**Small-World Minds Create the Illusion of Low-Dimensional Social Cognition Under Constrained Stimuli**

Junsong Lu1\*, Chujun Lin1,2

1 Department of Psychology, University of California San Diego, La Jolla, U.S.

2 Department of Psychology, Columbia University, New York, U.S.

**Author Note**

Junsong Lu  <https://orcid.org/0000-0001-6987-6228>

Chujun Lin  https://orcid.org/0000-0002-7605-6508

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\*Corresponding author *E-mail address*: jul140@ucsd.edu

# **Abstract**

A long-standing tradition suggests that social inferences are summarized by a few dimensions (e.g., warmth, competence). However, such findings relied on constrained stimuli (e.g., group labels, static faces). Studies using naturalistic designs instead reveal high dimensionality. We propose a new perspective that reconciles these views: mental representations of social inferences are structured as a growing network with small-world properties. In this structure, nodes (social inferences) are connected with only a few steps from one another, so even limited activation—elicited by constrained stimuli in only a small subset of nodes—propagates broadly across the network, producing covariation that mimics low-dimensional structures. However, these dimensions are not functional but emergent properties of network dynamics under constrained input. We demonstrated how this small-world-minds perspective accounts for classic phenomena—halo effect and psychological dimensions—as artifacts of stimulus limitations. We call for moving beyond low-dimensional paradigms to understand the complexity of social cognition. (150/150)

***Keywords***: person perception, social cognition, network analysis, computational modeling, naturalistic design

# **Introduction**

People have hundreds of different concepts to describe their inferences about other individuals and groups, such as their personality traits, intentions and emotions, and demographic characteristics1–4. How do people represent these concepts in their mind5? Traditionally, answers to this question have been dominated by low-dimensional models6–11, which assume that there are mental shortcuts—only a few core latent dimensions—that simplify the complexity of social inferences. For instance, when participants were asked to infer target individuals’ personality traits based on facial appearances, the variation in these inferences can be captured by only four latent dimensions, “warmth”, “competence”, “femininity”, and “youth”12.

This low-dimensional perspective is supported by two major lines of empirical findings. First, the halo effect, such as the beauty-is-good stereotype, which illustrates that people perceive individuals who look physically attractive to possess other positive qualities as well such as intelligent, healthy, and moral. Stereotypes like this suggest that perceivers compress inferences of an individual into a single broad evaluative dimension13–17. Second, a small number of core psychological dimensions, which are shown to account for a large amount of variance in the wide range of inferences people make about others, from personality traits, emotional states, to group stereotypes4,6–9,12,18.

Despite a long-standing literature supporting the low-dimensional perspective, a growing body of research instead points toward a high-dimensional social cognition19–29. For example, the emotional experiences elicited by naturalistic videos are captured by 27 distinct dimensions25. Our own work analyzing people’s free descriptions of targets in naturalistic videos shows that even 25 latent dimensions are not sufficient to capture the variance in social inferences20.

Why do some studies reveal low-dimensional structures, while others uncover high-dimensionality? We propose that this discrepancy stems from the small-world network properties of social cognition. Specifically, we argue that mental representations of social inferences are structured as a small-world network that grows in a specific way: as people learn more concepts of social inferences, the network expands while preserving many distinct nodes (social inference concepts) and maintaining short paths between them (one social inference can trigger another through a small number of inferences between them). By analogy, social connections between people are structured as a small-world network30: as we get to know more people, the network grows with more members, but we can also reach nearly anyone in the network through just a few intermediaries (a friend of a friend).

A small-world mental representation might be complex and have a large set of nodes; however, when people make inferences based on constrained stimuli, only a small subset of nodes is activated, and these activations propagate broadly across the network due to the short paths between nodes—mimicking activation patterns expected from a low-dimensional structure. Our small-world minds perspective is supported by multiple lines of empirical research and can reconcile the low-vs-high dimensional findings of social cognition.

We illustrate this small-world minds perspective in detail across four sections of this paper. First, we introduce the ongoing debate between the low-dimensional and high-dimensional accounts of social cognition. Second, we propose a small-world network account of social cognition that reconciles this debate. This section outlines the structure of the network and its dynamic interaction with environmental input. We present simulation results in the main text along with detailed mathematical derivations in the supplementary materials. We review evidence from neural and developmental research that supports the small-world network account of social cognition. Third, we apply this small-world minds framework to explain why prior studies have yielded both low-dimensional and high-dimensional findings. Finally, we conclude by advocating for a paradigm shift beyond low-dimensional psychology to better capture the complexity of human social cognition in the real world.

# **The Debate: Low- or High-Dimensional Social Cognition?**

We review evidence supporting both accounts from research conducted over the past 50 years. For the low-dimensional account, we highlight findings including the beauty-is-good stereotype and the small number of core psychological dimensions. For the high-dimensional account, we discuss more recent studies that challenge the validity of the few core psychological dimensions—and, in some cases, questions the latent dimensional structure altogether.

## **Low-Dimensional Social Cognition**

Dion and colleagues in 1972 first demonstrated that people tend to attribute positive qualities (e.g., socially desirable) to physically attractive individuals—an effect known as the beauty-is-good stereotype13. In these studies, participants view face images that vary in attractiveness and rate them on multiple traits. Subsequent research, including large-scale meta-analytic reviews in the 1990s, confirmed the robustness and prevalence of this stereotype14,16,31. For example, Eagjy and colleagues14 showed that this stereotype is more pronounced for interpersonal evaluations (e.g., sociability) and weaker for capability-related evaluations like intelligence and integrity.

These findings have sparked a large body of research investigating why people hold such a stereotype—namely, whether it reflects an objective correlation between attractiveness and positive traits, or whether it arises merely from cognitive heuristics. While meta-analyses reported minimal correlations between ground-truth attractiveness and positive traits16, some anecdotal links were found17,31–34, particularly with objective intelligence and health17,35–38. These links may be explained by the good genes hypothesis, which posits that facial attractiveness may signal genetic fitness, including higher intelligence and better health39.

The mismatch between perceived and measured links between attractiveness and traits has fueled theories that attribute these stereotypes to cognitive heuristics. For instance, Zebrowitz and colleagues proposed the overgeneralization hypothesis17,40,41: although facial attractiveness may correlate with certain traits at lower ranges of facial quality, perceivers generalize this limited validity across the full spectrum, giving rise to the beauty-is-good stereotype. This mechanism is further supported by recent research showing that the beauty-is-good stereotype is prevalence but the associations between attractiveness and actual traits are weak42–44. Collectively, these findings suggest that mental representations of social inferences are shaped by overly simplified heuristics.

Whereas the beauty-is-good stereotype reflects low-dimensionality within a single association (e.g., the attractiveness-intelligence association), a parallel tradition investigates how low-dimensional structures emerge from the interrelations among many traits.. This line of search dates back to Asch’s seminal work on impression formation in 194645. By asking participants to make inferences about a person described by a list of traits, Asch found that changing certain traits (e.g., “warm” vs. “cold”) dramatically shaped overall impressions of the person, highlighting the central role of those traits. Reanalyzing these data, Wishner46 showed that a trait’s impact on overall impressions depends on its intercorrelations with other traits. The stronger a trait correlates with others, the greater it influences overall impressions.

Building on this, Rosenberg et al.11 used dimension reduction methods to systematically analyze latent dimensions that drive highly correlated traits, identifying two to three such dimensions (e.g., sociality and intellectual desirability). Subsequent investigations apply such dimension reduction methods to a broader range of trait inferences to search for latent dimensions that determine overall impressions. Some argue that only two dimensions (the Big Two model) are necessary, such as warmth and competence, which recurrently emerge across domains and tasks4,47–51. Others propose a few more dimensions, such as three dimensions—morality, sociability, and competence—for familiar groups and individuals52,53, four dimensions—warmth, competence, femininity, and youthfulness—for facial impressions12, and five dimensions—openness, conscientiousness, extraversion, agreeableness, and neuroticism—for self-presented and peer-perceived personality6.

Despite variations in the number and interpretation of identified dimensions, most studies converge on the finding that a small number of dimensions explain the majority of variance in social inferences54. While these dimensions can be viewed as statistical summaries of social inferences, they are commonly interpreted as psychologically meaningful latent constructs (in particular, dimensions extract using latent factor analysis). The widely replicated Big Two dimensions, warmth and competence, are even proposed to serve a functional role by conveying information about others’ intentions and their ability to act on them 8,55,56, which are vital for survival4,8. Similar evolutionary interpretations have been proposed for other dimensions such as attractiveness, which signals mate quality and reproductive potential7,35. Furthermore, these low-dimensional findings are often justified with cognitive constraints: they are thought to offer an efficient way for the mind to simplify and manage complex social environments57,58.

## **High-Dimensional Social Cognition**

Despite the dominance of low-dimensional accounts in the field, recent studies have begun to challenge the idea that a few core dimensions are sufficient to capture the complexity of social inferences19–26,29. These newer approaches share two key features. First, rather than starting with a small set of predefined dimensions and constructing items to confirm them as in prior research, they use data-driven approaches that are agnostic to the dimensions and rely on diverse items and response formats20,23,59. For instance, Brooks and colleagues22 asked participants to rate 4,659 face images on 48 emotions and mental states, and found 28 facial expression dimensions. Using open-ended responses, Nicolas and colleagues28 identified 40 distinct dimensions that capture free descriptions of social groups.

Second, rather than using constrained stimuli such as isolated face images or short verbal descriptions as in prior work, these studies employ more naturalistic stimuli ranging from ambient images with contextual backgrounds to dynamic videos that convey richer multisensory information. For example, Cowen and Keltner25 showed participants 2,185 naturalistic video clips that depicted emotionally significant events (e.g., weddings), and identified 27 emotion dimensions that capture emotional experiences from these stimuli. Together, these two approaches suggest that the low-dimensionality doctrine and constrained experimental paradigms in prior research may have precluded a more complete understanding of social cognition. When the assumption of low dimensionality is relaxed and participants are presented with richer, more naturalistic input, we may identify more complex and ecologically valid mental representations.

While the studies discussed above reveal much more latent dimensions than traditionally assumed, they still operate within the latent dimensional framework. Others suggest that the latent dimensional framework may be insufficient altogether. For example, Connor and colleagues27 identified 14 dimensions of social attributions using naturalistic face images, which explained only 38% of the judgment variance. Similarly, our own work20 showed that even 25 dimensions accounted for less than 15% of the variance in unconstrained social inferences from naturalistic videos. Comparing the latent dimensional framework with a sparse network model that does not assume a set of latent factors underlying social inferences60,61, we found that the network model fit the data better and replicated the finding across three world regions (U.S., Europe, Asia) 20. These findings suggest that in naturalistic contexts, mental representations of social inferences may be more accurately captured by non-dimensional, association-based, network representations.

In summary, prior research provides support for both low- and high-dimensional accounts of social cognition. This tension highlights a fundamental gap in our understanding: what kind of mental representations could give rise to such seemingly contradictory findings? We propose a novel framework to address this gap in the next section.

# **A Small-World Network Model of Social Cognition**

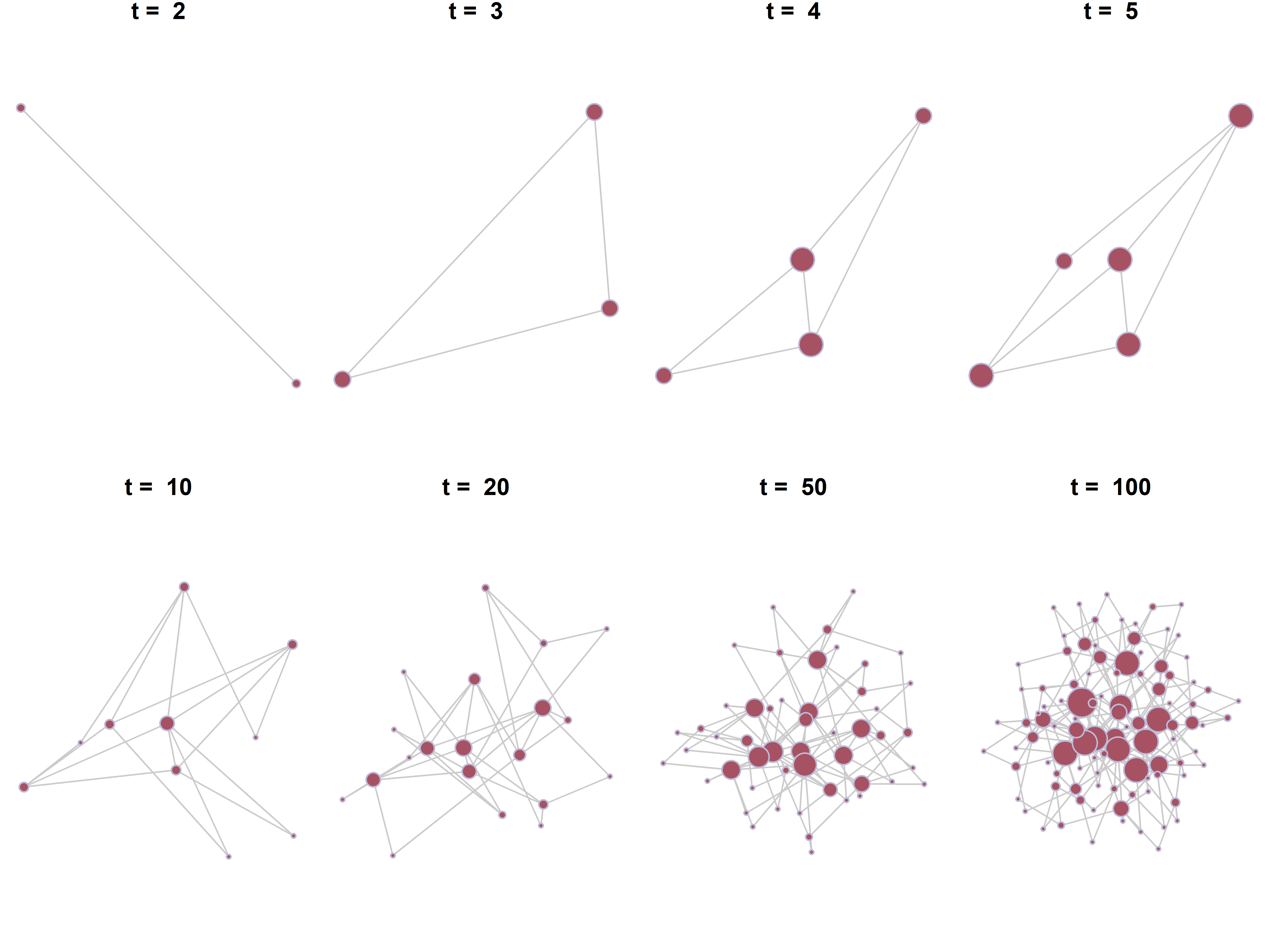
## **From Early Network Models to Small-World Thinking**

Cognitive scientists have long viewed the mind as inherently associative and thus have adopted a network approach to investigate mental processing62,63. Early work used networks to model semantic memory. In their seminal study, Collins and Quillian64 proposed that concepts are represented as nodes within a hierarchical tree. While elegant, this model is best suited for hierarchically organized concepts (e.g., animal categories) and does not easily generalize to capture mental representations of other concepts, such as color, faces, or social relationships65,66.

Researchers in sociology and physics provided insights into an alternative network structure that might inform mental representations: the small-world network. In the early 1960s, sociologist de Sola Pool and mathematician Kochen introduced the concept of “small world” in their analysis of social connections67. Their manuscript has been widely circulated and inspired the famous small-world experiment by Milgram68. The central idea, popularized by playwright John Guare as “six degrees of separation,” posits that anyone in a social network can be reached through a few intermediary connections.

Meanwhile, in a separate line of work unknown to sociologists at the time, Erdős and Rényi developed a random graph model69. They showed that when the average number of connections per node in this network increases beyond a certain threshold, a giant component emerges—an extensive cluster that connects the majority of nodes in the network. In this configuration, the maximum distance between any two nodes (the network’s diameter) decreases sharply. Relative to the size of the network (the number of nodes), this diameter becomes so small that nearly any two nodes become connected through only a few steps. This random graph model provides a useful demonstration of how small-world properties can arise once a network becomes sufficiently connected.

While informative, the random graph model assumes connections between nodes are formed randomly, typically resulting in a Poisson degree distribution. However, this assumption often fails to capture real-world systems, where link formation is driven by non-random mechanisms70–72. Instead, they often exhibit a power-law distribution, also known as a scale-free architecture: a few nodes (hubs) have many connections, while most have few (see Box 1 for more information). This architecture commonly arises from two generative mechanisms observed in a range of real-world networks (e.g., cellular networks, social structures, neural networks, and the Internet)71: growth, whereby networks expand by adding new nodes, and preferential attachment, where new nodes are more likely to connect with already well-connected ones70 (Fig. 1). These two mechanisms not only produce scale-free networks but also lead to small-world properties (Box 2): hubs act as shortcuts that link distant parts of the network, drastically reducing the average path length between any two nodes.



**Figure 1. Evolution of the Barabási-Albert Model.** Simulation of a growing network with 100 nodes, illustrating the two generative mechanisms of the Barabási-Albert Model: growth (at each time step, a new node is added to the network), and preferential attachment (new nodes are more likely to connect to highly connected nodes). Each new node forms two links to existing nodes. Over time (*t* = 2, 3, 4, 5, 10, 20, 50, 100), this generative process produces a scale-free architecture with a few highly connected hubs. These hubs act as shortcuts that drastically reduce the average path length between nodes, giving the network small-world properties.

**Box 1. Networks and Their Generative processes.** At the heart of network science is the concept of a network, a collection of nodes connected by edges that represent relationships or interactions. Early work in network science focused on the random network, which assumes that edges are formed independently and uniformly at random between nodes. More technically, a random network is generated by first assuming a set of nodes and then, for each pair of nodes, sampling the presence of a link from a Bernoulli distribution. To contextualize this process in the setting of friendship formation in a classroom, it implies that any two students have a fixed probability of becoming friends. While random graphs capture some properties of real networks, such as short path lengths, they fail to reproduce the highly uneven connectivity observed in many natural and social systems.

Scale-free networks address this limitation by exhibiting a degree distribution that follows a power law. This distribution indicates that a few nodes, or hubs, have disproportionately many connections. In a random network, the degree of a randomly chosen node typically lies close to the average degree ⟨k⟩, making ⟨k⟩ the characteristic scale of the network. In contrast, in a scale-free network the degree of a node can deviate greatly from ⟨k⟩, such that ⟨k⟩ does not define an intrinsic scale. For example, a node may have 100 connections in a network with an average degree of only 2.5.

A particular class of scale-free networks is growing networks. The growing network model illustrates the generative processes that give rise to scale-free properties. Specifically, a scale-free degree distribution can emerge from two mechanisms: growth and preferential attachment. Growth refers to the continuous addition of new nodes over time, while preferential attachment describes the tendency for new nodes to connect more often to already well-connected nodes, thereby creating hubs and reinforcing disparities in connectivity. These mechanisms demonstrate that network structure is not a static pattern but the outcome of dynamic generative rules. Consequently, statistical analyses of network structure, such as network diameter and hub dominance, provide insights into the underlying processes that shape networks.

**Box 2. The Small World Property**. The “small world” property, popularized as six degrees of separation, was first explored in sociology and social settings rather than in the context of psychological representations. It refers to the striking observation that any two people on Earth are likely connected through only a handful of acquaintances. In network science terms, this means that the path length between two randomly chosen nodes in a network is surprisingly short.

Why “surprisingly”? Much of our intuition about distance comes from physical space, where connections grow slowly with size. Imagine people arranged along a line: to reach someone at the far end, you would need to pass through nearly everyone in between. Even if people are arranged in a grid, the number of steps between two individuals still scales with the square root of the total population. By contrast, in a random network where each person has on average ⟨k⟩ acquaintances, the number of reachable nodes grows rapidly with distance: approximately ⟨k⟩ nodes at distance 1, nodes at distance 2, at distance 3, and in general at distance d. As a result, the average separation between individuals increases only logarithmically with population size: d ~ lnN/ln⟨k⟩. For example, if the global social network contains 8 billion people (N = 8 × 10⁹) and each has 500 acquaintances (⟨k⟩ = 500), the expected average distance is just over four steps.

Beyond random networks, the small-world property also appears in scale-free networks. These networks contain hubs, nodes with disproportionately many connections, that further shorten distances. A familiar example is the airline network: major hubs such as Atlanta or Dubai dramatically reduce the number of flights needed to travel between distant airports. In mathematical terms, hubs can reduce the scaling of average distance from *lnN* to *ln(lnN)*, a phenomenon known as the “ultra-small” property. Yet the effect of hubs is not always dominant. In some cases, hubs are not influential enough to substantially alter path lengths, and scale-free networks effectively approximate the behavior of random networks.

## **Small-World Mind Structure: Growth and Preferential Attachment**

We propose that the same generative mechanisms—growth and preferential attachment—also govern mental representations of social inferences. While the idea that conceptual knowledge in social cognition, such as mental representations of social inferences, may be structured as a network in the mind is not new3,19,73,74, the specific structural characteristics and underlying generative processes of such network remain unclear. Our account fills this gap by arguing that mental representations of social inferences are generated through growth and preferential attachment, giving rise to a network with small-world properties that balance complexity and efficiency.

The first generative mechanism, growth, addresses a fundamental computational challenge: how finite human minds can build increasingly complex social representations while keeping them tractable. This balance between complexity and tractability aligns with Piaget's theory of cognitive development, in which individuals assimilate new information into existing cognitive structures or accommodate it by modifying those structures75. Over time, these processes progressively build richer representations in a way that supports navigating complex social environments.

From an evolutionary perspective, the growth mechanism also offers computational advantages. Even if a representation is adaptive, such as correctly inferring the traits of a potential mate or collaborator, it does not need to be present from birth. Because complex mental representations are computationally costly to maintain, a representation can be acquired later when it becomes relevant. This growth mechanism aligns with the hierarchical sequence of social needs across lifespan76,77. For example, self-protection precedes status seeking, which in turn precedes mate seeking. Thus, concepts related to mating can be acquired later in life (e.g., inferences of family-orientated traits), whereas concepts important for detecting social threat (e.g., inferences of warmth) need to develop earlier.

The second generative mechanism, preferential attachment, characterizes how new information (e.g., new concepts) is incorporated into established mental representations. Intuitively, it follows a “rich-get-richer” pattern, where nodes (concepts) that already have many connections to other nodes are more likely to attract connections to new nodes. Mathematically, it is equivalent to a discrete-time stochastic process called the Chinese restaurant process (CRP), which has been widely used in nonparametric Bayesian models to explain categorization78,79 such as stereotyping80. In stereotype formation, preferential attachment manifests the tendency to categorize new individuals into more prevalent groups.

Although preferential attachment has not yet been applied to research on social inferences, it offers a clear prediction: new concepts of social inferences (e.g., inferences of family-oriented traits) will tend to be integrated with concepts that are already central to social inferences (e.g., inferences of gender). Importantly, evidence from cognitive modeling supports the broader psychological plausibility of this mechanism81. Resource rational analysis shows that preferential-attachment-like pattern can naturally emerge from a clustering process that minimizes representational complexity82. When complexity is defined as the entropy of cluster assignment distributions, the optimal use of limited cognitive resources favors assigning new items to existing clusters in proportion to their current size—precisely the pattern described by preferential attachment. This suggests that preferential attachment is cognitively efficient and therefore a plausible strategy for organizing mental representations.

Together, growth and preferential attachment provide generative mechanisms through which mental representations of social inferences can develop into small-world networks. This framework is fundamentally distinct from low-dimensional accounts, which posit a small number of fixed, core psychological dimensions underlying social cognition (e.g., warmth, competence) 8,55,83. These dimensions are considered fundamental and universal across lifespan, population, and judgments84. While low-dimensionality may accommodate human cognitive limitations, whether these dimensions accommodate the complex social environment remains debated20. Instead, our framework explains how complex, high-capacity mental representations can remain computationally efficient, not by constraining the system to a few dimensions, but by organizing it into a small-world architecture that supports rapid access to diverse inferences while preserving coherent central inferences.

## **Small-World Mind Dynamics: Spreading Activation and Environmental Inputs**

Having established how a small-world network for mental representations of social inferences can emerge from growth and preferential attachment, we now examine the dynamics that operate within this network. Specifically, we illustrate how information flows through the network and interacts with environmental inputs to produce social inferences.

In network models of cognitive processing, such as semantic memory, a central mechanism is spreading activation, in which activation of one concept spreads to and activates adjacent concepts in the network63. Spreading activation typically has two important characteristics. First, activation propagates recursively: initially activated nodes can receive feedback from related nodes that become activated later85. This recursive property creates dynamic patterns of mutual reinforcement within local regions of the network. Second, activation carries a limited cognitive resource: its signal strength decays over time and distance86,87, eventually returning to baseline resting levels3. Therefore, in a large network with long average path lengths—meaning many steps are required to connect distant nodes—activation can quickly dissipate before reaching distant parts of the network. Small-world networks, on the other hand, keep average path lengths short by linking distant regions through well-connected hubs, allowing activation to reach the entire network efficiently before the signal fades.

While network structure (e.g., large networks with or without small-world properties) determines how far and how quickly activation can spread, environmental inputs determine where activation begins. For instance, prior work conceptualizing mental representations of social inferences using networks, the dynamic interactive theory3, proposes that nodes (social inferences) differ in terms of their sensitivity to environmental inputs. Specifically, valence-related inferences are more sensitive to visual and auditory inputs resembling emotional expressions, enabling rapid automatic detection of social threat or safety. In contrast, more abstract inferences, such as personality traits, typically require detailed observation of behavior and sustained processing.

The interaction between environmental inputs and spreading activation can be thought of as a two-step process: environmental inputs selectively activate particular nodes in the network, and these nodes then transmit activation to their neighbors through recursive spreading. In a small-world network, this means that even activation that begins in a highly localized region—such as valence-related inferences triggered by emotional expressions—can quickly propagate to distant regions of the network, reaching conceptually unrelated inferences. Because this activation originates from the same source, the resulting spread produces similar patterns and levels of activation across a wide variety of nodes. As a result, even limited environmental inputs can create the appearance of broad, coordinated activation in mental representations with small-world properties.

## **Small-World Mind Plausibility: Neural and Developmental Evidence**

Although no empirical studies have yet directly tested whether mental representations of social inferences are organized in a network with small-world properties, preliminary support for this possibility comes from neural and developmental evidence.

### ***Neural Plausibility: How Social Inferences Mapped onto Biological Neural System***

Our proposed small-world network model of social cognition operates at Marr's algorithmic level: it specifies the rules by which mental representations are organized. However, any algorithmic model must be compatible with the implementation—the neural circuits that realize these representations in the brain. From this perspective, the question is whether known properties of biological neural networks could support a small-world organization of mental representations of social inferences.

There are two plausible neural implementations of the small-world mental representations of social inferences. The first is localist representation, in which each node (i.e., each social inference) corresponds to a single neuron or a very small, dedicated group of neurons. In this implementation, the efficiency of the mental representation network depends directly on the efficiency of the biological neural network. Early studies on the biological neural wiring in the worm C. elegans have found a small-world structure88 at the neuronal level, with similar neuronal-level structure subsequently found in cats, macaque monkeys, and even humans89,90. This suggests that if each social inference were represented by a single neuron (or a small group of neurons), their interconnections could in principle form a small-world network as well.

Although localist representation could, in principle, produce a small-world mental representations of social inferences, it is unlikely to be true. Higher-level mental representations such as those for semantic concepts are found to be scale-free: that is, nodes that represent semantic concepts in a network differ dramatically in the number of connections they have across orders of magnitude66. Higher-level mental representations of social inferences likely share the same scale-free architecture as semantic concepts. Thus, if one social inference maps onto one single neuron (or a small group of neurons), then neurons representing different social inferences should differ dramatically in their connections as well. Contrary to this prediction, neuroanatomical research shows that biological neurons typically have similar number of connections91.

Another plausible neural implementation of the small-world mental representations of social inferences is distributed representation highlighted in recent neuroscience research92–94. In this implementation, each node (i.e., each social inference) corresponds to a connectivity pattern across many neurons and their collective activation states. This is consistent with a recent theory proposing that social inferences emerge as equilibrium states reached through recurrent processing among thousands of neurons in parallel processing19. This implementation is also supported by empirical neuroimaging studies, which show that the medial prefrontal cortex represents both warmth inferences and competence inferences95. This suggests that the same neural ensembles can encode different social inferences via distinct activation patterns.

Distributed representation is not only neurally plausible but can also accommodate the scale-free properties observed in higher-level mental representations such as semantic concepts and likely social inferences. This implementation only requires that neuron-population-level activation patterns differ among one another in how strongly or frequently they are connected to other neuron-population-level activation patterns. At the same time, individual neurons maintain biologically realistic connectivity. Overall, these features make distributed representation both consistent with neural constraints and compatible with a small-world organization of social inferences.

### ***Developmental Plausibility: Evidence for Growth and Preferential Attachment***

From a developmental perspective, both theoretical considerations and empirical evidence point to a small-world organization of social inferences. Theoretically, growth and preferential attachment achieve cost–benefit efficiency by gradually constructing the network. Adding new nodes as development proceeds prevents the retention of outdated or less relevant knowledge, while linking them with few connections maintains sparsity (i.e., far fewer links than the maximum possible). These properties reduce the number of neural links and energy required for maintenance, while preserving the small-world topology that supports efficient activation propagation..

Empirically, two lines of research support both growth and preferential attachment underlying mental representations of social inferences. First, different social inference concepts are acquired at different times and the representations of them change over lifespan. Age-of-acquisition ratings for over 30,000 English words show that words related to the previously identified “valence” dimension are acquired early in development96, such as "nice" (acquired at age 3.95) and "kind" (4.89 years); whereas, words related to more abstract inferences are acquired later in development, such as sensitive (8.19 years) and extroverted (13.35 years). Developmental changes also emerge in the consistency of social inferences. When judging faces that vary in warmth on warmth related traits (within-concept judgment), agreement between individuals increases with age. This suggest that the “warmth” concept in childhood is not fully developed—children may have a smaller set of warmth-related inferences to draw upon, leading to more individual differences. In contrast, when judging faces that vary in competence on warmth related traits (between-concept judgment)97, adults agree less than children. This suggest that children’s “warmth” concept is less clearly differentiated from “competence” concept than adults, allowing cues for competence to influence warmth judgments. Together, these findings suggest that children’s mental representations for warmth are both less complete (fewer warmth-related nodes) and less specialized (more cross-concept connections) than adults, supporting a growing network account of mental representation of social inferences.

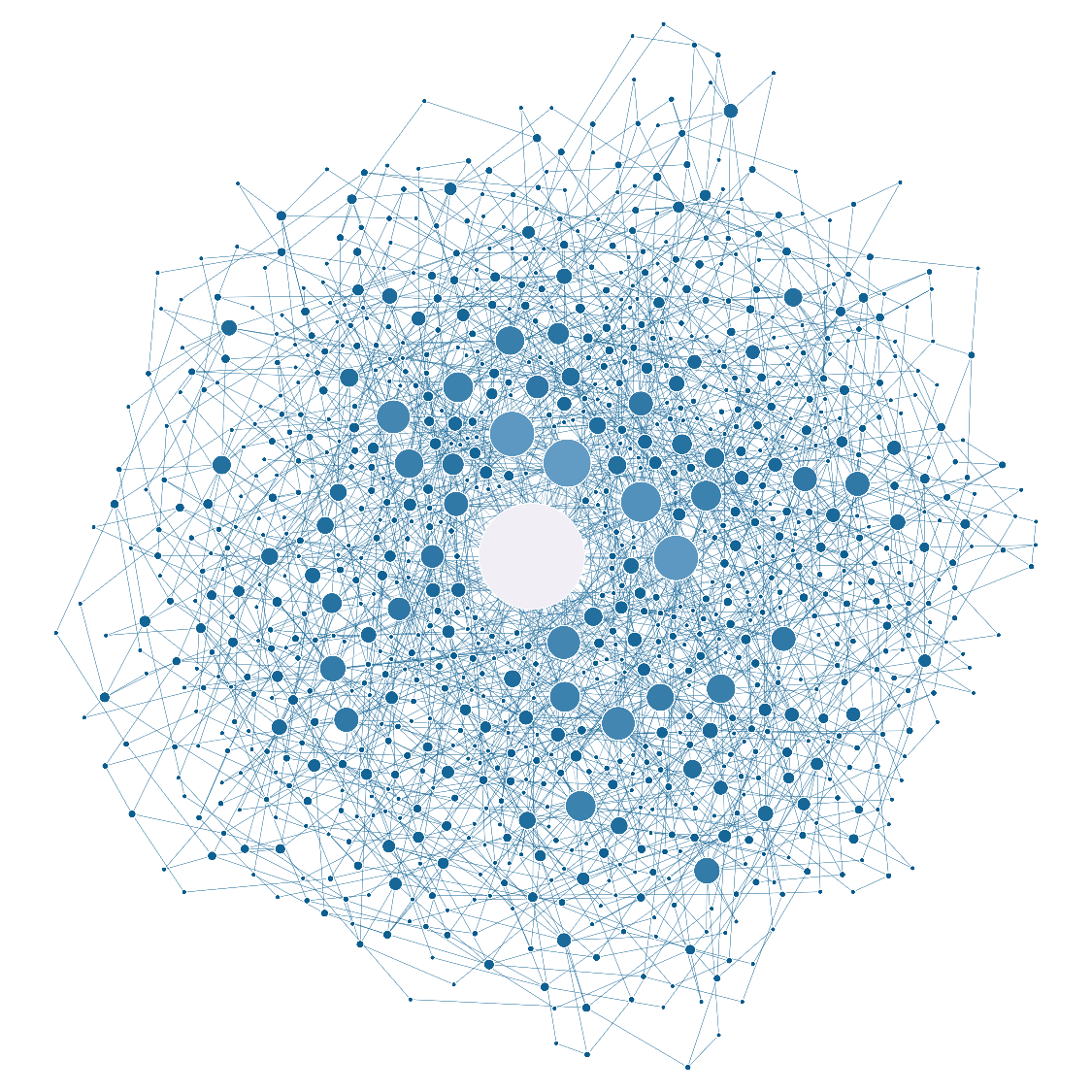
Second, social inference concepts that are acquired earlier in development (e.g., valence-related inferences) tend to correlate more with other social inference concepts. As noted above, valence-related concepts are acquired in early life. They often show stronger and more numerous correlations with other social inferences (i.e., usually showing greater explain variance when they form a factor) than competence-related inferences4,47–51. More broadly, words related to prior identified social dimensions are generally acquired early: for instance, “smart,” a key competence item, is estimated to be acquired at age 5.50, while "pretty", related to the attractiveness dimension, is acquired around 4.09 years. According to preferential attachment, early acquired concepts form more connections with other concepts, giving rise to the apparent social dimensions. The dominance of dimensions anchored in early-acquired concepts thus supports the role of preferential attachments. Together, developmental findings support both generative mechanisms that naturally produce small-world properties in mental representations of social inferences.

# **The Small-World Mind and the Low-Dimensional Illusion**

Having elaborated the small-world network structure, processing dynamics, and its plausibility, we now advance our central argument: previously observed low-dimensional social cognition can be understood as an emergent phenomenon when environmental input is constrained. We unpack this argument in three sections. We first provide formal analysis of the network model, deriving relationships between node distances (e.g., trait similarities in person perception) and their correlations. The demonstrations in the main text are targeted for a broad audience; for those interested in methodological details, more rigorous mathematical derivations are provided in the supplementary materials. Building on this structural understanding, we then show how the network can give rise to seemingly low-dimensional observations. We illustrate this with classical social cognitive phenomena, including the beauty-is-good stereotype and seemingly fundamental psychological dimensions such as warmth and competence.

**Small-World Network: Nodes Distances and Activations Correlations**

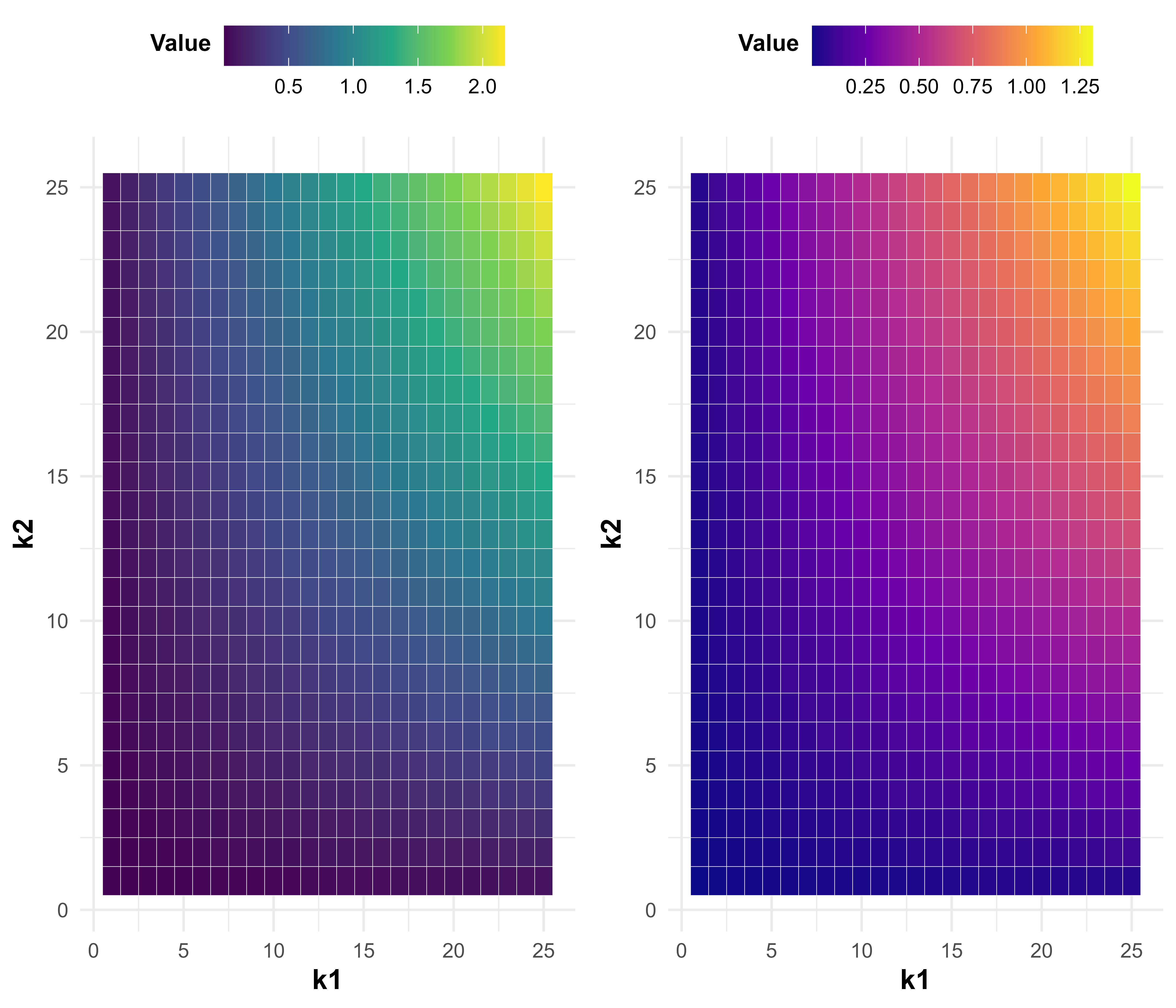
Networks generated through growth and preferential attachment mechanisms—that is, scale-free networks—exhibit ultra-small-world properties98,99. While randomly connected networks can display small-world properties, scale-free networks compressed connectivity even further. Specifically, the largest distance between nodes in scale-free networks scales with *ln(ln N)* rather than the typical *lnN* observed in random networks, where *N* represents network size. The average distance also behave similarly98. Because *ln(ln N)* grows extremely slowly, even very large scale-free networks maintain remarkably short distances between nodes. This unusually slow increase in the largest path length relative to network size arises from the presence of hubs—a few nodes with exceptionally high connectivity that can link distant network regions in remarkably few steps (Fig. 2). Applying this to mental representations of social inferences, it means that even conceptually distant inferences can influence one another and reach comparable activation levels despite their conceptual separation.



**Figure 2. A Scale-Free Network Generated through Growth and Preferential Attachment.** This network contains 1,000 nodes built through a simulated process. At each time step, a new node is added (i.e., growth) and connected to two existing nodes, with a higher probability of connecting to nodes that already have many links (i.e., preferential attachment). The size and color of each node are proportional to its degree (i.e., the number of connections), with larger nodes and lighter colors indicating higher degrees. The largest grey node in the center represents a hub, which provides shortcuts to connect otherwise distant nodes, helping to maintain short path lengths even as the network grows.

To build intuition about how closely connected nodes are within a growing network, we can derive the expected number of links between two nodes with degree and by a distance of *d* (e.g., with *d*-1​ intermediate nodes). In large networks, the probability of connection can be approximated by the expected number of links (see the supplementary materials). Thus, estimating the expected count of paths of length *d* provides a natural way to interpret connection probabilities between nodes at distance *d*.

Our calculation is based on the configuration model in complex network theory100,101, which is a commonly used starting point for analyzing a complex network (see supplementary materials). In brief, the expected number of links of length 1 (direct connections) between two nodes is proportional to the product of their degrees: the higher their degrees, the greater the likelihood of a direct connection between them. This logic extends to longer paths: for *d >* 1, the expected count of paths of length *d* still scales with the product of degrees but is amplified exponentially by a factor dependent on the network’s degree distribution. In real-world network, the expected number of links is often even higher due to assortative mixing102 (nodes connecting to other nodes with similar properties), where high-degree nodes tend to connect preferentially with other high-degree nodes.



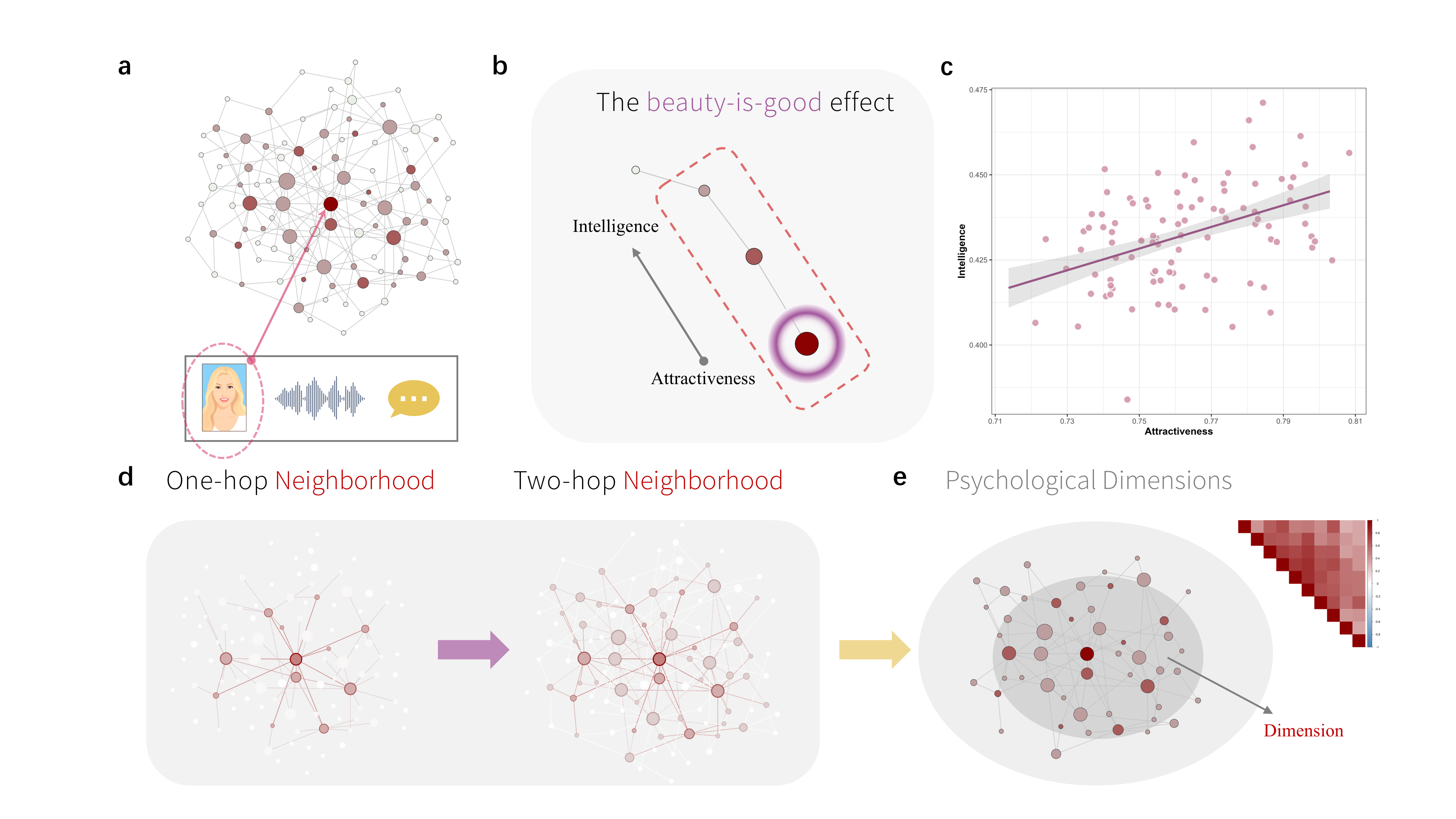
**Figure 3. Expected Number of Links between Two Nodes of Given Degrees.** Each density map displays the expected number of links (color) connecting two nodes with degrees k1​ (x-axis) and k2 (y-axis)​, calculated based on their degrees and the total number of edges in the network. The left panel is based on a network of 500 nodes with 3 links added at each time step; the right panel is based on a network of 200 nodes with 2 links added per step. Warmer colors indicate higher expected number of links connecting the two nodes. As predicted by the model, nodes with higher degrees are more likely to be connected.

After describing the distance between any two nodes in the network, we now turn to how activation spreads between them. When activation spreads through a network with some random noise at each step (i.e., moving from one node to the next)3, the correlation between the activation levels of two nodes becomes a function of their distance—shorter distances produce stronger correlations. In a weighted network (e.g., only a proportion of the activation can be propagated), these activation correlations are further influenced by the connection weights. In psychological networks, such as mental representations of social inferences, these connection weights may be relatively high due to the limited distinctiveness between different inferences103 (e.g., nice is semantically similar to kind), leading to strong correlations in activation levels between nodes. As a result, the activation levels of neighboring constructs tend to rise and fall together. This similarity in activation levels increases the correlations across the network, even between nodes that are farther apart.

## **Reinterpreting Beauty-is-Good in the Small-World Mind Framework**

The beauty-is-good stereotype are often seen as evidence for low-dimensional social inferences. We propose instead that a small-world mind can explain this effect. Specifically, we argue that previously found high correlations between perceived attractiveness and other positive traits are due to the efficient activation spreading in a small-world mind under constrained environmental inputs, indicating an emergent property of activation patterns (Fig. 4). In this section, we first provide theoretical demonstration of this argument. We then support this argument with simulation studies.

Consider the commonly reported correlation between perceived attractiveness and perceived intelligence17,43. If these two inferences are closely connected in a small-world network, their short path explains the strong correlation in their activations (e.g., behavioral ratings of these inferences). Indeed, empirically, perceived attractiveness and related inferences like “pretty”, “handsome” often hold a central position in the network due to its early acquisition and high accessibility, giving it a “first-mover” advantage20 (Fig. 4b). Perceived intelligence, shaped by cultural norms and folk theories43,104, is broadly connected to various trait inferences, contributing to its high degree. When constrained stimuli such as cropped-out face images are observed without auditory, semantic, or behavioral information (Fig. 4a), the activation in the network is sparse (i.e., only a few social inferences are activated) and concentrated on accessible nodes like attractiveness. The activation of attractiveness is then quickly passed to intelligence without significant decay due to the short paths in a small-world mind (Fig. 4b), creating the appearance of high correlation (Fig. 4c). In such constrained experimental settings where richer, multisensory social cues are missing, abstract social inferences (e.g., intelligence, morality) receive little direct activation from the environmental inputs but eventually obtain efficient activation through their short distance to frequently activated social inferences.



**Figure 4. Beauty-is-Good and Psychological Dimensions in a Small-World Mind.** (a) In typical studies, constrained stimuli, such as isolated face images, are used to elicit social attributions. (b) Empirical evidence105, including our prior work20, demonstrated that attractiveness-related inferences are often well-connected with other inferences, acting as a hub in the network. The node representing perceived attractiveness is easily activated by environmental inputs106,107, and its activation is rapidly transmitted to neighboring nodes, such as “intelligence.” This activation decays with distance but, due to the small-world property of the network, can quickly reach seemingly unrelated nodes like “intelligence,” producing proportional activation. (c) Our simulation revealed a strong correlation (*r* = 0.50, *p* < .001) between the initially activated node (e.g., attractiveness) and a two-hop neighbor (e.g., intelligence). (d) The initial activation of the central node (dark red) spreads to one-hop neighbors (directly connected nodes), then to two-hop neighbors (nodes that are indirectly connected through one intermediate node). Due to the short paths between nodes in a small-world network, similar activation levels efficiently spread across the entire network. (e) These similar activation patterns lead to high shared covariance across nodes (upper-right heatmap). When applied dimension reduction analyses to the activation levels of the nodes (e.g., behavioral ratings of different social inferences), only a few core psychological dimensions (e.g., one indicated by the central grey region) are needed to explain most of covariance in the activations across nodes.

A key prediction of our argument—that the small-world mind explains the beauty-is-good stereotype—is that this stereotype should weaken or even disappear when richer social information is available and when initial activations conflict. We conducted a simulation study to directly test this prediction. In our simulations, we introduced diverse environmental inputs to the network, giving many nodes relatively independent initial activations. We found sharp decreases in the correlations between the activation of attractiveness and other positive inferences (constrained stimuli: mean correlation = 0.58, *SD* = 0.14; naturalistic stimuli: mean correlation = 0.03, *SD* = 0.12), confirming our prediction (Fig. 5). Empirical findings are consistent with this prediction. For instance, prior research using face-only images often found a correlation between perceived attractiveness and warmth around 0.41108. In contrast, when naturalistic images including context such as body posture, movement, clothing, and situational cues are used, the correlation between attractiveness and perceived warmth drops to 0.12109. Similarly, using face-only images, prior studies often find a strong correlation between perceived attractiveness and intelligence (*r* = 0.81)43; this association becomes statistically insignificant and approaches zero (*r* = -0.04) in our own empirical research examining social inferences using video clips20.

图表

AI 生成的内容可能不正确。

**Figure 5. Simulation Showing the Low-Dimensional Illusion Decreases with Richer Inputs.** (a) When a single constrained stimulus is used—thus, only one or a few nodes are activated—the activations of different nodes quickly reach equilibrium and become similar. Each line represents the activation of a single node across time points. (b) When constrained stimuli are used as environmental input in our simulation, we calculated the correlations between activations of different nodes. The correlation heatmap indicates strong overall correlations (brighter red) between all nodes’ activations in the network. In this simulation, only a single latent dimension was identified, and it accounted for 60% of the variance in the nodes’ activations, consistent with the low-dimensional findings in prior research using constrained designs7,8. (c) When more complex environmental inputs (e.g., multisensory social information) are used, activations between nodes become less similar and more unstable. (d) As a result, the correlations between activations weakened, with a single latent factor accounting for only 12% of the variance, consistent with recent studies using naturalistic designs20,27.

## **Reinterpreting Psychological Dimensions in the Small-World Mind Framework**

The same logic helps explain why only a few latent dimensions can account for most of the variance in social inferences under constrained stimuli (Fig. 4d-4e). Specifically, we argue that these psychological dimensions are not fixed, functional bases that drive social inferences; instead, they are well-connected regions (i.e., communities) in the small-world network that emerge from activation dynamics shaped by environmental inputs. In this section, we first describe the methodological and statistical bases of the low-dimensionality found in prior research. We then explain the relations between these dimensions and environmental inputs. Finally, we discuss how this flexible relation between dimensions and environmental inputs is better captured using a network perspective.

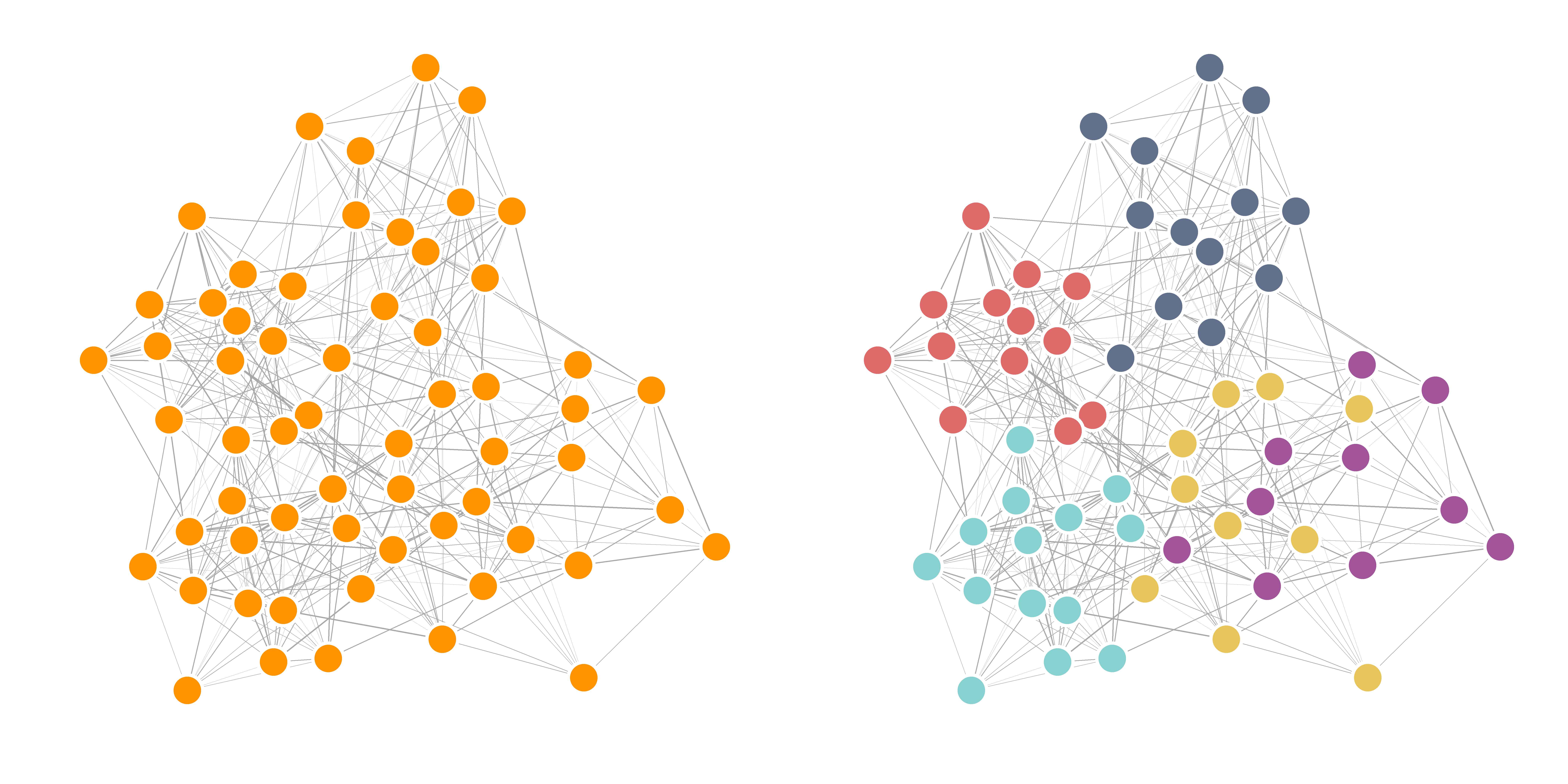
Prior studies often used constrained stimuli such as cropped-out face images and only a limited set of pre-selected trait words to investigate the psychological dimensions of social inferences. These practices raised concerns that the identified dimensions may reflect inadequate stimulus sampling51,110,111. Indeed, many studies relied on a priori theories, such as the warmth-competence framework, and selected trait words to match these dimensions. This introduced semantic redundancy and inflated inter-trait correlations. However, even when trait words were selected comprehensively without targeted dimensions, a low-dimensional structure often emerges when the stimuli are still constrained (e.g., face images)12,51. Our own work20 and recent evidence27 shows that when the constraints on stimuli and trait words are simultaneously relaxed, the evidence for a low-dimensional representation vanishes. This finding shows that the richness of environmental input plays a critical role in eliciting comprehensive social inferences and revealing the corresponding mental representation.

Statistically speaking, the prerequisite for dimensions to emerge is the high shared variance among measures (e.g., ratings on different social inferences)112,113. This can be evaluated using the Measure of Sampling Adequacy (MSA), which ranges from 0 to 1 and estimates whether a given inference shares sufficient variance with others to justify latent dimensions114. A low MSA value indicates that an inference has unique associations with other inferences that are not easily reducible to the shared variance with other inferences driven by latent dimensions. When the mental representation of social inferences is structured as a small-world network, MSA values become highly dependent on the environmental inputs. When constrained stimuli such as face images are used, only a few facially relevant nodes in the network are activated. These activations then spread in parallel, creating uniform influence across neighboring nodes, mimicking the statistical effect of a latent dimension. Thus, high shared variance between social inferences under constrained inputs does not reflect genuine structure of mental representations (i.e., low dimensionality), but rather emergent properties of the network.

The network perspective also informs why commonly identified dimensions map onto readily accessible environmental inputs. For instance, the warmth dimension in the Big-Two model is closely linked to facial expression cues8; the attractiveness dimension in the 3-D model7, and the femininity and youthfulness dimensions in the 4-D model12 are closely linked to facial cues. From our network perspective, environmental inputs activate a few directly relevant nodes, which in turn spread activation through short paths to other nodes (Fig. 4d). The resulting activation patterns align most strongly with the directly stimulated nodes, producing shared variance (i.e., “dimensions”) tied to those inputs (Fig. 4e).

When environmental inputs are naturalistic and diverse, the conditional independence assumption of latent dimensions is often violated. This assumption states that, once the variance driven by latent dimensions are accounted for, individual measures should no longer be directly related115–117. However, in naturalistic contexts, nodes sensitive to visual, auditory, and behavioral inputs are simultaneously activated. Because these inputs are not necessarily strongly correlated (e.g., attractiveness and measured intelligence44), they generate complex activation patterns and unique variances across the network. In another word, for instance, introducing node activations driven by behavioral information beyond static facial information will largely decrease common variance between nodes’ activations, and thus a few dimensions are insufficient to explain the variance across social inferences. This is empirically demonstrated in our prior work20 and the simulation (Fig. 5).

Formally, from the network perspective, the psychological dimensions previously found reflect potential communities in the network118. These communities are clusters of densely connected nodes that share similar activation patterns (Fig. 6). Empirical findings from both personality and person perception research have demonstrated the high similarity between traditional dimensions and communities in the network20,61,119. These activation-based communities can vary flexibly depending on the environmental inputs, explaining why dimension-like structures found in prior research vary dramatically depending on the stimuli7,12,27,83. Taken together, we argue that dimensions found in prior research are not fixed, functional structures that drives social inferences, but instead emergent properties of the network.



**Figure 6. Psychological Dimensions Are Communities in the Small-World Mind.** Left: A network without communities (densely connected regions) annotated. Right: the same network with communities annotated using colors. Communities are identified using community detection algorithms that focus on network structure between nodes118,120–122. Communities in the small-world mind serve as structural prerequisites for psychological dimensions to be detected when constrained environmental inputs are used. This occurs because when a node within a community is activated, the activation spreads to other nodes in the same community with fewer steps than to nodes outside the community. As a result, correlations based on behavioral measures tend to be higher among nodes within the same community.

# **Moving Beyond the Low-Dimensional Illusion of Social Cognition**

Taken together, our analyses in the above sections show that the seemingly low-dimensional patterns observed in social cognition are in fact an illusion—arising from the underlying small-world network structure of mental representations of social inferences and its interaction with constrained environmental inputs. Beyond this methodological reason, the persistence of low-dimensional conclusions in the field may reflect deeper cognitive and cultural biases toward simplicity.

Humans have a strong motivation to understand and find meaning in their experiences123. Given the inherent complexity of human psychology, this motivation compels researchers to create mental placeholders that establish feelings of certainty and understanding124—the low-dimensional models serve as good candidates. Beyond these cognitive tendencies, cultural norms in social science research favoring verbal descriptions over mathematical representations when communicating research findings also contribute to the popularity of low-dimensional solutions125. Results that are easier to interpret, communicate, remember, and reproduce tend to persist during social transmission; whereas, results that are more difficult to interpret, communicate, or remember are more often criticized and distrusted126. This is consistent with findings showing that transmission of social knowledge (stereotypes) over generations of participants compresses knowledge representations from high- to low-dimensional127. Similar mental compression processes may operate in scientific production and transmission, suggesting that our innate cognitive tendencies may systematically distort the understanding of the dimensionality of psychological spaces, favoring simplified models that are more readily communicated even if they are less accurate.

Moving beyond this low-dimensional “wishful thinking” is key to advancing an ecologically valid understanding of social cognition126. We believe that progress requires two complementary approaches: incorporating the complexity of real-world social interactions into experimental designs and developing quantitative mental models that make precise predictions about behavior. Specifically, we recommend reconceptualizing experiments as simplified models of real-world interactions rather than artificial manipulations of isolated variables128. Social cognitive processes such as impression formation typically extend beyond a single time slice or glimpses of faces, it will be helpful to incorporate multisensory information and dynamic social interactions in experimental designs. In addition, to better understand cognitive processes, simply manipulating environmental inputs may not be sufficient, as the way cues are integrated and combined can largely influence behavioral outcomes129–131. We recommend developing explicit mental representation models that can inform cognitive processes in naturalistic contexts, such as how complex environmental inputs are processed and transformed into behavioral responses.

In the current paper, for example, we modeled mental representations of social inferences explicitly as small-world networks following growth and preferential attachment mechanisms, and derived correlation patterns of node activations within these networks based on environmental inputs. This approach exemplifies a broader methodological philosophy: mental models functioning as systematic procedures that convert raw environmental inputs into specific behavioral outputs through well-defined mathematical transformations can provide more testable models of mental processes. For instance, we can manipulate a more precisely defined factor in this mental model and compare the model responses to human behavior to evaluate the model plausibility. Just as a recipe describing how to optimally combine ingredients to produce a dish, models describing psychological processes with precise mathematical functions126,132 may help us better understand cognitive processes in complex, naturalistic contexts.

# **Conclusions**

In this perspective, we propose that mental representations of social inferences are structured as a small-world network built through growth and preferential attachment. Using mathematical proofs and simulation studies, we showed that prior low-dimensional findings can emerge from a small-world network structure operating under constrained stimuli. Mechanistically, the small-world topology shortens the distance between seemingly unrelated nodes and results in strong correlations between node activation and behavioral responses. We advocate moving beyond low-dimensional thinking and paradigms to achieve a more ecologically valid understanding of how people perceive and organize social traits and behaviors.

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