Biocybernetics and Biomedical Engineering 46 (2026) 202–210

Contents lists available at ScienceDirect

Biocybernetics and Biomedical Engineering

journal homepage: www.elsevier.com/locate/bbe

Parameters selection for entropy measures in kinematic assessment of social intentions

Gianmaria Mancioppi [a], Erika Rovini [b,*], Jasmine Pani [b], Elisa Beccai [b], Auriane Gros [a,c,d], Valeria Manera [a], Filippo Cavallo [b]

[a] The CoBTeK, Université Cote d'Azur, 10 Rue Molière, 06100 Nice, France
[b] Department of Industrial Engineering, University of Florence, via Santa Marta 3, 50139 Florence, Italy
[c] Speech and Language Pathology Department of Nice, Faculty of Medicine, Université Côte d'Azur, Campus Pasteur, 28 Av. de Valombrose, 06107 Nice, France
[d] Clinique Gériatrique du Cerveau et du Mouvement, Centre Mémoire Ressources et Recherche, CHU de Nice, Institut Claude Pompidou, 10 Rue Molière, 06100 Nice, France

ARTICLE INFO

Keywords:
Approximate entropy
Motor intention
Social interaction
Inertial measurement
Sample entropy
Wearable sensors

ABSTRACT

This study investigates the use of entropy metrics to enhance traditional analysis of grasping movements. The authors examined whether signal unpredictability measures—Approximate Entropy (ApEn) and Sample Entropy (SampEn)—can reveal motor control aspects during reach-to-grasp actions. They aimed to determine if entropy could infer the movement's underlying intention, distinguishing social (SOC) versus individual (IND) goals. Wrist acceleration data were collected via wearable Inertial Measurement Units (IMU) from 12 older adults performing repetitive reach-to-grasp tasks in two conditions: IND (acting alone) and SOC (passing an object to an experimenter). The hypothesis predicted that social actions involve tighter motor control, resulting in lower entropy. ApEn and SampEn were computed using different parameter sets (embedding dimension m = 2, 3; similarity criterion r = 0.1, 0.2, 0.3). Mixed-model repeated measures ANOVAs and linear mixed-effects models assessed differences between conditions and parameters. Results showed significant effects of condition, m, and r, including m × r interactions. Both ApEn and SampEn yielded lower entropy in the SOC condition, confirming the hypothesis. ApEn showed greater robustness and consistency across parameter settings and preprocessing steps compared to SampEn. This study is the first systematic comparison of ApEn and SampEn for action-related time series in social versus non-social contexts. Findings highlight the impact of social context on motor control. ApEn, especially with lower m (2) and r (0.1–0.2), is recommended for future studies due to its reliability and sensitivity in distinguishing movement intention.

1. Introduction

Grasping is a complex, multifaceted motor act essential for interacting with the environment. It is a crucial topic of study in various scientific fields, from psychology to robotics. It represents an ability that humans develop over time, and its study could help characterize the level of maturation of the central nervous system in children [1] and serve as a proxy for healthy aging [2]. Furthermore, grasping analysis might provide valuable information in neurological conditions, such as stroke or Parkinson's disease, or in the rehabilitation field related to orthopaedical conditions. Eventually, it might represent a crucial aspect even in neuropsychological issues such as apraxia. Beyond clinical applications, its comprehension could be crucial also in the world of robotic prosthesis or to improve manipulation skills in industrial or companion robots.

For these reasons, the human hand and its capabilities—particularly grasping—have been the focus of extensive scientific literature [3,4,5]. Over the years, with the advent of new tools for movement assessment, a wide range of parameters has been employed to characterize and study grasping. In a seminal study, Jeannerod identified key kinematic parameters that should be examined in grasping, including: the movement time; the peak velocity; the time to peak velocity; the shape of the velocity profile; the acceleration peak; the time to peak acceleration; the peak deceleration; the time to peak deceleration; the grip size over time;

* Corresponding author at: Department of Industrial Engineering, University of Florence, via Santa Marta 3, 50139 Florence, Italy.
E-mail addresses: gianmaria.mancioppi@univ-cotedazur.fr (G. Mancioppi), erika.rovini@unifi.it (E. Rovini), jasmine.pani@unifi.it (J. Pani), elisa.beccai10@gmail.com (E. Beccai), auriane.gros@univ-cotedazur.fr (A. Gros), valeria.manera@univ-cotedazur.fr (V. Manera), filippo.cavallo@unifi.it (F. Cavallo).

https://doi.org/10.1016/j.bbe.2026.01.006
Received 3 July 2025; Received in revised form 20 November 2025; Accepted 30 January 2026
Available online 8 February 2026

the maximum grip aperture (MGA); and the maximum grip aperture time [6].

Interestingly, the kinematics of grasping is influenced by the intrinsic properties of the object relevant to the task. Notably, in a seminal review, Castiello compiled literature on how these properties affect grasping [3]. One key finding is that MGA is directly related to object size, with a linear relationship between the two [7]. Besides, Smeets et al. reported that heavier objects require more precise grasping compared to lighter objects, which can be grasped with a larger grip [5]. In contrast, Weir et al. demonstrated that object weight does not significantly affect the kinematics of grasping. These findings suggest that object weight may have been a confounding factor in previous studies investigating object size [8]. Another important factor appears to be object fragility. For example, visual information about an object's fragility significantly influences the reaching phase, leading to a prolonged deceleration phase and a delayed peak closing velocity of the fingers [9]. Additionally, the size of the contact surface plays a crucial role in grasping. Object width has been shown to significantly affect movement time, with smaller object widths resulting in longer movement times and an extended deceleration phase. Peak hand aperture is also dependent on object width, increasing proportionally as object width increases. Eventually, peak finger closing velocity is influenced by object width, with larger widths leading to higher peak closing velocities [10].

It has been suggested that human grasping is heavily influenced also by the meaning attributed to an object, and by the intentions associated with the action. Recent findings in behavioral neuroscience suggest that the execution of a motor act (*e.g.* grasping an object) is determined by the agent's intention (why we grasp), which tends to adapt the current motor act to better fulfill the intention which originated (*e.g.* grasp an object to pass it to someone or to use it directly) [11,12,13]. Consequently, kinematic analysis may serve as a powerful tool for investigating the mechanisms that facilitate social interactions. This is an intriguing piece of literature, which mostly includes the use of motion capture techniques to track upper limb kinematics of participants. Notably, in recent studies, researchers [14,15] have tried to characterize action kinematics in social and individual reach-to-grasp tasks using inertial measurement units (IMUs). The use of IMUs could expand the study of upper limb functionality making it more affordable and feasible also in clinical settings.

Strikingly, all of the aforementioned studies, including the two that employed IMUs to analyse grasping actions, employed spatiotemporal and kinematic parameters to characterize subjects' performance. According to Zanin [16] spatiotemporal and kinematic parameters answer the same "what" question regarding the characterization of motor phenomena, or better, "what is the subject doing?". Spatiotemporal parameters are those that assess how the body moves as a whole (e.g. speed) or how the grasping action is configure d (e.g. time to reach the object), while kinematic parameters focus on the motion description, describing the displacement of particular body segments around the different joints (e.g. angle of maximum opening of thumb and index finger). Zanin et al. suggest incorporating additional measures derived from the field of statistical physics. One of the main objectives of this branch of physics is to characterize the constituents of a system when only its emergent global dynamics are observable [16]. A key measure from this field is entropy, which quantifies the predictability of a signal. Concerning biological time series, entropy reflects the probability that similar patterns of behaviour will not be followed by additional similar patterns. This provides a measure of unpredictability in the time series, which could reflect changes in upstream motor control [17]. As such, entropy is crucial for identifying shifts in system dynamics and other structural aspects of a signal, offering insights into its temporal organization and underlying patterns [18]. Therefore, while kinematic analysis describes the specific characteristics of movement patterns, entropy quantifies their underlying regularity over time, offering valuable information about the motor control system. Together, these approaches provide a more comprehensive understanding of motor behaviour, providing insight into the control strategies that individuals use to perform different movements and about the adaptive capacity of the motor system, and offering researchers complements to the spatiotemporal and kinematic perspective for analysing and interpreting signals [18]. In this context, investigating entropy could provide a more comprehensive understanding of movement dynamics, control, and adaptability of grasping an object in neutral and social condition.

Among all the entropies measurements, the two most widely used algorithms are Approximate Entropy (ApEn) and Sample Entropy (SampEn). Both are built on the concept of Kolmogorov-Sinai entropy but try to overcome limitations of this algorithm concerning the presence of noise in the signal [19]. ApEn was designed for use with experimental data, specifically time series generated by biological processes. It quantifies the predictability of a time series by evaluating the likelihood that two segments of the signal are considered similar [20]. On the other hand, SampEn is very similar to approximate entropy but attempts to rectify some of the shortcomings of the ApEn algorithm. Concerning ApEn, some precautions are taken to avoid the issue of having to take the log0, which is undefined. However, as reported by Richman and Moorman [21], this leads to entropy values that are biased toward regularity. SampEn's modifications reduce the bias of the metric. Moreover, SampEn is mostly independent of the length of time series, which represents a great advantage when working with clinical data, since is more reliable than ApEn for short data sets [17].

Nevertheless, some caveats must be taken into account when researchers want to apply these two algorithms to their data. In particular, an influential work of Yentes and colleagues [17] addresses the principal pitfalls that could be encountered in the application of these techniques. Yentes and colleagues provide a practical guide for the adoption of entropy, when it is adopted with new protocols that are not well known and with short data sets. Authors stated that it is paramount to study the effect of changing the parameter values m (the embedded dimension), r (the similarity criterion) and N (the length of the time series) needed for the calculations of both ApEn and SampEn on short data sets with respect to human action (i.e. gait). For further information see paragraph Entropy algorithms in Materials and Methods. Secondly, authors state that it is crucial to describe the relative consistency of the algorithms concerning the parametrization of m, r and N. Furthermore, it is essential to assess the ability of each algorithm to distinguish between the target condition and a baseline or control condition [17].

In this work for the first time, entropy has been applied on time series coming from inertial data to identify two identical gestures performed in two conditions that differ on the intention behind the gesture (social or individual intention) [14,15] and we followed the guidelines proposed by Yentes and colleagues. In this work we have the following research hypotheses (RH):

- RH1: that the value of ApEn and SampEn would change as a function of m, r.
- RH2: that each algorithm would be able to discriminate between data coming from social and individual actions.
- RH3: that social action would demonstrate lower entropy levels reflecting a more intense motor control.

2. Materials and methods

2.1. Participants

Sixteen older adults were recruited at the Memory Center (CMRR) of Nice University Hospitals (CHU of Nice, France) and at the CoBTeK research laboratory of the Université Côte d'Azur in the context of Marco-Sens multicentric research protocol, which was performed in accordance with the Declaration of Helsinki and approved by the ethical committee CPP Ile de France (N° IDRCB: 2019-A00342-55). The participants were recruited between May and July 2023. Each of them

provided informed consent for this study. Five were male (31%) while 11 were female (69%). The average age was 72 years (standard deviation 8 years). All of them underwent a neuropsychological screening test (i.e. the Mini Mental State Examination −MMSE-) and no one exhibited major cognitive decline (MMSE > 24) [22].

Inclusion criteria were being right-handed, having no motor impairment of the upper limb or reduced motility, and being able to perform four tasks lasting five minutes in which they had to grasp and move a small object.

Notably, the sampling strategy focused on older adults, as the goal of this work is to characterise and deploy entropy-based kinematic measures in elderly populations. Recruiting an older cohort maximises ecological and clinical relevance and avoids extrapolating from younger adults, given known age-related differences in motor control, fatigue, and movement variability.

2.2. Instrumentation

We adopted a wearable system based on microelectromechanical sensors (MEMSs) that was composed of one module for upper limb motor assessment, called SensHand. It consists of four customised IMU-based boards, with one coordination unit included in a bracelet and three more units placed on the distal phalanxes of the thumb, index, and middle fingers, within finger thimble packages. The coordination unit communicates with the rings through custom spiral cables using the Controller Area Network (CAN-bus) standard (Fig. 1). Additionally, the bracelet unit synchronises the data exchange between the nodes of the device. The sampling frequency rate is 100 Hz. Bluetooth modules enable the wireless transmission of the acquired data to a remote personal computer. A graphical user interface allows clinicians to store data and to analyse the motion parameters offline [23].

2.3. Experimental procedures

The experimental protocol represents a modified version of the social grasp protocol presented by Manera and colleagues and Rovini and colleagues [14,15] and adapted from [24]. The subjects were asked to wear SensHand on the dominant hand. Participants were seated in a quiet room facing a rectangular table. They placed their dominant hand in the starting position, which was marked with a blue rectangle, located 3 cm away from the edge of the table in a midsagittal position, 15 cm away from the midsection (Fig. 2). A cylindric 3D-printed object (Ø = 5 cm, height = 8.5 cm) was positioned on the table in front of the participant at 21 cm from the starting position along the midsagittal plane (object position marked with a yellow square). After 5 s of acquiring the baseline static position with the relaxed hand placed on the table sideways a tone signalled to the participant to start the task. Participants were asked to reach and grasp an object in two conditions.

In the individual condition (IND), participants were required to reach the object and grasp it (phase 1); move it and place it inside a 3D-printed container (Ø = 7 cm; rim height = 3 cm) positioned on the table, 28 cm to the right of the object's initial location (marked by a green rectangle) (phase 2); return the hand on the starting position, remaining still for approximatively 2 s (phase 3); reach again the object (task part 4), return it to its starting position (task part 5), repositioned their hand to the initial starting point (task part 6) and remained still for approximately two seconds before starting the next trial. Participants repeated the task continuously for 5 min (Fig. 2 a). Notably, the 3D-printed container was designed to match the height and surface characteristics of a human hand positioned palm-up on the table. The container was not secured to the table; its design limited the displacement.

In the social condition (SOC), participants reached the object and grasp it (phase 1), handed it to a partner (phase 2), and return to the starting position (phase 3) and keep it still for approximately two seconds. Phases 1 and 3 were identical to the corresponding IND phases. The experimenter acted as the action partner and was seated to the right side of the partner with their wrist on the table in the target position with the fingers slightly bent forming a concave shape (like the 3D-printed target). The experimenter's hand remained completely still throughout the movement and did not initiate any grasping action. Upon object placement, the experimenter secured the object by closing the fingers. Following the participant's return to initial position (phase 3), the experimenter returned the object to the starting location. The task was repeated continuously for 5 min (Fig. 2 b).

Importantly, to mitigate fatigue effects, participants were instructed to interrupt the task at any time if they felt tired or uncomfortable. After each condition, they were explicitly asked whether they had experienced any fatigue. If participants reported fatigue and interrupted the trial or indicated that they had not performed the task correctly due to fatigue arising during execution, their recordings were excluded from the final analysis.

The order of administration of the IND and SOC conditions was randomized across participants.

The experimental protocol has been designed to be repetitive and produce cyclic signals to meet specific methodologic needs, discussed in the Signal Processing and Conclusions sections.

2.4. Signal processing and data analysis

The sensors worn on the subject's hand recorded the acceleration, angular velocity, and orientation of the hand for the entire duration of the two tasks. Data were off-line processed using MatLab® (The MathWorks, Inc., Natick, MA, USA). In particular, the magnitude of acceleration along the three axes (x, y, z), recorded by the coordination unit of the SensHand worn on the wrist by the subject (Fig. 1), was calculated as the square root of the sum of the squares of each element of the time series. This represents the absolute value of acceleration, regardless of its direction. The signal exhibits inherent cyclicality; therefore, an a priori hypothesis regarding its entropy level is required. The cyclic nature of the signal may reduce its entropy level, as seen in [25]. The

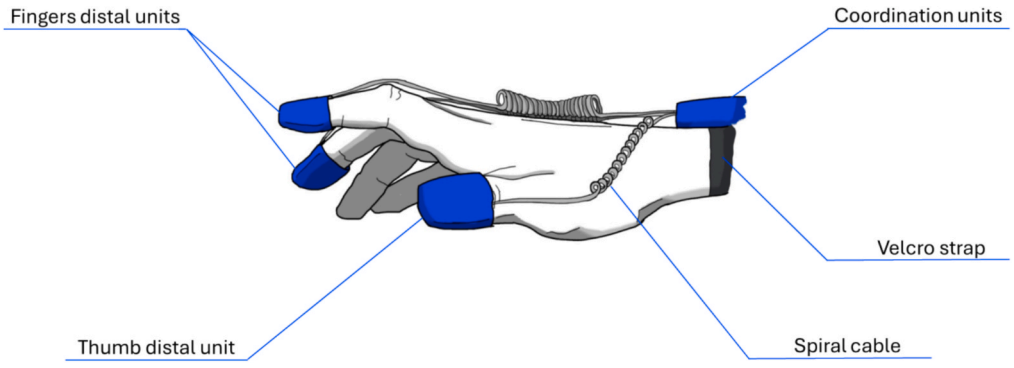

Fig. 1. SensHand System.

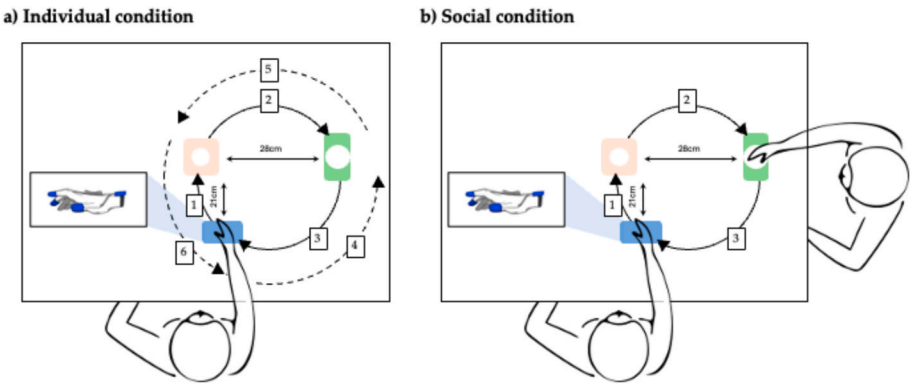

Fig. 2. Schematic representation of the experimental setup. The subject wore the SensHand on their dominant hand. The subject sat in front of a rectangular table with the hand in the starting position. Prompted by an auditory cue, they reached and grasped a cylindric object in two conditions. In the Individual condition (a), they performed the task alone. In the Social condition (b), they performed the task with a partner. The position of the hand of the experimenter and the 3D-printed target was identical. Breakdown of all phases in the IND and SOC conditions. The IND task consists of six phases: (1) reach and grasp the object; (2) move the object to the 3D-printed target; (3) return the hand to the rest position 1; (4) reach and grasp the object again; (5) replace the object at its starting position; and (6) return the hand to the rest position 2. In contrast, the SOC task includes three phases—namely, the first three phases of the IND task: (1) reach and grasp the object; (2) pass the object to the experimenter's hand; and (3) return the hand to the rest position.

acceleration-magnitude signal was filtered using a fourth-order Butterworth low-pass filter. The cut-off frequency was adaptively defined for each subject's time series as the fundamental frequency of the signal plus 2 Hz, where the fundamental frequency was obtained from the main peak of the power spectral density. The additional 2 Hz margin was chosen based on the typical temporal characteristics of the movement (lasting approximately 1 to 1.5 s), to ensure preservation of the fundamental component while attenuating higher-frequency noise. Therefore, the chosen cut-off frequency can be considered appropriate to remove unwanted high-frequency components and retain the frequency range relevant to typical human reach-to-grasp movements. This cut-off frequency was then normalised, following standard practice in digital filter design. Notably, recent studies reported that SampEn calculation could be susceptible to the effects of preprocessing in particular the use of Butterworth filtering, which may have reduced the algorithm's ability to detect condition-related signal variability [26].

Afterward, each subject's acceleration-magnitude signal was plotted and visually inspected to identify non-stationary events, such as signal drift. Simultaneously, the signals were examined to detect outliers and spikes.

As described in the Experimental Protocol section, in SOC condition subjects performed the task with the experimenter, who repositioned the target object at the starting location after each trial. In contrast, in IND subjects themselves moved the object from the goal back to the starting position after each trial. This procedural difference resulted in distinct signal patterns, as the movements were not identical. Therefore, in each IND task, the portion of the signal corresponding to the action of reach and grasp for the second time the object (IND phase 4), the action of moving the 3D printed object from the goal to the starting position (phase 5), and the final returning phase (phase 6) were identified, removed, and the remaining meaningful segments of the signal (phases 1, 2, and 3) were concatenated. Importantly, this procedure may influence entropy calculations, and results should be interpreted accordingly [25].

2.5. Statistical analysis

As reported in the participants' section, 16 subjects have been recruited in this study. Four of them have incomplete datasets and thus the statistical analyses were performed on 12 participants.

To investigate the RHs, two separate mixed-model repeated measures ANOVA were performed to investigate the effects of condition (IND or SOC), m, r, and their interaction on SampEn and ApEn. A random intercept for each subject was included to account for the within-subject variability.

The assumptions of normality of the residuals, sphericity, and homogeneity of the variances were checked using the Shapiro-Wilk, Mauchly's, and Levene's tests respectively. If the sphericity assumption was violated, the p values were corrected using the Greenhouse-Geisser method. On the other hand, if the homogeneity of the variances were violated, the entropy values were log-transformed and Levene's test was repeated. If the assumption was still not met, then linear mixed-effects model was performed. The model included condition, m, and r as fixed effects, along with their interactions. The subject was included as a random intercept to account for individual differences. After the linear mixed-effects model, Type III ANOVA Satterthwaite's approximation for degrees of freedom was performed. This approach accounts for violations of sphericity and unbalanced data, making it a robust alternative to repeated-measures ANOVA.

Post-hoc analyses for the interactions were conducted using estimated marginal means. Bonferroni correction was applied to adjust for multiple comparisons. To visualize the interactions, estimated marginal means were plotted.

A p value lower than 0.05 was considered statistically significant. The analyses were conducted in RStudio (version 4.4.2) using the "ez" [27], "emmeans" [28], and "lme4" packages [29].

3. Calculation

3.1. Entropy algorithms

In this work ApEn and SampEn have been adopted to estimate the randomness of a data series by analyzing patterns within the data [19] and quantify the likelihood that similar sequences of data points remain similar when the sequence is extended by one more point. Notably, a brief description of the two algorithms can be found in the following paragraphs.

3.1.1. ApEn

ApEn algorithm takes as input the time series data of length N, a tolerance interval r, and a vector length m. The time series of length N is divided into short vectors of length m, then, it is counted how many of these vectors are considered similar. To determine whether two vectors are similar, one compares each element in the vector with the corresponding element in the second vector. The two are considered similar if the differences are below the radius r (Eq. (1). The process is repeated with a vector of length of $m + 1$. Similar vectors of length m are counted and the log average found, and then similar vectors of length $m+1$ are

counted and the log average found. For the analysis of a time series with unknown structure, the idea is to compare the number of similar vectors of length m with the number of similar vectors of length $m+1$ and use the result as a measure of the randomness of the time series.

$$C_i^m(r) = \frac{(numberofjsuchthatd[x(i), x(j)] \leq r)}{n} \tag{1}$$

The method used by Pincus in the ApEn calculation to compare the counts for the different vector lengths is to calculate the function Φ, one for vectors of length m (Φ^m) (Eq. (2) and the other for vectors of length $m+1$ (Φ^{m+1}) (Eq. (3), then subtract them to find the approximate entropy (Eq. (4). The m or $m+1$ just denotes the chunk size used in calculating the Φ, and is not to be taken as indicating an exponent. Note that just as the C's depends on the r that was used, the Φ's will also depend on it.

$$\phi^m(r) = \frac{1}{N-m+1} \sum_{i=1}^{N-m+1} logC_i^m \tag{2}$$

$$\phi^{m+1}(r) = \frac{1}{N-m} \sum_{i=1}^{N-m} logC_i^{m+1} \tag{3}$$

$$ApEn = \phi^m - \phi^{m+1} \tag{4}$$

Values of approximate entropy will range from 0 to 2. Zero represents no entropy or a perfectly repeatable time series, while two represents a perfectly random time series [18,20].

3.1.2. SampEn

Data treatment for sample entropy is very similar to that of ApEn, yet it does not count self-matches, thus eliminating a bias towards regularity. It is still a probability measure and is defined as the negative logarithm of the conditional probabilities that two sequences similar for m points remain similar at the next point [21]. Moreover, SampEn takes the logarithm of the sum of conditional probabilities rather than the logarithm of each individual conditional property as ApEn does. Concerning the calculation of SampEn, the number of similar vectors is counted for length m and their conditional probabilities are summed and divided by $N-m$. This represents the value A_i. This procedure is then repeated for vector length of $m+1$ and represents the value B_i. Sample entropy is defined as follows:

$$\lim_{N\to\infty} -ln\frac{A_i}{B_i} \tag{5}$$

However, to resolve the limit, SampEn is calculated as follows:

$$-ln\frac{A}{B} \tag{6}$$

where:

$$A = \frac{(N-m-1)(N-m)}{2} A_i \tag{7}$$

and

$$B = \frac{(N-m-1)(N-m)}{2} B_i \tag{8}$$

SampEn is not defined for $A = 0$ (log0 is undefined), and for $B = 0$ (division by zero is undefined). Thus, the bias that was introduced into the ApEn algorithm by self-counting is not present in SampEn, but those cases where there are no matches other than self-matches are now undefined [18].

3.1.3. Parameter selection

A key consideration in the application of both ApEn and SampEn algorithm to experimental time series data is the selection of appropriate parameters. These include the r and m and N values. Typically, m is set to a value of 2 or 3 both for ApEn and SampEn [21,30]. Notably, SampEn does not have an upper limit, and if m is too large and r is small the entropy value may converge toward infinity. Generally, in data ApEn, r should be a value between 0.10 −0.25 times the standard deviation [18]. Whereas, concerning SampEn, Lake et al. suggested to choose the r parameter by finding a value that minimizes the relative error of sample entropy and the relative error of conditional probability [30]. Besides, m and N are related as the value of m depends on the length of N, where the N needs to be at least 10^m. Nevertheless, N has an enormous effect on the calculation of ApEn [18], while it seems to be independent for calculating SampEn [21].

Based on the current academic discussion regarding the choosing of parameters values there is no set combination of parameters that will be appropriate in all contexts, and a range of parameter combinations should be examined before data collection. Yentes et al. explored how parameters selection would affect both ApEn and SampEn [17]. Authors suggested that both measurements are sensitive to parameter choice, especially for short data sets, and suggested: 1) to include a N larger than 200 and appropriate to capture the dynamic of the system; 2) to examine different values of m ($m = 2$ and $m = 3$); eventually 3) to study several r values ranging from 0.1 and 0.3 [17]. Further, a parameter combination that demonstrates an abrupt change from the parameter combinations nearby, should be avoided.

4. Results

In the following paragraphs, the results will be presented separately for ApEn and SampEn. For each key finding that addresses one of the RHs, a corresponding reference will be provided.

4.1. ApEn

Normality assumption for the ApEn highlighted that the residuals were normally distributed ($p = 0.77$) and that the variances were homogeneous ($p = 0.37$). Yet, sphericity was violated for r, and the condition*r and m*r interactions.

Results from the repeated measures ANOVA revealed significant main effects of condition, m and r (Table 1). Additionally, there was a significant interaction between m and r, indicating that the effect of m on ApEn scores varied across the levels of r (Table 1) (RH1). The 2-way and 3-way interaction with condition were not significant, suggesting that m and r had a similar effect in both conditions (RH2).

As seen in (Fig. 3) estimated ApEn for the IND condition tends to be higher than SOC at each level of r, yet the two conditions have the same decreasing trend at increasing levels of r. Furthermore, there interactions with conditions were not statistically significant (Fig. 4 b).

Post-hoc pairwise Bonferroni-adjusted comparisons for m within each r level, showed that for $m = 2 and m = 3$ there were significant differences between all combinations of r ($p < 0.0001$). Additionally, at $r = 0.1$, $r = 0.2 and r = 0.3$ ApEn calculated with $m = 2$ was significantly higher than $m = 3$ ($p < 0.005$).

Table 1
Repeated measures ANOVA analysis on ApEn data.

	F (df)	p value
Condition (IND vs SOC)	10.26 (1,11)	**0.008**
m	1038.52 (1,11)	**<0.001**
r	944.94 (1.24, 13.65)	**<0.001**
Condition*m	2.23 (1,11)	0.16
Condition*r	0.87 (1.15, 12.69)	0.38
m*r	238.43 (1.11, 12.22)	**<0.001**
Condition*m*r	2.50 (2, 22)	0.11

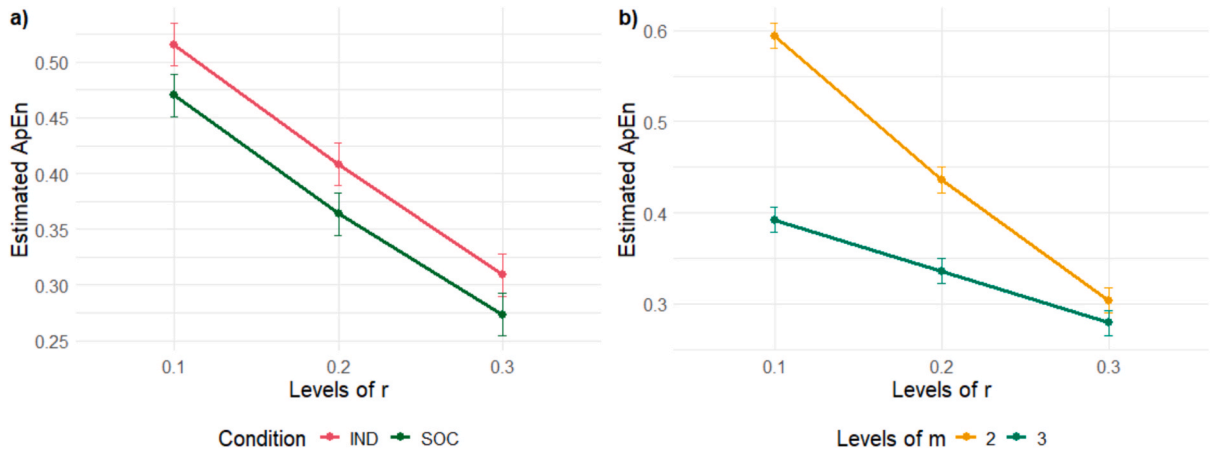

Fig. 3. a) Estimated marginal means for condition * r interaction; b) Estimated marginal means for m * r interaction.

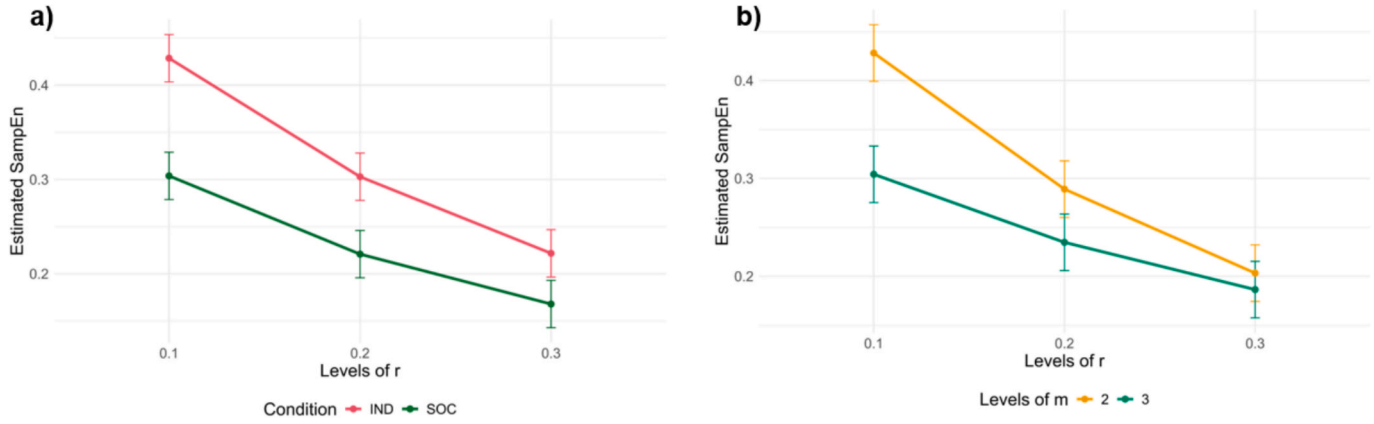

Fig. 4. a) estimated marginal means for condition * r interaction; b) estimated marginal means for m * r interaction.

4.2. SampEn

For SampEn the normality assumption was met ($p = 0.08$), yet the variances were not homogeneous ($p < 0.001$) and the Mauchly's test showed that the sphericity was violated for r and all the interactions with r (all $p < 0.001$). SampEn was log-transformed but the homogeneity of variances assumption was still not met. We therefore opted for a linear mixed-effects model. Type III ANOVA revealed significant main effects of condition, r and m and significant *condition**r and r*m interactions, whereas the *condition**m and *condition**r*m interactions were not significant ($p > 0.05$) (Table 2) (RH1 and RH2).

Post-hoc pairwise comparisons revealed that SampEn for the IND condition was significantly higher than SOC at all levels of r (all $p < 0.001$), although the effect decreases as r increases (Fig. 4 a) (RH3).

With respect to the m*r interaction, analysis of $m(m = 2 vs m = 3)$ levels across r conditions showed a significant effect at $r = 0.1 and r = 0.2$ ($p < 0.0001$), but no significant difference at $r = 0.3$ ($p = 1.0000$). Specifically, $m = 2$ consistently had higher SampEn than $m = 3$ at lower r levels, but this effect diminished as r increased (Fig. 4 b).

Table 2
Linear mixed-effects model analysis on SampEn data.

	Linear mixed-effects model, Type III ANOVA	
	F (df)	**p value**
Condition (IND vs SOC)	141.49 (1.132)	**<0.001**
m	79.3459(1.132)	**<0.001**
r	186.4539 (2.132)	**<0.001**
Condition*m	1.5132 (1.132)	0.22
Condition*r	7.9812 (2.132)	**<0.001**
m*r	18.4557 (2.132)	**<0.001**
Condition*m*r	0.6971 (2.132)	0.50

4.3. Exploratory analysis

Although the interaction effects *condition**r, *condition**m or three-way interactions were not statistically significant in the main analysis for ApEn, we conducted an exploratory analysis based on findings from SampEn. This choice is motivated by the tendency of ApEn to underestimate entropy due to its inclusion of self-matches, as discussed in the Entropy Algorithms section. Specifically, we examined whether differences between conditions (IND vs. SOC) emerged at $m = 2 and r = 0.1$, given that this combination showed meaningful effects in SampEn. This analysis aimed to investigate whether a similar pattern could be observed in ApEn, potentially revealing condition-related differences that were not evident in the omnibus tests.

ApEn was not normally distributed ($W = 0.89$, $p = 0.01$) and thus non-parametric analyses were preferred. The Wilcoxon-signed rank test for paired data was performed. There was a significant difference between IND and SOC ($V = 73$, $p = 0.005$), with IND having higher ApEn values than SOC (IND median $= 0.64$, IQR $= 0.03$; SOC median $= 0.58$, IQR $= 0.07$) (RH3).

5. Discussion

To our knowledge, no previous study has examined how entropy measures behave in a social reach-to-grasp paradigm, nor how the

parameterization of ApEn and SampEn may influence the detection of social vs. individual action dynamics. This represents a significant methodological gap, particularly given that entropy-based analyses are increasingly used to quantify the subtle structure of motor variability. As suggested by Yentes et al. [17], the selection of entropy parameters (e.g. m and r) is a crucial step when analyzing novel or complex motor signals. The present exploratory study addresses both gaps by evaluating how entropy measures derived from wrist accelerations acquired using wearable IMU sensors from 12 older adults vary across values of m and r and by testing whether these metrics are sensitive to the social aspect in which the action is performed (IND or SOC).

ApEn and SampEn were computed for all combinations of $m = 2$ and 3, and $r = 0.1$, 0.2, and 0.3 for both experimental conditions (IND and SOC). Statistical analyses were conducted to examine the independent and interactive effects of m, r, and condition on each entropy metric. The analyses revealed a clear main effect of condition, m, and r for both ApEn and SampEn, confirming our first hypothesis (RH1). Furthermore, they differed between the SOC and IND conditions (RH2) and higher entropy values in the IND compared to SOC were found across all parameters combinations both for ApEn and SampEn (RH3). This finding suggests that actions performed without an impending social interaction are characterized by greater irregularity and complexity in the acceleration signal. Conversely, the social context appears to reduce motor signal entropy, consistent with the idea that preparing to coordinate with another person requires greater motor control, predictability, and anticipatory structuring of the movement.

With respect to the m * r interaction, post-hoc analyses further showed that both ApEn and SampEn were influenced by different m and r combinations, although in distinct ways. ApEn demonstrated a clear and consistent decrease across increasing r values, and ApEn values computed with $m = 2$ were always higher than with $m = 3$. This parameter stability may be beneficial in experimental contexts where the primary goal is to identify parameter combinations that reliably maximise entropy-based differences between very similar conditions. For example, in clinical settings this may include assessing early or subclinical stages of disease, mild forms of social, cognitive, or physical impairment, or at-risk individuals, where subtle changes in motor variability may otherwise be difficult to detect with conventional measures. SampEn, by contrast, showed strong sensitivity only at lower r levels, with significant differences between $m = 2$ and $m = 3$ for $r = 0.1$ and $r = 0.2$, but not for $r = 0.3$. These findings indicate that while both metrics respond to changes in m and r, SampEn becomes less effective at capturing signal irregularity as r increases, whereas ApEn remains sensitive across the full parameter range.

Finally, a significant interaction between condition and r was observed for SampEn but not for ApEn. The fact that this IND–SOC difference diminishes at higher r levels suggests that SampEn's discriminative capacity is dependent on the choice of tolerance, emphasizing again the parameter sensitivity of this metric. Guided by the SampEn results, we identified $m = 2$ and $r = 0.1$ as a promising parameter combination for maximizing the detection of SOC vs. IND differences. Indeed, exploratory analyses confirmed that ApEn computed with these parameters also revealed higher entropy in IND compared to SOC.

Overall, IND yielded higher entropy than SOC possibly because of the distinct control strategies required by the two tasks. Social interaction imposes constraints that encourage more stable and less variable motor strategies, possibly reflecting enhanced top-down attention, increased sensorimotor monitoring, or tighter coupling between perceptual expectations and motor output. In the IND condition, participants may rely more on self-paced, exploratory, or less constrained motor plans, resulting in richer variability. In contrast, the SOC condition likely elicits anticipatory interpersonal coordination, prompting participants to regulate their movements more strictly to support successful interaction (e.g., timing alignment, spatial predictability, or communicative clarity). This interpretation aligns with work of social motor control showing the need for increased stability and reduced variability when actions carry communicative or cooperative significance [31].

5.1. Practical recommendations and implications

Based on the results of this exploratory study, it is possible to define some practical recommendations about the choice of the entropy algorithm to be used and the selection of the parameters.

Concerning the choice of the algorithm for entropy quantification, even if SampEn is theoretically less biased in short time series, in this exploratory study ApEn appeared more consistent and robust across conditions, parameter configurations, and preprocessing effects; SampEn is more susceptible to the effects of preprocessing (i.e., Butterworth filtering), which may have reduced its ability to detect condition-related signal variability in this study. Saying that the results of this study suggest that ApEn offered greater internal consistency, making it preferable when methodological robustness is a priority. Moreover, ApEn also shows greater discriminative ability between SOC and IND conditions. Notably, both for ApEn and SampEn, $m = 2$ provided higher entropy values and greater sensitivity than $m = 3$. Low values of r $(0.1, 0.2)$ were also associated with greater discrimination between experimental conditions, particularly for SampEn, while higher values of r tended to reduce entropy values. Interestingly, the observed lower entropy in the SOC condition for both algorithms supports the hypothesis that socially contextualized actions exhibit higher motor regularity, as mentioned in the above section it could reflect enhanced top-down cognitive control, motor planning, and anticipatory coordination during social interaction.

5.2. Limitations and future directions

This study presents a first comparative application of ApEn and SampEn to action-related time series within social and non-social contexts. Nevertheless, some limitations should be acknowledged.

First, the sample size was small, limiting the generalizability of the findings, which should be viewed as preliminary guidance for future work using entropy measures in social grasping. Second, the time series were relatively short, preventing the use of more advanced metrics (i.e. Multi-Scale Entropy). Third, differences between the IND and SOC tasks required segmenting and concatenating IND signals to obtain time series comparable to SOC. Although this approach has been adopted in studies involving clinical populations with constrained recording durations, it introduces two considerations: 1) slight variations in the experimental protocol between the IND and SOC conditions may have affected the temporal and cognitive characteristics of the movements; and 2) segmentation of cyclical movements in the IND task, followed by the concatenation, may have introduced non-linearities and discontinuities into the data series, potentially affecting the entropy estimates. These aspects were mitigated through task randomisation and careful monitoring of fatigue but should be considered when interpreting the results. Additionally, the target objects different between conditions (hand vs container), which may have influenced motor behaviour or planning despite efforts to standardise the procedures. Eventually, the 100 Hz sampling frequency exceeded the effective bandwidth of the acceleration signal which may introduced some oversampling. As highlighted in previous work [32], oversampling can linearise the time series, increasing the similarity between successive samples and thereby reducing ApEn/SampEn values. As both IND and SOC conditions were acquired and processed identically, in the present study, this effect is expected to influence primarily the absolute magnitude of entropy but minimized in comparing the conditions. Nevertheless, future work should systematically examine the impact of different sampling frequencies on entropy estimates and on the interpretation of kinematic variability in this population.

Future work on the topic should include larger sample sizes to validate the findings of this preliminary study, as well as the extension of the

framework to clinical populations, to evaluate whether entropy-based metrics can serve as biomarkers of motor control in social scenarios. This approach could be particularly relevant for clinical conditions characterized by impaired social interaction, such as apathy syndrome. In addition, future studies should address some methodological limitations of the present work, including the potential influence of inherent differences between the IND and SOC task structures (i.e., task phases and the differences between hand and container targets), refining the experimental design to disentangle whether the observed differences between conditions were driven by the intention component, the global motor sequence component, or a combination of both. As well as the use of signal segmentation and concatenation procedures, which may introduce subtle distortions in entropy estimation. Implementing more homogeneous task designs and continuous data acquisition protocols could help reduce these confounding factors and enhance comparability between conditions. Moreover, the use of longer time series would allow for the application of additional complexity measures, thereby enriching the characterization of motor behaviour across multiple time scales. Another promising direction for future research could be the study of entropy applied not only to acceleration data, as done in this work, but also to kinematic and spatiotemporal parameters extracted from the signals, such as movement time, time to peak velocity, and maximum grip aperture. This could provide complementary insights into movement variability and motor control. Eventually, testing different post-processing segmentation strategies, together with surrogate data analyses, may further enhance the robustness and interpretability of the results.

6. Conclusions

This study represents the first systematic comparison of ApEn and SampEn in this signal type and task context. While both algorithms were sensitive to differences between experimental conditions, ApEn provided greater robustness across parameter values. Based on the current results, we recommend using ApEn with low value of $m = 2$ and r in the range of $0.1 - 0.2$ as a practical starting point for future analyses of similar data. The lower entropy in social conditions supports the theoretical notion of increased motor control and structure during socially oriented actions. These findings offer practical guidance for future studies and lay the groundwork for the development of entropy-based metrics in social motor neuroscience.

Declaration of Generative AI and AI-assisted technologies in the writing process

During the preparation of this work, the author(s) used ChatGPT, an AI language model developed by OpenAI, in order to revise and improve the clarity and fluency of some parts of the English text. After using this tool, the author(s) reviewed and edited the content as needed and take (s) full responsibility for the content of the publication.

CRediT authorship contribution statement

Gianmaria Mancioppi: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Data curation, Conceptualization. **Erika Rovini:** Writing – review & editing, Validation, Supervision, Software. **Jasmine Pani:** Writing – review & editing, Writing – original draft, Visualization, Formal analysis. **Elisa Beccai:** Investigation. **Auriane Gros:** Investigation. **Valeria Manera:** Writing – review & editing, Validation, Supervision, Resources, Methodology, Conceptualization. **Filippo Cavallo:** Writing – review & editing, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgements

This publication was produced with the co-funding European Union - Next Generation EU, in the context of The National Recovery and Resilience Plan, Investment 1.5 Ecosystems of Innovation, Project Tuscany Health Ecosystem (THE), ECS00000017. Spoke 3. CUP: B83C22003920001.

References

[1] Nowak DA, Hermsdörfer J. Sensorimotor control of grasping: physiology and pathology. Cambridge University Press; 2009 [Chapter 17].
[2] Nowak DA, Hermsdörfer J. Sensorimotor control of grasping: physiology and pathology. Cambridge University Press; 2009 [Chapter 18].
[3] Castiello U. The neuroscience of grasping. Nat Rev Neurosci 2005;6(9):726–36.
[4] Nowak DA, Hermsdörfer J. Sensorimotor control of grasping: physiology and pathology. Cambridge University Press; 2009.
[5] Smeets B, Brenner E. A new view on grasping. Mot Control 1999:237–71.
[6] Nowak DA, Hermsdörfer J. Sensorimotor control of grasping: physiology and pathology. Cambridge University Press; 2009 [Chapter 10].
[7] Marteniuk RG, Leavitt JL, MacKenzie CL, Athenes S. Functional relationships between grasp and transport components in a prehension task. Hum Mov Sci 1990; 9(2):149–76.
[8] Weir PL, MacKenzie CL, Marteniuk RG, Cargoe SL, Frazer MB. The effects of object weight on the kinematics of prehension. J Mot Behav 1991;23(3):192–204.
[9] Savelsbergh GJP, Steenbergen B, Van der Kamp J. The role of fragility information in the guidance of the precision grip. Hum Mov Sci 1996;15(1):115–27.
[10] Bootsma RJ, Marteniuk RG, MacKenzie CL, Zaal FT. The speed-accuracy trade-off in manual prehension: effects of movement amplitude, object size and object width on kinematic characteristics. Exp Brain Res 1994;98:535–41.
[11] Cavallo A, Koul A, Ansuini C, Capozzi F, Becchio C. Decoding intentions from movement kinematics. Sci Rep 2016;6(1):37036.
[12] Patri JF, Cavallo A, Pullar K, Soriano M, Valente M, Koul A, et al. Transient disruption of the inferior parietal lobule impairs the ability to attribute intention to action. Curr Biol 2021;30(23):4594–605.
[13] Turri G, Cavallo A, Romeo L, Pontil M, Sanfey A, Panzeri S, et al. Decoding social decisions from movement kinematics. IScience 2022;25(12):105550.
[14] Manera V, Galperti G, Rovini E, Zeghari R, Mancioppi G, Fiorini L, et al. Grasping social apathy: the role of reach-to-grasp action kinematics for the assessment of social apathy in mild neurocognitive disorders. Journal of Alzheimer's Disease 2021;81(2):569–82.
[15] Rovini E, Galperti G, Manera V, Mancioppi G, Fiorini L, Gros A, et al. A wearable ring-shaped inertial system to identify action planning impairments during reach-to-grasp sequences: a pilot study. J Neuroeng Rehabil 2021;18(1–11).
[16] Zanin M, Olivares F, Pulido-Valdeolivas I, Rausell E, Gomez-Andres D. Gait analysis under the lens of statistical physics. Comput Struct Biotechnol J 2022;20:3257–67.
[17] Yentes JM, Hunt N, Schmid KK, Kaipust JP, McGrath D, Stergiou N. The appropriate use of approximate entropy and sample entropy with short data sets. Ann Biomed Eng 2013;41(2):349–65.
[18] Stergiou N. Nonlinear analysis for human movement variability. CRC Press; 2017.
[19] Delgado-Bonal A, Marshak A. Approximate entropy and sample entropy: a comprehensive tutorial. Entropy 2019;21(6):541.
[20] Pincus SM. Approximate entropy as a measure of system complexity. In Proc. 1991 national academy of sciences.
[21] Richman JS, Moorman JR. Physiological time-series analysis using approximate entropy and sample entropy maturity in premature infants Physiological time-series analysis using approximate entropy and sample entropy. Am J Physiol Heart Circu Physiol 2000;278:H2039–49.
[22] Folstein MF, Folstein SE, McHugh PR. "Mini-mental state". a practical method for grading the cognitive state of patients for the clinician. J Psychiatr Res 1975;12(3): 189–98.
[23] Cavallo F, Moschetti A, Esposito D, Maremmani C. Upper limb motor pre-clinical assessment in Parkinson's disease using machine learning. Parkinsonism and Related Disorders 2019;63:111–6.
[24] Becchio C, Sartori L, Bulgheroni M, Castiello U. The case of Dr. Jekyll and Mr. Hyde: a kinematic study on social intention. Conscious Cogn 2008;17(3):557–64.
[25] Yentes JM, Raffalt PC. Entropy Analysis in Gait Research: Methodological Considerations and Recommendations. 2021; 49(3), 979–99.
[26] Montesinos L, Castaldo R, Pecchia L. On the use of approximate entropy and sample entropy with centre of pressure time-series. J Neuroeng Rehabil 2018;15 (1):1–15.
[27] Lawrence MA. ez: Easy analysis and visualization of factorial experiments. Retrieved from http://cran.r-project.org/web/packages/ez/index.html 2013.
[28] Lenth R. emmeans: Estimated Marginal Means, aka Least-Squares Means. Retrieved from https://cran.r-project.org/package=emmeans 2025.
[29] Bates D, Mächler M, Bolker BM, Walker SC. Fitting linear mixed-effects models using lme4. J Stat Softw 2015;67(1).

[30] Lake DE, Richman JS, Griffin PM, Moorman RJ. Sample entropy analysis of neonatal heart rate variability. Am J Physiol Regul Integr Comp Physiol 2002;283 (3 52–3):789–97.

[31] Sabu S, Curioni A, Vesper C, Sebanz N, Knoblich G. How does a partner's motor variability affect joint action? PLoS One 2020;15(10):e0241417.

[32] Mesin L. Estimation of complexity of sampled biomedical continuous time signals using approximate entropy. Front Physiol 2018;9:710.