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Higher-order interactions shape collective human behaviour

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Federico Battiston[1] ✉, **Valerio Capraro**[2], **Fariba Karimi**[3,4], **Sune Lehmann**[5,6], **Andrea Bamberg Migliano**[7], **Onkar Sadekar**[1], **Angel Sánchez**[8,9] & **Matjaž Perc**[10,11,12,13]

Traditional social network models focus on pairwise interactions, overlooking the complexity of group-level dynamics that shape collective human behaviour. Here we outline how the framework of higher-order social networks—using mathematical representations beyond simple graphs—can more accurately represent interactions involving multiple individuals. Drawing from empirical data including scientific collaborations and contact networks, we demonstrate how higher-order structures reveal mechanisms of group formation, social contagion, cooperation and moral behaviour that are invisible in dyadic models. By moving beyond dyads, this approach offers a transformative lens for understanding the relational architecture of human societies, opening new directions for behavioural experiments, cultural dynamics, team science and group behaviour as well as new cross-disciplinary research.

The structure of social networks affects many aspects of human behaviour and, perhaps more than any other paradigm, lays bare the shortcomings of the 'economic man' perspective. Human beings do not simply strive to amass the greatest amounts of conveniences and luxuries with the least possible effort: because we are connected to others, we often take their desires and well-being into account in spite of our inherent self-interest. This line of thought leads to the perspective of the 'network man', who, driven by embeddedness in a network of social relations, exists and acts in a delicate balance between his well-being and sympathy for the well-being of others. Ample evidence exists that maintaining this balance affects most of our actions, from whom we vote for to what we eat and which partners we choose and why[1]. Apart from our behaviour, the complex connectedness of modern human societies can be seen in the ease of global communication and in the lightning speeds at which news and information as well as epidemics and financial crises spread[2].

Since the introduction of sociograms to describe social configurations by Moreno and Jennings[3], social network analysis has grown into a field of its own. New theories have been proposed, starting with Granovetter's essays on the importance of weak ties for increasing the reach of marketing, politics and information beyond the few people that are accessible through strong connections[4], as well as pioneering experiments, such as Milgram's work on the small-world phenomenon[5]. Using nodes and links to describe individuals and their pairwise relationships, network science is now a major paradigm in contemporary sociology and behavioural sciences, while at the same time being a vibrant research field in its own right[6–9].

Traditional social networks consist of agglomerates of dyads (or pairs), which together give rise to large, interconnected webs of human relations. Yet, this theoretical framework is not well suited for capturing a crucial feature of human behaviour—group interactions. In this Perspective, we discuss the limitations of the link as the single

[1]Department of Network and Data Science, Central European University, Vienna, Austria. [2]Department of Psychology, University of Milan Bicocca, Milan, Italy. [3]Graz University of Technology, Graz, Austria. [4]Complexity Science Hub, Vienna, Austria. [5]DTU Compute, Technical University of Denmark, Kongens Lyngby, Denmark. [6]Copenhagen Center for Social Data Science, University of Copenhagen, Copenhagen, Denmark. [7]Human Evolutionary Ecology Group, Department of Evolutionary Anthropology, University of Zurich, Zurich, Switzerland. [8]Grupo Interdisciplinar de Sistemas Complejos, Departamento de Matemáticas, Universidad Carlos III de Madrid, Leganés, Spain. [9]Instituto de Biocomputación y Física de Sistemas Complejos, Universidad de Zaragoza, Zaragoza, Spain. [10]Faculty of Natural Sciences and Mathematics, University of Maribor, Maribor, Slovenia. [11]Community Healthcare Center Dr. Adolf Drolc Maribor, Maribor, Slovenia. [12]Department of Physics, Kyung Hee University, Seoul, Republic of Korea. [13]University College, Korea University, Seoul, Republic of Korea. ✉e-mail: battistonf@ceu.edu

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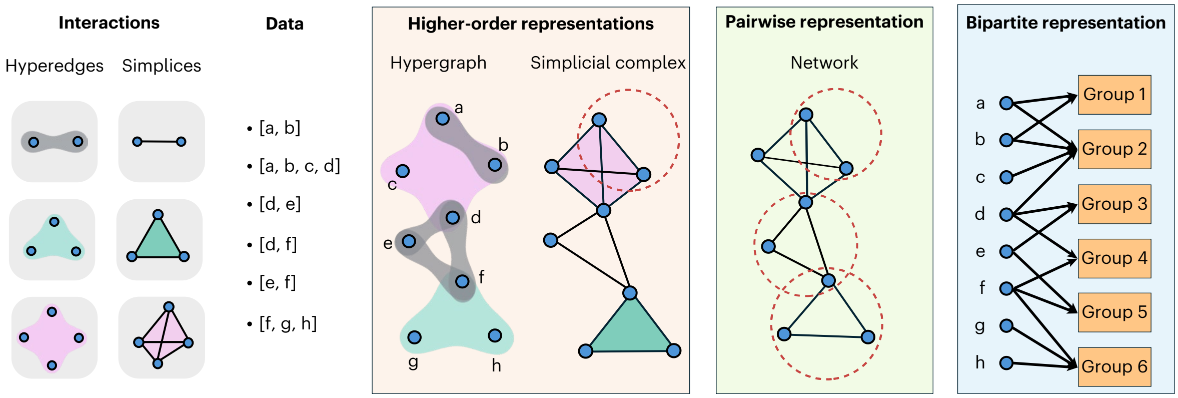

Fig. 1 | Higher-order representations of social network data. Given a dataset with non-dyadic interactions, they can be encoded via hyperedges or simplices. A *k*-hyperedge encodes an interaction among *k* individuals. A hypergraph, a collection of nodes and hyperedges, is the most flexible way to represent higher-order social networks. A simplicial complex, a collection of simplices, constrains the representation by enforcing the condition to have all possible subsets of the highest-order interaction also included in the complex. This leads to inaccuracies, as all lower-order interactions are automatically considered, losing the ability to distinguish between overlapping and non-overlapping interactions (red dashed circle). A pairwise representation is obtained by projecting the group interactions into cliques of pairwise interactions, thus making it impossible to retrieve the size of the original groups (marked in red dashed circles). A bipartite projection allows the distinguishability between different groups to be maintained, but here groups are represented in an indirect way, as a layer of nodes rather than edges or hyperedges.

fruitful modelling paradigm for social interactions, and we highlight the descriptive power of higher-order interactions, where individuals can be bound in groups of two but also three or hundreds, all at once. The potential impact of non-dyadic modelling approaches was recognized in the early 1970s by Atkin[10,11] and Berge[12]. However, it is only recently, thanks to unprecedented access to high-resolution social network data, that higher-order social networks have emerged as a natural solution to capture and model the interconnected structure of groups, which characterize many aspects of real-world social systems.

The limits of the classic network paradigm—and indeed the inherent irreducibility of higher-order interactions to pairwise interactions—become particularly evident when studying not only the structural organization of human relations but also human behaviour. As early as 1895, Gustave Le Bon pointed out that an individual immersed in a group for a long time loses their identity, becoming subject to the 'magnetic influence' given out by the crowd[13]. A few years later, Simmel further discussed the idea that group dynamics cannot be reduced to the sum of dyadic relationships[14] and emphasized that groups of three can facilitate the reconciliation and resolution of conflicts because of a third party (for example, a mediating country facilitating communication to find a mutually acceptable solution to a conflict) but also can create new conflicts (for example, a beneficiary who chooses between two conflicting sides to change the power balance). Drawing from the ideas of gestalt psychology, Lewin postulated that when groups are formed, they indeed become a unified system that cannot be understood by evaluating members individually[15]. In modern language, this translates into the ability to model new social phenomena and dynamics such as peer pressure, opinion formation and large-scale cooperation with the tools of higher-order social networks. However, in contrast to conventional social network analysis, which often infers group structures inductively from patterns of pairwise interactions, the hypergraph framework allows for a more direct (or deductive) representation of inherent group-level phenomena. This distinction is crucial for understanding social complexity that transcends dyadic relationships.

In what follows, we first describe the vocabulary and key concepts behind higher-order interactions. We then look into large-scale digital data as a trove of new opportunities for breakthrough explorations of human behaviour, from collaboration networks to high-frequency contact social networks. Lastly, we discuss recent research in which higher-order social networks have been used to obtain new insights on social phenomena, allowing us to reveal new mechanisms for group formation; improve the modelling of social contagion, cooperation and other forms of moral behaviour; and create opportunities for social experiments. We conclude with a summary of the key recent developments and outline promising directions for future research.

Higher-order interactions

Since its foundation, social network analysis has heavily relied on the mathematical framework of graph theory[16]. In its classical representation, a social network can be seen as a graph—that is, a collection of actors, represented as nodes, and links, describing the pairwise interactions among them. Despite being widespread, this framework has clear limitations when describing real social systems, where social interactions often occur in larger groups. To better represent these higher-order interactions, we can use more complex mathematical objects, which naturally allows us to capture social relations beyond the dyadic level[17]. The natural candidates to formally describe higher-order social networks are hypergraphs. Formally, a hypergraph

$$\mathcal{H} = \{V, E\}$$

is a collection of nodes V, representing the agents in the system, and their interactions E, described as hyperedges, generalizations of links that can encode relations not only between pairs of nodes but also among an arbitrary number of K partners[12].

Despite the focus on simple graphs, social network analysis has already attempted to go beyond a simple characterization of relations among pairs. At the micro-scale, non-dyadic interactions have been investigated by looking at cliques (fully connected small subgraphs whose members are all socially linked to each other) or other small motifs[18], highlighting frequently observed patterns of social interactions. At the macro-scale, much attention has been devoted to the organization of individuals into social clusters or communities[19,20].

However, extracting information about the real higher-order structure of social networks from traditional graph representation might be misleading. We illustrate these limitations through an example higher-order social network in Fig. 1. Hypergraphs[12] are the most flexible representation of higher-order social networks, allowing us to encode interactions of arbitrary group sizes without any particular constraints. In the case of simplicial complexes, the system is encoded as a collection of simplices, which combinatorially describe interactions not only among their members but also among all possible subsets[21,22]. For this reason, such a representation might not always be suitable, except in cases where the presence of a larger group interaction also implies the presence of all related interacting subgroups. Simplicial complexes have been widely used because their structure makes them well suited for methods from topological data analysis, which help uncover patterns in the 'shape' of data. However, from a combinatorial viewpoint, they are a restricted type of hypergraph and therefore often fail to capture the full complexity of higher-order interactions observed in real-world systems.

In a simple pairwise representation, groups are projected and represented as cliques of dyadic ties. This severely limits our understanding of the structure of interactions in the system, as the original groups generally cannot be retrieved. For instance, transitivity may either indicate the presence of one higher-order interaction involving three partners, or arise from combining three distinct social interactions among three pairs of individuals. The two situations are both frequent in collaboration networks, where a triangle may be associated with a single paper coauthored by a team of three individuals, or with three distinct papers produced by pairwise collaborations. Differences become even more relevant when interactions are inferred from co-occurrence in social groups. If we take a group photograph, a group meeting or an email chain and we draw dyadic links among all members of the group, this induces artificially high levels of transitivity in the system. Such distortions in network structure may lead to poor modelling choices when describing social dynamics, which are strongly affected by group mechanisms.

Past research has leveraged the language of pairwise networks in an attempt to explicitly describe higher-order interactions. This can be done by considering a particular type of bipartite graph, where one set of nodes describes individuals, and a second set of nodes accounts for groups, each individual being linked to the groups in which they participate[23,24]. While such representation does not distort the data, direct higher-order representations are preferable as they recover and expand the original framework of social network analysis, where nodes are reserved for social actors, and (hyper)links are used to model interactions among them. Hypergraphs also allow for a more intuitive grasp of many empirical features of real-world systems, such as the presence of nested and overlapping group structures, than bipartite projections do. Moreover, such a representation does not necessarily reduce to a simple graph when only dyadic ties are present. Finally, we note that higher-order approaches are complementary to coarse-grained views of social networks based on communities[19] and hierarchical structures[25], as hyperlinks allow for the detailed modelling of groups of different sizes at the micro-scale.

Indeed, hypergraphs provide a natural representation of real social systems in their complexity, which smoothly reduce to traditional networks when only pairwise interactions are present. They allow researchers to inherit a generalized toolkit of consolidated measures of social network analysis, from degree to centrality measures[26,27]. Recent research has focused on developing richer ways to describe higher-order connectivity. At the local level, such patterns can be quantified using higher-order clustering coefficients[28] and extensions of motif analysis[29,30]. At larger scales, new algorithms make it possible to detect community structure—both hard[31,32] and overlapping[33,34]—as well as core–periphery organization[35]. Hypergraphs are also particularly effective for representing the temporal evolution of social systems, where higher-order interactions change dynamically over time[36–39]. In parallel, efforts have been made to make such tools available to the research community, through libraries such as HGX[40], XGI[41] and HyperNetX[42]. In the next sections, we provide a quick overview of recent findings on the higher-order organization of social networks, from collaboration networks to face-to-face interactions, and discuss how the higher-order structure of real-world social systems affects social processes and collective behaviours.

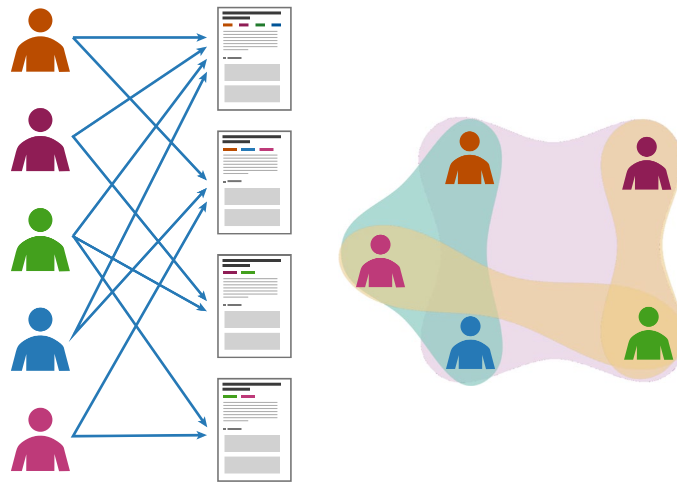

Fig. 2 | Collaboration hypergraph from affiliation data. Hypergraph of scientific collaborations, where each hyperedge represents the set of coauthors of an article.

Digital data

Affiliation and collaboration networks

Affiliation networks, where individuals are associated with groups, are a primary example of social systems that cannot be suitably described by simple graphs[16]. Indeed, affiliation with each group can be represented as a hyperedge of a social hypergraph. In the early 1980s, hypergraphs were first used to describe overlapping participation in voluntary organizations[43], ethnic groups[44] and religious celebrations[45]. This focus on group interactions soon served as a stimulus to develop new network tools, such as centrality measures explicitly taking into account higher-order social relationships[46–48]. In the late 2000s, multipartite systems based on folksonomy (a system of users collaboratively tagging and annotating data) were used to develop a systematic framework to represent these networks as hypergraphs on the basis of various projection protocols[49,50]. Moreover, group memberships can be exploited to define similarity among individuals by introducing a suitable association index[51,52].

Scientific collaboration networks are one of the most studied affiliation networks[53–55] (Fig. 2 and Box 1). In many fields, scientific advances are achieved not through the work of lone geniuses but through teamwork, with a tendency of pairwise collaborations to be less and less relevant than the outcomes of larger groups[56,57]. At the individual level, higher-order generalizations of local measures such as the node degree have been used to determine the relevance of scientists within scientific domains[58,59]. At the team level, some collaboration patterns have been found to be prevalent[60], with a sizable number of groups of coauthors often working together exclusively as a single unit[29]. If a group of people represents a true social structure (family, friends and so on), we expect to see that same configuration of nodes recurring repeatedly over time[61]. This tendency of repeated instances of groups is typical of collaborations in science and holds true in workplaces, where workers tend to form teams with similar sets of team members[62]. Building on this idea, researchers have identified persistent collaborations by detecting statistically significant higher-order interactions[63]. Most of these collaborations turn out to involve groups larger than pairs and are more likely to be geographically co-located than short-lived coauthorships[64].

Coauthorship networks have also been investigated through topological data analysis, providing a characterization of the 'shape' of collaborations[65]. Persistent homology, a recent computational technique to extract topological features of a simplicial complex at different spatial resolutions, has been applied to collaborations across different domains to get insights into collaboration patterns across

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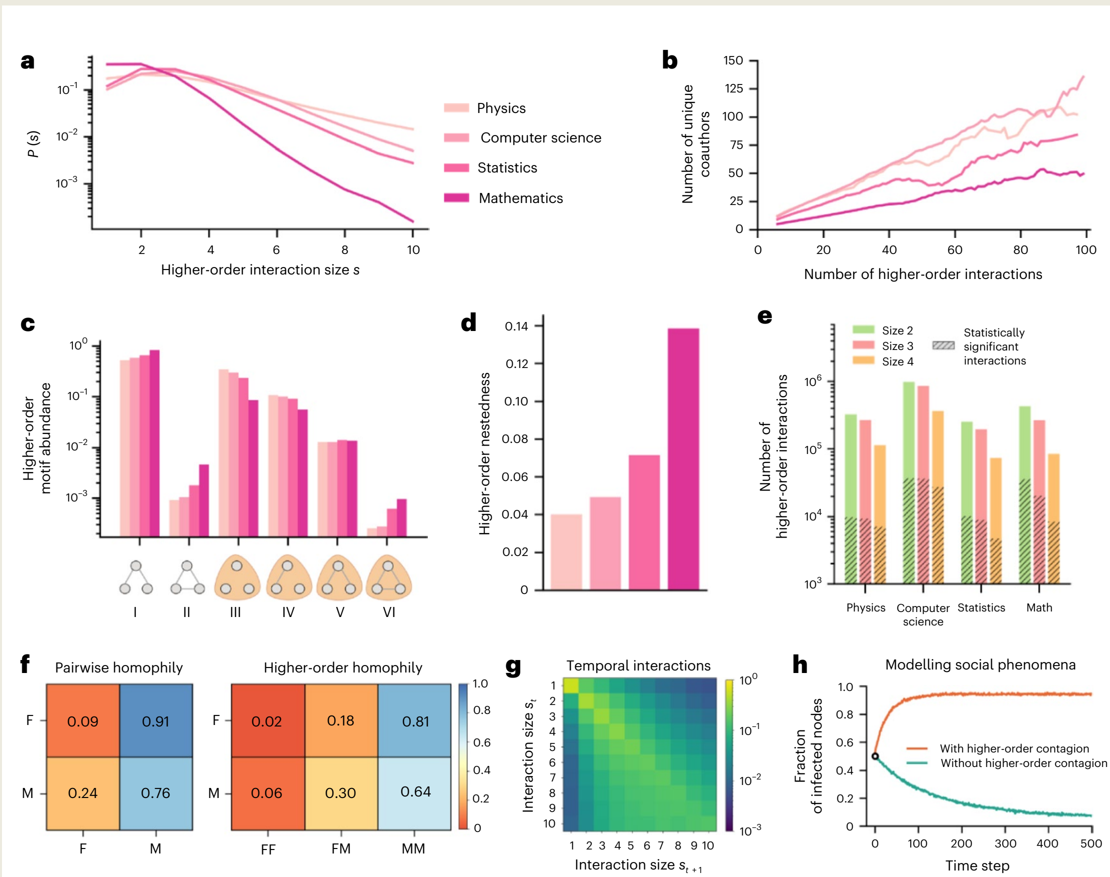
BOX 1

Higher-order analysis of collaboration hypergraphs

We demonstrate the power of higher-order networks by analysing collaboration patterns in different scientific domains, investigating arXiv coauthorship data (all papers uploaded between 2007 and 2022) in the fields of physics, computer science, statistics and mathematics. For each domain, we constructed a hypergraph $\mathcal{H}(\mathcal{V}, \mathcal{E})$, where each hyperedge denotes the set of coauthors participating in a paper. In the following, we illustrate a variety of higher-order measures and approaches of increasing complexity, capturing different facets of the architecture of real-world collaboration systems.



Box Fig. 1 | a, This panel displays the probability distribution of interaction sizes for various disciplines. Mathematics papers are typically written by the smallest teams. By contrast, physics papers are often produced by bigger collaborative efforts, as evidenced by the slower decay of *P*(*s*). **b**, Switching from single papers to career trajectories of the authors, this panel shows the number of unique coauthors for each author as a function of their total number of papers. For a fixed number of interactions, we observe a hierarchy among fields, with mathematicians forming fewer unique connections in their career. Note the inversion between physicists and computer scientists compared with the previous plot, indicating that while physicists tend to work in larger teams, they also have more persistent collaboration patterns than computer scientists. **c**, Analysing patterns of interactions at the micro-scale, this panel displays the abundance of different higher-order motifs for subgraphs of three authors[29]. Motifs II and VI reveal that statisticians and mathematicians frequently work in pairs (II), and when a larger team is formed, its members typically also collaborate through pairwise interactions (VI), suggesting the presence of a mechanism known as simplicial closure[28]. By contrast, motif III shows that in physics and computer science, groups do not require the presence of underlying dyadic ties. **d**, These findings are confirmed by looking at collaboration patterns at a larger scale by computing a measure of higher-order nestedness, which evaluates how much smaller groups are encapsulated in larger ones[287]. Due to the cost of processing high-dimensional data, it can be convenient to reduce a higher-order network by providing a simplified representation that still captures its essential higher-order structure. **e**, This panel shows the number of statistically significant co-occurring groups of coauthors across scientific domains, comparing their publication rate against a suitable null model that preserves the activity of each author[63]. **f**, Focusing on physics—the domain whose collaboration patterns display strongest higher-order character—this panel illustrates the higher-order dimension of homophily in social systems, evaluating gendered interactions separately for dyads and groups[98]. **g**, By exploiting the temporal nature of the data, this panel quantifies the transition probability $P(s_{t+1}|s_t)$ of switching team size in two consecutive papers[39]. For physics, authors who work in larger collaborations rarely revert to smaller teams. By contrast, mathematicians more regularly alternate between groups of different sizes (not shown). **h**, Finally, we illustrate the power of higher-order networks to model social phenomena such as contagion processes[124], finding that the spread of ideas and innovation on the collaboration hypergraph can be promoted by incorporating group mechanisms to describe peer pressure.

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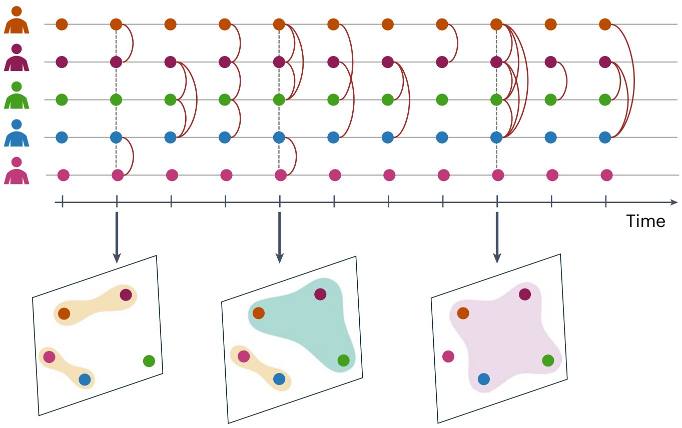

Fig. 3 | Temporal face-to-face contact hypergraphs. Time-resolved contact data can be described by a temporal hypergraph, where hyperedges describing proximity or face-to-face interactions among individuals are extracted at each observation time.

disciplines. As early as the 1970s, Atkin pioneered work on the potential of higher-order interactions, proposing a mathematical framework based on cohomology and q-analysis to encode higher-order interactions in affiliation data[10,11]. Real collaboration hypergraphs were found to have a peculiar structure, with more clustering and filled triangles than what was observed in randomized systems with the same number of nodes and connections[66]. An analysis of collaboration data from arXiv also showed that when three authors have collaborated as distinct pairs, there is a high chance that they also have all published joint papers together[67]. The strength of such a 'simplicial closure', a generalization of the well-known concept of structural holes for traditional networks[68], may differ according to the type of collaboration hypergraph and can also be used to differentiate social networks from biological systems[28]. Even if scientific fields were found to have quite different typical sizes of collaborations, the number of collaborative efforts in which each scientist takes part is generally comparable[67] (except for large-scale experiments such as collaboration at CERN for physics), a finding that could be associated with a maximum capacity for attention.

High-frequency contact networks

As discussed above, social structures, such as family and friends, result in the same configuration of nodes recurring again and again over time[61]. We also know that the relationships during a meeting of a group of four people cannot be reduced to six pairwise relations[69]. These two observations suggest that it is meaningful to describe real-world contact networks using hypergraphs. Furthermore, the hypergraph representation is particularly relevant when we include a temporal perspective of how social interactions unfold. This intuition has been confirmed as technological progress has made it possible to collect datasets on large social systems with high time resolution over extended periods. In perhaps the largest study of high-frequency contact networks, the Copenhagen Networks Study[70], Sekara et al.[71] observed the interactions of about 1,000 freshman students in five-minute time intervals over 36 months. In addition to physical proximity measured via Bluetooth, they recorded virtual forms of social proximity, including phone calls, text messages and social media interactions. They found the physical proximity network to be well described as temporal sequences of fully connected cliques or 'gatherings' lasting up to 12 hours, with a gathering of size K corresponding to a meeting of K individuals. While the nomenclature is different, a gathering of size K is essentially a hypergraph of size K. The authors also identified repeated gatherings over time (denoted 'cores'), corresponding to groups of individuals that would meet again and again across weeks and months. Analysing their dataset in terms of gatherings and cores rather than simple dyads allowed them to define and predict the social trajectories of individuals[71]. This dataset is available to researchers[72].

The Copenhagen Networks Study is neither the first nor the last study of high-frequency interaction data. Over the years, multiple field studies have used state-of-the-art technology to collect contact networks in diverse settings such as schools, universities, scientific conferences, hospitals, museums and corporate offices. Below, we highlight some major datasets on the composition and evolution of groups. A key example is the pioneering work in reality mining[73] from MIT's MediaLab, where students in an MIT dormitory were equipped with sensing smartphones. Started in 2008, the SocioPatterns project[74] collected longitudinal data on face-to-face interactions in a number of contexts such as a workplace, a scientific conference and a hospital[75]. Two datasets on contact networks at a scientific conference and a museum exhibition were collected and analysed by Isella et al.[76], while Génois et al.[77] collected face-to-face data using wearable sensors in a corporate office. Similar data involving health-care workers and patients at a hospital were collected by Vanhems et al.[78]. Other examples of such data are the StudentLife dataset from Dartmouth University[79,80], the Marseilles high-school student dataset[81] and Lyon primary-school student datasets[82]. In recent years, the DyLNet project collected high-resolution face-to-face data on preschool children over a period of three years[83]. Finally, high-frequency contact networks have also been inferred from other sources, such as connection to Wi-Fi routers[84] or colocation in GPS data[85].

More recently, higher-order representations have been directly leveraged to describe the evolution of social interactions in physical space with recurring groups, modelling them as a sequence of hyperedges of a hypergraph, as shown in Fig. 3. An analysis of face-to-face interactions across different contexts revealed that, no matter the size of social encounters, group interactions tend to be clustered closely in time, a phenomenon dubbed as burstiness[36]. In the recent past, Gallo et al.[38] proposed a systematic framework to measure correlations across time in higher-order networks. Using face-to-face data from multiple sources, they analysed the correlation of groups of different sizes across various time separations. Their analysis revealed that groups of similar sizes are significantly correlated even at a long timescale, thus reinforcing signatures of past gatherings. Furthermore, using these temporal correlations among groups of different sizes, they highlighted the differences between group formation and group segregation depending on group size. While that model considered social interactions from a group-membership perspective, Iacopini et al.[39] studied temporal group dynamics from a node-centric perspective. In particular, they found that individuals often move from larger groups to smaller groups and that groups form and break over time in small, incremental steps rather than changing suddenly, often forming large cores of central and tightly connected individuals[86].

Beyond humans, high-frequency proximity data have also allowed researchers to track the evolution of higher-order interactions in animal social networks[87]. An analysis of a vulturine guinea-fowl population has revealed that females and low-ranking group members take part preferentially in dyadic interactions, while males and more dominant group members are substantially more likely to engage in groups containing more than two individuals[88]. Beyond simple contacts, higher-order approaches have also been used to study non-dyadic communication patterns and vocal communication in birds, better revealing vocally coordinated group departures and informing models of cultural evolution of vocal communication[89].

Modelling social processes

Group formation and evolution

There is a substantial literature on social mechanisms that describes the formation and evolution of ties in social networks[90–93]. Focusing solely on dyadic interactions, however, this work does not incorporate the

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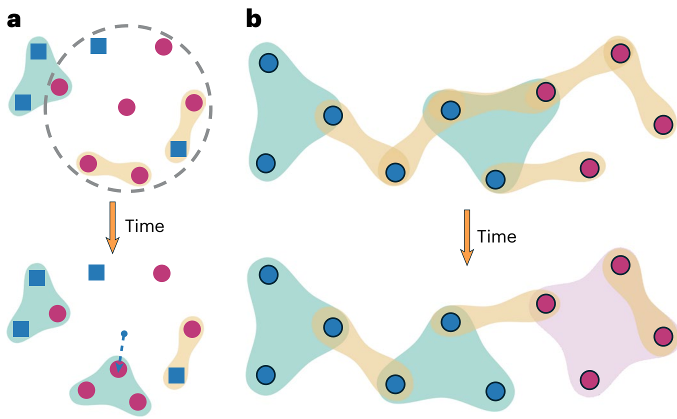

Fig. 4 | Higher-order models of group formation. a, Agent-based model describing the evolution of face-to-face interactions in physical space. An agent considers the groups lying within a spatial range (dashed circle on top) and decides to move and join one of them on the basis of their attractiveness (the dashed arrow at the bottom shows the movement). Group attractiveness depends on the properties of the group, such as its size and composition (here pink and blue can denote gender). **b**, Initial snapshot of a hypergraph where nodes with different inherent attributes are connected to each other through edges and hyperedges (top). With time, the nodes rewire themselves as dictated by group biases and preferences to form a highly segregated hypergraph with high homophily (bottom).

higher-order nature of many social interactions. Given the higher-order organization of real-world contact networks that we have summarized above, a stream of research has recently focused on proposing simple models able to reproduce the observed empirical patterns. Gallo et al.[38] introduced a model to generate a synthetic temporal hypergraph based on the memory of previous encounters. In particular, they showed that considering a hyperedge update process based on the past occurrences of specific hyperedges of various sizes reproduced real-life patterns of long-term group correlations as well as dynamics of group aggregation and segregation. By contrast, Iacopini et al.[39] proposed a model from a node-centric point of view. They considered that at each time step, an individual decides to either stay in the group or leave the old group and join a new group, on the basis of the history of time spent in the group as well as the trajectory of past encounters (often dubbed 'social memory'). Their model accurately reproduces the empirical patterns of group assembly and disassembly.

Another extension of this line of research concerns the introduction of signs—that is, having positive and negative links (for example, to represent friendships and enmities) in a collective of people. One of the key mechanisms behind the dynamics of signed networks is social balance theory[94]: loosely speaking, the fact that the friend of my friend is my friend and the enemy of my enemy is also my friend[95]. This implies that some triangles are stable (three people who are all friends with each other, or two people who are friends and are enemies of a third one) and others are unstable (two enemies with a common friend or three enemies). Naturally, this calls for a study of triangle motifs in networks as drivers of relationship creation and destruction[96]. In addition, higher-order networks provide a natural formalism to include other motifs (squares, pentagons and cycles of any length) that have also been shown to be relevant in temporal signed networks[97].

A crucial feature neglected by network-based models is that in contact networks, agents move in a physical environment. Indeed, simple frameworks based on mobile agents and individual attractiveness have been shown to successfully reproduce the temporal structure and bursty behaviour of dyadic interactions[91]. Beyond dyads, the spatiotemporal features of groups in human face-to-face interactions can be captured by agent-based models where each group is characterized by an intrinsic degree of social appeal, the group attractiveness, on which basis neighbouring agents decide whether to join the group or walk away[98], as illustrated in Fig. 4a. The framework can reproduce many properties of groups in face-to-face interactions, including their distribution, the correlation in participation in both small and larger groups, and their persistence in time, which cannot be replicated by dyadic models.

The above models can be enriched to account for individual features such as gender, unveiling complex homophilic patterns in groups of different sizes[98], which are not included in standard pairwise measurement of homophily (the tendency of individuals to associate with similar others)[99]. First, group-level interactions exacerbate homophily. In this way, homophily can exhibit multiplicative effects in the presence of a group, departing from traditional ways of measuring dyadic attractions[100,101]. This can lead to social segregation and inequality as groups form around shared attributes as depicted in Fig. 4b. In a consolidated society where people associate with similar others in multiple shared features such as socio-economic status, race and ethnicity, inequalities tend to become compounded[102], and higher-order interactions can amplify this compounding effect[103].

Social contagion

We now turn to the impact of group interactions on efforts to model the spreading of rumours, the adoption of norms and the diffusion of innovations. In biological contagion, such as epidemic spreading, the probability of infection between a pair of individuals i and j is proportional to the amount of time i and j spend together; in this sense, the probability of infection is inherently dyadic[104]. Thus, when an individual is connected to multiple other agents, we can consider each link as an independent source of infection (Fig. 5a). In the context of social contagion, the picture is less clear. Although it was initially considered similar and modelled in similar ways[105–107], we have now come to understand that 'complex' social spreading depends on the network configuration around a susceptible node[108–110]. Unlike the case of disease spreading, being exposed to a behaviour for ten hours by one person is different from being exposed to the same behaviour for one hour by ten people. Multiple mechanisms for social contagion have been proposed, starting with the threshold model[111,112], where multiple exposures are needed for spreading. Opinion dynamics models[113], such as the voter model[114] or majority rule models[115], are other examples of complex interaction dynamics in networks. Theories of complex contagion, where exposure to multiple sources is required for contagion (Fig. 5b), are supported by mounting experimental evidence that social spreading is different from disease spreading[116–122]. The detailed mechanisms behind complex contagion, however, are still not clear. In the computational domain, various epidemic models have been thoroughly explored, but the 'toy models' studied in this domain (see ref. 123 for an overview) are typically chosen for their analytical properties rather than realistic properties.

Recently, however, the use of a framework based on higher-order interactions has shown great promise in allowing us to explicitly model group interactions at the microscopic scale. The crucial novelty is that groups of different sizes may be associated with unequal infection rates, reflecting different degrees of social influence and peer pressure[124] (Fig. 5c). The model[124] mimics a social reinforcement process where group pressure can have an additive effect with respect to traditional pairwise transmission. If collective social influence associated with higher-order interactions is low, the system behaves like a traditional susceptible–infected–susceptible (SIS) model. There exists a critical threshold of pairwise transmissibility that separates two regimes: one where new ideas quickly die out and another where they persist in the population. Near this threshold the change is usually gradual, with only a small fraction of individuals adopting the idea. However, when groups exert strong social pressure, the threshold is lowered and the transition becomes abrupt, producing sudden large-scale shifts in collective adoption.

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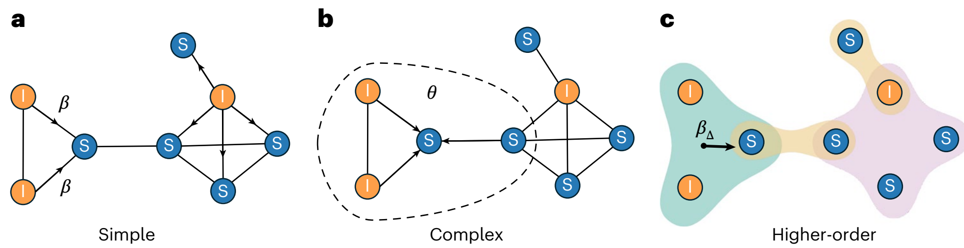

Fig. 5 | Models of social contagion. Social contagion models, where individuals can be in either a susceptible (S) or infected (I) state. **a**, In simple contagion, each link acts as an independent source of transmission, over which contagion occurs with probability β. **b**, In complex contagion, multiple exposures are required for transmission, and contagion happens if a sufficiently high fraction θ of contacts is infected. Nevertheless, the exact social structure is neglected, and all neighbours of a node are considered together regardless of whether they influenced a node as part of a group or not. **c**, The microscopic structure of groups is considered in higher-order contagion models, where groups modelled as hyperedges can have different infection rates depending on their size, allowing stronger (or weaker) transmission occurring in groups with probability β_Δ to be modelled.

This behaviour can be explained analytically by describing the temporal evolution of infection using a mean-field approach, which shows the emergence of co-existence between endemic and non-endemic stable regimes. Importantly, the bistability has social consequences: depending on the number of initially infected individuals, the propagation of a norm or behaviour may either diffuse widely into the population or die out. Differing from the traditional pairwise models of social contagion, this finding highlights the necessity of a critical mass to initiate social changes in society, as also observed for related dynamics of social conventions[125].

Originally obtained for homogeneous simplicial complexes, these results have been generalized to heterogeneous simplicial complexes[126] and hypergraphs[127,128], giving rise to a promising stream of new research aimed at characterizing contagion through better and more realistic models of social dynamics.

Cooperation

Cooperation in large groups of unrelated individuals distinguishes us most from other mammals, and it is largely due to these remarkable other-regarding abilities that we enjoy our evolutionary success[129]. Understanding the origin and evolution of cooperation in unfavourable situations has been a long-standing goal of natural and social sciences[130]. Over the years, multiple game-theoretic modelling approaches based on reciprocity[131,132], image scoring[133–135] and reputation[136–138] in collective action problems have been proposed to enhance our understanding of how prosocial behaviours emerge in social systems. These mechanisms can be broadly classified into five rules[139], one of which is network-based reciprocity, where repeated interactions among interconnected individuals lead to higher levels of cooperation. Innovative models leveraging these inherent pairwise structural patterns such as heterogeneous numbers of connections, ordered neighbourhoods in lattices, modular structures and multi-layer networks[140–144] have been shown to promote cooperation in social dilemmas. But this research has also revealed the many possible options of defining groups and attributing costs in classical networks. After all, many social encounters are group-based, where multiple individuals interact simultaneously and face the consequences together. It has been shown that group interactions in fact link individuals together even if they are not directly connected in a pairwise manner, simply due to their participation in the same group[145]. Moreover, group interactions imposed on classical networks tend to diminish the impact of topology on cooperation due to the averaging effect and the consequent emergence of well-mixed conditions, especially for large groups[146].

Taking into account higher-order modelling frameworks largely alleviates the difficulties encountered in pairwise interactions, suggesting that hypergraphs are a natural way to study public goods games in groups and how these group interactions influence the evolution of cooperation[147,148]. As a paradigmatic example, a standard public goods game on hypergraphs was shown to correspond exactly to the replicator dynamics in the well-mixed limit, thus providing an exact theoretical foundation—a null model—to study cooperation in groups[147]. The richness of higher-order modelling of evolutionary games, primarily manifested through the nonlinearity in payoffs of individuals in a group, was first exploited for well-mixed populations[149] as well as structured populations[150]. Building on the idea of synergy and discounting in groups, subsequent research extended the framework for hypergraphs, finding that increasing the effect of nonlinearity (that is, each additional cooperator in a group scales the payoff for all members nonlinearly) enhanced cooperative behaviour[151]. Importantly, nonlinearity represents a genuine case of higher-order interaction where group behaviour cannot be decomposed into multiple dyadic interactions. Along a similar direction, Wang et al.[152] explored multiplayer public goods games with arbitrary strategies beyond cooperation and defection, such as peer and group punishment, to find that higher-order effects are necessary for more precise modelling of public cooperation.

Going beyond the public goods game, Guo et al.[153] studied the evolution of cooperation in simplicial graphs with pairwise and three-body interactions for various social dilemmas such as the prisoner's dilemma, the snowdrift game and the stag hunt game. The inclusion of three-body interactions promoted the survival of non-dominant strategies and led to a transition from dominant defection to dominant cooperation depending on the underlying higher-order interaction patterns. Civilini et al.[154] introduced a group choice dilemma with the possibility to choose either a safe alternative (with a lower payoff) or a risky one (with a higher payoff). The model reproduced shifts in choices based on the group size, where the riskier options with higher rewards were chosen if a small fraction of individuals had a large number of connections, mimicking a power-law degree distribution in the associated hypergraph.

Even though specific multiplayer games were studied, until recently, there was a lack of a generalized framework to naturally incorporate higher-order structures into multiplayer game dynamics. Civilini et al.[155] filled this gap by building a framework for any social dilemma on hypergraphs as a specific case of the system illustrated in Fig. 6. By meaningfully assigning payoffs for all possible combinations of strategies for both pairwise and higher-order games, they provided a universal framework to analyse any mixture of two- and three-player social dilemmas. On the basis of their study, the emergence of cooperation in a higher-order prisoner's dilemma largely depends on (1) the presence of a minimally sufficient fraction of three-player interactions and (2) the existence of a small minority of initially committed cooperators. These two factors together contribute to push individuals to exhibit high levels of cooperative behaviour. Accounting for group-size-based strategies and increasing the structural overlap between interactions of different sizes further promotes cooperation[156].

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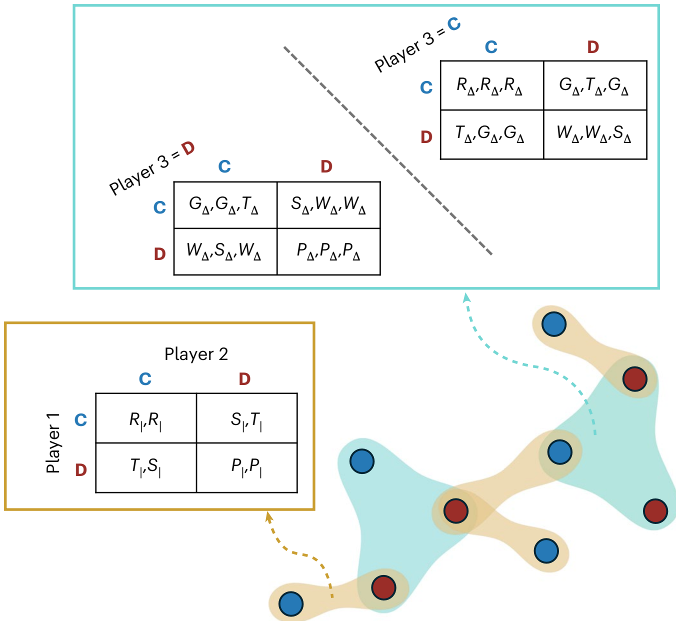

Fig. 6 | Multiplayer games on hypergraphs. A higher-order game on a hypergraph with 2-hyperedges (pairwise links) and 3-hyperedges. The players participate in games involving all their hyperedges and earn a payoff based on the payoff matrix for two-player games and the payoff cube for three-player games. R denotes the reward for mutual cooperation, while P denotes the penalty for mutual defection. A cooperator earns a payoff S (namely, sucker's payoff) against a defector(s), while a defector earns a payoff T (temptation to defect) when facing a cooperator(s). G_Δ and W_Δ, respectively, denote the payoff of a cooperator and a defector against a mixed group of a cooperator and defector. The subscript | and Δ, respectively, denote the pairwise and higher-order payoffs.

In the wider context of cooperation studies, a relevant mechanism to support the evolution of prosocial behaviour is group selection, according to which competition among groups can lead to the evolution of within-group cooperation[157]. Several works have explored this mechanism through theoretical models, numerical simulations and behavioural experiments, yielding complex results. For instance, while some studies have highlighted that group selection indeed leads to the evolution of in-group cooperation[158,159], others contend that this effect arises because group competition introduces a threshold for victory, acting as an additional incentive, and it is this alteration in incentives that bolsters cooperative behaviour[160]. Although notable, these studies generally view groups as simple aggregates of individuals, overlooking the hierarchical dynamics that could meaningfully affect group selection in real human societies. Using higher-order networks may thus provide new insights into how and when group selection fosters the evolution of in-group cooperation.

Beyond human behaviour, higher-order modelling frameworks have proved successful in studying the coexistence of species and the stability of ecosystems[161,162], and we refer interested readers to a focused review for a complete overview of the field[163]. All in all, the evolution of prosocial behaviour for any system of individuals participating in interactions of different sizes for any kind of collective action problem still remains elusive. Apart from cooperation, coordination and social learning have had important roles in cultural evolution in humans. Future work should investigate more diverse and realistic social encounters at various scales and validate the models in question using available data.

Truth-telling and other moral behaviours

Group conflicts often arise from moral conflicts[164–166], making the study of the evolution of morality essential for understanding social conflicts[167]. Moral conflicts typically exhibit a hierarchical structure, with various moral positions coalescing under broader macro-positions, making them naturally suited for representation in higher-order networks.

A critical dimension of moral behaviour is truth-telling, which is fundamental to human interactions and social cohesion. Self-serving lies are associated with adverse personal outcomes, such as marital dissatisfaction[168] and friendship dissolution[169], considerable economic losses due to tax evasion[170] and insurance fraud[171], and threats to democratic processes due to the spread of misinformation[172]. Behavioural scientists have developed various paradigms to study truth-telling, including the die-rolling paradigm[173], the matrix search task[174], the Philip Sidney game[175] and the sender–receiver game[176]. These experiments typically involve dyadic interactions. Yet, many real-world scenarios entail communication from one to many, such as politicians or journalists addressing the public, or within groups, such as company boards deciding on the disclosure of information[177].

Some theoretical work has investigated one-to-group, group-to-one and group-to-group communications[178–180], revealing that groups exhibit surprisingly sophisticated behaviours that are challenging to classify analytically. This increase in complexity arises partly because individuals within a group may interact among themselves and groups may be interconnected at a higher level. To overcome the challenges of mathematical analysis, researchers can turn to numerical simulations. However, these simulations have predominantly focused on one-to-one interactions[181,182]. To date, only one study has explored the evolution of truth-telling in the sender–receiver game with one sender and multiple receivers in higher-order structures[183], finding that truth-telling may evolve when groups of players (each consisting of one sender and multiple receivers forming a well-mixed population) are interconnected in hyperrings, particularly when the size of the hyperedges is small, and in real-life higher-order structures using the SocioPatterns database. Another study has examined the evolution of honesty in sender-receiver games played by one sender and multiple receivers belonging to communities, whose members may interact with some probability[184]. The authors found that the difference between the payoff corresponding to guessing the true state of the world and that of guessing the false state has an inverted-U-shaped effect on the evolution of truth-telling. We hope future work will extend these techniques to study the evolution of lying and truth-telling in various higher-order structures.

Beyond truth-telling, other moral behaviours such as trustworthiness in the trust game[185], decisions balancing equity against efficiency[186] and altruistic punishment in the ultimatum game[187] are also driven by moral considerations and often occur within group dynamics. Theoretical frameworks such as the moral foundations theory and the morality-as-cooperation theory suggest multiple dimensions of morality, many of which involve group interactions[188–191]. While some of these behaviours have been explored using well-mixed populations or classical networks, with a focus mainly on altruistic punishment[192–197], ingroup favouritism[198–203] and trust[204–211], research specifically addressing their evolution in higher-order networks is limited. We hope that future research will address this critical gap.

Social experiments in the laboratory

The past 30 years have witnessed how behavioural experiments have become the key tool to understand social behaviour in networks[212–214], superseding purely theoretical approaches based on paradigms such as *homo economicus* and its perfect rationality. A number of different contexts and interactions have been studied by means of experiments in structured populations, including coordination[215–217], public goods[218], cooperation[219], ultimatum games[220] and trading[221]. This body of work has established that strategic behaviour in groups depends on many factors that interact with each other in complicated manners[222,223]. Unfortunately, only a limited number of papers consider relatively large networks[224,225] due to the complexities associated with running experiments with sizable samples of participants. However, all experiments on networks have only analysed dyadic interactions: participants choose one of the available actions in the situation of interest, and that action affects all its connections in a pairwise manner. In this context, it should not be surprising that, to the best of our knowledge, there are no experiments on strategic games in hypergraphs.

This gap in the knowledge about human behaviour in experimental settings must be addressed if experiments are to become closer to realistic situations. Indeed, it has to be realized that in the case of groups, there is no structure in experiments, meaning that the context is that of a single (typically small) well-mixed population. However, the network structure used in experiments reflects more a set of dyadic interactions rather than people interacting as a group. In the experiments, people interact with their neighbours in the network, but this cannot be considered a bona fide group because every neighbour interacts with its own neighbours; that is, there is no structured interaction at the group level with other groups, and groups do not connect to each other as such. Hypergraph structures would allow researchers to overcome this limitation and bring experimental designs closer to applications. This would be the case, for instance, for studies of cooperation within organizations,[226] where often there are teams charged with different tasks that cooperate in groups and not as a result of individual dyadic interactions.

Experiments on strategic interactions in hypergraphs should be informed by the available knowledge on behaviour in group and network set-ups in the laboratory. When understanding group behaviour from the participants' level, it is important to take into account a number of features. First, behaviour in groups is affected by individual heterogeneity and beliefs about others: voluntary cooperation is inherently fragile, even if most people are not free riders but conditional cooperators[223]. Second, it has been shown[227] that initial contributors' decisions are affected by the behaviour of the group, while initial non-contributors' decisions are not, and letting individual behaviour be known by the group increases contributions even in groups consisting only of initial non-contributors. This type of feedback interaction between information at two different levels is also likely to arise when interactions take place in hypergraphs with their own group structure. In this context, it is important to keep in mind that when groups are large, the manner in which information is presented (for example, averages versus histograms) has strong implications for the distribution of individual behaviours[228,229]. In addition, when the strategic situation considered takes nonlinear effects into account, it has been shown that group size may increase cooperation in experiments[230,231]. This may have implications for hypergraphs, where hyperedges involve different numbers of individuals and therefore possibly different levels of cooperation. Network effects will also have their counterpart depending on the organization of hypergraphs. Experiments have shown[232,233] that the observed emergent behaviour is very sensitive to network details, such as community structure, centrality distribution and even having an even or odd number of connections. At the same time, the network structure may make the information complexity increase beyond what participants can grasp during experiments[221]. It is then clear that experiments on hypergraphs should begin with studying how these effects translate to a situation in which groups are the constituents of the population structure. Importantly, such experiments would have to deal with the complexity of the design, and a preliminary but crucial question would be to assess the extent to which participants understand the structure in which they are interacting.

Conclusions and outlook

The introduction of higher-order networks has substantially expanded our understanding of various social structures and phenomena. This methodology has enabled a deeper exploration of the topology of collaboration networks and the temporal dynamics of contact networks, has revealed new insights on how groups organize and potential biases in group formation, and has begun to unveil the multilevel nature of social processes such as contagion, cooperation, truth-telling and other moral behaviours. Arguably, this is just the beginning of a transformation that will touch virtually every field of research where networks have proved useful and where group interactions have a role. We conclude by identifying five novel research areas where the application of higher-order networks may yield substantial advancements. These areas are not meant to be exhaustive but represent major examples where higher-order networks are likely to bring new insights.

Computational challenges of higher-order social networks

While richer in information, higher-order social network representations also come with a variety of computational challenges. One challenge concerns data collection. While some datasets naturally come in the shape of hypergraphs, such as collaborations in science, in other cases current available data might be stored in dyadic format, even if the original systems had group interactions[74]. In this case, reconstructing the original polyadic relational structure requires additional information, such as fine-grained temporal resolution for each dyadic tie, so that cliques formed by co-occurring temporal dyads can be encoded as hyperedges. Newly developed inference techniques can help to reconstruct and predict groups even from simple projected graph structure[234], from the statistical analysis of temporal patterns[28,235] or considering the system community structure[33,34,236], using frameworks based on the higher-order stochastic block model. We hope that highlighting this challenge will promote the collection of relational data directly at the relevant higher-order level. A second challenge relates to the cost of higher-order representations[237], which have a higher dimensionality than traditional graphs. A number of techniques have been developed for efficient storage and efficient algorithm design[238] to mitigate the greater cost of higher-order analyses. Traditional graph representations are often inadequate for hypergraphs and simplicial complexes. To support a flexible set of queries and maximize efficiency, modern software systems often trade off memory for speed by simultaneously maintaining multiple complementary data structures[40,41], such as hash tables and sparse incidence matrices. For storage efficiency, tree-based encodings can be leveraged to compactly represent shared subsets[239], particularly when many hyperedges overlap. Approximate sampling methods offer another strategy for scaling algorithms, enabling computationally intensive tasks, such as motif detection[30], to be performed efficiently on large datasets with minimal loss in accuracy. The curse of higher dimensionality makes understanding when the structure of higher-order networks can be reduced without critical loss of information an important problem. Despite first answers from the field of dynamical systems[240,241], algorithms should be able to determine whether a higher-order representation is optimal simply by looking at the structural patterns of interactions and redundancies among groups of different orders. A final challenge concerns the development of a new class of null models, serving as a baseline against which real-world higher-order network structures can be compared and allowing us to understand which higher-order features are sufficient to explain the observed pattern. While a few works have already appeared on this matter[88,242–246], we believe that deeper attention should be given by the community to this topic, as new unexpected issues might arise. For instance, as the sampling space of higher-order networks is higher than that of traditional graphs due to a combinatorial explosion in all possible configurations of non-dyadic ties, a deeper exploration of the ensemble of the randomized configuration is in general necessary to achieve robust conclusions on the performed analyses.

Biases in group dynamics

The advantages offered by the higher-order interactions paradigm come with some hidden costs. Even though groups offer cumulative advantages, there might be biases and inequalities inherent to group dynamics. The formation of groups in networks can have uneven effects when some groups are systematically smaller than other groups (minorities), whereby their access to resources and information in networks is limited due to the structural constraints[247] that group-level homophily imposes. These structural constraints also affect network-based ranking and recommender algorithms used in social media[248], potentially reinforcing inequalities in artificial intelligence systems[249]. Furthermore, ideas from social balance theory[250] concerning the different structural roles of friendship ties and antagonistic ties should be taken into account while modelling group formation and group-level dynamics. Higher-order interactions might also affect the rich-club organization of social hubs and core–periphery structure, which in turn affect the formation of super-connected elites. In this way, higher-order interactions can amplify the influence of dominant groups, as power and resources tend to concentrate in well-connected clusters. The unequal distribution of resources combined with network effects increases inequalities for minorities in a nonlinear way[251]. To overcome such inequalities that are driven by higher-order effects in networks, computational models show promising new directions for testing the effectiveness of a variety of policies in social networks and online algorithms such as the influence of affirmative action and behavioural change in reducing inequalities[252] or implementing fairness methods in network-based online algorithms. Future work concerning group formation mechanisms should aim to integrate these inherent systematic biases into the models to bring them closer to understanding the inequalities present in real life.

Team dynamics

Many scientific and societal breakthroughs cannot be obtained by single individuals but need collective efforts of larger teams[56,62,253]. Despite the growing interest in teams, from science to management studies, most research has so far considered teams mostly as static entities, neglecting their dynamics and temporal evolution. For instance, in the science of science, most analyses consider the set of coauthors of a scientific article as an entirely different unit and link their compositional properties to success regardless of their previous collaboration history. In organization theory, some studies have performed multi-period observations of team activities through surveys of team members, but this approach is clearly limited to collecting fine-grained data about team activities over time[254]. New temporal data from science, open-source software developments[255] and escape rooms[256] have already opened the way to study temporal individual trajectories of networked individuals involved in group interactions. Beyond this, modelling frameworks such as temporal hypergraphs applied to management and innovation systems, and even sports, will allow us to characterize the dynamics and evolution of entire teams over time, as well as their interplay and interactions, allowing us to better understand the collective nature and emergence of embeddedness[257], social capital[258] and Matthew effects[259] in social networks.

Cumulative culture evolution

Human culture is uniquely complex due to its cumulative nature, shaped by contributions from many individuals and requiring the recombination of information[260]. Higher-order interaction frameworks offer new insights into cumulative cultural evolution, including how knowledge is shared and innovated within hunter-gatherer societies[261]. Hunter-gatherer groups are key to understanding cumulative culture, as human cognitive and cooperative skills evolved within the foraging niche over thousands of years[262–264]. For example, through generations of collective problem-solving, Congo hunter-gatherers developed extensive knowledge of medicinal plants, even though no single individual holds all of this information[265]. Like most Western cultural traits, hunter-gatherer culture was built collectively over generations. Higher-order network models have potential to clarify the group dynamics that drive cultural accumulation beyond dyadic exchanges. They could trace how information flows within hunting groups, storytelling events, rituals or collaborative tool-making. These models may also identify the optimal group sizes, compositions or interactions that enhance knowledge transfer and foster innovation[266–268]. Temporal hypergraphs, for example, can monitor how changes in group composition influence cultural resilience and innovation, highlighting the role of intergenerational or interpopulation transfers[269]. These processes may impact the rates of innovation and recombination, leading to cultural complexification. Future research should explore how group-level homophily or heterophily affects access to cultural information. Computational models incorporating higher-order effects could simulate how group structures influence cultural evolution. By focusing on these dynamics, researchers can develop more comprehensive theories, addressing key questions in human evolution, such as why cumulative culture emerged in the hunter-gatherer niche and remains rare in other species.

The evolution of languages

Languages typically emerge from evolutionary dynamics aimed at promoting communication among people[270,271]. Researchers have applied evolutionary game theory to examine how language develops within networks[272–275]. Yet, the role of higher-order networks in the evolution of language has thus far received little attention. Some aspects of the evolution of language may be better understood by taking group interactions into account rather than only dyadic interactions—for example, when groups develop unique linguistic features and dialects to mark boundaries with other groups[276]. Additionally, recent advancements in behavioural economics suggest that linguistic content notably influences people's behaviour[277], indicating potential coevolution of language and behaviour[278,279]. Studying the evolution of language, behaviour and their interaction through higher-order networks therefore represents a promising area of future research.

Policymaking

Policy interventions are critical for addressing collective challenges where individual interests may conflict with group welfare, such as climate change[280], shared marine resource management[281] and artificial intelligence[282]. Recent years have seen important moves towards the scientification of policymaking through so-called mega-studies, which test numerous potential interventions on the same participant pool to identify the most effective strategies[283–285]. However, while these studies provide an instant snapshot of the likely effects of some interventions, they do not take into account the dynamic and multilevel structure of the issue. Moreover, it is virtually impossible to test all potential interventions in behavioural experiments. Higher-order networks may revolutionize policymaking, as simulations on these networks can potentially compare the effects of many interventions at once, taking into account evolutionary and multilevel dynamics, therefore providing theory-driven suggestions for efficient policy interventions. Additionally, behavioural experiments involving higher-order networks could offer new insights into how the effectiveness of interventions propagates in human societies. For instance, a recent study evaluated the effectiveness of a large-scale health education programme through a friendship-nomination process inspired by network-based social contagion dynamics. The findings indicated that targeting via friendship nomination decreased the quantity of households required to achieve predetermined levels of village-wide adoption[286]. Future work might exploit the richness of higher-order contagion processes[124] for even more effective results.

Altogether, our Perspective unveils the need to move beyond dyadic approaches to capture the relational structure and dynamics of real-world social systems. We hope our work will stimulate more research on higher-order social networks to better understand how individuals assemble together and how group interactions shape collective human behaviour.

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Author contributions

F.B. and M.P. conceived the idea. F.B. and O.S. conceptualized the figures and data analysis for the box. O.S. created the figures and analysed the empirical dataset for the box. All authors contributed to writing, editing and reviewing the manuscript.

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Additional information

Correspondence should be addressed to Federico Battiston.

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