollick et al., 2001; Sawada et al., 2003; Van Dyck et al., 2013). For instance, the maximum acceleration of a movement strongly influences the perception of sadness and anger, with the former predicted by low acceleration values, and the former by higher values (Sawada et al., 2003). Similarly, happy movements are characterized by higher impulsiveness, velocity, and acceleration parameters (Van Dyck et al., 2013). The attribution of emotional expressions may thus be easier for highly variable yet predictable movements, leading to greater engagement of the audience with the varied timing dance phrases, consequently boosting their enjoyment ratings. Such an interpretation is consistent with the idea of a direct link between kinematic features of observed movement and movement expressivity (Sawada et al., 2003), but challenges the notion that differences in movement expressivity can not be explained by differences in movement kinematics (Christensen et al., 2019).

Furthermore, dance sequences with varied movement timing were rated as less reproducible relative to their uniform versions, and enjoyment correlated negatively with reproducibility judgments (see Fig. 5A). This result is consistent with findings reported by Cross and colleagues, in which non-dancer participants showed an enhanced preference for the dance steps rated as more difficult to reproduce (Cross et al., 2011). It also suggests that novice dance spectators apply the effort heuristic to dance and movement in much the same way as they apply it to the visual arts (Kruger et al., 2004). In this regard, our regression models for velocity and acceleration showed that kinematic information of the dancer's feet had a greater impact on both enjoyment and reproducibility evaluations than kinematic information of the dancer's hands (see Fig. 6). This difference can be potentially explained by the greater degree of freedom of movement of hand actions than that

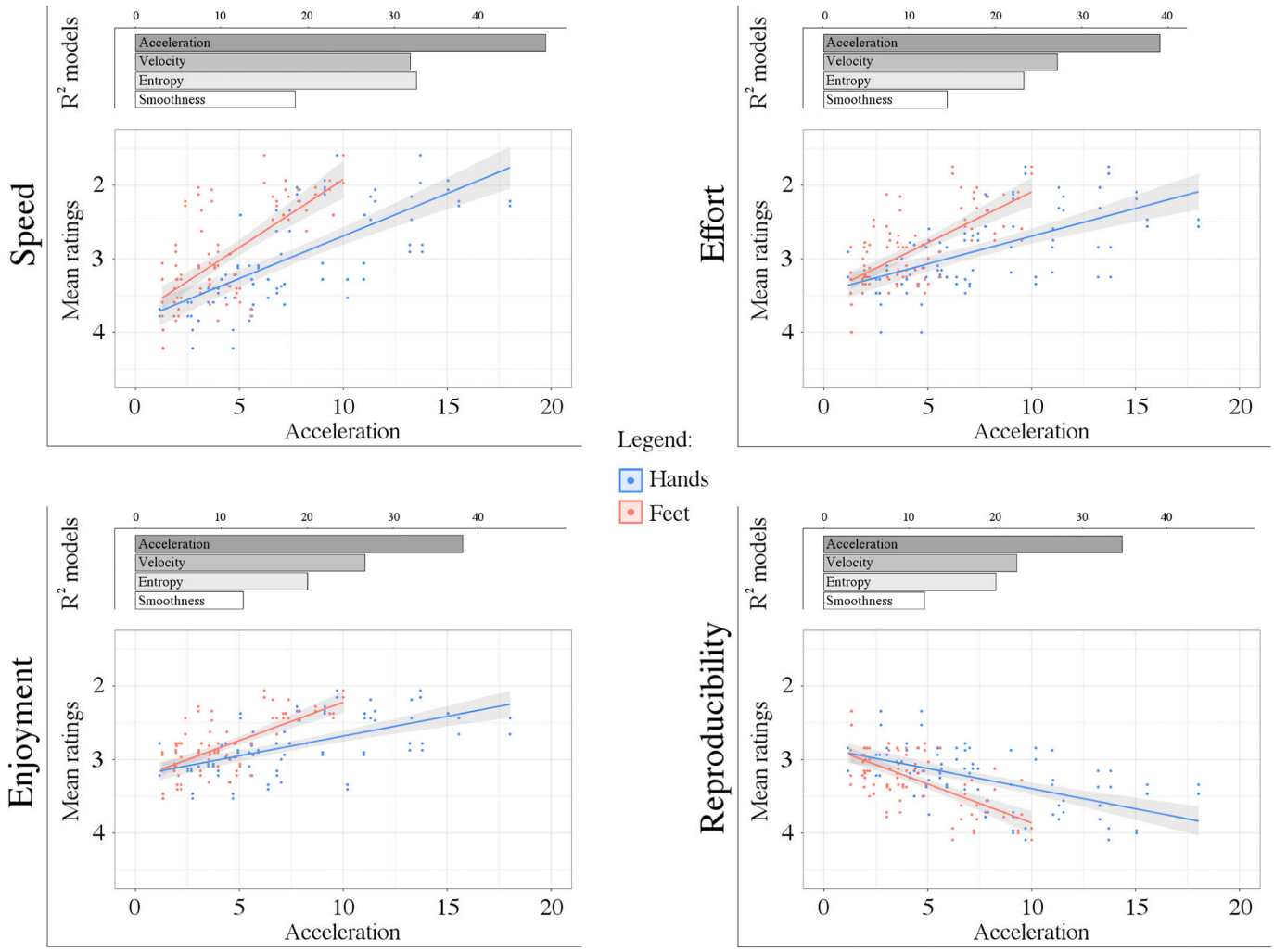

Fig. 6. Relative contribution of movement acceleration to dance aesthetics. For each rating scale, the bar plots illustrate the variance explained (% of R^2) by the regression models considering one out of the four kinematic parameters (acceleration, velocity, predictability/entropy, and variability/smoothness). The acceleration is the best predictor of the evaluations made by the observers. The scatterplots show the positive impact of acceleration on perceived speed, effort, enjoyment, and the negative impact on reproducibility. It is of note that lower limb acceleration has a greater impact on subjective judgments than upper limb acceleration.

of the feet. In contrast to hand actions, the kinematic variability of lower limb actions like walking, running, or jumping, is typically constrained by body weight. Hence, greater kinematic variability of the feet is more "remote from habitual movement" than kinematic variability of hand actions and should thus exert a greater influence on aesthetic movement perception.

Overall, uniform sequences appeared less effortful, yet the perceived effort was greater if dance videos were presented in the correct forward playback direction. Arguably, perceived effort was underestimated in the backward condition due to the reversal of the natural relationship between movement kinematics and gravity (Orlandi, Arno, & Proverbio, 2020, Orlandi, D'Incà, & Proverbio, 2020). Reduced sensitivity of action perception for time-reversed movements has been previously reported for walking (Maffei et al., 2014; Viviani et al., 2011) and for emotion recognition from dance (Christensen, Gomila, et al., 2016). Apart from effort judgments and in keeping with Christensen and colleagues (2016), participants in our study were not sensitive to playback direction. For spectators with little or no dance experience, dynamic changes in movement timing are the best predictor of dance appreciation, regardless of the playback direction of the videos.

Finally, we explored relationships between all four subjective rating categories (see Fig. 5). The positive relationship between speed and effort indicated increased perceived effort with increasing movement speed. This result is consistent with studies reporting greater perceived effort for running than walking (Hreljac et al., 2002). Also, speed and effort positively modulated enjoyment judgments, but negatively impacted reproducibility judgments. In this context, it is important to note that uniform velocity movements are often *more difficult* to perform than varied velocity movements, as they involve less momentum and require more muscular effort to maintain a constant speed (Pereira et al., 2016). For the aesthetic judgment of movement at least, perceived subjective effort matters more than the objective effort of the dance artists' performance.

Nevertheless, participants exhibited high agreement levels in all the four factors of interest, as shown by the interclass correlation coefficients (ICC). While the ratings for speed and effort were within the range of excellence (Koo & Li, 2016), those for enjoyment and reproducibility were within the range of goodness. This evidence suggests that, despite intrinsic individual differences in subjective ratings (Jacobsen & Höfel, 2002; Street et al., 2016), kinematic variability and predictability similarly modulated dance aesthetics. Such findings are far from guaranteed, since the aesthetic appreciation of artifacts of human culture (i.e., artworks, architecture) is typically more susceptible to individual differences (Jacobsen, 2010; Vessel et al., 2018) than that of natural objects or scenes. Certainly, further studies will be

required to clarify the impact of action timing on action aesthetics, and the role played by both the observers' level of dance experience and in cross-cultural contexts (Hanna, 2003).

In conclusion, we studied the role played by subtle variations in movement timing on both the objective kinematic features of dance movement, as well as the subjective perceptual evaluation of these movements. As hypothesized, the sequences characterized by greater timing variations were perceived as more enjoyable to observe relative to the same sequences uniformly executed. The former were also judged as faster, more effortful, and less reproducible compared with the latter. Our findings show that effective communication in dance is linked to kinematic variability and predictability and directly impacts on the aesthetic pleasure derived from watching dance. In keeping with the effort heuristic account, observers reported greater enjoyment of those dance movements that appeared harder to perform. We show that perceived effort does not just relate to what kinds of movements are performed, but also to *how* these movements are performed. Our findings point to the existence of kinematic aesthetic primitives of human movement – frequent, yet predictable velocity changes – that may be aesthetically relevant across a wide range of choreographic traditions, dance styles, and movement vocabularies from different cultures.

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CRediT authorship contribution statement

G.O., E.S.C. and A.O designed the study and developed the research question. A.O. performed and supervised data collection, and performed the data management and analysis. A.O. and G.O. wrote the manuscript. E.S.C. and G.O. provided critical review, discussion and revision of the manuscript. All authors approved the manuscript.

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Declaration of competing interest

The authors declare no competing interests.

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