ANNUAL REVIEWS

Annual Review of Developmental Psychology

Modeling Other Minds: A Computational Account of Social Cognition and Its Development

Zihan Wang,[1] Isaac Davis,[1] and Julian Jara-Ettinger[1,2]

[1]Department of Psychology, Yale University, New Haven, Connecticut, USA; email: julian.jara-ettinger@yale.edu

[2]Wu Tsai Institute, Yale University, New Haven, Connecticut, USA

Annu. Rev. Dev. Psychol. 2025. 7:13.1–13.25

The *Annual Review of Developmental Psychology* is online at devpsych.annualreviews.org

https://doi.org/10.1146/annurev-devpsych-111323-112016

Keywords

Bayesian models, computational tractability, intuitive theories, social cognition, social development, theory of mind, causal models

Abstract

This article reviews how humans come to understand other minds from a computational perspective. We propose that social development is structured around three abilities: (*a*) building representations of agents and minds from a small set of abstract primitives, (*b*) embedding these representations into a probabilistic causal model of rational action, and (*c*) using this model to interpret everyday behavior. For this third ability, we argue that using a full model of other minds is too computationally demanding. To manage this, people learn how to build simplified context-specific models that balance computational efficiency with explanatory power. Learning how to build these restricted scope models may be a central but understudied aspect of development, shaped in part through everyday conversation. All together, our framework offers a formal account of social development and highlights open questions about how this capacity emerges and develops.

Contents

1. INTRODUCTION

By the time they are 3, human children already have social skills that surpass those of adult chimpanzees and orangutans—our closest evolutionary relatives (Herrmann et al. 2007). They can talk about things no other species can (Deacon 1998), learn quickly from others (Gweon 2021), and become active members of social groups by spontaneously sharing knowledge (O'Neill 1996) and helping those in need (Warneken & Tomasello 2006).

But, as any parent can attest, their understanding of minds is still immature. The Russian poet Korney Chukovsky (1963) documented hundreds of everyday remarks that reveal how children often get others wrong. One 6-year-old, after being told that a pregnant woman had a baby in her tummy, asked in horror, "She ate up a baby?!" Another child wondered whether a rooster could "completely forget that he is a rooster, and lay an egg." Remarks such as these reveal children's poor grasp of what kinds of mental states are plausible (such as believing an adult might want to eat babies and that others would be fine with it) and how mental states relate to behavior (such as enabling or preventing the ability to lay eggs).

A core goal of cognitive development research is to build theories that capture what infants understand about the social world, the limitations in their reasoning, and what kind of conceptual change occurs over the first years of life. In this article, we argue that computational approaches to social cognition provide a powerful way to understand development. Specifically, computational frameworks suggest social cognitive development can be understood in terms of three interrelated problems: (*a*) how to represent other minds, (*b*) how to embed these representations into probabilistic causal models that relate mental states to behavior, and (*c*) how to use these models for everyday social reasoning. The first two problems have received substantial empirical attention, and we focus on how the developmental literature can be understood in computational terms. The third problem remains empirically understudied, but its importance becomes clear through computational formalizations. Thus, for this final component, we highlight the nature of the computational challenges that infants and children must solve but that we know surprisingly little about.

Throughout, our focus is on how children learn to think about other people's minds, although social reasoning goes beyond this capacity. Both children and adults also rely on representations of social categories (Rhodes & Chalik 2013, Shutts & Kalish 2021), relationships between individuals (Thomas 2024), and the norms and roles imposed by society (Jara-Ettinger & Dunham 2024). We therefore conclude with a brief discussion of how current computational frameworks can begin to account for these additional representations that allow people to understand one another.

Before we begin, it is helpful to consider what can be gained by taking a computational approach to social development. Computational theories have been at the heart of major advances across all domains of science (Wigner 1990). At a high level, computational theories share the same goals as cognitive theories expressed in everyday language. However, they differ by offering computable theories that can be implemented as programs. These models can then independently process events, build internal mental representations, and make decisions. In doing so, computational models generate precise, testable predictions about both internal representations and observable behaviors.

This approach contrasts with theories expressed in natural language. Language is inherently ambiguous (Piantadosi et al. 2012); most words have multiple meanings (Floyd & Goldberg 2021) and people interpret words in subtly different ways (Marti et al. 2023). These ambiguities can therefore limit the precision of our theories. Computational frameworks avoid this challenge by formalizing the exact representations and processes in computational terms. This makes a theory's predictions explicit and falsifiable. However, that does not mean that computational theories are inherently better than noncomputational ones. Most computational models emerged as formalizations of theories first expressed in plain language. In fact, early stages of theory development probably benefit from the expressive richness of natural language, which can then inspire new computational techniques that capture those ideas. Thus, while our goal is to interpret the developmental literature in computational terms, the core ideas largely originated within developmental science. The computational perspective simply allows us to clarify the exact representational components and computational processes involved in social reasoning and its development.

2. ADULT SOCIAL COGNITION

To discuss how social development can be broken down in computational terms, we first need to review how adults reason about other minds, which clarifies the end point of development. Different varieties of computational architectures have been used to model or replicate adult social cognition, including game-theoretic (Yoshida et al. 2008) and deep-learning approaches (Rabinowitz et al. 2018). Here we focus on a specific framework that is part of the broad family of Bayesian models of cognition (Griffiths et al. 2024) because it currently has the most extensive empirical support directly comparing its predictions with child and adult reasoning. In this framework, we can break down social cognition into three core questions: How do adults represent other minds (Section 2.1)? How do we represent causal relations between mental states and actions (Section 2.2)? And how do we use these causal models in social life (Section 2.3)? Our review is intentionally high-level, aiming to lay down only the essential information needed to discuss development. A detailed introduction to Bayesian models of adult social cognition can be found elsewhere (Jara-Ettinger et al. 2024).

Our starting point is the observation that adult social reasoning is strikingly accurate. While social misunderstandings and blunders are disproportionately memorable, they are overshadowed by the hundreds of smooth interactions we have everyday—from seamlessly avoiding collisions on a crowded street to deep conversations with close friends. Our natural ability to understand other minds is so powerful that it arguably outperforms the best existing scientific theories that attempt to do the same. Thus, our focus is on the representations and computations that explain how people so often get each other right.

2.1. Mental-State Representations

Adult representations of other minds are built around a key set of interconnected mental-state representations: beliefs, desires, and goals. Beliefs capture what the world is like in another person's mind. Desires capture what they would like the world to be like. And goals capture what they want to accomplish in the world, given their beliefs and desires.

These three key mental states are built over a basic representation of states of the world. A goal is a single target world state that the agent is trying to produce through their actions. Desires are a set of world states, each tagged with a reward that reflects its strength (which can include mutually incompatible states, such as wanting to eat healthily while also craving unhealthy food). Beliefs form a parallel representation, but each state is tagged with a probability that captures how much the agent believes the state to be true. Through these representations, it is then possible to build a basic causal model that captures how other people's minds drive their behavior.

2.2. Causal Relations

Mental-state representations are organized within a causal model that captures how they produce behavior and change in response to experience, structured around an expectation that people are, in fundamental ways, rational (Baker et al. 2017, Gergely & Csibra 2003). This does not imply that we expect people to always behave optimally and never make mistakes but only that people's behavior is reasonable, given what they're trying to accomplish and what they believe.

Computationally, this intuition can be formalized as an expectation that agents act to maximize their subjective utilities—the difference between the costs they expect to incur and the rewards they hope to attain (Gergely & Csibra 2003, Jara-Ettinger et al. 2016). Thus, according to our causal model, people are more likely to select and pursue whichever goals are most likely to yield the highest utilities, given the rewards specified by their desires and the costs of achieving them.

To illustrate this, imagine that a friend shows up to work on a national holiday. You know they do not usually bring lunch and tend to get hungry at around noon. If they have not realized that the popular, cheap coffee shop around the corner is closed, you can predict that they will try to go there. It has a good lunch, is nearby, and is affordable, making it a high-reward and low-cost option from their point of view.

The same causal model we used to predict behavior from mental states can also be used to infer mental states from behavior (Baker et al. 2017, Jara-Ettinger et al. 2020b, Jern et al. 2017, Lucas et al. 2014). Now suppose you did not know much about your colleague, but you see them leave at noon, walk to the usual spot, and return empty-handed. From this behavior, you could infer that they believed the lunch spot was open and intended to buy lunch. After seeing it was closed, they probably remembered it was a holiday and figured other options were closed too, leading them to just come back to work.

This kind of inference can be formalized as recovering the combination of beliefs and desires that, according to our causal model of rational action, would produce the observed behavior. This process captures a wide range of everyday intuitions people have about one another's behavior. For example, if someone knowingly incurs a high cost to achieve a goal, we can infer that the goal really matters to them (otherwise, the cost would outweigh the reward). Conversely, if they pass up a goal that is easy to attain, we can conclude they must really not care about it. Inferences such as these allow adults to infer others' abilities, preferences, knowledge, and even moral attitudes (for a review, see Jara-Ettinger et al. 2016).

Access to a causal model of rational action enables us to do far more than infer mental states. It allows us to accomplish a range of activities including predicting behavior, considering how these predictions change if the mental states of the situation were to be different, and using these predictions to decide how to interact with others (Allen et al. 2015, Ho et al. 2022b, Jara-Ettinger et al. 2020b). But doing so, as we discuss in the next section, is not necessarily easy.

2.3. Using Our Model of Other Minds

How exactly do people invert their causal model of other minds? A wealth of research suggests that the inferences described above can be characterized as Bayesian (e.g., Baker et al. 2017, Jern et al. 2017). That is, people's inferences about unobservable mental states reflect a combination of prior expectations about the kinds of mental states people generally hold, weighted by the likelihood that these mental states would explain the observed behavior according to our causal model (for a technical introduction, see Jara-Ettinger et al. 2024).

While this is a powerful approach, Bayesian inference can be computationally challenging to perform, particularly when our causal models are complex, the hypothesis space is vast, and the observed data are sparse. All of these challenges apply to our models of other minds: Computing how rational actors behave is complex (particularly on spatial environments), there is a vast range of configurations of possible mental states people can have, and the need to quickly understand others limits the time available for extended observation. How do we handle this?

These challenges are alleviated through at least three strategies. First, we simplify the causal relations between mental states and action. Rather than having a complete model of how mental states orchestrate behavior, we rely on a simplified representation where other people are simple utility maximizers—a good-enough approximation of everyday decision-making that generally gets others right. This simplification, however, limits our ability to fully explain other people's behavior, meaning we have to treat causal relations as probabilistic, rather than deterministic, to allow for small deviations in expected behavior.

The second strategy is that we simplify how we infer mental states. Rather than performing exact Bayesian inference, we approximate these inferences through combinations of heuristics and sampling-based strategies (Sundh et al. 2023, Vul et al. 2014). This allows us to make approximately correct inferences about mental states while reducing the computational burden of doing so.

Even with simplified causal relations and approximate inference techniques, our model of other minds can still be too unwieldy, given all the potential causes behind other people's behavior, such as their beliefs, desires, and preferences (Wellman 2014); their habits (Gershman et al. 2016); their emotions (Ong et al. 2019, Saxe & Houlihan 2017); and the social categories they belong to and have been socialized through (Amemiya et al. 2022). Considering all of these possible causes at once means we must navigate a vast hypothesis space, and isolating the contribution of each mental state would require many observations. But in everyday life, we often need to interpret other people's behavior quickly, with limited data and little opportunity to see the same person across many contexts.

The solution, we suggest, is that people do not rely on their full model of other minds in every situation. Instead, we build in-the-moment simplified models that ignore most causes, either setting them to a default value on the basis of prior expectations or outright dropping their contribution. For example, we might temporarily ignore someone's emotions when interpreting their behavior, or assume they know everything we know, allowing us to keep inference tractable. We call these restricted scope models: ad hoc, context-sensitive simplifications that isolate the most promising causal factors for explaining behavior in a given situation.

Forms of this idea trace back to early work in artificial intelligence (Dennett 1990) and have recently received attention in cognitive science (Greco 2023). But, to our knowledge, this has not yet been a direct topic of study in social cognition or cognitive development. At the same time, the literature on computational models of social cognition already provides indirect evidence that adults use restricted scope models. Nearly every computational model of adult social cognition is tailored to the task that participants complete. Some causal models ignore beliefs (e.g., Jern et al. 2017), others ignore emotions (e.g., Jara-Ettinger et al. 2020b), and others ignore competence (e.g., Baker et al. 2017). Critically, these models all share the same broad structure that can be considered a simplified subset of a larger causal model. And even though each study uses a different model that omits different mental states, each model still captures human intuitions with quantitative accuracy, meaning that people must be using different model variations depending on the context. Moreover, adding more mental states to these models would not necessarily preserve or improve their performance. For instance, people can often infer preferences from a single choice (Jara-Ettinger et al. 2020b, Jern et al. 2017), and simple models that neglect beliefs capture this behavior. Adding beliefs, however, would introduce additional explanations for behavior, such as false beliefs, which people do not consider in these tasks. This suggests that people adaptively build simplified models that capture the most relevant mental states for a given situation while ignoring or fixing the value of the rest. Consequently, proficient social reasoning requires more than a general causal model of minds: it also requires knowing how to strip down this model into restricted scope models that are tailored to the situation.

3. DEVELOPMENTAL ORIGINS

Over the past forty years, developmental scientists have mapped the origins of human social reasoning, producing a rich set of snapshots of social capacities at different ages. A central goal of developmental science is to infer the underlying developmental timeline from this empirical record.

This task poses two key challenges. The first challenge is how to organize the literature so that studies that tap into interconnected capacities are grouped. This is complicated by the fact that we cannot always tell a priori which capacities are related or unrelated. The second challenge is that empirical studies offer only indirect estimates of when a capacity emerges. Some capacities might emerge earlier than documented but simply remain untested (or are inherently difficult to test) in younger age groups.

The computational framework developed to understand adult reasoning offers a way to navigate through both challenges. For the first challenge, computational models clarify what representations are needed to succeed in different tasks, allowing us to organize the literature in terms of core representations and computations (e.g., as we show in Section 3.2), how both beliefs and desires depend on a basic world state representation). For the second challenge, computational models predict a logical order in which different capacities should emerge. Comparing this predicted sequence with the empirical timeline reveals what subsets of the literature are coherent as a whole, and what subsets of the literature are inconsistent with theoretical expectations, which can imply that some capacities emerge earlier than the literature suggests.

Specifically, from this perspective, social reasoning can be understood in terms of three components. The first consists of the basic set of representations that we use to reason about agents, their minds, and the contexts in which they operate (Sections 3.1 and 3.2). The second consists of a capacity to represent the causal relations between mental states, the environment, and behavior (Section 3.3). And the third consists of the capacity to use our causal models of how minds work to navigate the social world (Section 3.4).

3.1. Conceptual Primitives

According to computational frameworks, representations of other minds are built over two representational primitives: states and actions. States encode the context in which we interpret behavior. Consider Woodward's (1998) classic experiment where 9-month-olds watched a hand repeatedly reach for one of two objects, each in a fixed location. When the object locations were swapped, infants expected the hand to reach for the same object in its new location, rather than the alternate object in the familiar location, suggesting they were encoding the reach as goal-directed (a capacity later found to emerge as early as three months; Liu et al. 2019a).

From a computational perspective, this suggests that infants must be representing the object identities as part of the state. If the state represented only two objects but not their identities, infants would not interpret the object swap as a different state that could warrant a different action. Conversely, an overly detailed state representation can hinder generalization. For instance, if infants represented the hand reach in the context of the exact time of day, the table's material, the lighting conditions, and so on, trivial differences would count as different states where the infant would need to determine what consequences the change has on behavior.

At the same time, research suggests that infants might initially interpret action using high-fidelity state representations that contain more details than necessary. For example, 3-month-olds believe that an arm reach could be the result of a goal to grab a particular object or a goal to reach for whatever is in a particular location (Woo et al. 2024b), suggesting that both object identity and location are encoded in the state representation and are therefore both plausible goals. At six months, the state representation becomes object-biased, allowing infants to quickly encode the goal as being directed at the object and not the location (Woodward 1998). But this capacity is limited: 10-month-olds fail to generalize an agent's goal across state changes that adults might consider irrelevant, such as a room change (Sommerville & Crane 2009), suggesting they encode the arm reach within a state representation that contains more details than necessary. However, infants at this same age succeed when the action is accompanied by a vocalization that helps them attend to the relevant features of the state that guide generalization (i.e., the identity of the object rather than room) (Martin et al. 2017). This suggests that infants already have the capacity to represent states at varying degrees of detail but must learn how much detail to include and which details to focus on in a given context.

The second foundational representation consists of the actions agents can take. While body movements are continuous spatiotemporal motions, breaking them into categories (e.g., walking, reaching, grabbing) allows us to reason about them as discrete sequences of actions with observable consequences, making action understanding easier than would otherwise be possible. Research suggests that infants are already representing actions as discrete units by 6 months of age (Hespos et al. 2009, Wynn 1996) and as abstract categories (independent of the exact path or actor) by 10 months (Song et al. 2016). During this first year of life, infants continuously construct, refine, and revise their action categories through a combination of bottom-up and top-down strategies. In a bottom-up way, infants segment action by tracking the statistical regularities between consecutive movements (at 6 months) (Stahl et al. 2014) and introducing action boundaries when the movements produce a state change (at 6 months) (Hespos et al. 2010). In a top-down manner, they also introduce action boundaries whenever they identify the agent has fulfilled a goal or intention (Baldwin et al. 2001, Saylor et al. 2007).

Basic representations of states and actions must then be connected through a transition model that specifies how actions cause state changes. Infants begin to learn this transition model as early as 3 months, connecting an action with salient state changes (e.g., a hand touches an object, which immediately lights up) (Liu et al. 2019a) and, through first-person experience, testing how their own actions affect the world (Skerry et al. 2013, Sommerville et al. 2005). This capacity continues to become more sophisticated, such that by 12 months infants can learn state–action transitions through passive observation and by 15 months can generalize them to their own actions (Elsner & Aschersleben 2003).

Research with adults suggests there is another powerful strategy to learn action–state transitions without ever having to observe our own or others' actions. Instead, we can simulate the consequences of actions through our intuitive physics—our model of how the physical world works, centered around objects and forces (Battaglia et al. 2013, Hespos & vanMarle 2012). Through this strategy, adults can build fine-grained estimates of how long it would take for someone to complete a task, how much effort it would take, and how likely a plan is to succeed (Yildirim et al. 2019). Research suggests that preschoolers can also do this (Bennett-Pierre et al. 2018, Gweon et al. 2017). To our knowledge, however, it is unclear whether this capacity helps infants learn transition models, although one study has shown that 10-month-olds do expect actions to produce outcomes that are consistent with their intuitive physics, such as expecting that when an agent moves an object, another object resting on it will also move (Sommerville & Woodward 2005).

To summarize, our computational framework posits that to represent agency and minds, we must first represent actions, states, and their transitions. Consistent with this, the earliest findings in social cognitive development precisely establish these basic representations (**Figure 1**). At the same time, the computational framework predicts that representations of actions and states must precede representations of transitions, which connect the two. Yet, the literature we review shows transitions being represented at 3 months, but action segmentation is not documented until 6 months. This suggests that action segmentation emerges earlier than the literature reports.

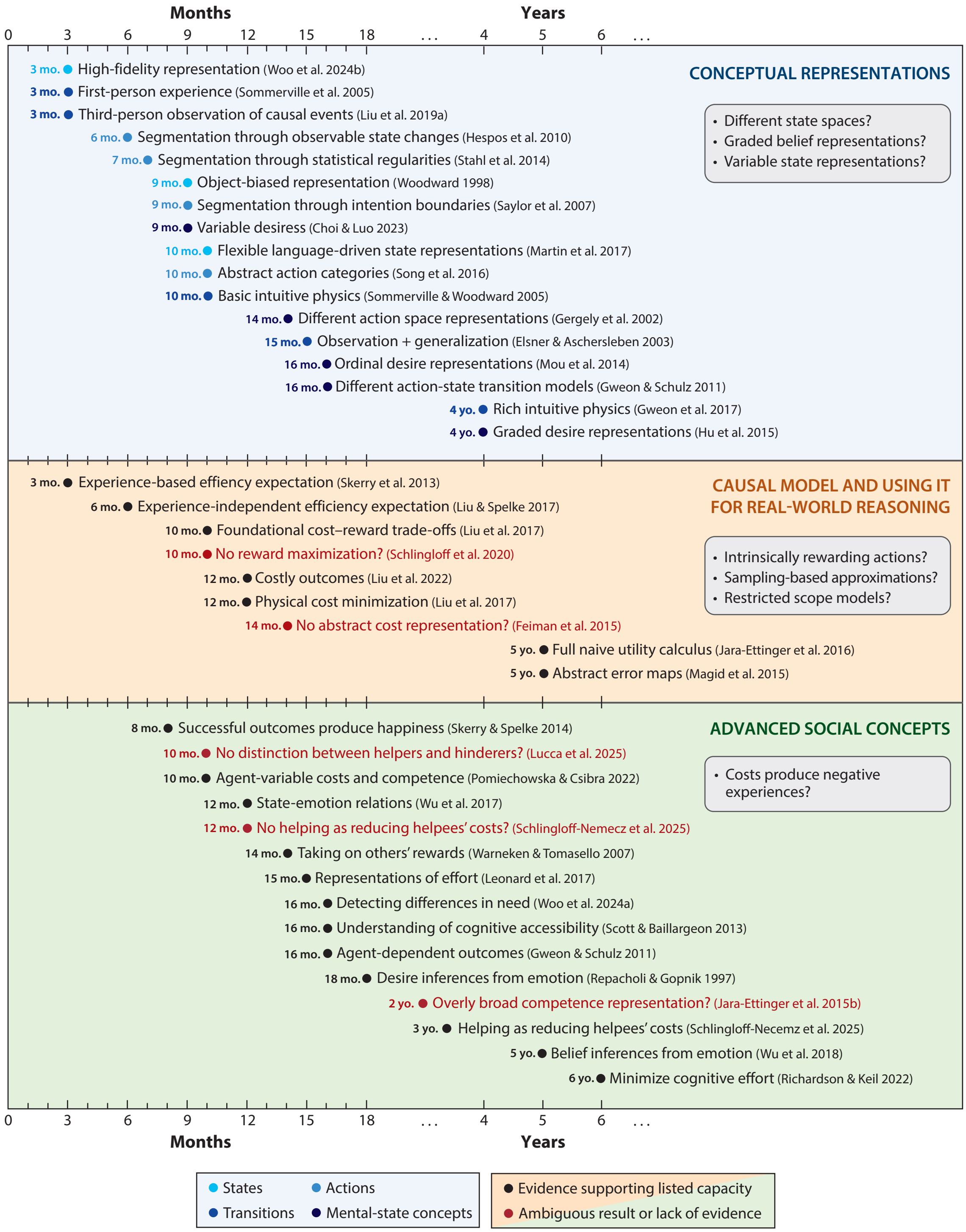
The developmental literature also implies that these representations are at least partially learned, rather than being entirely innate or the output of an inflexible visual perception module. This is evidenced by how infants use a combination of strategies to form action categories, determine how to represent relevant world states, and understand how actions affect those states.

3.2. Representing Agency and Minds

Once an infant can represent actions, states, and their causal relations, these primitives can be combined and extended to build a basic model of agents with minds.

The most minimal agent representations can be built by associating each agent with a target state that represents their goal, although such a lean representation would not even encode how the agent acts to fulfill this goal. The evidence reviewed in the previous section suggests that goals are part of our representation of agents by as early as 3 months of age.

This basic model of goals can be upgraded to capture desires, represented as a set of states, each associated with a numerical value that represents its strength or a preference ranking over states. The current literature suggests some form of this representation emerges before the first year of life. Nine-month-olds can already represent agent-variable desires (Choi & Luo 2023, Henderson & Woodward 2012), and 10-month-olds can represent an agent as having multiple desires, pursuing different ones depending on the context (Liu et al. 2017). Moreover, by 16 months, infants can make transitive inferences about others' preferences from pairwise choices (Mou et al. 2014). These studies suggest that, before the second year of life, infants represent agents as having multiple desires that are ordered and variable across agents, but this does not necessarily mean they represent them as having graded values. Instead, infants might represent desires as an ordered ranked list. It is not until age four that there is evidence of children representing graded desires in others (Hu et al. 2015).



(*Caption for* ***Figure 1*** *appears on following page*)

Figure 1 (*Figure appears on preceding page*)

Empirical studies that establish support (or lack thereof) for key building blocks of social cognition. The *x* axis represents age (transitioning from months to years), and each row corresponds to a target representation or computation proposed by the computational framework (e.g., agents, states, transitions). Each dot locates the earliest age at which a capacity has been tested along with the accompanying reference (although this is not always the sole source of support). Red-colored statements with question marks indicate ambiguous results or findings that suggest a lack of evidence at the tested age. Black-colored statements with question marks indicate capacities posited by the computational framework but that, to our knowledge, have not yet been tested in development. In some cases, the referenced work did not directly seek to investigate the posited capacity, but it nonetheless provides support for it.

In a similar way to how we use states to represent goals and desires, we can also use states to represent knowledge and beliefs. In its simplest form, we can represent other agents as having a different representation of the current state of the world, a capacity that the classical false-belief task tests (Wimmer & Perner 1983). Some evidence suggests that infants, as young as 7 months old, can already represent others as having different beliefs than their own (Kovács et al. 2010, Luo 2011, Southgate et al. 2007), but the effects have been difficult to replicate, even with older toddlers (Kampis et al. 2021), raising the question of when exactly infants and children have variable state representations.

A more complex representation that adults use to reason about each others' beliefs consists of probability distributions over world states. Even if infants can represent other agents as holding false beliefs about the world (Onishi & Baillargeon 2005), they might use a simpler representation that tags a single state as the agent's belief (similar to tagging a single state as the goal). This would enable infants to represent other agents as holding a different belief about the world, but would not support representing others as having uncertainty over multiple possible states. To our knowledge, no study has yet established whether infants possess this more sophisticated probabilistic understanding of belief. However, to represent others as holding multiple possibilities in mind, infants would first need to represent multiple possibilities themselves. This is a current topic of debate: Some research argues that children cannot hold multiple possibilities in mind until around age 4 (e.g., Leahy & Carey 2020), while other work on preverbal logic suggests that this capacity might arise by 12 months (e.g., Cesana-Arlotti et al. 2025).

According to our computational framework, state representations can also be extended to capture additional kinds of beliefs that have not received as much attention in cognitive development. Beyond having different representations of the current state of the world, we can also represent other agents as having different representations of the entire state space (i.e., their representation of all the ways the world could differ from our own). This means we can represent others as underestimating what is possible (i.e., they represent a smaller state space than we do) or as knowing of possibilities beyond our awareness (i.e., they represent a larger state space). For example, imagine a table with three boxes in a line. The boxes on the two ends are empty, and the center box has an apple inside. Here we can represent another person as having a different belief about which box has the apple (different state representations), but we can also represent them as holding a different set of possibilities in mind (different state space representations), such as thinking there could, in principle, be something different than an apple inside the box.

To our knowledge, it is unknown when children understand that others might hold a different representation of the space of possibilities. Anecdotally, infants and children often hand unfamiliar objects to their parents, suggesting they recognize that these objects could have states that they do not know about (e.g., maybe the object does something interesting) and that adults likely know these states and the actions to instantiate them.

Above, we discuss how the state space can be used to represent goals, beliefs, and desires. Similarly, the action space can be used to represent more complex forms of agency. Specifically, we can associate each agent with two action spaces: the one they believe they have (i.e., what they think they can do) and the one we believe they have (i.e., what we think they can actually do). This capacity emerges in children as young as 14 months, who can already represent the actions available to others as varying by context (Gergely et al. 2002), and by 18 months, they proactively help others when they themselves can perform a relevant action that the adult cannot (Warneken & Tomasello 2006).

Finally, we can also represent others as having different transition models and beliefs about them. Developmental research on this ability is limited, but some evidence suggests it emerges by 16 months. At this age, infants can track when an adult is more effective at producing desirable state changes and will seek their help to achieve them (Gweon & Schulz 2011). This suggests that infants already differentiate the effects of their own actions and those of others' actions.

To summarize, in our computational framework, representations of agency and mental states are built upon the conceptual primitives of states, actions, and their transitions. Building off these representational primitives, infants and children start to construct models of other agents who may have different beliefs, desires, and goals (state representations) than their own. They also come to understand that the actions available to each agent may also differ (action space representations) and that different actions can lead to different states (different transition models). The research we review here shows that infants have access to these representations by the end of the first year and throughout the first half of their second year of life.

At the same time, the framework points to richer representations in adults that have been overlooked in developmental research. In particular, we know little about when children or infants begin to represent others' beliefs as probability distributions over possible world states, when they conceptualize different agents as representing different state spaces, or when they treat desires as graded in strength rather than as ordinally ranked.

3.3. Modeling Rational Action

To be useful, representations of beliefs, desires, and goals must be organized within a causal model that specifies how they drive behavior. In adults, this model is structured around the expectation that agents will pursue goals where the expected rewards outweigh the expected costs for attaining them, called a naive utility calculus (Jara-Ettinger et al. 2016) (Section 2).

One hypothesized precursor to a full naive utility calculus is an initial expectation that agents complete their goals efficiently. This expectation can be implemented in several ways. The simplest implementation is an expectation that agents minimize features such as distance and time to goal completion. A richer version represents actions as consuming energy, with efficiency meaning that agents minimize energy expenditure. While we do not know the exact implementation, some form of an efficiency-based causal relation between goals and actions is available as early as 3 months, where infants, after first-hand experience in a task, expect other agents to complete their goals in an efficient way, as if they understand that actions expend energy and that this expenditure should be minimized (Skerry et al. 2013). At 6 months, infants show an experience-independent expectation for efficient action (Liu & Spelke 2017). And by 12 months, their representation of physical costs becomes more abstract, incorporating factors such as risk (Liu et al. 2022).

In adults, however, cost representations are far more abstract, extending beyond physical effort and risk to also capture subjective dimensions. For instance, we can learn that someone dislikes chocolate and treat that dislike as a cost in our model of their preference and behavior, despite its valuable caloric content. Beyond that, we can also represent social costs, such as the cost of having to spend time with someone we dislike or the cost of disagreeing with others, or even idiosyncratic costs, such as not enjoying sunshine or finding mornings unpleasant. To our knowledge, there is no clear evidence that children and infants have abstract cost representations. Cost representations might initially be grounded in physical dimensions and later get upgraded into abstract cost representations. While this has not yet been a direct topic of study, some indirect evidence suggests that infants do not yet have an abstract representation of costs. When 7- and 14-month-old infants see an agent consistently avoid an object, they do not appear to be able to represent this behavior as purposeful avoidance (Feiman et al. 2015), something that is trivial for adults because we can simply attribute an abstract cost to reaching for the object (representing that the agent dislikes the object or does not want to hold it for some reason unrelated to energy expenditure).

To reach an adult-like causal model, we must also understand that agents act to maximize rewards and that rewards and costs trade off with one another. Here, research suggests that an understanding of the trade-offs emerges before the first year, as 10-month-old infants infer that higher costs should be justified by greater rewards (Liu et al. 2017). But at the same time, they do not expect agents to prefer plans that yield three food items over one (Schlingloff et al. 2020), which is surprising given that, in first-person tasks, 10-month-olds do consistently prefer to reach for three crackers over one (Feigenson et al. 2002). This suggests that infants do not yet understand reward maximization in others or they do not yet realize that a numerically higher number of treats is more rewarding for others.

While we do not yet know when this develops, what is clear is that this causal model is mature in preschoolers. For instance, 5-year-old children judge that an agent incurring a high cost must expect an even higher reward and that refusing to pursue a high reward means the costs were too high (Jara-Ettinger et al. 2015a), and they apply these expectations to communicative interactions (Jara-Ettinger et al. 2020a), people's epistemic behavior (Aboody et al. 2021), and prosocial behavior (Jara-Ettinger et al. 2015b).

To summarize, the empirical literature suggests that infants organize mental-state representations within a causal model of rational action as early as 3 months, but it is not initially implemented as an assumption that agents act to maximize utilities. If it were, then both cost minimization and reward maximization should be special cases that infants succeed at. However, expectations of cost minimization emerge by 3 months, whereas the expectation of reward maximization is not yet robust at 10 months. This suggests that infants likely update and upgrade their model of rational action throughout the first years of life.

A second key finding is that 10-month-olds understand basic cost–reward trade-offs but do not seem to expect that more rewards are better. One possibility is that their naive utility calculus is incomplete and they do not yet understand that agents maximize rewards. But it is also possible that infants do not yet know how to estimate subjective rewards from material outcomes (e.g., perhaps not realizing that three objects could be three times more rewarding than one object). Relatedly, we do not know when infants begin to represent abstract costs, which might further suggest that learning to represent costs and rewards is an important dimension of social development.

3.4. Learning to Use Our Models of Others

As our mental models of other people become richer, they also become harder to use. The more variables, parameters, and causal relations a model encodes, the more computation is needed to estimate its parameters and manipulate it for inference and prediction. Even simple models of other minds can demand a prohibitive amount of computation to do anything beyond basic reasoning tasks (Blokpoel et al. 2010). This suggests that infants and children must not only acquire a model of other minds but also learn how to use it effectively.

Research on computational modeling has highlighted two general approaches for improving tractability. The first involves using more efficient (though often less accurate) methods for manipulating our mental model, such as through sampling-based approximations. For instance, consider trying to explain someone's behavior in terms of their knowledge, desires, competence, effort, and emotional attitudes. The hypothesis space, just by virtue of all combinations of mental states, would be too large to evaluate exhaustively. Instead of considering every possible configuration, we can approximate these inferences by sampling a limited set of mental-state configurations, determining what behavior they would produce, and comparing this to the observed behavior. Indeed, many of the well-documented biases in human statistical reasoning are consistent with sampling-based approximations of more complex computations (Lieder et al. 2012, Parpart et al. 2018, Vul et al. 2014), and patterns of variability in children's judgments suggest that they may also engage in sampling-based approximations for probabilistic inference (Denison et al. 2013). Critically, the number of samples we draw creates a trade-off between computation and accuracy such that children might need to implicitly learn how many samples to draw depending on the level of precision required for mental-state inference in different social activities.

While approximation can help, it is not a cure-all: Many common inferences cannot be tractably approximated at all (Kwisthout et al. 2011), and in some cases approximation may be even more costly than exact inference (Davis 2024). A second key approach is therefore to avoid deploying our full model of reasoning about other minds in every situation and, instead, to build context-specific simplifications that make reasoning and inference easy (Greco 2023). Indeed, out of all the mental states and social factors we could represent, only a small subset is likely relevant in any given context (Glymour 1987): We might need no belief representation at all to predict a bus driver's response when we pay our fare, only a coarse qualitative belief representation (e.g., "knows" versus "does not know") to determine whether a colleague has heard some breaking news, and a more fine-grained representation (e.g., a graded distribution over possible knowledge states) to evaluate someone's expertise on a complex topic. The capacity to build these restricted scope models might be one of the most fundamental distinctions between early and mature social cognition. It could help explain why young children and infants often succeed in experimental tasks but struggle to demonstrate comparable social proficiency in real-world situations. Developmental studies, by necessity, strip away factors that are not relevant to the task, and young children are scaffolded to focus on the critical constructs and causal relations—either through language or through nonlinguistic familiarization procedures. From this perspective, infants and children are being presented with the right restricted scope model needed for the task, eliminating the need for them to independently adapt their representations and hiding their emerging ability to do so.

Beyond offering a potential major source of development, this view might also shed light on some forms of everyday parenting. To illustrate with an anecdote, while developing these ideas in a busy coffee shop, one of this article's authors noticed a parent walk in with their toddler. The child appeared overwhelmed by the complexity of the environment (dozens of chairs and tables, multiple doors and walls covered in text, shelves full of different snacks and drinks, and groups of people engaged in conversation), leaving them unsure about how to navigate the space. From the perspective we propose here, representing the full complexity of the environment—every person and their minds and every aspect of the physical layout—impeded the child's reasoning, and they did not know how to determine which aspects mattered and which did not. The parent then began communicating with their toddler in a way that could be construed as providing restricted scope models. The parent told their child that they could either approach the counter to learn about snack options from the server or sit down while the parent handled it. This communicative act gave the child a simplified model of the situation, isolating key states and actions that they could reason about, ultimately helping them to decide they wanted to approach the counter. As new situations arose, the parent sequentially highlighted relevant states, actions, and the role of people in the environment, enabling the toddler to exercise agency through these restricted scope models that they were not yet able to build independently.

While we believe this challenge is central to social development, it likely applies to all domains of high-level cognition. In all cases, children face the task of determining which restricted scope model to apply in any given context. Intuitively, these models should be complex enough to reason about the world with sufficient accuracy for the situation at hand. Managing this trade-off might involve small, incremental changes, such as initially representing preferences categorically (e.g., which object does this person like better?) and upgrading them to continuous variables as needed (e.g., how much, exactly, does this person like each object?). It may also require more dramatic shifts, even replacing the model entirely, such as abandoning mental-state representations in favor of group-level stereotypes or role-based scripts (Fiske & Neuberg 1990). The biggest challenge is that computational work does not yet have a satisfying account as to how adults might build restricted scope models, although some recent work suggests neurosymbolic architectures might be a promising avenue (Brooke-Wilson 2023, Wong et al. 2023). Some recent work also suggests that adults can flexibly adjust their mental representations on the basis of constraints and task structure (Correa et al. 2023, Ho et al. 2022a, Tomov et al. 2020), but this work has primarily focused on nonsocial domains (although see Burger & Jara-Ettinger 2020), and we do not know much about its development or role in social cognition. However, some work on imagination and explanation has argued that children can build abstract representations of what constitutes a good explanation (called abstract error maps) (Schulz 2012), and by age 5, they use these representations to guide how they interact with the environment (Magid et al. 2015). This capacity might serve as a mechanism for determining what kind of restricted scope model is necessary in a given situation.

4. WHAT DRIVES DEVELOPMENT?

Our review so far offers a way to interpret social development in terms of the building blocks posited by computational modeling. The studies we review show which representations infants and children have at different ages but not how they transition from one representation to the next.

Part of the answer lies in general maturational factors that affect children's ability to reason about other minds. These factors fall outside the scope of our modeling framework. In particular, reasoning about minds that are different from our own often requires us to suppress our own representations of the world, especially in verbal tasks. Because of this, the development of executive function affects children's performance (Devine & Hughes 2014), and reducing the need to compare conflicting representations helps younger children to pass these tasks (Setoh et al. 2016).

At the same time, several of the transitions we review cannot be explained by domain-general development alone as they involve development that is specific to social cognition. Here, computational models also offer a way to categorize types of development and specify what is required for children to build more sophisticated models of other minds.

First, infants and children must continuously expand and refine their representations of world states, actions, and their transitions. Here, research suggests that everyday opportunities to act and observe others act are enough to drive this process (see Section 3.1). Through repeated exposures, children can segment actions, encode their consequences, and learn what is the right state context through which to interpret them.

Next, infants and children also need to acquire more complex mental-state representations and embed them in a causal model of rational action. Here, the developmental literature suggests that these representations undergo categorical upgrades, and the capacities established in older ages are always computational extensions of the capacities established in younger ones, showing an alignment between the empirical data and our computational framework. This means that infants' representational primitives do not include just states, actions, and causal relations but also a type of metarepresentational system that can transform basic representations into more complex ones, such as attaching probabilities to world states to build graded belief representations. Theoretical work has proposed that formal systems from mathematics, such as lambda calculus, are strong candidates for this metarepresentational system and that it supports conceptual change across all domains of high-level cognition (Piantadosi et al. 2016, Ullman & Tenenbaum 2020). Under this view, when infants and children are confronted with social behaviors that their current mental models fail to explain, they search for revised representations and causal structures with greater explanatory power. How this system then proposes and evaluates modifications to the causal model is one of the biggest open questions in computational cognitive science (Griffiths et al. 2024, Ullman et al. 2012, Yang & Piantadosi 2022).

Past work has generally focused on model upgrades driven by an internal search system that identifies representations and causal relations with better explanatory power. However, the same parent–child conversations that we hypothesize help children learn how to build the appropriate restricted scope models might also help them learn the structure of a causal model or rational action and build more complex mental-state representations. This is consistent with evidence that social experiences directly shape children's ability to reason about other minds: Children whose parents reference mental states more frequently tend to pass false-belief tests at an earlier age (Ensor et al. 2014, Ruffman et al. 2002), and children with older (but not younger) siblings also pass these tests earlier (Brown et al. 1996, Ruffman et al. 1998).

One limitation is that these studies use broad measures of mental-state conversation, but finer-grained analyses could distinguish between at least three different types of mental-state talk: (*a*) explaining the causal relations between mental states and actions, (*b*) highlighting the most relevant mental states in a situation, and (*c*) identifying the appropriate mental-state inferences. Thus, these types of conversations might correspondingly help children solidify their causal model, learn which restricted scope models apply to different situations, and confirm they can make the right inferences independently.

5. FROM MINDS TO RELATIONSHIPS AND SOCIETIES

The model we review above represents the core architecture for understanding other people. Here we review how these building blocks can be extended to capture richer forms of social reasoning (Section 5.1) and discuss aspects of social reasoning that go beyond what these models capture (Section 5.2).

5.1. Building More Complex Models of Other Minds

To begin, representations of costs and rewards can be easily extended to interpret behavior in terms of more complex concepts such as cooperation, competence, and mental effort.

5.1.1. Scope of costs and rewards. First, we can move beyond the assumption that only actions are costly and only outcomes (states) are rewarding. Instead, we can encode actions as inherently rewarding and outcomes as potentially costly. This allows us to reason about situations where the action itself is intrinsically rewarding (e.g., dancing) and situations where the outcome is undesirable (e.g., feeling tired the next morning). To our knowledge, there is no direct evidence yet on whether infants can encode actions as intrinsically rewarding. However, there is reason to believe this ability might emerge early in infancy, as infants would otherwise be confused by everyday pleasurable behaviors such as dancing. By contrast, there is some evidence that 12-month-olds understand that outcomes can be costly: They expect agents to avoid dangerous cliffs, indicating that they encode the potential cost of a negative outcome (in this case, falling into a pit and disintegrating) (Liu et al. 2022).

We can also represent agents as being able to take on the costs and rewards of others: an adopted utility calculus (Powell 2022). This capacity undergoes development. Some recent evidence suggests that understanding of notions of helping or hindering might not yet be set at 10 months (Lucca et al. 2025). However, by 14 months, infants are already capable of spontaneous, unrewarded helping in a variety of simple situations, suggesting an early form of altruistic motivation (Warneken & Tomasello 2007). By 16 months, infants prefer agents that help those that need it the most (Woo et al. 2024a), and by 18 months, infants can also infer other people's rewards and take them on themselves (Sommerville et al. 2018, Warneken & Tomasello 2006). At the same time, it is possible that toddlers do not yet have an adult-like concept of helping as taking on another agent's utility: 12-month-olds do not expect helping actions to reduce the helpee's cost, but this expectation emerges by age 3 (Schlingloff-Nemecz et al. 2025). Brief reciprocal interactions can also prime young children to behave altruistically, suggesting such social experiences may also scaffold the development of helping behavior (Cortes Barragan & Dweck 2014).

In addition to physical energy expenditure, mature reasoning about others requires considering their mental effort (Berke et al. 2023). By age 4, children recognize that more complex tasks require greater mental effort and expect agents to minimize mental effort (Liu et al. 2019b), and by age 6, they also understand that harder tasks require more thinking (Richardson & Keil 2022). A basic form of this understanding might emerge by 16 months of age, when infants expect agents to prefer goals that are more cognitively accessible (Scott & Baillargeon 2013).

5.1.2. Effort and competence as variability within and across agents. We can also represent variability within and across agents with respect to costs and rewards, allowing us to construct notions of effort and competence. A foundational concept of competence can emerge by recognizing that different agents can incur different costs for the same actions, an understanding that is in place by age 4 (e.g., a stronger agent being able to lift the same box more easily than a weak agent) (Aboody et al. 2021, Jara-Ettinger et al. 2020a). Children can also use the time an agent takes to complete a task to infer their agent-specific competence (Leonard et al. 2019, Muradoglu & Cimpian 2020). By 16 months, infants can also represent a failure to produce an outcome as agent-dependent (Gweon & Schulz 2011). And, even at 10 months, infants can represent costs as varying across agents, judging an agent who jumps over barriers as more competent than the one who detours around them (Pomiechowska & Csibra 2022). At the same time, this understanding of competence might be overly simplified and generous: Toddlers show a halo effect, believing that physically competent people are also nicer (see experiment 3 in Jara-Ettinger et al. 2015b), suggesting that they might first represent other agents through a single unified notion of competence that later gets separated into multiple related notions that apply to different domains.

Similarly, we can also extend representations of actions and their outcomes so that they are modulated by a representation of effort that the agent chooses to exert. This understanding appears to be in place in 15-month-old infants, who adjust their levels of persistence by observing how much adults persist through challenges (Leonard et al. 2017, Lucca et al. 2020).

5.1.3. Reasoning about subjective experiences. The computational framework so far represents other agents as abstract systems that pursue goals, without any reference to subjective experiences. As adults, however, we recognize that other people have rich subjective experiences and emotions that influence their behavior. These subjective experiences can be directly connected to costs and rewards. Intuitively, costs evoke negative subjective experiences, whereas rewards evoke positive ones. For adults, this association defines what it means for something to be a cost or a reward, and explains why we expect agents to maximize rewards and minimize costs.

By 8 months, infants already expect successful outcomes to produce observable happiness (but they do not expect failed outcomes to produce sadness) (Skerry & Spelke 2014). To our knowledge, however, it remains unknown whether infants believe that costs generate negative subjective experiences (e.g., fatigue or negative emotions) or whether this expectation is abstract and detached from expectations of experience. If infants hold this belief, they might, for instance, expect agents who exerted higher costs to exhibit more visible signs of tiredness than those who achieved the same goal with lower costs.

Over time, children continuously expand the set of expectations of how different mental states produce detectable emotions and vocalizations. By 12 months, infants can already distinguish a range of emotional vocalizations that express different meanings such as surprise and sympathy (Wu et al. 2017). Through this understanding, infants and children can use observed emotional displays to support inferences about others' mental states such as their beliefs and desires (Repacholi & Gopnik 1997; Wu et al. 2018, 2021).

5.2. Beyond Utility-Based Models of Other Minds

Above, we focus on how utility-based systems, built over representations of states and actions, allow us to reason about others' behavior. However, humans also have a rich understanding of social groups and relationships that cannot be easily reduced to utility-based representations.

From infancy, we readily build categories of people and expect members of the same social category to behave similarly and support one another (Dunham 2018, Liberman et al. 2017). While these categories can be learned by observation alone, many of them are transmitted linguistically, via generic statements, which provide children an understanding of relevant social categories and their stereotypical content (Rhodes et al. 2024). These categories then affect not only how we understand others but also how we behave, such as favoring activities pursued by peers of the same gender (Shutts et al. 2010).

Infants also have rich internal concepts of relationships within and across social categories (Jara-Ettinger & Dunham 2024, Thomas 2024). For instance, 8-month-olds go beyond encoding social categories to also represent the closeness of relationships between individuals (Thomas et al. 2022b). And by 12 months, they can identify potential social partners on the basis of how others interact with their parents (Thomas et al. 2022a).

Although computational work in this area is limited, utility-based frameworks might not fully capture representations of social relationships. While agents in social relations often adopt each others' utilities, this might stem from a more basic representation of relationship, rather than encompassing the complete concept of relationship itself. At the same time, some work on adult reasoning about social groups suggests that these representations follow principles similar to those used to reason about individual minds: Social groups are represented via structured causal models that we use to infer and predict behavior (Davis et al. 2022). Like models of other minds, these structured causal models also appear to be built on a set of conceptual primitives that can be flexibly combined to build increasingly complex models of social worlds, but rather than relying on mental states, they appeal to roles, norms, and relations (Jara-Ettinger & Dunham 2024).

As with models of individual minds, using a comprehensive model of agents in society that includes their social categories and group membership is probably too complex for everyday reasoning, particularly when we also consider the person's mental states. This suggests that effective use of reasoning about relations may also require the capacity to synthesize restricted scope models that simplify these complexities for everyday reasoning.

One interesting difference between our representations of social groups and models of minds is that, in many cases, children and adults might represent social categories and their behaviors without a clear understanding of the underlying causes. For instance, children may believe boys are more likely to pursue certain activities without having a causal model for why this occurs. In such cases, they can attribute the underlying cause of a behavior to an intrinsic categorical essence (e.g., "boys like blue") (Gelman 2003, Rhodes & Mandalaywala 2017).

Although computational research in this area is limited, what the evidence so far suggests is that reasoning about social groups might follow the same broad principles as reasoning about other minds: conceptual primitives organized within a causal model, which is then simplified for context-specific reasoning. At the same time, the way we reason about these social relations suggests there are additional conceptual primitives and causal relations that cannot be fully reduced to the utility-based models we apply to individual minds.

6. CONCLUSIONS AND LOOKING FORWARD

This review has two goals: first, to analyze the social cognitive development literature using the computational primitives and building blocks proposed by models of adult social reasoning and, second, to use this framework to identify key representations and computations in social reasoning that remain understudied in development.

To address the first goal, we organize the literature around three foundational questions: (*a*) What are the representational primitives that infants use to build more complex representations of agency and minds? (*b*) When and how are these representations embedded within a causal model of how mental states produce behavior? (*c*) And how is this model used for everyday social reasoning?

Viewed through a computational lens, the developmental literature reveals a strikingly coherent sequence. With a few exceptions, such as action–state transitions being documented earlier than action segmentation, the documented order of social capacities aligns with their computational complexity. This does not imply that the reported onset ages are accurate. These capacities might emerge earlier but have simply not been tested yet in younger infants. Nonetheless, taken at face value and framed computationally, the literature presents a possible developmental timeline: As early as 3 months of age, infants already have access to conceptual primitives needed to build models of agency and of other minds. Over the first year of life, these representations of states, action, and transitions expand through both bottom-up and top-down strategies to build an increasingly rich library that helps us understand agent behavior and its consequences in the world. These primitives are then used to model agency and minds, with richer representation established between 10 and 18 months, suggesting this might be a period of important conceptual learning. From the outset, these representations are embedded within a causal model that initially instantiates a narrow notion of rationality as efficiency or physical cost minimization and gradually becomes a unified model of rationality as expected utility maximization.

For our second goal, the computational framework reveals important representations and computations that are necessary for mature social reasoning that remain understudied (question mark statements in **Figure 1**). One particular area is the construction of restricted scope models, which we hypothesize are critical for everyday social reasoning to be computationally tractable.

The idea that infants and children must learn to synthesize restricted scope models helps solve some puzzles in early development. On the one hand, infant social cognition appears surprisingly sophisticated in experimental settings. On the other, young children's real-world social reasoning is much more limited and brittle than one would expect from the literature. In our view, this gap reflects the developing ability to create restricted scope models. In lab tasks, infants succeed because the experimental procedures cue the appropriate restricted scope model: There is only a small number of agents and objects, and familiarization procedures highlight the features and causal relations that infants should attend to. By contrast, in the real world, children must generate the appropriate restricted scope model on their own. Without this ability, the same reasoning capacities established in controlled lab settings fail in natural settings.

This view also helps reconcile cultural and nativist accounts of social cognition (e.g., Heyes 2018, Spelke 2022). Representational primitives (i.e., concepts of action, state, and action–state relation) and the structure of the causal model of other minds emerge early and are culturally universal. But the restricted scope models people use in the real world are learned, in part, through social interactions and cultural learning, producing cross-cultural variation. For instance, some cultures may emphasize always representing emotional states on restricted scope models, whereas others might prioritize emotionless models of rational action.

Beyond the theoretical gaps highlighted by the computational framework, our review also shows a gap in the literature. Most of what we know about social cognition comes from either infants (3–18 months) or preschoolers (ages 4+), with comparatively less known about 2- and 3-year-olds. This is a general challenge in cognitive development given the well-known methodological difficulty of studying young toddlers, as neither infant methods (such as violation of expectation) or early childhood methods (such as storybooks with prompts to answer questions) work well. Filling this gap is critical for understanding the early development of social reasoning, particularly for knowing (*a*) when children begin to represent abstract nonphysical costs, (*b*) when their causal model implements full-blown notions of expected utility maximization, and (*c*) how they begin to use restricted scope models.

Our review focuses on classical mental-state representations, but recent work has begun to uncover additional kinds of representations that may also be critical to human social intelligence: representations of cognitive processes such as perception, attention, and reasoning (Berke et al. 2023). Here, research suggests that adults are surprisingly proficient at tracking cognitive processes (for a review in the context of communication, see Rubio-Fernandez et al. 2024). Here, we know little about how this capacity develops, although some recent work suggests this might be an area of important development that is not adult-like until at least age 6 (Rui et al. 2025).

To conclude, our review weaves together two timelines. The first timeline reflects the logical sequence of concept acquisition predicted by our computational framework. For instance, a transition model cannot precede representations of states and actions. The second timeline comes from the empirical record from developmental science, which establishes the ages at which infants and children succeed at different tasks. Should these two timelines align perfectly? This is not necessarily the case, for two reasons. First, the theoretical sequence specifies only the logical dependencies between concepts, starting with the most basic primitives. But infants might start out with a more advanced system than just the foundational primitives. For instance, they might understand from birth that actions are costly and outcomes are rewarding. Second, the developmental timeline does not necessarily reflect the true onset of each representation or capacity. Many of these capacities might emerge earlier, but current experimental methods might not be sensitive enough to evaluate them (and, of course, it is also possible that these capacities have been overestimated and actually develop later than we currently believe; e.g., Lucca et al. 2025).

In this sense, the goal of the computational framework is not to provide a perfect fit to the empirical record but to guide future work by identifying gaps in our understanding of social cognition. The predicted logical order of concepts helps identify which capacities may emerge earlier than documented and which should emerge later, such that failures in infants would not be surprising. More importantly, the framework draws attention to components of social reasoning that need more study, such as understanding different state spaces, graded beliefs, abstract costs, intrinsically rewarding actions, and restricted scope models. This is one of the key contributions formal models provide across fields. In the same way that formal models in other fields have driven major discoveries—such as the Higgs boson or dark matter—we believe that computational models in developmental science have the same potential for understanding the origins of intelligence. Ultimately, we hope this approach will help us understand what makes humans such precocious social reasoners, the challenges they confront throughout their early years, and how they ultimately overcome them.

DISCLOSURE STATEMENT

The authors are not aware of any affiliations, memberships, funding, or financial holdings that might be perceived as affecting the objectivity of this review.

ACKNOWLEDGMENTS

The authors thank Gergely Csibra, Susan Hespos, Julia Leonard, Shari Liu, Jessica Sommerville, Brandon Woo, Amanda Woodward, and the Computational Social Cognition Lab for helpful conversations. This work was supported by National Science Foundation CAREER award BCS-2045778.

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