

Social Networks and Cognition, Beliefs, and Attitudes

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Abstract

Human cognition and social activity have historically evolved in tandem, in plain sight of one another, with our social networks simultaneously driving and being shaped by our cognitive capacities. In the present, the dynamic between sociality and cognition is undergoing a significant shift as artificial intelligence and computational tools increasingly mediate our interactions. These technologies extend beyond facilitating connections; they actively reshape cognitive processes, perceptions, and the structure of our social networks. This shift—toward social behaviors shaped by increasingly opaque algorithmic processes, rather than solely by human agency—raises non-trivial questions about the antecedents and consequences of human sociality, as well as the essence of connection in a socially augmented world. While this is but another chapter in the story of technological development, it is unique in requiring those who study human sociality to account for a new player—one of our own creation. In this chapter we review research on the cognitive underpinnings of human social behavior, and explore how these connections are increasingly being reshaped by powerful new tools.

Introduction

The story of *Homo Sapiens*, is often imagined as Rudolph Zallinger's (1965) well-known painting, *The Road to Homo Sapiens*.³ This illustration presents a series of figures, beginning with one resembling a chimpanzee and concluding with a recognizably modern, apparently civilized, and quite muscular version of an adult human. The work's enduring popularity is reflected in the frequency with which it is satirically adapted. Yet, every version of this iconic image shares a common flaw: every instance of the figure is solitary. It shows a man alone, complete in and of himself. But humans have always been social and the story of human evolution is not merely about individual advancement but about the social connections that have defined our species. And so the story of *Homo Sapiens* is not simply a story of bigger brains and better tools, it is at its core a network story.

As we will briefly review, there is good reason to think that the high intelligence characteristic of *Homo Sapiens* emerged in no small part to enable us to cope with social, as opposed to physical, challenges. As a consequence, the way that we process information, develop views of the world, and make judgments— in other words, our cognitions, beliefs, and attitudes— necessarily influence how we build and use our social networks. Therefore, if we want to understand how we build networks “out there” (i.e., in the world) we need to understand how our brains evolved and how they work to represent social networks “in here” (i.e., in the mind).

Humans are evolved systems, and our social networks exhibit features shaped by the evolutionary process. However, while reflecting on the historical role of evolution, we must not overlook the profound impact of modernity, and particularly of modern technologies. These technologies do not merely overlay our evolved social structures but interact with them, sometimes reinforcing and other times disrupting

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³ More often known as “The March of Progress”.

patterns established over millennia. With the rise of the internet, ubiquitous computing, internet-mediated audio and video communications, and generative AI, it has become easier and cheaper than ever to interact with physically distant individuals as well as with artifacts that behave as if they were human individuals themselves. This unprecedented ability is likely to accelerate as newer, more advanced, and more affordable virtual and augmented reality technologies emerge. The evolution of these communication tools is an amplification of our innate social capabilities and we are now co-evolving with these technologies. We as a society are granting various forms of artificial intelligence the leeway to evolve both alongside and independently of us, endowing them with the power to influence processes that we either cannot or do not observe. Crucially, we do not always even recognize when we are interacting with them. As such, even as we look back on the forces that shaped our social capacities, we must also consider how these new affordances interact with, ameliorate, and exacerbate our evolved limitations.

In this chapter, we review some of the burgeoning research on how human cognition, beliefs, and attitudes impact social networks, before arguing for the critical importance of understanding how modern and future technologies will interact with our evolved competencies. We recognize the reality that online life, and face-to-face life, are not distinct and separable, and that generative AI tools are increasingly part of the web of interactions that define human life. Likewise, we adopt the perspective that neither the digital nor the analog reality is more fundamental than the other. Instead, both are intimately interwoven into a twenty-first century whole that we confront using capacities evolved hundreds of millennia ago on the plains of Africa. In this light, the integration of AI into our social structures should be seen as a continuation of the human story—another chapter in our ongoing adaptation to a changing world. The story of how this confrontation plays out ultimately comprises the next chapter in the story of *Homo Sapiens*.

The Rise of Human Cognition

Few would dispute that humans are a highly intelligent species, but while we may be comfortable enjoying the benefits of this intelligence, the explanation for its emergence is considerably more problematic. In an adult human the brain accounts for approximately 3% of body mass but consumes (regardless of activity) 20-25% of our metabolic resources (Rolfe and Brown 1997; Sokoloff 1960). Fully one fifth to one quarter of all of the calories we consume are used solely to support our brains. The balance is even more skewed in children, who may devote as much as fifty percent of their metabolic budget to supporting the central nervous system (Kennedy and Sokoloff 1957). As a consequence, high intelligence is an extraordinarily costly adaptation for a species to adopt and so the advantage it provides must be compelling. But what might this advantage have been?

Many potential explanations for the rise of human intelligence focus on physical challenges that high intelligence allows a species to overcome. Often these explanations center on the need to identify or obtain food resources either by predicting when they are available or facilitating the process of extracting them from the environment (e.g., Clutton-Brock and Harvey 1980; Melin et al. 2014; Parker 2015). The difficulty is that most of these tasks are static over long spans of time and so can be readily solved by either biological adaptation or learning. The use of tools may also exhibit this property, as tools that suffice for a given task need not be developed further or provoke a self-reinforcing cycle of technological improvement. Indeed, simple tool use has been observed in a number of extant species including chimpanzees, baboons and dolphins among others (Cheney and Seyfarth 2019; Mann et al. 2012) without the runaway technological improvement characteristic of humans. High levels of problem solving

intelligence- what most often underlies judgments of intelligence- can be replaced by other solutions that are less energy intensive than high intelligence.

The “Social Brain Hypothesis” (Dunbar 1998; Dunbar and Schultz 2017; Humphrey 1976) provides a compelling solution to this dilemma by arguing that high intelligence evolved to service social, rather than physical needs. Social life permits organisms to benefit from mutual defense, cooperative food gathering, and shared child rearing. Yet, individuals are constantly surrounded by others who prefer the same food, shelter, and mating opportunities. Maximizing benefit therefore requires striking a balance between the Scylla of selflessness towards the group and the Charybdis of egotistic devotion to self. More intelligent individuals are thought to be better at this task, and will leave the most offspring as a result. Inevitably, their genes will be more represented in the next generation, which as a result will be slightly more intelligent on average than the one that came before. However, unlike physical challenges, the scale of the problem increases in proportion to the average capacity of the population to solve it, and thus there will be a persistent benefit to increasing intelligence. In short, humans became so smart because we encountered a challenge that increased in proportion to the intelligence that we used to overcome it: ourselves. This feedback loop between social complexity and cognitive development is critical to understanding the evolution of human intelligence.

If this account is correct, then our brains should be measurably connected in some fashion to our social groups and especially to our social networks. Robin Dunbar (1992) evaluated this proposition by examining the relationship between primary group size and the neocortical ratio (i.e., neocortex volume divided by the remaining volume of the brain) for thirty-eight primate genuses, ranging from *Avahi* (i.e., certain lemurs) to *Pan* (i.e., chimpanzees and bonobos, our closest extant non-human relatives). He found a positive correlation between neocortical ratio and primary group size, and used it to predict that human primary groups should contain roughly 150 individuals. This estimate has come to be known as “Dunbar’s Number,” and subsequent research has supported Dunbar’s model and, by extension, the Social Brain Hypothesis (e.g., Barton 1996; Kudo and Dunbar 2001; Dunbar 1993, 1995, 2018; Gonçalves, Perra and Vespignani 2011). Moreover, recent research indicates that network recall is robust even in the face of cognitive declines associated with Alzheimer’s disease or dementia (Roth et al. 2021), implying that this function may be among the most fundamental. In short, while the debate is far from over, the evidence supports a link between the growth of our brains and the growth of our networks. This link suggests that the structure of our social networks is not merely a byproduct of our cognitive abilities but a driving force behind their development.

Networks in the Mind

While evolutionary processes explain the rise of human brains, Smith et al. (2012) propose a strong framework to connect events occurring in the mind⁴ to outcomes realized at the level of networks. Their framework begins with the *potential network*, which includes all individuals that the person knows, potentially including persons who have never been met but of whose existence the person is aware (e.g., celebrities). Obviously, the number of such persons is very great and it is impossible for anyone to think concretely about all members of the potential network simultaneously. Instead, individuals will draw persons out from long term memory and into working memory to populate the *cognitively activated network*. It is important to note that potential networks extend beyond just human connections. As

⁴ For clarity, we use the term “brain” to refer to the physical organ humans use for cognition whereas “mind” refers to the state of computation in that brain. As a loose analogy, brain is to a computer’s hardware as mind is to a computer’s software.

humans, we naturally think in relational ways, consistently creating and populating networks not only of people but also of ideas and concepts. Bringing individuals into working memory can be deliberative, as when we search our memory for someone who may have information about a new job, but can also be automatic and even triggered by an environmental stimulus, such as recalling a relationship or loved one based on smell or sight. Individuals then select who they will contact from those in working memory and act to do so, thereby creating a *mobilized network*. Lastly, individuals who consent to interact (i.e., respond favorably to being contacted) become the *realized network*.

The first two stages of Smith et al.'s model focus on memory processes: to think about networks it is necessary for networks to enter the mind. However, this task involves significant difficulties. Individuals must, at the very least, be able to track and make decisions about their own direct connections to others. But the greatest benefits come from tracking the relations between our associates (i.e., relations that do not include ourselves). For example, identifying when two others have begun, or ended, a romantic relationship is crucial for achieving a variety of goals (e.g., pursuing a desired romantic partner, avoiding committing a faux pas). Unfortunately, the number of such relationships grows rapidly as group size increases and so the cognitive expense of maintaining it can quickly become burdensome. More concretely, a group of size n includes $n(n-1)$ possible relations among all members.⁵ As a result, in a group of ten one would need to track as many as ninety different relationships, only nine of which include oneself (i.e., are direct). An increase in group size from ten to fifteen would both produce a linear change in the number of direct relations from nine to fourteen, and a super-linear increase in the number of indirect relations from eighty-one to one hundred and ninety-six. This implies that even small increases in group size result in heavy increases in the cognitive demands on the organism. Dunbar's model (Dunbar 1992; eq. 1) grapples with this issue by implicitly assuming that larger brains are more efficient,⁶ but no explanation is provided for how this is achieved. Yet, research (e.g., Bernard, Shelley and Killworth 1987; McCarty et al. 2001; DiPrete, Gelman, McCormick, Teitler & Zheng 2011; Killworth, Johnsen, Bernard, Shelley, & McCarty 1990) suggests that human core networks may often exceed the estimates generated by Dunbar's model, requiring still greater improvements in efficiency. So how do humans manage networks with large brains that, paradoxically, appear to not be quite large enough?

Prior research shows that recall of network structures containing social information (e.g., people connected through friendship ties) is more accurate than recall of identical non-social networks (e.g., locations linked by roads: Janicik & Larrick, 2005; Simpson, Markovsky, & Steketee, 2011; Van Kreveld & Zajonc 1966). Yet, comparing observed interaction to recalled interaction (e.g., Bernard and Killworth 1977) reveals disagreement at the dyadic (i.e., person-to-person; Bernard and Killworth 1977), triadic (i.e., three-person group; Killworth and Bernard 1979/1980), and clique (i.e., larger saturated group; Bernard, Killworth and Sailer 1979/1980) levels. At the same time, humans are highly successful in remembering overall group structure as well as typical patterns of interaction, as opposed to specific interaction events (Freeman, Freeman and Michaelson 1988, 1989; Freeman and Romney 1987; Freeman,

⁵ We assume that relations can be asymmetric (e.g., person A considers person B to be a friend while person B does not view person A the same way). Assuming symmetry would not substantially alter the conclusions.

⁶ According to the model, if the neocortical ratio of an organism increases from 0.96 to 3.22 (i.e., across the range of extant non-human primates from *Avahi* to *Pan*) the estimated number of direct ties that organism could maintain would increase by roughly 64 while the number of indirect ties it could track would increase by approximately 4,250. A further rise in its neocortical ratio to 4.1 (i.e. equivalent to *homo sapiens*) would increase the estimated number of direct ties the organism could manage by approximately 83 and the number of indirect ties it could track by roughly 17,600. Put differently, the model indicates that the smaller increase in neocortical ratio from *Pan* to *Homo* (i.e. +0.88) would produce a more substantial gain in the ability to track and manage social relations than would the larger increase in neocortical ratio from *Avahi* to *Pan* (i.e. +2.26).

Romney and Freeman 1987). Therefore, taking this research as a whole, it appears that humans are not remembering the detailed interactions but are instead populating and maintaining a perception of how social interactions are typically structured.

These existing patterns of recall are an example of schemas, which have long been known to simplify and accelerate the learning process (e.g., Bartlett, 1932; Brewer & Treyens, 1981; Martin, 1993; Neisser, 1967). Early work on schemas in social networks (De Soto 1960) found that recall was easier when network structure was consistent with the implicit schema (e.g., when nodes linked by asymmetric directed edges were “influenced by” rather than “friends with” other nodes). Subsequent research has produced supporting results (Fischer, 1968; Picek, Sherman, & Shiffrin, 1975; Sentis & Burnstein, 1979; Walker, 1976; see also Welch-Ross & Schmidt, 1996). Individuals recall networks organized by kinship (Brewer & Yang, 1994), context (Brewer & Garrett, 2001), and geographic location (Brewer & Garrett, 2001; Killworth & Bernard, 1982) schemas more quickly and more accurately.

Schemas can also function as compression heuristics (Brashears 2013), or rules that allow social networks to be reconstructed from partial information. For example, if triadic closure is common in networks, then successfully recalling that two edges in a triad are present allows one to infer that the third should also be present. The existence of the rule therefore makes perfect recall of all of the individual relationships unnecessary; assuming accurate memory for some fraction of the relationships, the rule can be used to reconstruct the rest. Research shows that triads and kin relations function as compression heuristics (Brashears 2013; Brashears, Hoagland and Quintane 2016), that by default recall appears to focus on triads (Brashears and Quintane 2015), that female recall of networks appears superior to male recall (Brashears, Hoagland and Quintane 2016), and that not only is affective balance a compression heuristic, but recall of affect appears to be separable from recall of the relationship itself (Brashears and Brashears 2016; Omodei, Brashears and Arenas 2017). These heuristics represent an evolutionary strategy to cope with the cognitive limitations imposed by our finite brain capacity, allowing us to manage complex social environments more efficiently. Humans achieve high levels of recall efficiency not by increasing the capability of our brain, but by developing a set of competencies in our minds.

Compression heuristics help explain the disconnect between observed and recalled interactions identified in prior literature. Individuals develop and employ compression heuristics based on interactions that they have observed (Son, Bhandari, and FeldmanHall 2023) or based on cues inherent in the context. Once such compression heuristics are in use, memory for specific interactions is largely discarded. As a result, when asked to recall specific interactions they rely on the heuristic and mismatches between observed and reported interactions partly result from portions of the reconstructed network that are heuristic consistent as recalled but not as experienced. Because many compression heuristics are widely applicable across many different networks as well as shared by many individuals (e.g., triadic closure), many recall errors will tend to appear systematically rather than at random. If social networks are the result of social actions, and action is shaped by the sometimes inaccurate recall provided by the use of compression heuristics, then we can and should expect that the heuristics used by individuals will, over time, help to shape the structure of the network.

In summary, compression heuristics work to simplify the transition from the *potential network* to the *cognitively activated network*. However, in doing so they shape the set of persons available for transition into the *mobilized network* (i.e., one cannot reach out to a contact who is not remembered) as well as influence subjective judgments about who will respond favorably to mobilization. Therefore at the individual level as well as the network level, events in the mind shape the structure of the *realized network*.

Motivations for Sociality: Understanding the "Why" Behind Social Behavior

While it is well established that social interactions offer numerous benefits—such as improved mental health, enhanced well-being, and stronger community ties—these benefits alone do not explain why individuals are motivated to engage in social behavior. Just as the knowledge of the benefits of exercise does not automatically create a fit individual, understanding the benefits of social connections does not necessarily motivate social behavior. Social motivations are especially important for networks because conversion of the *cognitively activated network* into the *mobilized network* depends in part on the goals of the individual. Put differently, cognition provides the foundational capacity to mobilize a network but motivation speaks to the desire to use this capacity to produce social relations. A variety of sociological, psychological, and social-psychological factors underlie prosocial motivations.

Psychological Motivations: The Need for Belonging and Social Validation

At the core of human social behavior is the psychological need for belonging. This need is not merely a desire for companionship but a fundamental aspect of human nature that drives people to seek out connections with others. Abraham Maslow, in his hierarchy of needs, identified belongingness as a basic human need, crucial for psychological well-being (Maslow, 1943). People are inherently motivated to form relationships and be part of social groups because these connections provide a sense of security, identity, and meaning.

Social validation, the need to be recognized and valued by others, further reinforces social behavior. When individuals receive positive feedback from their social interactions—whether through verbal affirmations, social media likes, or inclusion in social activities—it bolsters their self-esteem and encourages them to continue engaging socially (Leary, 2001). This validation is a powerful motivator, often driving people to align their behaviors with social norms and seek approval from their peers (Baumeister & Leary, 1995).

These mechanisms are frequently leveraged to accomplish objectives, for example in public health and wellness campaigns. Knowledge of the benefits of regular exercise or mindfulness practices often isn't enough to sustain behavior change. As a result, many initiatives incorporate elements of sociality to boost motivation. Group exercise classes, fitness clubs, and public performance tracking (such as apps that share workout progress with friends) are all designed to inject the motivations and rewards of sociality into the pursuit of personal health goals. These campaigns recognize that people are more likely to commit to and sustain behaviors when they are socially engaged and feel validated by their peers.

Sociological Influences: Social Norms and Cultural Expectations

Social motivations are also shaped by sociological factors, particularly the influence of social norms and cultural expectations. Social norms, the unwritten rules that govern behavior in society, play a significant role in motivating individuals to engage in social activities. These norms dictate what is considered appropriate or desirable behavior within a given community, and individuals often conform to these expectations to gain social acceptance and avoid social sanctions (Cialdini & Trost, 1998).

Cultural context further shapes these motivations. In collectivist cultures, where group harmony and interdependence are valued, individuals may feel a stronger obligation to participate in social activities and prioritize group needs over personal desires (Triandis, 1995). In contrast, in individualist cultures, where personal autonomy and self-reliance are emphasized, social motivations might be driven more by personal goals and the pursuit of individual achievements within a social framework (Markus &

Kitayama, 1991). These cultural and social norms are also reflected in how health and wellness campaigns are tailored to different audiences. For instance, in collectivist societies, campaigns may emphasize group activities or communal benefits, such as community fitness challenges or collective mental health initiatives. In more individualistic cultures, the focus might be on personal achievement within a social context, such as earning badges for workout milestones that are then shared with a broader online community.

Social-Psychological Factors: The Role of Identity and Self-Concept

Social motivations are also intricately linked to an individual's identity and self-concept. Social identity theory posits that a significant part of a person's self-concept is derived from their membership in social groups (Tajfel & Turner, 1986). People are motivated to engage in social behavior because it reinforces their identity and provides a sense of belonging to something larger than themselves. This identification with social groups can influence behavior in profound ways, driving individuals to conform to group norms, adopt group values, and engage in behaviors that enhance their standing within the group. Moreover, self-determination theory suggests that individuals are motivated by a desire to fulfill their needs for autonomy, competence, and relatedness (Deci & Ryan, 2000). Social interactions provide opportunities to satisfy these needs, especially the need for relatedness, which involves feeling connected to others and having meaningful relationships. When individuals perceive that their social environment supports these needs, they are more likely to be motivated to engage in social behavior. In the context of public health campaigns, these social-psychological factors are often leveraged to create a sense of community and shared identity around health goals. For example, fitness challenges that involve team-based goals or public mental health awareness campaigns that encourage community participation tap into the individual's desire to belong and contribute to a larger cause. These campaigns not only promote the behavior (e.g., exercising or engaging in mental health practices) but also foster a collective identity that motivates continued participation.

Attitudes Toward Sociality: The Impact of Personal and Environmental Factors

While the need for belonging and social validation, as well as the influence of social norms and identity, are powerful motivators, not everyone is equally motivated to be social. Personal factors, such as personality traits and past experiences, can significantly influence one's attitude toward social interactions. For instance, individuals who are naturally more extraverted tend to seek out and enjoy social interactions more than those who are introverted (Costa & McCrae, 1992). Similarly, individuals who have had positive social experiences in the past are more likely to be motivated to engage in social behavior, while those with negative experiences, such as social rejection, may be more hesitant (Leary, 2001). Environmental factors, including the social and cultural context in which individuals are embedded, also play a crucial role. Social environments that are supportive, inclusive, and rich in opportunities for meaningful interaction can enhance social motivation. In contrast, environments that are hostile, exclusionary, or lacking in social resources can diminish one's motivation to be social.

In the foregoing we review how cognition and social activity are tightly coupled, and how humans are motivated to engage in social activity for a variety of reasons. In the sections that follow, we explore how this legacy is changing as a consequence of the convergence of cognition and computation, and how this convergence is reshaping our social worlds. As we examine the role of AI and cognitive offloading, we hope it will become clear that understanding the motivations behind social behavior is not just a matter of psychological or sociological interest—it is essential for navigating our relationships with

fundamentally new and largely autonomous technologies that represent a categorical shift in our species' narrative. The shift from purely human-driven social motivations to a landscape where our social behaviors are shaped by algorithms and computational processes demands a re-examination of what it means to be social. While our innate social capacities and motivations will remain, the unknown lies in how they will interact with emergent technologies. As AI and digital platforms become more embedded in our daily lives, they do more than just facilitate connections; they influence our cognitive processes, alter our perceptions, and potentially redefine our social networks.

From Cognition to Computation

Behavioral scientists are accustomed to discussing thought in terms of cognition, but it is similarly accurate to regard it as computation. This shift in perspective is crucial as it aligns human thought processes with the operations of the digital tools we increasingly rely on. Indeed, the term “computer” was once a job title, referring to a person who executed mathematical computations (e.g., for artillery trajectory tables) and only later came to refer exclusively to electronic computers. In parallel,⁷ while the operation of the human brain is not fully understood, it remains possible that it is a Turing complete system. If this is the case, then a human brain can in principle be fully emulated by any other Turing complete system; much as human minds can perform the computations of electronic computers (albeit more slowly), electronic computers could host human minds in silicon. In short, the distinction between cognition and computation is likely more apparent than real. The computational underpinnings of cognition are particularly relevant because of the tremendous increase in the availability of artificial computation (i.e., computation not performed by human brains). For example, the first general-purpose electronic computer, ENIAC at the University of Chicago, became operational in 1945 and could execute approximately 5,000 instructions per second. In contrast, the Apple iPhone 6 released in 2014 was capable of executing over 3.36 billion instructions per second. Fast forward to now, and the iPhone 15 is capable of executing an estimated 50 billion instructions per second. This marks an extraordinary progression in less than 80 years, from the 5,000 instructions per second of the room-sized ENIAC to a device that fits in your pocket and is millions of times more powerful.

We should expect the widespread availability of computation to impact human social behavior, not least because humans have long made use of technology to enhance their own cognition. For example, James Farley, Campaign Manager for President Franklin Delano Roosevelt, pioneered the use of a “Farley File,” or a file containing information on any other people he, or his charge, had met. When preparing for a scheduled meeting, this file allowed FDR to quickly relearn details personally relevant to the other (e.g., the names of spouses and children) and thus to appear more interested, charismatic, and ultimately persuasive. This fairly simple data storage and recall device reliant on paper files and human clerks enhanced FDR's networking capability, and by extension more powerful computational technologies must have an even greater potential impact.

At a minimal level, modern information and communications technologies (ICT) operate as enhanced versions of things like the Farley File. First, computational devices can provide enhanced data storage and retrieval, essentially allowing individuals to magnify their ability to utilize information. Second, computational devices can serve as components in communications systems that allow individuals to overcome limitations of distance. Email, online discussion forums, and social media all partly function in this manner and allow individuals to economize on the time needed to maintain

⁷ Pun intended.

contacts, thereby allowing larger networks to be maintained with similar levels of effort (e.g., Feld 1981). Third, these technologies essentially expand the pool of interactants from those nearby to potentially anyone on Earth, with the necessary result that many relationships will become more superficial even as they become more numerous (e.g., Mayhew and Levinger 1976). In all of these examples, modern ICT represents only an enhancement of existing capacities, with electronic data storage and retrieval offering an improved approach to what the Farley File could already do. Likewise, the loosening of the constraints of geography had already begun with the rise of the postal service and telephony. But the modern artificial intelligence revolution goes beyond enhancing prior capacities and instead permits the rise of “cognitive offloading,” to which we now turn.

Cognitive Offloading

Cognitive offloading refers to the use of external tools to reduce the cognitive load on our brains. This practice can involve simple actions like setting reminders on a smartphone (i.e., automating recall) to complex tasks like using algorithms to manage large datasets (i.e., automatic thought; Risko & Gilbert, 2016). Humans are increasingly offloading not just cognitive tasks, but responsibility for managing social connections to digital platforms and algorithms as a natural amplification of our evolved capacities. Offloading social tasks to digital platforms like Facebook, LinkedIn, and Twitter helps us to manage our social connections by reminding us of birthdays, operating much as a Farley File might. But they go well beyond such simple tasks by suggesting new connections (thereby directly shaping realized networks) as well as by curating news feeds (shaping our knowledge of our associates, and world, as a consequence). These platforms employ sophisticated algorithms to prioritize information and interactions that align with our interests and behaviors (Gilbert, 2015). As such, use of these algorithms is inherently rewarding to most persons, in that it gives us more of what we are already interested in, and thus is unlikely to fall out of use.

Cognitive offloading in principle offers individuals enhanced capabilities, but it also incorporates a number of negative features. First, this algorithmic management can lead to unintended consequences, such as the formation of echo chambers (Cinelli et al., 2021). Research has shown that algorithmic recommendations tend to amplify content that elicits strong emotional responses, such as anger and out-group animosity, which can further entrench divisive viewpoints (Cinelli et al., 2021; arXiv.org, 2024). This outcome is not a flaw in the system, but rather an intended consequence of algorithms designed to maximize engagement. The result is a digital environment where users are less likely to encounter diverse perspectives, which can hinder open discourse and mutual understanding. Moreover, this consequence is the logical outcome of the intended operation of the system, rather than a defect. Algorithms that prioritize engagement often favor sensational or controversial content, as it tends to attract more attention and interaction, potentially creating a “race to the bottom,” where content creators prioritize virality over truthfulness (aicontentfy.com, 2024). This can inadvertently promote the spread of misinformation, as false or misleading information is frequently more engaging than factual content. Research has also shown that individuals tend to offload tasks to algorithms to enhance efficiency and reduce mental effort, which can lead to a reduction in their own organic cognitive capabilities (Mirage News, 2024). The shift from reliance on biological cognition to digital aids can gradually diminish our intrinsic cognitive abilities, as our brains adapt to the reduced demand for certain types of mental effort. Excessive digital media use has been associated with symptoms resembling attention deficit hyperactivity disorder (ADHD) due to the constant stimulation and rapid shifts in attention demanded by digital content (Nikkelen et al., 2014; Sibley & Cox, 2018). This overuse can also lead to digital dementia,

characterized by memory loss and reduced cognitive abilities, as individuals increasingly rely on technology for information storage and retrieval (Spitzer, 2012; Manwell et al., 2022). Frequent media multitasking is linked to reduced gray matter density in brain regions associated with cognitive and emotional regulation, indicating potential negative impacts on brain structure and function (Loh & Kanai, 2014). Additionally, the overreliance on digital tools for simple tasks, such as using GPS for navigation, can impair spatial memory and cognitive mapping abilities (Dahmani & Bohbot, 2020).

Cognitive offloading is not a static phenomenon, akin to setting a machine in motion. Instead, it is a dynamic and continuously evolving process, requiring us to engage in ongoing adaptation—much like dialing in a race car or rifle sights, except in this case, the target is perpetually moving. The impact, both positive and negative, of ICT is also contingent on its algorithmic opacity, or the extent to which the decision-making processes of AI systems are not transparent or understandable to users. This lack of transparency arises from several factors, including the technical complexity of AI systems, proprietary protections, and the dynamic nature of machine learning algorithms that continuously update and evolve based on new data (California Law Review, 2024; Lazer et al. 2014). Algorithmic opacity can lead to disparities in how information is accessed and used. Algorithms can unintentionally reinforce existing biases or create new forms of inequality by favoring certain types of content or interactions over others. Indeed, the things we make bear our fingerprints. The increasing reliance on these opaque systems has significant implications for data privacy and democratic values. For instance, the EU's General Data Protection Regulation (GDPR) aims to address some of these concerns by mandating algorithmic transparency and data protection. However, research suggests that even robust regulatory frameworks like the GDPR may not be sufficient to fully mitigate the risks posed by algorithmic opacity (California Law Review, 2024).

Opacity also exacerbates the fundamental challenge of understanding how technology influences our decisions and interactions by disrupting our innate cognitive expectations of clear cause-and-effect relationships. Humans are naturally inclined to be "press button—see outcome" creatures, a cognitive tendency that underpins much of our interaction with the world around us. This includes not only our direct social interactions but also our engagement with the machines and algorithms designed to facilitate and mediate these interactions.

As technological systems continue to operate with increasing opacity, the natural cognitive process of understanding cause-and-effect relationships is disrupted. Arthur C. Clarke famously observed that "any sufficiently advanced technology is indistinguishable from magic." Today, the "magic" of modern algorithms has a categorically distinct impact on our minds and social interactions compared to prior technologies like the telegram or telephone. These algorithms, which govern much of our digital interactions, function in ways that are often hidden from users, making it difficult to predict how inputs will result in specific outputs. This lack of transparency can create cognitive dissonance, where expected outcomes fail to align with actual results, leaving users confused and distrustful. Such uncertainty undermines our ability to form reliable mental models of how these systems operate, which are crucial for effective decision-making and social interaction. This disconnect is particularly problematic in the context of social networks, where algorithms play a significant role in shaping the information we consume and the connections we form. From a social capital perspective, these algorithms mediate much of the information we input and output. When we cannot understand or predict how algorithms curate content or suggest social connections, it challenges our ability to manage and interpret our social worlds. The brain's reliance on clear feedback loops is thwarted, leading to a diminished sense of control and agency in our digital interactions. In the best-case scenario, this results in frustration and efforts to remedy the cognitive

dissonance. However, in the worst-case scenario, individuals may abandon these efforts altogether, passively accepting an opaquely curated social world.

Research supports the notion that user attitudes toward algorithmic opacity are closely tied to this cognitive disruption. For example, studies have shown that users prefer human decision-making processes in high-stakes situations because they perceive them as more transparent and predictable, aligning with our cognitive need for clear cause-and-effect relationships (Saxena et al., 2020). However, when algorithms are perceived as highly capable and their operations are made more transparent, trust and appreciation for these systems increase (Ananny & Crawford, 2018). Transparency not only fosters trust but also helps restore the cognitive coherence disrupted by opaque systems. Yet, as we increasingly delegate social decision-making to these algorithms, our cognitive processes must adapt to a new reality—one where traditional mental shortcuts and heuristics may no longer suffice in navigating social networks shaped by algorithmic decisions that are neither fully understood nor predictable (Rahwan et al., 2019).

This shift challenges our ability to maintain cognitive coherence in our social lives. The brain, which evolved to manage and interpret complex social networks through direct, observable interactions, now faces the task of dealing with mediated relationships shaped by opaque algorithms. The result is a potential erosion of our cognitive abilities to process social information and make informed decisions, as we increasingly rely on systems that do not operate according to the clear and understandable rules we are accustomed to. In essence, the opacity of modern technological systems disrupts the cognitive processes that are fundamental to human social interaction. As these systems continue to evolve, it becomes increasingly important to address these cognitive challenges. Enhancing transparency and making algorithmic processes more understandable are not just technical concerns—they are essential steps in preserving the cognitive capacities that allow us to navigate and thrive in our social worlds..

As we grapple with these shifts, it is non-trivial to recognize that our tools evolve both under our watch and beyond our observation, shaping and powering not only the processes that enable human-to-human interaction but also those that mimic such interactions. This co-adaptation requires continuous vigilance and adjustment as we strive to align our technological environments with our cognitive and social needs.

Implications for Social Connectivity

The growing role of AI in managing our informational environments has profound implications for human cognition and social connectivity. The content we consume shapes our beliefs, attitudes, and behaviors, and the increasing reliance on algorithmically curated information means that our cognitive processes are being influenced in ways we may not fully understand. This reliance on AI-driven content delivery risks creating informational silos, where exposure to diverse perspectives is limited, potentially narrowing our cognitive horizons and reducing our capacity for critical thinking. The potential for algorithms to create biased or narrow informational pathways can limit our exposure to new ideas and critical thinking opportunities, ultimately affecting our ability to make informed decisions.

AI's role in curating social interactions affects social connectivity. For example, beyond overt interests, algorithms can suggest social connections or prioritize content based on deeper, less immediately visible factors such as tone of speech, behavioral patterns, or deep psychological similarities (e.g., via a complex latent variable analysis). These algorithmic connections may be less apparent but are designed to tap into fundamental human social needs, potentially fostering deeper, more meaningful interactions. Although these connections may seem false or irrelevant initially, they have the potential to

develop into strong relationships if given the opportunity to co-mingle and interact (Piccardi et al., 2024). Facilitating ties based on deep similarities rather than superficial characteristics can help remedy the effects of echo chambers by identifying a basis for successful relationships that cross socially meaningful boundaries. This approach can reduce polarization and encourage bonding across digital channels, fostering a more connected and less fragmented society (PLOS ONE, 2018). At the same time, the creation of new connections based on deep underlying commonalities has the potential to break down barriers between extremist groups that we might prefer to see isolated. For example, the tale of the modern white nationalist movement is one of disparate distinct groups finding common cause substantially via the aid of electronic media (Hoffman & Ware, 2024). As we grapple with the opaque nature of algorithmic systems and their profound impact on our cognitive processes and social interactions, it's crucial to recognize that these digital interactions also challenge another fundamental aspect of human cognition: the ability to forget.

Forgetting, Social Networks, and Artificial Intelligence

Forgetting is not merely a failure of memory—it's an essential cognitive process that allows us to function effectively in our daily lives. Just as the opacity of algorithms can disrupt our cognitive coherence, the permanence of digital records and interactions can interfere with our natural ability to prioritize relevant information, let go of past mistakes, and focus on the present. Forgetting supports mental health by enabling us to move on from traumatic experiences and maintain a coherent sense of self. However, in a world where every interaction is stored, analyzed, and retrievable, the inability to forget can lead to cognitive overload, anxiety, and hindered decision-making, trapping individuals in a perpetual present where the past is never fully resolved or left behind (Schacter, 2001). Forgetting is also vital in social relationships, where it allows individuals to forgive and move past conflicts, contributing to social cohesion. Traditionally, social networks evolved naturally, with some connections fading over time. However, in an era where every interaction is digitally recorded and accessible, the capacity to forget and forgive diminishes. This can lead to static networks where old ties persist even when they no longer serve a purpose, potentially stifling the formation of new relationships and the evolution of social dynamics (Mayer-Schönberger, 2011).

The inability to forget is further complicated by the emerging capabilities of AI and algorithm-driven technologies, which amplify the ability to relive past experiences. The ease of revisiting old photos, videos, and social media posts can be both comforting and disconcerting, potentially trapping them in past identities and experiences, making it difficult to fully move on and evolve (Turkle, 2011). Increasingly, digital traces—such as social media activity, emails, and other online interactions—are used to create facsimiles of people who have passed away. AI-driven chatbots, like those developed by companies such as Eternime and Replika, mimic the personalities and communication styles of individuals based on their digital footprints, allowing for continued "interaction" with deceased loved ones. While this may offer solace to some, it also introduces complex ethical questions about consent, the nature of memory, and the psychological impact of interacting with digital ghosts (Bassett, 2015).

This modern form of digital archiving stands in stark contrast to historical methods of preserving and transmitting ideas across generations. Consider, for example, Francis Yockey, a 20th-century white nationalist whose manifesto, "Imperium," remains influential in certain right-wing ethnonationalist circles. While Yockey's ideas have persisted through a static, text-based medium, imagine the impact if his ideology were preserved and propagated through an AI-driven version of himself. Unlike a book that waits for readers to discover it, an AI Yockey could proactively seek out audiences, engage with them,

and even adapt its message to resonate more effectively. This ability to actively disseminate and perpetuate ideas represents a significant amplification of the influence that historical texts like "Imperium" can wield, raising profound questions about the ethical implications of digital immortality and the preservation of controversial or harmful ideologies through AI.

Limitations and Inequalities in Digital Interactions

Digital interactions, while ubiquitous, often fall short of the richness provided by face-to-face communication. Non-verbal cues, essential for effective communication and social bonding, are frequently lost in digital formats. Neuroimaging studies suggest that these digital interactions fail to fully engage brain regions involved in processing social stimuli, leading to a less complete sensory and emotional experience compared to in-person exchanges (Derks et al., 2008; Gronewold & Engels, 2020). This creates a scenario similar to consuming "junk food"—a plethora of interactions that fill up social time but leave the individual socially malnourished. Prior research (Tufekci and Brashears, 2014; Bassett, 2015) corroborates this, finding that many people do not perceive online relationships as "real," highlighting the inadequacies of digital communication in fulfilling social needs.

As these limitations become apparent, individuals increasingly turn to digital tools and AI systems to manage their social and cognitive tasks. This reliance on technology represents a form of cognitive offloading, where the brain outsources memory, decision-making, and social connection management to external systems. However, this offloading is not without consequences. While AI can enhance our ability to process and manage vast amounts of information, it also introduces new challenges, such as algorithmic opacity and unintended biases that can influence our social networks and decision-making processes in ways we may not fully understand.

Adaptation and Co-evolution with AI

Despite the transformative impact of AI, humans remain anchored by evolutionary processes that shape our basic tendencies, preferences, and abilities. Our evolutionary heritage serves as both a foundation and a constraint, shaping how we interact with and adapt to AI. We are self-interested, at-times rational beings that nevertheless have fluid beliefs, emotions, and desires. Thus, our adaptiveness in the face of AI is predicated on the continued relevance, and relative inflexibility, of our evolutionary endowments. Human cognition is deeply rooted in evolutionary mechanisms that have been fine-tuned over millennia. For instance, the "fight or flight" response is a product of our evolutionary heritage, significantly influencing our decision-making processes in high-stress situations (Psychology Today, 2023). Likewise, the way humans form social bonds and hierarchies has been influenced by our evolutionary past as social animals living in groups where cooperation and competition were crucial for survival (Harari, 2014). The human tendency to seek patterns and make quick decisions based on heuristics is another evolutionary trait designed to enhance survival by allowing rapid responses to environmental stimuli (Kahneman, 2011). These traits persist in the digital age, influencing how we interact with AI and other digital technologies.

While being a product of human minds, AI operates on fundamentally different principles. Its decisions are based on data analysis, probability estimations, and pre-established objectives, devoid of the physiological and emotional nuances that characterize human cognition (Frontiers in Neuroscience, 2024; MDPI, 2022). This dichotomy highlights the potential for AI to complement human decision-making by providing perspectives and problem-solving approaches that are beyond, or simply different from, human cognitive capabilities (World Economic Forum, 2023). However, this also introduces risks, particularly

the tendency for humans to anthropomorphize AI, leading to misunderstandings and misjudgments. Humans interacting with agentic AI may have a tendency to understand it as if it is thinking like a human. Indeed, research shows that current tools understand relationships similarly to humans, but non-identically (Wang, Cui and Kleinberg 2024).

The interplay between human nature and AI technology will define the future of social networks and human cognition. As AI becomes more integrated into our daily lives, it will continue to shape and be shaped by our behaviors and preferences. This co-evolutionary relationship suggests that while AI can enhance human capabilities, it must be designed and implemented in ways that align with human values and needs to foster a synergistic relationship (Scientific American, 2023). Moreover, the concept of "digital cognition" extends beyond simple interaction; it reflects a new form of cognitive partnership where AI and human intelligence work together. This partnership can lead to enhanced decision-making processes, where AI provides data-driven insights and humans contribute contextual understanding and ethical considerations. The potential for AI to process vast amounts of data quickly and identify patterns can significantly augment human capabilities, especially in complex problem-solving scenarios (Frontiers in Neuroscience, 2024). The success of this partnership will depend on maintaining transparency, trust, and alignment with human values. This relationship also emphasizes the need for a human-centric approach to AI development. As AI systems become more advanced, ensuring they remain transparent, understandable, and aligned with human values will be crucial. The goal is not to replicate human cognition but to create a complementary system that leverages the strengths of both human and machine intelligence (MDPI, 2022). For example, in health care settings AI can analyze medical data more quickly and accurately than humans, identifying patterns and potential health issues that might be missed by human doctors. However, the ultimate decision-making should involve human doctors who can consider the emotional and ethical aspects of patient care, which AI might overlook (Psychology Today, 2023). This ensures that while AI plays a critical role, the final authority remains with humans who can contextualize AI's outputs within broader social and ethical frameworks.

Conclusion

The current narrative of *Homo sapiens* is a story about the origins and influence of social networks on the evolution of human cognition, beliefs, and attitudes. Our intelligence did not evolve in isolation but was driven by the complex social environments we navigated, where cooperation, competition, and communication were essential for survival. In turn, or perhaps in parallel, human beings developed deeply rooted motivations and attitudes towards sociality. This interplay between social structure and cognitive development has defined our species, shaping not only how we think but also how we connect with others. For better or worse, this relationship has also defined the technologies we create, how we envision using them, and how we actually use them.

As we approach yet another new chapter in the ongoing story, where yet another game-changing technology is redefining what it means to be social—much like written language, telegrams, the telephone, and newspapers did—the same forces that once shaped our evolution continue to play a crucial role. The internet and ubiquitous computing have continued to expand our social networks beyond physical boundaries, introducing new dynamics that influence how we perceive the world and interact with each other. These technologies have amplified our innate social capabilities, allowing us to connect with distant individuals and manage vast amounts of information with ease. However, they have also introduced challenges, such as the risk of echo chambers, misinformation, and the erosion of the richness found in face-to-face interaction.

The rise of AI, however, is a paradigm shift. We have created a technology that talks back, connects, educates, and will likely argue and disobey. We have made it, in a sense, in our own image and explicitly asked it to know us and mimic us. This is a technology that not only responds to us but also generates knowledge, processes, and interactions on our behalf. We simultaneously engage with AI, build it, and entrust it to perform tasks independently—almost like a friend who completes our work without needing constant guidance. While AI presents both opportunities and risks, it has the potential to enhance our cognitive abilities, assist in decision-making, and foster deeper connections by identifying commonalities that might otherwise go unnoticed. However, AI's influence on our social networks and cognition is not without consequences. The opacity of algorithmic mechanisms, the potential for reinforcing biases, and the creation of new forms of inequality are all concerns that must be addressed as we integrate AI into our daily lives.

As we navigate this rapidly evolving landscape, it is imperative that we approach the co-evolution of humans and AI with a focus on ethical considerations and human values. The success of this partnership will depend on maintaining transparency, trust, and alignment with the fundamental principles that have guided human social behavior for millennia. Our tools, while evolving at an unprecedented pace, must be shaped in ways that enhance rather than undermine our cognitive and social capacities.

In the end, the future of human-AI interaction will be defined by how well we adapt to these new realities. The journey of Homo Sapiens has always been one of adaptation and innovation, leveraging tools to overcome challenges and expand our capabilities. As we move forward, we must continue to harness the potential of digital technologies and AI, but with a vigilant eye on ensuring that these tools serve to enrich our social networks, reinforce our cognitive strengths, and ultimately enhance the human experience. The next chapter in our story will be written by how we choose to integrate these technologies into the fabric of our social lives, ensuring that the essence of what it means to be human is preserved and elevated in the process.

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