Trends in
Cognitive Sciences

CellPress

Review

Minds and markets as complex systems: an emerging approach to cognitive economics

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Cognitive economics is an emerging interdisciplinary field that uses the tools of cognitive science to study economic and social decision-making. Although most strains of cognitive economics share commitments to bridging levels of analysis (cognitive, behavioral, and systems) and embracing interdisciplinary approaches, we review a newer strand of cognitive economic thinking with a further commitment: conceptualizing minds and markets each as complex adaptive systems. We describe three ongoing research programs that strive toward these goals: (i) studying narratives as a cognitive and social representation used to guide decision-making; (ii) building cognitively informed agent-based models; and (iii) understanding markets as an extended mind – the Market Mind Hypothesis – analyzed using the concepts, methods, and tools of Coordination Dynamics.

Highlights

Cognitive economics uses cognitive science to understand economic decision-making.

We review research streams that conceptualize both minds and markets as complex adaptive 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 such as the Market Mind Hypothesis consider minds and markets to be one continuous complex system. Coordination Dynamics is one useful framework for analyzing this system.

Minds and markets as complex systems

Cognitive economics (see Glossary) is an interdisciplinary field that uses the tools of cognitive science to understand economic decision-making [1–5]. It recognizes the strengths and limitations of traditional approaches within both fields, using the insights of cognitive science to improve economics and vice versa. In this article, we highlight an emerging trend within cognitive economics, which we term ‘systems cognitive economics’. The central goal of this approach is to understand both minds and markets as complex systems – evolving, decentralized collections of parts that collectively and dynamically solve adaptive challenges [6–9]. Although this is not the only approach to cognitive economics, we focus on complexity-oriented strains in this overview because we believe these approaches are particularly promising for providing insights that transcend disciplines and levels of analysis, and which therefore exemplify the broader ethos of cognitive science.

Intellectual commitments of (systems) cognitive economics

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 [10–13]. Rather than taking economic theory as its starting point (often with an eye toward its flaws), cognitive economics instead takes the nature of the mind as its starting point. 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. Box 1 summarizes some historical and contemporary approaches within the field.

Cognitive economics shares two key commitments of cognitive science: (i) understanding mental activity at multiple levels of analysis; and (ii) using a variety of theoretical and methodological approaches. To this set of shared commitments, systems cognitive economics adds an additional commitment: (iii) viewing minds and markets as instances of complex systems.

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Box 1. Historical and contemporary approaches to cognitive economics

Cognitive economics dates back at least to Simon's [100] early explorations of **bounded rationality**, although economists such as Hayek [101], Knight [27,76], and arguably even Smith [21,102] had begun to incorporate ideas about cognition into economic analysis before cognitive science emerged as a discipline. For example, whereas neoclassical economics conceptualizes firms as unitary profit-maximizing entities, cognitive approaches to the firm recognized that firms are themselves composed of parts which do not necessarily share a single goal but process information in a decentralized manner [103,104]. Germane to our complexity-oriented approach, the idea of markets as complex systems has itself been highlighted in economics, although it has not yet achieved mainstream status [105].

The field has blossomed in many directions since those early advances. For example, Simon's notion of bounded rationality has been formalized in resource rationality accounts, which demonstrate how seemingly irrational behaviors can have a rational basis, such as economizing on cognitive resources [106–108] or implementing trade-offs among goals [109,110]. This work can also be seen as complementing **ecological rationality** approaches [15] that highlight the adaptiveness of decision-making strategies such as heuristics. As another example, **virtual bargaining** models [111,112] provide a more cognitively plausible alternative to game theory, using the idea that in the absence of communication, people often act as though they had struck an explicit bargain in order to ground social behavior in cognition. 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 [113–115]. **Belief-based utility** models [116,117] 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.

Much of the aforementioned work was initiated within psychology and neuroscience, but economists too have taken increasing notice of cognition in their models. Models of risk preferences and belief updating have benefited from increasingly sophisticated understanding of cognitive and neural mechanisms, particularly the role of imprecise or noisy representations [118–121]. Yet other streams of work provide fresh glimpses at classic questions, such as measuring universalistic moral beliefs to understand altruistic behavior [122], studying the structural properties of rules to quantify the cognitive complexity implicit in various decision-making procedures [123], and examining what role markets might play in weeding out biased beliefs [124].

Levels of analysis

Many cognitive scientists are familiar with Marr's [14] 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 physical, e.g. neural, substrate that implements those representations and processes). Marr hoped that cognitive scientists tackling a problem from multiple angles would create a cascade through these levels.

Although these levels of analysis may be useful for analyzing some cognitive systems, they lack descriptive power for understanding systems that include extensive interactions with other agents or with the environment. Thus, to these traditional levels of analysis, cognitive economics adds an orthogonal dimension of analysis (Figure 1) – the trichotomy of cognition, behavior, and systems.

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 [12]. However, cognitive economists generally 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 out of the recognition 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 [13,15]; Kahneman and

Glossary

Agent-based model: simulation model in which a population of agents interact, such that the emergent behavior of the system can be studied.
Behavioral economics: branch of economics that examines economic decisions in terms of more psychologically plausible assumptions compared to traditional economics.
Belief-based utility: approaches that assume that economic agents aim to maximize utility from cognitive states, rather than only tangible consumption.
Bounded rationality: form of rationality achievable given the cognitive and environmental limitations of human decision-makers.
Cognitive economics: interdisciplinary field that uses the tools of cognitive science to understand economic decision-making.
Combination problem: 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).
Complex adaptive system (CAS): collection of diverse, specialized, organized components that co-evolve with the environment.
Coordination Dynamics (CD): multiscale approach to understanding how the many parts and processes of living things are coordinated in space and time for specific functions and tasks.
Ecological rationality: form of rationality that uses cognitive mechanisms (e.g., simple heuristics) that are effective in the environment to which they are adapted.
Fluctuations: small deviations surrounding an otherwise stable state that may grow as a system approaches instability.
Market Mind Hypothesis (MMH): two-pronged notion that economic activity constitutes a collective mind (market-as-mind) and that mental activity comprises market-like forces (mind-as-market).
Mediation problem: decision-maker's task of transducing information from the environment into a format conducive to action (e.g., probabilities in classical decision theory).
Metastability: in CD, the capacity of a complex system to express integrative (collective) and segregative (individual) tendencies at the same time.

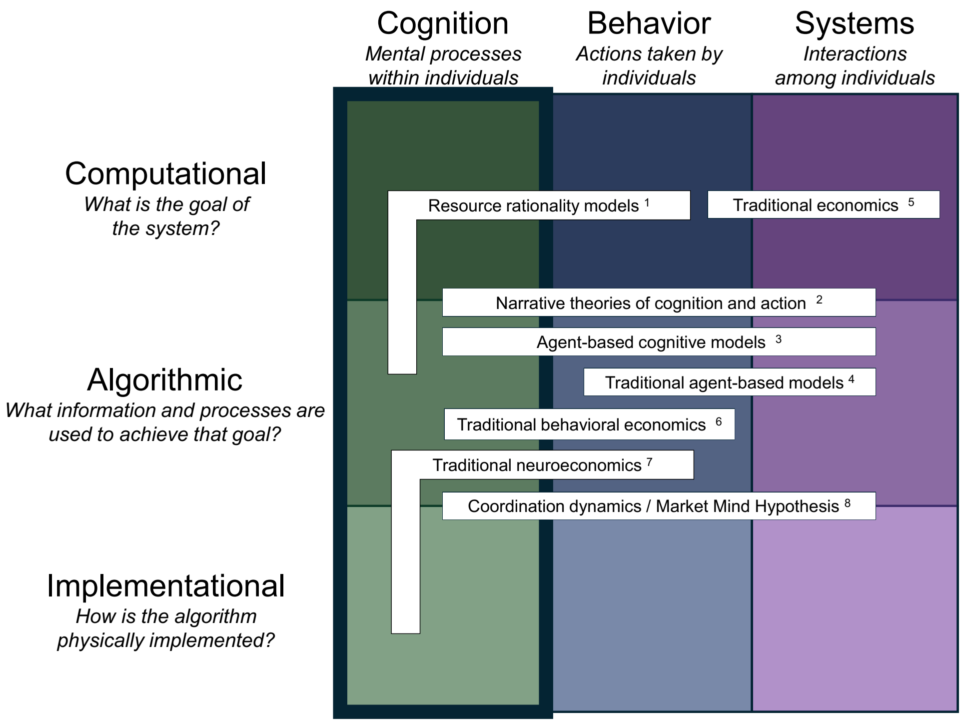

Figure 1. Levels of analysis and approaches to cognitive economics. Marr's traditional levels of analysis (computational, algorithmic, implementational) are listed vertically, whereas the levels of analysis added by cognitive economics (cognition, behavior, systems) are horizontal. The thick line around the green cognition level reflects that cognitive science has traditionally focused on mental processes within individuals, which has been criticized by postcognitive approaches that highlight the links between cognition and action (the behavioral level) and society (the systems level). Our positioning of specific approaches is intended as only a rough classification. [1]Resource rationality approaches attempt to explain cognitive algorithms in terms of organisms' higher-order goals such as efficient deployment of cognitive resources. These models often attempt to explain otherwise irrational behaviors. [2]Narrative theories [37] posit specific mental representations and processes (algorithmic level) that individuals use to solve the fundamental problems of decision-making under uncertainty (computational level). These representations (cognitive level) manifest in behavior and therefore become socially shared and subject to cultural evolution (systems level). [3,4]Traditional agent-based models focus on how simple assumptions about behavior scale up to emergent systems-level behavior. Agent-based cognitive models take a further step of grounding individual behavior in cognitive models. [5]Traditional economics examines how individual behavior (idealized as self-interested goal optimization) scales up to emergent systems-level outcomes. Policy-oriented economic analysis works backwards by specifying the desired systems-level goals and determining the incentives that would produce the individual behavior required to achieve that goal. [6,7]Behavioral economics traditionally focuses on individual (often irrational) behavior, sometimes with an eye toward how (often flawed) algorithms or representations produce that behavior. Neuroeconomics examines how those algorithms are implemented in the brain. [8]Coordination Dynamics examines the mathematical and neurological basis of information flow in coordinated systems, including the brain, body, and social relations. The Market Mind Hypothesis examines the relationship between individual human consciousness – including cognitive and affective states – and the collective consciousness of economic markets.

Tversky began their careers as cognitive psychologists and incorporated productive analogies between judgment and vision [12], while neuroeconomics has investigated the brain systems that implement some of the calculations studied by behavioral economists [10]. Yet, as behavioral economics has matured, it has developed its own largely autonomous set of theoretical practices, which we believe has shielded the field from some of the more recent advances in cognitive science.

Individual behavior composes the systems level through which dyads, groups, organizations, and societies interact. Here, we believe cognitive science can learn from traditional economics, which focuses on how behavior can aggregate, often in unintuitive ways [16]. However, the models

Multistability: feature of complex systems that expresses switching between multiple possible states rather than remaining in a single stable state.
Neuroeconomics: branch of neuroscience that identifies the neural mechanisms underlying the discoveries of behavioral economics.
Phase transitions: sudden changes in a system's behavior as a parameter crosses a critical threshold.
Reciprocal causality: 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.
Resource rationality: 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.
Rhythmic coordination: expression of order in time such as the coordination of movements with a regular temporal structure.
Virtual bargaining: cognitively informed extension of game theory in which agents act as though they were able to communicate a binding agreement.

used by economists usually assume (unbounded) rationality and self-interest. 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 [17]. Yet, such theories rarely are grounded in cognitive models but instead adopt the same maximizing framework as traditional economic 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 [18]). We believe the same is true for the three analytic levels of cognitive economics (systems, behavioral, and cognitive). There are many examples of research programs that provide insight across two levels, but only limited instances of successfully unifying all three [19]. Among the research programs we describe in the following sections, 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, as when markets allocate resources through price discovery [20,21]. Every discipline on both the original and extended list of cognitive sciences has contributed to the research programs we describe here.

Complex adaptive systems

A **complex adaptive system (CAS)** is a system "that involves many components that adapt or learn as they interact" [7]. These coalitions of diverse components are organized across multiple levels "such that organization persists or grows over time without centralized control" [6]. 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 [14]. 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 [22,23], despite many differences, agree that minds are open systems that learn from interactions with their environments.

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
Multilevel	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 (e.g., 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

Based on analyses and examples from [6–9,25]. 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.

Behaviorally, CASs reciprocally coevolve 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 rather than achieving 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 [19,24]. 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 the parts of a CAS 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. Markets use price signals to balance supply and demand, but individual consumers 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 multilevel CAS [25] and therefore cannot be understood independently. Societies are composed of minds; therefore, models of collective behavior must begin with lower-order assumptions about individual minds. However, minds are embedded in societies; therefore, the environment to which our minds are adapting is constantly changing. Each research program in the following section is an effort to attack this problem.

Approaches to complex systems in cognitive economics

In this section, we consider three extended examples of how to analyze the joint mind–economy system. One approach, largely continuous with traditional representationalist approaches in cognitive science, focuses on the role of narrative representations and processes in individual decision-making, along with ways that those narratives become socially shared. A second approach relies on simulation models to examine the emergent implications for social interaction of various possible assumptions about individual cognition. A final set of post-cognitivist approaches use the science of coordination to study the interactions among the many parts of the mind–economy system.

Narratives

Economists have long distinguished between risk (choices where the probabilities of each option are quantifiable) and uncertainty (where probabilities cannot be calculated) [26,27]. 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 – for example, 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 [28]. 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 [29–37]. For example, Shiller has argued that narratives circulating throughout the economy seem to influence economic activity [37], such as perennial narratives about greed causing inflation or automation causing unemployment. It appears that such narratives can create self-fulfilling prophecies or bubbles [37,38]. 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 2) [35,39]. 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 narratives or narrative fragments to gain reputation and persuade).

Evidence for CNT is drawn from a variety of sources, including laboratory experiments, large-scale econometric data analyses, and interview studies of large-stakes financial decision-makers [40–44]. 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 [45] had suggested that this was true for categorical thinking; that is, if the categorization of an object 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 certain when using those narratives to make further predictions [40,41].

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 [46–49]). Narrative thinking does not neatly fit into the dual-systems dichotomy of automatic versus effortful processes [50]. The narrative construction and evaluation processes of CNT draw on a range of (seemingly automatic) heuristics [51–54], yet the process of

Box 2. 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) [35]. 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 [125] replaces probabilities with decision weights that differ from the true probabilities. Conviction Narrative Theory (CNT) [35,39] proposes an entirely different architecture wherein 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 builds on recent advances in the cognitive science of causality [40,51–54], 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 [126,127], CNT posits several coherence principles that govern the plausibility of a narrative.

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; that is, 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 [128].

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, the approach of CNT is distinct from both classical decision theory and more familiar behavioral alternatives.

constructing and simulating narratives has the (seemingly effortful) phenomenology of a sustained process. Finally, like earlier conceptions of narratives in economics [37], CNT suggests that the cultural propagation and evolution of narratives is crucial to both individual and societal decision-making, but 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 [55] and its social consequences [37], 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, such as Bayesian inference, connectionist networks, and production systems, have successfully formalized theories of individual cognition. However, these tools are not ideally suited for understanding cognition and behavior that transcend 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 [56,57]. 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) [58] and Axelrod's prisoner dilemma tournaments (which demonstrated the benefits of tit-for-tat strategies) [59].

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 behavior of the model 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 3) examines how cognitive and social dynamics affect the expression of attitudes [60]. SST draws on cognitive science theories, particularly decision by sampling [61] and relative rank theory [62], 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 [63], how individual memory processes give rise to collective memory phenomena [64], how environmental uncertainty can drive the evolution of social learning [65], and how social comparison and magnitude insensitivity could explain voting patterns for income redistribution [66].

Markets as extended minds

Whereas the aforementioned approaches fit within traditional computationalist paradigms, one emerging framework draws instead on newer post-cognitivist paradigms. These approaches,

Box 3. 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 [60].

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 others' attitudes (as well as one's own) [61]. Second and third, agents experience a negative emotional reaction both to expressing an attitude overly dissimilar from that in their social group (extremeness aversion) [129] and from their own intrinsic attitude (authenticity preference) [130]. Finally, agents do not compute extremeness and authenticity in terms of the central tendency of the distribution, but their relative rank within that distribution [62]. 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.

sometimes summarized as 4E cognition [22,23,67–70], propose that cognition does not occur only in the head: cognition is embodied (occurring throughout our bodies); enactive (occurring through sensory and motor activity); embedded (occurring through interaction with physical and social environments); and therefore, extended (all of these cognitive activities collectively constitute the mind). 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)** [3,25,71]: 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 [72,73]. 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 [20], 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 [21].

However, just as the extended mind of the market manifests distributed information, the MMH suggests that it manifests distributed consciousness [74,75]. A century ago, the economist Frank Knight argued that consciousness itself is the foundation of economic behavior [76], but it was difficult to seriously elaborate this idea at the time given the primitive scientific understanding of consciousness. Arguably, however, more recent advances in the cognitive science of consciousness have made the mind–body problem itself more tractable [77]. The MMH therefore proposes 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)** [78–81] (Box 4). Inspired originally by theories of pattern formation in open, nonequilibrium systems [24,82], 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 [19]. 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 [83]. The generalized HKB model [81], for example, shows how a broad range of coordinated behavior arises from the nonlinear interaction among multiple elements [84]. At the level of the brain, such coordination may take the form of empirically observed rhythms or neuromarkers underlying social interaction [85,86]. The HKB model and its derivatives have been used to explain many different experimental findings, from early studies of bimanual coordination and its neural correlates [87–89] to the sophisticated patterns of ballet [90]. 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.

Box 4. 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 [83], has been extended in several ways to account for the variety of coordination phenomena. One extension concerns symmetry breaking, reflecting that the parts of a system 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 were 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 components of the system.

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, for example, of tasks and individual intentions [19], 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' metaphor of the stream of consciousness as the flight of a bird whose journey comprises perchings (phase gathering and integrative tendencies of CD) and flights (phase scattering and segregative tendencies of CD). 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 summary, 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 [80], thereby opening the door to new discoveries.

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 [91]. The brain too is a 'geography of rhythms' tied to specific cognitive functions [92]. In the economic case, rhythms can include the seasonality of certain commodity prices and the comovement of interest rates. These modes of coordination need not be fixed; instead, they may switch between several different possible **multistable** states [93], 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 [91].

Phase transitions occur when a system undergoes a sudden change in behavior due to a small change in a parameter crossing a critical threshold. These have been observed in a wide range of coordinated human behaviors, including dance and sports [90,94], as well as the human brain itself [95]. 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 [96], 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' [97]. 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 become bankrupt. 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 behavior between individuals, allowing them to adapt to changes in the environment and maintain stable patterns of interaction [84]. By continuously adjusting their informationally based dynamics, coordinated systems can maintain **metastable** tendencies [19,98]: 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 [99].

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. 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 in the preceding text – 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. These research agendas are ambitious and diverse, yet committed to the common enterprise of transcending levels of analysis to understand how collective social and economic behavior emerges from cognition. They exemplify the past of systems cognitive economics and suggest its future (see Outstanding questions).

Although we have focused on three approaches that share a clear commitment to minds and markets as complex systems, it is reasonable to ask whether systems cognitive economics is a truly distinct approach, or whether instead this view is implicit in many other research agendas within cognitive economics. On the one hand, we do not wish to put words in the mouths of other cognitive economists, who may not subscribe to every tenet of the complexity-oriented approach. For example, **resource rationality** models (Box 1) are paradigmatic examples of cognitive economics (using economic notions such as scarcity and trade-offs to analyze individual decisions, such as the allocation of effort) but generally make no attempt to analyze the systems level of interacting agents.

However, there is perhaps a case to be made that the enterprise of cognitive economics, taken as a whole, is intrinsically committed to a complexity-oriented approach. For example, cognitive science broadly is committed to multidisciplinarity, but not every cognitive scientist uses every method (or even more than one); similarly, cognitive scientists agree that the brain is crucial to mental activity, yet cognitive models often do not focus on the implementational level. Perhaps the same is true for complexity. From a few basic and seemingly uncontroversial notions – that markets are composed of minds, yet minds are embedded in markets; that both minds and

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 causality? 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 – for example, about behavioral biases and irrationality – reconcilable with systems 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 the equivalent prescriptive (or prophylactic) framework systems cognitive economics look like, if indeed it is possible?

markets evolve with adaptive pressures – it seems implicit that minds and markets comprise a continuous system. Perhaps this is the case whether the analysis relies on tools traditional to cognitive science (as in narrative theories), to complexity science (as in agent-based models), to post-cognitivist approaches (as in coordination dynamics), or others we cannot yet imagine.

Acknowledgments

SGBJ is supported by grants from Canada's Natural Sciences and Engineering Research Council (NSERC) and Social Sciences and Humanities Research Council (SSHRC). PRS is supported by the Didasko Educational Charity. JASK is supported by The FAU Foundation (Eminent Scholar in Science).

Declaration of interests

The authors declare no competing interests.

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