Trends in
Cognitive Sciences

CellPress

Opinion

Simplifying social learning

Leor M. Hackel,[1,*] David A. Kalkstein,[2] and Peter Mende-Siedlecki[3]

Social learning is complex, but people often seem to navigate social environments with ease. This ability creates a puzzle for traditional accounts of reinforcement learning (RL) that assume people negotiate a tradeoff between easy-but-simple behavior (model-free learning) and complex-but-difficult behavior (e.g., model-based learning). We offer a theoretical framework for resolving this puzzle: although social environments are complex, people have social expertise that helps them behave flexibly with low cognitive cost. Specifically, by using familiar concepts instead of focusing on novel details, people can turn hard learning problems into simpler ones. This ability highlights social learning as a prototype for studying cognitive simplicity in the face of environmental complexity and identifies a role for conceptual knowledge in everyday reward learning.

Highlights

Social interactions present complex learning challenges.

Recent computational models of learning assume people negotiate a tradeoff between complex-but-difficult behavior and easy-but-simple behavior.

Humans have social expertise that lets them simplify difficult learning problems, reducing detailed scenarios to familiar social concepts that can subsequently guide learning.

People can therefore use learning strategies that achieve flexible social behavior with easy cognition, using the earlier work of concept development to simplify the later work of complex choice.

Accounting for pre-existing conceptual knowledge and expertise can enrich models of reinforcement learning in familiar environments.

Challenges of social learning

Social learning is a vital but complex task. To navigate social life, people must remember a diverse array of people and interactions, reason about relationships between people, and learn that different behaviors are appropriate in different social settings. Social learning therefore would seem to require complex learning computations [1], and social cognition would seem to support complex planning [2].

Yet, people often seem to navigate social interactions intuitively, and people need to manage their social lives without computational overload. Social complexity therefore creates a puzzle: how do people seem to learn easily in social interactions in the face of staggering complexity? Here, we outline complex and simple strategies represented in recent computational models of learning and then present an expanded framework that can address this puzzle. This framework identifies how RL can give rise to complex social cognition and social behavior. Through this approach, we offer a mechanistic view that integrates social concepts with computational underpinnings of cognition and informs how RL can explain complex real-world choices.

Complexity in social learning

One account of how people navigate social interactions draws on cognitive models of RL. Such models describe how people learn by performing actions and experiencing reward feedback [3,4]. Formally, RL is often studied in cases defined by states of the world (e.g., locations in a maze), actions (e.g., turning left or right), and rewards (e.g., food). An agent's goal is to choose actions that maximize its long-run expected future reward, given that any action it takes will influence which state it moves into next.

Learners can use distinct algorithms to solve this challenge. In **model-free learning** [4] (see Glossary), a learner directly estimates the long-run value of an action based on past experience. This learner does not need any internal model of the environment explaining how or why their action produced reward. Instead, they can simply repeat previously rewarded actions, averaging across past experiences to assign values to actions. When rewards are better than expected, people become more likely to repeat the same action, whereas when rewards are worse than

[1]University of Southern California, Los Angeles, CA 90089, USA
[2]Stanford University, Stanford, CA 94305, USA
[3]University of Delaware, Newark, DE 19716, USA

*Correspondence: lhackel@usc.edu and https://www.hackellab.org (L.M. Hackel).

 https://doi.org/10.1016/j.tics.2024.01.004

expected, people become less likely to repeat the same action. When people interact with others, they might similarly learn who to approach or avoid through model-free reward feedback. For instance, if a student visits Dr Smith's office and receives extensive help each time, they may learn that the action 'approach Dr Smith' leads to reward.

Although model-free learning is computationally simple, it is relatively inflexible. First, because it focuses on past rewards with no understanding of the environment, it performs poorly when faced with new environments or options [5]. Model-free learners may repeat rewarded actions habitually, even when an action no longer advances one's goals – for instance, visiting Dr Smith even after passing her class [6]. In addition, because reward was attached specifically to the action approach Dr Smith, a model-free learner would not generalize to new professors who could help during office hours [7]. Second, because model-free learning averages across experiences, it is slow and incremental. A model-free learner would therefore display poor one-shot learning [8], such as learning to approach Dr Smith for help after hearing her deliver a particularly illustrative analogy in class, and would learn inefficiently about context-dependent rewards, such as learning that Dr Smith provides rewarding advice about physics but not about relationships [8].

A second, more sophisticated way people learn about others is through a class of algorithms known as **model-based learning,** wherein learners employ an internal model of the world to understand how to reach reward [4]. Rather than directly learning the long-run value of each action, model-based learners evaluate actions in terms of how they lead to new states of the world. Specifically, model-based learners can build a **cognitive map** of the environment that identifies how different states relate to one another and/or how actions lead to outcomes, allowing them to plan new routes to reward [7,9–12] (Figure 1A, Key figure). For instance, a student could recognize that Dr Smith and Dr Jones play analogous roles in the classroom; reason that both have relevant knowledge, duties, and interests; and infer that visiting Dr Jones will lead to a positive outcome as well. This kind of **generalization** is a hallmark of flexible behavior. A model-based learner can also adapt their behavior quickly, immediately using new knowledge about their environment to plan a path to reward [13]. However, model-based learning has a steep computational price, requiring slow, effortful deliberation, which people prefer to avoid [14–16].

A third learning strategy, which also allows flexible decisions, is **episodic RL**. Here, learners draw on details of particular episodes to estimate future rewards [17,18]. Like nonparametric statistical methods, this strategy allows nonparametric approximation of the value of an action, sampling details of individual events rather than storing a world model or averaging over experiences. Episodic RL allows people to learn from small amounts of data, such as a single social interaction (Figure 1B) [8]. In addition, by storing event details in **episodic memory**, people can later identify features of the episode relevant to predicting reward, flexibly drawing on past experience in new situations [17]. Finally, episodic RL can support context-dependent choice. People encode rich details of the temporal, visual, and spatial context of events, and reencountering those details can spark memories of events from that context, leading people to make contextually appropriate decisions [19]. For example, after recalling a fall afternoon on which Dr Smith gave an illuminating explanation of general relativity, a student might turn to Dr Smith for help understanding special relativity (but not for advice on method acting). However, storing and sifting through large amounts of information can carry representational and attentional costs [20–22].

Flexible choice can thus emerge from building a world model that identifies relations between entities (model-based learning) and from encoding details of events (episodic RL), both of which entail cognitive costs. Both strategies have increasingly been linked to shared roots in the hippocampus, which supports multiple kinds of relational memory**,** or memories that bind

Glossary

Abstractions: representations that result from identifying commonalities across distinct objects or events.
Cognitive map: a mental representation that identifies relationships between states of the world, actions, and/or stimuli.
Episodic memory: memory for a specific event that is tied to a particular time and place.
Episodic reinforcement learning: a class of RL algorithm that samples the details of specific past events to estimate the expected value of actions.
Generalization: transferring knowledge acquired in one context to a different context.
Knowledge structure: a network of interconnected concepts that includes concepts and associations between them.
Model-based learning: a class of RL algorithms that uses an internal model of the environment to compute the expected value of actions.
Model-free learning: a class of RL algorithms that learns the expected value of actions by performing those actions and receiving reward feedback.
Semantic concept: a category that groups distinct objects, events, patterns, or people underneath a common abstract label, like justice, love, or family.
Trait: stable characteristics inferred from observed behaviors.

CellPress

Key figure

Action representation in complex and simple social learning

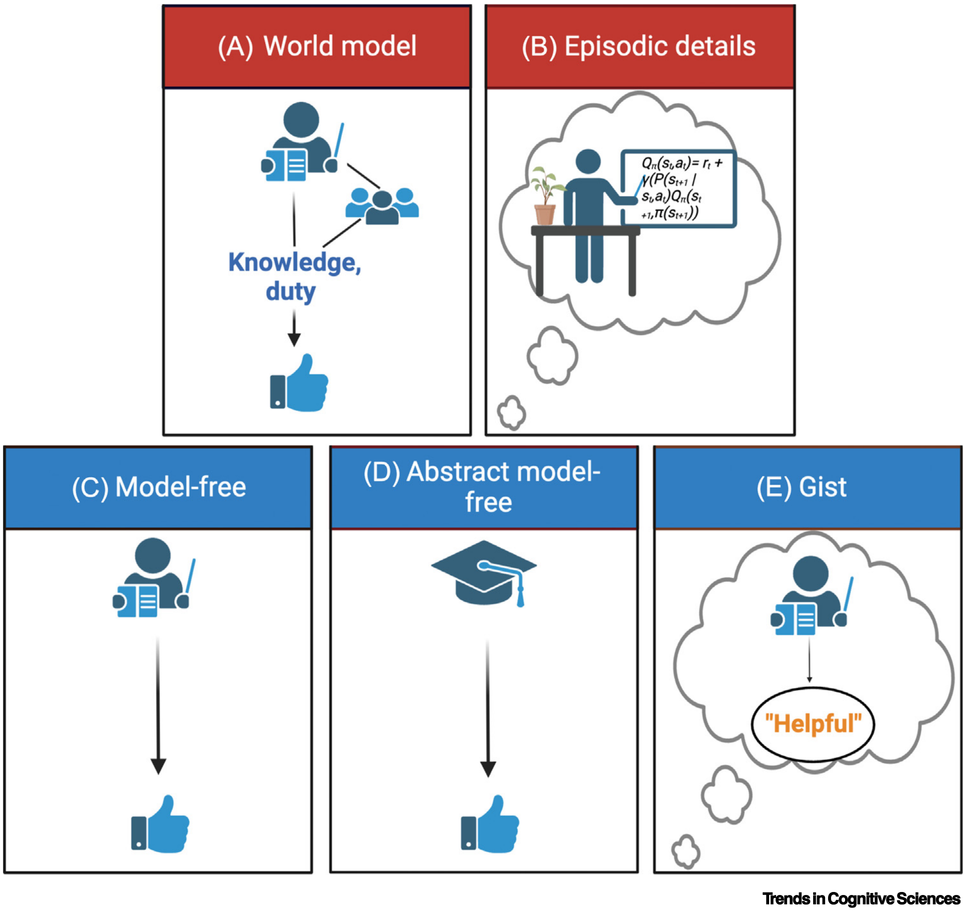

Figure 1. People can encode action and reward in multiple ways in social interaction. In this example, a student approaches Dr Smith's office and experiences illuminating help, providing a rewarding experience. (A) To achieve complex behavior, a learner could use a model of the world, instantiated in a cognitive map, that specifies Dr Smith's role in the class in relation to students and/or that specifies a causal model explaining why approaching Dr Smith will lead to reward. By using this cognitive map, a student can generalize to a new professor (Dr Jones), recognizing that a new professor occupies the same role and will lead to the same outcomes. (B) Through episodic memory, the student could encode details of the exact interaction in which they received help. By later retrieving these details, they can make flexible choices based on any features present in the interaction. (C) In traditional model-free learning, the student associates Dr Smith with reward. This learner would not generalize to new choices, such as visiting Dr Jones. (D) Through social expertise, a student could use an abstract representation of 'approach the professor' and learn this action yields reward; this learning can be model-free, with no consideration of why the professor led to reward. Such a learner could generalize with low cognitive effort to a new individual categorized as a professor. (E) Through expertise, the student could encode an abstract representation of a specific interaction with the professor, reducing details to a gist summary indicating the professor was helpful. The student could generalize this simpler representation to a diverse array of new situations, such as asking the professor for help fixing a broken bicycle or asking for a letter of recommendation.

entities together [13]. This includes traditional episodic memory, which binds together details of an event, as well as forming associations between stimuli, recognizing configurations of features, and building a cognitive map of the environment (Box 1) [8,10,11,13,23].

Box 1. Brain bases of abstract reward generalization

When people generalize reward learning across novel abstract roles, representations of task structure have been observed in hippocampus (HC) and ventromedial prefrontal cortex (vmPFC)/orbitofrontal cortex (OFC) in some studies [10,11], and in dorsolateral prefrontal cortex (dlPFC) and rostrolateral prefrontal cortex (rlPFC) in other studies [12] (Figure I). Responses in HC/OFC have been proposed to reflect a cognitive map used to form novel inferences, whereas responses in dlPFC/rlPFC have been proposed to reflect action control in light of task structure [94,95].

When people generalize familiar knowledge, rlPFC activation appears to dissipate, potentially reflecting a shift toward automaticity [96]. In these cases, what regions represent abstract relations? One possibility is that HC and vmPFC/OFC represent cognitive maps of both novel and familiar relations. Supporting this view, vmPFC and HC have been implicated when people use familiar schemas to encode new information [97]. In social interactions, HC responses reflect a partner's position in a cognitive map of power and affiliation – two familiar social dimensions [98]. Similarly, responses in lateral OFC reflect the influence of trait knowledge on context-dependent social choices [99].

However, studies of abstract social choice typically examine goal-directed decisions, in which people explicitly draw on social knowledge to navigate an environment. During model-free learning, a second possibility is that distinct neural regions represent abstract inputs to reinforcement.

Social abstraction is linked to several default mode network structures–regions that respond more at rest and less during effortful tasks [100]. First, posterior superior temporal sulcus (pSTS) responds when people perceive social relations [101,102], and pSTS has been proposed to help compose a gestalt cortex that underlies effortless understanding of scenes [103]. Second, anterior temporal lobe (ATL) responds when people consider semantic social concepts [104,105] and stores abstract social knowledge about specific individuals [67]. Finally, dorsomedial prefrontal cortex (dmPFC) responds when people spontaneously form abstract impressions from specific social behaviors [106,107]. Individuals who report greater social expertise show stronger responses in dmPFC when they form abstract explanations of social behaviors versus nonsocial events [108].

Altogether, these regions may support effortless social abstraction. Indeed, when people reason about social (vs. nonsocial) relations, they respond more quickly and show stronger responses in pSTS and dmPFC; by contrast, reasoning about nonsocial relations involves stronger responses in the HC [55]. Future work can test whether regions linked to social abstraction support model-free abstract RL or whether common regions represent abstract relations across goal-directed and model-free learning.

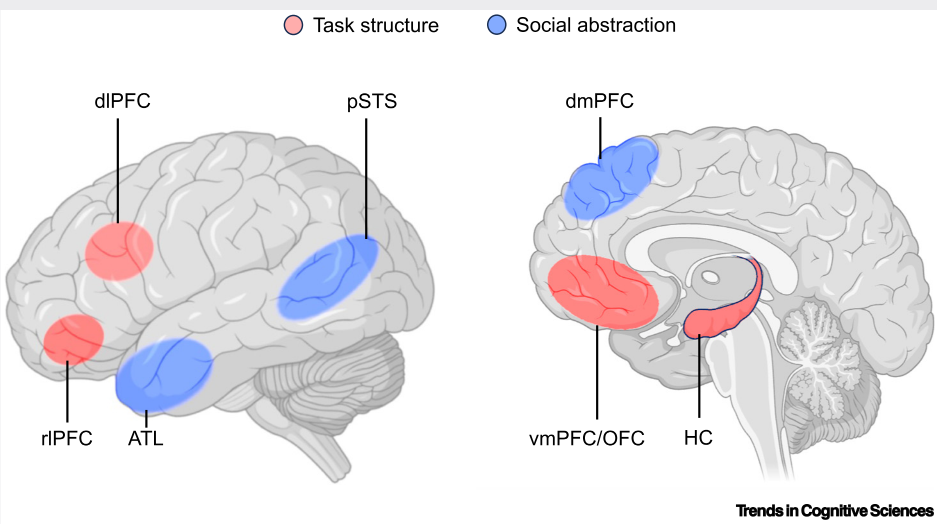

Figure I. Brain regions linked to generalization and social abstraction. Approximate locations of brain regions linked to representations of task structure and social abstraction. Abbreviations: ATL, anterior temporal lobe; dlPFC, dorsolateral prefrontal cortex; dmPFC, dorsomedial prefrontal cortex; HC, hippocampus; OFC, orbitofrontal cortex; pSTS, posterior superior temporal sulcus; rlPFC, rostrolateral prefrontal cortex; vmPFC, ventromedial prefrontal cortex.

In the case of social cognition, people do use cognitive maps of social ties to infer what new individuals will be like [10,24], use social knowledge to plan paths to rewards [2], and recall details of interactions to decide who to approach again [8]. Yet, humans do not have unlimited cognitive resources. The question then remains, how do people often navigate complex social interactions with apparent ease?

Simplifying social learning: traditional accounts of reinforcement

Traditional learning accounts assume people navigate tradeoffs between easy-but-simple behavior and complex-but-difficult behavior: for instance, people use both model-based and model-free learning to some degree, but when people have fewer cognitive resources available or less motivation to exert effort, they revert to model-free learning [14,25]. This traditional view suggests one straightforward answer to simplifying social learning: if complex learning grows difficult, people could rely on simpler reward learning algorithms (Figure 1C).

Do people form simple reward associations in social interactions? A growing body of evidence indicates the answer is yes, with simple reward learning complementing more complex forms of behavior. People gravitate toward partners who provide rewarding outcomes, such as money or acceptance, even when these rewards do not reflect a partner's character or intentions [26–30]. For instance, if two individuals share half their resources, they reveal equivalent generosity, but if one starts with US$10 and one starts with US$15, the latter offers a greater reward. People persist in choosing rewarding partners even after reward contingencies change and these partners no longer offer greater benefits [26,29,30], consistent with the proposal that people form social habits [6]. By prompting positive affect, rewards also lead people to like others more and see others in a more favorable light [26,27,30]. This kind of reward learning has been linked to ventral striatum [26] – a key region for positive affect and reward-based reinforcement [31,32] – and in tasks dissociating model-free and model-based reinforcement, model-free learning has been found to contribute to social evaluations [28,33].

Although this kind of learning may not predominate in social behavior, it can have important consequences for social outcomes, including economic inequality [34,35], ostracism [36], intergroup relations [30,33], and interactions online. Online behavior offers a useful real-world test case, given that people receive quantifiable feedback in the form of likes, which activate common reward pathways in ventral striatum [37]. The extent to which people generate posts, express outrage, or spread misinformation on social media follows principles of reward learning and habit [38–40].

Yet, people often seem to adaptively navigate even complex social environments without cognitive overload. How might people go beyond simple reward associations without taking on additional cognitive labor? We next describe an expanded account that identifies routes to more complex behavior without more difficult cognition.

Simplifying social learning: an expertise account of reinforcement

Humans have social expertise: from infancy, humans spend countless hours paying attention to and interacting with other humans. Through these experiences, people develop a wealth of abstract **semantic concepts** that organize the world into meaningful units with linguistic labels (e.g., family) [41]. We propose that expertise allows flexible decision-making with low cognitive cost, helping people turn difficult learning problems into easier ones. Specifically, expertise can simplify how people think about relations between elements of an event (as in a world model) and details of events (as in remembering particular episodes).

Expertise allows people to easily represent their environment using familiar abstract concepts. Abstract concepts collapse across distinct objects and events to identify higher-level commonalities making them functionally equivalent [42,43]. For example, the social category 'waiter' collapses across a variety of people to identify commonalities: they are restaurant employees who take orders and deliver food. Abstract concepts can simplify social interactions by focusing individuals on aspects that matter for their goals and omitting those that do not. Knowing that the person you are talking to is a waiter provides structure to the interaction – it allows you to infer what kinds of questions they can answer, what topics are appropriate, and what role they play in your dining experience. That said, a customer would not need to remember details of the waiter's eye color or favorite hobbies to order food. This process corresponds to state abstraction in RL, in which a learner reduces the size of a state space by treating distinct states of the world as equivalent, thus simplifying learning [44,45].

While the work of acquiring abstract social concepts occurs over an extended period of development [46,47], once this work is performed, social concepts can easily be applied to new circumstances without retrieving details of the events through which the concepts were formed [48]. With experience, knowledge becomes semanticized, shifting from detailed knowledge of specific events held in episodic memory ('I was at Washington Square Park last Saturday') to more general fact-like knowledge held in semantic memory ('I pass Washington Square Park on my way to work') [48,49]. More generally, with extensive practice, effortful cognition can become automatic, spontaneous, and effortless [50]. Finally, language also facilitates reasoning about abstract relationships [51,52], and semantic concepts provide people with linguistic labels that help them easily recognize **abstractions**. Although non-experts can also recognize abstract commonalities, expertise and language thus let people do so with greater ease [51,53].

Consistent with a social expertise perspective, adults spontaneously recognize abstract roles more easily in social as opposed to nonsocial scenes [54], reason more easily about social as opposed to nonsocial relations [55,56], focus more on abstract patterns in social as opposed to nonsocial learning [27,57], and easily identify abstract causes to explain sparse social behavior [58]. Moreover, although no physical pattern defines social relations like help or harm, people are so practiced at recognizing these relations that doing so has hallmarks of automatic perception rather than deliberate reasoning [59–61].

These tendencies simplify how people mentally represent the inputs to RL. When lacking expertise, model-based learners must reason about relationships between elements of a task and episodic learners must recall details of a scene. By contrast, experts can draw on semantic concepts describing relations or episodes, retrieving precompiled abstractions that leave details behind [48]. By automatically mapping new situations to these concepts, people lower the costs of social learning while maintaining intermediate flexibility.

Simplifying relations

When people interact with others, they might represent their actions in terms of specific individuals they encounter. If a student learns that the action approach Dr Smith leads to reward, they must explicitly transfer their knowledge to Dr Jones by considering commonalities between them – that is, encoding relations between them in an explicit world model. However, when people encounter familiar social concepts, they can effortlessly construe their actions in terms of abstract roles (approach the professor). In this manner, people can effortlessly use state abstraction along with a matching abstract action set.

This shift in representation can make model-based planning easier and more powerful. First, familiar abstractions reduce the cognitive costs of planning by eliminating irrelevant details [20].

Second, they allow model-based learners to generalize their plans to new situations in the same domain [62]. Third, expertise helps learners plan more deeply, evaluating the consequences of their actions farther into the future. In tree search algorithms, learners choose actions by evaluating how actions lead to new states, which consequently branch into new possible actions and states. Expertise lets people search more deeply ahead, in part because experts represent relevant task features more sharply and more quickly [63]. Accordingly, after extensive practice with a task, people make more model-based choices and plan more deeply despite planning more quickly [63,64].

Yet, people can also engage in flexible behavior without needing model-based planning at all. By effortlessly recognizing social roles described by concepts, people may directly associate these roles with model-free reward. For instance, by construing Dr Smith as a professor, a student could easily generalize to a new professor (Dr Jones) without explicitly considering commonalities or likely outcomes (Figure 1D). People can thus achieve complex behavior through a simple algorithm (model-free learning) with abstract inputs (familiar roles). This strategy has successful parallels in machine learning (Box 2).

In recent work, we found that humans indeed use model-free learning with abstract inputs [65]. Participants learned to approach characters who led to rewarding stock dividends. Some characters owned the same stocks as one another, meaning that participants could use a cognitive map of task structure to generalize across them (Figure 2). However, characters also enacted the familiar social concept of helping, with one character in the role of helper and one in the role of recipient of help. Some, but not all, helpers led to the same stocks. Nonetheless, if people intuitively encode others as helpers and have rewarding experiences with these individuals, they may learn that helpers offer high model-free reward value. In turn, they may generalize this

Box 2. State abstraction in model-free RL algorithms

Existing machine learning algorithms have enabled generalization using model-free learning combined with state abstraction. For instance, deep Q networks' combine a deep neural network with model-free RL. The deep neural network learns abstract state representations from high-dimensional inputs, such as identifying relevant states of a computer game from all pixels onscreen. The value of these states is learned through model-free reinforcement. This approach produces human-level performance in multiple games [109]. Notably, after training, some game states that are perceptually dissimilar, but similar in value, have been found to elicit similar encoding in the network, highlighting abstract representations of states based on goal-relevant task features [109].

Alternatively, a model-free learner can identify an underlying function that links states to rewards; for instance, moving from west to east might predict more uncomfortable weather. Here, a linear regression model could predict the value of new states by regressing previous rewards onto previous east–west locations. Real-world cases usually involve more complex and unknown functions. Algorithms such as Gaussian process regression – a nonparametric Bayesian approach – can estimate the shape of arbitrarily complex functions, assigning similar value to similar states [110,111]. This algorithm can remain model-free by directly mapping features of states to value [112,113]. At the same time, it can generalize to new states (e.g., a point further west than previously explored).

Humans appear to use this strategy as well, generalizing across physical or conceptual distance by learning the degree of correlation between nearby states [114,115]. However, Gaussian process regression can be computationally costly [113], and less is known about the cognitive costs of such learning in humans.

Given vast experience with social interactions, it is possible that adults have already learned key functions mapping social interaction to reward, allowing another form of easy model-free generalization. For instance, people may directly learn the value of traits in a low-dimensional trait space, such as learning that generous individuals tend to be valuable partners. People could therefore generalize to new partners, assigning model-free value to new individuals perceived as generous. This possibility could explain why learning about generosity evokes prediction errors signals in ventral striatum, overlapping with but dissociable from reward prediction errors [26]. This kind of model-free function learning could complement more flexible uses of gist memory as described in the main text. Social expertise would thus let people simplify interactions into abstract features that serve as inputs to Gaussian process regression.

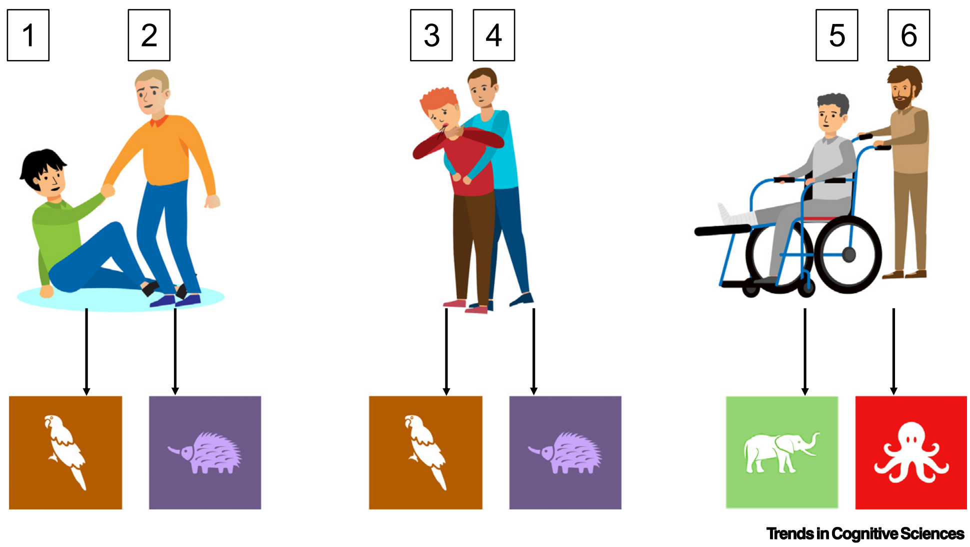

Figure 2. Dissociating model-based generalization and generalization through social concepts. In the task used in [65], participants learned about characters who owned stocks in one of four companies (Brown Parrot Corporation, Purple Porcupine Company, Green Elephant Industries, and Red Octopus Group). Characters appeared in pairs across different scenes, which enacted the abstract concept of help in different ways. By choosing a character on each round, participants received a dividend from that character's stock; dividends could be small or large. A traditional model-free learner would interact with the same individual again after receiving a large reward. For instance, after choosing Character #2 and receiving a large reward, this learner would only choose Character #2 again. A model-based learner would use task structure to generalize across the first two scenes: after choosing Character #2 in Scene 1 and receiving a large reward, this learner would also become more likely to choose Character #4 in Scene 2, since this character leads to the same stock. A concept-based learner would construe all characters as helpers or recipients of help and use these roles to generalize across all three scenes: after choosing Character #2 and receiving a large reward, they would also become more likely to choose Character #6 in Scene 3, since this character is also a helper, even though this character cannot lead to the same stock. Figure adapted, with permission, from [65].

knowledge to new helpers, even when new helpers own a different stock and cannot lead to the same reward. Indeed, after choosing a helper and getting rewarded, participants were more likely to choose a new helper, even when there was no reason to do so based on task structure. When compared with a control condition with no social roles, participants who saw social roles responded more quickly despite generalizing more, breaking the traditional link between abstract generalization and cognitive cost.

Social concepts thus simplified reward generalization, letting people effortlessly represent an abstract role (choose helper) and attach model-free reward to it. People similarly learn the value of abstract goals – which can be accomplished through multiple specific means – via model-free reinforcement [66]. People may also learn the model-free value of other abstractions described by social concepts, such as social groups, with consequences for intergroup behavior [30,33]. Notably, even traditional model-free learning requires some degree of abstraction, such as abstracting stimulus identity over space and time (the blue slot machine) or maintaining a constant representation of an individual's identity (Tom Cruise) across modalities such as seeing their face or name [67]. The inputs to model-free learning can thus exist on a spectrum of abstraction from concrete motor movements (go left [68]) to individual identity (Tom) to broader categories (helpers).

Nonetheless, learning about more abstract concepts offers more flexibility than traditional model-free learning about one stimulus, because learners can generalize across individuals who share an abstract role. Conversely, it is less flexible than model-based learning because learners do not explicitly consider paths to reward. This strategy would therefore be adaptive in an environment whose distribution of rewards coincides with one's existing concepts – which is often the case, given that concepts are developed to explain consistencies in one's environment [42]. However, when the environment diverges from one's concepts, this strategy can lead people to overgeneralize prior learning. For instance, generalizing from Dr Smith to all professors may cause a student to waste valuable studying time if they approach a professor who is disengaged and unhelpful.

While social learning offers a useful prototype for studying the role of expertise in complex learning, people also use expertise to recognize abstractions in nonsocial domains [53], suggesting everyday learning might often be easier than anticipated by existing research. Studies of human RL often illuminate how people learn about new relationships in unfamiliar settings through effortful reasoning. Yet, everyday learning often occurs in familiar settings. Expertise may simplify learning in these cases, which may explain patterns observed in prior work. For instance, people make more model-based choices when a task is framed with an intuitive narrative [69]. These findings have been interpreted to mean that narratives clarify potential confusion about task instructions [69], but familiar narratives also make it conceptually easier for people to represent task structure and follow contingencies [70]. Outside the laboratory, aging individuals often show higher susceptibility to scams [71], but this decline is countered by high financial literacy, which tracks semantic abilities like vocabulary and word retrieval [72]. As people gain expertise and distill episodes into semantic concepts, they may shift from effortful control to easier use of abstractions for model-based and model-free learning.

Simplifying details

People can represent the behavior of others with specifics, such as a waiter recalling a customer leaving a US$20 tip. Retrieving such episodic details supports one-shot learning and context-dependent choice [8,19]. Yet, social life offers an overwhelming number of details to track across countless contexts. Here too, conceptual expertise can help by automatizing abstraction, allowing people to simplify representations of interactions.

Theories of memory assert that people encode events not only as verbatim memories, reflecting exact details of an event, but also as simpler gist memories, reflecting abstract meaning [73]. Gist memories reduce details (a 30% or 70% chance of rain) to relative rankings (more likely vs. less likely), termed ordinal gist, or even simpler categories (some chance vs. no chance), termed categorical gist. People typically gravitate to the simplest representation they can use [74], and the gist representation people use shapes their decision-making. For instance, teens who consider risk categorically (no risk is better than some) make fewer risky choices than teens who consider risk in relative terms (less risk is better than more) [75]. Crucially, experts rely on gist more than novices; while novices focus on details, experts extract meaning [74,76].

As social experts, humans easily simplify details of interactions ('he tipped $20') to abstract **trait** concepts (he was generous), losing details while gaining meaning (Figure 1E) [77,78]. Again, this abstraction is cognitively efficient and seemingly automatic: people spontaneously encode trait impressions even under cognitive load and with no explicit goal to do so [79]. These impressions bear the hallmarks of gist memories: people encode trait impressions in parallel with verbatim memories of social events [77], and trait memories last longer than verbatim memories [79–81]. Moreover, we recently found that people gravitate to the simplest impression available, representing social feedback as ordinal gist (more competent, less competent) or categorical gist (competent, incompetent), and make choices based on gists rather than episodic details alone [82].

By reducing data to a lower-dimensional space [83], gists require lower representational complexity and lower encoding costs than verbatim details [20,21,84]. Moreover, by automatically applying familiar dimensions rather than deliberately identifying new ones, gists reduce the attentional costs of identifying reward-predictive features of an event [22].

Although people might use gists to predict model-free value – for instance, learning that generous partners are valuable (Box 2) – people can also draw on individual interactions using gist-based RL, maintaining some flexibility of episodic RL but using a lower-dimensional space. Accordingly, gists allow easy one-shot learning. After learning how much an individual donated to a charity, perceivers can reduce that amount to a gist of some or none, facilitating inferences of generous or stingy, respectively. Perceivers draw on these gists when choosing whether to reward others for their generosity, even when accounting for verbatim memory [82].

Social gists also support context-dependent choices, letting people choose partners based on the traits required by a given setting. Abstract concepts identify not only commonalities across separate entities but also distinctions from other abstract concepts [85]. For example, the concept adult groups all humans above a certain age while distinguishing them from humans below that age. Through abstract concepts, people can easily track meaningful patterns in behavior across settings while ignoring irrelevant details. For instance, people learn context-dependent traits (‘this person is competent at math but not verbal questions’) even when they fail to learn equivalently complex but less familiar reward contingencies (‘this person delivers high reward when playing with one slot machine but not another’) [78]. In real-world social networks, students turn to peers high in empathy to share personal news but turn to peers high in positive affect to have fun [86]. Despite unique experiences with one another, students form shared impressions of empathy and positivity and use these impressions to make context-dependent choices.

Finally, after mapping behaviors onto pre-existing dimensions (generous), people can flexibly decide how to use those gists later, much as episodic learners can flexibly identify relevant details of a scenario. For instance, after learning that an individual is kind, perceivers might avoid that individual as a teammate for a competitive game [87]. Moreover, because trait concepts form a broader **knowledge structure**, they again allow people to generalize in novel settings. People know how different traits relate to one another in others around them, such as knowing that someone cooperative is likely to be trustworthy but not assertive [88,89]. People therefore generalize their learning to new traits, such as assuming that a person who is polite is also friendly [90], allowing social choices in new settings [78]. Similarly, people can spontaneously infer goals in others [91] to generalize knowledge to new situations [92] with little effort.

Again, expertise can help people accurately predict others’ behavior when the environment matches pre-existing concepts but can harm predictions when the environment betrays pre-existing concepts. When a simplified representation of an environment has been previously valuable, people persist in using it even when it is no longer optimal [93]. Accordingly, gist-based learners may automatically reduce behaviors to familiar dimensions even when those dimensions are no longer relevant. Indeed, people choose generous partners in economic tasks even when doing so is not optimal [26,27]. Moreover, when people watch players cooperate or defect across economic games in multiple contexts, they ignore thousands of possible patterns characterizing others’ choices and focus on patterns reflecting common human motives (e.g., greed, risk aversion) [92]. Consequently, perceivers predict a player’s choices more accurately when choices reflect those motives, but not when choices are engineered to reflect the opposite motives, which are statistically identical but psychologically unlikely.

Concluding remarks

Social learning is complex. Traditional accounts suggest people must either follow simple model-free reward contingencies or pay a cost to use flexible learning computations. Although people use these strategies, humans also have social expertise that can simplify learning problems, allowing flexible behavior with low cognitive cost. People effortlessly and spontaneously recognize abstract social concepts that describe roles (mentor, helper), behaviors (generous, competent), and other social patterns. These concepts reflect semantic knowledge, representing generalized abstract relationships without retrieving specific details. People can use pre-compiled abstract concepts to facilitate planning, associate abstract social roles with model-free reward, or encode the gist meaning of an interaction, allowing them to generalize reward and make adaptive choices with cognitive ease. Although these strategies cannot replace every kind of complex social learning, they can support flexible behavior through simple cognition in familiar settings, complementing more elaborate learning [1,2]. However, people risk automatically mapping new situations to familiar abstractions even when they are not optimal, posing a limit to flexibility [93].

This framework demonstrates how RL supports complex social behavior, bridging social cognition with computational principles of RL. While this proposal applies to any domain where humans have expertise, social interaction offers an informative test case; although not all humans are chess or bird experts, nearly all humans have social expertise and must navigate complexities of social interaction. Social learning can thus serve as a prototype for studying how people navigate complex everyday environments, building a bridge for future research between the study of concept development and the study of adaptive choice (see Outstanding questions).

Acknowledgments

The authors thank Stephen Read, Payam Piray, and members of the University of Southern California (USC) Social Learning & Choice Laboratory for helpful comments and discussion.

Declaration of interests

No interests are declared.

Outstanding questions

How does conceptual expertise influence RL in nonsocial domains?

How do reward learning and concepts co-develop? Reward might prompt comparison between distinct events, leading people to recognize commonalities and develop abstract concepts. Alternatively, reward – whether extrinsic or due to intrinsic curiosity – might directly refine state representations, leading to concepts that describe states with similar value.

How does social expertise relate to social well-being? Is effortless learning or effortful planning more predictive of adaptive social choice and positive relationships across different situations in daily life?

Do people form model-free value associations with abstract social groups, beyond semantic associations typically considered to comprise stereotypes? Would different interventions be needed to change behavior as a result?

How do goal-directed and model-free abstract learning interact? Do people sometimes use goal-directed reasoning to recognize relevant concepts and then deploy those concepts in a model-free manner?

How and when do social concepts emerge across development? Specifically, what computations allow children to identify abstract commonalities across distinct people and events, and do children perform better at abstract RL in social as opposed to nonsocial domains?

What brain regions support RL in the presence of familiar social concepts?

To what extent is social expertise learned, and to what extent does the brain's self-organization prior to learning generate inductive biases that promote efficient social learning?

How do abstract representations shape learning from others? Just as learning about others requires complex cognition, so does learning from others, yet people seem to transfer lessons from observing others to themselves easily. How do abstraction and familiarity support this learning?

References

1. FeldmanHall, O. and Nassar, M.R. (2021) The computational challenge of social learning. *Trends Cogn. Sci.* 25, 1045–1057
2. Ho, M.K. *et al.* (2022) Planning with theory of mind. *Trends Cogn. Sci.* 26, 959–971
3. Sutton, R.S. and Barto, A.G. (2018) *Reinforcement Learning: an Introduction*, MIT Press
4. Daw, N.D. *et al.* (2011) Model-based influences on humans' choices and striatal prediction errors. *Neuron* 69, 1204–1215
5. Gillan, C.M. *et al.* (2015) Model-based learning protects against forming habits. *Cogn. Affect. Behav. Neurosci.* 15, 523–536
6. Wood, W. (2017) Habit in personality and social psychology. *Personal. Soc. Psychol. Rev.* 21, 389–403
7. Doll, B.B. *et al.* (2015) Model-based choices involve prospective neural activity. *Nat. Neurosci.* 18, 767–772
8. FeldmanHall, O. *et al.* (2021) Hippocampus guides adaptive learning during dynamic social interactions. *J. Neurosci.* 41, 1340–1348
9. Karagoz, A.B. *et al.* (2023) The construction and use of cognitive maps in model-based control. *J. Exp. Psychol. Gen.*, Published online December 7, 2023 https://doi.org/10.1037/xge0001491
10. Park, S.A. *et al.* (2020) Map making: constructing, combining, and inferring on abstract cognitive maps. *Neuron* 107, 1226–1238.e8
11. Baram, A.B. *et al.* (2021) Entorhinal and ventromedial prefrontal cortices abstract and generalize the structure of reinforcement learning problems. *Neuron* 109, 713–723.e7
12. Vaidya, A.R. *et al.* (2021) Neural representation of abstract task structure during generalization. *eLife* 10, e63226
13. Biderman, N. *et al.* (2020) What are memories for? The hippocampus bridges past experience with future decisions. *Trends Cogn. Sci.* 24, 542–556
14. Kool, W. *et al.* (2017) Cost-benefit arbitration between multiple reinforcement-learning systems. *Psychol. Sci.* 28, 1321–1333
15. Collins, A.G. (2017) The cost of structure learning. *J. Cogn. Neurosci.* 29, 1646–1655
16. Kool, W. *et al.* (2018) Planning complexity registers as a cost in metacontrol. *J. Cogn. Neurosci.* 30, 1391–1404
17. Gershman, S.J. and Daw, N.D. (2017) Reinforcement learning and episodic memory in humans and animals: an integrative framework. *Annu. Rev. Psychol.* 68, 101–128
18. Bornstein, A.M. *et al.* (2017) Reminders of past choices bias decisions for reward in humans. *Nat. Commun.* 8, 15958
19. Bornstein, A.M. and Norman, K.A. (2017) Reinstated episodic context guides sampling-based decisions for reward. *Nat. Neurosci.* 20, 997–1003
20. Ho, M.K. *et al.* (2022) People construct simplified mental representations to plan. *Nature* 606, 129–136
21. Greene, N.R. and Naveh-Benjamin, M. (2023) Differential attentional costs of encoding specific and gist episodic memory representations. *J. Exp. Psychol. Gen.* 152, 3292–3299
22. Leong, Y.C. *et al.* (2017) Dynamic interaction between reinforcement learning and attention in multidimensional environments. *Neuron* 93, 451–463
23. Duncan, K. *et al.* (2018) More than the sum of its parts: a role for the hippocampus in configural reinforcement learning. *Neuron* 98, 645–657

24. Son, J.-Y. *et al.* (2021) Cognitive maps of social features enable flexible inference in social networks. *Proc. Natl. Acad. Sci.* 118, e2021699118
25. Otto, A.R. *et al.* (2013) The curse of planning: dissecting multiple reinforcement-learning systems by taxing the central executive. *Psychol. Sci.* 24, 751–761
26. Hackel, L.M. *et al.* (2015) Instrumental learning of traits versus rewards: dissociable neural correlates and effects on choice. *Nat. Neurosci.* 18, 1233–1235
27. Hackel, L.M. *et al.* (2020) Reinforcement learning in social interaction: the distinguishing role of trait inference. *J. Exp. Soc. Psychol.* 88, 103948
28. Hackel, L.M. *et al.* (2019) Model-based and model-free social cognition: investigating the role of habit in social attitude formation and choice. *Front. Psychol.* 10, 2592
29. Cho, H.J. and Hackel, L.M. (2022) Instrumental learning of social affiliation through outcome and intention. *J. Exp. Psychol. Gen.* 151, 2204–2221
30. Hackel, L.M. *et al.* (2022) Group value learned through interactions with members: a reinforcement learning account. *J. Exp. Soc. Psychol.* 99, 104267
31. Garrison, J. *et al.* (2013) Prediction error in reinforcement learning: a meta-analysis of neuroimaging studies. *Neurosci. Biobehav. Rev.* 37, 1297–1310
32. Pool, E.R. *et al.* (2022) Differential contributions of ventral striatum subregions to the motivational and hedonic components of the affective processing of reward. *J. Neurosci.* 42, 2716–2728
33. Kurdi, B. *et al.* (2019) Model-free and model-based learning processes in the updating of explicit and implicit evaluations. *Proc. Natl. Acad. Sci.* 116, 6035–6044
34. Hackel, L.M. and Zaki, J. (2018) Propagation of economic inequality through reciprocity and reputation. *Psychol. Sci.* 29, 604–613
35. Melamed, D. *et al.* (2022) Inequality and cooperation in social networks. *Sci. Rep.* 12, 6789
36. Lindström, B. and Tobler, P. (2018) Incidental ostracism emerges from simple learning mechanisms. *Nat. Hum. Behav.* 2, 405–414
37. Sherman, L.E. *et al.* (2016) The power of the like in adolescence: effects of peer influence on neural and behavioral responses to social media. *Psychol. Sci.* 27, 1027–1035
38. Lindström, B. *et al.* (2021) A computational reward learning account of social media engagement. *Nat. Commun.* 12, 1311
39. Anderson, I.A. and Wood, W. (2023) Social motivations' limited influence on habitual behavior: Tests from social media engagement. *Motiv. Sci.* 9, 107–119
40. Ceylan, G. *et al.* (2023) Sharing of misinformation is habitual, not just lazy or biased. *Proc. Natl. Acad. Sci.* 120, e2216614120
41. Atzil, S. *et al.* (2018) Growing a social brain. *Nat. Hum. Behav.* 2, 624–636
42. Rosch, E. *et al.* (1976) Basic objects in natural categories. *Cognit. Psychol.* 8, 382–439
43. Gilead, M. *et al.* (2020) Above and beyond the concrete: the diverse representational substrates of the predictive brain. *Behav. Brain Sci.* 43, e121
44. Andre, D. and Russell, S.J. (2002) State abstraction for programmable reinforcement learning agents. In *Proceedings of the AAAI Conference on Artificial Intelligence*, pp. 119–125
45. Abel, D. *et al.* (2018) State abstractions for lifelong reinforcement learning. *PMLR* 80, 10–18
46. Boroditsky, L. (2007) Comparison and the development of knowledge. *Cognition* 102, 118–128
47. Christie, S. (2017) Structure mapping for social learning. *Top. Cogn. Sci.* 9, 758–775
48. Renoult, L. *et al.* (2019) From knowing to remembering: the semantic–episodic distinction. *Trends Cogn. Sci.* 23, 1041–1057
49. Robin, J. *et al.* (2019) Spontaneous memory retrieval varies based on familiarity with a spatial context. *Cognition* 190, 81–92
50. Schneider, W. and Shiffrin, R.M. (1977) Controlled and automatic human information processing: I. Detection, search, and attention. *Psychol. Rev.* 84, 1–66
51. Gentner, D. (2016) Language as cognitive tool kit: how language supports relational thought. *Am. Psychol.* 71, 650–657
52. Loewenstein, J. and Gentner, D. (2005) Relational language and the development of relational mapping. *Cognit. Psychol.* 50, 315–353
53. Goldwater, M.B. *et al.* (2021) Analogy generation in science experts and novices. *Cogn. Sci.* 45, e13036
54. Kalkstein, D.A. *et al.* (2020) Person-centered cognition: the presence of people in a visual scene promotes relational reasoning. *J. Exp. Soc. Psychol.* 90, 104009
55. Mason, M.F. *et al.* (2010) Specialization in relational reasoning: the efficiency, accuracy, and neural substrates of social versus nonsocial inferences. *Soc. Psychol. Personal. Sci.* 1, 318–326
56. Cosmides, L. (1989) The logic of social exchange: has natural selection shaped how humans reason? Studies with the Wason selection task. *Cognition* 31, 187–276
57. Kalkstein, D.A. *et al.* (2016) Social learning across psychological distance. *J. Pers. Soc. Psychol.* 110, 1–19
58. Read, S.J. (1987) Constructing causal scenarios: a knowledge structure approach to causal reasoning. *J. Pers. Soc. Psychol.* 52, 288
59. Hafri, A. and Firestone, C. (2021) The perception of relations. *Trends Cogn. Sci.* 25, 475–492
60. De Freitas, J. and Hafri, A. (2024) Moral thin-slicing: forming moral impressions from a brief glance. *J. Exp. Soc. Psychol.* 112, 104588
61. McMahon, E. and Isik, L. (2023) Seeing social interactions. *Trends Cogn. Sci.* 27, 1165–1179
62. Pouncy, T. *et al.* (2021) What is the model in model-based planning? *Cogn. Sci.* 45, e12928
63. van Opheusden, B. *et al.* (2023) Expertise increases planning depth in human gameplay. *Nature* 618, 1000–1005
64. Economides, M. *et al.* (2015) Model-based reasoning in humans becomes automatic with training. *PLoS Comput. Biol.* 11, e1004463
65. Hackel, L.M. and Kalkstein, D.A. (2023) Social concepts simplify complex reinforcement learning. *Psychol. Sci.* 34, 968–983
66. Cushman, F. and Morris, A. (2015) Habitual control of goal selection in humans. *Proc. Natl. Acad. Sci.* 112, 13817–13822
67. Wang, Y. *et al.* (2017) Dynamic neural architecture for social knowledge retrieval. *Proc. Natl. Acad. Sci.* 114, E3305–E3314
68. Shahar, N. *et al.* (2019) Credit assignment to state-independent task representations and its relationship with model-based decision making. *Proc. Natl. Acad. Sci.* 116, 15871–15876
69. Feher da Silva, C. and Hare, T.A. (2020) Humans primarily use model-based inference in the two-stage task. *Nat. Hum. Behav.* 4, 1053–1066
70. Murphy, G.L. and Medin, D.L. (1985) The role of theories in conceptual coherence. *Psychol. Rev.* 92, 289–316
71. James, B.D. *et al.* (2014) Correlates of susceptibility to scams in older adults without dementia. *J. Elder Abuse Negl.* 26, 107–122
72. Weissberger, G.H. *et al.* (2023) The cognitive correlates of financial literacy in older adults. *Clin. Gerontol.*, Published online May 29, 2023 https://doi.org/10.1080/07317115.2023.2217190
73. Brainerd, C.J. and Reyna, V.F. (2001) Fuzzy-trace theory: dual processes in memory, reasoning, and cognitive neuroscience. *Adv. Child Dev. Behav.* 28, 41–100
74. Reyna, V.F. *et al.* (2014) Developmental reversals in risky decision making: intelligence agents show larger decision biases than college students. *Psychol. Sci.* 25, 76–84
75. Mills, B. *et al.* (2008) Explaining contradictory relations between risk perception and risk taking. *Psychol. Sci.* 19, 429–433
76. Wing, E.A. *et al.* (2022) The structure of prior knowledge enhances memory in experts by reducing interference. *Proc. Natl. Acad. Sci.* 119, e2204172119
77. Winter, L. and Uleman, J.S. (1984) When are social judgments made? Evidence for the spontaneousness of trait inferences. *J. Pers. Soc. Psychol.* 47, 237–253
78. Hackel, L.M. *et al.* (2022) Context-dependent learning in social interaction: trait impressions support flexible social choices. *J. Pers. Soc. Psychol.* 123, 655–675
79. Todorov, A. and Uleman, J.S. (2003) The efficiency of binding spontaneous trait inferences to actors' faces. *J. Exp. Soc. Psychol.* 39, 549–562
80. Falvello, V. *et al.* (2015) The robustness of learning about the trustworthiness of other people. *Soc. Cogn.* 33, 368–386
81. Todorov, A. and Olson, I.R. (2008) Robust learning of affective trait associations with faces when the hippocampus is damaged, but not when the amygdala and temporal pole are damaged. *Soc. Cogn. Affect. Neurosci.* 3, 195–203

82. Hackel, L.M. and Mende-Siedlecki, P. (2023) Two modes of social impressions and their effects on choice. *J. Exp. Psychol. Gen.* 152, 3002–3020
83. Tamir, D.I. and Thornton, M.A. (2018) Modeling the predictive social mind. *Trends Cogn. Sci.* 22, 201–212
84. Fiske, S.T. (1993) Social cognition and social perception. *Annu. Rev. Psychol.* 44, 155–194
85. Murphy, G.L. (2010) What are categories and concepts? In *The making of human concepts*, pp. 11–28, Oxford University Press
86. Morelli, S.A. *et al.* (2017) Empathy and well-being correlate with centrality in different social networks. *Proc. Natl. Acad. Sci.* 114, 9843–9847
87. Melnikoff, D.E. and Bailey, A.H. (2018) Preferences for moral vs. immoral traits in others are conditional. *Proc. Natl. Acad. Sci.* 115, E592–E600
88. Stolier, R.M. *et al.* (2020) Trait knowledge forms a common structure across social cognition. *Nat. Hum. Behav.* 4, 361–371
89. Elder, J. *et al.* (2023) Mapping the self: a network approach for understanding psychological and neural representations of self-concept structure. *J. Pers. Soc. Psychol.* 124, 237–263
90. Frolichs, K.M. *et al.* (2022) Incorporating social knowledge structures into computational models. *Nat. Commun.* 13, 6205
91. Moskowitz, G.B. and Olcaysoy Okten, I. (2016) Spontaneous goal inference (SGI). *Soc. Personal. Psychol. Compass* 10, 64–80
92. van Baar, J.M. *et al.* (2022) Latent motives guide structure learning during adaptive social choice. *Nat. Hum. Behav.* 6, 404–414
93. Ho, M.K. *et al.* (2023) Rational simplification and rigidity in human planning. *Psychol. Sci.* 34, 1281–1292
94. Boorman, E.D. *et al.* (2021) Cognitive maps and novel inferences: a flexibility hierarchy. *Curr. Opin. Behav. Sci.* 38, 141–149
95. Vaidya, A.R. and Badre, D. (2022) Abstract task representations for inference and control. *Trends Cogn. Sci.* 26, 484–498
96. Davis, T. and Goldwater, M. (2021) Using model-based neuroimaging to adjudicate structured and continuous representational accounts in same-different categorization and beyond. *Curr. Opin. Behav. Sci.* 37, 103–108
97. Sommer, T. *et al.* (2022) The assimilation of novel information into schemata and its efficient consolidation. *J. Neurosci.* 42, 5916–5929
98. Tavares, R.M. *et al.* (2015) A map for social navigation in the human brain. *Neuron* 87, 231–243
99. Kobayashi, K. *et al.* (2022) Neural representations of others' traits predict social decisions. *Proc. Natl. Acad. Sci.* 119, e2116944119
100. Raichle, M.E. (2015) The brain's default mode network. *Annu. Rev. Neurosci.* 38, 433–447
101. Marrero, H. *et al.* (2020) Enhancing memory for relationship actions by transcranial direct current stimulation of the superior temporal sulcus. *Brain Sci.* 10, 497
102. Masson, H.L. and Isik, L. (2021) Functional selectivity for social interaction perception in the human superior temporal sulcus during natural viewing. *NeuroImage* 245, 118741
103. Lieberman, M.D. (2022) Seeing minds, matter, and meaning: the CEEing model of pre-reflective subjective construal. *Psychol. Rev.* 129, 830–872
104. Zahn, R. *et al.* (2007) Social concepts are represented in the superior anterior temporal cortex. *Proc. Natl. Acad. Sci.* 104, 6430–6435
105. Amodio, D.M. (2019) Social Cognition 2.0: an interactive memory systems account. *Trends Cogn. Sci.* 23, 21–33
106. Mende-Siedlecki, P. (2018) Changing our minds: the neural bases of dynamic impression updating. *Curr. Opin. Psychol.* 24, 72–76
107. Ma, N. *et al.* (2011) Spontaneous and intentional trait inferences recruit a common mentalizing network to a different degree: spontaneous inferences activate only its core areas. *Soc. Neurosci.* 6, 123–138
108. Spunt, R.P. and Adolphs, R. (2015) Folk explanations of behavior: a specialized use of a domain-general mechanism. *Psychol. Sci.* 26, 724–736
109. Mnih, V. *et al.* (2015) Human-level control through deep reinforcement learning. *Nature* 518, 529–533
110. Lucas, C.G. *et al.* (2015) A rational model of function learning. *Psychon. Bull. Rev.* 22, 1193–1215
111. Schulz, E. *et al.* (2018) A tutorial on Gaussian process regression: modelling, exploring, and exploiting functions. *J. Math. Psychol.* 85, 1–16
112. Engel, Y. *et al.* (2003) Bayes meets Bellman: the Gaussian process approach to temporal difference learning. In *Proceedings of the 20th International Conference on Machine Learning*, pp. 154–161
113. Chowdhary, G. *et al.* (2014) Off-policy reinforcement learning with gaussian processes. *IEEE/CAA J. Autom. Sin.* 1, 227–238
114. Wu, C.M. *et al.* (2018) Generalization guides human exploration in vast decision spaces. *Nat. Hum. Behav.* 2, 915–924
115. Wu, C.M. *et al.* (2020) Similarities and differences in spatial and non-spatial cognitive maps. *PLoS Comput. Biol.* 16, e1008149