

Information integration and the latent consciousness of human groups

James R. Watson^{a,*}, Alexander Maier^b, Álvaro Novillo^c, Ignacio Echegoyen^{c,d}, Ricardo Resta^e, Roberto López del Campo^e, Javier M. Buldú^c

^a Oregon State University, USA

^b Vanderbilt University, USA

^c Complex Systems Group & G.I.S.C., Universidad Rey Juan Carlos, Spain

^d Universidad Pontificia Comillas, Spain

^e Mediacoach - LaLiga, Spain

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ABSTRACT

We have applied Integrated Information Theory, a mathematical framework for studying consciousness, to human collectives. Specifically, we have analyzed soccer teams, drawing parallels between neuronal activity in the brain and player activity on the field. We investigated whether soccer teams integrate information in a quantifiable manner, and whether this predicts team performance. Utilizing player position data from 100 matches in the Spanish LaLiga, we derived activation time series of players throughout matches, akin to the activation time series of neuronal activity. For subsets of players, the measure of information integration Φ was calculated. Our results indicate that player groups exhibit non-zero and variable Φ values over time, suggesting that soccer teams integrate information during matches. Top-performing teams such as FC Barcelona, Real Madrid, and Atlético Madrid displayed significantly higher Φ values compared to other teams. Additionally, the difference in average Φ between competing teams correlated positively with relative shots on goal, implying that higher information integration is associated with better performance. Positive values of Φ suggest a “latent consciousness” at the group level, but because it is (far) lower than the level of consciousness of individual players, it is not realized. This approach offers insights into human collective behavior and practical implications for coaching strategies. This study also demonstrates that information integration can be quantified for complex systems generally, including animal collectives and larger human social structures, and in doing so, information integration can be thought of as a general measure of complexity.

1. Introduction

What distinguishes the workings of a brain, composed of billions of neurons, from those of a soccer team, composed of 11 players? Although these systems differ in scale, composition, and their overall purpose, both can be understood as collectives of relatively simple units - neurons in the brain, or individual players on the field - that integrate information about their environment and from which a well-functioning whole emerges. Fundamentally, both the human brain and soccer teams can be considered complex

* Corresponding author.

E-mail address: james.watson@oregonstate.edu (J.R. Watson).

information processing systems, a term once used to describe neural networks [1–6], even if they are objectively very different from one another. If information processing describes how a system receives, transforms, stores, and outputs information, then information integration describes how different parts of a complex system work together. Information integration is central to our understanding of complex systems more generally, from cells to ecosystems to economies and societies, because it helps us understand how diverse components interact, adapt, and give rise to emergent behavior ([7],). Consequently, there is great interest in developing methods for quantifying information integration in complex systems and relating these measures to system function [8].

1.1. Information integration and consciousness

Beyond its role in explaining complex systems, information integration has also been central to philosophical debates about the nature of consciousness. For example, Leibniz’s mill argument [9] is a thought experiment that suggested that consciousness cannot arise from purely material, mechanical processes that integrates information, even in a complex machine of similar complexity as the human brain. The argument proposes that if we were to scale up a complex machine (for example a computer) to the size of a mill and enter it, we would only find parts pushing and interacting, with nothing that could explain the presence of consciousness. Related is Block’s [10] “China Brain” thought experiment, which asked whether a system of billions of individuals passing signals and integrating information in neuron-like fashion would itself be conscious. These thought exercises underscore an important question: is consciousness simply the functional outcome of integrated computations, or does it represent a qualitatively distinct ontological state?

If brain function is assumed to be deterministic and consistent, then any model faithfully replicating neuronal interactions, even with human individuals as stand-ins, should in theory produce identical outputs (i.e., consciousness; [11,12]). Yet our intuition rejects the idea that such collectives give rise to phenomenal consciousness. This tension reveals the philosophical challenge: even when large-scale simulations reproduce computational rules, they fail to explain why the brain is accompanied by conscious experience while other collectives are not. As a result, a robust scientific theory of consciousness must specify the conditions under which integrated information produces subjective experience and when it does not.

1.2. Information integration in human groups

Integrated Information Theory (IIT) provides a framework for addressing these questions [13–15]. IIT posits that consciousness is identical to integrated information, which is denoted Φ in IIT, and offers both qualitative principles and quantitative tools for identifying mechanisms that support it. In particular, there are two aspects of IIT that make it appealing for exploring the question of whether a collective (such as a large group of people) could have some form of consciousness. First, the Exclusion Principle of IIT specifies that among the many subsystems capable of integrating information, in a brain say, consciousness corresponds to the set of interacting elements with the maximum Φ [15]. Second, IIT is substrate-agnostic, implying that consciousness could, in principle, arise in any system that meets the necessary criteria for information integration [16].

Applied to human groups, IIT predicts that collectives such as a team of individuals, could have non-zero measures of information integration (Φ), but that these levels would be far below the threshold for realized consciousness, because information integration within individual brains would exceed that of the group. Because of the Exclusion Principle, IIT acknowledges that information integration can happen at the group level, simultaneously to information integration at the individual level, and that this group level information integration could be thought of as a form of latent consciousness. It has yet to be empirically quantified whether human (or animal) groups integrate information, and going further, whether information integration correlates with collective performance.

1.3. Information integration in soccer

Soccer provides an especially useful context for examining these questions. Soccer matches are complex, dynamic systems in which individuals continuously integrate information through visual perception, auditory communication, and planned coordinated action. Players adapt to changing conditions by combining local information into emergent collective behaviors that end up determining the outcome of matches, i.e., who wins and who loses [17]. Research in sport science has already developed tools to capture many of these dynamics: passing networks quantify how information flows through a team and reveal trade-offs between centralized and distributed coordination [18,19]; analyses of player locations through time can be used to measure synchronization, entropy, and clustering, offering insight into how spatial information is integrated to maintain shape and adapt to match conditions [18]. High-performing teams appear to balance stability and flexibility, operating near the edge of order and disorder [20].

Building on these approaches, we apply IIT’s methods for quantifying information integration (Φ) to soccer player position data. Our first hypothesis is that soccer teams do indeed integrate information in the way described by IIT, and then second, that higher levels of information integration within a team predict better outcomes relative to opponents. We use this analysis of soccer not only as a testbed for theories of collective behavior, but also as an empirical domain in which the principles of IIT can be extended beyond the brain to human groups, as it may be from the process of information integration that the “gel”, or the “flow”, or the cohesion of a team emerges, leading to better (or worse) outcomes [21]. If correct, this demonstration of the applicability of IIT to systems other than the brain, has implications both for understanding team performance in soccer, and also how complex systems more generally operate, and specifically for exploring the broader question of whether and how consciousness might emerge in complex systems where information is integrated through the operations of its component parts.

2. Methods

To explore the hypothesis that human groups integrate information in a way that is similar to the brain, we conducted the following analysis: 1) Soccer player position data was cleaned and parsed, 2) from these data, transition probability matrices for system states were computed, then 3) we used Integrated Information Theory to compute Φ , the measure of information integration (and consciousness) from the transition probability matrices. We then, 4) compared estimates of Φ with measures of success. Two additional analyses were performed, 5) a null test, and 6) we explored how our results changed with different sizes of player groups.

2.1. Data synthesis and parsing

Soccer player position data (i.e., two-dimensional location as a function of time t) for all players in two teams playing one another in a match, for 100 matches were obtained for the Spanish National League (LaLiga) during the 2018/2019 season. These data come from Mediacoach® tracking system, which makes use of the Tracab Optical Tracking system, a multi-camera system that records each player's position on the pitch at 25 frames per second. A detailed description of this dataset and the optical tracking system can be

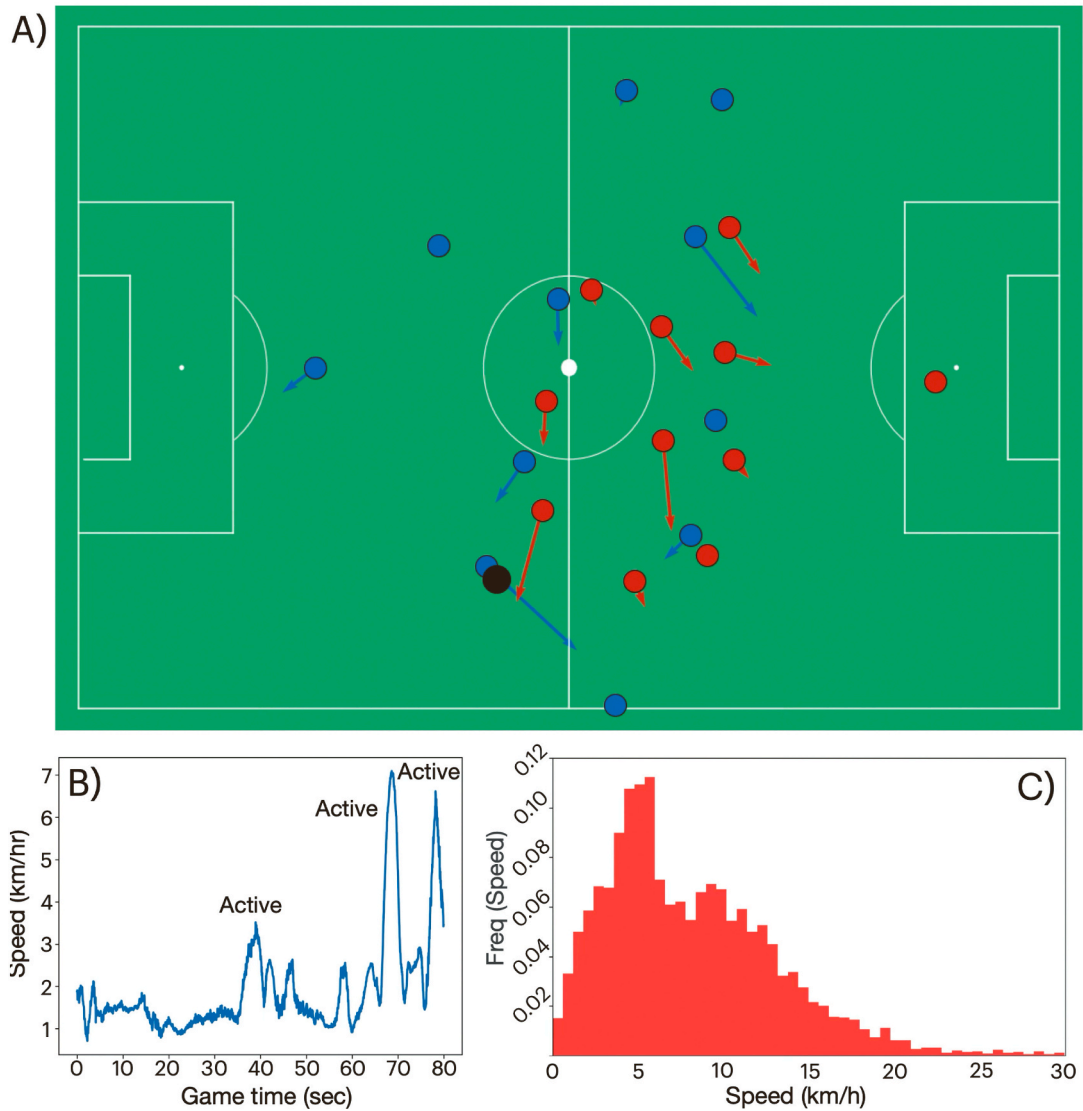


Fig. 1. A) Snapshot of player position data from a soccer match. The ball is indicated by the black dot, and the teams' players are identified in red and blue. Player velocities are identified by the arrows. B) Speed timeseries for a particular player. Highlighted periods of activity are identified by fast speeds. C) Frequency histogram of speed for a particular player. At least two modes appear around 5 and 10 km/h, and these bi-modal distributions identify a slow mode (walking) and a fast mode (running/sprinting) in soccer players, which we use to identify when a player is "inactive" and "active" respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

found in Novillo et al. [4]. This is a standardized dataset, in that the same data collection and quality control methods have been applied to all matches. With these raw data, for each player in each team in all matches, their speeds over time were computed from their positions (see Fig. 1A for an illustration, and Fig. 1B for a player speed timeseries). At this point several data parsing steps were made.

First, we examined average locations and speeds for all players in a team to identify the goalie. Goalies invariably have a slower average speed than all other players and remains close to their own goal, so this approach is efficient. Once identified, we excluded the goalies from all teams from all further analysis. Goalies have a unique role in a soccer team, and their spatial behavior is also unique. Consequently, we decided to remove them from further analysis, to better capture information integration among the other non-goalie players, which have similar spatial behaviors and informational processes (e.g., passing using feet only). See Fig. S1A for an example player speed heatmap (data for each team and each match were stored as matrixes). In this figure it is possible to see the goalie (player 0), who has speeds consistently lower than all others.

A second parsing step was to identify those players that were substituted off the field, and which substitutes came on in their place. Parsing substitutions was more challenging. As you can see in Fig. S1A, it is relatively obvious to the human eye which player is substituted for which substitute. However, there were issues relating to red cards, where a player is sent off and no substitute comes on in their place. Another issue to contend with is when two players were substituted at the same time (i.e., two players come off the field, and two new players come on the field), which is a common occurrence in soccer matches. We developed a method for dealing with these issues, focusing on the use of each player's speed timeseries, to create one continuous speed timeseries for each position on the field, rather than for each individual player. As an illustration, in Fig. S1A the players that were substituted off during the match are those with NaNs (white spaces). The substitutes that came on in their places are those whose speeds become non-NaN at the same time. For example, Player 5 was substituted for Player 13 towards the end of the match. Where a red card occurred, we just removed that entire position from the set of speed timeseries for a match. In the 100 matches that we analyzed, this only happened once.

The results of this data parsing steps were 10 speed timeseries, one for each position on the field (not the goalie), for each team, for all matches. From these speed time series (see Fig. S1 for examples), we defined time states when each player was "active" or "inactive" (e.g., Fig. 1B), which is described in more detail below. Interestingly, from the speed time series for whole teams, there is evidence of cascading behavior as subsets of players speed up or slow down collectively (Fig. S2A). These long-range interactions and evidence of collective behavior could be indicative of (being near to) criticality, which is known to be a property of other complex systems like the human brain [22–27].

Another consideration was the timescale of sampling of player positions (and hence speeds). The original data included player positions 25 frames per second. We down sampled these data resulting in speed estimates every half second. At this timescale, the raw player speed data included considerable noise, corresponding to idiosyncratic movements. To better capture more intentional and persistent (collective) spatial behaviors we applied an 8 s moving average window to all player speed timeseries. Other moving average window sizes were explored [4 s, 16 s, 32 s, 48 s] and our results are only impacted at the larger window sizes where speed timeseries become so smoothed that they lose the patterns associated with information integration. Once smoothed we analyzed player speed histograms (e.g., Fig. 1C). Across all players, speed histograms were bimodal, where slower speeds correspond to walking and faster speeds correspond with running / sprinting. We also discovered that player timeseries are stationary; we expected players to get tired over the duration of a match, and for their average speed to decrease, however we did not find evidence of this.

From the speed time series, we created binary activation time series analogous to neuronal activity time series analyzed in systems neuroscience. These binary activation time series can be used to compute Φ [28]. Simply computing the median speed of each player and then setting times when a player's speed is greater than this value to 1, and times when the player's speed is less than (or equal to) this value to 0, is sufficient for creating these binary player activation time series for every soccer player in every match (Fig. S2B). Other ways of possible binarization include i) associating active states with acceleration and inactive states with deceleration or ii) associating active states with speeds greater than the average of all other players in one's team at any given time (and conversely for inactive states). From here on though, results are shown for calculations derived from activity time series generated from the first approach (high and low speed modes), but we found that our results hold across the two other methods for defining active and inactive states. Ultimately, the binary activity timeseries contain information about activation layers, that is, at any given time there are sets of players that are active and inactive, and it is these players with these states that cause a subsequent activation or deactivation of players in the next time step. This is the core causal process underpinning neurons in a brain, and similarly for soccer players in a team. One (set of) player's state(s) affects that of another's (as well as their own) through time.

2.2. Constructing transition probability matrices

From binary activation timeseries we then computed Transition Probability Matrices (TPMs) for system states (e.g., Fig. 2A). System states are defined by the set of players that are active and inactive at any given time. The rows of the TPM identify all possible system states at time t , and columns of the TPM identify all possible systems states at time $t + 1$. TPM elements are the probabilities of the system transitioning from a given state at time t , to another system state at $t + 1$. The TPM is a 2D matrix that describes a Markov chain. Importantly, this Markov chain does not describe the isolated transitions between activation states of individual system elements. Instead, it describes the transitions of *entire system states*, where each state consists of the activation state of *all* system elements (i.e., players). In other words, IIT's formalism never *reduces* the system to an atomistic level but studies the *system as a whole*. As a result, the ensuing analysis captures more than pairwise interactions within the system and includes both the influence of players onto themselves as well as higher-order interactions beyond the pairwise level. This is an important feature of IIT in the context of this analysis of information integration by soccer teams, since higher-order interactions lie in the blind spot of many traditional data

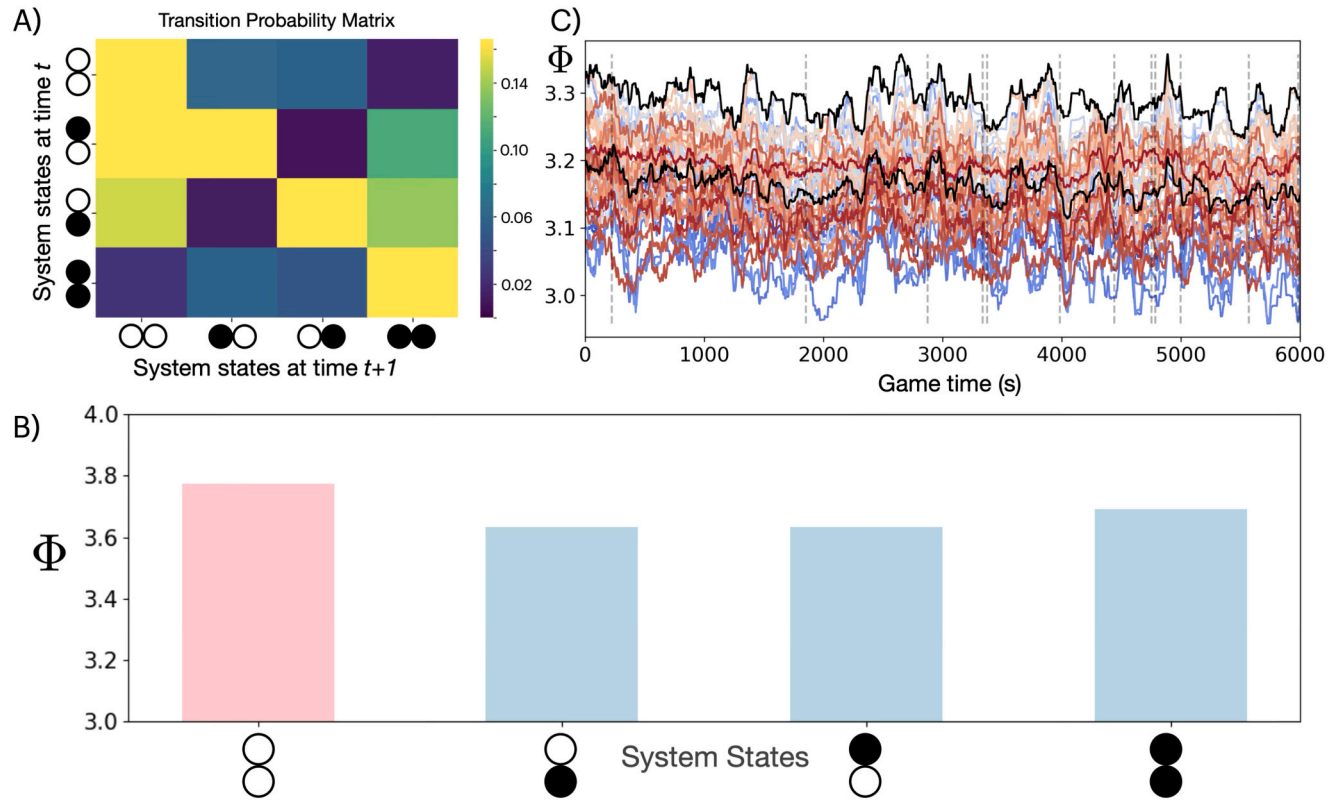


Fig. 2. A) Example Transition Probability Matrix (TPM) over system states for a pair of players. Rows correspond to system states (i.e., defined by which players are active, black dots, and inactive, white dots) at time t , and columns correspond to system states at time $t + 1$. Transition probabilities are calculated from multivariate player activity timeseries and identified by the colorbar. B) Φ over system states, integrated over the duration of the match. This figure highlights that for player pairs, the dominant states are either both all players active or inactive. C) From the TPM, IIT's measure of consciousness called Φ is computed, for all possible pairs of players in a given team. This creates 45 Φ timeseries (y-axis), one for each player pair in a team, for the duration of the match (x-axis). Colors are used to separate timeseries visually (and note, we have passed a running average over timeseries). The top black line identifies the maximum Φ over time, and the black middle line identifies changes in the average Φ over time, and grey vertical lines identify times with a shot on goal.

analysis techniques, such as Pearson (cross-)correlations, mutual information, or Granger causality, that rest on strictly pairwise considerations [29–31].

IIT's mathematical apparatus analyzes the TPM using do-calculus [32,33] to determine the causal power of one system state onto another. To do this, two sets of data are needed: the TPM describing the Markov chain, and a structural causal model (SCM) describing the possibility space (usually in the form of a Directed Acyclic Graph) of all possible pairwise causal interactions between all system elements. Typically, an IIT analysis would utilize causal intervention in the system to conclusively derive the transition probabilities. In our case (and most empirical scenarios where the transition probabilities cannot be derived a priori), this is not possible. However, if given a large enough data sample within which all relevant states are transitioned between, an observationally derived TPM will converge, or asymptote towards, an TPM derived from intervention [33,34]. This is why we chose to create one TPM per match, leveraging all the data over ~ 90 min of play to populate the TPM. The second required step, establishing an SCM, is relatively straightforward in comparison: The most probable, parsimonious, and plausible assumption for a soccer team is that every player could (at least in theory) affect the behavior (activity status) of any other player, including themselves. So the SCM is a fully connected network. This is well known for soccer teams, where long-range visual and auditory signals are regularly passed among all players.

We constructed the TPM by searching over the binary timeseries of all players, to estimate the transition probabilities from one system state to another, for all system states. However, even with binary activation states (you could imagine a system with elements having more than two states, on or off), the size of the TPM grows very quickly. Indeed, the number of elements in the TPM grows as 2 to the power of the number of players, all squared. So, with a team of 10 players (11 minus the goalie), the TPM has 2^{10} system states. This makes the computation of the TPM particularly difficult, as the time series data will not necessarily include enough samples of all possible systems states to confidently estimate transition probabilities. The size of the TPM with 10 players also makes the subsequent do-calculus computations very expensive. Given these numerical challenges, we developed a simpler alternative. Instead of computing the TPM for all 10 players at once, we computed the TPM for all possible combinations of *player pairs*, for each team in a match. With 10 players, there are $C(10,2) = 45$ possible pair combinations. Furthermore, with player pairs, the resulting TPMs are only 4×4 matrices, corresponding to the system states: one player on, the other off, and vice versa; both players on, and both players off. This reduction in the size of the TPM means that there was always enough data in the player activation timeseries to confidently estimate transition probabilities, and also to compute Φ without need for extraordinary computational power.

2.3. Computing Φ timeseries

We constructed TPMs for all player pairs, for each team, and for all matches. Specifically, for each match, each team would have a set of 45 TPMs, one for each player pair combination. These 45 TPMs were then used to compute Φ , the measure of integrated information (and ultimately consciousness) from IIT. We used the Py Φ toolbox to do so [35], which includes a series of functions for quantifying the degree of integrated information (i.e., Φ) in a system by analyzing how its elements causally influence one another. A graphical summary of the underlying computations can also be found in Leung et al. [28].

Calculating Φ involved the following key steps: A) First, we transformed the state-by-state TPMs previously described to a state-by-node format, rendering it compatible with the Py Φ python package (see [28] for details). B) Using the converted TPM, a Py Φ network was instantiated, assuming a (potential) all-to-all structural causal model (SCM) to be tested by the IIT algorithms for intrinsic causality (the system having causal power over itself). C) For each possible system state (the pair of players being studied) a subsystem within the Py Φ network is created, and its Φ -structure computed. D) The algorithmic calculations performed by Py Φ have been comprehensively described previously [13,35]. Briefly, Py Φ examines how much information can be derived from a current system state regarding the previous and immediately next system states given the known transition probabilities compared to a complete lack of knowledge regarding the system's transitional probabilities. This step allows for quantification of information using “intrinsic distance” (a unique measure for the difference between two sets of probabilities) as units ([36–38]; see Zaemzadeh and Tononi [39] for a detailed explication of the differences between bits in Shannon information and IIT's units of information). These computations are then iterated for various “graph mutilations” of the SCM. That is, each computation is repeated after replacing the established transition probabilities associated with each system element (assumed to be a node in the SCM) with noise distributions (statistical marginalization). The result of these computations is a single scalar called “system Phi” or Φ_s . Determining the state with maximal Φ_s , IIT then “unfolds” the system in that state by computing a simplicial complex (hypergraph) termed the Cause-Effect-Structure. This topological object describes the web of all causal interactions (from first to the n -th order) that are set up by the system state and quantifies each of their “strengths” as well as their “overlap”. Both these measures then get collapsed to a final scalar measure called “big Phi” or Φ , which is the final step of the analysis.

The outcome of these computations results in one Φ value per system state, for a given player pair under study. Conventionally, only the system state with maximal Φ is of interest (as the Exclusion Principle states that only maximal Φ truly exists). For our purposes, however, we were interested in how a system of players evolves over time, and so we computed timeseries of Φ . We did this by looking back at each time point and assessed the system state (which is characterized by the activation timeseries, i.e., which sets of players are active or inactive at any given time), and then we associated that time-point with the value of Φ associated with that system state. Doing this resulted in a time series of Φ for each player pair. In other words, by assuming that the TPM of the system, generated by the players, was constant we were able to derive a measure of integrated information over time. For each team in each match, 45 Φ time series were constructed.

2.4. Comparing Φ with measures of success

With measures of Φ for all player sets, we then performed an analysis comparing Φ values with measure of success. Specifically, we performed two analyses. First, we aggregated all values of Φ from all player pairs from all matches from the top three teams: FC Barcelona, Real Madrid and Atlético Madrid. We then compared the distributions of Φ , from these top teams, with the distribution of Φ from player sets from all other teams. The comparison was conducted quantitatively using Kolmogorov-Smirnov tests.

The second analysis was to compare the number of shots on goal with average Φ values, where the average Φ for a team was simply

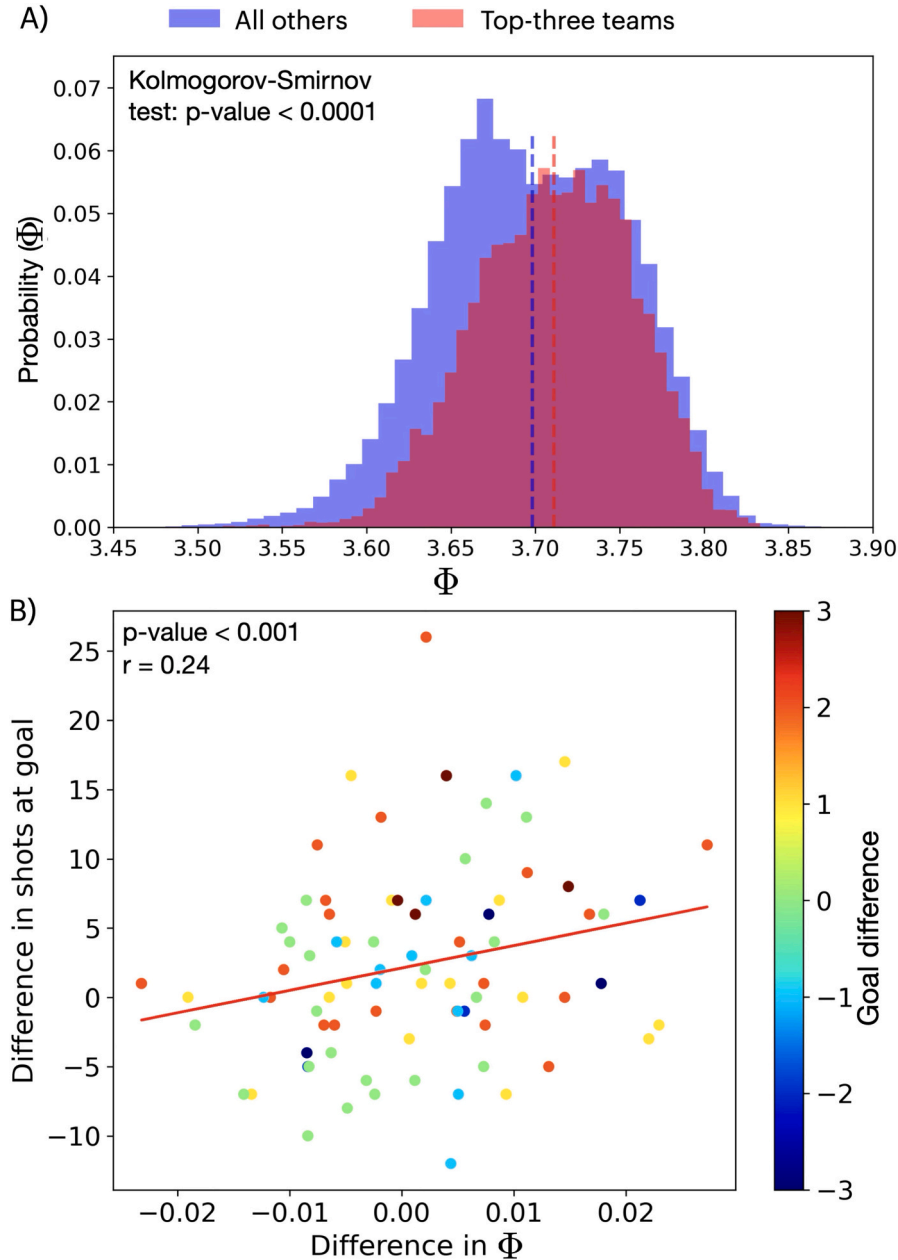


Fig. 3. A) Probability density functions of Φ for the top three teams in La Liga (FC Barcelona, Real Madrid and Atlético Madrid) in red, and all other teams in blue. A Kolmogorov-Smirnov test identifies that the top-teams have significantly higher values of Φ (K-S statistic = 0.17, p -value < 0.0001). B) The difference in the number of shots at goal (y-axis) against the difference in average Φ for two teams playing one another. A significant positive correlation is quantified using linear regression ($r = 0.24$, p -value < 0.001). Colors identify goal difference; there is a positive correlation between the number of shots on goal and the number of goals, but we do not use the number of goals as a measure of success as it is less sensitive than the number of shots on goal. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

the average over player pairs and over time. We also compared the difference in the average Φ between two teams playing one another, with the difference in the number of shots on goal. For both univariate analyses, quantified using Ordinary Least Squares, we found slight but significant positive relationships. The difference in the number of goals corresponds with the difference in the number of shots on goal, as one might expect, but although an obvious measure of success, it is less useful for describing the overall ability for one team to dominate another. This is because there are few goals scored in a match, and hence it is not a sensitive measure of success.

2.5. Shuffle control null tests

To test that whether the results are different from what one would expect from random, we developed a null test. This null test included repeating the analysis of Φ described above, but for player pairs where one player was substituted for a random player (i.e., a random player's speed timeseries), drawn from a random match (but not the match under study). With this substitution made, the analysis is performed exactly following the steps outlined above, leading to a calculation of Φ for each player pair, from each team, for all matches. We then concluded the null test by examining a) the difference in average Φ between the three top teams (FC Barcelona, Real Madrid, Atlético Madrid) and all others, and b) the correspondence between the average difference in Φ values for teams playing one another, and the difference in their number of shots on goal.

2.6. Results from larger sets of players

In addition to performing the analysis of player pairs, we applied our methodology to player trios. Just like player pairs, we computed Transition Probability Matrices and Φ for all possible combinations of three players, for each team, for all matches. Choosing three players from sets of ten (i.e., 11 minus the goalie) leads to 120 possible trio combinations. Hence, for each team, in every match, we computed 120 transition probability matrices and time series estimates of Φ .

We also performed a limited exploratory analysis of player quartets. With four players in a set, there are 210 possible player sets. The computational requirements of analyzing all 210 player sets are high, mostly due to the size of the transition probability matrix, which with 4 players is 16×16 , and the computational run-time for executing the necessary Py Φ code was excessively long (it took weeks to complete an iteration of the player trio analysis using current state of the art computing). This meant that it was not possible to complete a full analysis of Φ for all player quartet sets. The computational limits found in analyzing player quartets highlight a key advance that needs to be made if these kinds of calculations are to be done for larger sets of elements (neurons or players). Ideally, it would be possible to calculate Φ for an entire team (or for two teams playing one another). Unfortunately, for a full team of 11 players, the transition probability matrix balloons to $4,194,304 \times 4,194,304$, which presents an extreme challenge for the current IIT approaches.

3. Results

The first main result is the observation that the values of Φ from player pairs are non-zero (the minimum requirement for consciousness). In Fig. 2B we show Φ values for all possible system states for a player pair from one match; all values are around 3.6, with maximum values occurring on all-on and all-off states. We used these estimates of Φ to then construct time series of Φ over time, where we see variability over time (Fig. 2C). This suggests that groups of soccer players – as dynamic causal systems – do indeed integrate information. This result highlights that a player group acts as a wholistic system, on top of, and thus somewhat independently of, the individual player's brains. This is perhaps not surprising, but it is a simple and useful observation.

The variability over time in Φ could also be indicative of changes in the state of play of the match, such as instances of sustained pressure or periods leading up to a goal being scored (Fig. 2C, grey lines identify key in-game moments). However, this is not the focus of this analysis, but we acknowledge that it would be very interesting to analyze information integration at shorter in-game timescales. Instead, we performed two analyses at the whole-match timescale. First, we looked at the distribution of Φ values over all player pairs and matches, for each team. We then made two groups of teams. The first group consisting of FC Barcelona, Real Madrid and Atlético Madrid, the three top teams in the Spanish league at the time. The second group consisted of all other teams in the Spanish League. We then performed a Kolmogorov-Smirnov test to identify whether the Φ values from the FC Barcelona, Real Madrid and Atlético Madrid group were consistently and significantly higher than those of all other teams (Fig. 3A). Indeed, we find this to be so to a high degree of significance (p -value < 0.0001 , K–S statistic = 0.17).

The second analysis was to compare the number of shots on goal with average Φ , where the average Φ for a given team is the mean Φ over time, for all player pairs, and then the mean over all player pairs from a given match (Fig. S3). Here, we find a slight but significant positive relationship (Pearson $r = 0.23$, p -value < 0.005), highlighting that Φ , i.e., information integration, captures an aspect of performance in soccer teams. We additionally analyzed the difference in the number of shots on goal as a function of the difference in average Φ between two teams playing one another. This simple univariate analysis revealed another slight but again significant positive relationship (Fig. 3B; Pearson $r = 0.24$, p -value < 0.001), suggesting that the team with the greater Φ , has more shots on goal than the other team. We explored whether the difference in average Φ relates to the difference in the number of goals, but did not find a strong quantitative relationship. However, the number of goals and the number of shots on goal are correlated (see Figs. 3B and S3 marker colors). The number of shots on goal is a more sensitive measure of team success in that there are always more shots on goal than there are goals, and indeed there can be many matches without any goals, but many shots on goal.

In order to verify that these results are not an outcome of chance, we redid the above analyses but with a null model generated by changing to the underlying player activation time series. For every pair of players for which we calculated Φ , instead of using players

from the match being analyzed, we replaced one with a random player from a randomly chosen match and team. This severe intervention completely removed any correlation between the difference in the number of shots on goal and the average difference in Φ (Fig. S4; Pearson's $r = 0.01$, p -value >0.1); as well as the removing differences in Φ for the top teams ($K-S$ statistic $= 0.09$, p -value >0.01).

We explored the outcomes of our analyses with larger groups of player sets (i.e., player trios and quartets). With player trios there are 8 possible system states, corresponding to all possible combinations of active/inactive states for each player in a trio set. Consequently, Transition Probability Matrices for player trios are 8×8 in size (Fig. S5A) and like those for player pairs, these matrices are structured and asymmetric (although there are qualitatively similar patterns in upper and lower triangular parts). The majority of Φ values are larger than those from the analysis of player pairs, with values in the range 4.5 to 7 (relative to 2–3.5 for player pairs). Similarly to player pairs, the systems states with largest average values of Φ where the all-active or all in-active states (Fig. S5B). Timeseries of Φ for each player trio (i.e., 120 timeseries; Fig. S5C) show patterns like those observed for player pairs, with highs and lows possibly corresponding to in-game events, although we do not pursue this line of research here.

Just like the results for player pairs, we examined the distribution of Φ values for player trios, comparing the distribution of those from the top teams (FC Barcelona, Real Madrid and Atlético Madrid) with all others, and we also examined the correspondence between the difference in the average team Φ and the difference in the number of shots on goal. Interestingly, unlike the unimodal distributions of Φ found for player pairs (Fig. 3A), a bi-modal distribution was discovered when analyzing player trios (Fig. S6A). The two modes correspond with the system states shown in Fig. S5B, where the low mode corresponds to times when there is only one player in the trio that is active or inactive. The high mode corresponds to times when all players in the trio are either all active or inactive.

This bimodality suggests that the identity of the players comprising a trio (and who is in/active) is important. Unfortunately, we did not use the metadata on which player was in what position, which is required to confirm which trio configuration corresponded with which Φ mode. Nevertheless, the presence of multiple Φ modes suggests that there are different kinds of coordinated spatial behavior among certain triplet configurations, and we can imagine that certain sets of players include those that are strategically linked and those that are less so. For example, a midfielder and two strikers will often work together, through trained plays, in a highly coordinated (and repeated) manner. In contrast, a defender and two strikers are less likely to be coordinated spatially (although it is not uncommon, just less so relative to a mid-fielder). Because we iterate through all possible combinations of players to make 120 trio sets, invariably only a few of these trios will correspond with players strategically linked together, resulting in two distinct Φ modes (Fig. S6B). Nevertheless, this still revealed that the top three teams had significantly larger Φ values as per the Kolmogorov-Smirnov test ($K-S$ statistic $= 0.1$, p -value <0.01), but this might be a result of the difference between the lower modes only. The bimodal distribution also complicates the comparison of the difference in the number of shots on goal with the difference in the average Φ . This is because an average Φ over player trios will not be a good representation of the two modes. There was a weak positive (but not statistically significant) relationship (Fig. S6B; Pearson's $r = 0.11$, p -value >0.01). For the null analysis, results with player trios were the same as with player pairs; all correlation between the difference in shots on goal and the difference in Φ were removed (Pearson $r = 0.05$, p -value >0.1).

For player quartets, we were constrained in what analyses we could accomplish by computational limits. However, we did explore computing transition probability matrices (Fig. S7A) and determinations of Φ (Fig. S7B). Like for smaller player sets, the transition probability matrices show structure and are asymmetric, and the maximum values of Φ correspond with all active and all inactive system states. The values of Φ vary across system states, with the all-active and all-inactive states once again having maximal values. In general, though, the Φ values are much larger than those found for player pairs and players trios and thus a general result is that Φ values increase with player set size (Figs. 2B, S5B and S7B). To compare, we found that Φ for player pairs was typically around 3, Φ for player trios was typically around 7, and Φ for player quartets range between 80 and 100.

4. Discussion

The goal of this analysis was to examine human groups, specifically soccer teams, through the lens of Integrated Information Theory [13,15]. We used player position data to construct time series of player activity, analogous to data you might find in studies of neuronal activity (e.g., [40]). With these data, we then applied mathematical methods from IIT, specifically the computation of Φ which is a measure of integrated information and ultimately consciousness. We discovered that values of Φ for soccer teams are non-zero and variable over time, and that larger values correspond with measures of success, namely the top teams have significantly larger values of Φ relative to the other teams that perform less well, and the difference in average Φ between two teams playing one another corresponds with the difference in the number of shots on goal. These results suggest that soccer teams (not just the individual players), are complex dynamical systems that integrate information over scales of organization as they work towards achieving their objective, namely winning a match [18].

Does this mean soccer teams are conscious? Certainly not, soccer teams are not experiencing reality as we do, and indeed our analysis only considers the Integrated Information Theory of consciousness. Even though IIT has been the focus on a growing body of empirical analysis (e.g., [28,41–46]) as well as debate (e.g., [47–49]), there are many other theories of consciousness [50]. Moreover, we did not follow the strict prescription of IIT. For example, we binarized player states using their bimodal speed distributions, equating high speeds with “activation”, and importantly we generated TPMs from observational data rather than direct causal intervention. We were also limited in our analysis to small player subsets (player pairs, trios and quartets) as well as a fixed temporal resolution (sampling rate). These decisions were dictated by necessity, but we note that our measure of IIT's Φ is still a pragmatic estimate. Importantly, IIT concurs with our intuition that our data shows that the collective behavior of the players, while integrating

information towards a positive value of Φ , does not suggest emergence of a new form of consciousness because the values of Φ from soccer player sets are likely far below that for an individual's brain. This prediction is based on IIT's Exclusion Principle, which states that among overlapping sets of elements in a system, only one set can constitute a conscious experience, and this set is the one that maximizes integrated information (Φ ; [15]). In simpler terms, the human brain generates far more integrated information than that of a soccer team, thus it remains the locus of consciousness.

Our analysis does predict that it might be theoretically possible for a large set of humans to interact in such a way as to create values of Φ that exceed that of any individual's brain. We see this indirectly in our results, specifically in that the value of Φ increases with the number of players analyzed. Values of Φ for player pairs were typically around 3, whereas values of Φ for player trios were around 6 to 7, and values of Φ for player quartets ranged upwards to 70 (compare Figs. 2B, S5B and S7B). This suggests that as the number of individuals comprising a group increases, to say many billions, then the value of Φ may exceed that found for a human brain (which has yet to be computed). According to IIT, exceeding this threshold might not only lead to the emergence of a collectively construed "super-consciousness" but simultaneously cause all involved individuals' consciousnesses to cease. Given current technical limitations, we still face major hurdles preventing us to determine Φ for human brains and large human groups, but the overall premise of our study, asking whether causal interactions within human groups could lead to consciousness, is affirmed by IIT. Another way to interpret this is to consider human groups exhibiting some form of *unrealized latent consciousness*.

The Exclusion Principle has been the focus on much debate [16] and it is worth exploring the consequences of relaxing the assumption. In a soccer team there are a collection of human individuals who are conscious (we do not doubt this). However, it seems logically possible that human groups - pairs, trios, quartets, the defense, the forwards, a whole team, two teams together for example, might also exhibit a small level of realized (and not just latent) consciousness, and that these two levels of consciousness, at the individual and the group levels, might coexist, and perhaps interact, or even superimpose. This idea is at odds with the Exclusion Principle, and therefore with the current iteration of IIT (and our own line of reasoning outlined above). However, relaxing or replacing IIT's current axioms (such as exclusion) provides appealing hypotheses to explore.

An interesting anecdotal perspective in this regard describes what it is like to "lose oneself" in a group, especially in (team) sports where play is very fluid and continuous [51]. This experience of becoming somewhat "unconscious" while playing a role in a larger group is also experienced by musicians [52]. Furthermore, sports players and musicians alike have described this "flow state" as a point when training and muscle memory takes over [53]. Information is processed quickly, and integrated over scales of organizations rapidly, from pairs to trios to whole groups. In soccer, information is passed (and thus integrated) using verbal and visual signals, and an individual's behavior - what they do - is responsive not just to these signals, but to the position and spatial organization and momentum of play. Information about the environment is being integrated along with predicted information about what will happen next, based on a player's training and ability to anticipate what will happen [5]. All players in both teams will be performing this kind of information integration all the time. In sum one might consider a soccer team as being comprised of somewhat unconscious component parts, i.e., the individual players, integrating information rapidly to create a whole that is greater than the sum of its parts. Whether or not this contributes to the discussion about the Exclusion Principle is up for debate. Certainly, it is intriguing to think about witnessing (and possibly measuring) a decrease in Φ at the individual level, and an increase in Φ at the group level during moments of collective action (such as a soccer match).

Given our finding that Φ corresponds with measures of success, it is interesting to think about (coaching) decisions that maximize group or team Φ . We studied information integrated over the entire period of soccer matches, roughly 90 mins. However, it is obvious to see, from Fig. 2C (grey vertical lines identify shots on goal from either team), that calculations of Φ can be informative at shorter timescales. Specifically, as a match evolves there are certain plays such as corner or free kicks, periods of time where one team dominates the other, and shifts in momentum. While we have not analyzed these patterns of play, that happen over minutes say, derivations of Φ could be performed at these timescales using the player position data in hand, which could help in coaching decisions, specifically in terms of how players can act cohesively during these different types of play. In addition, this information could also help in making in-game changes to strategy and in terms of making key substitutions, that maximize a team's Φ . Similarly, over longer timescales (i.e., between games and seasons), one can imagine that predictive analytics could be developed that help a coach maximize a team's Φ , based on who is recruited. There is also the potential for measurements of Φ to inform strategies that maximally disrupt an opposing team's cohesion. One can imagine that these kinds of analyses could be performed on the opposing team, helping to identify key players or groups of players that are central to that team's ability to integrate information. Much of this might already be known by coaching staff and players, but only qualitatively. Developing a parallel quantitative framework around the optimization of Φ (or the maximal disruption of Φ for the opposition) would likely be useful.

If coaching decisions are being made based on Φ , then it is important to consider what processes Φ is actually measuring in a soccer team. Information integration in a soccer team will describe how well a team operates as a whole. Its cohesion. This will be reflected in the team's cause and effect structure, and how quickly activity states respond to one another. The underlying processes determining a team's cause and effect structure include passing, which forces teammates to react, verbal and visual communication, which signals to teammates a certain action to take, and also the success of set-plays, where teammates know where and when to be, and what to do (without having to signal). In particular, information integration (Φ) will describe well a particular style of play known as tiki-taka. A famous team for this style of play is the Barcelona FC team from the early 2000s, which enacted short and high-frequency passes between multiple players and had complex player interactions in general. Φ is likely to be a good measure of this style of play. In contrast there are alternative styles of play, such as playing the long-ball from goal or counterattacking, that will likely have lower levels of Φ because they do not depend on whole-team cohesion. Thus, Φ does not capture the effectiveness of these other styles of play, and indeed the tiki-taka style of play was not always successful against the potentially low Φ styles of play, and so there should caution over when and how to use measures of Φ to guide coaching decisions.

Theoretically, it is possible to reproduce this analysis – the application of IIT to compute Φ from timeseries of activity – for animal collectives, for example fish schools and animal herds. The field of animal collective behavior has long acknowledged the importance of social information in determining collective behaviors (e.g., [54–57]), and it would be potentially informative to explore information integration in animal groups using the methods from IIT. The novel contribution would be to examine the integration of information over scales of organization (that is how individuals impact the behavior of the group, and how the behavior of the group impacts the individual) and not just information passing between pairs of individuals but through hyperedges. Additionally, exploring how information integration occurs for larger and larger human social groups, for whole communities perhaps, could potentially provide insight into society. Societies have been conceptualized as performing a form of “collective computation” [58,59], and information integration is central to this. Indeed, the term “Complex Information Processing Units” used to describe early neural networks [3] aptly describes many complex systems, from societies to animal groups to soccer teams, because they all integrate information across scales of organization, as they each perform their unique form of collective computation.

It is interesting then to think of how our societies are evolving in their ability to integrate information [59]. Just like how a soccer coach might want to make a certain substitution, or recruit a certain player, to maximize their team’s collective Φ , we can think of the technologies, political economy and other institutions as determining a society’s ability to integrate information and to perform well at solving certain kinds of problems (or not well, as might be the case currently when it comes to collective action problems; [60]). In thinking about the application of IIT and the calculation of Φ for complex information processing systems [3] such as brains or large human groups, it is also possible to think of Φ as a measure of complexity. There are many measures of complexity (e.g., [61–64]), but information integration and specifically Φ uniquely captures not just the first order interactions that define common measures of complexity, but also hypergraph structures [65]. Recently, Assembly Theory has helped us to understand and measure the complexity of molecular complexes (and potentially more) as informational lineages [66]. This relatively new theory has contributed to our understanding of the evolution of life from simple dead things (e.g., molecules) that do not integrate information, to our highly complex brains, from which we know consciousness arises, to our global society, which we can also think of as integrating information. There is potential for IIT and the measure of consciousness Φ , as a more general measure of complexity, to contribute to this line of inquiry too, and conceptualize the emergence of complex structures in the universe (e.g., the human brain, human society) over millions of years, based on the level to which information is integrated. Indeed, if we can theoretically compute Φ for any arbitrarily large Complex Information Processing Unit, like our modern-day global society, then we may find that it is the most complex thing in the universe that we know of.

CRedit authorship contribution statement

James R. Watson: Writing – original draft, Supervision, Project administration, Methodology, Investigation, Formal analysis, Conceptualization. **Alexander Maier:** Writing – original draft, Validation, Methodology, Investigation, Formal analysis. **Álvaro Novillo:** Software, Data curation. **Ignacio Echegoyen:** Writing – review & editing, Investigation, Conceptualization. **Ricardo Resta:** Writing – review & editing, Data curation. **Roberto López del Campo:** Writing – review & editing, Data curation. **Javier M. Buldú:** Writing – review & editing, Supervision, Data curation, Conceptualization.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.chaos.2025.117627>.

Data availability

Test data and all code are available at: https://github.com/watsonjr/Latent_Consciousness_Of_Human_Groups.

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