Hayek and the Machines

by James L. Caton

CHOPE Working Paper No. 2025-07
June, 2025

Center for the History of Political Economy at Duke University

Hayek and the Machines

James L. Caton

Contents

This work has benefitted from general discussions with Bruce Caldwell during my stay at the Center for the History of Political Economy. Discussion of methodological tensions have been helped from conversations with Walter Weimer. Views presented and all errors are my own.

Abstract

This work identifies the intellectual influences that supported Hayek's computational perspective as well as recognition that Hayek received from computational theorists in the decades following the publication of *The Sensory Order*. Having outlined Hayek's computational approach, I argue that 1) recognition of the approach suggests that agent-based computation is a natural extension of Hayek's work, 2) that a computational perspective helps should revise our interpretation of Kirzner's critique that Hayek's agent is a Robbinsean maximizer, and 3) that we should be careful not to reduce description of human decision-making to the structure provided by models of artificial intelligence, useful as these might be.

1. Hayek and the Machines

F. A. Hayek is a Nobel winning economist and social theorist. Known early on for his work in Austrian capital and business cycle theory, the limits of classical equilibrium theorizing led him to describe processes that typically enabled the underlying assumptions in economic theory. Hayek's efforts, especially those that led to the publication of "Degrees of Explanation" and other essays composing his *Studies in Philosophy, Politics, and Economics* (1967), were largely focused on the development of a theory of complex phenomena that would enable the articulation of economic theory in a manner consistent with the vision presented in "Economics and Knowledge". This theory would focus on the formation and transmission of knowledge and information required for decentralized coordination.

What would this theory look like? There have been various presentations of economic complexity, including by many scholars who draw inspiration from Hayek (see, for example,Butos and Koppl 1997; Koppl 2002; Koppl, et al., 2015; Koppl and Langlois 2001). Others have drawn inspiration from Hayek in computational modeling (Baum 1999; Vriend 2002; for similar approach, see Bylund 2015; Keyhani 2019). Standardization of complex economics has proved elusive. This is true, too, for a Hayekian theory of complex economics. Many have focused on the emergence of spontaneous order in the work of Hayek. However, in order to understand Hayekian complexity, emergent features and all, we must focus on Hayek's computational microfoundations. How do autonomous agents engage in plan formation, execution, and revision? This was precisely the question raised by Hayek in "Economics and Knowledge". Any notion of emergence must include the agents whose interactions generate and are guided by emergent phenomena, especially with regard to the emergence of knowledge and institutions (Butos and McQuade 2002; 2006). Much attention has been given to Hayek's work on emergence, but detail of Hayek's computational foundations remain to be fully explored.

Some have stumbled upon the striking similarity between Hayekian social theory and computation, but have treated it more as a happy accident than as an intentional feature. While arguing that agent-based computational models are consistent with Hayekian theory, Nicholas Vriend, in humility, concludes that "[i]t would probably be presumptuous to judge whether Hayek might have been an ACE, but it seems clear that ACE is social theory in a Hayekian tradition (Vriend 2002, 837)." Similarly, Miller and Drexler (1988a; 1988b; 1988c) drew inspiration from Hayek to create markets composed of programs competing for computing resources. Baum (1999) also uses a similar framework, leveraging distributed learning in a competitive environment, to solve block stacking problems. Paul Lewis (2017) recognizes Hayek's computational foundations, but focuses on its relationship to complexity and emergence rather than situating Hayek's work within the broader context of computational literature.

2. Within Systems and Between Systems

Hayek's vision of a complex social theory gained clarity during the course of his work on *The Sensory Order*, with a wave of social theorizing that integrated similar complexity in the decades that followed (Caldwell 2014). In *The Sensory Order*, Hayek recognized that scientists must accept a methodological dualism that bifurcates discussion of microfoundations and the emergent phenomena that arise during the course of interaction between components of a system (Hayek 1952, 8.47). This does not mean that the two phenomena are not related, but rather, that in sufficiently complex systems, like the human nervous system, a model of the exact mechanisms linking individual components and emergent phenomena they generate - i.e., consciousnes - must distinguish between different, if related, logics of two domains.

The response of the nervous system is correlated with inputs from the environment. The activation of vast and overlapping complexes of neurons enables subsymbolic classification. Hayek extrapolates this pattern to structures of classification that employ explicit logic that comprises human knowledge. Emergent features of the system, like human consciousness, must be treated as entities themselves. Hayek was not alone in drawing this conclusion. John von Neumann recognized this necessity for irreducibly complex systems and even drew from Godel's proof on undecidability to support his view (Neumann 1966, 47; for further discussion on Hayek, Godel, and methodological dualism, see Feser 2011; Hauwe 2011). And Godel himself, with a bit of nuance, agreed with this view (1966, 53-57; see also Weimer 2021). Specifically, he viewed the problem of irreducible complexity as being informed by Turing's *halting problem.* That is, one cannot know for certain whether or not a program will ever run to completion without actually running the program. By implication, the details of program execution must remain obscure absent execution. Turing showed that even if a program is created specifically to identify whether or not another program will run to completion, that program cannot guarantee that it, itself, will run to completion if it passes itself as an argument to itself. In similar manner, Hayek emphasized the epistemic difficulties that arise when a sufficiently complex system is given the task of modeling itself. This analytical bifurcation has led many scholars inspired by Hayek to focus on emergence in Hayekian thought. We will first identify the *emergent* side of this dichotomy.

Paul Lewis (2017) recognizes methodological tension between a computational approach and emergence. Hayek himself recognized this tension in referring to "pragmatic dualism" that is required for describing the relationship between human cognition and the neural activity with which it is correlated. Hayek surmised that we understood well enough that a connection between the two domains exists but are incapable of articulating precisely how the two realms are connected. Lewis argues that Hayek's later work on emergence in social theory depended less on computational foundation and focused on emergent properties such as shared rules. That is, emergent structures, such as systems of rules, are treated as entities unto themselves. This is easier to understand concerning the structure of rules in a human society as rules can long outlive any individual participant in society, whereas the rules that might describe the nature of interpretation implicit in the responses of one's nervous system emerge and die with the life and death of the living being. Shared rules governing agent interaction requires a community of members who adopt these rules as guides to interactions amongst one another. Yet, a system of shared rules may persist for tens or even hundreds of generations, maintaining coherence across time.

With the persistence of institutions in mind, we can surmise that humans are themselves institutional beings (in much the same way that one might say that "man is a poltical animal"). Any human being's sense of identity is a function of cultural and institutional context. This subsumes the members of the community or society that participate within it.

> [T]he properties of the individuals which are significant for the existence and preservation of the group, and through this also for the existence and preservation of the individuals themselves, have been shaped by the selection of those from the individuals living in groups which at each stage of the evolution of the group tended to act according to such rules as made the group more efficient. (Hayek 1967, 284)

Given the tension between computational foundations and emergence identified by Lewis, it is worth noting that Hayek's discussion also applies to "some sort of reduplicating mechanical structures (278n3)." Despite the shift in focus, Hayek does not seem to have divorced his study of emergent phenomena from their computational foundations.

Whatever the system studied, the operation of that system can only be understood by a description of the set of rules that relate the parts of that system. A well formulated system of rules should, thus, be capable of shedding light on that system's history. Through close observation and reasoning through thought experiments, the theorist should be capable of providing a rule-based description that is coherent with the behavior of the observed phenomena.

While it is helpful to recognize Hayek's change in emphasis across his work that seems to have occured into the 1960s, as Hayek indicates above, his description of rule-based systems is compatible and a consequence of his theorizing of systems composed of machines. In *The Sensory Order* and "Degrees of Explanation", for example, a system is clearly treated as a deterministic machine. Hayek describes responses to impulses received by the central nervous system as being "described as 'mechanical' in the most general sense of the word (Hayek 1952, 5.63)", but immediately proceeds to explain that the open ended development of interpretation of the environment by the nervous system, what he describes as "highly purposive character of the action of the central nervous system" (Hayek 1952, 4.5), integrates the concept of adaptation which is quite different from what one typically means by mechanical. Hayek uses the term causal to include this open-ended, deterministic explanation, noting that the theorist is interested in identifying "the causal mechanism determining the phenomenon in question" so that one's model reflects this causal mechanism (Hayek 1955, 221; see also Feser 2011). The more the model is accurately specified, the more that "this range [of outcomes] will be narrowed until we reach the point when the system is completely determined and only one value of the remaining variable possible (222)." Even if the world operates as a deterministic model, human ignorance of the correct data, the correct model, and the correct parameter specifications demand our humility. This interpretation is consistent with Veetil and Boettke who describe "indeterminism" as a consequence of one's ignorance of the true model of the world (Boettke and Veetil 2016, 47). (A substantive discussion concerning limits of the machine metaphor is provided in Weimer's forthcoming "Minds, Machines, and Metaphors: or, Why You Cannot Make an Adequate Model of the Mind as a Machine" in *Cosmos + Taxis.*)

As he shifts his focus to rule-based systems, Hayek decreases emphasis that the agent or system under concern is a deterministic machine, yet this feature does not disappear. Kirzner critically interpets Hayek's deterministic mode of theorizing, noting that in the background of Hayek's analysis is the "Robbinsean maximizer" and that the content of agent knowledge is unspecified (Kirzner 1979):

> [T]he truth is that [Hayek's] propositions about individual plans that continue to to presume no specific preference structures and no specific production possibilities must continue to be empty propositions, despite any postulated pattern of learning information. Indeed the empirical element introduced by Hayek not only fails to fill with factual content the empty formal propositions that make up the logic of choice, it leaves these propositions themselves exactly as empty as it finds them (1979, 25).

Kirzner explains in his critique of Robbins that an economic theory that reduces decision-making to the ultimate end of maximizing utility, abstracting away from the economic content of choice (Kirzner 1960, for conversations comparing Robbinsean maximizing to praxeology, see 108-186). For a theory where knowledge and information are given, this is an appropriate concern. Kirzner asserts that Hayek leaves the reader with an agent whose actions are rule-guided at the level of preference and rule-constrained at the level of institutions, but that the rules are presented as especially general abstractions that do not integrate praxeological guidance provided by Mises (1949). But agents that are actively modeling the environment and acting upon their own preference functions are, in fact, choosing between alternative actions as their actions are a consequence of these choices. One might right criticize more sophisticate rule structures used for utillity maximizing as deferring the problem of choice to yet a higher level, robbing the agent of autonomy by creation of a simulacra of such autonomy. But if one's aim is to create a model capable of describing human action without asserting that the ontology of the model correctly identifies human will, which is not an aim of economic theory, then Hayek's computational approach is appropriate.

Unfortunately, Hayek was not in a position to articulate a more sophsticate view of computational agents given the state of his own knowledge and the nascency of artificial intelligence at the time that he developed his computational point of view. Hayek desired to provide exactly what Kirzner claims that he failed to provide. Caldwell (2016) shows that Hayek attempted to elaborate the relationship between praxeology and his empirical theorization in the Virginia lectures. According to James Buchanan, though, Hayek failed to add clarity beyond insights he had already developed (Caldwell 2016, 173). Delineation of praxeological principles, whether due to their emergence or due to explicit encoding in agent decision-making, would have been required of Hayek had he constructed a model to convey the operation of the economic system in terms conveyed across his body work. His work on complexity provided the principles to guide the construction of such a model. I believe that its simplicity may have been the cause of Hayek's frustration.

3. Computation as a Natural Extension of Hayekian Theory

Before considering praxeological principles, we should first consider Hayekian complexity through the lens of computation. Robert Axtell notes that "aspects of Hayek's work represent a 'fresh interpretation' of current thinking about complex adaptive systems (Axtell 2016, 64)." Though themes upon which Axtell focuses are not conveyed in terms of finite state machines, he notes that complexity "has been around since the end of World War II" and includes Neumann's "self-repoducing automata" (64,65; see also Neumann 1966). Focus on the relationship of Hayek's work to a theory of automata will show that application of modern methods informed by Hayekian theory is a natural, rather than an arbitrary, extension of his theorizing.

In Hayek's computational approach, the finite state machine (or finite automata) is the theoretical device he chooses to develop his social theory beyond the purely deductive *apriorism* of his mentor, Ludwig von Mises. This may seem strange since Hayek certainly was not building any programs to be executed on a computer. Rather, the logic of finite state machines served as the foundational description of his agents. This brings clarity to both the nature of Kirzner's (1979) critique that Hayek's agent was a Robbninsean maximizer and the extent to which this critique is problematic.

Hayek does not elaborate the nature of the agent's preference function as he intended to clarify mechanisms that enable coordination. So Hayek's elaboration of coordination, for example through the price mechanism, leans on economizing agents with heterogeneous knowledge (Hayek 1945). Hayekian agents are capable of learning, which means that their preference functions are not static. Strong parallels can be drawn from models whose agents are guided by highly flexible algorithms.

It is helpful, then, to define the finite state machine that supported Hayek's theorizing and use this concept to relate Hayek's work to modern computational methods. In his *Introduction to the Theory of Computation*, Michael Sipser elaborates the meaning and context of the finite state machine (he uses the term finite automata): "Finite automata are good models for computers with an extremely limited amount of memory (2013, 31)." "The formal definition says that a finite automaton is a list of those five objects: set of states, input alphabet, rules for moving, start state, and accept states (35)." Using more modern language to describe what is essentially an finite automaton whose action is guided by a Markov Decision Process, Ashwin Rao and Tikhon Jarvis explain:

> The goal of the *Agent* at any point in time is to maximize the *Expected Sum* of all future *Rewards* by controlling (at each time step) the *Action* as a function of the observed *State* (at that time step). This function from *State* to *Action* at any time step is known as the *Policy* function. So we say that the agent's job is exercise control by determing the *Optimal Policy.* (Rao and Jarvis 2023, 6)

Development of a computational approach to perception and decision-making naturally demands agent valuation subject to constraints. The description bears resemblance to textbook microeconomic theory and the dynamic models promoted by Thomas Sargent. (Sargent is an evangelist for economic computation, but is not particularly interested in using the tools to convey epistemic difficulties faced and overcome by market actors. see Sargent and Stachurski 2024). I add only the caveat that the use of the word agent here is loose as the system modeled in many of these cases is essentially a single agent. The description of decision-making, however, bears strong resemblance to reinforcement learning agents. Although modern computational macroeconomics models are certainly not Hayekian, these methods can fit within the same umbrella.

The agents described by the Rao and Jarvis are not the perfectly knowledgeable optimizers following doctrines of textbook graduate microeconomic theory. These agents actively engage in a process of trial and error, adjusting decisions according to their evolving belief of the true state of the world and the true structure that governs state transitions. They update their models of the world to the extent that they find their predictions are incorrect and, therefore, not optimal. The authors observe the challenge that faces their artificially intelligent agent is the same that the agents of Hayek's theory face:

> The other problem one encounters in real-world situations is that the Agent often doesn't know the *model* of the environment. By model, we are referring to the probabilities of state-transitions and rewards. . . This means the Agent has to simultaneously learn the model (from the real-world data stream) and solve for the optimal policy. (2023, 10)

State transition probabilities can be estimated with guidance of a model of the environment or probabilities of state transitions can be learned from observed data without restrictions imposed by a model (Rao and Jarvis 2023, 439-449; see also Sutton and Barto 2020, 160-191). In the case of model building, error might arise from incorrect model structure. Notice that a model can be structured so that there is a zero percent chance of transitioning from state A_i to state A_j, thus indicating a network of state transitions where state nodes are not fully connected. If a model is not provided to the agent, then it must interact with the environment to build structures that guide expectation of state transitions. The agent in this case will be subject to *ad hoc propter hoc* reasoning, which is also subject to error. A well-trained modeler is aware of these tradeoffs.

Classification of relevant objects and processes in the environment is not a straightforward task. Often methods of classification may, for example, rely upon encoding of the environment (as in natural language processing) or upon interpretation of granular data that is processed by a neural network (as is the case with image processing). While these might be useful metaphors, human reasoning obviously does not follow the precise path of any of these methods. A model coherent with the human experience would, for example, need to account for balancing decisions guided by "greedy" algorithms with the need for contingencies. When making plans, entrepreneurs do not optimize only looking one period into the future, do not assume all relevant information is contained in the state of one or a limited number of previous periods (i.e., as in the cas of Markov chains), and may have empirically lumpy discounting preferences that reflect a wide variety of ends to be simultaneously pursued. Although our models intended to describe human action will have much overlap processes by which an agent determines choice, there will be features that the modeler will simply be unable to integrate. Entrepreneurs may, for example, forgo significant profit opportunities in the pursuit of multiple, overlapping goals. Thus the optimal policy of an entrepeneur may include delaying capital investment decisions to the latest possible moment in order to reduce risk, as exemplified by Kirzner's discussion of unfinished plans (Kirzner 1966). And the entrepreneur may be unable to explicitly articulate their reasoning, especially when engage in projects with a high degree of novelty and, therefore, that include high levels of uncertainty.

I anticipate that many subtle features can and will be implemented by theorists interested in modeling process as the cost of learning and employing computational methods has been sufficiently reduced in recent decades. Successful integration with mainstream approaches will require, however, that graduate programs shift focus to the development of computational skills. Thankfully, these skills significantly augment the value of econometric training. The shift toward dynamic programming by mainstream macroeconomists also places a modeling consistent with a Hayekian approach much closer to the mainstream of economics than one might expect, of course with the caveat that Hayek was interested in modeling learning and communication that enabled economic coordination. The method of reinforcement learning described above allows for both approaches. Robust formulation of these methods lie outside of the scope of further discussion as my intention is to contextualize Hayek's approach in light of computational approaches that impacted his theorizing and current methods that are relevant to his approach in light of the relationship of his theorizing to finite state machines.

4. Hayekian Complexity and Economics

Hayek intended to restate economic theory in terms of a theory of complex phenomena. In his first of the four Virginia lectures, Hayek highlights this distinction in his assessment of the limitations of Misesian praxeology (for helpful discussion on this issue, see Scheall 2015; 2017):

> It is true that at least one distinguished economist, a scholar whom I greatly admire and to whom I owe much inspiration, inisists that the whole theory of human action, including all economic theory, is of such an *a priori* character. . . . Professor von Mises tends to overlook that this logical groundwork does not yet provide an explanation of how things actually happen. (Hayek 1961, 384)

Praxeological principles are a good description of human action, but human interaction and learning that occur over the course of execution of plans reflecting actor preferences generate empirical details that tangibly impact outcomes within society. We would commit a fallacy of composition to attribute to the economy as a whole the principles that guide and constrain individual action (Hayek 1937). Hayek recognized that we must move from the realm of deduction from first principles that describe human action to the realm where action is, itself, carried out. This requires a blueprint of an agent's decision-making process. No matter what the rule at this level of analysis, agents appear to be Robbinsean maximizers as, by definition, any action chosen is optimal in the limited sense that it is best according to the rule that selected it. Agents must rank potentially viable decisions. Whether using a continuous utility score or a complex array of contingencies, the decision that the agent enacts is the one given priority. The agent believes that it is the best action in light of expected constraints. Thus agent preference is revealed by action. Although the particular process used to represent human decision-making depends upon the theorists goals, there is no getting away from this teleology of one wishes to model human action.

Different than textbook microeconomics, a computational approach allows agents to interact directly as they form their models of the environment that guide their plans. Thus, agent models and plans include and are impacted by one another (Hayek 1961, 385). This is the same sort of adaptation that Hayek used to differentiate his explanation from a limited view of mechanical explanation. If Hayek's agents are Robbinsean maximizers, these agents maximize utility, in part, by actively building the models that guide their behavior.

Kirzner had the disadvantage of thinking in terms of textbook microeconomics when approaching maximizing decisions. Thus, he imagined that Hayek's agents were simply economizing in light of given ends. Preference functions, however, can take varied forms that can be outlined explicitly in a computational program. A common approach is for an agent to maximize a CES utility function. The employment of traditional utility maximization is not the only form that a preference function may take. And there is no need to assert any of the unrealistic assumptions of the perfectly competitive model. Unlike the agents used in dynamic macroeconomic models, Hayekian agents actively theorize about the environment and rulesets guiding their own behavior. Models of this sort force the agent to relate abstract utility maximizing to the empirical content of choice. Agent choice at the level of the agent's model of the environment, which includes the rules that generate action, confronts Kirzner's concern about genuine choice. This active modeling impacts the ends pursued by an agent, for example, by virtue of defining the target and structure of the agent's loss function. An agent's unique interpretation of the environment impacts behavior derived by virtue of maximization of expected utility.

To the extent that the environment generates any novelty, artificially intelligent machines must actively reform their classificatory schemes. A map of state transitions is a fundamental part of the architecture of a finite state machine. Computational agents are such machines. And Hayekian agents, to guide their decisions, model their environment as such a machine. Agents may include probabilistic state transitions based upon context. And they may even actively build models that employ abstraction to define states and triggers of states transitions and that restrict linkages between states (i.e., the map of state transitions may not be fully connected).

5. Hayek's Computational Perspective

In "Within Systems and Between Systems", Hayek is explicit about the connection of his framing to von Neumann's finite *automata*, a synonym for finite state machine:

> The field in which the general properties of a class of phenomena are derived from the general principle by which they are defined, a field to which indeed our particular problem belongs, is the general theory of machines or, as J. von Neumann has recently called it, the "logic of automata". (Hayek Unpublished [2017], 364)

Hayek goes on to indicate that:

"[t]he general theory of classifying machines . . . may not be sufficient to specify in detail the operation of any such classifying machine of a sufficient degree of complexity to be of practical interest; but it will indicate the range of phenomena which may be produced by machines of this type (364)."

He then imagines interplay between two systems where the effects of the interplay is conveyed as state transitions:

> 49. . . . Let us assume two similar systems so constituted that they are capable not only of hunting a moving object (which we will call the prey) but also showing symbols of each class they form in observing the movement of their prey and the environment, and of taking appropriate notice in doing so of events which they cannot observe directly but which affect them only indirectly via the symbols shown by the other system. . . .
>
> 50. There can, in the first instance, be little question that machines could be constructed which in certain states (corresponding to the "intention" of catching the prey) will take such action as their internal representation of the environment indicates as leading to the capture of the prey. . . . What is required for this is sensitivity for signals from such obstacles (we shall discuss this entirely in terms of optical signals) and an apparatus for classifying such signals in a manner which produces an appropriate modification of the movements of the system. (Hayek Unpublished [2017], 380)

The states of mutually interacting systems transform in a manner corresponding to one another. This description of two systems echoes John von Neumann's discussion of finite automata: "Once we have (1) the description of an automaton, (2) its initial conditions (state), and (3) a description of the signals that will reach it from its environment, we can calculate what its state will be at each successive moment." In the case of Hayek's descriptions, each automaton's environment includes another automaton. Elsewhere, he speaks using the same kinds of abstraction:

> [B]y a system we shall throughout understand a persistent structure of coherent material parts which are so connected that, although they can alter their relations to each other, and the system thereby can assume various states, there will be a finite number of such states of which the system is capable, that these states can be transformed into each other through certain orderly sequences, and that the relations of the parts are interdependent in the sense that, if a certain number of them are fixed, the rest is also determined. (Hayek Unpublished [2017], 365)

We are left with little doubt that not only was Hayek's theorizing compatible with finite automata; his theorized agents *were* finite automata.

Hayek was influenced by work in computation and complexity. The dependence of arguments in *The Sensory Order* upon the work of cyberneticists like McCulloch (1948; also Pitts and McCulloch 1947) and Ross Ashby (1945; 1946; 1947a; 1947b; 1948) places Hayek's theoretical conception of neurons and the nervous system firmly within the paradigm of finite automata (on influence of cybernetics on Hayek, see Oliva 2015; Lewis 2016). Hayek's work was recognized by Frank Rosenblatt, whose Perceptron is widely viewed as a landmark development in the history of machine learning and who also modeled human neurons as finite automata (Rosenblatt 1958; 1961; see Mitchell 2019; Crevier 1993; McCorduck 2004). Hayek was invited to present a paper at the 1960 *Symposium on the Principles of Self-organization* where presentations included discussion of machines, automata, computers, systems, and states of these. Although he did not present a paper, due to difficulties with his health, he did chair presentations by Frank Rosenblatt and David G. Willis. Whether talking about automata, computer hardware, neural networks, or cybernetic systems, determinism is a common theme that runs implicitly and explicitly throughout discussions from the conference.

Warren Weaver's discussion of the advantages of modeling organized complexity, not simply through statistics, but through the creation of autonomous entities is reflected in "Degrees of Explanation". Hayek describes the search for "mechanism" wherein rules governing behavior enable some sets of outcomes and exclude others (Hayek 1955, 217). In other words, a system may only be able to transition to a limited number of states from its current state.

In "Degrees of Explanation", Hayek describes the process of "model-building". His discussion of the limitation of such models parallels his discussion of the limits of mechanistic description:

> Any model defines a certain range of phenomena which can be produced by the type of situation which it represents. . . . [W]e know that, *if* the mechanism is the same, the observed structures must be capable of showing some kinds of action and unable to show others; and if, and so long as, the observed phenomena keep within the range of possibilities indicated as possible, that is so long as our expectations derived from the model are not contradicted, there is good reason to regard the model as exhibiting the principles at work in the more complex phenomenon (Hayek 1955, 221).

Now, if we consider Hayek's comparison of model predictions with empirical observation alongside his comment from "Facts of the Social Sciences", that the "these so-called 'facts' are rather precisely the same kind of mental models constructed by us from elements which we find in our own minds as those we construct in the theoretical social sciences" and that any attempt to define historical facts "must take the form of a mental reconstruction, of a model, in which intelligible individual attitude form the elements", we can infer that the theories of the scientist, which include theories of agent mental contents, can be elaborated in the form of a program that defines the states, interpretation, and decisions of the agent or class of agents that are the object of theorizing (Hayek 1943, 9-10).

Thus, we can revise Vriend's hypothesis that "[i]t would probably be presumptuous to judge whether Hayek might have been an ACE." Hayek modeled according to the logic of finite state machines. Agents in an agent-based model are such machines. Thus, it is hardly presumptuous to assert that Hayek "might have been an ACE" supposing he was positioned to construct computational models. But, if my assertion is correct, why haven't economists and computational theorists broadly recognized Hayek's computational foundations?

6. Recognition of Hayek's Contribution to Computation

Limited recognition of Hayek's computational microfoundations is, perhaps, an accident of history. Unfortunately, most economists are not concerned about philosophy. And most computational theorists are not familiar with economics. Economists familiar with Hayek's work see his approach as being altogether different from their graduate training. Rigid disciplinary boundaries makes the connection between Hayek's work and computation not obvious to the average economist. Yet, the *The Sensory Order*, an expansive elaboration of causal reasoning with computational foundations, appears to have gone mostly unnoticed amongst computational theorists.

This perception should not lead one to miss the serious recognition that Hayek's work has, in fact, positively received by a variety of scholars interested in computation and neurology. Within the first decade of publication, *The Sensory Order* was recognized by Frank Rosenblatt in his development of the Perceptron, a landmark development in neural networks that applied a simple neuron for the purpose of classification. This work put Rosenblatt in the company of McCulloch and Pitts as a leading researcher on computational neural networks, often referred to as *machine learning* (see Russel and Norvig 1995 20-22, 761; Crevier 1993, 102-7; McCorduck 2004, 104-107; Mitchell 2019, 24-32). This leadership explains why Marvin Minsky, who was perhaps the leading voice in artificial intelligence more generally, twice cited Hayek and even discussed the "Philosophical Consequences" (the last chapter) of *The Sensory Order*. And either Marvin Minsky or Allen Newell included *The Sensory Order* on a recommended list of readings at least as early as 1959 (Pierce 1959). Minsky initially included Hayek's book among a large collection of literature that he conceived of as being broadly related to artificial intelligence (Minsky 1961a). About this collection, Minsky noted that "[t]here are surely many errors in the assignments of papers to the categories, both for those I have not read, and for those which I did not fully understand (Minksy 1961b, 39)."

Minsky would soon follow up concerning the "Philosophical Consequences" of *The Sensory Order*. In this chapter of *The Sensory Order*, Hayek argues, drawing on Godel's undecidability proof, that "it means that no explaining agent can ever explain objects of its own kind, or of its own degree of complexity, and therefore, that the human brain can never explain its own operations (Hayek 1952, 296 [8.69])." Minsky was not the first to note the tension of this "pragmatic dualism". A decade earlier, despite viewing Hayek's presentation of the microfoundations of consciousness as "the best word I have ever heard spoken from this platform", Edwin Boring viewed Hayek's dualism as a discomforting incosistency that "troubles me all through discussion", though he kindly notes that Hayek's view "makes sense, but it is not common sense (Boring 1953, 183; see Lewis 2016)." Minsky's evaluation was much harsher. He vehemently disagreed with Hayek's claim and his use of Godel's undecidability proof to support it, arguing that this "ignores the power of recursive description as well as Turing's demonstration that (with sufficient external writing space) a "general-purpose" machine can answer any question about a description of itself that any larger machine could answer (Minsky 1961b, 28)." Minsky's response simply punts the problem as he, in essence, expands the size of the program to explain the program. While this might justify his own faith that the methodological gap can be bridged, Minsky recognizes that the problem remains unresolved:

> We could not give up this division [between mind and body] even if we wished to - until we find a unified model to replace it. Now, when we ask such a creature what sort of being it is, it cannot simply answer "directly:" it must inspect its model(s). And it must answer by saying that it seems to be a dual thing - which appears to have parts - a "mind" and a "body." Thus even the robot, unless equipped with a satisfactory theory of artificial intelligence, would have to maintain a dualistic opinion on this matter. (Minksy 1961b, 28)

Notice that Minsky maintains that such a dualistic approach will only perisist "until we find a unified model to replace it." In 1962, when discussing the need for what can broadly be described as "connectionist" theories of mind, Minsky cites Donald Hebb (1949), whose work on perception was widely recognized, including by Rosenblatt, but leaves out *The Sensory Order*. This could be viewed as a coincidence, however, Minsky laments that "[t]here seems to have been very little analysis of 'association' types of learning (Minsky 1962, 39)." Of course, such learning is fundamental to Hayek's descsription of the role of the nervous system that Minsky had twice recognized in works published the previous year.

The link between Hayek and Hebb's approaches as well as Hayek's unique contribution of a system of classification is well documented (e.g., Simmons 1963; Nagy 1962; 1990; Edelman 1982; Marsh 2010; Weimer

1977; Smith 1997; Fuster 2011; Malsburg 1986; 2024). And despite Hayek's lamentations about a lack of interest, there was a fair amount of citation of *The Sensory Order* among those interested in neurology and perception. Semantic scholar records nearly 20 separate citations in the field before 1980, and several more are not included in that list (Bonin 1955; Kelvin 1956; Fantz 1958; Triandis 1959a; 1959b; Gibson 1960; Bevan 1961; Bauer and Cooper 1964; Havelka 1968; Schiff and Dytell 1971; Nicholson 1972; Bain 1973; Weimer 1973; 1976; Natsoulas 1974; Globus 1976; Anliker 1977; Schnitzer 1978; Goldsmith 1978). Another neuroscientist, John Taylor, dedicated an entire chapter to (unsuccessfully) rebutting Hayek's philosophical consequences after, in January 1953, he had reached out to Hayek to share this same manuscript and followed up in September 1953 to coordinate a panel discussion with himself, Hayek, and Hebb at the "International Congress of Psychology in Montreal" (Taylor 1962; Hayek Papers box 52, folder 33). Perhaps this is only a coincidence, but a mathematical appendix from Taylor's book, was coauthored by Seymour Papert, Minsky's colleague and coauthor. Both Tayolor and Papert had previously worked togther on a project on perception (Taylor and Papert 1956).

As far as I am aware, only two scholars interested in computation, aside from Rosenblatt, cited Hayek in the decades following Minsky's (1961b) critique (George 1962; 1963; Good 1965; 1972). We cannot know for certain the extent to which recognition of *The Sensory Order* would have persisted in the following decades, but it is fair to recognize that Minky's view of Hayek did not help his case. Consistent with this concern, Jack Cowan has not kept quiet about Minsky's role in bringing the first epoch of neural network research to a close (Anderson and Rosenfield 1998, 108; Husband, et al., 2008, 431-446). (It is possible that a slow down in research citing *The Sensory Order* was also a consequence of, according to Jack Cowan, circulation of preprints of *The Perceptron* (Minsky and Papert 1967) that were distributed during the early 1960s. The work was widely viewed as emphasizing the limits of neural network research. Thus, Minsky's critique of Hayek occurred within a larger campaign against Rosenblatt's Perceptron.

Minsky's critique may seem damning, but Hayek's view is supported by Von Neumann. Neumann agreed that (as discussed earlier) Godel's undecidability proof indicates that methodological dualism is required to analyze systems of sufficient complexity. Perhaps if Hayek had succeeded in maintaining interest of computational theorists, some would have been motivated to develop Hayekian models. We do know that in 1988, Hayek received recognition from two pairs of authors within computer science. These citations appear to been part of the revival of interest in neural networks, marked starkley by the publication of the now canonical *Parallel Distributed Processing: Explorations in the Microstructure of Cognition*, published by David Rumelhart, James McClelland, and the PDP Research Group. This revolution in artificial intelligence caught the attention of the editors of *Daedalus* who published an issue titled *The Artificial Intelligence Debate:*

False Starts and Real Foundations. In that issue Jack Cowan, who had attended the *Symposium on Principles of Self-organization* alongside Hayek in 1960, and David Sharp cite Hayek with regard to classification and Hopfield Nets, a type of neural network popular at the time (Cowan and Sharp 1988a; see also Cowan and Sharp 1988b). This citation would be unremarkable except for the fact that Hayek's work had not been cited by computer scientists since the 1960s. Cowan's engagement in neural network research - he worked with Warren McCulloch - makes it quite likely that he had been familiar with *The Sensory Order*, even if only indirectly through Rosenblatt's work.

In the same year, two other computer scientists, Mark Miller and K. Eric Drexler, the latter of whom would soon complete his dissertation under Marvin Minsky, wrote several chapters in *The Ecology of Computation* that included Hayekian themes and explicitly drew from Hayek's work (Miller and Drexler 1988a; 1988b, 1988c). The authors sought explicitly to draw insight from Hayek on distributed information processing. The authors derived insight from and even modeled computation in light of Hayek's work on complexity, although they did not draw from *The Sensory Order*.

This work received notice from Don Lavoie, an economist at George Mason University, who was alerted concerning this work thanks to one of his students, Bill Tulloh (Lavoie, Baetjer, and Tulloh 1990). This recognition led to collaboration of Miller, Drexler, and Phil Salin with these academics. Although not a coauthor with Miller and Drexler, Salin appears to have introduced Miller and Drexler to Hayek's work (Lavoie, Baetjer, and Tulloh 1990). Salin had received a bachelor's degree in economics from UCLA in the early 1970s, and was influenced by the approach of Armen Alchian and William Allen (Tulloh 2024). The collaboration was short-lived, however, as Salin died in 1991. Mark Miller and Bill Tulloh went on to work together, eventually founding Agoric Systems, but further development of Hayekian computational models of human economic activity was not pursued even though Hayekian principles guided the work at Agoric Systems.

These efforts bore various, if scattered, fruit. In the mid-to-late 1990s, computer scientist Eric Baum believed that the market-based approach described by Miller and Drexler may be a useful means of distributed learning. Baum suggests this approach to artificial intelligence researchers before the phenomenal success of deep learning methods. Baum constructs what he called the "Hayek machine" where property rights were used to coordinate and assign credit for solutions to the block world problem (Baum 1999). Baum's work has mostly gone unrecognized by economists with similar interest, including Vriend (2002) and myself (Caton 2017; 2019). And neither was it recognized in an article title "Frederich Hayek and the Market Algorithm" published in the Journal of Economic Literature (Bowles, et al., 2017). In his review of Hayek's influence on complexity, Robert Axtell, a leader in agent-based computation, mentions Baum (1999), but includes no more than a brief, one sentence summary of the Hayek machine (Axtell 2016, 90). Baum's work has also gone unnoticed in recent discussions of economic calculation and artificial intelligence (Boettke and Candela 2023, Bickley et al., 2022; Gmeiner and Harper 2024; Acemoglu 2023). Baum's work did receive attention from artificial intelligence researchers, including Hofstadter student Melanie Mitchell who refers to the work as "economics-inspired AI" (2006). Further development of explicitly Hayekian insight following this branch remains to be seen.

7. Hayekian ABMs: Evolution or Praxeology?

Having defended the thesis that Hayek theorized using computational foundations and having shown that his work was serious enough to gain the respect of computational theorists, I will now confront Kirzner's critique that Hayek's agents were Robbinsean maximizers by detailing the decision-making processes of agents in a computational model. Strictly speaking, these agents are utility maximizers, but their interaction with and modeling of the environment can include significant levels of detail and complexity that serve as a useful metaphor for entrepreneurship and the market process.

What principles would guide the construction of an agent-based model that builds from Hayekian theorizing that treated agents as finite automata? Drexler and Miller, Baum, and Vriend all provide various implimentations of models consistent with Hayek's theorizing using finite automata. Hayek's development of agent *understanding* and of shared *understanding* provides the elements required for representing the uniqueness of an agent's perception and for an explanation of plan formation and coordination that is typically absent from modern presentations of economic theory (Hayek 1962, 248-249; for further development see North 2005, Crawford and Ostrom 1995, Koppl 2002). It is precisely this emphasis that gives a Hayekian approach an advantage in developing unique agent-based models that exhibit coordination in a decentralized economy, even ones composed of relatively myopic agents. While economic principles guide some agent decisions, often these principles are integrated into agent strategy only over the course of agent interaction.

As theorists, we imbue agents with preferences that accord with economic principles. Yet, Becker's assertion that demand curves slope downward simply due to the existence of limited budget constraints suggests that acting agents are naturally subject to these economic principles (Becker 1962). We should expect that some range of economic principles will naturally be reflected in the results of our process-oriented simulations that include purposive agents. Even if agents are not intentionally attempting to maximize profits, competition between agents whose survival depends upon the creation of value for other agents will tend to promote the development and spread of relatively efficient methods of production and exchange. For example, Caton (2017) finds that the level of expected wealth for an agent choosing from among strategies tends to converge to the same value in such a Hayekian simulation. Agents in this model have access only to local information. They have little idea of what strategy is best or what are the optimal prices of goods. They instead use a combination of experimentation and copying of strategies from relatively wealthy trading partners.

Miller and Drexler provide some reasonable guidance that is helpful in light of their expertise in computation (1988c). Miller and Drexler (1988a) show that even for a market whose agents are programs that compete for computational resources, praxeological concepts are required for the market to function. These include property rights that delineate control, definition of purpose, valuation of resources through bidding, and exchange that is intended to facilitate the agents goal. Property rights are a feature of object oriented programming in the sense that an object - that is, an instance of an abstraction called a class - can own attributes, methods, and even other objects. They also recognize the critical role of exchange.

The market of concern for Miller and Drexler is a market whose actors are programs competing for computational resources required to complete their assigned tasks. For the required computation, "storage and processing power must be allocated and managed . . . As with processor time, storage will have a price relative to other resources, and this price will vary across different media, locations, and times (Drexler and Miller 232 1988b, 233)." Since the task of these agents is given, the authors take foregranted the agent is driven toward a particular purpose. Computational resources are goods, to be attained at some cost, that support the ultimate end of program execution. This is a constrained vision, fitting the purpose of the authors. Agents may also be left the task of defining their own purpose, constrained by factors governing their survival.

Exchange, of course, requires agents that identify goods to be pursued and their quantities, definition of willingness to pay and accept for goods exchanged, and an agreement by buyer and seller upon a price between these (for buyer and seller). Typically, presentations of economic theory convey willngness to pay/accept as being determined by an agent's utility function that reflects diminishing marginal utility. A simple bid-adjustment rule, however, could be used instead. Agents can set their willingness to pay/accept based upon the relative scarcity of the good.

In past work, I have created agents that set a target level for each good. When the target level is exceeded (not reached), the agent lowers (raises) the willingness to pay/accept (Caton 2017) and may also raise (lower) the target quantity of the good (Caton 2019). This simple rule reflects the principle of diminishing marginal utility in a manner that is difficult to distinguish from the effect of a fixed budget constraint. I do not suggest that this rule is *the* correct rule. In a current working paper, agents employ target ratios (Johnson, et al., 2025). Likewise maximization of utility according to a CES utility function is also not necessarily the only rule that should be used to guide agent action. And more intelligent agents could actively form their own rules to test in the marketplace.

I have identified a minimal set of features that are required for an agent-based model informed by a Hayekian vision of complexity economics. These include the following: property rights that delineate control, definition of agent purpose or recognition of purpose that emerges from evolutionary forces (i.e., survival), attribution of good status implied by purpose, ongoing valuation of goods (and bads) by these purposive agents, and exchange that is intended to facilitate agent ends. Experimentation and evolutionary selection are sufficient to generate strategy improvements by tending to remove the worst performing strategies and, consequently, selecting for relatively more efficient strategies (Foss and Klein 2012).

While one task involved in the construction a model following a Hayekian vision is to identify the minimal set of rules that are required to convey the principles of economic theory, the modeler may wish to observe agent strategies that are relatively complex and that reflect the praxeological foundations of the Kirznerian entrepreneur. One may, for example, employ reinforcement learning with a neural network to determine agent action based upon context would be consistent with a Hayekian framing of agent *understanding*. That is, the neural network (I mean this generally, not restricted to a particular form e.g., backpropogating, recurrent, or convolutional neural networks) is, consistent with Hayek's description, a system of "multiple classification", and such a "classifying system may in this sense be regarded as embodying a theory of the external world which enables it to predict (=produce the representative of) the events which the former will cause in the environment (Hayek Unpublished [2017], 366)." The model of an acting agent serves as a guide for decisions intended to influence the future.

A model may obliquely improve one's ability to predict. In this manner the simplified evolutionary descriptions of Alchian (1950) and Becker (1962) may be useful for understanding the context of entrepreneurial activity. Artificially intelligent, computational agents can expand our understanding beyond evolutionary inertia. Kirzner identifies the theoretical leap that must be made:

> When not all decisions dovetail, some will not be able to be implemented, bringing about disappointments in plans. These disappointments - the forms in which the market reveals the absence of full co-ordination among plans - lead to plan revisions. If economic theory is to tell us anything at all, it must explain the direction of these revisions in plans-and for this rationality must be retained. (Kirzner 1962, 384)

The question lingering is not so much whether the model I have described includes plan revisions. It must. Rather, to what extent does foresight play a role in plan revision?. The agents I have described largely succeed through force of momentum. Competition removes the worst performing strategies. And agents emulate, in part or whole, the best performing strategies of which they are aware. But in this approach, success of the innovating agent is dependent upon luck and not at all upon foresight. Agents try stuff. Competition and herding perform the labor of ordering these diverse efforts.

By incorporating agent intelligence, whereby agents actively simulate the environment with varied models that enable explicit predictions about the value of various actions, we can simulate agents who can test their foresight. Entrepreneurial agents might even attempt to generate results that contradict their predictions by taking actions that their models suggest would not be optimal. Agents that use reinforcement learning to actively model the environment and test these models significantly outperform agents that blindly experiment, even when such naive agents learn from the best performing strategies that they happen across (Johnson and Caton In Progress).

Kirzner was right. The rationality of human entrepreneurs is not adequately modeled through simplistic models of utility maximization or even heuristic agents whose strategies evolve as I have described, even if market coordination is adequately conveyed through these principles. A minimalistic theory of market process is not a complete theory of entrepreneurship. Still, the definition of the baseline model is a necessary starting point. More advanced models of learning can better represent entrepreneurial action and process that concern Israel Kirzner, even if they do not perfectly model human rationality.

8. Conclusion

Perhaps the above paragraphs seem to provide too simple a description given that Hayek found himself unable to articulate a praxeological theory of exchange that was to his liking. However, it may be that the power of these simple principles was hidden from Hayek due to his inability to construct computational models informed by these principles. Hayek's classification of emergent phenomena may have been clearer had Hayek been aided by empirical models that could have helped him further develop his intuitions. Kirzner's critique of Hayek - that he did not provide sufficient praxeological detail - may reflect that Hayek was himself aiming for a minimalist description of functional markets. There is nothing improper about adding additional details that enable differentiation between agent alertness to arbitrage opportunities and agent creativity that significantly alters the regime of profit opportunities. The minimalist model of market process may leave desired features like the law of diminishing marginal utility to be observed only as artifacts of the computational model. This would not deny that the agent architecture could intentionally include these features beyond discovery incidental to a process of trial and error.

The question remains under what conditions can the emergent economic features that interested Hayek be integrated into the model. Hayek concerned himself with emergent subjective features that seem to parallel a Mengerian description of stages of production as well as emergence of rules, also discussed by Menger (1871; 1883). Consistent with Kirzner's description of unfinished plans, Hayek wished to better described the complexty of economic plans, attempting to distinguish between various cases where possible relationships between means and ends could be many to one, one many, or many to many (Hayek 1961, 389-394; Kirzner 1966; for recent theorizing along these lines, see Sarasvathy 2001). I am also reminded of Armen Alchian's discovery of the material used to produce nuclear weapons using knowledge of timing of the project and changes in prices of stocks of producers of candidate materials (Newhard 2014). But the comparison, goes deeper. Decisions of computational agents who actively engage in modeling and adaptation to the environment seem closer to genuine human choice. We are left to ask, what are the similarities between such agents and humans and what features distinguish them? When the optimal decision is not apparent or non-existen, such a variety of productive plans should be observed amongst agents competing under similar condition. While we cannot truly step into the mind of a real world entrpreneur, we can see the diversity of and similarity between outcomes as evidence of a set of options that are conceivable by competing entrepreneurs. And, we can observe the rules and parameter values guiding agent decisions within an agent-based computational model.

My aim here has been more limited. I have sought to elaborate the context behind Kirzner's critique of Hayek's theorizing. The critique is spelled out in terms of Robbinsean maximizing. While sensible given Kirzner's context, this judgment is consistent with critiquing Hayek for his employment of finite automata. I think, however, Kirzner's critique of his maximizing agents fails to recognize 1) the practically infinite variety of models that agents can use to guide their decisions and 2) the potential for creativity that is enabled by more advanced forms of artificial intelligence that, nonetheless, are still engaged in maximizing some objective function. Computational modeling thus supports a reframing of Kirzner's (1979) critique of Hayek. Hayekian theory can be further clarified through the development of models whose agents are guided by such complex decision-making structures. Computational models are a legitimate extension of the Hayekian research program.

9. References

Acemoglu, D. (2023). "Hayek Vs. AI Socialism." *The International Economy* Spring 2023: View Article

Anderson, J. A. and Rosenfield, E. (ed.) (1998) *Talking Nets: An Oral History of Neural Networks.* Cambridge, MA: The MIT Press: View Book

Anliker, J. (1977). "Biofeedback from the Perspectives of Cybernetics and Systems Science". in ed., Beatty, J. and Legewie, H. *Biofeedback and Behavior*: View Article

Ashby, R. (1945). "The physical origin of adaptation by trial and error." *Journal of General Psychology* 32: 13-25.

Ashby, R. (1946). "Dynamics of the Cerebral Cortex." *American Journal of Psychology* 59 (4)

Ashby, R. (1947a). "Principles of self-organizing dynamic systems" *Journal of General Psychology* 37

Ashby, R. (1947b). "Dynamics of the Cerebral Cortext: Automatic Development of Equilibrium in self-organizing systems"*Psychometrica* 12

Ashby, R. (1948). "Design for a Brain." *Electronic Engineering* 20

Axtell, R. (2016). Hayek Enriched by Complexity Enriched by Hayek", *Advances in Austrian Economics: Revisiting Hayek's Political Economy* 21, 63-121: View Article

Bauer J. and Cooper, R. (1964). "Effects of Posterior Cortical Lesions on Performance of a Brightness-Discrimination Task." *Journal of Comparative and Physiological Psychology*View Article

B. Bain. (1973). "Toward a Theory of Perception: Participation as a Function of Body-flexibility.". The Journal of General Psychology89 (2), 157-296: View Article

Baum, E. (1999). "Toward a Model of Intelligence as an Economy of Agents." *Machine Learning* 35, 155-183: View Article

Becker, G. (1962). "Irrational Behavior and Economic Theory." *Jouranl of Political Economy* 70 (1): 1-13: View Article

Bevan, W. (1961). "Perceptual Learning: An Overview". *Journal of General Psychology*View Article

Bickley, S. J., Chan, H. F., and Torgler, B. (2023). "Artificial Intelligence in the Field of Economics."*Scientometrics* 127, 2055-2084: View Article

Boettke, P. and Candela, R. (2023) "On the Feasability of Technosocialism." *Journal of Economic Behavior and Organization* 2023: View Article

Boettke, P. and Veetil, V. (2016). "Models of Human Action." *Cosmos and Taxis* 3 (2-3), 45-55: View Article

Bonin, G. (1955). "Toward an Anthropology of the Brain."*Annals of the New York Academy of Sciences* 63 (4), 505-509: View Article

Bowles, S., Kirman, A. and Sethi, R. (2017). “Retrospectives: Friedrich Hayek and the Market Algorithm.” *The Journal of Economic Perspectives* 31 (3): 215-230.

Butos, W. and Koppl, R. (1997). "The Varieties of Subjectivism: Keynes and Hayek on Expectations." *History of Political Economy* 29 (2), 327-359: View Article

Butos, W. and McQuade, T. (2002). "Minds, Markets, and Institutions: The Knowledge Problem in Hayek's Thought." in Ed., Birner, J., Garrouste, P., and Aimar, T. *F. A. Hayek as a Political Economist: Economic Analysis and Values.* London: Routledge.

Butos, W. and McQuade, T. (2005). "The Sensory Order and Other Adapative Classifying Systems." *Journal of Bioeconomics* 7: 335-358.

Bylund, P. (2015). “Signifying Williamson's Contribution to the Transaction Cost Approach: An Agent-Based Simulation of Coasean Transaction Costs and Specialization.” *Journal of Management Studies* 52, no. 1: 148–74.

Caldwell, B. (1988). "Hayek's Transformation" *History of Political Economy* 20 (4), 513-541: View Article

Caldwell, B. (2016). "F. A. Hayek and the Economic Calculus." *History of Political Economy* 48 (1), 151-180: View Article

Caldwell, B. (2004a). *Hayek's Challenge: An Intellectual Biography of F. A. Hayek* Chicago: University of Chicago Press: View Book

Caldwell, B. (2004b). "Some Reflections on F.A. Hayek's The Sensory Order." Journal of Bioeconomics 6, 239-254: View Article

Caldwell, B. (2014). "Introduction" in Hayek, F. A. *The Market and Other Orders* Chicago: University of Chicago Press: View Article

Caldwell, B. and Lausinger, H. (2022). *Hayek: A Life, 1899-1950..* ChicagoL University of Chicago Press.

Caton, J (2017). "Entrepreneurship, Search Costs, and Ecological Rationality in an Agent-based Economy" *Review of Austrian Economics* 30, 107-130: View Article

Caton, J. (2019). "Creativity in a Theory of Entrepreneurship" *Journal of Entrepreneurship and Public Policy* 8 (4), 442-469: View Article

Cowan, J. and Sharp, D. (1988a). "Neural Nets." Quarterly Review of Biophysics 21 (3), 365-427: View Article

Cowan, J. and Sharp, D. (1988b). "Neural Nets and Artificial Intelligence." Daedalus 117 (1), 85-121: View Article

Crawford, S. and Ostrom, E. (1995). "A Grammary of Institutions" *American Poltical Science Review* 89 (3), 582-600: View Article

Crevier, D. (1993). *AI: The Tumultuous History of the Search for Artificial Intelligence* New York: Basic Books.

Fantz, R. (1958). "Visual Discrimination in a Neonate Chimpanzee." *Perceptual and Motor Skills* 8 (3), 59-66: View Article

Feser, E. (2011). "Hayek, Popper, and the Causal Theory of Mind." *Advances in Austrian Economics* 15, 73-102.

Fuster, J. M. (2011). "Hayek in Today's Cognitive Neuroscience." *Advances in Austrian Economics* 15, 3-11.

Foerster, H. and Zopf Jr., G. (1961). *Principles of Self-organization, International Tracts in Computer Science and Technology and Their Application, Volume 9* New York: Pergamon Press.

Foss, N. and Klein, P. (2012). *Organizing Entrepreneurial Judgment: A New Approach to the Firm.* Cambridge: Cambridge University Press.

George, F. H. (1962). *The Brain as a Computer.* Oxford: Pergamum Press.

George, F. H. (1963). "Finite Automata and the Nervous System." *Progress in Brain Research* 2, 37-52: View Article

Gibson, J. (1960). "The Concept of the Stimulus in Psychology." *American Psychologist* 15 (11), 694-703: View Article

Globus, G. (1976). "Mind, Structure, and Contradiction" in ed., Globus, G., Maxwell, G., and Savodnik, I. *Consciousness and the Brain: A Scientific and Philosophical Inquiry*: View Chapter

Gmeiner, R. and Harper, M. (2024). "Artificial Intelligence and Economic Planning." *AI & Society* 39, 985-1007: View Article

Goldsmith, D. (1978). "An Automateable single-axis Circumradial system part I: Electrical servos for smaller models". *Journal of New Music Research*, 117-157: View Article

Good, I. (1965). "Speculations Concerning the First Ultraintelligent Machine". *Advances in Computers* 6, 31-88: View Article

Good, I. (1972). "Food for Thought." In: Nicholson, J.P. (eds) *Interdisciplinary Investigation of the Brain. Advances in Behavioral Biology.* Springer, Boston, MA. View Chapter

Hancock, M. (2024). "Spontaneity and Control: Friedrich Hayek, Stafford Beer, and the Princiiples of Self-Organization." *Modern Intellectual History*, 1-20: View Article

Hauwe, L. (2011). "Hayek, Gödel, and the Case for Methodological Dualism." *Journal of Economic Methodology* 18 (4), 387-407: View Article

Havelka, J. (1968). *The Nature of the Creative Process in Art: A Psychological Study*The Hague: Martinus Nijhoff.

Hayek Papers, Box 52, Folder 33, Taylor, James G. 1953-1954: View Archive Reference

Hayek, F. A. (1937). "Economics and Knowledge." *Economica* 4 (13), 33-54: View Article

Hayek, F. A. (1943). "The Facts of the Social Sciences." Economica, 10(1), 1–18.

Hayek, F. A. (1945). "The Use of Knowledge in Society." *The American Economic Review* 35 (4), 519-530: View Article

Hayek, F. A. (1952). The Sensory Order: An Inquiry into the Foundations of Theoretical Psychology. Chicago, IL: University of Chicago Press.

Hayek, F. A. (1955). "Degrees of Explanation." *British Journal of the Philosophy of Science* 6 (23), 209-225: View Article

Hayek, F. A. (1961[2014]). "A New Look at Economic Theory." in Ed., Caldwell, B. *The Market and Other Orders* University of Chicago Press.

Hayek, F. A. (1962 [2014]). "Rules, Perception, and Intelligibility." in Ed., Caldwell, B. *The Market and Other Orders* University of Chicago Press.

Hayek, F. A. (1967). *Studies in Philosophy, Politics, and Economics.* Chicago: University of Chicago Press.

Hayek, F. A. (Unpublished [2017]). "Within Systems and about Systems." in Ed., Vanberg, V. J. *The Sensory Order and Other Writings on the Foundations of Theoretical Psychology.* Chicago: University of Chicago Press: View Book

Hebb, D. O. (1949). *The Organization of Behavior: a Neuropsychological Theory* New York: Wiley: View Book

Husband, P., Holland, O., and Wheeler, M. (2008). *The Mechanical Mind in History.* Cambridge, MA: The MIT Press.

Johnson, Z., Caton, J., Miljkovic, D., and Rayamajhee, V. (2025). "The Market Algorithm as Genetic Algorithm." Working Paper:View Article

Kelvin, R. P. (1956). "Thinking: Psychologists and Physiology." *Acta Psychologica* 12, 136-151: View Article

Keyhani, M. (2019). "Computational Modeling of Entrepreneurship Grounded in Austrian Economics: Insights for Strategic Entrepreneurship and the Opportunity Debate." *Strategic Entrepreneurship Journal* 13 (2), 221-40.

Kirzner, I. (1962). "Rational Action and Economic Theory." *Journal of Political Economy* 70 (4), 380-385.

Kirzner, I. (1966). *An Essay on Capital.* New York: Augustus M. Kelley.

Kirzner, I. (1979). *Perception, Opportunity, and Profit: Studies in the Theory of Entrepreneurship.* Chicago: University of Chicago Press.

Koppl, R. (2002). *Big Players and the Economic Theory of Expectations.* New York: Palgrave Macmillan.

Koppl, R. (2009). "Some Epistemological Implications of Economic Complexity." *Journal of Economic Behavior and Coordination* 76 (3), 859-872: View Article

Koppl, R. and Langlois, R. (2001). "Organization and Language Games." *Journal of Management Studies* 5, 287-305: View Article

Koppl, R., Kauffman, S. Felin, T., and Longo, G. (2015). "Economics for a Creative World."*Journal of Institutional Economics* 11 (1), 1-31: View Article

Lavoie, D., Baetjer, H., and Tulloh, W. (1990). "High-tech Hayekians: New Directions in Austrian Economics." *Market Process*8, 120-147.

Lewis, P. (2016). "The Emergence of 'Emergence' in the Work of F. A. Hayek: A Historical Analysis."*History of Political Economy* 48 (1), 111-150: View Article

Lewis, P. (2017). "Ontology and the History of Economic Thought: The Case of Anti-reductionism in the work of Friedrich Hayek." *Cambridge Journal of Economics* 41 (5), 1343-1365: View Article

Malsburg, C. (1986). "Am I Thinking in Cell Assemblies." *Brain Theory*, 161-176: View Article

Malsburg, C. (2024). Fodor and Pylyshyn's Critique of Connectionism and the Brain as Basis of the Mind."

McCorduck, P. (2004). *Machines Who Think: A Personal Inquiry into the History and Prospects of Artificial Intelligence*. CRC Press.

McCulloch, W. (1948). "A Recapitulation of the Theory with a Forecast of Several Extensions." *Teleological Mechanisms* ed., Frank, L. K. *Annals of the New York Academy of Science* 50.

Mitchell, M. (2006). "Complex Systems: Network Thinking." *Artificial Intelligence* 170, 1194-1212: View Article

Mitchell, M. (2019). Artificial Intelligence: A Guide for Thinking Humans New York: Farrar, Straus, and Giroux: View Article

Miller, M. S. and Drexler, K. E. (1988a). "Comparative Ecology: A Computational Perspective" in *The Ecology of Computation* (Ed.) B. A. Huberman. Amsterdam: North-Holland: 51-76.

Miller, M. S. and Drexler, K. E. (1988b). "Incentive Engineering for Computational Resource Management." in *The Ecology of Computation* (Ed.) B. A. Huberman. Amsterdam: North-Holland: 231-266.

Miller, M. S. and Drexler, K. E. (1988c). "Markets and Computation: Agoric Open Systems" in *The Ecology of Computation* (Ed.) B. A. Huberman. Amsterdam: North-Holland: 133-176.

Minsky, M. (1961a). "A Selected Descriptor-Indexed Bibliography to the Literature on Artificial Intelligence." Institute of Radio Engineers Transactions on Human Factors in Electronics HFE 2(1): 39-55.

Minsky, M. (1961b). "Steps Toward Artificial Intelligence." *Proceedings of the IRE* 49 (1), 8-30: View Article

Minsky, M. (1965). "Matter, Mind, and Models." *Artificial Intelligence Memo* (77), Massachusetts Institute of Technology: View Article

Minsky, M. (1967). *Computation: Finite and Infinite Machines* Englewood Cliffs, NJ: Prentice-Hall.

Mises, L. (1949 [1996]). *Human Action: A Treatise on Economics.* Indianapolis, IN: Liberty Fund, Inc.

Nagy, G. (1962). *Analogue Memory Mechanisms for Neural Nets: A Thesis Presented to the Faculty of the Graduate School of Cornell University in Partial Fulfillment of the Requirements for the Degree of Doctor of Philosophy* Ithaca, NY: Cornell University.

Nagy, G. (1990). "Neural Networks-Then and Now." *IEEE Transactions on Neural Networks* 1 (1), 316-318: View Article

Natsoulas, T. (1974). "The Subjective, Experiential Element in Perception." *Psychological Bulletin* 81 (10), 611-631: View Article

Newhard, J. M. (2014). "The Stock Market Speaks: How Dr. Alchian Learned to Build the Bomb." *Journal of Corporate Finance* 27, 116-132: View Article

Neumann, J. (1966). *Theory of Self-Reproducing Automata* ed. A. W. Burks. University of Illinois Press: Urbana, IL.

North, D. (2005). *Understanding the Process of Economic Change* Princeton: Princeton University Press.

Oliva, G. (2015). "The Road to Servomechanisms: The Influence of Cybernetics on Hayek from *The Sensory Order* to the Social Order." *CHOPE Working Paper No. 2015-11.*

Pitts, W. and McCulloch, W. (1947). "How We Know Universals: The Perception of Auditory and Visual Forms." *The Bulletin of Mathematical Biophysics* 9, 127-147.

Rao, A. and Jarvis, T. (2023). *Foundations of Reinforcement Learning with Applications in Finance.* New York: Chapman and Hall/CRC.

Rosenblatt, F. (1958). "The Perceptron: A Probabilistic Model for Information Storage and Organization in the Brain." *Psychological Review* 65 (6), 386-408: View Article

Rosenblatt, F. (1961). *Principles of Neurodynamics: Perceptrons and the Theory of Brain Mechanisms* Cornell Aeronautical Laboratory: View Article

Rosser, B. (1999). "On the Complexities of Complex Economic Dynamics." *Journal of Economic Perspectives* 13 (4), 169-192: View Article

Sarasvathy, S. D. (2001). "Causation and Effectuation: Toward a Theoretical Shift from Economic Inevatibility to Entrepreneurial Contingency." *Academy of Management Review* 26 (2), 243-263: View Article

Sargent, T. and Stachurski, J. (2024). *Dynamic Programming.*: View Article

Scheall, S. (2015). "Hayek the Apriorist?" *Journal of the History of Economic Methodology* 37 (1), 87-110: View Article

Scheall, S. (2017)."What is extreme about Mises's Extreme Apriorism." *Journal of Economic Methodology* 24 (3), 226-249: View Article

Schiff,W. and Dytell, R. (1971). "Tactile Identification of Letters: a Comparison of Deaf and Hearing Childrens' Performances." Journal of Experimental Child Psychology11 (1), 150-164: View Article

Schnitzer, M. (1978). "Toward a neurolinguistic theory of language". *Brain and Language* 6 (3), 342-361: View Article

Smith, B. (1997). " The Connectionist Mind: A Study of Hayekian Psychology." in Hayek: Economists and Social Philosopher: A Critical Retrospective. London: Macmillan, 9-29.

Sipser, M. (2013). *Introduction to the Theory of Computation* Boston: Cengage Learning.

Sutton and Bartow (2020). *Reinforcement Learning: An Introduction* Cambridge: MIT Press.

Taylor, J. (1962) *The Behavioral Basis of Perception.* New Haven, CT: Yale.

Taylor, J. and Papert, S. (1956). "A Theory of Perceptual Constancy." *British Journal of Psychology* 47 (3), 216-224: View Article

Triandis, H. (1959a). "Cognitive Similarity and Interpersonal Communication in Industry." *Journal of Applied Psychology* 43 (5), 321-326: View Article

Triandis, H. (1959b). "Categories of Thought of Managers, Clerks, and Workers about Jobs and People in an Industry." *Journal of Applied Psychology* 44 (5), 297-302: View Article

Triandis, H. (1960). "Cognitive Similarity and Communication in a Dyad." *Human Relations* 13 (2): View Article

Tulloh, B. (2024). Private Correspondence.

Vriend, N. (2002). "Was Hayek an Ace?" *Southern Economic Journal* 68 (4), 811-840: View Article

Weaver, W. (1948). "Science and Complexity."*American Scientist* 36 (4), 536-544: View Article

Weimer, W. B. (1973). "Psycholinguistics and Plato's paradoxes of the Meno.". *American Psychologist* 28 (1), 15-33: View Article

Weimer, W. B. (1976). "Manifestations of Mind: Some Conceptual and Empirical Issues." *Manifestations of Mind: Some Conceptual and Empirical Issues* in ed., Globus, G., Maxwell, G., and Savodnik, I. *Consciousness and the Brain: A Scientific and Philosophical Inquiry*: Read Chapter

Weimer, W. B. (1977[1982]). "Hayek's Approach to the Problems of Complex Phenomena: An Introduction to the Thoretical Psychology of *The Sensory Order*". in Ed., Weimer, W. B. and Palermo, D. S. *Cognition and the Symbolic Processes: Vol. 2*, 241-285.

Weimer, W. B. (2021). "Problems of a Causal Theory of Functional Behavior: What the Hayek-Popper Controversy Illustrates for the 21st Century - Part 1" *Cosmos and Taxies* 9 (11/12), 1-30.