COGNITIVE ECONOMICS: MINDS AND MARKETS AS COMPLEX SYSTEMS

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Abstract

This article reviews *cognitive economics*—an emerging interdisciplinary field that uses the tools of cognitive science to study economic and social decision-making. Despite its eclecticism, Cognitive Economics shares several intellectual commitments: (i) Conceptualizing minds and markets each as complex adaptive systems; (ii) Bridging cognitive, behavioral, and systems levels of analysis; and (iii) Embracing interdisciplinary approaches, including social sciences beyond the traditional scope of cognitive science. We describe three ongoing research programs that strive toward these goals: (i) The study of narratives as a cognitive and social representation used to guide decision-making; (ii) The use of cognitively informed agent based models; and (iii) Understanding markets as an extended mind, analyzed using the concepts, methods, and tools of Coordination Dynamics.

Keywords: Decision-making, behavioral economics, narratives, agent-based models, the extended mind, coordination dynamics

Highlights

- Cognitive economics uses cognitive science to understand economic decision-making.
- Theoretically, the field conceptualizes both minds and markets as complex adaptive systems. Methodologically, the field bridges disciplines and levels of analysis (cognitive, behavioral, and systems).
- Narrative theories of decision-making examine the cognitive and social representations and processes that govern decision-making under uncertainty.
- Agent-based cognitive models study how cognitive mechanisms at the individual level can contribute to emergent systems-level phenomena.
- Post-cognitivist approaches consider minds and markets to be one continuous complex system. Coordination Dynamics is one useful framework for analyzing this system.

Cognitive economics is an emerging interdisciplinary field that uses the tools of cognitive science to understand economic decision-making [1-4; see **Glossary**]. It recognizes the strengths and limitations of traditional approaches within both fields, using the insights of cognitive science to improve economics and vice versa. This article aims to demonstrate that cognitive economics is a distinct approach with particular intellectual commitments by explicating those commitments and providing recent examples.

Cognitive economics is distinct from its more famous cousins, **behavioral economics** and **neuroeconomics**. Behavioral economics mainly demonstrates how humans differ from the rational agents of economic theory, while neuroeconomics mainly identifies neural correlates of those irrational behaviors [5-7].

Rather than starting with economic theory and identifying its flaws, cognitive economics instead starts from the nature of the mind and its relationship to collective behavior. Cognitive economics recognizes that both minds and economies are *complex systems*—evolving, decentralized collections of parts that collectively and dynamically solve adaptive challenges [8-11]. Cognitive economics shares the commitments of cognitive science to understanding systems at multiple levels of analysis and using a variety of theoretical and methodological approaches. As such, cognitive economics tends to be more eclectic and less prescriptive than its cousins. Although these approaches are complementary, they focus on different questions and sometimes reach different conclusions.

Intellectual Commitments of Cognitive Economics

Complex Adaptive Systems

A **complex adaptive system (CAS)** is a system which "involve[s] many components that adapt or learn as they interact" [11]. These coalitions of diverse components are organized across multiple levels "such that organization persists or grows over time without centralized control" [8]. Brains, immune systems, ant colonies, ecosystems, and economies are often given as examples. These are open systems, embedded in a broader environment, which is crucial for driving their evolution.

Table 1 divides the canonical properties of CASs into *structural properties*—related to how parts are organized relative to one another—and *behavioral properties*—related to the states and outputs of the system as a whole. Roughly speaking, the "complex" aspect of CASs refers to their structure and the "adaptive" aspect to their behavior.

Structurally, the components of CASs are diverse, specialized, and organized across multiple levels. For example, whereas the initial stages of visual processing are retinotopic (i.e., related to small receptive fields within the retina), subsequent stages draw on larger receptive fields but become more sensitive to features (e.g., vertical or horizontal orientation), and even later stages to more abstract properties such as objecthood [12]. These processes occur in parallel (e.g., different neurons detecting stimuli for different parts of the visual field) and in a distributed, bottom-up manner. Finally, these processes are regulated through feedback mechanisms: Even if the visual system itself delivers erroneous percepts, as in optical illusions, we are often able to learn through experience not to act on them. Both this representational perspective and its post-cognitivist alternatives [13-14], despite many differences, agree that minds are open systems that learn from interactions with their environments.

Behaviorally, CASs reciprocally co-evolve with their environments. This often involves recombining components in response to feedback. For example, genetic recombination allows new phenotypes to emerge, while cultural evolution occurs when ideas collide and recombine. Because they are reflexively adapting to a changing environment, CASs rarely reach a true "equilibrium" state; even when such an equilibrium could be theoretically identified, the system tends to move *toward* it. Whereas substances can transition from one equilibrium state to another as a parameter changes (e.g., a solid to a liquid as temperature rises), brains and societies are constantly in flux [15-16]. If oil became increasingly scarce or solar power increasingly abundant, this would surely lead to many social changes—but *not* to a steady-state. Overall, the interactions among a CAS's parts lead to behavior that is more than just the aggregation of individual parts but may be qualitatively different. People can think, but neurons do not. Economies allocate resources and discover prices, but investors and workers do not.

A key insight to which we repeatedly return is that markets and other collective cultural enterprises are CASs in which the fundamental units (individual minds) are *themselves* CASs. Minds and societies form a multi-level CAS [17] and therefore cannot be understood independently. Societies are *composed* of minds; so models of collective behavior must begin with lower-order assumptions about individual minds. But minds are *embedded* in societies; so the environment to which our minds are adapting is constantly changing. Each research program below is an effort to attack this problem.

Levels of Analysis

Many cognitive scientists are familiar with Marr's [18] levels of analysis—computational (the goal of the cognitive system), algorithmic (the representations and processes required to transform inputs into the desired outputs), and implementational (the neural substrate that implements those representations and processes). Marr hoped that cognitive scientists tackling a problem from multiple angles creates a cascade through these levels.

Without uniformly endorsing the details of Marr's view, cognitive economics too identifies the need to analyze the dual CAS of mind–society on multiple levels, but different levels are needed (**Figure 1**).

Like mainstream behavioral economics, cognitive economics recognizes the importance of *individual behavior*. Behavioral science is the "central social science," as behavior mediates the relationship between cognitive mechanisms and systems-level social processes; cognition that is not somehow manifested in behavior will not influence economic or other societal outcomes. Thus, questions of individual rationality and bias are certainly relevant to understanding both minds and markets, as reflected in the long history of work on this topic [19]. However, cognitive economists view the behavioral level as *necessary* but not *sufficient*.

Individual behavior is composed of a nest of subpersonal *cognitive processes* such as attention, perception, memory, emotion, and inference that lead to action. Cognitive science was born as a discipline when we came to recognize that behavior could not be explained using purely behavioral laws of reinforcement, but instead required deeper cognitive explanations. Some cognitive insights are certainly incorporated into behavioral economics, especially the idea of heuristics [19-20]; Kahneman and Tversky began their careers as cognitive psychologists and incorporated productive analogies between judgment and vision [19], while neuroeconomics has investigated the brain systems that implement some of the calculations studied by behavioral economists [7]. Yet, as behavioral economics has matured, it has developed its own largely autonomous set of theoretical practices, which we believe has largely shielded the field from more recent advances in cognitive science.

Individual behavior composes into the *systems* level through which dyads, groups, organizations, and societies interact. Here, we believe cognitive science has a great deal to learn from traditional economics, which focuses on how behavior can aggregate, often in unintuitive ways [21]. However, the models used by economists almost invariably assume self-interest and (unbounded) rationality. There are some exceptions to this, such as work in behavioral finance that attempts to understand how irrational market behavior could lead, in equilibrium, to observed patterns in market prices [22]. Yet, such models rarely are grounded in cognitive models but instead adopt the same maximizing framework as traditional models, while relaxing one or more assumptions.

Cognitive scientists have learned that conjoining their three levels of analysis (computational, algorithmic, and implementational) can be hugely fruitful, yet the number of unalloyed success stories is limited (perhaps low-level vision is still the best example [12]). The same is true, we believe for cognitive economics' three analytic levels (systems, behavioral, cognitive). There are many examples of research programs that provide insight across two levels, but only limited instances of successfully unifying all three (see [15]). Among the research programs we describe below, such a cascade can be uniformly said to be an aspiration, but rarely fully achieved to date.

Intellectual Pluralism

Cognitive economics, like cognitive science generally, is intellectually pluralistic. Psychology, neuroscience, philosophy, computer science, and anthropology are among the core disciplines on which it draws, all grappling in their own way with understanding how intelligence works. To this standard list, we would add economics, sociology, and political science—fields that examine the systems level and, at their best, attempt to bridge levels by understanding how emergent societal behavior is grounded in, while influencing, individual behavior. Economics in particular has embraced the idea that individual-level behavior can aggregate into higher-level patterns that were intended by no individual—"the result of human action, but not the execution of any human design" [23]—as when markets allocate resources through price discovery. Every discipline on both the original and extended list of cognitive sciences has contributed to the research programs we now turn toward describing.

Illustrative Research Programs in Cognitive Economics

Narratives

Economists have long distinguished between risk (choices where the probabilities of each option are quantifiable) and uncertainty (where probabilities cannot be enumerated) [24-25]. A situation may be uncertain because the potential outcomes cannot all be enumerated or because the underlying data-generating model is unknown or changing. Although many real-world situations—e.g., choosing a career, starting a business, selecting a life partner—resemble uncertainty rather than risk, standard models in both classical and behavioral economics reduce uncertainty to risk [26]. Is it possible to craft a theory of decision-making under uncertainty *without* probabilities?

One suite of alternative approaches posits *narratives* as core to decision-making [27-31]. For example, Shiller has argued that narratives circulating throughout the economy seem to influence economic activity [31], such as perennial narratives about greed causing inflation or automation causing unemployment. It appears that such narratives can create self-fulfilling prophecies or bubbles [31-33]. Whereas Shiller's economic analysis lives primarily at the behavioral level (narrative contagion) and systems level (self-fulfilling prophecies and bubbles), a fuller accounting of narratives would examine the mental representations and processes underpinning these behaviors.

One such account is Conviction Narrative Theory (CNT; **Box 1**) [27-28]. The key mental representation posited by CNT is the *narrative*—a structured mental model that coordinates causal, analogical, temporal, and valence information to make sense of a situation. CNT is a *sociocognitive* theory because it posits both cognitive processes—using narratives to explain evidence, simulate the future, and affectively evaluate that future—and social processes—communication of (fragments of) narratives to gain reputation and persuade.

Evidence for CNT is drawn from a variety of sources, including lab experiments, large-scale econometric data analyses, and interview studies of large-stakes financial decision-makers [34-39]. For example, one implication of CNT is that people typically *adopt* the most plausible narrative as a whole rather than assigning probabilities to different narratives. Prior work in category-based induction [40] had suggested that this was true for categorical thinking; i.e., if an object's categorization is ambiguous, people assume that the object belongs to one or the other category when predicting its properties, rather than taking a weighted average as prior models had assumed. However, recent work suggests that this property of cognition is far more general. When engaging in tasks such as causal explanation or economic decision-making, people act as though the single most likely narrative is true when using those narratives to make further predictions [34-35].

CNT has a range of implications. It challenges both classical and behavioral models in economics by eschewing probabilities in lieu of narratives and by rejecting a monolithic construct of 'utility', proposing it instead be analyzed in terms of its component emotions (a task which other work has begun to do [41-43]). Narrative thinking does not neatly fit into the dual-systems dichotomy of automatic versus effortful processes [44]: CNT's narrative construction and evaluation processes draw on a range of (seemingly-automatic) heuristics [45-49], yet the process of constructing and simulating narratives has the (seemingly-effortful) phenomenology of a sustained process. Finally, like earlier conceptions of narratives in economics [31], CNT suggests that the cultural propagation and evolution of narratives is crucial to both individual and societal decision-making, yet cannot be understood solely at the individual level. If future research can integrate models of individual-level narrative representations with societal-level models of narrative evolution [50] and its social consequences [31], such an endeavor could result in a graceful cascade from the cognitive to the behavioral to the systems level.

Cognitive Models of Emergent Collective Behavior

Traditional cognitive modeling tools—e.g., Bayesian inference, connectionist networks, production systems—have successfully formalized theories of individual cognition. However, these tools are not ideally suited for understanding cognition and behavior that transcends the individual and collective level of analysis.

The modeling tool of choice for collective behavior is the **agent-based model** (ABM), which has been used in economics, political science, sociology, ecology, and other fields that examine how collective phenomena emerge from individual-level behavior [51-52]. ABMs are simulations in which agents interact using a set of (often very simple) rules; the modeler then examines the (often surprising) collective phenomena that result. Well-known ABMs include Schelling's model of segregation (which showed how massive segregation can result from small individual preferences) [53] and Axelrod's prisoner dilemma tournaments (which demonstrated the benefits of tit-for-tat strategies) [54].

Traditional ABMs make simplistic assumptions about individual behavior that are not well-grounded in cognition. The costs and benefits of (over)simplification are not so different from rationality assumptions in mainstream economics; in both cases, this allows the modeler to clearly see what is driving the model's behavior and can result in more general explanations. At the same time, potential insight is left on the table since the emergent behavior might differ markedly with more realistic assumptions; moreover, some collective behaviors may be intrinsically linked to deeper-seated cognitive mechanisms. Thus, some recent ABMs introduce more plausible cognition within individual agents while balancing this against the need for simple and transparent models. Such models can be considered agent-based *cognitive* models.

For example, Social Sampling Theory (SST; **Box 2**) examines how cognitive and social dynamics affect the expression of attitudes [55]. SST draws on cognitive science theories, particularly decision by sampling [56] and relative rank theory [57], to underpin the dynamics *within* individual agents and implements agent-based models to understand the dynamics *between* agents. Although SST makes more complex assumptions about individual cognition compared to most ABMs, the payoff is significant. Within one framework, SST can explain why individuals sometimes *do* express their true attitudes despite social pressure (*backfire effects*), why and when attitudes become more extreme over time (*polarization*), why people with popular attitudes can nonetheless believe themselves in the minority (*pluralistic ignorance*), and more.

Recent years have seen increasing use of agent-based cognitive models, helping to understand the links between cognitive and social phenomena. For example, such models have been used to show how social groups can form even in the absence of shared identity [58], how individual memory processes give rise to collective memory phenomena [59], how environmental uncertainty can drive the evolution of social learning [60], and how social comparison and magnitude insensitivity explain voting patterns for income redistribution [61].

Markets as Extended Minds

Whereas the above approaches fit within traditional computationalist paradigms, one emerging framework draws instead on newer "postcognitivist" paradigms. These approaches, sometimes summarized as '4E cognition' [62], highlight that cognition does not occur only in the head: cognition is 'embodied' (occurring throughout our bodies [63]), 'enactive' (occurring through sensory and motor activity [64]), 'embedded' (occurring through interaction with physical and social environments [13,65]); and therefore is 'extended' (all of these cognitive activities collectively constitute the mind [66-67]). Such approaches are well-suited to understanding minds and markets as one extended CAS that transcends levels of analysis. The strong version of this view is the **Market Mind Hypothesis (MMH)** [3,17,68]: The two-pronged notion that economic activity constitutes a collective mind ("market-as-mind") and that mental activity comprises market-like forces ("mind-as-market").

Informally, investors have long spoken of a "market mind" over-and-above those of individual investors [69-71]. The MMH suggests that the market—embodying conscious humans and their technologies—intersubjectively extends investors' minds, warts and all. Economists have demonstrated how markets "know" things that no individual market participant knows [72], as when prices seamlessly adjust to allocate scarce resources according to supply and demand or when the division of labor permits intricate coordination to produce complex goods [73].

But just as the market's extended mind manifests distributed information, it also seems to manifest distributed consciousness [74-75]. Indeed, although the economist Frank Knight long ago concluded that consciousness itself is the foundation of economic behavior [76], it was difficult to seriously elaborate this idea until recent advances in the cognitive science of consciousness have made the mind–body problem itself more tractable [77]. The MMH argues that it is now time to tackle the *economic* mind–body problem. From a macroeconomic perspective, this consists of explaining how the (psychological) financial markets reflexively interact with the (physical) real economy. Or to put the point more generally, how do individually conscious minds collectively coordinate behavior?

To begin answering this question, MMH draws on **Coordination Dynamics (CD)** [78-82] (**Box 3**). Inspired originally by theories of pattern formation in open, nonequilibrium systems [83-85], CD uses the concepts of self-organization and the methods and tools of nonlinear dynamical systems to understand how coordination emerges from the informationally-based coupling between the many parts and processes of living things [15]. The individual elements can be anything from neurons in the brain, to limbs of a person, to persons in a group, or (in the case of MMH) to stocks, goods, and other assets in markets. Those exchanges that use or generate information are particularly important. A notable feature of CD is **reciprocal causality**: as patterns form and change at the collective level, the very components whose interaction creates them are modified in an evolving dynamic.

The information exchange between components of a complex system can be studied using dynamical models such as the Haken-Kelso-Bunz (HKB) model and its descendants [86]. The generalized HKB model [82], for example, shows how a broad range of coordinated behaviour arises from the nonlinear interaction among multiple elements [87-88]. At the level of the brain, such coordination may take the form of empirically observed rhythms or neuromarkers underlying social interaction [89-90]. The HKB model and its derivatives have been used to explain many different experimental findings, from the early studies of phase transitions in bimanual coordination on which it is based [91] and their neural correlates [92-93], to the sophisticated patterns of ballet [94]. As a framework that has been applied to coordination in many (human) complex systems, CD provides a common theoretical apparatus for understanding cognitive economics across levels of analysis. Among those relevant to minds and markets are rhythmic coordination, phase transitions, and fluctuations.

Rhythmic coordination refers to the coordination of movements that have a regular temporal structure. For example, think of the familiar experience of an audience clapping; sometimes, through no intention of any individual, the audience members synchronize so that the clapping is in unison [95-96]. The brain too is a 'geography of rhythms' tied to specific cognitive functions [97]. In the economic case, rhythms can include the seasonality of certain commodity prices and the co-movement of interest rates. These modes of coordination need not be fixed; instead, they may switch between several different possible **multistable** states [98], such as between a boom and a recession, consensus versus contrarian investing, growth-phase versus value-phase, or bear versus bull markets. Just as random clapping can give way to synchronized clapping without any individual intention, so can random market movements give way to a crash [96].

Phase transitions occur when a system undergoes a sudden change in behaviour due to a small change in a parameter crossing a critical threshold. These have been observed in a wide range of coordinated human behaviours, including dance and sports [94,99], as well as the human brain itself [100]. This suggests that the HKB-like models offer a potential framework for understanding herding of investors in markets. In the case of herding, as for so many phenomena in complex systems, the collective behavior cannot be deduced from aggregating the individual data because it is the *interaction* among the components that drives it. Perhaps the prototypical example of a phase transition in a financial market is that from one mood to another [101], which need not reflect the moods of individual investors. As the famed investor George Soros put it, "markets are not supposed to have moods . . . Yet they do" [102]. His philosophy of reflexivity is all about reciprocal causality in the economic system, as investors' beliefs and emotions impact the market, which in turn impacts those beliefs and emotions.

Fluctuations are changes to the level of an otherwise stable system component, like a neuromarker or a price, which (typically) either revert to the original stable pattern or (rarely) lead to a phase change. For example, although the profit margins of companies are constantly fluctuating, they normally revert to their long-term mean—but occasionally portend bankruptcy. CD does not view fluctuations as just noise or random variation, but as a fundamental source of variability crucial to coordination form and function. Fluctuations in the timing of movement patterns can serve as sources of information for the flexible coordination of behaviour between individuals, allowing them to adapt to changes in the environment and maintain stable patterns of interaction [88]. By continuously adjusting their informationally-based dynamics, coordinated systems can maintain **metastable** tendencies [15,103]: a subtle balance between stability and flexibility, allowing them to adapt to new challenges and opportunities. How this balance is struck depends on a wide range of factors, including the complexity of the task, the make-up of the individuals, and the strength of the coupling [104].

Overall, using CD as a framework to understand how markets can act as extended minds, yielding coordinated activity across multiple scales, may be a promising way forward for a "post-cognitive" cognitive economics that complements more traditional representationalist approaches within cognitive economics. To the extent that prior approaches can be criticized as populating the economic world with robots—optimal ones in the case of mainstream economics or irrational ones in the case of behavioral economics—a post-cognitive approach is better-suited to understanding the role of consciousness in economic and social activity. The distributed approach taken by CD and MMH may also be better-suited to understanding both minds and markets as self-organized systems without appeal to homunculi-like central executives or planners.

Concluding Remarks

The three approaches outlined above—narrative approaches that encompass the individual and social representations underlying decision-making; agent-based cognitive models that explain how collective behavior emerges from individual cognition; and post-cognitive approaches that use coordination dynamics to understand the extended mind–market system—all have in common a desire to conjoin cognitive, behavioral, and emergent social processes within the same framework.

Space prohibits us from detailed discussion of several other nascent approaches sharing a philosophical kinship. For example, **resource rationality** models [105-106] simultaneously demonstrate the rational basis of seemingly irrational behaviors (complementing **ecological rationality** approaches [20]) while formalizing the "mind-as-market" notion that minds must ration scarce cognitive resources. **Virtual bargaining** models [107-108] use the idea that in the absence of communication, people often act *as though* they had struck an explicit bargain, providing cognitive grounding for social behavior. **Belief-based utility** models [109-110] show how people have preferences over mental states, such as beliefs, which can themselves become objects of economic transactions like more traditional goods and services. Research on people's mental models of the economy has the potential to explain how (possibly erroneous) beliefs about social institutions such as markets can themselves influence how those institutions operate, for instance through feedback mechanisms such as politics [111-112].

These research agendas are ambitious, diverse, yet committed to the common enterprise of transcending levels of analysis to understand how collective social and economic behavior emerges from cognition. They organize the past of the field and suggest its future (see **Outstanding Questions**). We are optimistic that when this nascent field is next reviewed, space will be at even more of a premium as its new insights are recited.

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Declaration of Interests

The authors declare no competing interests.

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Glossary

- **cognitive economics:** A branch of cognitive science that examines economic cognition, behavior, and interactions as components of a complex system.
- **behavioral economics:** A branch of economics that examines economic decisions in terms of more psychologically plausible assumptions compared to traditional economics.
- **neuroeconomics:** A branch of neuroscience that identifies the neural mechanisms underlying the discoveries of behavioral economics.
- **complex adaptive system (CAS):** A collection of diverse, specialized, organized components that co-evolve with the environment.
- **mediation problem:** The decision-maker's task of transducing information from the environment into a format conducive to action (e.g., probabilities in classical decision theory).
- **combination problem:** The decision-maker's task of deducing, from their beliefs and desires, the appropriate action (e.g., the action that maximizes expected utility in classical decision theory).
- **agent-based model:** A simulation model in which a population of agents interact, such that the emergent behavior of the system can be studied.
- **Market Mind Hypothesis (MMH):** The two-pronged notion that economic activity constitutes a collective mind ("market-as-mind") and that mental activity comprises market-like forces ("mind-as-market").
- **Coordination Dynamics (CD):** A multiscale approach to understanding how the many parts and processes of living things are coordinated in space and time for specific functions and tasks.
- **multistability:** A feature of complex systems that expresses switching between multiple possible states rather than remaining in a single stable state.
- **reciprocal causality:** The causal pattern in complex, coordinated systems in which component-level behavior creates collective patterns, which in turn modify component-level behavior. Closely related to the notion of *reflexivity* from finance, in which investor psychology impacts markets, which impacts investor psychology.
- **rhythmic coordination:** An expression of order in time such as the coordination of movements with a regular temporal structure.
- **phase transitions**: Sudden changes in a system's behavior as a parameter crosses a critical threshold.
- **fluctuations:** Small deviations surrounding an otherwise stable state that may grow as a system approaches instability.
- **metastability:** In CD, the capacity of a complex system to express integrative (collective) and segregative (individual) tendencies at the same time.
- **resource rationality:** A form of rationality that trades off conservation of cognitive resources against other goals (e.g., accuracy). These models are often used to re-interpret cognitive biases as rational responses to limited cognitive resources.
- **ecological rationality:** A form of rationality that uses cognitive mechanisms (e.g., simple heuristics) that are effective in the environment to which they are adapted.
- **virtual bargaining:** A cognitively informed extension of game theory in which agents act as though they were able to communicate a binding agreement.
- **belief-based utility:** Approaches that assume that economic agents aim to maximize utility from cognitive states, rather than only tangible consumption.

Box 1: Conviction Narrative Theory.

Theories of decision-making must explain how people solve two distinct challenges. The **mediation problem** refers to the need for beliefs that can "mediate" between evidence obtained from the world (inference) and action taken on the world (preference) [27]. In classical decision theory, probabilities are simultaneously an *output* of inference (e.g., the chance that an individual, unidentified animal is from the category "tiger") and an *input* to preference (e.g., evaluating the desirability of running away). The **combination problem** refers to the need to combine beliefs and desires to decide among potential actions. In classical decision theory, decision-makers maximize their *expected* utility (combining the probabilities of outcomes with their utilities). Alternatives to this approach typically assume that probabilistic reasoning is flawed; e.g., prospect theory [113] replaces probabilities with "decision weights" that differ from the true probabilities. Conviction Narrative Theory (CNT) proposes an entirely different architecture in which reasoners eschew probabilities altogether.

According to CNT, a narrative is a structured representation of a situation that coordinates causal, analogical, temporal, and valence information in a unified mental model. Although CNT draws on recent advances in the cognitive science of causality [34,46-49], narratives are not *merely* causal models because they draw on a richer set of analogical associations to background knowledge that allows decision-makers to select, from among many possible causal relationships, those seen as most situationally relevant. Drawing on prior models of analogy and explanation [114-115], CNT posits several coherence principles that govern a narrative's plausibility.

CNT posits four processes. Narrative *explanation* involves selecting the most appropriate narrative or constructing a new one, based on three sources—available evidence, background knowledge, and socially-supplied narratives communicated by others. Narrative *simulation* involves 'running' that narrative forward to anticipate plausible futures given different choices. Narrative *evaluation* uses imagined affective responses to those futures to motivate approach or avoidance behaviors, i.e., choosing that future versus a different one. Finally, narrative *communication* involves sharing (fragments of) one's internal mental representation to others, which might in turn be taken up in others' representations and choices if the communication is persuasive [116].

Rather than probabilities, CNT proposes that *narratives* are the currency of thought, which mediates between inference and preference. Rather than maximizing expected utility, CNT proposes that *affective evaluation* of the imagined futures generated from those narratives are the means of combining beliefs and values. Thus, CNT's approach is distinct from both classical decision theory and more familiar behavioral alternatives.

Box 2: Social Sampling Theory.

Social Sampling Theory (SST) examines how an expressed attitude depends on both the individual's own intrinsic attitude and the attitudes expressed in their social environment [55].

SST models individual agents' cognition using four processes for which there is independent evidence. First, agents *draw on small samples* of the expressed attitudes in their social group in order to infer the distribution of other's attitudes (as well as one's own) [56]. Second and third, agents experience a negative emotional reaction both to expressing an attitude overly dissimilar from that in their social group (*extremeness aversion*) [117] and from their own intrinsic attitude (*authenticity preference*) [118]. Finally, agents do not compute extremeness and authenticity in terms of the central tendency of the distribution, but their *relative rank* within that distribution [57]. For example, if your neighbors vary widely across the political spectrum but the *average* is a center-right attitude, then it is less aversive to express a center-left attitude than if your neighbors *all* express center-right attitudes. This is because the relative rank of a center-left attitude within the more widely dispersed distribution is not very extreme, but the same attitude would have a very extreme rank compared to a tightly dispersed distribution.

SST can explain numerous phenomena, but we focus on polarization to illustrate how the model works. Agents are arranged in a spatial grid, endowed with a private attitude, and observe the expressed attitudes of their neighbors. At each time step, agents have the opportunity to move to a different, random location; they decide whether to do so based on which location maximizes utility. Since agents gain utility from authentically expressing their private attitude and disutility from expressing attitudes that are extreme relative to their neighbors, they will move to locations where their attitudes are less (locally) extreme. This leads to segregation: Expressed attitudes become more similar within neighborhoods over time. Crucially, it also leads to *polarization*—expressed attitudes become more *extreme* over time because agents are less prone to distort their private attitudes due to social pressure. This is a stylized demonstration of a widely applicable lesson: As people surround themselves with sources that agree more homogeneously with their privately held attitudes, they are more prone to express those attitudes in their most extreme form. Thus, even as the underlying distribution of attitudes within a society remains the same, the expression of those attitudes can become ever more extreme.

Box 3: Coordination Dynamics.

Coordination is fundamental to life. As a famous economist was fond of saying, think of the coordination necessary to bring your morning cup of tea from the foothills of the Himalayas to the kitchen table!

Coordination Dynamics (CD) examines how complex systems composed of many interacting elements can produce functionally relevant behavioral patterns that evolve on multiple timescales. The most elementary form of CD, the HKB model [86], has been extended in several ways to account for the variety of coordination phenomena. One extension concerns *symmetry breaking*, reflecting that a system's parts are typically *heterogeneous*, while another accommodates *many* interacting parts and processes.

A key concept of CD is the order parameter (OP) or collective variable. This is a number or function that physicists have used to characterize various forms of order in matter and phase transitions between them. HKB's use of order parameters to capture coordination states constituted a breakthrough in understanding coordination, spawning the entire field of CD. Why? Because the *order parameter dynamics* was shown to capture laboratory findings such as multiple states, transitions, and fluctuations in coordination. Key dynamical aspects of the OP concern stability, instability, multistability, and metastability. OPs carry *information* regarding the functional relation or coupling between the system's components.

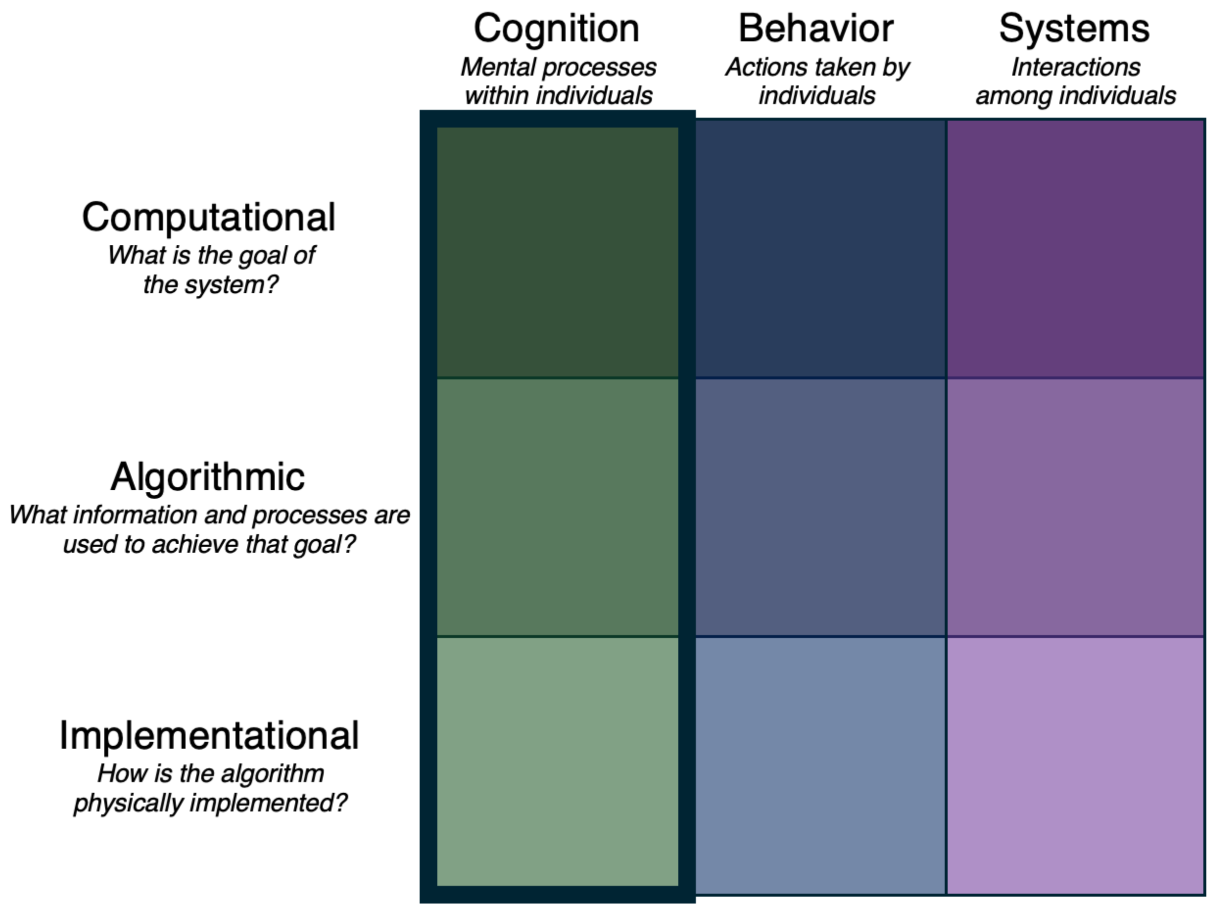
One key OP is the relative phase, ϕ, which is defined in the interval $[0,2\pi]$. This means that for CD, the OP can take on an infinite number of values, but due to *constraints*, e.g. of tasks and individual intentions [15], only a few values of the relative phase are multi- and metastable. The symmetry breaking that creates metastability allows coordinative systems never to get trapped or stuck in stable states but to flexibly switch between them, dwelling for variable times in one pattern of coordination before escaping to another. This resembles William James's metaphor of the stream of consciousness as the flight of a bird whose journey comprises 'perchings' (CD's phase gathering, integrative tendencies) and 'flights' (CD's phase scattering, segregative tendencies). In the human brain, both tendencies are crucial: the former to summon and create thoughts; the latter to release brain regions to participate in other acts of being, knowing, and doing [79].

In sum, understanding basic forms of coordination and the ways they can change represented a real step forward in bringing CD to many different fields, including economics and social neuroscience [119], thereby opening the door to new discoveries.

Outstanding Questions

- What is the best way to implement a cognitive model of narrative construction and simulation? For example, how do people rank the plausibility of narratives when heuristics lead to different conclusions, and how do people select which 'branch' of a plausible narrative to simulate when imagining the future?
- How do cognitive and social processes contribute to the cultural evolution of narratives?
- Are there general principles for identifying which cognitive mechanisms should be incorporated into an agent-based cognitive model and which can be safely abstracted?
- Social institutions—such as markets and governments—play powerful roles in economic and societal outcomes. To what extent do cognitive factors (e.g., mental models) versus social forces (e.g., incentives) govern their evolution, function, and demise?
- Can we use CD models to understand not just the similarities between minds and markets, but their *reflexivity* or reciprocal causation? For example, by measuring and time-stamping these patterns in data from both investors' minds and the market mind, might we find the economic equivalent of neural correlates?
- What is the best way to understand market mood and its relationship to individual cognition? To what extent can theories of cognition and affect in individual minds inform the economic mind-body problem?
- To what extent are insights from behavioral and neuroeconomics—e.g., about behavioral biases and irrationality—reconcilable with the complex systems framework of cognitive economics? Which behavioral biases are not reducible to ecological or resource rationality?
- A major outcome of behavioral economics has been its framework for "nudging" individual behavior, which has been both widely used and widely criticized. What might cognitive economics' equivalent prescriptive (or prophylactic) framework look like—if indeed it is possible?

Figure 1: Levels of analysis.



Note. Marr's traditional levels of analysis (computational, algorithmic, implementational) are listed vertically, whereas the levels of analysis of cognitive economics (cognition, behavior, systems) are listed horizontally. The dark black box around the green "cognition" level reflects that cognitive science has traditionally focused on mental processes within individuals, which has been criticized by enactive and extended cognition approaches that highlight the links between cognition and action (the behavioral level) and society (the systems level).

Table 1: Properties of complex adaptive systems (CASs) as applied to minds and markets.

Property	Description	Examples in Minds	Examples in Markets	
			Real Economy	**Financial Economy**
Structure				
Modularity	Units are diverse and specialized	Specialized neurons, mental processes, brain regions	Specialized firms, specialized workers	Specialized asset classes, specialized securities
Multi-level	Larger units contain smaller units	Neurons embedded within regions, embedded within circuits	Workers embedded within organizational units, embedded within firms	Securities belonging to an industry/sector
Parallelism	Tasks are subdivided and performed simultaneously	Parallel processing of sensory information	Division of labor	Diversification of portfolios
Distributed	Control is decentralized	No homunculus	No central planner	No central auctioneer
Feedback	System states are influenced by internal and external feedback loops	Reinforcement learning	Supply and demand	Price signals between real and financial economy
Behavior				
Adaptation	The system evolves in response to feedback	Individual learning, biological evolution	Price adjustments, cultural evolution	Price discovery, completion of markets
Anticipation	The system makes tacit predictions about future external states	Prediction error minimization	Inventory management	Derivatives, like futures
Recombination	Elements of the system form novel combinations	Neural plasticity, creativity	Innovation, technological change, mergers	Financial engineering, portfolio structuring
Nonequilibrium	The system might *tend* toward an equilibrium but rarely reaches it	Uncertainty, noise	Real economy inefficiencies and frictions	Financial market inefficiencies and frictions
Emergence	The system as a whole has properties that individual elements do not	Consciousness, high-level cognition	Efficient resource allocation, market failures, consumer sentiment, the "invisible hand"	Efficient capital allocation, market crashes, market mood

Note. Based on analyses and examples from [7-11, 14]. These properties are not intended to be exhaustive, nor does every CAS exhibit all of them. The division of properties into 'structural' and 'behavioral' is our own and admittedly somewhat artificial.