scientific reports

OPEN

Graph-like organization of non-spatial knowledge about social closeness in movie narratives

Federica Santacroce[1,3]✉, Giorgia Committeri[1,3], Rosalia Di Matteo[1], Davide Di Censo[2,3], Carlo Sestieri[2,3] & Annalisa Tosoni[1,3]

Research in cognitive science has progressively highlighted the notion of geometric representations (map and graph-like structures) for storing and organizing knowledge in both spatial and non-spatial domains. It's unclear, however, whether these representations aid in organizing knowledge from unconstrained and naturalistic episodic encoding and whether it is possible to identify objective episodic parameters that support the implicit construction of structural-semantic knowledge. Here, we investigated how statistical regularities in a movie narrative contribute to the generalization process underlying social knowledge's gradual construction and organization. Using the narrative of a TV series, participants watched five episodes and then performed a retrieval task in which they rated the strength of social relationships between characters (i.e., social closeness). An objective graph of social closeness, based on parameters extracted from the teleplay, was compared to subjective social graphs derived from participants' judgments. The results revealed a strong correlation between the two graphs and highlighted the importance of physical co-occurrence in shaping social representations. The generalization process was independent of awareness of task demands, suggesting an implicit mechanism. Additionally, increased episodic exposure improved both the inter-subject stability and the coherence of the social graphs, supporting the notion that repeated episodic experiences enhance semantic representations. These findings emphasize the role of episodic statistical regularities as building blocks for the organization of non-spatial, conceptual knowledge in graph-like structures.

Keywords Generalization, Social knowledge, Statistical regularities, Graph-like representation, Movie narratives

The term "cognitive map" was first introduced by Tolman[1] as a fundamental departure from stimulus-response theories based on studies on rat navigation in traditional mazes. Tolman's idea was that rats weren't just strengthening advantageous connections through positive reinforcements but were forming mental representations of the environment as they navigated, creating mental pathways to reach their goals. About two decades later, O'Keefe and Dostrovsky's groundbreaking discovery in 1971[2] provided a potential neural foundation for this theoretical claim. Their recordings of hippocampal neurons in mice, later termed "place cells" due to their place-specific activation, suggested the presence of a physical counterpart of the cognitive map. Since then, numerous studies have supported the notion that the hippocampus encodes a map-like representation of the environment[3,4] relegating its processing to purely spatial encoding (for a review see[5].

At the same time, an alternative viewpoint emerged, overcoming the potential limitations of the original definition of the cognitive map on two main fronts. The argument challenges the notion that cognitive maps are purely spatial computations on one side and that cognitive mapping exclusively resides in the hippocampal formation, with place cells as the sole computational element, on the other[6] (see also[7] for a dual-system model of cognitive mapping). In this manuscript, we will focus on the first criticism that concerns the nature of cognitive computations underlying the mental representation of sensory experience. Reviewing a large set of studies conducted on rats' behaviour, Eichenbaum proposed that cognitive spatial representations are formed from spatial cues when these cues are the only regularities in the experimental protocol. Indeed, when other behavioural, non-spatial regularities were introduced, hippocampal activity appeared to reflect these behavioural patterns[8]. Studies involving humans have demonstrated a similar trend of encoding regularities

[1]Department of Psychology (DiPSI), University "G. D'Annunzio" of Chieti-Pescara, Chieti-Pescara, Italy. [2]Department of Neuroscience, Imaging and Clinical Sciences (DNSIC), University "G. D'Annunzio" of Chieti-Pescara, Chieti-Pescara, Italy. [3]Institute for Advanced Biomedical Technologies (ITAB), University "G. D'Annunzio" of Chieti-Pescara, Chieti-Pescara, Italy. ✉email: federica.santacroce.fs@gmail.com; federica.santacroce@unich.it

beyond mere spatial cues[9–11]. On this basis, a new model was proposed that extended the concept of a purely spatial cognitive map to that of memory space[8,12]. The building blocks of this memory space are defined in terms of precise event coding, with two broader components that capture temporal sequences of events (sequential encoding) and common features between the events (nodal encoding), respectively. In this context, cognitive representations, whether spatial or non-spatial, deviate from the rigidity of Cartesian spatial maps, taking the form of flexible relationships among learned facts and events of the world that are integrated into a singular memory network. This perspective is not far from Tolman's original proposition and is also consistent with the computational demonstration by Muller[13]who introduced the concept of the cognitive graph as a connection model considering the differential timing of activations akin to Hebbian binding (see also[14] for a more recent discussion on cognitive maps and cognitive graphs).

Over time, research around the concept of cognitive maps has mainly developed along two distinct lines, one focusing on spatial navigation and the other on episodic memory. More recently, however, a functional overlap between neurocognitive mechanisms supporting the spatial and non-spatial domains has been particularly emphasized in theoretical reviews on memory and spatial navigation[15–17] (see also[18] for a. more critical view). According to a strict version of these reconciliation proposals, navigation mechanisms can be viewed as the ancestral basis from which more complex forms of semantic, autobiographical, and episodic memory have phylogenetically developed[17]. This has motivated human behavioural investigations on the shared mechanisms between spatial navigation and memory functions[19,20]. Evidence for cognitive mapping of physical and abstract space also in other non-primate species[21,22] suggests a raw form of early relational memory that initially served to navigate physical space and has been later up-cycled for the development of high-level declarative memories. As recently suggested[12] it is plausible that a general relational, organizational mechanism, probably located in the hippocampus, serves both memory and navigation, as reflected in the argument that "remembering a route taken is simply a prominent example of episodic memory, and a cognitive map of the environment is simply a prominent example of a semantic memory structure".

In more recent theoretical proposals, the contribution of cognitive mapping in the memory domain has been explored through spatial-geometric computations, such as calculating physical distances and angles[23,24]. For example, two studies identified a time- and space-dependent activation pattern during the exploration of a virtual environment, emphasizing the encoding of distance and order of sequences[25,26]. Although these studies are clearly within the memory domain, they nonetheless maintain an experimental protocol that is still very much related to spatial navigation. Moreover, the investigated dimensions of space and time are intrinsically structured and are manipulated by the experimenter to provide a known reference structure for encoding. In this way, the cognitive process under investigation remains limited to sequential encoding. These studies are of great value, as they pioneered in translating the concept of cognitive maps from spatial to abstract representations. However, further efforts are needed to test the mechanisms behind the progressive construction of conceptual representations abstracted from the spatio-temporal context of episodic events.

Within the domain of non-spatial, conceptual knowledge, a novel line of research has proposed a cartesian-like space as the organizing principle of knowledge, where abstract concepts are represented as points in a space defined by a few, typically two, selected dimensions[23]. For example, in an fMRI study, some symbols were associated with bird silhouettes that varied in two characteristics, leg and neck length. The results indicate that participants implicitly placed the symbols in a Cartesian abstract space defined by the selected dimensions[27]. The same low-dimensional organization was also described for pre-defined dimensions (e.g. power and affiliation) of social knowledge[28,29]. Of note, while these studies have significantly advanced the field of cognitive mapping by extending the idea of geometric representations to the abstract domain of social space, one still unresolved question is whether this model also applies to the implicit construction of knowledge from multi-dimensional, naturalistic experience. More specifically, while these studies have emphasized the notion of a Euclidean-like organizational structure of non-spatial knowledge, the experimental design was based on implicit training or explicit instruction about pre-selected and continuous feature dimensions. Although the reductionist perspective of low-dimensional space is useful for describing the organizational principles of task-relevant abstract dimensions, it is still unclear whether such geometrical structures might also support the organization of non-spatial dimensions during naturalistic encoding. Indeed, spontaneous, non-spatial experience is typically multidimensional and can probably be better represented in terms of graph-like structures consisting of locations (concepts) connected by path (features)[14]. In the social domain, for example, people can be represented in a map-like structure defined by some experimentally defined continuous feature dimensions (e.g. power and affiliation; popularity and competence) or in terms of graph-like structures based on social networks (e.g. social relatedness). Few studies have used graph-like structures to generate stimulus sequences during implicit learning paradigms (e.g. sequences of items corresponding to transition matrices with an underlying graph structure)[30–32]. At the same time, recent behavioural[33]neuroimaging[34]and computational[35] studies have shown that graph-like structures based on character co-occurrence in naturalistic stimuli can capture emerging social and semantic knowledge. These findings support the idea that simple statistics extracted from real-world narratives can reflect meaningful relational structures. Parallel work in the affective domain demonstrates that the brain similarly extracts structured representations from continuous narrative input, generating affective gradients and dynamic network responses aligned with unfolding events[36–38]. Together, these studies point to a general capacity for learning higher-order regularities from rich audiovisual experience.

In the present study, we aim to investigate the process underlying the construction of social knowledge from the naturalistic encoding of narrative events in healthy adult participants. We exploited the encoding of a movie narrative (i.e. a TV series including 5 episodes), whose episodic social information (i.e., descriptions of interactions' events) was objectively detectable from the available movie teleplay. Then, a retrieval task required participants to subjectively estimate the social closeness between the movie's characters. We next performed a model comparison between the graph extracted from the participants' judgments and an objective graph derived from an in-house model that detects statistical regularities from the interactions' events of the movie teleplay. By manipulating the knowledge about the task requirements across two versions of the study protocol (i.e. interleaved vs. sequential encoding/retrieval across two groups, see methods section for more details), we further tested the implicit nature of the social knowledge construction process. We finally examined the degree to which the construction process was modulated by the amount of episodic information, by computing the graphs' correlation at different time points of the movie encoding (first vs. fifth episode of the movie narrative). This study advances previous research along three main methodological lines. First, we use an automated algorithm to extract multiple objective parameters from the teleplay, not only physical co-occurrence, but also verbal mentions and exclusivity of relationships, yielding a composite model of social structure. Second, we relate this model to social proximity judgments collected in an implicit condition, where participants had no prior knowledge of the retrieval task during viewing, allowing us to isolate spontaneous structure learning. Third, we show that this alignment between subjective and objective graphs strengthens progressively with increasing exposure, suggesting a dynamic process of abstraction that unfolds over time.

Materials and methods
Participants
A total sample of $N=40$ participants with no history of neurological or psychiatric disorders and no previous familiarity with the TV series were enrolled in the study after providing informed consent. Participants were randomly assigned to an explicit ($N=20$, 11 females; aged 18–34; mean age: 27) or an implicit ($N=20$, 10 females; aged: 19–37; mean age: 25) version of the study protocol. Participants were naïve to the study goals and the research design until the end of the experiment, when a final debriefing made participants aware of the study's aims. Written informed consent was obtained from all individual participants included in the study. The study was approved by the Departmental research review board (prot. N° 2/2023) of G. D'Annunzio University of Chieti - Department of Neuroscience, Imaging and Clinical Science in accordance with relevant guidelines and the Declaration of Helsinki.

Stimuli and procedure
As illustrated in Fig. 1A, the study protocol included a series of encoding sessions conducted in five consecutive days. In each session, participants watched one episode of the TV series "Patrick Melrose" consisting of 5 episodes in total (1-hour episode per day for 5 days). This TV series was selected based on the following criteria: 1) the availability of the teleplay, 2) the presence of several characters to allow the formation of a wide map of social relationships, 3) different kinds of social relationships between characters, and 4) a storyline that begins and ends within a few episodes. Episodes 1–4 were encoded at home on a standard personal laptop, whereas the

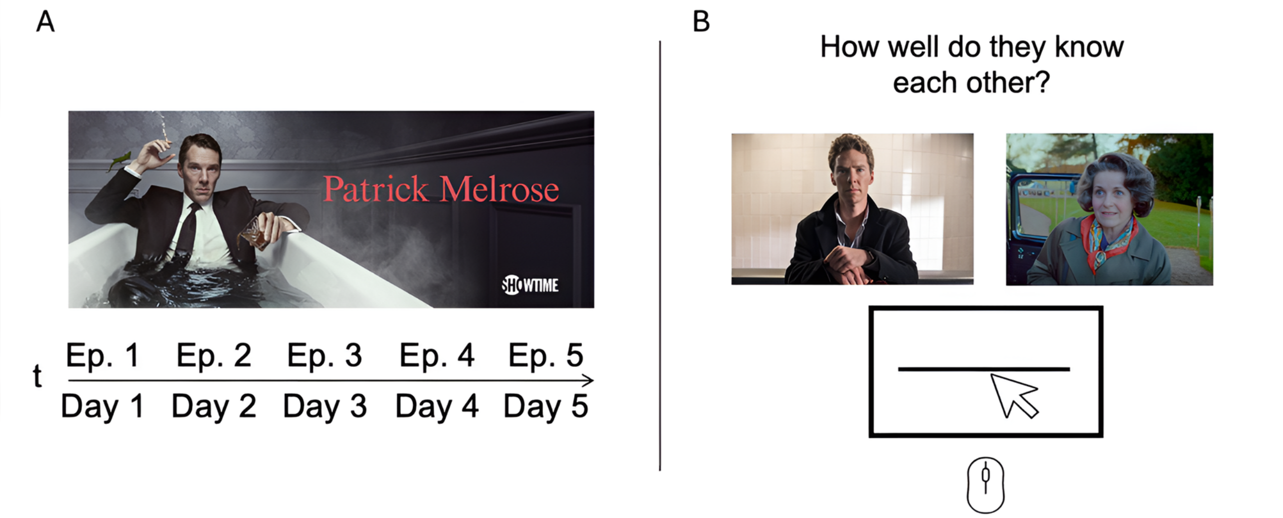

Fig. 1. Experimental paradigm. The figure shows the structure of the experimental paradigm for the two phases of the experiment. (**A**) encoding phase in which participants watch 5 episodes of the TV series "Patrick Melrose" on 5 different days (1 h per episode), (**B**) retrieval phase in which participants were presented with pairs of TV series characters and were asked to judge how well they know each other with a click on a visual analog scale (VAS), representing the continuum of social inter-relationship.

last episode was encoded in a darkened testing room on a 17' LCD computer monitor (1024 × 768 pixels, 60 Hz refresh rate) positioned at ~ 60 cm from the participants using VLC media player version 2.20.

While the encoding procedure was the same for both groups, the retrieval session differed according to the explicit/implicit distinction. To assess whether the generalization process was modulated by knowledge of task demands (see introduction), an "explicit" group performed the retrieval task at the end of each encoding session, whereas an "implicit" group performed the retrieval task only at the end of the fifth encoding session. Thus, the implicit group was not aware of the task's demands while watching all the episodes of the TV series. In the retrieval session, participants were asked to judge the strength of the social relationships between pairs of characters appearing in the narrative. At the end of the final session, participants completed a debriefing interview. Members of the implicit group were asked whether they had anticipated a task involving the characters' social relationships, and all reported that they had not. Members of the explicit group reported that, from the second episode onward, they paid closer attention to character interactions, consistent with the instructions they had received. In each trial of the retrieval session (Fig. 1B), participants were shown a pair of pictures for 2 s depicting two among 16 characters appearing in the five episodes. They were instructed to indicate the strength of the social inter-relationship of the pair by selecting the corresponding point of a visual analog scale (VAS) representing the continuum of social inter-relationship with a mouse click. The instructions made clear that the line was made of 1000 points representing the range of social strength from 0 (far apart, extreme left of the line) to 1000 (close together, extreme right of the line). A total of 120 distinct pairs were presented, with two repetitions of each pair to counterbalance the left-right position of the picture on the screen ($N = 240$). The VAS remained on the screen until a judgment was given and was followed by an intertrial interval (ITI) of 500 msec. No feedback was provided.

The retrieval session was performed in the same testing room and with the same equipment as the last encoding session. E-Prime 3.0 software (Psychology Software Tools) was used to present stimuli and collect responses.

Definition of the social models (objective-subjective)

The central core of the study was to explain and fit the subjective measures of social knowledge derived from the retrieval task using objective indices extracted from the teleplay. To this aim, we selected a set of variables that potentially support the process of generalization of the movie experience in abstract, social knowledge.

We assumed these variables could be identified from the teleplay depicting social interactions between characters. Specifically, an ad-hoc routine was developed, which scrolled the teleplay to collect objective measures about three specific indices of social interactions between the characters' pairs selected for the retrieval task: (1) the times one character mentioned the other ("mention" algorithm), (2) the times two characters were physically present in the same scene ("physical co-occurrence" algorithm), and (3) the exclusivity of the relationships ("exclusivity" algorithm). The mention algorithm captures verbal interactions that are not accompanied by visual co-presence. We parsed the time-aligned teleplay to detect any instance in which a speaker refers to another named character; each mention increments a directed edge from the speaker to the referent, regardless of whether the latter is on screen. This includes phone conversations, off-screen dialogue, or narration, providing relational information not available through visual analysis alone. The three algorithms were differently weighted and calculated based on the assumed relevance for the subjective social judgment. Specifically, under the rationale that real, physical interactions are associated with stronger relational knowledge than imagined or mentalized interactions, the "physical co-occurrence" algorithm was double-weighted with respect to the "mention" algorithm (2 vs. 1 weight). Along the same line, based on the assumption that one-to-one relationships are associated with stronger relational knowledge than group-based relationships, the "exclusivity" algorithm was derived from the previous algorithms and defined as the weights of each pair's relationship (calculated by parameters 1–2) divided by the number of characters (two or more) present in each scene. This approach reflects the idea that interactions in more exclusive (i.e., smaller) social contexts may convey stronger relational cues. Notably, the exclusivity algorithm was not treated as a separate parameter but as a weighting factor applied to the mention and co-occurrence scores. Specifically, each interaction was weighted by the inverse of the number of characters present in the scene. To test whether our conclusions depend on the a priori weighting scheme (physical co-occurrence = 2; mention = 1; exclusivity as a weighting factor), we additionally computed an unweighted composite model in which the three indices contributed with equal weights. The two composite models (weighted vs. unweighted) were then directly compared in the statistical analyses described below.

Each algorithm returned a weight for each pair of characters based on the specific variable of interest. In addition, following the above-described rationale and assumptions, the algorithms were entered into a nested model in which the first level only weighted the contribution of the "mention" variable, and the next levels progressively considered the cumulative contribution of the additional variables (i.e. second level: mention" + "physical co-occurrence"; third level: mention" + "physical co-occurrence" + "exclusivity").

The outcome of the global nested model was represented in a graph-like plot using the Gephi 0.10 software. As shown in Fig. 2A, the resulting graph included 16 nodes (characters) and 120 edges (characters' pairs), whose thickness indicated the estimated weight of the nested model. A graph representing the behavioural measures (subjective graph) was obtained from the group-level mean estimates of the social rating for each pair of characters collected during the retrieval task (Fig. 2B). Group-level mean estimates were obtained by averaging single-subject estimates associated with trial repetition of the social rating. Both measures of social relationships were scaled from 0 to 1000 to compare the objective and subjective graphs. As reported in the following section, subjective measures of performance were either averaged across the explicit and implicit groups or treated as separate between the two groups as a function of the specific research question and statistical analysis employed in the study. When considering subjective estimates averaged across the two groups, only measures extracted

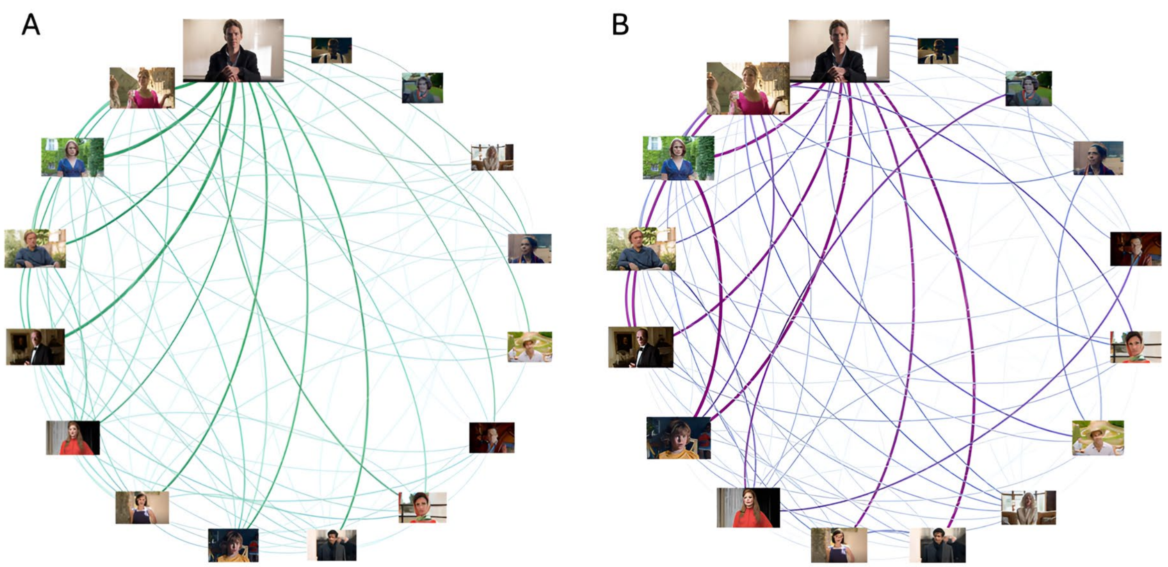

Fig. 2. Social graphs. The figure shows two graph-like representations of the social relationships between the characters of the TV series depicted as circular plots. The nodes represent each character, and the edges correspond to the relationships between each pair of characters. (**A**) objective graph in which the relationships (green edges) were estimated by the in-house algorithms, (**B**) subjective graph in which the relationships (purple edges) were derived from the participants' judgments in the retrieval phase.

from the last episodes were considered for the explicit group (i.e. note that the implicit group performed the retrieval task once, at the end of episode 5 encoding).

The rationale underlying our objective graph is conceptually similar to that of CoCharNet, a system for deriving character relationships from on-screen co-occurrence[35]. However, our approach differs in four key aspects. First, edge weights were derived in a fully automatic fashion by parsing the written teleplay, thus avoiding manual frame-by-frame annotation. Second, in addition to physical co-presence, each edge incorporated verbal mentions and a measure of exclusivity, resulting in a richer and multimodal estimate of relationship strength. Third, the graph was computed separately for each of the five episodes, enabling a dynamic assessment of how the objective structure evolves over time and aligns with behavior. Finally, and most importantly, we validate the model against participants' subjective similarity judgments, thereby providing a cognitive benchmark for the inferred social structure.

Statistical analysis

All statistical analyses were performed in Python using the SciPy, pandas and pingouin packages.

To assess the global correlation between the objective and the subjective social graph, we compared the subjective judgments of social relationships and the objective measures obtained from the global nested model. Furthermore, to test whether the correlation between objective and subjective measures differed between the implicit and explicit groups, we conducted separate analyses for each group and statistically compared the resulting correlation coefficients using permutation tests. We also repeated the analysis using both a weighted and an unweighted objective model, and compared the results via permutation testing, in order to evaluate the impact of our arbitrary weight assignment.

To achieve these aims, we applied a Mantel test, which computes the structural similarity between the two distance graphs based on Pearson's correlation coefficients. Specifically, the representational structure of each graph (i.e. separately within the objective and the subjective graph) was defined based on the Euclidean distance between each pair of characters. An absolute difference was then calculated between the two group comparisons and between the two model comparisons. A permutation test was used to assess the statistical significance of the obtained difference values based on 10.000 random rearrangements of the group/model-level labeling.

To control that the nature of the correlation between the two graphs specifically reflects the social dimension, we obtained a measure of similarity between characters' pairs based purely on perceptive features and correlated the resulting perceptive graph with the subjective graph. The perceptual features were assessed by computing a structural similarity index (SSIM) based on perceptual similarity (i.e., structure, luminance, and contrast) between the characters' images. A Pearson's correlation was next computed between this last objective graph based on perceptual similarity and the subjective graphs used in the formed analysis. To ensure comparability across scales, the subjective and perceptive values were scaled to values ranging from 0 to 1. We therefore assumed that the participants' judgments were not explained by the perceptual similarity of the characters.

We additionally compared the graph similarity across different levels of the nested model ("mention", "mention + physical co-occurrence"; "mention + physical co-occurrence + exclusivity") using Pearson's correlation between the single-level estimates and the single-subject estimates of the behavioural rating across the total sample of participants ($N = 40$). The obtained correlational values ($n = 120$) were statistically compared using the Kruskal-Wallis test with the 3 levels as the independent factor. Pairwise post-hoc comparisons were conducted using Mann-Whitney U test. To isolate the unique contribution of each algorithm and avoid cumulative (nested) effects, we re-ran the model comparison on four single-parameter objective graphs: (i) mentions only; (ii) mentions weighted by exclusivity; (iii) physical co-occurrences only; and (iv) physical co-occurrences weighted by exclusivity. As previously mentioned, exclusivity was treated as a weighting factor (1/n for each pair within a scene with n physically present characters) and was therefore not analyzed as an independent predictor. For this analysis, we computed a Mantel correlation between the subjective rating and each of the four objective parameters, using 10,000 permutations to determine statistical significance. We then compared all pairs of parameters using permutation tests on Δr (label swap within each pair at every iteration) and corrected the p values using the Benjamini–Hochberg method.

Finally, we assessed whether cumulative episodic experience was associated with a progressive change in graph similarity by separately considering the social rating obtained after each of the five encoding sessions in the explicit group. To this aim, we computed a Pearson's correlation between the single-episode estimates of the nested model ($N = 5$) and the single-subject estimates of the behavioural rating of the explicit group ($N = 20$). The correlational values ($N = 100$) were statistically compared using the Kruskal-Wallis test with the episode as the independent factor. Pairwise post-hoc comparisons were finally conducted using Mann-Whitney U test. To assess the level of agreement across participants, we calculated the sample variance of the 20 individual correlations between subjective ratings and objective graphs for each episode. Variance heterogeneity across episodes was tested using Bartlett's test. We further tested for a monotonic trend in variance reduction over episodes using Spearman's rank correlation between episode number (1–5) and variance.

Results

Objective-subjective social similarity

Consistent with our predictions, the Mantel test indicated a significant correlation between the nested model estimates — both the weighted and the unweighted models — and the behavioural rating in both the explicit and implicit groups (see Supplementary Materials, Table S1). This indicates a robust alignment between the model's estimates and the participants' judgments on a retrieval task about social knowledge of a complex narrative (i.e., social closeness between the movie's characters). No significant group differences emerged in the objective-subjective correlations (unweighted model: Δr = 0.036, pFDR = 0.6555; weighted model: Δr = 0.127, pFDR = 0.0884), justifying the aggregation of the two groups in subsequent analyses. When comparing the fit of the two models to subjective ratings, the weighted model showed a significantly better correspondence than the unweighted one (Δr = 0.232, $p = 0.0451$). This supports the hypothesis that direct, physical interactions contribute more strongly to the construction of relational knowledge than imagined or mentalized interactions. Therefore, we adopted the weighted model for all further analyses.

Perceptual similarity control

The results of a control analysis on a model based on perceptual similarities between the selected pairs of characters of the narrative indicated no significant correlation with the behavioural measures of social relationships between the same characters ($r = -0.007$, $p = 0.94$). This result indicates that subjective judgments were not influenced by characters' perceptual similarity, supporting the idea that the relationship between the subjective and the objective models reflects the unique contribution of social knowledge.

Objective-subjective social similarity across parameters

As displayed in Fig. 3, the result of the non-parametric test compared the correlation values between the objective and the subjective social graphs across the three levels of the nested model (Kruskal-Wallis test) indicated a statistically significant difference between the three model levels (H = 68.45, df = 2, $p < 0.001$). Pairwise post-hoc comparisons indicated significantly lower correlation values in level 1 than in level 2 (Hedges' g = − 2.66, $p < 0.001$) and level 3 (Hedges' g = − 2.25, $p < 0.001$). The difference between algorithm 2 and algorithm 3 was marginally significant (Hedges' g = 0.35, $p = 0.087$) with higher correlation values in level 2 than in level 3. These suggest a major contribution of the "physical co-occurrence" (level 2) to the model fit as well as a scarce impact of the "exclusivity" parameter (level 3) in explaining variance about subjective measures of social knowledge. When tested independently, physical co-occurrence showed a significantly stronger correlation with the subjective graph than mention ($r = 0.726$ vs. $r = 0.346$; both pFDR = 0.0002), and this advantage was confirmed by a Δr permutation test (Δr = 0.380, pFDR = 0.011). Adding exclusivity as a normalization factor did not significantly improve the model fit: neither physical co-occurrence vs. physical co-occurrence + exclusivity (Δr = 0.022, pFDR = 0.558) nor mention vs. mention + exclusivity (Δr = -0.014, pFDR = 0.910) yielded significant differences. Moreover, the difference between the normalized models (physical co-occurrence + exclusivity vs. mention + exclusivity) was reduced and only marginally significant (Δr = 0.344, pFDR = 0.060), suggesting that normalization made the predictors more similar. Taken together, these findings indicate that the parameters contribute unequally when considered in isolation, with physical co-occurrence carrying most of the explanatory power. In contrast, exclusivity acts as a largely neutral or even confounding factor, reducing the distinctiveness between predictors rather than enhancing model–judgment alignment (See Figure S1.)

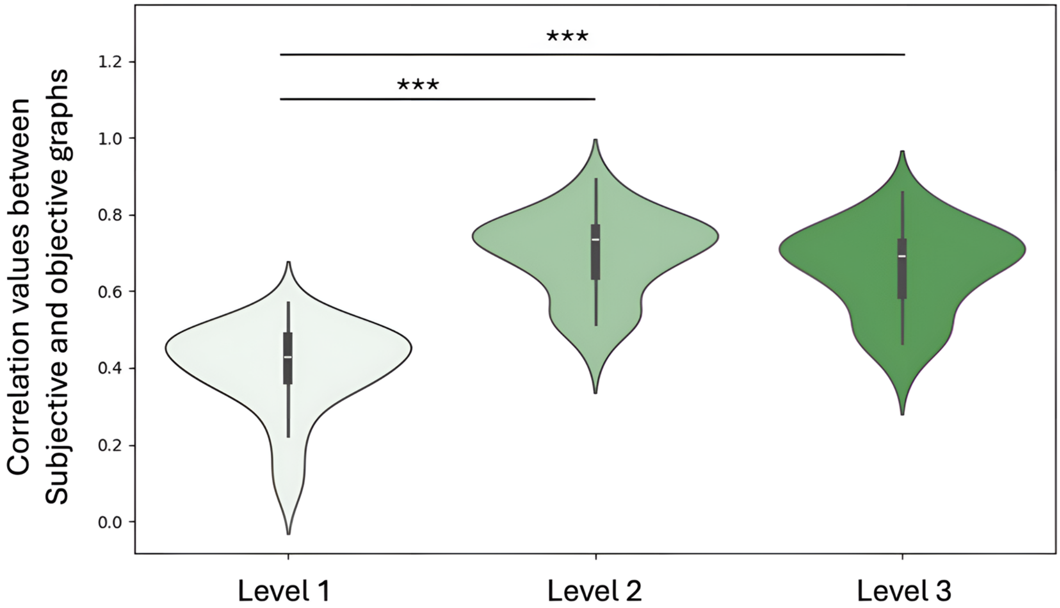

Fig. 3. Objective-subjective graph similarity across levels of the model. The violin plots depict the distribution of correlation values between subjective and objective graphs for the three levels of the nested model (Level 1 = mention, Level 2 = mention + physical co-occurrence, Level 3 = mention + physical co-occurrence + exclusivity). The inner box plots display the interquartile range (IQR), with the white horizontal line representing the median and the whiskers extending from the first (25th percentile) and third (75th percentile) quartiles to the smallest and largest values within 1.5 times the IQR. ***$p < 0.001$.

Objective-subjective social similarity across episodes

The comparison of the correlation values between the objective and the subjective social graphs derived from each of the five episodes of the TV series in the explicit group (Fig. 4), performed through a Kruskal-Wallis test, indicated a significant modulation in the correlation across episodes ($H = 29.77$, $df = 4$, $p = 0.000005$). Specifically, post-hoc comparisons indicated significant differences in the correlation between episodes 1 vs. 2 (Hedges' $g = -0.93$, $p < 0.001$), 3 (Hedges' $g = -0.96$, $p < 0.001$), 4 (Hedges' $g = -1.54$, $p < 0.001$), and 5 (Hedges' $g = -1.53$, $p < 0.001$). Additionally, significant differences were observed between episodes 3 vs. 4 (Hedges' $g = -0.65$, $p = 0.05$) and 5 (Hedges' $g = -0.70$, $p = 0.05$). Of note, since the Hedges' g values always refer to the previous episode, the negativity of these values is consistent with the expected direction of the effect of an increase in correlation as the episodes progress. No significant differences were found between the other comparisons (all $p > 0.05$). Consistent with the idea that memory generalization promotes convergence, variability among participants declined over episodes. Variances of the correlation coefficients were 0.015, 0.012, 0.007, 0.004, and 0.007 for Episodes 1 to 5, respectively. Bartlett's test indicated significant variance differences ($\chi^2 = 9.87$, $df = 4$, $p = 0.043$), and Spearman's correlation revealed a significant monotonic decrease across episodes ($\rho = -0.90$, $p = 0.037$).

Discussion

The present results contribute to a growing body of research investigating how structured knowledge is represented in memory across both spatial and non-spatial domains[23,39]. Traditionally, non-spatial domains such as social and conceptual knowledge have been modeled using map-like representations, in which information is embedded in a low-dimensional Euclidean space defined by experimenter-specified reference axes, for example, social traits such as power and affiliation[29] semantic similarity[27]or visual dimensions[40]. More recently, a complementary approach has explored graph-based representations, in which items are encoded as discrete nodes linked by relational edges, independent of a global reference frame[14]. This framework has been used to investigate how the brain encodes statistical regularities between stimuli that are temporally, but not semantically, linked[32]beginning with studies using artificial sequences organized by experimenter-defined topologies[30,31]. Related work has shown that participants can also acquire relational structure in experimentally defined social graphs[41] and more recent studies have extended this approach to naturalistic contexts, demonstrating that semantic or social graphs can be extracted from character co-occurrence patterns in real-world movies[33,34].

Our study aligns with this recent line of evidence by showing that participants' subjective social knowledge reflects a graph-based representation of narrative structure, derived from multiple objective features of the

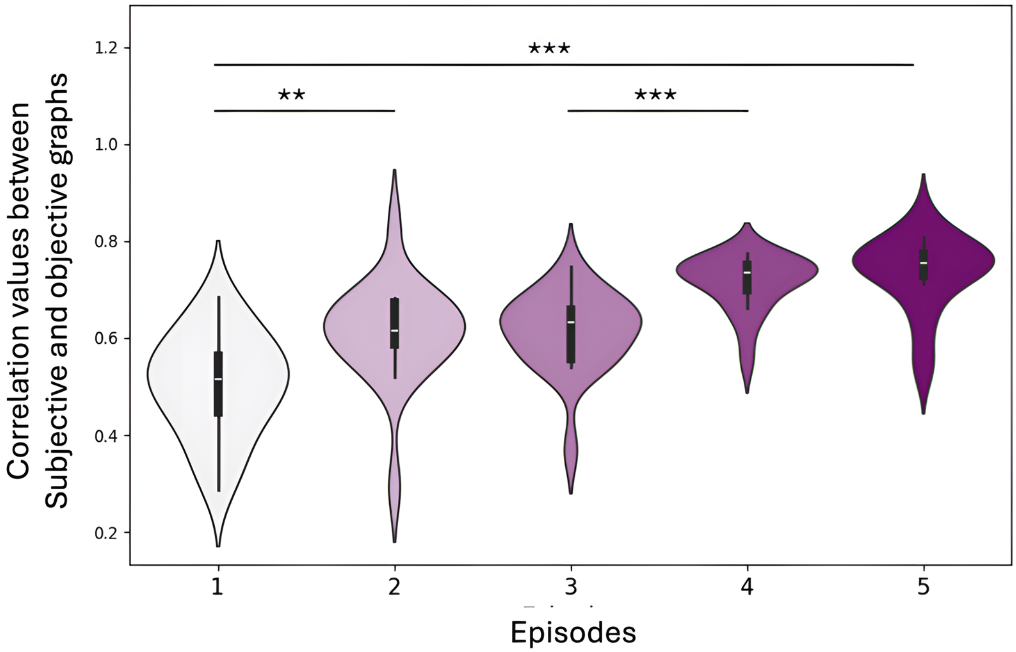

Fig. 4. Objective-subjective graphs similarity across episodes. The violin plots depict the distribution of correlation values between subjective and objective graphs for the five episodes of the TV series. The inner box plots display the interquartile range (IQR), with the white horizontal line representing the median and the whiskers extending from the first (25th percentile) and third (75th percentile) quartiles to the smallest and largest values within 1.5 times the IQR. ***$p < 0.001$, **$p < 0.01$.

teleplay (co-occurrence, mentions, exclusivity). Importantly, unlike map-like studies that presuppose reference axes, our method does not impose any a-priori dimensional structure. Instead, it captures how social proximity is implicitly reconstructed from relational experience, suggesting that non-metric, topology-based representations may be a core component of naturalistic social memory. At the neurobiological level, we hypothesize that the structure encoded by our objective co-occurrence graph reflects the kind of situational and relational coding attributed to the posterior-medial (PM) cortico-hippocampal network. This system, including hippocampus, parahippocampal cortex, and posterior cingulate, has been shown to encode statistical regularities from relational experience[34]in line with the PM–AT framework proposed by Ranganath & Ritchey[42]. A more specific functional subdivision of the PM system, proposed by Epstein et al.[43]distinguishes between context retrieval, the reinstatement of structural scaffolds such as social groups, and orientation, which involves locating individuals within those scaffolds along dimensions like power or affiliation. Since our task required reconstructing social relationships without positioning individuals along predefined axes, it likely engaged hippocampal-supported context retrieval more than orientation-related processes.

Using complex, naturalistic stimuli and explicit ratings of social relationships among characters, we show that simple narrative features, such as co-occurrence and verbal mention, can partially explain how viewers begin to organize social information. These objective parameters likely support the emergence of relational knowledge, though they do not obviously capture the full richness of social reasoning. The observed significant correlation between the subjective social graph estimated from the participants' rating and the objective social graph obtained from the model estimates confirms the goodness of fit of the selected model's parameters (mention, physical co-occurrence, and exclusivity). Crucially, the correspondence between objective and subjective social graphs remained significant when all parameters were equally weighted, indicating that our findings are not driven by arbitrary parameter choices. However, a direct comparison via paired permutation testing showed that the original, weighted model provided a significantly better fit to behavioral data. This suggests that participants implicitly assign greater importance to physical co-occurrence when constructing social representations, relative to mentions and exclusivity.

Differently from relevant studies presented in the introduction, in which the encoding/retrieval of information was based on pre-determined dimensions of knowledge[30]here we provided no external frame of reference during the encoding phase. Of relevance, the structure of the social graph extracted from the narrative was unknown to participants and was not directly manipulated in the experimental design. Instead, the structural features of the graph were inferred using a model-based approach informed by episodic events of social interactions extracted from the teleplay. Albeit conceptual representations are long assumed to derive and develop from repeated episodic experience, few studies have employed such a bottom-up approach to study how these representations are gradually formed from accumulating experience. Rather, a more consistent bulk of memory research has focused on the (top-down) modulatory mechanisms underlying the effect of pre-existing semantic knowledge and schematic representations on the encoding of new episodic experience/information[44–46]. For example, recent studies have recently shown that memory for time of video clips extracted from a previously encoded movie is systematically modulated by script-based prior knowledge about conventional movie temporal structure (e.g., beginning-middle-end template)[47,48]. In general, findings from different areas of memory research collectively support the notion that prior knowledge actively affects memory encoding and retrieval by defining the "semantic scaffolding" structure in which new information is coherently accommodated for behavioural responses and performance[49]. Here, we provide empirical evidence that statistical regularities of episodic experience represent the building blocks and raw inputs for organizing knowledge in high-level conceptual representations. Specifically, we showed that among the features studied, the ones that more significantly contributed to the construction of high-level knowledge about social relationships between movie characters, i.e. social relatedness, are the statistical regularities of social interactions in the narrative episodes (e.g. physical co-occurrence in a movie scene).

Developmental psychology has paid much attention to perceptual similarity as a regularity that enables children to form basic semantic categories without a true understanding of taxonomic relatedness[50,51]. However, perceptual similarity cannot support more complex forms of conceptual representations in adults, such as those associated with social knowledge. Consistently, no significant correlation was found in the current study between subjective estimates of social relatedness and the matrix of perceptual similarity between the characteristics. This shows that, in the presence of complex narrative material, high-level conceptual knowledge formation is based on the extraction of statistical regularities beyond the perceptual domain. Among the flexible processing mechanisms useful in explaining the interaction between experienced episodic events and high-level representations in the human mind, Unger et al.[52] proposed a new form of statistical regularity based on the general co-occurrence of entities or labels. Consistently, the results of the statistical comparison between the three levels of the nested model indicated that the social parameters that best accounted for the subjective rating of social knowledge were the physical co-occurrence of the characters in the movie scenes. Taken together, these results suggest that statistical regularities are the fundamental mechanism for organizing episodic information into semantic, conceptual networks, thereby contributing to semantic knowledge formation, which has so far largely been neglected in statistical learning research[53,54]. Furthermore, we can argue that tracking the co-occurrence of entities in experience is a useful mechanism for establishing relationships between these entities, whether categorical or social, not only in children but also in adults.

The implicit nature underlying the tracking of statistical regularities is another non-trivial aspect that emerged from this study. In fact, many studies have shown that we learn highly complex relational structures implicitly[30,55]. As mentioned above, our experimental paradigm extends the concept of organizing knowledge into complex structures to a highly ecological approach. A few studies have addressed such complex forms of social semantic knowledge. Surprisingly, even in these cases, basic mechanisms come into play and spontaneously shape the experience. The fact that we found no difference between participants who were aware of the task demands after the first encoding session and those who remained unaware until the last encoding session suggests that the mechanism underlying the transformation of episodic into semantic material is not task-dependent. Rather, it appears to be an implicit mechanism that serves the process of semantic generalization and happens spontaneously. Although both episodic and semantic memory are traditionally viewed as forms of explicit memory[56] which is effectively the case, at least in their use (e.g., in conscious recall), the mechanisms that drive the transformation from episodic experiences to semantic knowledge appear to be, at least in the present context, effortless. This viewpoint is supported by a recent study by Nagy et al.[57] who described the process of semantic compression of episodic memories. The authors have suggested that semantic compression operates as a probabilistic generative model capable of synthesizing and reconstructing experiences based on latent variables. The latent variables adapt to the environmental statistics and aid in predicting future observations. This reconstruction, described as a predictive and automatic process, generates 'gist-like' memories, i.e., based on the essence of the experience rather than precise details[58].

Having established that the performance of the explicit group did not differ from that of the implicit group, we had a closer look at the former group to assess the influence of gradually adding relevant episodic material on social representation. In particular, we were interested in extending the dated notion that semantic memory is built on repeated episodic experiences[59,60] from a highly controlled and artificial setting to a more ecological one based on new complex material. The observation that the subjective-objective correlation increases as participants viewed additional episodes is consistent with the theoretical framework that episodic experiences provide the raw material for semantic generalization. Each new episode enriches the pool of data from which statistical regularities are extracted, thereby refining and stabilizing the resulting semantic maps[46]. Furthermore, repeated episodic exposure can reduce potential ambiguities arising from previous poor coding and promote the integration of new information into existing schemas, a process likely mediated, at a neural level, by hippocampal-neocortical interactions[61,62]. Over time, this process yields robust and increasingly shared semantic representations, highlighting the importance of episodic repetition in constructing accurate and coherent semantic representations. Consistent with this view, the inter-subject variance of objective-subjective correlation decreased across episodes, suggesting that the social map became progressively more robust and stable across participants, taking the form of a shared semantic representation (or schema), as originally suggested by Bartlett & Burt[63]. This could also be partially explained through the phenomenon of neural alignment, according to which when several people observe the same events, their neural patterns align[64] to produce similar and robust memory representations[65].

The higher variance after Episode 1 echoes the results by Nguyen et al.[66] who found that subtle differences in narrative understanding can fragment neural synchrony when contextual cues are sparse. As relational evidence accumulates, however, individuals' social maps become both more accurate and more similar. A further qualitative aspect emerges when the correlation is examined on an episode-by-episode basis. After sharp increases in episodes 1 and 2, the correlation stabilizes in episode 3, which introduces a significant time leap and reconfigured relationships in the plot. It might be suggested that the relational scaffolding learned in the first two episodes suddenly becomes poorly predictive of the new narrative state, forcing viewers to redefine social space before routine updating can resume. This pattern reflects the distinction between cognitive map learning, which uses hippocampal and postero-medial circuits to acquire a new relational structure, and situational model maintenance, which uses default-mode regions to integrate ongoing information with an existing framework[67,68]. We believe that our behavioural data captures the outcome of both phases, but we are not yet able to distinguish their contribution. Future studies combining graph metrics with neural event segmentation analyses[69] are needed to determine how abrupt contextual changes can temporarily decouple map acquisition from online situation updating.

Limitations, open issues, and future investigations

This study provides initial behavioural evidence that viewers extract social structure from naturalistic narratives by integrating cues such as co-occurrence, mention, and scene exclusivity. Since these cues can be measured algorithmically, the approach is operator-independent and captures, albeit loosely, a character's narrative prominence: a protagonist who dominates the screen or dialogue will inevitably accumulate more co-occurrences and mentions in our counts. However, the model remains rooted in surface statistics and does not yet incorporate richer character-centered narrative dimensions such as emotional salience, inferred mental states or character motivations, factors that, according to previous work, are spontaneously detected during film viewing. Indeed, prior work shows that viewers spontaneously track affective gradients during film viewing[36–38] encode moral affiliations in large-scale control and mentalizing networks[70] and abstract narrative schemas through hippocampal-default mode interactions[71,72]. Future studies should therefore extend the present framework by adding explicit, automatically extracted character-level covariates, such as character screen time, speakingtime, or dialogue frequency, and higher-order features that capture conflict, affect, or goal structure.

A complementary limitation concerns the subjective measure itself. Our single VAS rating captures only a slice of social knowledge and likely blends semantic associations with mentalizing inferences. Although debriefing confirmed that participants interpreted the scale holistically, multidimensional ratings could better capture the complexity of the construct and reveal which facets of closeness (e.g., trust, intimacy, hierarchy) are most salient. At the same time, the current approach cannot distinguish whether our social-closeness measure primarily reflects semantic memory or relies more heavily on social cognition. Future work could couple the VAS with multidimensional behavioural tasks and trait measures (e.g., empathy, narrative engagement) to disentangle how dispositional factors and specific cognitive processes shape the emerging social map.

Finally, while our focus was on social relationships, the ability to extract structured representations from narratives may generalize across domains. Future work should explore whether these processes rely on common or domain-specific computational principles.

Conclusion

In summary, our findings provide additional insights into the mechanisms underlying the transformation of episodic experiences into structured semantic knowledge. By leveraging an ecological paradigm, we demonstrated that statistical regularities in social interactions serve as the foundation for constructing high-level representations of social knowledge, independent of explicit task demands. On the one hand, this extends our current understanding of the mechanisms underlying semantic memory by bringing together the traditionally separated research fields of cognitive, developmental, and statistical learning psychology. On the other hand, it opens new research questions about the formation and understanding of social networks in the new digital age (e.g. social networks, virtual interactions, digital communications). The observed convergence between subjective and objective social structures over repeated exposure underscores the role of episodic accumulation in shaping stable and shared semantic representations. Furthermore, our results suggest that this transformation occurs implicitly, reinforcing the idea that semantic generalization is a spontaneous and fundamental cognitive process. Future research should explore the neural correlates of this transition and investigate whether similar principles apply to other forms of conceptual knowledge beyond the social domain.

Data availability

The code that supports the findings of this study has been deposited in https://GitHub.com/DavideDCD/Keepinmind.

Received: 14 April 2025; Accepted: 25 August 2025
Published online: 03 October 2025

References

1. Tolman, E. C. Cognitive maps in rats and men.
2. O'Keefe, J. & Dostrovsky, J. The hippocampus as a Spatial map. Preliminary evidence from unit activity in the freely-moving rat. *Brain Res.* **34**, 171–175 (1971).
3. Olton, D. S., Branch, M. & Best, P. J. Spatial correlates of hippocampal unit activity. *Exp. Neurol.* **58**, 387–409 (1978).
4. Muller, R. & Kubie, J. The effects of changes in the environment on the Spatial firing of hippocampal complex-spike cells. *J. Neurosci.* **7**, 1951–1968 (1987).
5. Nadel, L. The hippocampus and space revisited. *Hippocampus* **1**, 221–229 (1991).
6. Cohen, N. J. & Eichenbaum, H. *Memory, Amnesia, and the Hippocampal System* (MIT Press, 1994).
7. Bottini, R. & Doeller, C. F. Knowledge across reference frames: cognitive maps and image spaces. *Trends Cogn. Sci.* **24**, 606–619 (2020).

8. Eichenbaum, H., Dudchenko, P., Wood, E., Shapiro, M. & Tanila, H. The hippocampus, memory, and place cells. *Neuron* **23**, 209–226 (1999).
9. Heit, G., Smith, M. E. & Halgren, E. Neural encoding of individual words and faces by the human hippocampus and amygdala. *Nature* **333**, 773–775 (1988).
10. Heit, G., Smith, M. E. & Halgren, E. Neuronal activity in the human medial Temporal lobe during recognition memory. *Brain* **113**, 1093–1112 (1990).
11. Fried, I., MacDonald, K. A. & Wilson, C. L. Single neuron activity in human hippocampus and amygdala during recognition of faces and objects. *Neuron* **18**, 753–765 (1997).
12. Eichenbaum, H. The role of the hippocampus in navigation is memory. *J. Neurophysiol.* **117**, 1785–1796 (2017).
13. Muller, R. U., Stead, M. & Pach, J. The hippocampus as a cognitive graph. *J. Gen. Physiol.* **107**, 663–694 (1996).
14. Peer, M., Brunec, I. K., Newcombe, N. S. & Epstein, R. A. Structuring knowledge with cognitive maps and cognitive graphs. *Trends Cogn. Sci.* **25**, 37–54 (2021).
15. Milivojevic, B. & Doeller, C. F. Mnemonic networks in the hippocampal formation: from Spatial maps to Temporal and conceptual codes. *J. Exp. Psychol. Gen.* **142**, 1231–1241 (2013).
16. Schiller, D. et al. Memory and space: towards an Understanding of the cognitive map. *J. Neurosci.* **35**, 13904–13911 (2015).
17. Buzsáki, G. & Moser, E. I. Memory, navigation and theta rhythm in the hippocampal-entorhinal system. *Nat. Neurosci.* **16**, 130–138 (2013).
18. Ekstrom, A. D. & Hill, P. F. Spatial navigation and memory: a review of the similarities and differences relevant to brain models and age. *Neuron* **111**, 1037–1049 (2023).
19. Committeri, G. et al. Egocentric navigation abilities predict episodic memory performance. *Front. Hum. Neurosci.* **14**, 574224 (2020).
20. Fragueiro, A. et al. Travel in the physical and mental space: a behavioral assessment of the phylogenetic continuity hypothesis between egocentric navigation and episodic memory. *Evol. Psychol.* **19**, 147470492110408 (2021).
21. Lazareva, O. F., Kandray, K. & Acerbo, M. J. Hippocampal lesion and transitive inference: dissociation of inference-based and reinforcement-based strategies in pigeons: transitive inference and hippocampus. *Hippocampus* **25**, 219–226 (2015).
22. DeVito, L. M., Kanter, B. R. & Eichenbaum, H. The hippocampus contributes to memory expression during transitive inference in mice. *Hippocampus* **20**, 208–217 (2010).
23. Bellmund, J. L. S., Gärdenfors, P., Moser, E. I. & Doeller, C. F. Navigating cognition: Spatial codes for human thinking. *Science* **362**, eaat6766 (2018).
24. Behrens, T. E. J. et al. What is a cognitive map? Organizing knowledge for flexible behavior. *Neuron* **100**, 490–509 (2018).
25. Bellmund, J. L., Deuker, L. & Doeller, C. F. Mapping sequence structure in the human lateral entorhinal cortex. *eLife* **8**, e45333 (2019).
26. Deuker, L., Bellmund, J. L., Navarro Schröder, T. & Doeller, C. F. An event map of memory space in the hippocampus. *eLife* 5, e16534 (2016).
27. Constantinescu, A. O., O'Reilly, J. X. & Behrens, T. E. J. Organizing conceptual knowledge in humans with a gridlike code. *Science* **352**, 1464–1468 (2016).
28. Park, S. A., Miller, D. S. & Boorman, E. D. Inferences on a multidimensional social hierarchy use a grid-like code. *Nat. Neurosci.* **24**, 1292–1301 (2021).
29. Tavares, R. M. et al. A map for social navigation in the human brain. *Neuron* **87**, 231–243 (2015).
30. Garvert, M. M., Dolan, R. J. & Behrens, T. E. A map of abstract relational knowledge in the human hippocampal–entorhinal cortex. *eLife* **6**, e17086 (2017).
31. Schapiro, A. C., Rogers, T. T., Cordova, N. I., Turk-Browne, N. B. & Botvinick, M. M. Neural representations of events arise from Temporal community structure. *Nat. Neurosci.* **16**, 486–492 (2013).
32. Tacikowski, P., Kalender, G., Ciliberti, D. & Fried, I. Human hippocampal and entorhinal neurons encode the Temporal structure of experience. *Nature* **635**, 160–167 (2024).
33. Jolly, E. et al. People are represented and remembered through their relationships with others. https://doi.org/10.31234/osf.io/bw9r2 (2023).
34. Karagoz, A. B., Morse, S. J. & Reagh, Z. M. Cortico-hippocampal networks carry information about characters and their relationships in an extended narrative. *Neuropsychologia* **191**, 108729 (2023).
35. Jai, E. Jung & Quang dieu tran. CoCharNet: extracting social networks using character co-occurrence in movies. https://doi.org/10.3217/JUCS-021-06-0796
36. Lettieri, G. et al. Emotionotopy in the human right temporo-parietal cortex. *Nat. Commun.* **10**, (2019).
37. Lettieri, G. et al. Default and control network connectivity dynamics track the stream of affect at multiple timescales. *Soc. Cognit. Affect. Neurosci.* **17**, 461–469 (2022).
38. Lettieri, G. et al. Dissecting abstract, modality-specific and experience-dependent coding of affect in the human brain. *Sci. Adv.* **10**, (2024).
39. Schafer, M. & Schiller, D. Navigating social space. *Neuron* **100**, 476–489 (2018).
40. Theves, S., Fernandez, G. & Doeller, C. F. The hippocampus encodes distances in multidimensional feature space. *Curr. Biol.* **29**, 1226–1231e3 (2019).
41. Son, J. Y., Bhandari, A. & FeldmanHall, O. Cognitive maps of social features enable flexible inference in social networks. *Proc. Natl. Acad. Sci. USA* **118**, e2021699118 (2021).
42. Ranganath, C. & Ritchey, M. Two cortical systems for memory-guided behaviour. *Nat. Rev. Neurosci.* **13**, 713–726 (2012).
43. Epstein, R. A., Patai, E. Z., Julian, J. B. & Spiers, H. J. The cognitive map in humans: Spatial navigation and beyond. *Nat. Neurosci.* **20**, 1504–1513 (2017).
44. Cutting, J. E. Narrative theory and the dynamics of popular movies. *Psychon Bull. Rev.* **23**, 1713–1743 (2016).
45. Gilboa, A. & Marlatte, H. Neurobiology of schemas and schema-mediated memory. *Trends Cogn. Sci.* **21**, 618–631 (2017).
46. Van Kesteren, M. T. R., Ruiter, D. J., Fernández, G. & Henson, R. N. How schema and novelty augment memory formation. *Trends Neurosci.* **35**, 211–219 (2012).
47. Frisoni, M., Di Ghionno, M., Guidotti, R., Tosoni, A. & Sestieri, C. Reconstructive nature of Temporal memory for movie scenes. *Cognition* **208**, 104557 (2021).
48. Frisoni, M., Di Ghionno, M., Guidotti, R., Tosoni, A. & Sestieri, C. Effects of a narrative template on memory for the time of movie scenes: automatic reshaping is independent of consolidation. *Psychol. Res.* **87**, 598–612 (2023).
49. Audrain, S. & McAndrews, M. P. Schemas provide a scaffold for neocortical integration of new memories over time. *Nat. Commun.* **13**, 5795 (2022).
50. Quinn, P. C. & Johnson, M. H. Global-before-basic object categorization in connectionist networks and 2-month-old infants. *Infancy* **1**, 31–46 (2000).
51. Sloutsky, V. M., Kloos, H. & Fisher, A. V. When looks are everything: appearance similarity versus kind information in early induction. *Psychol. Sci.* **18**, 179–185 (2007).
52. Unger, L., Savic, O. & Sloutsky, V. M. Statistical regularities shape semantic organization throughout development. *Cognition* **198**, 104190 (2020).
53. Matlen, B. J., Fisher, A. V. & Godwin, K. E. The influence of label co-occurrence and semantic similarity on children's inductive generalization. *Front. Psychol.* **6**, (2015).

54. Wojcik, E. H. & Saffran, J. R. Toddlers encode similarities among novel words from meaningful sentences. *Cognition* **138**, 10–20 (2015).
55. Cleeremans, A., Destrebecqz, A. & Boyer, M. Implicit learning: news from the front. *Trends Cogn. Sci.* **2**, 406–416 (1998).
56. Tulving, E. *Organization of Memory* (Academic, 1972).
57. Nagy, D. G., Török, B. & Orbán, G. Optimal forgetting: semantic compression of episodic memories. *PLoS Comput. Biol.* **16**, e1008367 (2020).
58. Higgins, I. et al. β-VAE: learning basic visual concepts with a constrained variational framework. *Under Review as a Conference Paper* (2017).
59. Tulving, E. Memory and consciousness. *Can. Psychol. / Psychologie Canadienne*. **26**, 1–12 (1985).
60. McClelland, J. L., McNaughton, B. L. & O'Reilly, R. C. Why there are complementary learning systems in the hippocampus and neocortex: insights from the successes and failures of connectionist models of learning and memory. *Psychol. Rev.* **102**, 419–457 (1995).
61. Rissman, J. & Wagner, A. D. Distributed representations in memory: insights from functional brain imaging. *Annu. Rev. Psychol.* **63**, 101–128 (2012).
62. Kumaran, D., Hassabis, D. & McClelland, J. L. What learning systems do intelligent agents need? Complementary learning systems theory updated. *Trends Cogn. Sci.* **20**, 512–534 (2016).
63. Bartlett, F. C. & Burt, C. Remembering: a study in experimental and social psychology. *Brit J. Edu Psychol.* **3**, 187–192 (1933).
64. Hasson, U., Ghazanfar, A. A., Galantucci, B., Garrod, S. & Keysers, C. Brain-to-brain coupling: a mechanism for creating and sharing a social world. *Trends Cogn. Sci.* **16**, 114–121 (2012).
65. Chen, J. et al. Shared memories reveal shared structure in neural activity across individuals. *Nat. Neurosci.* **20**, 115–125 (2017).
66. Nguyen, M., Vanderwal, T. & Hasson, U. Shared Understanding of narratives is correlated with shared neural responses. *NeuroImage* **184**, 161–170 (2019).
67. Yarkoni, T., Speer, N. K. & Zacks, J. M. Neural substrates of narrative comprehension and memory. *NeuroImage* **41**, 1408–1425 (2008).
68. Zwaan, R. A. & Radvansky, G. A. Situation models in Language comprehension and memory. *Psychol. Bull.* **123**, 162–185 (1998).
69. Baldassano, C. et al. Discovering event structure in continuous narrative perception and memory. *Neuron* **95**, 709–721e5 (2017).
70. Weber, R., Hopp, F. R., Eden, A., Fisher, J. T. & Lee, H. E. Vicarious punishment of moral violations in naturalistic drama narratives predicts cortical synchronization. *NeuroImage* **292**, 120613 (2024).
71. Baldassano, C., Hasson, U. & Norman, K. A. Representation of real-world event schemas during narrative perception. *J. Neurosci.* **38**, 9689–9699 (2018).
72. Cohn-Sheehy, B. I. et al. The hippocampus constructs narrative memories across distant events. *Curr. Biol.* **31**, 4935–4945e7 (2021).

Acknowledgements
We thank Dr Milan Janosov for his technical and theoretical support on network science during the design of the project.

Author contributions
F.S conceptualized and designed the study, enrolled the participants, acquired and analyzed the data, and wrote, edited, and reviewed the manuscript. G.C, C.S, R.D.M. and A.T conceptualized and designed the study, edited, and reviewed the manuscript. D.D.C. developed the ad-hoc objective model (see "Definition of the social models (objective-subjective)" in the Method section).

Funding
This work was funded by the European Union - Next Generation EU - Mission 4 Component 1 CUP D53D23020750001 and by a grant of the Fundação Bial (grant ID: A-38431) to GC. This work was conducted under the framework of the Departments of Excellence 2023–2027 initiative of the Italian Ministry of Education, University and Research for the Department of Neuroscience, Imaging and Clinical Sciences (DNISC) of the University of Chieti-Pescara.

Declarations

Competing interests
The authors declare no competing interests.

Additional information
Supplementary Information The online version contains supplementary material available at https://doi.org/10.1038/s41598-025-17427-x.

Correspondence and requests for materials should be addressed to F.S.