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COMMENTS

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Emergence mechanisms of group consensus in social networks

Abstract Reaching consensus within larger social network groups has emerged as a pivotal concern in the digital age of connectivity. This article redefines group consensus as the emergence of collective intelligence resulting from self-organizing actions and interactions of individuals within a social network group. In our exploration of extant research on group consensus, we illuminate two frequently underestimated, yet noteworthy facets: Dynamism and emergence. In contrast to the conventional perspective of consensus as a mere outcome, we perceive it as an ongoing, dynamic process. This process encompasses self-organized communication and interaction among group members, collectively guiding the group towards cognitive convergence and viewpoint integration. Consequently, it is imperative to redirect our focus from the outcomes of group interactions to an examination of the relationships and processes underpinning consensus formation, thus elucidating the mechanisms responsible for the generation of group consensus. The amalgamation of cognitive contexts and accurate simplification of real-world scenarios for simulation and experimental analysis offers a pragmatic operational approach. This study contributes novel theoretical underpinnings and quantitative insights for establishing and sustaining group consensus within the realm of engineering management practices. Concurrently, it holds substantial importance for advancing the broader research landscape pertaining to social consensus.

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1 Introduction

The consensus, acknowledged for its undeniable importance within systems, groups, and society, has garnered extensive attention in academic research, strategic reports, and government publications. Klapp (1957) aptly likened the significance of “consensus” in social science to that of “energy” in physics. In a certain sense, manifestations of consensus can be discerned in terms of social culture, structure, norms, roles, symbols, and institutions. However, with the advent of the Internet, notably the proliferation of social media, decentralized connectivity has given rise to larger and more intricate network groups. Social networks have evolved into pivotal platforms for information dissemination, sharing, remote collaboration, social interaction, opinion monitoring, and risk management. Their relevance spans diverse domains including project management, public health, crisis management, business, and marketing.

Nevertheless, while the development of social networks has ushered in opportunities in these fields, it has also brought forth a plethora of potential risks. These risks include information filtering and bias, social network abuse, information security and privacy concerns, conflicts, disinformation, and rumors. The significance of these risks is particularly pronounced in the absence of consensus within a social network community. For instance, when project team members or stakeholders diverge in project goals, priorities, or reporting requirements, communication may become convoluted, potentially resulting in the loss or misunderstanding of information and hindering critical decisions pertaining to the project, such as resource allocation and scheduling. Furthermore, the dearth of consensus within social networks can precipitate social fragmentation and hostility, particularly concerning political matters. When social network groups maintain highly divergent views, the absence of dialogue and consensus can fuel political polarization and, in extreme cases, incite social unrest. Consequently, achieving consensus within these larger groups has surfaced as a pressing concern in this era of digital connectivity.

Conventional research on group consensus in decision-making has typically characterized it as the ultimate state achieved through group interactions: Complete agreement or varying degrees of agreement (Scheff, 1967; Cabrerizo et al., 2014; Herrera-Viedma et al., 2014). Consequently, approaches to identifying consensus mechanisms typically assess the presence and strength of consensus at the representational level (Herrera-Viedma et al., 2007; Chiclana et al., 2013). Furthermore, the enhancement of group consensus is often attributed to the cumulative effort and skill contributions of its members. However, these research traditions tend to oversimplify or overlook the uncertainties inherent in consensus formation (Oppenheimer et al., 2007). In particular, in social networks characterized by decentralization, individuals engage in self-organized participation and interaction, where group consensus spontaneously emerges from individual actions guided by simple rules and devoid of centralized coordination (Baronchelli, 2018).

This review of existing studies on group consensus asserts that group consensus within social networks possesses two distinctive and often-neglected characteristics: Dynamism and emergence. In contrast to the earlier static perception of consensus as a fixed outcome, this study underscores the dynamic nature of consensus and its emergence through self-organized behaviors and interactions among individuals. Within the context of social networks, we redefined group consensus as the emergence of collective intelligence, a process marked by cognitive convergence and the convergence of viewpoints driven by group members engaged in self-organized communication and interaction. This redefinition of group consensus under the purview of social networks enhances our understanding of their nature. To delve deeply into the mechanism of group consensus generation, it is imperative to shift the focus from the outcomes of group interactions to the underlying relationships and processes. Consequently, approaches and strategies for identifying consensus mechanisms should transcend superficial representations and instead explore the establishment of relationships between connections and representations, thereby elucidating the impact of this relational logic on the emergence of group consensus. In particular, the incorporation of cognitive contexts is essential for the accurate simplification of the complexities of reality in simulations and experimental analyses.

Reconceptualizing the concepts, properties, and mechanisms of group consensus within the context of social networks has the potential to furnish fresh theoretical foundations and quantitative viewpoints to bolster the establishment and endurance of group consensus in the domain of engineering management practice. Engineering management entails the intricate coordination and oversight of complex projects and teams. Delving into the dynamic process of group consensus formation within social networks alongside a meticulous examination of the behaviors and interactions exhibited by heterogeneous individuals during this process can yield invaluable insights. In turn, these insights can be harnessed to address the challenges that frequently manifest in project management and teamwork within the sphere of social networks.

On a broader scale, this innovative theoretical perspective assumes significance in the advancement of research on social consensus.

2 Group consensus as a form of collective intelligence

Whether collectives possess greater wisdom than individuals has been a topic of perennial exploration that has drawn continued and sustained attention. The study of collective behavior has uncovered two contrasting viewpoints regarding collectives: One, as articulated by Le Bon (2002), characterizes them as "the unconscious crowd", while the other portrays them as astute decision makers (Kelly, 2009). The divergent interpretations of collective behavior outcomes serve as a reminder of the complexity inherent in the structure, mechanisms, and effects of group behavior when considering the concept of group consensus.

In the era of Web 2.0, social networks have propelled humanity into a globalized and interconnected "network society" (Castells, 1996). Individuals from diverse geographical regions, cultural backgrounds, knowledge levels, and spheres of influence converge into distinct groups based on shared interests or beliefs. Social networks have dismantled geographical, cultural, and class boundaries, facilitating transparent, egalitarian, direct, and instantaneous communication and interaction. However, these networks have significantly enlarged group sizes and complexities, yielding multifaceted and heterogeneous outcomes of collective behavior. Group dynamics within social networks can lead to three potential consequences: Group consensus, polarization, and fragmentation (Noorazar, 2020). Group consensus epitomizes the ideal state of communication and interaction within network groups, exemplifying collective intelligence that surpasses individual capacities.

Conventional research on group decision making defines consensus as the ultimate state achieved through group interactions, entailing either complete or partial agreement (Scheff, 1967). These two states have given rise to distinct conceptual definitions of a group consensus. One defines consensus as a complete and unanimous agreement among group members, suggesting that group interactions exclusively result in either a complete consensus or its absence. Alternatively, a more flexible definition perceives consensus as the shared orientation of group members, where a “complete consensus on an issue exists in a group when there is an infinite series of reciprocating understandings between group members concerning the issue” (Scheff, 1967). Varying degrees of group consensus can be inferred based on the level of shared orientation. This nuanced measurement of consensus has gained acceptance among numerous researchers (Herrera-Viedma et al., 2007; 2014; Chiclana et al., 2013; Cabrerizo et al., 2014).

The predominant focus of research on group decision-making revolves around organized and institutionalized groups formed with specific objectives. In contrast, groups formed through expansive social networks exhibited distinct differences. Social network groups are characterized by their larger scales, heightened heterogeneity in network relationships, and decentralized network structures. In decentralized social networks, group consensus spontaneously emerges from individual actions guided by uncomplicated rules free from central coordination. This collective behavior conceals the emergence of collective intelligence.

The fundamental distinction between collective intelligence and collective behavior lies in the fact that, with regard to collective intelligence, the essence resides not in the outcome itself, but rather in whether the individuals constituting the group have gained or applied perceptions or insights that were previously unavailable to them when working or contemplating individually (Weschsler, 1971). The study of collective intelligence traces its origins back to a century-old contest that involves the estimation of a bull’s weight. British statistician Francis Galton analyzed 800 collected guesses and made a remarkable discovery: When individual guesses were averaged, the collective, as a whole, accurately estimated the actual weight of the bull, despite the majority of individual guesses being erroneous (Galton, 1907). This phenomenon, in which collective judgment surpasses individual judgment, has become widely recognized as “the wisdom of the crowd” and has garnered substantial attention (Surowiecki, 2004; Page, 2007; van Dolder and van den Assem, 2018). It has found successful applications in diverse domains such as economic forecasting, medical diagnostics, and weather prediction. Distinguishing itself from the statistical conception of crowd wisdom, collective intelligence is a ubiquitous and distributed form of intelligence arising from the collaboration and competition among numerous individuals (Lévy, 1997). In this sense, collective intelligence shares common ground with swarm intelligence, which involves “two or more individuals independently, or at least partially independently, acquiring information, and these different packages of information are combined and processed through social interaction, providing a solution to a cognitive problem that cannot be implemented by isolated individuals” (Krause et al., 2010). Some scholars differentiate between these two concepts, suggesting that collective behavior typically pertains to the emergent behavior of groups of cognitively simple entities (e.g., insects, robots, and simulation algorithms), whereas collective intelligence alludes to phenomena involving entities endowed with higher cognitive capabilities (e.g., humans) (Salminen, 2012).

The research perspective on collective behavior underscores that the nature of the outcome assumes central importance in the context of group consensus, with the enhancement of consensus often attributed to the cumulative efforts or contributions of the skills exhibited by group members. Nevertheless, these research traditions tend to oversimplify or overlook the uncertainties inherent in reaching a consensus (Oppenheimer et al., 2007). As an emergent property of collective intelligence, group consensus in social networks encompasses not only the degree of cognitive coherence among group members regarding a specific objective but also a dynamic process in which interconnected heterogeneous individuals, through self-organized communication and interaction, drive cognitive convergence and integration of viewpoints across the entire group.

3 Characteristics of group consensus in social networks

In the specific cognitive context of a network society, group consensus fundamentally represents a cognitive practice aimed at seeking equilibrium. Group consensus has two primary characteristics.

A notable characteristic of group consensus within social networks is its dynamism. Previous research has often approached consensus as the final state resulting from group interactions, typically considering it as a single equilibrium state generated by the model. In this view, group consensus is depicted as an absorbing state that is assumed to persist perpetually (Castellano et al., 2009). However, within social networks, group consensus is better understood as a soft consensus that emerges from the dynamic and iterative processes of group negotiation (Cabrerizo et al., 2014). Consequently, as the cognitive context, social relationships, and scale of social networks evolve, group consensus transitions from one equilibrium to a new state. Feedback mechanisms play a pivotal role in this evolutionary process. Through these feedback mechanisms, group members adapt their opinions during communication and interaction, based on feedback from other connected individuals. Gradually, this iterative feedback fosters a relative degree of consensus among members of the social network (Hassani et al., 2022). This understanding leads to the pertinent question: How does consensus (or order, coordination, and agreement) emerge from chaotic behaviors or discourse (Baronchelli, 2018)? The second characteristic, often overlooked yet of greater significance, is its emergence, which provides a philosophical framework for addressing this question. Emergence refers to the dynamic generation of collective properties, behaviors, structures, or patterns at the macro level through the interaction of constituent parts at the micro level (de Wolf and Holvoet, 2004). These emergent properties are novel, implying that they are not inherent to the individual components constituting the whole (Crutchfield, 1999).

Baronchelli (2018) categorizes consensus mechanisms into two modes based on the influence of centralized institutions: In the presence of centralized institutions, certain actors or mechanisms can exert global influence on consensus formation (examples include authorities, leadership, broadcasting, and explicit incentives for collective coordination); and in the absence of centralized institutions, consensus emerges spontaneously "either from the interaction between agents or from some predefined individual behavior". For instance, conventional group decision-making methods (such as the Delphi method) shape group consensus under the influence of a centralized system, where a moderator ensures the proper implementation of the consensus process, and if necessary, suggests that experts adjust their opinions and narrow their differences (Alonso et al., 2010). However, within social networks, the establishment of crucial social issues, norms, and cultures predominantly arises through spontaneous emergence from extensive communication and interactions among heterogeneous individuals.

A noteworthy characteristic of social networks is the replacement of centralized top-down structures with decentralized network structures. This transformation has given rise to a discourse space characterized by self-organization. Within this space, by embodying the principles of freedom, equality, and openness, individuals can transcend traditional constraints and effectively utilize various social tools to connect with broader communities. They engage in dialogue, interactions, collaborations, and even collective endeavors (Shirky, 2008). The emergent nature of group consensus in social networks closely aligns with the decentralized structure of group interactions. Furthermore, as the number of members increases, the potential for interactions among members grows exponentially rather than linearly (Kelly, 2009), imparting complexity to groups and signifying that heterogeneous groups composed of diverse individuals can generate emergent phenomena.

Examining group behavior from an emergence perspective offers a bottom-up explanation of the interplay between microlevel social interactions and macrolevel social patterns. This aids in identifying pivotal nodes and moments in the group interaction process (Corning, 2002). The crucial distinction between "the unconscious crowd" and "the intelligent crowd" lies in the distinct conceptions of groups. The former characterizes groups as blind, impulsive, fanatical, and gullible, suggesting that once individuals form a group, they forfeit their individuality and succumb to groupthink or collective unconsciousness (Le Bon, 2002; Janis, 2008). In contrast, the latter emphasizes the diversity and independence of the individuals constituting the group. Surowiecki (2004) postulated that the prerequisites for collective intelligence encompass diversity, independence, and decentralization. When a group lacks diversity and independence, it devolves into a mob. However, it can manifest collective intelligence when it preserves diversity and independence. Woolley et al. (2010; 2015) asserted that collective intelligence depends not only on group composition (e.g., members' skills, diversity, and intelligence) but also on group interaction (e.g., structures, processes, and norms). Focusing on the emergent characteristics of group consensus facilitates observations of the macro-level dynamics of group interactions and influences stemming from micro-level group composition and interaction.

4 Discerning the mechanisms of consensus formation in social networks

As previously noted, social networks offer advantages and potential to facilitate the establishment of group consensus. However, the intricate and diverse composition of these groups and their interactions introduces significant uncertainty into the consensus-building process within networked communities. Consequently, the mechanisms underlying the generation of group consensus on social networks exhibit distinctive characteristics.

Recognizing consensus in social networks as the emergence of collective intelligence necessitates a shift in our approach to understanding the mechanisms of group consensus. We should redirect our focus on the outcomes of group interactions to underlying relationships and processes. Instead of solely assessing the existence and strength of consensus from a representational perspective, we should investigate the establishment of a logical connection between representation and relationships, and how this logical relationship influences the generation of group consensus.

Agent-based modeling (ABM) presents a crucial avenue for deciphering the mechanisms that give rise to "emergence" in group consensus. ABM is widely regarded as "holding the potential for a revolutionary advancement in social science theory" because it allows for the consideration of individual heterogeneity and network structures while describing emergent phenomena (Bankes, 2002). Specifically, ABM employs computer-based tools to simulate the dynamic behavior of cognitive agents. By designing numerous heterogeneous and adaptive agents and commencing with their micro-level behavior and interaction mechanisms, ABM describes, explains, and predicts the dynamic emergence of macro-level phenomena (Axelrod, 1997). ABM facilitates the examination of agent behavior, motivations, relationships, and the resulting macro-level outcomes (Bankes, 2002). The extensive ABM research on group polarization and depolarization reveals how factors such as elements of information dissemination (information content, media types, and algorithmic recommendation techniques) and social network structures (social influence) can hinder the formation of consensus (Geschke et al., 2019; Sobkowicz, 2023). Importantly, the ABM does not treat these factors as isolated variables with linear effects on the experimental outcomes. Instead, it explores the interactions between these factors and how group members engage with one another, leading to collective characteristics that differ from their individual attributes. For instance, Geschke et al. (2019) incorporated influences from individuals, social dynamics, and media technology into their agent-based model to simulate and analyze the characteristics of opinion formation across 12 different information-filtering scenarios.

The achievement of group consensus within social networks depends on certain "conditions of reachability" (Bure et al., 2017). For example, Zollman (2012) suggested that while increased contact enhances consensus and truth, indiscriminate augmentation of interpersonal contact may not effectively enhance group cognitive performance. The key to simulating group consensus mechanisms is the identification of simple and universal rules. The effectiveness of these rules determines the accuracy of a model. The introduction of complex individuals and interactive relationships into the model represents two critical avenues for enhancing their effectiveness.

(1) Given the intricacy of group composition, particularly the introduction of heterogeneous and diverse agents into the model. The consensus mechanism of network groups was initially explored by Degroot (1974). In the Degroot model, agents iteratively refine their opinions by considering their own viewpoints and those of neighboring agents within the social network, aiming to achieve a consensus among all participants. However, it should be noted that this represents a simplification of real-world scenarios. In practical social network contexts, the rules governing individual opinion updates and influence among individuals tend to exhibit considerable variation. Zhou et al. (2020) extended the Degroot model by incorporating a self-evaluation process before deciding whether to update opinions. They introduced the concept of stubbornness coefficients, in which higher coefficients render it more challenging for agents to modify their initial perspectives. By introducing agents with a propensity for steadfastness in their beliefs, the Degroot model can only occasionally converge to a consensus after iterative evolution. Chen et al. (2021) introduced bias coefficients for each agent to investigate how bias levels within the network structure and nodes affect the achievement and stability of the population's final equilibrium. Their research revealed that, in tightly connected networks, an unstable opinion equilibrium arises when agents possess relatively weak biases.

(2) In light of the intricacies of group interactions, specifically the exploration of the influence of different interaction patterns among agents on the formation of group consensus (Green et al., 2007). Previous studies have predominantly concentrated on two avenues: Trust relationships (Wu et al., 2015) and opinion evolution (Liu et al., 2021; Zhang et al., 2021), both of which have undergone extensive simulation (for an exhaustive review, refer to Dong et al. (2018)). For example, Li et al. (2013) extended the Deffuant-Weisbuch model by integrating a trust function to model trust among like-minded agents. They examined the convergence characteristics of opinion dynamics and explored the underlying factors that marked the transition from opinion polarization to consensus. The trust function employed is a discontinuous, non-increasing function of opinion divergence. Bure et al. (2017) distinguished between principals and other members in their opinion dynamics model. Principals can influence the opinions of other members, whereas the latter do not mutually influence each other. They explored two scenarios: One in which principals directly influenced each other and another in which such influence was absent. They established conditions for a limit influence matrix based on the model parameters in each scenario. Their findings revealed that consensus could not be universally attained under all circumstances.

When employing ABM to investigate the mechanisms of group consensus, it is imperative to avoid overlooking or underestimating the significance of the critical structural uncertainties that manifest during the process (Oppenheimer et al., 2007). Moreover, it is equally important to avoid a common pitfall in computational social science research, which involves neglecting the verification of a model's reliability and validity. To effectively address real-world social phenomena, it is essential to regard the relationship among empirical data, model construction, and model validation as an iterative and continuous process, ensuring that the model accurately captures the intricacies of consensus formation.

5 Conclusions and discussion

With the rapid evolution and widespread adoption of social networks, various facets of engineering management, including project communication, collaboration, talent management, risk identification and mitigation, publicity, marketing, and customer interaction and feedback, are increasingly used in digitally interconnected environments. This signifies that project participants exhibit greater diversity in terms of their backgrounds, geographical locations, and areas of expertise. Establishing and sustaining consensus among heterogeneous individuals engaged in social networking scenarios is of paramount importance for coordination and decision-making processes.

This study introduces a novel perspective on consensus that perceives it as the emergence of collective intelligence. It contends that within social networks, group consensus not only encompasses the degree to which members collectively form a cohesive comprehension of a specific objective, but also represents a dynamic process in which interconnected and diverse individuals drive the entire group toward cognitive alignment and the convergence of perspectives through self-organized communication and interaction. This perspective is poised to assist managers in gaining deeper insight into and effectively managing the dynamic relationships within teams. It has the potential to enhance team effectiveness, optimize resource allocation, improve decision making, and streamline project progress management.

On a broader scale, within decentralized and segmented social network structures, the efficacy of a top-down approach aimed at achieving collective objectives while maintaining group consensus is limited. The existence of phenomena such as group polarization, groupthink, and the false consensus effect provides empirical support for this assertion (Janis, 2008; Song and Boomgaarden, 2017; Cinelli et al., 2021). As the demand for large-scale group consensus continues to grow, the time, human resources, and associated costs linked to consensus building rise significantly, thereby introducing a substantial degree of uncertainty into the attainment of group consensus (Dong et al., 2018).

In this study, we conceptualized group consensus within social networks as the emergence of collective intelligence. This concept encompasses a dynamic process involving cognitive alignment and integration of perspectives at the group level, facilitated by interconnected heterogeneous individuals engaging in self-organized interactions. Embracing an "emergent" perspective enables us to shift away from outcome-centric, top-down cognitive models of the past, redirecting our focus towards the process of group consensus formation. This perspective aligns seamlessly with the characteristics of collective cognition within a decentralized network society.

Groups constitute fundamental units of the social sphere, defining the essence of human existence (Brown and Pehrson, 2019). Consequently, re-evaluating the concepts, attributes, and mechanisms of consensus within social network groups can provide innovative theoretical foundations and a quantifiable standpoint for conducting more comprehensive investigations into social consensus. It is imperative to acknowledge that a consensus is a context-dependent social phenomenon. While modeling, predominantly through ABM, offers an analytical avenue for understanding the structural factors and mechanisms underpinning consensus generation, most studies confine themselves to simulation exercises devoid of validation within real social contexts. The intricacies of real-world social dynamics frequently transcend the boundaries of researchers' imaginations that are embedded in their models. Thus, future research on group consensus mechanisms should prioritize cross-validating empirical and simulated data to gain a more profound understanding of the mechanisms propelling social consensus and to identify more efficient pathways for consensus generation.

Competing Interests The authors declare that they have no competing interests.

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