Center for Research in Economics, Management and the Arts

Behavioural Economics, What Have we Missed? Exploring "Classical" Behavioural Economics Roots in AI, Cognitive Psychology, and Complexity Theory

Working Paper No. 2021-21

CREMA Südstrasse 11 CH - 8008 Zürich www.crema-research.ch

Behavioural Economics, What Have we Missed?

Exploring "Classical" Behavioural Economics Roots in AI, Cognitive Psychology, and Complexity Theory

Steve J. Bickley[1,2] and Benno Torgler[1,2,3*]

Affiliations: [1]School of Economics and Finance, Queensland University of Technology, 2 George St, Brisbane QLD 4000, Australia
[2]Centre for Behavioural Economics, Society and Technology (BEST), 2 George St, Brisbane QLD 4000, Australia
[3] CREMA – Centre for Research in Economics, Management, and the Arts, Südstrasse 11, CH-8008 Zürich, Switzerland

Contribution prepared for the forthcoming book: Morris Altman (Ed.) (2022). *Handbook of Research Methods and Applications on Behavioural Economics*. Edward Elgar

Abstract: In this chapter, we ask (conceptually and methodologically) what exactly is behavioural economics and what are its roots? And further, what may we have missed along the way? We argue that revisiting "classical" behavioural economics concepts and methods will benefit the wider behavioural economics program by questioning its yardstick approach to 'Olympian' rationality and optimisation and in doing so, exploring the 'how' and 'why' of economic behaviours (micro, meso, and macro) in greater detail and clarity. We also do the same for fields which share similar ontological and epistemological roots with "classical" behavioural economics. In particular, cognitive psychology, complexity theory, and artificial intelligence. By engaging in debate and investing thought into multiple layers of the ontology-epistemology-methodology, we look to engage in 'deeper' (and potentially more profound) scientific discussions. We also explore the utility and implications of mixed methods in behavioural economics research, policy, and practice.

Keywords: Behavioural Economics, Cognitive Psychology, Complexity Theory, Artificial Intelligence

* For helpful comments and suggestions thanks are due to Alison Macintyre.

We associate the 'foundational' elements of a science with its ontology and epistemology—i.e., its conception of the make-up of its subject matter and its theory of what constitutes scientific knowledge (and relatedly, what is required to establish that a statement is proper scientific knowledge), respectively. The 'higher level' we associate with a science's methodology—i.e., its means of pursuing that knowledge.

Spiegler and Milberg (2014, p. 315).

1 Introduction

Behavioural economics (BE) "tries to explain (and ultimately, to apply these findings into practice) why individuals frequently make [*seemingly*] irrational choices, and why and how their behaviour does not match the patterns predicted by neoclassical models" (Diacon, Donici & Maha, 2013, p. 29). While BE's value in explaining individual behaviours is clear, it is less clear whether and how it contributes to any greater understanding of the associated social phenomena that may emerge (Heap, 2013):

> Quite a few economists identify themselves as behavioural economists these days. Although they share common characteristics, they do behavioural economics (BE) in significantly different ways. Many of them would be hard pressed to articulate exactly what it is that makes them behavioural economists (Tomer, 2007, p. 463).

So, in this chapter we ask (conceptually and methodologically) what exactly is BE and what are its roots? And further, what may we have missed along the way?

Kao and Velupillai (2015) make the clear distinction between modern behavioural economics (MBE) and classical behavioural economics (CBE): distinguished by their methodological, epistemological, and philosophical approaches, norms, and ideals. Sent (2004) made a somewhat similar observation, referring to CBE and MBE as "old" and "new" BE, respectively. MBE remains largely within the orthodox neoclassical framework of 'optimisation under constraints', attempting to improve the realism of its mathematical modelling by "providing it with more realistic psychological foundations" (Camerer and Loewenstein, 2004, p. 1) and hence, is to some degree 'stuck' within the concepts and methods typical of neoclassical economics. In contrast, CBE questions whether BE should break free entirely from the incumbent neoclassical paradigm, questioning both its ontology (i.e., the complex and interconnected nature of dynamics networks of historically- and context-defined agents as opposed to representative agents in idealised, axiomatic worlds) and epistemology (i.e., algorithmic, adaptive, rationally bounded agents as opposed to those which demonstrate 'Olympian rationality and optimisation' (see Simon (1983,1990), within some perfectly-specified task environment). Ultimately, MBE is the dominant (and lasting) form of BE evident in the literature today and

> [t]he transition period ended in favour of efforts to strengthen mainstream economics by taking rationality as the yardstick as opposed to ones to develop an alternative squarely based on bounded rationality" (Sent, 2004, p.747).

We argue that revisiting CBE concepts and methods will benefit the wider BE research program by questioning its yardstick approach to 'Olympian' rationality and optimisation and in doing so, exploring the 'how' and 'why' of economic behaviours (micro, meso and macro) in greater detail and clarity. We will then do the same for fields which share similar ontological and epistemological roots with CBE and BE more generally. In particular, cognitive psychology, complexity theory, and artificial intelligence (AI). By revisiting CBE (and related fields) we look to engage in 'deeper' (and potentially more profound) scientific discussions of ontological and epistemological importance (Spiegler & Milberg, 2014), as opposed to the seemingly more method-focused contributions of MBE. Although the latter are undoubtedly important in their own right, they may not allow BE to live up to its full potential in improving the predictive power of contextualised and boundedly rational economics. To compare and guide the combination of methods typical of each field, we present a conceptual framework we call 'CMM' (constrained methods matrix), extending the impact and relevance of Minsky's (1992) causal diversity matrix (CDM) to BE and the social sciences more generally by incorporating measures of informational complexity and uncertainty. Behavioural economists and social scientists can use CMM to guide their selection of tools and methods of investigation with respect to the *problem faced* (i.e., number of potential causal factors and the scale of their effects), the c*omplexity* (i.e., volume, variety, and velocity – 3 of the 4 V's of Big Data) and *uncertainty* (i.e., information is partial or not representative, not fully reliable, and/or inherently imprecise and/or there is conflicting evidence (Bhatnagar and Kanal, 1986) – i.e., veracity, the last of the 4 V's of Big Data) of the information, data, and knowledge available at hand to solve the problem. Together – with both concepts *and* methods – we argue this will overcome the current awkward phase in which BE finds itself (somewhat neoclassical, somewhat behavioural) and enable a more contextualised and boundedly rational economics with greater predictive power and real-world relevance.

In the next section, we introduce and detail the common ground between concepts in MBE and CBE, as well as the major departures between the two streams of BE. We then extend this exploration to the fields of cognitive psychology, complexity theory, and AI in Sections 2.2, 2.3, and 2.4, respectively. In Sections 3.1 to 3.4 we do the same for methods as opposed to concepts, leveraging the aforementioned CMM methods framework (see Figure 3 in Section 3) as a guiding hand. In Sections 4.1 and 4.2 we identify future research directions for concepts and methods (respectively) which we deem as promising research avenues for the continued advancement of BE towards real-world relevance and practicality. In particular, we discuss cognitive models, micro, meso, and macro foundations, and Big Data for concepts and neuroscience, agent-based models (ABM), and AI for methods. We then provide concluding remarks to summarise our primary theses; we as a discipline (BE) must look back *and* side-to-side for insights and methods from other research paradigms, practice academic bravery and resilience, and widen the scope of BE policy and practice by learning to compare and combine a more diverse suite of conceptual foundations and methodological toolkits.

2 Concepts

Methods can become somewhat of a means to an end, heavily influenced by the deeper levels that define key aspects of research investigations: *Which phenomena are worthwhile to study? What can be (practically) measured? What assumptions can we make? What defines successful scientific knowledge generation?* Whilst we do not suggest that methods are defined wholly and completely by the deeper levels of scientific knowledge, we recognise the influence of conceptual thinking on the creation and adaptation of methods to test (confirm or reject) more 'foundational' scientific speculations and hence, explore which concepts BE may embrace from CBE and its related fields. Doing so will provide context to the methods explored in Section 3.

2.1 CBE and MBE

Kao and Velupillai (2015, p. 247) stress that:

> One of the most essential and concrete line separating MBE and CBE is that rational behaviour is adaptive or procedural in CBE; this makes rational behaviour naturally algorithmic and the need to underpin it with a model of computation enters right on the ground floor of theory and its empirical counterparts. Given the nature of adaptive behaviour and the complex environment in which it takes place, optimisation principles and equilibrium analysis become meaningless and nearly infeasible.

CBE takes the view of agents and institutions as information processing systems (Simon, 1979), underpinned by algorithmic and computational resources and procedures, and engaging with complex decision problems. Under this lens, agents and institutions receive information from their (local) surrounding environment as inputs to internal decision-making processes and procedures, which they modify and adapt to suit the specific needs of the current context (i.e., task environment). CBE, in contrast to MBE, assumes no underlying preference order (utility curve) and postulates that agent decision-making, at any level and against any institutional setting, is subject to bounded rationality and emulates satisficing behaviours. CBE also focuses on the behaviour of agents and institutions in disequilibrium or non-equilibrium situations, as opposed to focusing on behaviours in or near equilibrium (a special case of collective economic behaviour) as is the case with MBE; which, in doing so, "accepts mathematical analysis of (uncountably) infinite events or iterations, infinite horizon optimisation problems and probabilities defined over s-algebras and arbitrary measure spaces" whereas, "CBE only exemplifies cases which contain finitely large search spaces and constrained by finite-time horizon" (Kao and Velupillai, 2015, p. 240). Adaptive and satisficing economic behaviour seems natural (and intuitive) within ever evolving, time-space constrained, and history-dependent (socio)economic systems where turbulence – due to both endogenous *and* exogenous activity and events – keeps the system in a non-equilibrium or disequilibrium state. Hence, it justifies the requirement for agents to constantly assess and re-assess the performance and efficiency of their decision-making heuristics and behaviours; or in other words, to think about their thinking and adjust themselves accordingly. Lo (2017) offers fruitful insights in the area of financial markets, using the idea of adaptive agents[1] who are boundedly rational and therefore make suboptimal decisions, but also learn from past experience and revise their heuristics via negative feedback. Lo uses the term "approximately rational" (p. 188) as individuals adapt to their environment. Maladaption, for example, emerges when heuristics are taken out of the environmental context in which they emerged. Lo also criticized the resistance to applying common sense, such as when bounded rationality is rejected for a long time:

[1] Scholars such as Vernon Smith and Gerd Gigerenzer built their arguments around adaptability, survival, and ecological rationality. They clashed with the more static perspective of a reference frame paradigm around the work of Amos Tversky and Daniel Kahneman (see, Smith, 1989; 2005; Gigerenzer 2004; Kahneman and Tversky, 1996; Gigerenzer, 1996). For a discussion, see also Lewis (2017) and Torgler (2021a). Eric Wanner attempted to assemble a working group on experimental economics at the Russell Sage Foundation, including Vernon Smith or Charles Plott together with Kahneman or associates; however, it did not work out due to such fundamental different theoretical interests (Heukelom, 2014). For more details, see also later discussion.

> A little- known fact about the economics profession is that economists (including me) suffer from a psychological condition best described as "physics envy." Physicists can explain 99 percent of all observable physical phenomena using Newton's three laws of motion. Economists wish we had three laws capable of explaining 99 percent of all observable behavior in our professional purview. Instead, we probably have ninety- nine laws that explain 3 percent of all economic behavior, and it's a source of terrible frustration for us. So we sometimes cloak our ideas in the trappings of physics. We make axioms from which we derive seemingly mathematically rigorous universal economic principles, carefully calibrated simulations, and the very occasional empirical test of those theories. However, several physicists have pointed out to me that if economists genuinely envied them, they'd place much greater emphasis on empirical verification of theoretical predictions, and show much less attachment to theories rejected by the data, neither of which seems to characterize our profession. In fact, I believe we suffer from a much more serious affliction: theory envy (p. 209).

Essentially, CBE focuses on "discovering the empirical laws that describe behaviour correctly and as accurately as possible" (Sent, 2004, p. 742), as opposed to focusing only on empirical laws that satisfy mathematical axioms and strong assumptions for optimising behaviours. Under a framework of bounded rationality and satisficing, agents and institutions are only able to make use of information which is readily accessible to them (information that is often inherently incomplete and approximate, see e.g., McCarthy (2000) for further discussion) and only to the extent that their available cognitive and computational resources enable. In other words, one cannot make use of information which is not made available either by perception on the part of the individual or deception by others, and one is not able to perform computations which require greater computational resources than those presently available or for which one has the capacity to employ. Intelligent decision makers (whether human, animal, or artificial) are dealing with computationally complex problems and hence, navigating through 'deep', complex, and less-structured search spaces; often making use of heuristics (i.e., decision rules) and performing satisficing behaviours (e.g., "close enough is good enough" behaviour) to reduce complexity and achieve something which is at least satisfactory to their needs, wants, desires, or goals (Simon, 1996a). Their behaviours may turn out to be some best approximate of the optimising behaviours exhibited by 'Olympian' rationalists in certain situations and contexts, but more often than not, they do not reach such 'Olympian' status. This 'deeper' interpretation or understanding of bounded rationality (as opposed to the MBE interpretation which stops at the boundedly rational decision-making capabilities of computationally constrained agents) necessitates and encourages an accurate and computational approximation of both the agent *and* the environment to which they contribute, shape, and adapt in order to become algorithmically implementable.

2.2 Cognitive Psychology

In building a more accurate picture of the *individual* in economics, cognitive psychology takes the view of humans as *information processing systems* (Simon, 1979), similar to CBE. Sternberg and Sternberg (2016) define cognitive psychology as the "study of how people perceive, learn, remember, and think about information (…) [and relatedly,] learn, structure, store, and use knowledge." This makes possible the algorithmic representation of decision-making procedures and processes that are used when agents face complex (socio)economic problems" (pp. 3-16). Herb Simon (1996b) points out in his autobiography *Models of My Life* that his most important years of life as a scientist were 1955 and 1956. In the last months of 1955, he focused his attention and efforts to the psychology of human problem solving – or to the more precise – to discovering the symbolic processes that humans use in thinking:

> Henceforth, I studied these processes in the psychological laboratory and wrote my theories in the peculiar formal languages that are used to program computers. Soon I was transformed professionally into a cognitive psychologist and computer scientist, almost abandoning my earlier professional identity" (p. 189)

Simon, together with Al Newell (whom he first met in 1952 at RAND), and Cliff Shaw (who was an outstanding systems programmer) saw the use of the computer as a general processor for symbols and therefore, thoughts. They invented list-processing languages to create the Logic Theorist (LT), which was the first computer program able to solve non-numerical problems via selective search, therefore pioneering AI. Herb Simon and Allen Newell presented their Logic Theorist at the 1956 symposium on information theory at MIT, a moment George Miller described as the birthday of cognitive science, as well as his own rejection of behavioralism and cognitive awakening (Gazzaniga, Ivry and Mangun, 2019; Hunt, 2007). In his autobiography, Herb Simon (1996b) stresses that:

> I have always celebrated December 15, 1955, as the birthday of heuristic problem solving by computer, the moment when we knew how to demonstrate that a computer could use heuristic search methods to find solutions to difficult problems. According to Ed Feigenbaum, who was a graduate student in a course I was then teaching in GSIA, I reacted to this achievement by walking into class and announcing, "Over the Christmas holiday, Al Newell and I invented a thinking machine." (If, indeed, I did say that, I should have included Cliff Shaw among the inventors.) Of course, LT wasn't running on the computer yet, but we knew precisely how to write the program (p. 206).

George Miller recollects his thoughts after a sabbatical year at the Center for Advanced study in the Behavioral Sciences at Palo Alto:

> I realized I was acutely unhappy with the narrow conception of psychology that defined the Harvard department. I had just spent a year romping wildly in the sunshine. The prospect of going back to a world bounded at one end by psychophysics and at the other by operant conditioning was simply intolerable. I decided that either Harvard would have to let me create something resembling the interactive excitement of the Stanford Center or else I was going to leave (Hunt 2007, p. 591).

Miller therefore set out to build a new centre devoted to the study of mental processes; in collaboration with Jerome Bruner, he established the Harvard Center for Cognitive Studies[2] (Hunt, 2007) which has had an important influence in the history of Behavioural Economics (Heukelom, 2014). Daniel Kahneman and Herb Simon were both part of this interdisciplinary centre. Eric Wanner did his PhD thesis under Miller, and Roger Brown. Wanner who started his career as an assistant professor at Harvard had a big impact on getting behavioural economists organised as a field or research. When Wanner moved to the Sloan Foundation in 1984, he created the Behavioural Economics program (under the presidency of Albert Rees):

> Wanner proposed a new plan on the application of cognitive science to economics. The new plan gradually sharpened during 1982 and 1983. In early 1983, Wanner mentioned as "a possible area for investment" for the Sloan Foundation the theme of "what might be called the psychological foundations of economic behavior (Heukelom, 2014, p. 152).

After Wanner was appointment president of the Russell Sage Foundation in 1986, a joint program with the Sloan Foundation emerged. The Behavioural Economics Program consumed a large portion of the annual spending at Russell Sage (in 1987 up to almost 50 percent) (Heukelom, 2014); however, after Rees retired, the Sloan Foundation stopped supporting the

[2] For a detailed discussion on what Cohen-Cole termed "instituting the science of mind" with Harvard's Center for Cognitive Studies, see Cohen-Cole (2007).

program and in 1992 the board of Russell Sage tried to end the program, succeeding in the summer of 1992. However, a Behavioural Economics Roundtable survived with an annual endowment of $100,000 (Heukelom, 2014).

Computer science had the largest impact on cognitive psychology relative to other influences such as neuroscience or the study of language (Hunt, 2007). Newell, Simon, and Shaw's General Problem Sover (GPS) (1959) was a program developed around the agenda of understanding information processing and human problem solving (for a detailed discussion, see Torgler, 2021b) and brought "a metamorphosis in cognitive psychology by giving psychologists a more detailed and workable conception of mental processes than any they had previously had, plus a practical way to investigate them" (Hunt, 2007, p. 595). For Simon, the importance of the computer was comparable to the microscope for biology: "It provided a way to set up experiments in such a manner as to test constructs which had been formulated for psychological processes in a sharp and unequivocal manner" (Crosson 1992, p. 440).

Decision problems – particularly those which are vague, uncertain, ambiguous, and ill-structured – characterise much of everyday human and (socio)economic decision making. Owing to this complexity, humans (limited in their ability to optimise 'rationally') can instead satisfice and use decision rules based on the often incomplete and approximate information currently available to guide their efforts and help them achieve their goals. Indeed, in facing such complex decision problems "…deductive means are of limited value due to undecidabilities and unsolvabilities, [so] agents consciously resort to non-deductive means for solving decision problems" (Al-Suwailem, 2011, p. 485) and as such, humans often rely on heuristics (e.g., decision rules, rules of thumb) and biases to reduce cognitive load and effort and achieve (subjectively) satisfactory outcomes. Many such heuristics and biases have been identified in the BE, psychology, and social science literature (Benartzi & Thaler, 2007; Gilovich et al., 2002; Tversky & Kahneman, 1974). Simon (1996b) recollects in his autobiography that:

> The dissertation contains the foundation and much of the superstructure of the theory of bounded rationality that has been my lodestar for nearly fifty years. The idea had its origins in the Milwaukee recreation study, was reinforced by what I had discovered about the boundary conditions of rationality in the California tax incidence study, and was not contradicted by any of the management or other human experiences I had had in my six working years, or in the years that preceded them (p. 86).

Moreover, when referring to his book *Administrative Behavior* he points out:

> Now the idea of bounded rationality, which appears to be the most novel and original component of the work, is not specifically an organizational concept. It applies as fully to individual decision making as to organizational decision making. By the age of twenty-five, I had already had ample experiences in life to understand the limits of the economists' framework of maximizing subjective expected utility as applied to actual human behavior. The scantiness of my experiences with organizations posed no particular limit to my development of an alternative approach to decision making (p. 87).

Under the humans as *information processing systems* framework, it is important to understand how humans perceive and make sense of approximate concepts (McCarthy, 2000) and also ill-structured problems. It is also important to understand how humans generate, represent, accumulate, and adapt their knowledge from experience, learning, culture, and genetics alike. Minsky (1988) derived the idea of a K-line to explore agent learning and knowledge generation, representation, adaptation, and evolution. A K-line is a snapshot of a mental state (or sequence of mental states) that when later activated will put you into a similar state and hence, can be used to guide decision making and behaviours. For example, suppose that:

> [y]ou want to repair a bicycle. Before you start, smear your hands with red paint. Then every tool you need to use will end up with red marks on it. When you're done, just remember that red means 'good for fixing bicycles.' Next time you fix a bicycle, you can save time by taking out all the red-marked tools in advance. If you use different colors for different jobs, some tools will end up marked with several colors. That is, each agent can become attached to many different K-lines. Later, when there's a job to do, just activate the proper K-line for that kind of job, and all the tools used in the past for similar jobs will automatically become available" (suggestion by Kenneth Haase who was a student of Minsky – Minsky (1988), p. 82).

This concept of a K-line could be used to help model and understand knowledge acquisition, accumulation, storage, retrieval, and adaptation in human, animal, and artificial agents alike and equally, in networks (societies) of agents. For example, when an agent successfully solves a complex decision problem, a new K-line could be initiated and its relation to other K-lines established. When facing the same (or a similar problem), the new K-line can be activated and hence, emotions and mental processes similar to those activated during the initial problem-solving event can be aroused to help guide the search for a suitable solution in the current problem. In doing so, we ask crucial questions such as: *how was the problem solved previously? what were the failed attempts and why did they fail? how should a similar failure be avoided in the future?* When faced with a novel decision problem, similarities and differences to problems faced previously can be identified and their associated K-lines activated (and adapted) for use in light of the current problem and task environment. In a sense, we engage counterfactual thinking (Costello & McCarthy, 1999) in exploring the various *what ifs* and learn from these non-experiences when performing in the current problem environment. In other words, we can explore situations that we do not actually experience and hence, in some sense we may simulate these experiences whether we do this consciously[3] or not. The malleability (i.e., adaptivity) of individual K-lines – in other words, their *elaboration tolerance* (McCarthy, 1998) – determines the ability to incorporate new experiences, knowledge, and information into existing knowledge structures and cognitive frameworks which may simultaneously operate (or self-organize) on more than one (hierarchical) level of cognition.

This – we would say – is a slightly more ambitious (and comprehensive) programme in comparison to Kahneman's (2011) "thinking fast and slow" with only two levels (i.e., the fast system 1 and the slow system 2). Such "dumbbell" mentalities can be a useful nicety (simplification) for empirical analyses but can lead to false analogies and constrained thinking (Minsky, 1988). With only two systems we aggregate all kinds of "slow" thinking together as one; as if to say that planning, optimisation, and resourcefulness are of the same nature and dynamics and hence, worthy of the same categorisation. For example, Sloman (2001) presents H-Cogaff, a three-level architecture which supports simultaneous, interdependent, adaptive reactive, deliberative, and reflective processes and thinking. This allows two levels of 'system 2' thinking; one which thinks about issues and problems at hand, and one that performs meta-cognition (i.e., thinking about thinking), but Sloman does not reject the idea of more levels of cognition. Minsky's (2007) *Emotion Machine* offers another such multi-level (6 levels) cognitive architecture, including instinctive, learned, deliberative, reflective, self-reflective, and self-conscious processes and thinking, further unravelling the full gamut of potential human (and animal) cognition, and leaving room for future discoveries and breakthroughs via

[3] We would like to express some caution in our interpretation of 'conscious'. Here, we mean whether we are aware of performing such counterfactual thinking and mental simulation/extrapolation or whether such thinking (to at least some extent) is performed 'behind the scenes' and hence, we are not aware of it.

a flexible, multi-level framework[4]. Whilst originating in the AI field, these conceptual frameworks can provide useful ways to think about cognition in human, animal, and artificial agents alike. Surprisingly, there has been some reluctancy among cognitive psychologists to invest more efforts into such multi-level frameworks or unified theories of cognition as suggested by Newell in his 1987 William James Lectures at Harvard University (Newell 1994). Psychology gravitates towards small and easily testable micro-theories (for a discussion see Bach 2009, p. 7). The work on cognitive architectures was driven by understanding cognition through construction and designing:

> [K]nowing how to design something like X is a requirement for understanding how X works... Of course doing explicit design is consistent with leaving some of the details of the design to be generated by learning or adaptive processes or evolutionary computations, just as evolution in some cases pre-programs almost all the behavioural capabilities (precocial species) and in others leaves significant amounts to be acquired during development (altricial species). In the altricial case, what is needed is higher-order design of bootstrapping mechanisms (Sloman and Chrisley 2005, pp. 153-154).

Newell (1994) also points out:

> That the human has a cognitive architecture is tantamount to there actually being a mechanics of the mind. In principle, it should be possible to follow the actual trajectory of the mind as it zigs and zags its way through the forests of facts that cover the hillsides of a specific task. We all understand that the mind and the situations it inhabits are so complex and inaccessible that actually computing such a trajectory will seldom be possible. The temptation is all too easy to view cognitive theory as but a convenient sort of abstract fiction—useful to compute some molar phenomena, but not able to track the molecular zigs and zags… But human cognition, though undoubtedly nonlinear, is also shaped strongly to adapt behavior to attain the person's goals. A sufficiently developed theory of cognition should be able to follow a person's intendedly rational moves, if enough is known of the task environment and the person's goals and knowledge (pp. 367-368).

2.3 Complexity Theory

Complexity theory is a collection of concepts and methods used to identify, characterise, analyse, and manage[5] complex systems; studying emergent and adaptive agent behaviours in such systems and settings defined by time-space and historical-time constraints and characteristics. Complex systems are themselves made up of a large number of interacting parts which interact in non-simple and complex ways (Simon, 1962); furthermore, they are typically dissipative, open structures (Foster, 2005) that exchange energy and information with their surrounding environment. The emergent phenomena and behaviours of such systems which evolve over time are often highly unpredictable from observation of the constituent parts alone. As summarised nicely by Gomes and Gubareva (2020):

> Complexity emerges because of the heterogeneous nature of agents. Agents are not alike; they differ in their preferences, endowments, expectations, hierarchical position, degree of connectivity, and ability to engage in successful interactions, among other features. Furthermore, as the interaction takes place, agents learn, adapt, and mutate, leading to a systematic and never-ending evolutionary process where both the individual agents and the whole socioeconomic structure are subject to constant and perpetual change. Out-of-

[4] For a discussion on the importance of cognitive architectures for economics see Torgler (2021b).

[5] Manage, in our use here, is the use of 'control' measures (e.g., policy interventions, regulation, stimulus packages, and incentive schemes) to keep complex systems within desirable or specified bounds.

> equilibrium dynamics are the rule and not the exception. […] The behaviour of humans coevolve with the environment; cooperation and competition, the formation and dissolution of alliances, the establishment of new relations and loss of others, introduce systematic changes in the intended goals and in the strategies followed to attain them. The changing nature of agents in a complex system preserves the micro-diversity and generates emergent phenomena that fuels the evolutionary dynamics of the ecosystem as a whole. Stability is not an inherent characteristic of the economy or any of its constituent parts; on the contrary, [socio]economic ecosystems are unstable, evolutionary and complex (p.3).

Human systems (e.g., social, industrial, economic, cultural, or artificial) often involve a large number of heterogenous (e.g., varied preferences, follow different rules and with varying levels of ability and opportunity) human agents who act and react almost simultaneously (i.e., in real time) and may be spread across varied geographical proximities when they do so. Such systems often exhibit complexity as they behave qualitatively different from the random Brownian motion assumed in conventional econometric theories (Mandelbrot & Hudson, 2004). Human systems often exhibit complex behaviours such as non-linearity, sharp discontinuities, and highly unpredictable collective properties which are not attributable merely to the aggregate sum of individual agents' behaviour (Holling, 2001). Thus, the complexity approach in economics is essential to enable greater realism in theory and modelling and to shed light on the intra- and inter-systemic causal relations between variables which help fuel the self-organisation, non-linearity and endogenous feedback mechanisms evident in most 'real world' data of complex human systems (Choudhury, 2013)[6].

Most complex systems, whether human, natural, or artificial, are dynamic and hierarchical in structure with each level serving two functions: to conserve and stabilise conditions for faster and smaller levels, and to generate and test novelty/innovations and survival/optimisation strategies (Simon, 2001). Prigogine (1980) observed that each level of a hierarchical system operates on a different spatio-temporal scale and constantly evolves in function and form over time. Rather than a reference to top-down authoritative control, hierarchical in the sense conveyed here refers to semi-autonomous and interacting levels (subsystems and agents) which communicate a small set of local information or resource constraints to the next higher (slower and coarser) level in the system. The formation of hierarchical structures is not uncommon in human social and societal systems: individuals form groups, groups form organisations and markets that make up cities, societies, nations, and global sub-regions (Helbing, 2009). Such hierarchical structures exhibit near decomposability meaning approximately independent short-run behaviours of individual agents and long-run dependence of individual agents' behaviour on collective behaviours (Simon, 1962).

Ceddia et al. (2013), drawing on Ulanowicz (1997), generalise such hierarchical systems by approximating to three nested levels of hierarchy, each of which operate on a comparatively different but related spatio-temporal scale, with feedback loops as depicted in Figure 1. Although, there is no specific limit as to the configuration of feedback and feedforward loops between hierarchical levels and contextual information often enters the stage at every level as depicted by the red and blue dotted lines, respectively. The focal level is the level of focus for the main phenomena of interest by the research team (e.g., monthly indicators of economic growth of a certain local government county). The upper level corresponds to the level immediately 'above' the focal level (e.g., the state or nation in which the local government county resides) in which the system and focal level is embedded and reflects the macro influences on focal level dynamics. The lower level corresponds to the level immediately

[6] For a discussion of complexity in psychology with a focus on the theory of nonlinear dynamical systems see the edited volume by Guastello, Koopmans, and Pincus (2009).

‘below’ the focal level (e.g., the decision-making processes of households, businesses, individuals, and institutions which co-exist and interact within the local government county) containing the constituent parts or components of the focal level.

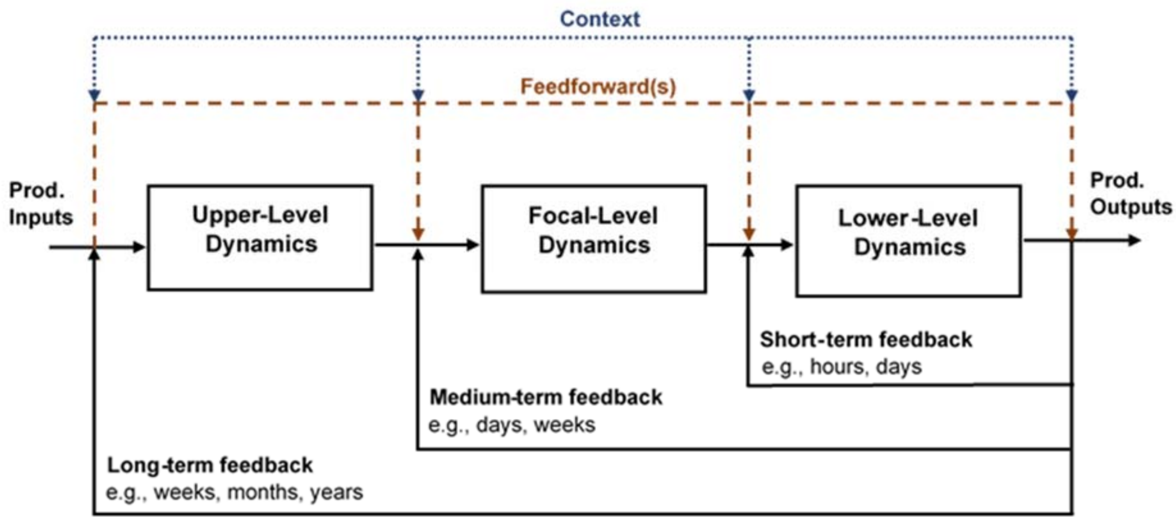

Figure 1: Nested feedback loops of a hierarchical system composed of three levels: the upper level, the focal level, and the lower level.

As Simon (1962) states, for “most systems in nature, it is somewhat arbitrary as to where we leave off the partitioning, and what subsystems we take as elementary” (p. 468). Thus, the model depicted in Figure 1 provides a flexible conceptual framework for the modelling of complex human socioeconomic systems which can be adapted for micro-, meso-, *and* macro-economic analyses. Coupled with a varied and wide analytical toolkit, complexity theory can redefine how evolutionary and adaptive economics processes and procedures rise and fall over time-space constrained, historically dependent contexts and environments. Fascinating opportunities are available for behavioural economists to think about how such a perspective feeds back in the public policy area and policy solutions in general. Colander and Kupers (2014) provide wonderful insights with respect to a complexity policy frame that creates government solutions allowing an eco-structure conducive to giving people the institutional space to self-organize in ways that solve social problems. Complexity does not mean that the social system becomes unpredictable and uncontrollable; we simply need the proper concepts, methods, and building blocks to better explore complexity. Behavioural economics can contribute to the derivation of such solutions, as they will require a good understanding of how people make choices, and how people influence each other in the decision-making process.

2.4 Artificial Intelligence

> “The quest for artificial intelligence (AI) begins with dreams – as all quests do. People have long imagined machines with human abilities – automata that move and devices that reason.” (p. 19) (Nilsson, 2009)

Not all approaches in AI are created (or dreamed) equal, nor do they focus on the same aspects or measures of intelligence, as demonstrated by the varied design of intelligent agents. Indeed the road to ‘true’ AI has been long, winding, and bumpy, and our final destination still remains out of reach. Russell and Norvig (2010) identify and cluster the four main approaches to AI:

thinking humanely, *thinking rationally*, *acting humanely*, and *acting rationally*. As depicted in Figure 2 below, these clusters are defined by their focus (thought processes/procedures or observable behavioural phenomenon) and measure of humanness (rationally bounded and human-like or "Olympian" rationality). Such clusters have led to a vast and varied literature.

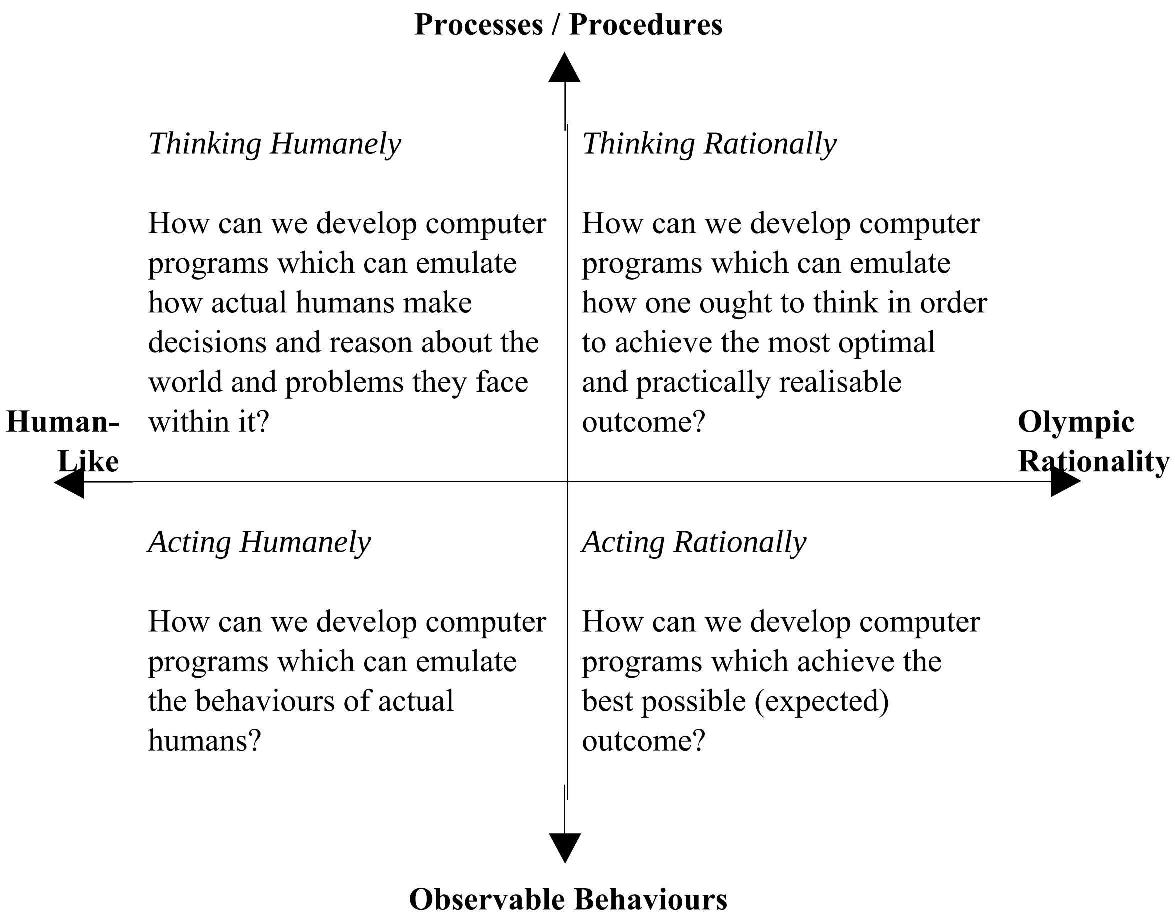

Figure 2: Approaches to Artificial Intelligence Studies

For the most part, the rational-agent or *Acting Rationally* approach has dominated AI research owing to its generality and mathematical foundations. In particular, AI methods such as machine learning (ML) and deep learning (DL) – iterative methods of learning based on probability theory and statistics – have helped humans achieve great engineering feats, even under circumstances where there remain large uncertainties in current states, observations, and future predictions. These approaches, classed 'narrow' AI, are typically domain- and problem-specific and hence, lack the breadth of knowledge and adaptability to new situations that is expected of 'true' or general AI systems (Baum et al., 2011; Goertzel & Pennachin, 2007); particularly when operating in complex decision environments where perfect rationality (i.e., perfect knowledge of the problem space, unlimited cognitive capabilities, and hence consistency in observed behaviours) is likely to be infeasible. In the long run, these 'narrow' approaches to AI will need to be replaced with more realistic models which can operate within the realms of pre-defined (user-specified) objective functions without requiring that these functions be completely and correctly specified (i.e., can deal with uncertainty) (Russell & Norvig, 2010). A mixed and integrated approach to the various AI methods (i.e., Ways of

Thinking) may prove to be what is needed to advance AI technologies to human-level (Minsky, 1992).

The procedural-behavioural and rational-descriptive debates in AI are somewhat akin to debates in CBE and MBE. The former looks to "describe[s] behaviour correctly and as accurately as possible" (Sent, 2004, p. 742) and does not shy away from the unobservability of mental procedures and processes. Hence, CBE aligns more closely to the human-centred approaches to AI. MBE, in contrast, takes 'Olympian' rationality as basis from which to measure the efficacy of decision making and hence, appeals to the 'narrow' AI approaches mentioned previously. Some have argued (Beal & Winston, 2009; McCarthy, 2007; Minsky, 2007; Nilsson, 1995) that a return to the original aims and goals of 'classical' AI – being the understanding, modelling, and replication of human mental processes, decision making, and reasoning – will be what ultimately catapults the field of AI towards human-level AI and in doing so, meet the high expectations of industry, government, and the general public alike. Along the same line of thinking, a mutual enrichment of knowledge, concepts, and methods between AI and behavioural economics will be of great benefit to both fields. For example, those theoretical cognitive architectures mentioned towards the end of Section 3.2, or Riecken's (1994) practically realised 'M' software assistant: an architecture of integrated agents where "many different reasoning processes, societies of agents, are integrated in order to realize a software assistant capable of performing a broad range of tasks" (p. 107). Such applied and theoretical cognitive architectures could breathe new life into the 'micro' of behavioural economics *and* the study of the individual, their interactions with others, and their networks, institutions, and systems more generally.

3 Methods

Referencing AI and cognitive modelling specifically, but no less applicable to the methodological challenges (quarrels) faced in economics, behavioural economics, and the other social sciences alike, Sloman (2008) notes:

> The first difficulty arises because rival researchers argue about whose algorithm, architecture or form of representation is best, instead of studying the structure of the space of alternatives and the trade-offs involving those options. There usually is no 'best' alternative. (p. 4)

As our econometric and statistical methods have become stronger (and equally our focus on specialising and mastering these methods), we tend to lose sight of the bigger picture and on the alternative methods available for solving real world problems. Rather than celebrating and welcoming diversity of approach and process, silos of accepted methods begin to form in academic fields wherein norms support the incumbent approach – and perhaps if lucky, the gradual incorporation of alternative (yet often similar) methods into practice. Bach (2009) points out a field's credibility

> may be due to their focus on an area that allows a homogenous methodology and thus, the growth and establishment of scientific routines, communities, and rules of advancement. But this strictness comes at a price: the individual fields tend to diverge, not just in the content that they capture, but also in the ways they produce and compare results. Thus, it not only becomes difficult to bridge the terminological gaps and methodological differences in order to gain an integrative understanding of an individual phenomenon – the results from different disciplines might completely resist attempts at translation beyond a shallow and superficial level (pp. 7-8).

Rather than engage in this never-ending debate on which methods, representations, or algorithms may be "best", Minsky (1992) offers what we think is a very powerful (and intuitive) conceptual tool to encourage diversity in AI problem-solving methods: the causal diversity matrix (CDM). The CDM captures nicely the diversity in approaches required to reach human-level AI, arguing that to attain *true* "expert" status, AI systems of the future will need versality in their Ways to Think as "no single method works well for all problems" and "different kinds of problems need different kinds of reasoning" (Minsky, 1992, p. 1). Given the current (and narrow) method-focused contributions of MBE, we see that a conceptual framework such as the CDM could provide the impetus (and starting point) for behavioural economists (and social scientists more generally) to look beyond what is mainstream and common practice, and to engage more deeply with a wider suite of concepts, tools, methods, representations, and algorithms than currently available within the bounds of MBE. Similar calls have been made for methodological diversity with the idea of triangulation (Ramsay, 1998) or parallel non-equivalent descriptions (Giampietro and Mayumi, 2000) and mixed methods more generally (Cronin, 2016), providing further support for the use of such a visual tool in the CDM methods matrix. We believe this will help lift us out of our current methods rut and hurl us towards a deeper understanding of human behaviour that we so desperately need in (socio)economic policy and practice.

Here we extend Minsky's (1992) CDM by incorporating measures of informational complexity (i.e., volume, variety, and velocity) and uncertainty (i.e., veracity), as we can only solve a problem with the data (i.e., stimuli with no meaning and perhaps not yet registered), information (i.e., interpreted data) and knowledge (i.e., learned information incorporated into the agent's current and future reasoning resources)[7] that we currently have available (see Figure 3). This includes information from both our own previous experiences and existing knowledge, and also the data and information we can extract from our environment and the specific task at hand. Hence, we propose to name this matrix the Constrained Methods Matrix (CMM) owing to the restricted nature of the rationally bounded agents that we are and the boundedly rational environments in which we are embedded. The CMM can guide one's choice of method and in particular, for the problems (often 'wicked') faced by behavioural economists (and social scientists more generally) which we believe require a more diverse approach than we have currently seen within the literature. We also believe that CMM can make more tractable those problems which were previously intractable, by way of manipulating informational uncertainty and complexity. For example, we may significantly increase the volume and variety of data available in the current problem-solving environment to increase informational complexity and move us toward methods like analogy-based reasoning, fuzzy logic, and neural networks. It is important to remember that the matrix partitions are not hard lines and hence, the overlap of methods (similarity across method classes) is not uncommon.

In the following subsections we use the CMM to situate each of CBE, MBE, cognitive psychology, complexity theory, and AI with respect to the typical methods of choice employed by the researchers in each (sub-)field. We by no means suggest that these are the only methods employed in these fields; however, we see the value in this exercise comes from looking outside standard practice. By typifying (albeit somewhat crudely) each field, we can then begin to contrast and compare them in a more structured way. For each method, once we commit to the method *and* to the way it should be used, we can make predictions that can be scientifically tested on the basis of assumptions (and hypotheses) embedded within the specific method. We can then go on to seek out differences, synergies, combinations, and transformations between the insights offered by each method and hence, approach the same problem or phenomena from

[7] See Aamodt and Nygard (1995) for an AI perspective on data, information, and knowledge, and Boisot and Canals (2004) for an (evolutionary) economics perspective.

multiple perspectives. Whenever a problem presents difficulties, we can "start to switch among different *Ways to Think*—by selecting different sets of resources that can help you to divide the problem into smaller parts, or find suggestive analogies, or retrieve solutions from memories—or even ask some other person for help" (Minsky, 2007, p. 4). This concept of multiple *Ways of Think* can equip BE (and social science) researchers, practitioners, and proponents with the tools and mindset to approach a problem from many perspectives and hence, gain some deeper appreciation for the mechanisms, relationships, and context at play.

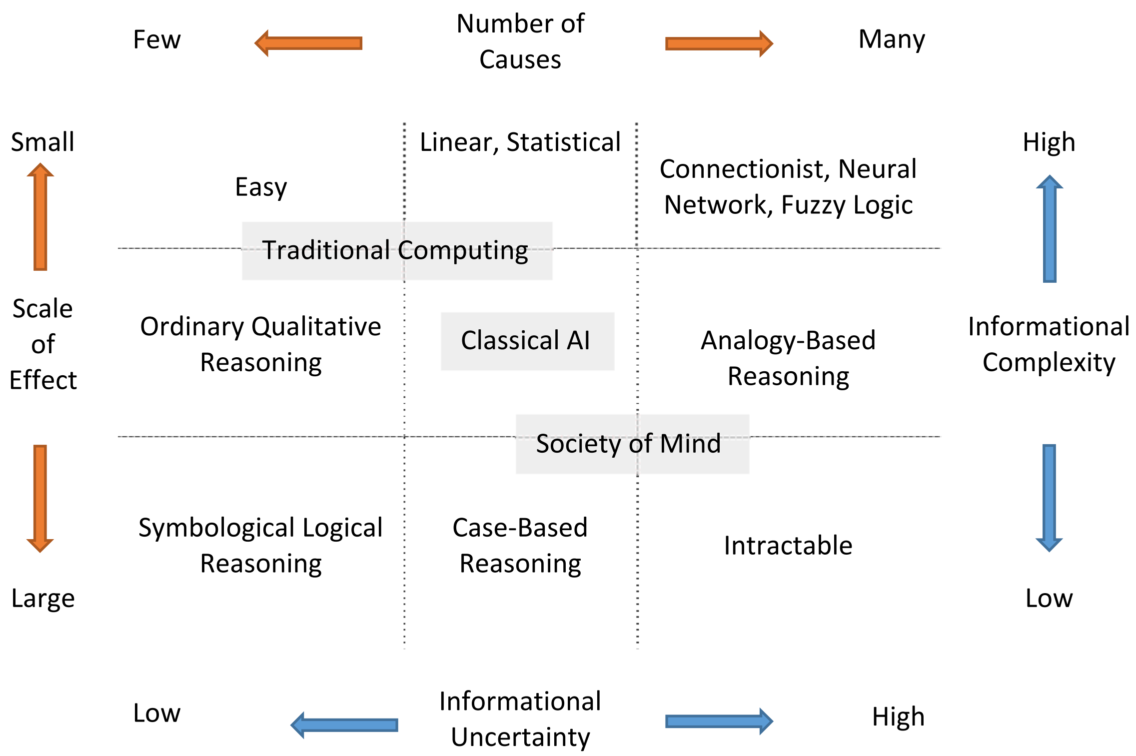

Figure 3: The Constrained Methods Matrix (CMM)

3.1 CBE and MBE

Kao and Velupillai (2015 p. 249) stress that:

> MBE is fostered by Orthodox Economic Theory, Game Theory, Mathematical Finance Theory and Recursive Methods, Experimental Economics and Neuroeconomics, Computational Economics and Subjective Probability Theory. CBE [… on the other hand,] is based fundamentally on a model of computation – hence, Computable Economics – computational complexity theory, nonlinear dynamics and algorithmic probability theory."

By and large, behavioural economists in general "draw on evidence of many kinds and are comfortable using different methods to generate such evidence" (Angner and Loewenstein, 2007, p. 688), suggesting that behavioural economists may be somewhat comfortable with CMM to begin with. However, MBE (and economics in general) has generally tended towards the heavy use of mathematical axioms, formal logic, and statistical methods for prediction and modelling, and are increasingly turning to/accepting of neural network AI methods (hybrid or not) such as ML and DL, algorithms capable of self-learning from large stores of structured and unstructured data. CBE on the other hand, is interested in evolution and the processes of becoming and structural change, and hence suits more the use of "softer" empirical approaches, using narratives to describe events with specific attention to context (spatial and temporal), particularly in situations where the behaviours and systems in question are complex and mostly unpredictable (Ramos-Martin, 2003). Hence, CBE perches itself more towards the middle-left of CMM. However, its major proponents did not shy away from venturing across its fuzzy methodological boundary lines, retaining a flexible approach to problem solving. Whilst there is nothing wrong with either positioning, some mutual enrichment may breathe new life into otherwise spice-less (or spice-low) fields of research.

Narratives "focus on a qualitative/quantitative understanding which describes:

- the human context for the narrative; the hierarchical nature of the system;
- the attractors which may be accessible to the system;
- the hierarchical nature of the system;
- the attractors which may be accessible to the system;
- how the system behaves in the neighbourhood of each attractor, potentially in terms of a quantitative simulation model;
- the positive and negative feedbacks and autocatalytic loops and associated gradients which organize the system about an attractor;
- what might enable and disable these loops and hence might promote or discourage the system from being in the neighbourhood of an attractor; and
- what might be likely to precipitate flips between attractors." (Kay et al., 1999, pp. 728-729)

Hence, narratives can inform policymakers and the community "about:

- possible future states of organization of the system;
- understanding of conditions under which these states might occur;
- understanding of the trade-offs which the different states represent;
- appropriate schemes for ensuring the ability to adapt to different situations;
- and perhaps most importantly, the appropriate level of confidence that the narrative deserves; that is our degree of uncertainty." (Kay et al., 1999, p. 728-729)

BE (and economics in general) tends to still focus on statistical aggregation of behaviours (individual, firms, organizations), albeit with improved psychological foundations. However, what we are missing is specific focus on the outliers (e.g., entrepreneurs, innovators) (Schwartz, 2019) which typically fall outside or are omitted from the 'average' populations of interest. In other words, those that violate the three typical "degrees of deviation" from perfect rationality observed in real humans (Rabin, 1998): sensitive to reference levels, loss aversion, and other-regarding preferences; naïve inference/extrapolation and confirmation bias; and framing effects, preference reversals, and unclear self-goals and preferences. More importantly, we are missing the individual 'micro' in our micro-economic foundations, especially when then aggregating up to the macro level, owing in part to the complexity of non-linear and dynamic systems. Such studies could extend on the work by Schelling (2006) on how the behavioural characteristics of individuals lead to social aggregates and shape the characteristics of their aggregates also. The computational foundations of CBE lend themselves nicely to this gap and it is popular to use ABM to implement such (see Section 4.2.2 for a more detailed discussion of ABM). Individuals (and their differences – outliers and all) can be algorithmically implemented and hence, their behaviours, interactions, and self-organising structures can be examined with greater clarity. We can then choose whether to aggregate individual behaviours for macro-analyses or to home in on individual (sub)populations for more targeted analyses. Heterogeneity can be modelled much better in an ABM framework compared to mathematical models that rely mostly on a limited number of different types. For example, when Shiller (1984) explored stock prices and social dynamics, he relied only on two types: smart-money investors and ordinary investors who are faced with uncertainty and act as noise-traders, which means that the estimated value is based at least in part on noise; therefore, decisions are too optimistic or too pessimistic. Stuart Kauffman (2016) shows that we cannot mathematize much of economic life or the evolution of the economy. Together with narratives, the computational modelling of CBE can be equipped by behavioural economists (and social scientists more generally) to improve the tractability and real-world applicability of their models and forecasts, and at the same time, ease the barriers to effective communication and understanding in policymakers, researchers, and the general public.

3.2 Cognitive Psychology

McBride and Cutting (2017) classify the approaches in cognitive psychology into three broad streams: case studies (for theory generation), correlational studies (for theory testing), and experimental studies (for prediction from theory). Its diverse methodological toolkit includes lab, field, and natural experiments (with defined treatment and control groups and sufficient control of salient dependent and independent variables); psychobiological research, e.g., measuring brain activity during the completion of a cognitive task using functional magnetic resonance imaging (fMRI) technology or electroencephalogram (EEG); self-reports; case studies; naturalistic observation; and computer simulations and artificial intelligence (Sternberg & Sternberg, 2016). Thus, as a diverse and interdisciplinary field, cognitive psychology (and its various sub-branches, e.g., social psychology, developmental psychology) methods expand through the middle-left to top-right of CMM. The early ambitions of cognitive psychology researchers may have been greater with the generation(s) of researchers – such as Herbert Simon, Allan Newell, Marvin Minsky, Margaret Boden, and Aaron Sloman – focused on applying cognitive psychology to “classical AI” (or general AI). The “Mind as Machine” approach (Boden, 2008) has been mutually beneficial for the fields of cognitive psychology (by way of allowing simulation and testing of theories) and AI (by way of inspiring forms, processes, and structures for models) alike. Bach (2009) stresses that

> [t]he goal of building cognitive architectures is to achieve an understanding of mental processes by constructing testable information processing models […] The integration of regularities obtained in experimental psychology into the architecture is not just a re-formulation of what is already known but requires an additional commitment to a way this regularity is realized, and thus a more refined hypothesis, which in turn makes further predictions that can be taken into the lab of the experimental psychologist […] the path of designing, implementing, and experimentally testing cognitive architectures seems to be the only productive way to extend philosophy of mind beyond its given bi-millennial heritage (pp. 13, 16).

Of particular interest to BE is the increasing use of neuroscience techniques to explore the neurophysiological underpinnings of human behaviour, and economic decision making more specifically (Camerer, Loewenstein, and Prelec, 2005; Loewenstein, Rick and Cohen, 2008). Historically, behavioural neuroscience has been at the core of the cognitive revolution. However, the interest shifted away from thought processes towards physical events but retained a natural interest in identifying how and where memory works at the cellular level (Hunt, 2007, p. 600). However, neuroscience has been limited by the physically available measures:

> We can tell from physical measures that the left temporal region of the brain is active when we read, but we cannot discriminate the activity induced by reading Shakespeare from that induced by reading Agatha Christie. Therefore, in order to explain representational-level thought, we must introduce a detailed theory of the functions required to produce such thinking. This is the point at which a computational theory of information processing, in the abstract, becomes essential (Hunt 1989, p. 605).

The problem is that neuroscientists have biased towards focusing on what they could observe. Thus far, they have failed to progress substantially in the *Way to Think* – and therefore in areas such as knowledge representation; features that provide human thinking with its resourcefulness; or how our brains constructs new mental objects and process. Fascinating AI theories were neglected; hence, we could begin to find ways of testing theories of human cognition such as K-lines, with the goal of determining whether this explains how humans actually learn and represent knowledge. Network science is another interesting research avenue gaining increasing popularity in cognitive psychology, cognitive science (Vitevitch, 2020), and economics alike. But connectionists have emphasized that thinking does not proceed in a computer-like serial manner, but rather as a parallel-processing system (Rumelhart and McClelland, 1987; McCelland et al., 1987). This has not advanced attempts to find new avenues for improving on the pioneering cognitive architectures, despite the fact that parallel elements are also included in systems such as Soar. Newell (1994), for example, stresses:

> Though widespread, the opinion that symbolic-systems models of cognition are somehow so serial that they cannot be made to jibe with the brain's organization and speed of operations is simply misguided…There are, of course, massively parallel aspects of Soar. Production systems form a massively parallel recognition-memory system. But production systems are no more parallel than they have always been, even though they also often seem to be taken as the epitome of symbolic systems and rule-based behavior. There is more than a little clash here between what production systems are technically and the role they have been cast in by the rhetoric of dissent against symbolic systems (p. 486).

However, progress among more intelligent computation systems such as quantum computing is providing new interesting avenues for merging those insights and expanding theoretical and practical boundaries (Bickley et al., 2021). Adding these to complexity theory is a natural progression towards more structure into the methodological approaches. Churchland and Churchland (1990), for example, stress that

> [i]n the brain, axons projecting from one neuronal population to another are often matched by axons returning from their target population. These descending or recurrent projections allow the brain to modulate the character of its sensory processing. More important still, their existence makes the brain a genuine dynamical system whose continuing behavior is both highly complex and to some degree independent of its peripheral stimuli (p. 35).

3.3 Complexity Theory

Manson (2001) clusters complexity theory by three major research directions and their associated concepts and methods: *algorithmic complexity*, focused on the difficultly faced in describing system characteristics and closely linked to mathematical complexity and information processing theories; *deterministic complexity*, dealing with largely stable systems prone to sudden discontinuities via the interaction of few key variables and closely linked to chaos, contagion, and catastrophe theories; and *aggregate complexity*, concerning how individual elements work in parallel to create systems which exhibit complex and varied behaviours and linked closely to self-organisation and emergent behaviour theories. Concepts and methods from non-linear dynamic systems theory, non-equilibrium thermodynamics, dissipative structures, self-organisation theory, catastrophe theory, self-organised criticality, anti-chaos and chaos theory are some of those included under the 'complexity' banner (Mathews et al., 1999), all looking to help explain and characterise different aspects of complex system behaviour. For example, catastrophe theory focuses on discontinuous and out-of-equilibrium system states, attempting to mathematically describe sharp discontinuities in agent behaviours and (r)evolutionary change over time and hence, can be useful in studies of innovation and organisational change.

Complexity theory can be traced back to similar conceptual frameworks in the study of neural networks (McCulloch & Pitts, 1990), cybernetics (Wiener, 1961), and cellular automata (von Neumann, 1966), thus situating itself from the left-middle across to the top right of the CMM matrix[8]. Complexity theory also owes a large portion of its theory and methodological toolkit to general systems theory and shares a similar sentiment of anti-reductionism and holism by acknowledging the complex, indivisible interactions between sub-systems and agents (Von Bertalanffy, 1972), thus demonstrating some focus on methods of analogy-based reasoning also. Simon (1962) argued that in contrast to general systems theory, complexity science should not try to attribute standard properties which are applicable across all physical, biological, and social systems. Rather, complexity science should search for common properties among diverse kinds of complex systems. Despite the promising nature of complexity science, the acceptance and application of complexity theories to the social sciences (outside the use of non-linear modelling methods) is still in its early stages (Elsner, 2017; Mathews et al., 1999). Perhaps this is due to a lack of general consensus on what exactly constitutes a complex system in the first place and how it can be quantitatively determined in a robust and reliable manner (Mitchell, 2009). Nonetheless, complexity theory offers a useful conceptual and methodological toolkit for the study and understanding of multi-scale, hierarchical systems; human, animal, natural, artificial, and ecosystem alike.

3.4 Artificial Intelligence

Adapted from Minsky's (1992) CDM, the CMM matrix can be used fluently within the AI problem solving domain. As discussed previously in Section 2.4, the *Acting Rationally* approach in AI has led the field for the last few decades, situated more firmly towards the top-right of the CMM matrix. Logical reasoning algorithms dominated the AI landscape in the 1950s before more data-driven approaches (of today's primary focus) came to rule, but there are efforts to combine the two approaches (unified or hybrid) in what are being dubbed neuro-symbolic AI (Alexandre, 1997; De Raedt et al., 2020). Hilario (1997) provides an overview of strategies for such integration of symbolic and neural AI methods. Russell and Norvig (2010) offer a descriptive account of the various methods used in AI, aligned to each of the four approaches discussed in Section 2.4. The *Acting Humanly* approach in AI combines six disciplines: natural language processing, knowledge representation, automated reasoning, ML, computer vision, and robotics; thus, they are AI-as-engineering as well as AI-as-science problems. The *Thinking Humanly* approach leverages heavily on cognitive science, with new knowledge typically generated in three ways: introspection, psychological experiments, and brain imaging. Hence, concepts and methods overlap strongly with works in cognitive psychology. The *Thinking Rationally* approach is built firmly on logic (formal and symbolic) with probability theory enabling reasoning with uncertainty. Finally, the *Acting Rationally*

[8] For an excellent overview on complexity theory, see Mitchell (2009).

approach in AI encourages a somewhat more mixed approach with a mix of inference and deduction. The same disciplines mentioned in the *Acting Humanly* approach also apply here in the *Acting Rationally* approach; however, most algorithms are still considered 'narrow' AI for their heavy domain-focus and lack of generalisability/diversity in Ways to Think. By engaging multiple representations and *Ways to Think* about a problem and its possible solution(s) we can march towards triangulation (Ramsay, 1998) and the use of parallel non-equivalent descriptions (Giampietro and Mayumi, 2000), which, if pointing towards a common factor, can help us to be (more) sure that our findings are at least somewhat generalisable.

Advances in text/semantic analysis using AI methods (Benlahbib and Nfaoui, 2020) would be of great interest to BE in exploring the role and dynamics of narratives, for example, in exploring the shifts in media sentiment and public opinion. Perspectives such as narrative economics (Shiller, 2017; Shiller, 2019), the formation of public opinions as a complex adaptive system (Ginneken, 2003; Mehdi et al., 2013), and storied spaces as the human equivalent of complex adaptive systems (Baskin, 2008) could inform such efforts. AI methods such as ML and DL are proven in Economics and Finance for predicting observation values and movements, classifying and/or clustering observations, and forecasting observations (Gogas and Papadimitriou, 2021). Other notable ML methods applied in economics-related fields include anomaly detection, credit card fraud detection, aquatic product export volume prediction, stock price prediction, mobile social commerce, e-banking failures, customer behaviour, and recommender systems (Nosratabadi et al., 2020). Further, the design of an AI agent forces one to consider how such an artificial system or entity should think and behave. To do so, we may look to something more familiar, i.e., human thinking and behaviours. Thus, AI can help us in the attempt to design human-like agents, or in situations where it is desired to be more rational than the typical human might be. Further, AI could also be used in the data generation process. Costello and McCarthy (1999) explain 'useful counterfactuals', detailing a possible method of increasing the size of training datasets:

> The performance of learning algorithms improves when they have more examples. Counterfactuals are one way to collect more examples than can be found by direct experience. Often it is better to imagine a data point than to experience it (p. 4).

AI is intrinsically reliant on the computational infrastructure it uses to undertake its mission(s), so further advancements are enabled by technological innovations relating to computational hardware, cloud computing architectures, and more recently, quantum computing (Dunjko and Briegel, 2018), as well as other enabling technologies such as Big Data, IOT, and blockchain (Rabah, 2018). The overlap between AI and quantum computing methods and technologies allows re-visiting what one may learn from expert systems (Bickley et al., 2021), vastly popular during the earlier days of practical applications of AI in research and industry.

4 Future Directions

Although promoting the link between sciences and humanities has been called the greatest enterprise of the mind (Wilson, 1998), the analytical techniques developed in the classical Newtonian framework may not be able to successfully explain human behaviour (Bouchard, 2008). Indeed, as this deterministic framework was developed to model mechanical systems (Boulding, 1956), there is reason to suppose that humans do not follow the requisite assumptions of Newtonian-style mathematics (Kitto and Kortschak, 2013). Hence, new methods are needed to develop more sophisticated models that can handle the complex interdependencies between underlying assumptions, observed communications, and the resulting individual behaviours. But how can such an advance be achieved? How do social systems emerge from the interactions of their constituent individuals (Torgler, 2019)? Do they exhibit *downward causation* (Campbell, 1990) or is a bottom-up model still possible? These questions, which have preoccupied many fields, including sociology, anthropology, psychology, and economics, are not unique to the social sciences. Similar questions were asked in the hard sciences throughout the last century in fields such as cybernetics, nonlinear science, and systems theory, and have produced myriad models of complex behaviour (Holland, 1995; Mitchell, 2009; Page, 2011; Miller and Page, 2007).

In the following sections, we first highlight research directions in light of the above questions for the conceptual advancement of BE, with particular focus on cognitive models, *micro*, *meso*, and *macro* foundations, and Big Data. We then do the same for methodological advancement in the areas of neuroscience, ABM, and AI in particular.

4.1 Concepts

4.1.1 Cognitive Models and Architectures

> "We need to open the black box of decision making, and come up with some completely new and fresh modelling devices" (Rubinstein, 2003, p. 1215)

Minsky, Singh and Sloman (2004) – speaking specifically of AI agents, but no less applicable to the study of human agents – propose 8 types of reasoning: spatial, physical, bodily, visual, psychological, reflective, conversational, and educational[9]. We can think of these types of reasoning as methods between which agents (human or artificial) can choose (and/or use in parallel) to explore their world, gather information, interact with others, and navigate their many problems, opportunities, and dilemmas – and ultimately, to enact their goals and visions through action. In tandem with the hierarchical cognitive models discussed first in Section 2.2, we can then begin to construct more sophisticated agents to test our theories and intuitions, using the multiple *Ways to Think* in CMM (see Figure 3) to facilitate such artificial thinking and reasoning processes. We must not only focus on goals as "it is not enough to know its goals. We must know also a great deal about its internal structure and particularly its mechanisms of adaptation" (Simon, 1959, p. 255).

Cognitive models based on massive parallel information integration could be explored *within* a bounded rationality framework of satisficing rather than as an extension to the neoclassical utility-maximisation. Kunda and Thagard (1996), for example, developed a parallel processing model of impression formation which considers the joint and independent influence of stereotypes and individuating information. Sloman (2001) and Minsky (2007) both call for considerations of different hierarchical levels of cognition, distinguishing between different forms of reactive, deliberate, and reflective thinking in their 3- and 6-level cognitive models, respectively. The importance of this distinction has still not yet been made in BE, and in the social sciences more generally. Kahneman's (2011) schema of system 1 and 2 is an encouraging first step but such "dumbbell" thinking can constrain thinking and lead us down the path of oversimplifications and false analogies (Minsky, 1988). Somewhat of a paradigm shift in cognitive psychology is situated, distributed, and embodied (SDE) cognition (Petracca, 2017). Cognition in the SDE framework is *situated* (contextualised and linked with action), *distributed* (using the resources of social and technological institutions, and their environment in order to succeed), and *embodied* (indivisible from an evolutionarily formed, physical and

[9] See also the work of Howard Gardner (1993, 2006) who has pioneered the idea of multiple intelligences.

dependent time-space path) (Hommel, 2015). Despite the fact that some consider SDE a departure from bounded rationality, we contend that they do not need to be mutually exclusive theories; SDE can sit firmly within the bounded rationality framework, as can bounded rationality in SDE. To us, both research campaigns offer elements which the other may not and hence, we contend a 'best of both worlds' approach may be more suitable than use of either in isolation.

Thus, further exploration of cognitive models, architectures, mechanisms, and structures is warranted alongside further advancement of goal-oriented behaviour and decision models. For example, one could equip an AI agent with CMM to find multiple ways to help solve problems and represent situations, (non)experiences, and problem-specific task environments for future recall, reasoning, and learning. Like CDM, CMM is a useful preliminary tool to enable/assist such thinking processes, but further work can be done to identify other salient dimensions to compare and combine the methods of CMM. For example, methods of CMM can be aligned to the independence of causal factors, similarity to previous problems, expressivity of the representation/explanation, tractability (speed/efficiency) of the inference, ease of representation, and robustness/reliability (Singh, 2003).

4.1.2 Micro, Meso, and Macro Foundations

The fact that complex emergent patterns are notoriously difficult to identify (Kitto, 2008) and even more difficult to simulate mathematically presents a major challenge: how to model the ways in which a set of individuals form an emergent society that in turn affects them. In other words, treating groups, organisations, and societies as if they were organisms or open complex living systems (Torgler, 2019)[10]. Because the new economy is organic – that is, always discovering, creating, and in process (Arthur, 2006) – knowledge, information, and insights are key resources in a constantly changing world where possibilities and problems are created, as ongoing ecological interactions call for additional responses (Torgler, 2019):

> In such an environment, entities are not always stable and events not always repeatable, presenting significant challenges for the empiricist. Hence, understanding change in these settings requires comprehending the dynamic communication and feedback channels within the system, as well as the architecture and design of social institutions (p. 215).

Equally, a varied set of representations and methods is required for handling, sorting, and adapting this knowledge for use in everyday life. Conventional economic and financial modelling methods have placed strict (often unrealistic) assumptions on human decision-making processes to help control for this complexity and non-linearity, to ease the computational requirements and appease long-standing mathematical methods of optimisation and equilibrium (Foster & Metcalfe, 2012). However, these methods have trouble accounting for the rare, yet significant events such as stock market crashes, bank runs, large-scale industrial safety incidents, radical shifts in public opinion and media hysteria events. Further, the conventional macroeconomic methods for aggregate summation of individual agents' behaviour does not hold for complex systems, as the fundamental assumption that agents are homogenous and rational clearly no longer holds when looking at 'real world' data (Kirman, 2010). Nowadays, it is more widely accepted that humans (and the systems they form) are boundedly rational and rely on behavioural (biases) and decision-making rules (heuristics) to govern their everyday decision-making (Castelfranchi, 2000), and "what is urgently needed is

[10] For a discussion how economics and social science questions can be explored and modelled in a manner similar to a living or biological system, see Torgler (2016).

the development of new theories concerning the emergence, maintenance and decline of meso rules since it is these that stand between the macro and the micro and provide the order and continuity in the economic system that allow us to consider it a 'system' rather than some kind of statistical 'random walk'" (Foster, 2004, p. 32). This is different from the *quasi*-micro foundations of mainstream macroeconomics, "a micro-foundation based on assumptions of no heterogenous agent interaction", thus allowing limited room for communication, even "when, for many people, it is precisely the heterogenous agent interaction that leads to central characteristics of the macro economy" (Holt, Rosser and Colander, 2011, p. 365). Complexity theory can provide the foundation from which to explore the process and issues of (socio)economic system formation, as opposed to resource allocation alone (Tabb, 1999). That is, how an economy merges and grows, reacts and adapts in structure and dynamics over time and can be used to shed new light on classic economics problems by developing models which can account for complex economic phenomena not just at equilibrium but in out-of-equilibrium states as well (Arthur, 2014).

4.1.3 Big Data

As the rise of Big Data has profound implications for the way science is done, it is pertinent to think about what impact this may have on the study and practice of behavioural economics. Big Data is already pervasive and "[s]ince computers are now involved in many economic transactions, Big Data will only get bigger." (Varian, 2014, p. 24). One such promising area for the application of Big Data is in understanding patterns of human mobility and interaction, the antecedent of most economic activity. In general, human mobility data have some deep-rooted regularities (Song et al., 2010). Identifying these offers ways of developing accurate predictive models that are scientifically grounded, can help in understanding and improving our societal well-being and public health, and inform how we might cope with crises such as pandemics, climate/weather disasters, and other nasty and often unexpected events. Big Data provides new opportunities in understanding the dynamics of social interactions by observing actual behaviour rather than just beliefs (Pentland, 2014; Torgler, 2019). Mobility data allow us to harness human digital footprints or "digital bread-crumbs" of our activities (Almaatouq et al., 2016, p. 407). Mobility data can include origin-destination pairs, travel modes (e.g., roads, rail, walking, cycling), places of visits, duration of visits, and number/diversity of human interactions, to name a few, and such data can also be associated with demographic information including age, gender, race, and nationality. This provides a richness of information and context on individual patterns of movement and social behaviour not formerly possible with more rigid and traditional policy instruments (Bickley, Macintyre, and Torgler, 2021).

In an interview with *The Edge*, Sandy Pentland points that "[w]hat those breadcrumbs tell is the story of your life. It tells what you've chosen to do". Such data also contribute to a better understanding of the social context and social fabric, and how they influence human behaviour and interactions. If we can observe some of the things an individual does, then we can infer (most of) the rest by comparing them to the people with whom they regularly hang out and interact, and in this sense, begin to understand (and intervene) in the formation and persistence of complex social phenomena and emergent outcomes based on individual patterns of behaviour and mobility. The analysis of human mobility data is the basis of understanding how people and groups are connected together and mingle (mix) over time. Pentland notes the importance of this, as for a long time Big Data left humans out of the equation. Mobility data can enable powerful early-warning systems for extreme events such as pandemics or societal irregularities related to, for example, health and well-being, or civil unrest and conflicts. Eagle and Greene (2014) use the term “syndromic surveillance” (p. 159), stressing that the use of a number of different data sources allow identification of clustered symptoms of illness in the early stage. Allowing (and enabling) policymakers to work with systems that make use of this kind of data to recommend early actions (e.g., shutting down public infrastructures such as schools and public transport) can enable more timely decision making and reduce societal damages inflicted by, for example, an unexpected infectious disease such as COVID-19. Thus, Big Data can act as a preventive tool that creates real-time data to inform health-care providers as well as public policymakers and other agencies about acute threats and problems (Eagle and Greene 2014). Equally, we can leverage AI and Big Data to further progress on our commitments to Sustainable Development Goals (Vinuesa et al., 2020) by helping to interpret and monitor the environment, guide our problem-solving process, design strategies and action plans, and decide when/if to carry them out. We can also leverage this to encourage, support, and carry out sustainability innovation and entrepreneurship (Bickley, Macintyre and Torgler, 2021), and adapt business models in light of findings (Di Vaio et al., 2020).

4.2 Methods

4.2.1 Neuroscience

Neuroscience is expected to provide important insights into human cognition and behaviour “either directly or because neuro-science will reshape what is believed about psychology which in turn informs economics” by allowing one to “infer details about how the brain works” (Camerer, Loewenstein and Prelec, 2005, p. 9). Thus, neuroscience is not just important for setting the stage for research in cognition but it also lays the foundation upon which higher order thinking and reasoning processes take place, like those required for representing and solving problems faced by agents (human, animals, or artificial) in their everyday life. In principle, all neuroscientific tools can be used to investigate (socio)economic decision making; however, Kenning and Plassmann (2005) group the various methods into two categories according to their subject of study: methods for measuring electromagnetic activity of the brain (e.g., magnetoencephalography (MEG) and EEG), and methods for measuring changes of cerebral blood flow or metabolism (e.g., positron emission tomography (PET) and fMRI). Essentially, the *where* of cognition is more precisely answered by the methods for measuring changes in cerebral blood flow or metabolism (fMRI and PET), whereas the *when* is better assessed by EEG and MEG, so a combination/hybrid of both approaches would deliver the best results. Insights from neuroscience can offer both incremental and more radical contributions to economics (Camerer, Loewenstein and Prelec, 2005): incremental by adding variables to or modifications of conventional models of decision making based on empirical evidence, radical by questioning the implicit assumptions of conventional decision-making models and potentially re-defining them in alignment with real-world observations. Unfortunately, such neuroscientific methods are often unviable in natural environments due to the restrictive nature of technologies underlying the data capture process, and hence, ecological validity is called into question. Fortunately, as the story has been told in experimental economics, as long as decisions are related to real consequences then ecological validity can hold (Reuter and Montag, 2016) provided that the researchers’ implicit and explicit assumptions are not violated. Regardless, neuroscientific methods can help in both informing and clarifying our models of human cognition and allows to test the various theories and models of human cognition and help to determine, for example, the neurobiological bases of pro-social behaviours (Harbecke and Herrmann-Pillath, 2020). Technological advances in neuroscience around wearable, nonintrusive, and non-invasive instruments provide new avenues in the area of behavioural economics by studying the human mind and human behaviour in the real world rather than the laboratory (for a detailed discussion, see Torgler, 2019).

4.2.2 Agent-based Models (ABM)

In ABM, a system is modelled as a collection of autonomous decision-making units called agents, wherein each agent assesses its situation and makes decisions based on a set of rules that allows to track individuals and their interactions in networks (of networks) of agents over time and space (Bonabeau, 2002), hence enabling fine-grained analyses of individual behaviours and emergent phenomena in networks and systems of agents. In other words, "ABM allows the disaggregation of systems into individual components that can potentially have their own characteristics and rule sets" (Crooks and Heppenstall, 2012, p. 85). ABMs have demonstrated clear potential in helping to analyse, characterise, and define complex systems of many agents through the evolution and application of simple agent rules over time (Yang, 2020) and are heavily used in complexity science analyses. ABMs enable a direct representation of layered and hierarchical systems and their upward and downward effects on a particular observed phenomenon (Gräbner, 2017). However, ABMs suffer several issues, including agent granularity (i.e., corresponding to some level of lumpiness and a 'small numbers' effect), non-linear dynamics which present difficulties in parameter estimation, and difficulties with model replication and comparison (LeBaron, 2016). Model development should focus heavily on building comprehensive models that operate in the context of the observed reality and can deliver testable predictions about agents' behaviours within such a context to support empirical testing. The strength of such agent-based models is their ability to visualise system dynamics that are otherwise difficult to solve mathematically (Reilsback and Grimm, 2012). In particular, one such approach may use a micro-specification to explore the evolution of norms and conflict dynamics based on predefined (local) communication channels or rules (bottom-up approach) while still observing the macro-structure (societal implications) and the time required for the system to attain equilibrium or observe out-of-equilibrium dynamics (e.g., the long-lived transient behaviours suggested by Epstein, 2006, p. 23). There are many ABM tools and software programs; Abar et al. (2017) provide a comprehensive account of the state-of-the-arts. Advanced AI techniques such as goal-oriented action planning (GOAP) may also enrich the practice and design of ABMs (Zhang, Shen and Miao, 2009), initialising agents with goals (and sub-goals) from which agents can choose to realise desired outcomes through actions and sub-actions aligned to each goal and its sub-goals.

4.2.3 Artificial Intelligence

Comparisons and combinations of different 'ways of thinking' (see e.g., Figure 3) are important; the methods through which data are collected, curated, and integrated into scientific modelling are essential in understanding our world (Coveney et al. 2016). Varian (2014) stresses that "[d]ata manipulation tools and techniques developed for small datasets will become increasingly inadequate to deal with new problems. Researchers in ML have developed ways to deal with large datasets and economists interested in dealing with such data would be well advised to invest in learning these techniques" (pp. 24-25). As ML is predictive while econometrics is explanatory and historically based on economic theory, a combination of both tools is fascinating but also challenging. In general, data analysis in statistics and econometrics can be classified into four groups: 1) prediction, 2) summarization, 3) estimation, and 4) hypothesis testing (Varian, 2014). Using different methods has the ability to use both AI and econometric methods to explain the same phenomenon from different perspectives. Further, traditional data analytics techniques cannot deal with Big Data – Big Data are often noisy, and, unlike survey data, not collected to answer specific questions. AI can therefore help overcome these deficiencies and barriers. In addition, AI methods can be implemented first, and followed by attempts to explain what is going on to better understand the underlying correlations and co-occurrences; hence, moving towards a causal relationship and a situation where one (or both) method(s) inform each other. Thus, a combination of cross-validation and trying to reveal fundamental processes can be beneficial in the decision-making process or in generating meta-knowledge (knowledge about knowledge) (Zheng et al., 2017). Mullainathan and Spiess (2017) stress that

> "[f]or empiricists, these theory- and data-driven modes of analysis have always coexisted. Many estimation approaches have been (often by necessity) based on top-down, theory-driven, deductive reasoning. At the same time, other approaches have aimed to simply let the data speak. ML provides a powerful tool to hear, more clearly than ever, what the data have to say" (pp. 103-104).

Thus, these approaches are not in conflict *per se*, and both approaches may be important when trying to understand human behaviour, interactions, and networks (and networks of networks), with the aim being to predict human responses to future events and novel circumstances. Exploring such a relationship is particularly important when working with new data that are subject to high-dimensionality and when predictions are an important policy problem and/or objective. AI offers the chance to take further leaps and bounds in practice and policy with advances in the hardware side of computation; namely, cloud computing and quantum computing (Dunjko and Briegel, 2018) among other enabling technologies such as Big Data, IOT, and blockchain (Rabah, 2018). These technological advances allow to revisit what one may learn from expert systems (Bickley et al., 2021), for example.

5 Concluding Remarks

In summarising this chapter, we now return to the two questions posed in the introductory section: *what exactly is BE?* and *what may we have missed along the way?* By revisiting BE's conceptual and methodological roots, we aimed to shed light on these questions and point our readers towards potentially fruitful avenues of research and exploration. Equally, we hope we have enriched our readers with a refreshing array of diverse conceptual and methodological topics covered, and that our readers see the importance and validity of incorporating such topics into their own (socio)economic policy and practice.

In exploring the first question, we see that BE is a diverse and interdisciplinary field. Its proponents and subscribers are comfortable in wielding a diverse range of methods and instruments and making use of evidence from outside of economics. The distinction between old (classical) and new (modern) BE has also been made: the former (CBE) sought to depart more drastically from the standard neoclassical paradigm, questioning its relevance and real-world applicability; the latter (MBE) remained within the neoclassical optimisation framework, seeking instead to improve (or repair) the psychological underpinnings of neoclassical methods and models. There is a general appreciation for the diversity in approach that BE maintains; however, as discussed in Section 3, further work can be done to foster multiple *Ways to Think* about a problem, much in the spirit of triangulation, parallel non-equivalent descriptions, and mixed methods more generally.

In exploring the second question, we see that the MBE interpretation of bounded rationality is narrow, omitting the bounded nature of the environment itself (i.e., context) and focusing only on the limited information processing capabilities of the decision maker. We have also conveyed an (increasing) appreciation for the true complexity of human systems where aggregates cannot be reduced to the sum of individual constituents, particularly in a constantly changing world where possibilities and problems are created, as ongoing ecological interactions call for additional responses. Complexity theoretic approaches provide a useful conceptual framework and methodological toolkit to explore and characterise such problems. Last but not least, we contend that behavioural economics and the social sciences more generally will benefit greatly from paying closer attention to the design and application of cognitive models in various intelligent agents (human, animal, artificial). To gain a deeper appreciation for the procedures, mechanisms, and thought processes which underly (socio)economic decision making we must venture further into the individual and seek to shed light on the 'black box' of human decision making. Only then can we build, from the ground up, more contextualised and rationally bounded economics with greater predictive power and real-world relevance.

References

Aamodt, A., & Nygård, M. (1995). Different roles and mutual dependencies of data, information, and knowledge—an AI perspective on their integration. *Data & Knowledge Engineering*, *16*(3), 191-222.

Abar, S., Theodoropoulos, G. K., Lemarinier, P., & O'Hare, G. M. (2017). Agent Based Modelling and Simulation tools: A review of the state-of-art software. *Computer Science Review*, *24*, 13-33.

Alexandre, F. (1997). Tools and experiments for hybrid neuro-symbolic processing. In *Proceedings Ninth IEEE International Conference on Tools with Artificial Intelligence* (pp. 338-345). New Jersey, USA: IEEE.

Almaatouq, A., Radaelli, L., Pentland, A., & Shmueli, E. (2016). Are you your friends' friend? Poor perception of friendship ties limits the ability to promote behavioral change. *PloS One*, *11*(3), e0151588.

Al-Suwailem, S. (2011). Behavioural complexity. *Journal of Economic Surveys*, 25(3), 481-506.

Angner, E., & Loewenstein, G. (2007). Behavioral economics. In U. Mäki, D. Gabbay, P. Thagard & J. Woods (Eds.), *Handbook of the philosophy of science: Philosophy of Economics* (pp. 641-690). Amsterdam, NL: Elsevier Science.

Arthur, W. B. (2006). The Nature of Technology: What It Is and How It Evolves. New York, USA: Free Press.

Arthur, W. B. (2014). Complexity Economics: A Different Framework for Economic Thought. In W.B. Arthur (Ed.), *Complexity Economics* (pp. 1-29). Oxford, UK: Oxford University Press.

Bach, J. (2009). Principles of synthetic intelligence Psi: An architecture of motivated cognition. Oxford, UK: Oxford University Press.

Baskin, K. (2008). Storied Spaces: The Human Equivalent of Complex Adaptive Systems. *Emergence: Complexity and Organization*, *10*(2), 1-12.

Baum, S. D., Goertzel, B., & Goertzel, T. G. (2011). How long until human-level AI? Results from an expert assessment. *Technological Forecasting and Social Change*, *78*(1), 185-195.

Beal, J., & Winston, P. H. (2009). Guest Editors' Introduction: The New Frontier of Human-Level Artificial Intelligence. *Intelligent Systems*, *24*(4), 21-23.

Benartzi, S., & Thaler, R. (2007). Heuristics and biases in retirement savings behavior. *Journal of Economic Perspectives*, *21*(3), 81-104.

Benlahbib, A., & Nfaoui, E. H. (2020). A hybrid approach for generating reputation based on opinions fusion and sentiment analysis. *Journal of Organizational Computing and Electronic Commerce*, *30*(1), 9-27.

Bhatnagar, R. K., & Kanal, L. N. (1986). Handling uncertain information: a review of numeric and non-numeric methods. *Machine Intelligence and Pattern Recognition*, *4*, 3-26.

Bickley, S.J., Macintyre, A., & Torgler, B. (2021). Artificial Intelligence and Big Data in Sustainable Entrepreneurship. CREMA Working Paper Series 2021-11, Centre for Research in Economics, Management, and the Arts (CREMA), Zurich, Switzerland.

Bickley, S.J., Chan, H.F., Schmidt, S.L., & Torgler, B. (2021). Quantum-Sapiens: The Quantum Bases for Human Expertise, Knowledge, and Problem-Solving, forthcoming in: *Technology Analysis & Strategic Management*. For an Extended Version with Applications, see CREMA Working Paper Series 2021-14, Centre for Research in Economics, Management, and the Arts (CREMA), Zurich, Switzerland, http://www.crema-research.ch/papers/2021-14.pdf.

Boden, M.A. (2008). Mind as machine: A history of cognitive science. Oxford, UK: Oxford University Press.

Boisot, M., & Canals, A. (2004). Data, information and knowledge: have we got it right? *Journal of Evolutionary Economics*, *14*(1), 43-67.

Bonabeau, E. (2002). Agent-based modeling: Methods and techniques for simulating human systems. *Proceedings of the National Academy of Sciences*, *99*(suppl. 3), 7280-7287.

Bouchaud, J. P. (2008). Economics needs a scientific revolution. *Nature*, *455*(7217), 1181-1181.

Boulding, K. E. (1956). General systems theory—the skeleton of science. *Management Science*, *2*(3), 197-208.

Camerer C. F., & Loewenstein, G. (2004). Behavioral Economics: Past, Present, Future. In C. Camerer, G. Loewenstein, & M. Rabin (Eds.), *Advances in Behavioral Economics* (pp. 1-52). Princeton, USA: Princeton University Press.

Camerer, C., Loewenstein, G., & Prelec, D. (2005). Neuroeconomics: How neuroscience can inform economics. *Journal of Economic Literature*, *43*(1), 9-64.

Campbell, D.T. (1990). Levels of organization, downward causation, and the selection-theory approach to evolutionary epistemology. In E. Tobach & G. Greenberg (Eds.), *Scientific methodology in the study of mind: Evolutionary epistemology* (pp. 1-17). Hillsdale, NJ: Erlbaum.

Castelfranchi, C. (2000). Through the Agents' Minds: Cognititve Meaditors of Social Action. *Mind & Society*, *1*(1), 109-140.

Ceddia, M. G., Bardsley, N. O., Goodwin, R., Holloway, G. J., Nocella, G., & Stasi, A. (2013). A complex system perspective on the emergence and spread of infectious diseases: Integrating economic and ecological aspects. *Ecological Economics*, *90*(C), 124-131. DOI: 10.1016/j.ecolecon.2013.03.013.

Choudhury, M. A. (2013). Complexity and endogeneity in economic modelling. *Kybernetes*, *42*(2), 226-240.

Churchland, P. M., & Churchland, P. S. (1990). Could a machine think? *Scientific American*, 262(1), 32-39.

Cohen-Cole, J. (2007). Instituting the science of mind: intellectual economies and disciplinary exchange at Harvard's Center for Cognitive Studies. *The British Journal for the History of Science*, *40*(4), 567-597.

Colander, D., & Kupers, R. (2014). Complexity and the art of public policy: Solving society's problems from the bottom up. Princeton, USA: Princeton University Press.

Costello, T. & McCarthy, J. (1999). Useful Counterfactuals. *Linköping Electronic Articles in Computer and Information Science*, *3*(2), 1-28.

Coveney, P. V., Dougherty, E. R., & Highfield, R. R. (2016). Big Data need big theory too. Philosophical Transactions of the Royal Society A: Mathematical, Physical and Engineering Sciences, 374(2080), 20160153.

Cronin, B. (2016). Multiple and mixed methods research for economics. In F.S. Lee & B. Cronin (Eds.), *Handbook of Research Methods and Applications in Heterodox Economics*. Cheltenham, UK: Edward Elgar Publishing.

Crosson, F. J. (1992). Psyche and the computer: Integrating the shadow. In S. Koch & D.E. Leary (Eds.), *A Century of Psychology as Science* (pp. 437-451). Washington, USA: APA Publishing.

Crooks, A. T., & Heppenstall, A. J. (2012). Introduction to agent-based modelling. In A. Heppenstall, A. Crooks, M.L. Lee & M. Batty (Eds.), *Agent-based models of geographical systems* (pp. 85-105). Dordrecht, NL: Springer.

De Raedt, L., Dumančić, S., Manhaeve, R., & Marra, G. (2020). From statistical relational to neuro-symbolic artificial intelligence. *arXiv preprint*, arXiv:2003.08316.

Diacon, P.-E., Donici, G.-A., & Maha, L.-G. (2013). Perspectives of Economics--Behavioural Economics. *Theoretical and Applied Economics*, *20*(7), 27-32.

Di Vaio, A., Palladino, R., Hassan, R., & Escobar, O. (2020). Artificial intelligence and business models in the sustainable development goals perspective: A systematic literature review. *Journal of Business Research*, *121*, 283-314.

Dunjko, V., & Briegel, H. J. (2018). Machine learning & artificial intelligence in the quantum domain: a review of recent progress. *Reports on Progress in Physics*, *81*(7), 074001.

Eagle, N., & Greene, K. (2014). Reality mining: Using Big Data to engineer a better world. Massachusetts, USA: MIT Press.

Elsner, W. (2017). Complexity economics as heterodoxy: Theory and policy. *Journal of Economic Issues*, *51*(4), 939-978.

Epstein, J. M. (2006). Generative social science: Studies in agent-based computational modeling (Vol. 13). Princeton, USA: Princeton University Press.

Foster, J. (2005). From simplistic to complex systems in economics. *Cambridge Journal of Economics*, *29*(6), 873-892.

Foster, J., & Metcalfe, J. S. (2012). Economic emergence: An evolutionary economic perspective. *Journal of Economic Behavior and Organization*, *82*(2-3), 420-432.

Gardner, H. E. (1993). Frames of mind: The theory of multiple intelligences. New York, USA: Basic Books.

Gardner, H. E. (2006). Multiple Intelligences: New Horizons. New York, USA: Basic Books.

Gazzaniga, M., Ivry, R., & Mangun, G. (2014). Cognitive neuroscience: the biology of the mind (Fourth edition.). New York, USA: W.W. Norton & Company.

Giampietro, M., Mayumi, K., 2000. Multiple-scale integrated assessment of societal metabolism: introducing the approach. *Population and Environment*, *22*(2), 109-153.

Gigerenzer, G. (1996). On narrow norms and vague heuristics: A reply to Kahneman and Tversky. *Psychological Review*, *100*, 592-596.

Gigerenzer, G. (2004). Striking a blow for sanity in theories of rationality. In: M. Augier & J. G. March (Eds.), *Models of a man: Essays in memory of Herbert A. Simon* (pp. 389-409). Massachusetts, USA: MIT Press.

Gilovich, T., Griffin, D., & Kahneman, D. (2002). Heuristics and biases: The psychology of intuitive judgment. Cambridge, UK: Cambridge University Press.

Ginneken, J. V. (2003). Collective behavior and public opinion: rapid shifts in opinion and communication. New Jersey, USA: Lawrence Erlbaum.

Guastello, S. J., Koopmans, M., & Pincus, D. (Eds.). (2008). *Chaos and complexity in psychology: The theory of nonlinear dynamical systems*. Cambridge, UK: Cambridge University Press.

Goertzel, B., & Pennachin, C. (2007). Artificial general intelligence (Vol. 2). Dordrecht, NL: Springer.

Gogas, P., & Papadimitriou, T. (2021). Machine Learning in Economics and Finance. *Computational Economics*, *57*(1), 1-4.

Gomes, O., & Gubareva, M. (2021). Complex Systems in Economics and Where to Find Them. *Journal of Systems Science and Complexity*, *34*(1), 314–338. DOI: 10.1007/s11424-020-9149-1.

Gräbner, C. (2017). The Complementary Relationship Between Institutional and Complexity Economics: The Example of Deep Mechanismic Explanations. *Journal of Economic Issues*, *51*(2), 392-400.

Harbecke, J., & Herrmann-Pillath, C. (Eds.). (2020). Social Neuroeconomics: Mechanistic Integration of the Neurosciences and the Social Sciences. London, UK: Routledge.

Heap, S. P. H. (2013). What is the meaning of behavioural economics? *Cambridge Journal of Economics*, *37*(5), 985-1000.

Helbing, D. (2009). Managing Complexity in Socio-Economic Systems. *European Review*, *17*(2), 423-438.

Heukelom, F. (2014). Behavioral economics: A history. Cambridge, UK: Cambridge University Press.

Hilario, M. (1997). An overview of strategies for neurosymbolic integration. In R. Sun F. Alexandre (Eds.), *Connectionist-Symbolic Integration: From Unified to Hybrid Approaches* (pp. 13-36). New Jersey, USA: Lawrence Erlbaum Associates.

Holland, J. H. (1995). Hidden order: How adaptation builds complexity. New York, USA: Basic Books.

Holling, C. S. (2001). Understanding the Complexity of Economic, Ecological, and Social Systems. *Ecosystems*, *4*(5), 390-405.

Holt, R. P., Rosser Jr, J. B., & Colander, D. (2011). The complexity era in economics. *Review of Political Economy*, *23*(3), 357-369.

Hommel, B. (2015). The theory of event coding (TEC) as embodied-cognition framework. *Frontiers in Psychology*, *6*, 1318-1318.

Hunt, M. (2007). The Story of Psychology. Victoria, AUS: Anchor Books.

Kao, Y.-F., & Velupillai, K. V. (2015). Behavioural economics: Classical and modern. *The European Journal of the History of Economic Thought*, *22*(2), 236-271.

Kahneman, D. (2011). Thinking, fast and slow. New York, USA: Macmillan.

Kahneman, D., & Tversky, A. (1996). On the reality of cognitive illusions. *Psychological Review*, *103*, 582-591.

Kauffman, S. A. (2016). Humanity in a creative universe. Oxford, UK: Oxford University Press.

Kay, J. J., Regier, H. A., Boyle, M., & Francis, G. (1999). An ecosystem approach for sustainability: addressing the challenge of complexity. *Futures*, *31*(7), 721-742.

Kenning, P., & Plassmann, H. (2005). NeuroEconomics: An overview from an economic perspective. *Brain Research Bulletin*, *67*(5), 343-354.

Kirman, A. (2010). The Economic Crisis is a Crisis for Economic Theory. *CESifo Economic Studies*, *56*(4), 498-535.

Kitto, K. (2008). High end complexity. *International Journal of General Systems*, *37*(6), 689-714.

Kitto, K., & Kortschak, R. D. (2013). Contextual models and the non-Newtonian paradigm. *Progress in Biophysics and Molecular Biology*, *113*(1), 97-107.

Kunda, Z., & Thagard, P. (1996). Forming impressions from stereotypes, traits, and behaviors: A parallel-constraint-satisfaction theory. *Psychological Review*, *103*(2), 284.

LeBaron, B. (2016). Financial price dynamics and agent-based models as inspired by Benoit Mandelbrot. *The European Physical Journal Special Topics*, *225*(17), 3243-3254.

Lewis, M. (2017). The undoing project: A friendship that changed the world. New York, USA: Penguin Books.

Loewenstein, G., Rick, S., & Cohen, J. D. (2008). Neuroeconomics. *Annual Review of Psychology*, *59*, 647-672.

Lo, A. W. (2017). Adaptive Markets: Financial Evolution at the Speed of Thought. Princeton, USA: Princeton University Press.

Mandelbrot, B. B., & Hudson, R. L. (2004). The (Mis)Behavior of Markets: A Fractal View of Risk, Ruin, and Reward. New York, USA: Basic Books.

Manson, S. M. (2001). Simplifying complexity: a review of complexity theory. *Geoforum*, *32*(3), 405-414.

Mathews, K. M., White, M. C., & Long, R. G. (1999). Why Study the Complexity Sciences in the Social Sciences? *Human Relations*, *52*(4), 439-462.

McBride, D. M., & Cutting, J. C. (2017). Cognitive psychology: Theory, process, and methodology. New York, USA: SAGE Publications.

McCarthy, J. (1998). Elaboration tolerance. In. Miller, R. & Shanahan, M. (Eds.), *Fourth Symposium on Logical Formalizations of Commonsense Reasoning* (pp. 198-216), London, UK.

McCarthy, J. (2000). Approximate objects and approximate theories. Palo Alto, USA: Stanford University Press.

McCarthy, J. (2007). From here to human-level AI. *Artificial Intelligence*, *171*(18), 1174-1182.

McClelland, J. L., Feldman, J., Hayes, P., & Rumelhart, D. E. (1987). Parallel distributed processing, Vol 2: Psychological and Biological Models. A Bradford Book. Massachusetts, USA: MIT Press.

McCulloch, W. S., & Pitts, W. (1990). A logical calculus of the ideas immanent in nervous activity. *Bulletin of Mathematical Biology*, *52*(1-2), 99-115.

Mehdi, M., Juliane, E. K., Pantelis, P. A., & Hansjörg, N. (2013). Social influence and the collective dynamics of opinion formation. *PLoS ONE*, *8*(11), e78433.

Miller, J.H. & Page, S.E. (2007). Complex Adaptive Systems: An introduction to computational models of social life. Princeton, USA: Princeton University Press.

Minsky, M. (1988). The society of mind. London, UK: Pan Books.

Minsky, M. (1992). Future of AI Technology. *Toshiba Review*, *47*(7), 1-3.

Minsky, M. (2007). The Emotion Machine: Commonsense Thinking, Artificial Intelligence, and the Future of the Human Mind. New York, USA: Simon and Schuster.

Minsky, M. L., Singh, P., & Sloman, A. (2004). The St. Thomas common sense symposium: designing architectures for human-level intelligence. *AI Magazine*, *25*(2), 113-113.

Mitchell, M. (2009). Complexity: A guided tour. Oxford, UK: Oxford University Press.

Mullainathan, S., & Spiess, J. (2017). Machine learning: an applied econometric approach. *Journal of Economic Perspectives*, *31*(2), 87-106.

Newell, A. (1994). Unified Theories of Cognition. Massachusetts, USA: Harvard University Press.

Newell, A., Shaw, J. C., & Simon, H. A. (1959). Report on a general problem solving program. In *IFIP congress* (vol. 256, p. 64).

Nilsson, N. J. (1995). Eye on the Prize. *AI Magazine*, *16*(2), 9-9.

Nilsson, N. J. (2009). The quest for artificial intelligence. Cambridge, UK: Cambridge University Press.

Nosratabadi, S., Mosavi, A., Duan, P., Ghamisi, P., Filip, F., Band, S., Reuter, U., Gama, J., & Gandomi, A. (2020). Data science in economics: Comprehensive review of advanced machine learning and deep learning methods. *Mathematics*, *8*(10), 1–25. DOI: 10.3390/math8101799.

Page, S. E. (2011). Diversity and complexity. Princeton, USA: Princeton University Press.

Pentland, A. (2014). Social physics: How good ideas spread-the lessons from a new science. London, UK: Penguin Books.

Petracca, E. (2017). A cognition paradigm clash: Simon, situated cognition and the interpretation of bounded rationality. *Journal of Economic Methodology*, *24*(1), 20-40.

Prigogine, I. (1980). From being to becoming: time and complexity in the physical sciences. New York, USA: W.H. Freeman.

Rabah, K. (2018). Convergence of AI, IoT, big data and blockchain: a review. *The Lake Institute Journal*, *1*(1), 1-18.

Rabin, M. (1998). Psychology and economics. *Journal of Economic Literature*, *36*(1), 11-46.

Ramos-Martin, J. (2003). Empiricism in ecological economics: a perspective from complex systems theory. *Ecological Economics*, *46*(3), 387-398.

Ramsay, J., (1998). Problems with empiricism and the philosophy of science: implications for purchasing research. *European Journal of Purchasing and Supply Management*, *4*, 163-173.

Riecken, D. (1994). M: An architecture of integrated agents. *Communications of the ACM*, *37*(7), 106-146.

Reilsback, S. F. and Grimm, V. (2012). Agent-based and individual-based modelling. Princeton, USA: Princeton University Press.

Reuter, M., & Montag, C. (2016). Neuroeconomics—An Introduction. In M. Reuter & C. Montag, *Neuroeconomics* (pp. 1-10). Berlin, Heidelberg: Springer.

Rubinstein, A. (2003). "Economics and psychology"? The case of hyperbolic discounting. *International Economic Review*, *44*(4), 1207-1216.

Rumelhart, D. E., & McClelland, J. L. (1987). Parallel distributed processing: Explorations in the Microstructures of Cognition, Volume 1: Foundations. A Bradford Book. Massachusetts, USA: MIT Press.

Russell, S. J., & Norvig, P. (2010). Artificial Intelligence-A Modern Approach, Third International Edition. London, UK: Pearson Education London.

Schelling, T. C. (2006). Micromotives and macrobehavior. New York, USA: W.W. Norton & Company.

Schwartz, H. (2019). Is Behavioral Economics Losing Its Way? Available at SSRN 3354835.

Sent, E.-M. (2004). Behavioral economics: how psychology made its (limited) way back into economics. *History of Political Economy*, *36*(4), 735-760.

Shiller, R. J., Fischer, S., & Friedman, B. M. (1984). Stock prices and social dynamics. *Brookings Papers on Economic Activity*, *1984*(2), 457-510.

Shiller, R. (2017). Narrative Economics. *The American Economic Review*, *107*(4), 967-1004.

Shiller, R. (2019). Narrative Economics: how stories go viral & drive major economic events. Princeton, USA: Princeton University Press.

Simon, H. A. (1959). Theories of decision-making in economics and behavioral science. *The American Economic Review*, 49(3), 253-283.

Simon, H. (1962). The Architecture of Complexity. Proceedings of the American *Philosophical Society*, *106*(6), 467-482.

Simon, H. A. (1983). Reason in Human Affairs. Palo Alto, USA: Stanford University Press.

Simon, H. (1990). Reason in human affairs. Palo Alto, USA: Stanford University Press.

Simon, H. (2001). Complex Systems: The Interplay of Organisations and Markets in Contemporary Society. *Computational & Mathematical Organisation Theory*, *7*(1), 79-85.

Simon, H. A. (1979). Information processing models of cognition. *Annual Review of Psychology*, *30*(1), 363-396.

Simon, H. A. (1996a). The sciences of the artificial. Massachusetts, USA: MIT Press.

Simon, H. A. (1996b). Models of my life. Massachusetts, USA: MIT Press.

Singh, P. (2003). The Panalogy Architecture for Commonsense Computing Brief Description.

Sloman, A. (2001). Beyond shallow models of emotion. *Cognitive Processing*, *2*(1), 177-198.

Sloman, A. (2008). Putting the pieces together again. In R. Sun (Ed.), *Cambridge Handbook on Computational Psychology* (pp. 684-709). Cambridge, UK: Cambridge University Press.

Sloman, A., & Chrisley, R. L. (2005). More things than are dreamt of in your biology: Information-processing in biologically inspired robots. *Cognitive Systems Research*, *6*(2), 145-174.

Smith, V. L. (1989). Theory, experiment and economics. *Journal of Economic Perspectives*, *3*(1), 151-169.

Smith, V. L. (2005). Behavioral economics research and the foundations of economics. *The Journal of Socio-Economics*, *34*(2), 135-150.

Song, C., Qu, Z., Blumm, N., & Barabási, A. L. (2010). Limits of predictability in human mobility. *Science*, *327*(5968), 1018-1021.

Spiegler, P. M., & Milberg, W. (2014). Methodenstreit 2013? Historical Perspective on the Contemporary Debate Over How to Reform Economics. *The Forum for Social Economics*, *43*(1), 7-7

Sternberg, R. J., & Sternberg, K. (2016). Cognitive psychology. Toronto, CAN: Nelson Education.

Tabb, W. K. (1999). Reconstructing political economy: the great divide in economic thought. London, UK: Routledge.

Tomer, J. F. (2007). What is behavioral economics? *Journal of Socio-Economics*, *36*(3), 463-479.

Torgler, B. (2016). Can tax compliance research profit from biology? *Review of Behavioural Economics*, *3*, 113-144.

Torgler, B. (2019). Opportunities and challenges of portable biological, social, and behavioral sensing systems for the social sciences. In G. Foster (Ed.), *Biophysical measurement in experimental social science research* (pp. 197-224). Massachusetts, USA: Academic Press.

Torgler, B. (2021a). The Power of Public Choice in Law and Economics, Center for Research in Economics, Management and the Arts (CREMA), Working Paper No. 2021-04, Zurich.

Torgler, B. (2021b). Symbiotics> Economics?. Center for Research in Economics, Management and the Arts (CREMA) Working Paper No. 2021-15, Zurich.

Tversky, A., & Kahneman, D. (1974). Judgment under uncertainty: Heuristics and biases. *Science*, *185*(4157), 1124-1131.

Ulanowicz, R. E. (1997). Ecology, the ascendent perspective. New York, USA: Columbia University Press.

Varian, H. R. (2014). Big data: New tricks for econometrics. *Journal of Economic Perspectives*, *28*(2), 3-28.

Vinuesa, R., Azizpour, H., Leite, I., Balaam, M., Dignum, V., Domisch, S., Felländer, A., Langhans, S. D., Tegmark, M., & Nerini, F. F. (2020). The role of artificial intelligence in achieving the Sustainable Development Goals. *Nature Communications*, *11*(1), 1-10.

Vitevitch, M. (2020). Network science in cognitive psychology. London, UK: Routledge.

von Bertalanffy, L. (1972). The History and Status of General Systems Theory. *Academy of Management Journal*, *15*(4), 407-426.

von Neumann, J. (1966). Theory of Self-Reproducing Automata. Illinois, USA: University of Illinois Press.

Wiener, N. (1961). Cybernetics: or control and communication in the animal and the machine (2nd ed. ed.). Massachusetts, USA: MIT Press.

Wilson, E.O. (1998). Consilience: The unity of knowledge. New York, USA: Vintage Books.

Yang, J. (2020). Two tales of complex system analysis: MaxEnt and agent-based modeling. *The European Physical Journal Special Topics*, *229*(9), 1623-1643.

Zhang, H., Shen, Z., & Miao, C. (2009). Enabling goal oriented action planning with goal net. In *2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology* (vol. 2) (pp. 271-274), Washington, USA.

Zheng, E., Tan, Y., Goes, P., Chellappa, R., Wu, D., Shaw, M., Sheng, O., & Gupta, A. (2017). When Econometrics Meets Machine Learning. *Data and Information Management*, *1*(2), 75–83. DOI: 10.1515/dim-2017-0012.