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RESEARCH

The coevolution of technology, markets, and culture: the challenging case of AI

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Abstract

Artificial intelligence (AI) is at the center of economic, social, political, and ethical debate. For the first time in human history, since the appearance of writing, a new type of "intelligence" is impacting the very nature of social relationships. New technologies are not only changing the operating model of markets and value chains in an accelerated way but also in how information is generated and processed, how labor, social relations, and culture evolve, etc. In this paper, we pursue two main goals. First, to set up an analytical framework in which cognitive, technical, and cultural dynamics are intertwined with the processes of deployment of economic action. Secondly, we utilize this framework to explore some key features and challenges of AI and its impact on coevolutionary processes at the cognitive, market, and cultural levels. We devote special attention to the consequences that AI may have for the concept of (economic) rationality and the formation of action plans. We conclude that AI will massively enhance agents' spaces of action by improving efficiency and exploring new possibilities. However, AI will not change the nature of human action and the structure of the evolution of the economic system.

Keywords Artificial intelligence (AI) · Rationality · Action plans · Markets · Technology · And culture · Coevolution

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> Mind connects to Society through Human Action and the reverse is also true. Individual action is interaction from which social institutions emerge which, in turn, shape human action in a complexly evolving real-time process. (Lewin, 2015: 358)

1 Introduction

Socio-economic processes are embedded in and are the outcome of the interactive deployment of human intentional action. As such, economic processes are not autonomous, that is, independent of other human (e.g., cultural, technological, and institutional) and non-human (e.g., natural environment) processes. Consequently, the evolution of any economic system depends, at the micro level, on the interactive deployment of agents' intentional action, and at the meso and macro levels on the coevolution of the cultural, technological, and institutional (and natural) systems. All these interactions are bidirectional, and coevolutionary (Almudi & Fatas-Villafranca 2021), and they are the subject of increasing attention (see, for example, Santa Fe Institute 2024).

Two main mechanisms govern evolutionary processes. The first one is the variation-selection-retention algorithm (Beinhocker 2011); the second mechanism consists of the recombination of existing devices, rules, ideas, and plans (Smith 1795; Schumpeter 1934; Simon 1969; Koppl et al. 2023). New combinations that result from the recombination of knowledge (Antonelli 2017) and activities are the main source of the renewed variety that evolutionary processes need to operate. Economic history provides numerous examples of how technology, rules, and institutions interact with the economy (North 2005). A much less discussed topic is the impact of culture on the economy and the impact of economic evolution on culture (Mokyr 2002; North 2005; McCloskey 2006, 2015; Hodgson 2023).[1]

As economic history shows, technological novelties—in particular general-purpose technologies (GPT)—trigger continuous or radical readjustments in the modes of interaction, in the functioning of existing markets and the opening of new ones (and the disappearance of others)—Schumpeter (1934 [1983]), Freeman and Louça (2001), Perez (2002). They also imply reassignments of political and social power (including geopolitics) and the emergence of new challenges. In his book about the nature of technology, Brian Arthur (2009: 11–12; 215) claims that "[w]e are moving from an era where machines enhanced the natural—speeded our movement, saved our sweat, stitched our clothing—to one that brings in technologies that resemble or replace the natural—genetic engineering, artificial intelligence, medical devices implanted in our bodies."

Artificial intelligence (AI) is one of these GPTs. Although its origin dates back to the mid-50 s: AI technology (or, according to Mitchell, (2019) a

[1] There are prominent exceptions such as Marx, the Austrian School, Sombart, Pareto, and Weber.

combination of technologies generally considered as AI)[2] has recently acquired a strong momentum, and it is at the center of economic, social, political, and ethical debates—as many articles at *The Economist*, *Bloomberg Technology*, and *The MIT Sloan Management Review* illustrate. For the first time in human history, since the appearance of writing, a new type of "external intelligence" has emerged and is impacting the very nature of human and social relationships. The advances in information technologies (ITCs) are not only changing the operating model of markets and value chains in an accelerated way (for example, logistics) but also transforming societies in a radically new way, because of the scope and speed of transformations, and their impact on cognitive and cultural dynamics.

The deepest and perhaps most important transformation has to do with the way information is processed and generated—especially in the case of generative AI—because it is starting to influence decision-making modes and models. Thus, the use of algorithms, decision-making rules, the scoring of agents and markets, the strategic use of big data, etc. are increasingly common and generate costs and benefits. Additionally, the emergence of AI is introducing increasing complexity in economic systems through new layers of interaction into social, cultural, and economic dynamics: the increasing speed of technological and organizational changes; the redefinition of human capital, capabilities, and skills (Acemoglu et al. 2022; OECD 2023); new virtual assets and markets; and changes in decision rules—decisions that imply all kind of ethical issues, as the examples of autonomous vehicles and weapons show. On the other hand, generative artificial intelligence, chatbots, machine learning, AI-ChatGPT, etc. are raising high—perhaps disproportionate—expectations that may end in a new technological bubble.

Aside from practical and technical issues, the consequences of AI at the theoretical level are also of great importance for Economics. Questions such as: How will the growing use of AI affect the deployment of intentional action by human agents? What will be the impact of AI on the formation of expectations and how are the outcomes of human interaction mediated by AI shape agents' intentional plans? How will AI affect planning and decision-making in the context of increasingly complex organizations that use this type of technology? Does AI challenge the very concept of (economic) rationality? What will be the place and role (if any) of creativity and entrepreneurship in the new emergent context? Should deserve the economist's attention.

This paper pursues two main goals. First, to offer an analytical framework in which cognitive, technical, and cultural dynamics are intertwined with the processes of deployment of economic action. Sections 2 and 3 develop this analytical framework. Secondly, we use this framework to explore some key features and challenges of AI and its impact on coevolutionary processes. We devote special attention to the consequences that AI may have for the concept of (economic) rationality and the formation of action plans. Section 4 applies the analytical framework and Sect. 5

[2] AI is in fact a bunch of technologies that include expert systems and machine learning. For an excellent introduction, see Mitchell (2019). Following Siegel (2024: xxv-xxvi), by AI we will refer here to machine learning, generative AI, deep learning, and predictive analytics, but will not consider artificial general intelligence, natural language processing, rule-based systems, and computer vision.

addresses the question of rationality. The paper's main claim is that AI will enhance enormously agents' spaces of action and improve efficiency in exploring new possibilities. However, AI will not change the nature of human action and the structure of the evolution of the economic system.

2 Action and social processes

2.1 Action plans

The basic analytical unit of evolution in our approach is the concept of an action plan. An action plan is the agent's projective linkage of scarce means (which may include other subordinate-specific actions) to goals (or ends) (Rubio de Urquía, 2005). The very nature of an action plan is the projective character of the ordering involved. The interactive deployment of agents' plans of action configures the socio-economic processes which, in turn, creates new possibilities of action for people and societies; they also constitute the basis of the evolution of complex evolutionary socio-economic systems (Muñoz et al., 2011; Muñoz and Encinar, 2014). Economic processes are a special kind of processes deployed within global human action in historical time. The outcomes of economic processes appear in many different forms (production of goods and services, consumption, investment in physical and human capital, exchange and trade, rules, organizations, institutions, etc.). These outcomes—which are recorded in statistics, organizational forms, physical and social technologies, etc.—are the consequences of human interaction.

Economic agents form plans of action and deploy interactively the sequences of actions included in those plans. At each instant of time and for each agent, the individuals that populate the economy (1) *form* bundles of alternative courses of action imagined and deemed possible (Shackle 1979: 26); (2) *adopt*, within those bundles, the courses of action (plans) that they want to make effective because they consider them as the best options (with subjective criteria) in the decision context[3]; (3) deploy the sequences of actions envisaged in these plans to attain the expected goals—it is an *interactive deployment* of actions because they interact with the physical and social milieu—; and (4) *evaluate* and *revise* their plans. For the purpose of this paper, the two critical steps are the constitution of action plans and the interactive deployment of those actions.

Firstly, when forming the bundles of action plans, each agent, departing from his intentional state (Searle, 1983), determines what he *believes* he can do, what he *wishes* to do, and *how to proceed* in a social context. Thus, the formation of personal action plans depends on the particular sets of personal characteristics of the agents: their internal structures of beliefs, attitudes, values, and representations of reality. These sets of elements define what each person perceives as existing, based on what he knows, feels, and wants. Rubio de Urquía (2005) has referred to this structure as

[3] We say "adopt" instead of "select" because there is a personal implication in this operation that goes beyond mere selection. For simplicity, we assume here that agents adopt only one plan at each instant of time. However, in general, it is possible to deploy two or more plans at the same time.

the *personal ensemble*.[4] Personal ensembles are idiosyncratic and critical in understanding, the connections of individuals' plans with culture, technology, and society.

Secondly, economic processes are put into motion when agents have to choose among their bundles of plans, those courses of action that they will interactively unfold. Once a decision is made, each agent undertakes the external actions according to the action plan to produce the expected outcomes. Agents deploy their planned actions in interaction with the physical and social reality in which they live to transform that reality according to their intended goals. Agents evaluate what is being produced (reached) according to their sequences of planned actions and goals. As far as what is being executed and achieved conforms to what was previously planned, they would judge whether their action is efficient (Muñoz and Encinar, 2019). Deviations (partial success or failure) from planned sequences of actions and pursued goals eventually would determine adjustments to the action plans—including their partial and even total removal.

2.2 Coordination and reflexivity

A society is an order, and an order implies coordination. Hayek (1937: 41) raised the question of coordination of planned action. For him, equilibrium means the compatibility of the different plans that the individuals composing the society have made for action in time—economic equilibrium is an equilibrium of expectations. In a similar vein, Hahn (1974) refers to equilibrium as a situation in which agents' policies (as he calls courses of action) do not change. In Walrasian general equilibrium theory, ex-ante feasibility and consistency of plans are essential properties for coordination (see Debreu 1959: 100). However, in historical (or more realistic) processes, due to interaction, ex-post coordination is not at all guaranteed. On the contrary, the usual outcome is that economic processes are in disequilibrium (Antonelli 2017). This fact gives rise to the continued evaluation and revision of plans by economic agents. Revision (and learning) provide a basic feedback mechanism that continuously renews the source of variety (including novelties) that feed evolutionary processes. Soros (2013) has referred to this feedback mechanism as reflexivity (see also Beinhocker 2013). Reflexivity, which can manifest in different ways depending on the nature of the feedback mechanisms that individuals use, establishes a bi-directional connection between the formation of plans and the evaluation of the outcome in terms of the achievement of pursued goals. As in the case of technologies, routines, and norms, successful courses of action are retained and replicated; the other are revised, removed, or abandoned in a replication-like process (Almudi and Fatas-Villafranca 2018). Thus, reflexivity establishes a *dynamic nexus* between individual and social reality. Learning processes and the formation of expectations are linked to reflexivity.[5]

[4] Rather similar notions are *constructs* (Kelly, 1963), *shared mental models* (Denzau and North 1994), *space of representations* (Loasby 1999), *personal agency beliefs* (Harper 2003), etc.

[5] Reflexivity does not necessarily imply increasing coordination in itself; on the contrary, it is perfectly possible to have a type of revision of plans that involves greater discoordination of the individual and social process because reflexivity can introduce or reinforce biases in action.

2.3 Expectations

Human action is projective, look at the future. Human beings do not know the future course of events; the universe is so complex (Loasby 1999) that radical uncertainty is pervasive. Nevertheless, we are compelled to act, to reach (or change) our desired states or goals. How do humans manage this situation? Kelly (1963), as Hayek (1952), stresses the human ability to generalize and use analogy: humans are good at imposing patterns on their surrounding world. Thus, pattern matching is the way we perceive, remember, and comprehend reality. On this basis, humans can be seen as *scientists* who construct theories (*conjectures*) about how the physical and social world work in the face of uncertainty. Action plans are conjectures. According to Koppl (2002: 107), "The point of our plans is precisely to change events, to move them from the path they would otherwise take." Agents make plans only in the field of action or part of the world they think they can control (at least to some degree) giving them "enough subjective predictability to expect the desired result with the required degree of confidence. That field of action is filled with hypothetical propositions of the type: 'If I do this, that follows.'" (Ibid.) Expectations integrate into the action plans of agents, setting and shaping the goals of action as desired future states of the system and the sequence of actions to produce them. Thus, agents' plans can be also conceived as experiments based on conjectural knowledge to coordinate their activities with other agents. Available scientific and tacit knowledge and the evolution of technology raise expectations about new niches of opportunities related to ends and means.

Expectations can evolve, and that impacts the constitution of plans and the actions deployed by agents. Concerning the future, there is a key role for imagination and creativity (Lewis 2017; Koppl et al. 2015). Agents also use (develop and adapt) conventions (Keynes 1936), routines, institutions, and technologies to manage uncertainty (Loasby 1999). Additionally, besides conjectural knowledge (Popper 1972; Loasby 1984), other elements concur in the explanation of economic change. For instance, the dynamics of goal setting, the hierarchical rearrangement and the eventual removal of goals of action, and the intentionality of the agents (Muñoz et al., 2011). Davis (2017) connects reflexivity, complexity, and uncertainty.

2.4 Recombination as a source of novelty

The evolution of a system depends both on the particular elements of which it is composed and on the particular pattern of connections between them (Potts 2000). Plans form network structures of actions and goals. People in different circumstances usually develop different connections and the boundaries of interpretative frameworks they use are given by their personal "mental maps." Knowledge and its application are always context-limited, depend crucially on the action situation, and are culturally embedded. These structures are continuously changing because individuals and expectations change and because of reflexivity. It is over the renewed variety of connections embedded in plans that selection and retention mechanisms operate (Metcalfe and Foster 2004). All this happens at the micro level.

At a meso level, the interaction of purposeful action makes systems and subsystems—such as machines, computers, the Internet, routines, rules, institutions, and informal norms—emerge. A socio-economic system can be seen as a system composed of near-decomposable subsystems or modules of different kinds that are coordinated and embedded in a particular complex system architecture (Simon 1996). Structural change and the emergence of new properties—including technologies, institutions, rules, and markets—are the consequence of recombining different links among these systems. Experimental tinkering (Jacobs 1977; Koppl et al 2019) plays an important role in making connections. From within, actors recombine the different elements of the subsystems—mainly plans—according to their expectations and the evaluation they attach to the "observed" outcomes of interaction. Recombining connections is a particularly appropriate method for processes that must proceed by experimentation. Trial and error are typically guided by conjectures that are intended to produce particular results, although most conjectures are refuted and unintended consequences are rather common.[6] Path dependence is another common feature of complex systems. One put into motion, the evolving system—the economy, the sector, the industry, the firm—generates new knowledge, artifacts, and sets of rules (e.g., novelties), which undermines some established knowledge but also supplies the elements for further innovation in a creatively destructive process (Schumpeter 1934).

2.5 Complementarity and entrepreneurship

The different subsystems that build a higher-order level system must be complementary for the higher-order system to work. Complementarity -a reconfiguration of what is connected to what- plays a prominent role in evolutionary processes. According to Dopfer et al. (2016), complementarity can take two distinct forms in evolutionary economic systems: downward complementarity and upward complementarity. The former implies increasing specialization and the division of labor, and proceeds by division, differentiation, and reorganization—basically a Smithian process. The latter—the discovery of emergent complementarity between extant or new components and products—proceeds by making new combinations or cross-fertilization among seemingly different inputs; it is an essentially Schumpeterian process (ibid., p.755). The economic system is made up of complementary modules and its dynamics depend on the predominant type of complementarities at work. Downward complementarity emerges from a process of ongoing modularization that breaks an already existing whole into parts. It is a source of economizing gains, due to specialization at the level of the parts, which results in greater efficiency at the level of the whole. Increasing variety at the modular level also drives increasing economic complexity at the level of substitute inputs. In contrast, upward complementarity is

[6] However, in order to assess the effectiveness of such experiments, some conditions of stability are needed.

the creation of new wholes from existing parts; it involves recombining existing factors of production to create new technologies, goods, and services that can lead to new markets and industries. The emergence and coevolution of Internet-based technologies and AI are examples of upward complementarity.

According to the distinction between downward and upward complementarity, we may distinguish two kinds of entrepreneurship (Dopfer et al., 2016: 758). In the case of downward complementarity, agents are alert to opportunities for personal gain that can be tapped by arbitraging hidden inefficiencies (entrepreneurship à la Kirzner, 1999). Upward complementarity implies visionary agents that create novelty through forming new combinations as described by Schumpeter. Schumpeterian entrepreneurs assemble existing parts into new wholes that configure new resources. Entrepreneurship associated with upward complementarity can generate a new "meso trajectory," the actualization of a new set of rule-combinations (Blind 2017), but it has also a disruptive or destructive effect at the meso-macro level as existing meso-level structures of rules are re-coordinated (Dopfer and Potts 2008). Both types of entrepreneurship are present in AI technology and are deployed by both entrepreneurs and users.

2.6 Business plans and evolution

Typically, evolution is understood in terms of the familiar mechanism of variation, selection, and retention, a process of search algorithm, through a combinatorial design space. According to Beinhocker (2011: 400–404), the algorithm of evolution is particularly good at searching for designs that are fit for their purpose within such almost infinite spaces of possible designs. Decomposability, modularity, and recombination would explain how that design space is formed. The size of a design space depends on the number of modules or dimensions that the design can be varied on, and the number of possible variants for each of those modules or dimensions.

We can identify three design spaces relevant to economic evolution and the multi-stage development and production of AI. Firstly, physical technologies, that is, methods and designs for transforming matter, energy, and information from one state into another in pursuit of a goal (or goals). Secondly, social technologies, the methods and designs for organizing people in pursuit of a goal or goals, which include rules and institutions. And, thirdly, business plans, a design space that binds physical and social technologies together in enterprises or projects that pursue economic goals—for example increasing profits, cutting costs, increasing market share, etc. Thus, economic evolution can be seen as a process of co-evolutionary search through these three design spaces. Agents seek superior levels of fitness on these "landscapes" (Kauffman 1993). Fitness depends on purposes that are integrated into entrepreneurs' business plans. This view assigns a prominent role to entrepreneurs: as new physical and social technologies are discovered and rendered using experimental tinkering, they are combined and recombined into new business plans which are rendered into firms. The working of tose firms then changes the physical and social fitness function, leading to changes in the business plan fitness function and so on, creating a co-evolutionary process.

3 The co-evolutionary character of technology, culture, and markets

Technology, institutions, and culture are complex evolutionary subsystems that co-evolve and configure the higher-order socio-economic system. The connections among these different subsystems ultimately refer to the individual level. Thus, the evolution of the whole system is linked to agents' purposive action. The knot that intertwines all the elements of the different subsystems is the personal ensemble (Sect. 2.1): where conjectural knowledge (both individually acquired and socially transmitted) and expectations converge in the formation of agents' action plans—production, consumption, business plans.

3.1 Technology

Arthur (2009: 192) conceives the economy "as the set of arrangements and activities by which a society satisfies its needs. […] An economy is a gigantic container for its technologies; a huge machine with many modules or parts that are its technologies—its means of production." In his work, Arthur has stressed the purposeful character of technology. According to him, technology is composed of purposed systems: "a technology is a programming of phenomena (physical or behavioral) to our purposes" (Arthur 2009: 51). Examples of technologies include business organizations, legal systems, monetary systems, and contracts: they are all means to purposes (Arthur 2009: 54). In a similar vein, Nelson (2002: 22) includes institutions as a form of social technologies.

In both cases, physical and social technologies are continuously changing as far as agents experiment with them and recombine their elements to improve the efficiency of their actions as well as exploring, through recombination, new opportunities. When a new technology emerges, a new subsystem (a new module) emerges, or an existing one upgrades, the topology of the network of connections of physical devices, rules, expectations, goals, and plans change. The emergent and evolutionary character is the product of creativity and interaction (Schumpeter 1947; Khan 2020).

3.2 Culture

Technological change is a restless process based on human curiosity and entrepreneurship.[7] And its intensity depends, among other things, on the cultural milieu in which entrepreneurs operate. According to Harper (2003: 132), "each society has cultural characteristics particular to its circumstances that might influence how entrepreneurship is manifested and how markets are coordinated and that might therefore promote different patterns of economic development."

Culture is a complex concept that can be conceptualized in many different (and to some extent contradictory) ways.[8] "Cultural and social phenomena are largely

[7] "Every technology contains the seeds of a problem, often several." (Arthur 2009: 200).

[8] In general, culture is the form of a society, and a society is formed by the population that share common culture. A society is an order, compounded of organizations, institutions, rules, etc. and a certain *ethos*.

mental phenomena" (Harper 2003: 137). Culture mainly refers to underlying values, moral principles, beliefs, norms, roles, and cognitive styles that are shared to some degree by members of a social group together with its external manifestations. For the purpose of this paper, we focus on "subjective" or "mental" culture and the social dimension of culture. For North (2005: 50), "culture consists of the intergenerational transfer of norms, values, and ideas." The main role of culture is described as a process that permits the learning of prior generations to have a more direct effect in learning of subsequent generations. Learning is always local, derived from the specific environment (both physical and intellectual) of a society. As changes occur in that environment, they are gradually assimilated into the socio-cultural linguistic inheritance and embodied in the artificial structure.

Hayek views culture as a process of transmission of accumulated stock of knowledge. Moreover, Hayek (1960: 27) includes in knowledge all the human adaptations to the environment which were derived from experience—habits, skills, emotional attitudes, as well as institutions. For Rubio de Urquía (2005) culture is "a social dynamic for transporting information" and provides the connection between culture and action plans. The key connecting element is the personal ensemble. It is in "the ensembles of people that the culture and institutions of a society are located." (Rubio de Urquía, 2005: 88–89).[9] Cultural dynamics along with the cognitive dynamics (what we know or think we know and how we know) and the ethical dynamics of agents (what is, or they consider it is, good for them) are especially incidental in the constitution (transformation) of personal ensembles that produce action plans. Culture—or, more properly, the (ongoing) process of cultural interaction—provides "social ensembles" of beliefs, values, etc., i.e., the usual "raw material" for the formation of personal ensembles (Encinar & Muñoz, 2005).[10] It is within a cultural process that the person develops his existence, plans, and acts (Fig. 1).

3.3 Markets

Belief systems embody the internal representations of the human landscape. Institutions—as well as routines and organizations—are structures that humans impose on that landscape to reduce (manage) uncertainty and produce the desired outcome (remember Kelly's constructs). Culture informs institutions and, in turn, these inform people how to proceed —the "rules of the game"— and use information in specific contexts (North 1990: 42). Of course, changes in the institutional framework entail changing the incentive structure of the society (Baumol 2001). The response of humans to novelties depends on how novel they are and on the cultural heritage carried by the actors. Economies that had evolved a cultural heritage that led them to

[9] Due to plasticity, culture can reconfigure patterns of the brain. See, for example, McDermott (2017).

[10] A matter of enormous importance that we cannot deal with here is what social ensembles of beliefs, etc. and what elements are socially transmitted to the people of society and how that transmission takes place. In general, the ensembles of people are different, even though those people are very similar to each other, and their ensembles have many things in common, because each person makes an original combination of these elements. This is the reason why there is so much heterogeneity of plans.

innovate institutions of impersonal exchange dealt successfully with this fundamental novelty (others do not). One of these innovative institutions is the market.[11]

Mainstream economists usually take markets for granted and center their research on properties such as efficiency, informational asymmetries, market failures, etc. However, the price system, incomes, preferences, etc., are not given but are emergent, living, evolving phenomena. Markets provide an environment or place of interaction (Wagner, 2010); they are systems for governing transactions (Williamson 2002). The only constant element is the human propensity to exchange. Austrians see the market as a process (an entrepreneurial process Kirzner (1992, 101)). Evolutionary economists focus their research on how markets evolve, information (collected by the price system), and expectations are generated.

Defining markets in system terms should also emphasize that they are systems that generate dynamic processes that interact (coevolve) with other systems. For example, Arthur (2009: 192) includes markets within social technology that coevolve with physical technologies because these, to develop, need those markets to be found, and "the existing structures of the economy must be re-architected to make use of the new domain." (Arthur 2009: 157). In this context, the role of entrepreneurs can by no means be exaggerated. Entrepreneurs are the agents of change (Gerschlager 2012; Metcalfe 2004).[12] They combine and recombine creatively the different structures and modules, within the socio-economic system. These new combinations integrate their business plans. As far as culture provides the raw materials "to produce" plans, entrepreneurship "is utterly shaped by culture, and it fundamentally consists in interpreting and influencing culture" (Lavoie 1991: 36) and is often expressed through markets.

3.4 Coevolution

Two or more "evolving domains coevolve if these domains causally influence each other in such a way that this multidirectional influence shapes the innovation, replication, or selection processes that are specific to each domain. In this way, the multiple evolving realms linked by evolution are dynamically codetermined" (Almudi and Fatas-Villafranca 2021: 8). These realms can be manifold. For North, the sources of change are demography, the stock of knowledge, and institutional settings; for Arthur, it is the technology that changes and institutions have to adapt to it.

In each instant of historical time, each culture provides the context for cognition (beliefs, theories, etc.) and adoption (according to values and goals) of plans. In a specific institutional setting embedded within that culture, people use available technology to reach their goals. Technological innovations open new opportunities for developing new business plans and lifestyles. Given their common character, physical and social technologies coevolve, and as far as social technologies evolve,

[11] In Williamson's terms, culture is a higher-level institution than markets. The differential response of economies to the move from personal to impersonal exchange is illustrative (Greif 2006).

[12] This does not mean that the role of consumers is merely passive. In many contexts, it is the consumer experience that selects or co-determines the direction of change. See Bianchi (1998) and Earl (2017).

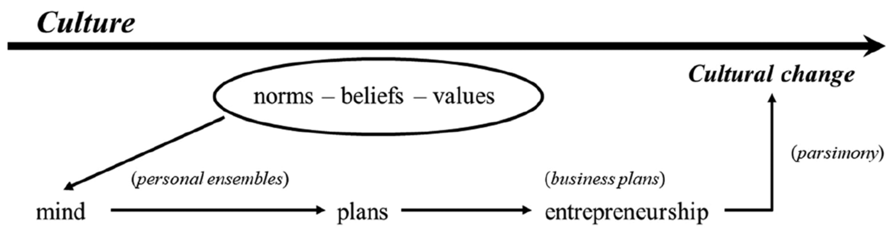

Fig. 1 Cultural change and elements

"new 'institutions' and social technologies come into the picture as changes in the modes of interaction—new modes of organizing work, new kinds of markets, new laws, new forms of collective action—that are called for as the new technologies are brought into economic use" (Arthur 2009: 23) Agents interact in markets—and at other levels, including their "ideologies" (Almudi et al. 2017)—taking notice of what is new, what does work and what is now deemed possible. Efficiency and reflexivity reconfigure agents' plans. Novelties challenge (some) existing norms and institutions that must be accommodated to the new realities. Entrepreneurs, the agents of change, connect the different subsystems when forming their business plans. New combinations (of physical and social technologies) reshape all the subsystems—including culture—and their connections, configuring the evolutionary process of structural change of the complex system. Figure 2 shows the interplay of the main subsystems.

4 AI and human action: opportunities, challenges, and limitations

4.1 AI and human action

AI is a bunch of cross-cutting technologies that are used for a wide range of processes. Despite its aura of state-of-the-art technology, it is essentially advanced statistics that operates on the principle of learning from historical data "to recognize patterns, make predictions, comprehend linguistic structures, and conduct image recognition tasks" (Davidson, 2024: 1).[13] This is achieved, for example, using machine learning (ML) algorithms which can "learn" and "adapt" based on the data they process. AI develops in two steps. First, AI uses data to generate using ML a *predictive model* or a *predictive score*.[14] The second step is the use of the model for a given purpose—for example, to design a new marketing strategy.

[13] AI can be categorized into two types: narrow (weak) AI, which is designed to perform a specific task and general (strong) AI, which can perform any intellectual task that a human being can do. All existing AI technologies, including LLM, are examples of narrow AI.

[14] The model is what has been learned from data. An example is a *decision tree* model.

The main unifying theme in AI is the concept of *intelligent agents*.[15] According to Russel and Norvig, “AI has focused on the study and construction of artificial agents *that do the right thing*. What counts as the right thing is defined by the objective *we provide* to the agent.” (Russel and Norvig, 2021: 22, italics added) Artificial agents receive *percepts*—the content they perceive from the environment through sensors—and perform actions through *actuators*. Each artificial agent operates within a system that implements a function that maps percept sequences to actions that interact with other agents’ actions and the corresponding changing environment which properties may be fully or partially observable. Additionally, these artificial intelligent agents may “learn” from interaction.[16] Following Russell and Norvig, it is possible to model four types of artificial agents: simple, model-based, goal-based, and utility-based reflex agents. The first type ignores the rest of the percept history; the second one has some sort of internal state (memory) that depends on percept history and thereby reflects at least some of the unobserved aspects of the current state; the third type is the reflex agent which also takes into account some sort of goal information that describes desirable situations—what connects to search and planning—; and the last one refers to agents that can internalize a performance measure through, for example, an expected utility function. Thanks to these types of *reflexivity*, a learning element (or process) can be added. This element is responsible for making improvements. It is possible to add additional elements to this basic structure, for example, strategies. This can be done through a *problem generator*. This device would suggest actions to agents that would lead them to new and informative experiences. Additional concepts such as *belief state* (a set of possible worlds) and *state estimation* (maintaining the belief state) can be introduced in this context (see Fig. 3) to mimic some kind of “creativity” in these simulations. Also, planning can be considered more in-depth on contingent planning in partially observable environments and include hierarchical planning.

Finally, the fundamental question has to do with the kind of rationality to be attached to these artificially intelligent agents. The first option is to assume perfect limited rationality—that is, acting appropriately when there is not enough time to do all the computations one might like. However, achieving perfect limited rationality—always doing the right thing—is not feasible in complex environments because the computational demands are too high. Nevertheless, the hypothesis of perfect rationality is a good starting point for analysis that later can be adapted according to the specific problem at hand. We will come back to rationality in Sect. 5.

It is quite straightforward to appreciate the similarities (and differences) between artificial intelligent agents and the economic agents we have referred to in our analytical framework.[17] Table 1 summarizes them.

[15] For each possible percept sequence, a rational or intelligent agent “should select an action that is expected to maximize its performance measure, given the evidence provided by the percept sequence and whatever built-in knowledge the agent has” (Russell and Norvig 2021: 58).

[16] There are different ways to represent these functions, such as reactive agents, real-time planners, and decision-theoretic systems. The agent program takes the current percept as input whereas the agent function refers to the entire percept history.

[17] The approach is also rather similar to ABM modeling (see Epstein and Axtell 1996; Gallegati and Kirman 2012).

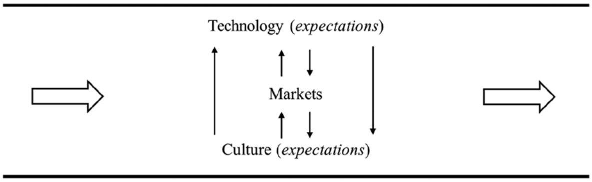

Fig. 2 The co-evolution of technology, culture, and markets

It is not strange to appreciate most of the similarities, as far as AI trying to mimic human decision processes. In this sense, there are plans (strategies), expectations (predictive models), feedback mechanisms (reflexivity/reflective agency), and so on. However, there are genuinely human characteristics that are almost impossible to translate into AI agents, such as culture, imagination, creativity, and knowledge.

4.2 Opportunities and challenges

The main opportunities offered by AI are aimed at efficiency gains through the automatization of processing huge amounts of data. AI can do many things in the economy, such as increasing productivity, enhancing innovation, creating new sectors and jobs, and improving living standards. AI can be also seen as a powerful complementary subsystem that can be integrated into various aspects of business operations, from automating routine tasks to making *data-driven decisions*. But its main use would be supporting human decision-makers confronted with *uncertainty*: AI could be used to relax the limits imposed by agents' bounded rationality. Specifically, "AI can help set agendas by scanning environments, formulate problems by providing contextual insights, identify creative alternatives through combinatorial abilities, select options by modeling scenarios and enable rapid experimentation cycle." (Weiser and von Krogh 2023: 711) In this sense, AI may be integrated into business plans that, as shown in Sect. 2.6, coevolve with other social subsystems.

As with any new technology, AI demands the recombination of capital structures (Endres and Harper 2019), and the availability and congruency (Sabherwal and Grover 2024) of other technologies—in particular, ITC—and complementary subsystems—for example, the Internet. AI also demands adaptation and eventually the emergence and development of new institutional settings and markets, as well as in-depth cultural changes. For instance, AI may be integrated into higher-education services changing the architecture of such services (for example, online training programs) in several ways (Harper et al 2021) and enhancing educational opportunities among the population. On the contrary, societies that were not able to generate (enough) institutional and cultural dynamism to accommodate novelties linked to AI would put its full deployment and advantages at risk. These are the cases, for example, of too-restrictive regulations that limit the use of AI for privacy protection reasons; cultural systems that are reluctant to innovate; and educational systems that are not able to introduce new approaches and innovative learning practices and approaches in subjects such as mathematics, statistics,

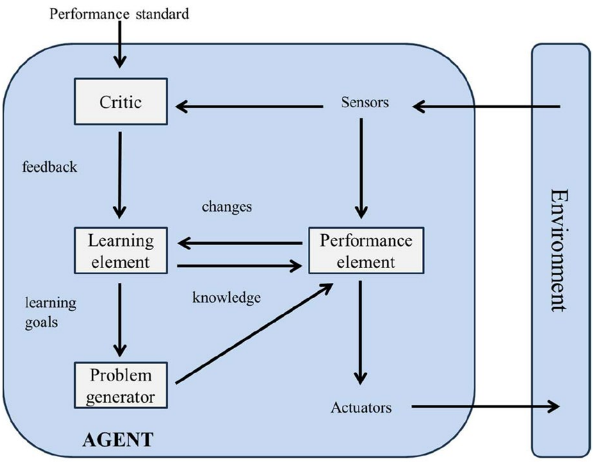

Fig. 3 A general learning agent (it includes learning goals). Source: Fig. 2.15 in Russell and Norvig (2021: 74)

Table 1 Similarities and differences between the economic agent and the AI intelligent agent

Human action framework	AI intelligent agent
Plans	Strategies
Bunch of action plans	Predictive models
Not given goals and actions	Given goals and actions
Ensemble of beliefs, values, etc	Belief state
Expectations and conjectures	Probabilities
Reflexivity	Reflective agent
Knowledge and learning	Information and learning
Rules, institutions, etc	Rules and constraints
Culture	Environment
Imagination, tinkering, creativity	Problem Generator
Structural change/emergent properties	Efficiency

and humanities.[18] Typically, these situations are common in not entrepreneurial-friendly societies.

On the other hand, there are many risks and challenges associated with AI that have to do with ethics (think, for example in the use of information in social media, autonomous vehicles, etc.); the development of lethal autonomous weapons (Summers and Coronado 2023); surveillance security and privacy; fairness and bias; trust and transparency; increasing inequality associated with near zero marginal cost economies (Rifkin 2014) where the winner-takes-all; the implications for power and geopolitics (the control of chip production, strategic commodities, etc.); increasing market concentrations and increasing role of big players; and even who produces and control AI (Project Syndicate 2023).

[18] This is particularly urgent in the case of economics! (See Arthur 2023, esp. Section 2.2).

But there is something new that entails the main challenge: generative AI might end up displacing decisions from human beings to machines. This may put creativity at risk as well as, due to the lack of experience, in the case of younger generations, reproduce (automatically) or multiplicate errors. As Siegel points out, AI failure is usually human failure: for AI technology to succeed, "we now need improvements in humans—in the way of understanding and leadership—more than technology itself"—(the Machine Learning Paradox) (Siegel 2024: 26). Education in the humanities could play a very important role in this regard.

4.3 Limitations

The main limitations of AI, at least in its current state of the art, refer to goals, expectations, and knowledge. Once created and learned, an AI model's purpose is to generate predictive scores (probabilities)—of, for example, a borrower's risk of default. The next step is to deploy the model, that is, the operationalization, integration, or implementation of the model in a particular context. Both steps depend critically on the purposes of designers. AI projects are business-oriented, purposive. Together with the proper infrastructure needed for deployment, organizations need a well-established business practice. Most AI projects fail because operationalization is only addressed as an afterthought. Thus, the connection of the model to the business plan is critical.[19]

Regarding goals, there is the so-called *value alignment problem*, which is the problem of achieving agreement between our true preferences and the objective we put into the machine. The values or objectives put into the machine must be aligned with those of the human designer. But goals are in the mind of the designer or user of the machine, not in the AI system. The situation is even worse in the case of expectations. AI models cannot incorporate true expectations. In general, an intelligent AI agent's choice of action at any given instant of time can depend only on its built-in knowledge and on the entire percept sequence observed to date, but not on anything it has not perceived or can imagine.

However, the most fundamental limitation comes from the concept of knowledge. Loasby has stressed this issue. According to him, "logical operations determine only a small proportion of human actions… it is the growth of knowledge about how to get things done that has been the central phenomenon of economic evolution." (Loasby 1999: 139) Logical operations belong to the world of rational choice models. However, knowledge has a conjectural nature, and "non-logical processes are essential to scientific discovery" (Barnard 1938: 306). AI models, to work, need some kind of completeness and closed models. "But completeness can never be assured, because of the obstacles to knowledge"—in particular Hume's critique—[20];

[19] Siegel (2024) points out that this is usually the weaker point in ML projects: What has been the model developed for? Is there a strategic role for AI in the organization of knowledge?

[20] According to Loasby (1999: 2), Hume's problem refers to "the impossibility of certain, or justified, knowledge of universal laws, other than the knowledge of logical relationships. The instances that we observe, even when supplemented by the reported observations of others—which, of course, are not necessarily reliable—cannot be more than a tiny fraction of all possible instances, and they crucially and necessarily exclude all observations from the future.".

and "the achievement of sufficient closure to make logical deductions possible by human beings (or even by computer logic) requires all rationality to be bounded, either explicitly or by default" (Loasby 1999,12). The role of expectations, imagination, and creativity (Felin & Holweg, 2024) can by no means be exaggerated. But is there room in AI technologies for these concepts?

5 A new kind of rationality?

AI researchers have been able to create computer programs that perform some tasks better, more accurately and faster than humans. However, AI researchers have been (so far) unable to replicate many tasks.[21] In any case, AI needs to specify some kind of rationality to work. In its most simplified version, Olympic or axiomatic rationality could be assumed. To learn, AI models need large amounts of data—the inputs that form the basis for training processes—which are historical data that must be specified, formatted, and informed with goals. The rationality of AI has generally been associated with bounded rationality. Although the most common approach is the one closest to Simon (1957), there are nevertheless other varieties of bounded rationality (see Gonzalez 2017; Tisdell 2023) to be considered. An example is Gigerenzer's (2021) concept of ecological rationality. However, bounded rationality is a characteristic that is predicated on human beings, not on machines. On the contrary, AI provides tools and models that assist agents in managing uncertainty. According to Davidson (2024: 1), AI can help overcome this problem (how to deal with a world in which radical uncertainty is pervasive) by processing large amounts of data, finding patterns and insights, and making predictions and recommendations.

According to Felin and Holweg (2024), the great success of AI in games, tests, and other cognitive tasks that involve high-level reasoning and thinking has led many scholars to "argue that—due to human bias and bounded rationality—humans should (or will soon) be replaced by AI in situations involving high-level cognition and strategic decision making." Many AI practitioners dream of an artificial intelligence that mimics or surpasses natural intelligence. There exists a promise of Artificial General Intelligence (AGI)—a kind of AI that possesses or will possess "the capacity to understand, learn, adapt, and implement knowledge across a broad range of tasks, at a level equal to or indistinguishable from that of a human" (Russell and Norvig, as cited by Davidson, 2024: 2). AGI would imply the "machine's ability to independently solve problems, make decisions, *plan for the future*, understand complex ideas, learn from experience, and apply knowledge to different domains" (Ibid. italics added). However, this image could be misleading. All existing AI technologies are examples of narrow AI that cannot solve the knowledge problem as described, for example, by Austrian economists.[22] The reason is that the economic knowledge

[21] Currently, "AGI remains theoretical and is mostly constrained to science fiction." (Davidson, 2024: 2).

[22] "AI can go some way to resolving information problems but cannot resolve contextual knowledge problems" (Davidson, 2024: 3). To what extent this can be considered a way of thinking is something that has been raised by many philosophers (see Han 2021).

problem is pervasive and only partially manifests itself in bounded rationality. At best, AI can resolve the neoclassical interpretation of bounded rationality.[23]

Loasby (1999: 36) has pointed out that "the reasoning capacity to which economists assign logical priority cannot achieve priority in an evolutionary sequence; and it remains a scarce resource." Loasby refers to what he has called Hume's problem: given the impossibility of certain knowledge of universal laws (from the mere accumulation of evidence in a given direction) other than the knowledge of logical relationships. Logical choice requires closure, and that closure cannot itself be logical. "Our logical capacity is therefore limited, and may be domain-specific, but our neural systems are capable of acquiring new specialist skills, including skills in developing new 'knowledge that,' by making new connections" (Loasby 1999: 130). New ideas cannot emerge only from logical arguments. Because of incomplete (and conjectural) knowledge, humans choose by making connections and in making connections, they use imagination. This connects with Felin and Zenger's (2017) argument that "novel" or "great" strategies come always from theories. Theories provide a mechanism for identifying new data, a way of "intervening" in the world, experimenting, and problem-solving. Thus, a firm's or entrepreneur's strategy "represents a set of contrarian beliefs and a theory—a unique, firm-specific point of view—about what problems to solve, and how to organize and govern the overall process of value creation." In its current state of the art, AI seems not compatible with human creativity, as Felin and Holweg (2024: 28) exemplify with the invention of aviation: given all empirical evidence available at the end of the nineteenth century, AI will not have been able to "predict" the development of the aerospace industry at the beginning of the twentieth century.[24] The role of the "creator personality" (Schumpeter 1932 [2005]) can by no means be exaggerated.

6 Concluding remarks

ChatGPT has popularized the use of AI among professionals, researchers, and students. Discovering emerging patterns from the use of trillions of data and the generation of predictive models is no longer a possibility but a reality that applies in health, finance, marketing, language translation, logistics, etc. The use of this general-purpose technology will dramatically increase productivity in many sectors, by automating tasks and aiding in decision-making. The main benefit of this technology would consist of saving cognitive resources that can be used in more creative ways. Moreover, AI and its applications have opened technical and operational opportunities to be explored and have also raised high (and in some cases scary) expectations about its impact on cognitive capabilities, markets, and culture. As in previous occasions in human history, this dramatic technological change implies the need to develop new skills, capabilities, and organizational forms. The process of adaptation will be harmful for many but will be very beneficial for most. There is a key role here for political economy.

[23] According to Gonzalez, (2017: 397), AI belongs "to the sciences of the artificial because they work on designs that search for specific aims, following selected processes in order to achieve expected results.".

[24] Of course, this is not to say that AI cannot be used in a creative way.

However, the main uncertainties and challenges have to do with the very purpose of this technology which is aimed to help but also to make decisions on behalf of human beings. In this sense, one important caveat around is whether AI will impact the nature of human action and socio-economic processes. According to the framework developed in this paper, the answer is negative: narrow AI—AGI is still a promise—will not change the nature of human action and the evolving complex character of the economic system. Humans' action plans—in particular humans' goals—are necessary to direct and nurture socio-economic evolutionary processes. AI cannot resolve bounded rationality problems as it was originally defined by Simon, because AI, as well as human beings, collide with the most fundamental obstacle to human knowledge summarized in Hume's problem. All in all, AI is a very useful and powerful tool that can be used by agents to form their plans, enhance agents' spaces of action, and creatively experiment with new combinations. Technology, markets, and culture will coevolve to adapt and absorb this new technology and the new combinations that thanks to the use of AI will emerge.

AI is raising and will raise many questions and challenges in the near future. As this bunch of technologies develops further research would be needed. In this article, we have limited to present an analytical framework that would allow for a systematic analysis of the implications of AI for co-evolutionary processes.

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