Introduction: Artificial intelligence should meet natural stupidity. But it cannot![1]

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INTRODUCTION

Some time ago the *Financial Times* headlined an article with the question "Will you talk about your finances with a 'chatbot'"? Chatbots are Artificial Intelligence (AI) algorithms that answer customer questions in a chat. There are already several on the market, such as MyEva by Wealth Wizard, a British digital consulting company, or the chatbots of the American Pefin, which claims to have been the first in the world to offer AI consulting. Advice ranging from retirement advice to financial investments looks like it will soon be offered in spoken language. So is AI replacing human consulting in the world of finance? Will we decide our financial future with robots in the near future? What are the real potential of AI?

The approach, at the basis of financial chatboxes and almost all contemporary AI, is based on the connectionist program, now declined with "machine learning" and "deep learning." It claims to have a downhill road ahead. The extraordinary achievements of Deep Blue in chess and Alpha Go in the Go game seem to bear this out. In my opinion, however, the reality is not so rosy. The interviews with the entrepreneurs of financial chatbots, in the FT article, highlight this. There are two skeptical judgments of a substitute development of AI with respect to humans. In the first place, an algorithm does not have that corporeal dimension that allows it to have emotions and to interact emphatically with the human subject. It is not enough to be a great data grinder to intercept the hidden details of human psychology, to understand its real propensity for risk and to transmit trust to the customer. Second, we live in an unstable, uncertain and unpredictable world. Finance is one of the typical examples of this uncertainty. In this uncertain world, the forecast failures of Google's Big Data-based algorithms prove this. It is not enough to analyze millions of data to find stable configurations that predict the future. As the philosopher David Hume already argued and years later Karl Popper, there are no logical and epistemological justifications for induction. From this point of view, the

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good human financial advisor can never be replaced by a data-grinding neural network. The reason lies precisely in the fact that he will use simple heuristics and rules of thumb which will have the possibility of making better predictions than AI chatboxes or computational algorithms.

This example introduces us directly to the main question: If machine learning and Big Data AI are deeply flawed are we able to simulate human intelligence and is the human mind artificially replicable in a machine? AI was born in 1956 at Dartmouth College and the dominant model was the computational model of the mind. The mind was seen as the software of the brain and the AI should have the aim to simulate the discoveries of cognitive sciences about mental activity. According to McCarthy, Minsky and others, the goal was to "make the machine to behave in a way that would be considered intelligent if a human being would do the same" (McCarthy et al., 1955). But the human mind is not only cold computations and rational information processing. Neurocognitive sciences and behavioral sciences were showing in the late 1980s and the following years that the mind is also emotion, intuition, passion, bodily sensations and motor abilities. That is, the natural mind is able to adapt to the environments and to tasks because it is often not cold rational intelligent, but hot irrational stupid. And the mind is impotent to reason and decide without the body.

The simulation of the human mind might be possible with the advancement of cognitive science research on memory, thinking, reasoning, emotion, decision making and embodied cognition. But the attempt should avoid the Rationality Bias of "Human Intelligence as Optimal Computation Device," that is, thinking that the mind is mainly the ability to process optimally data and to conform to the principle of logic, probability and utility. On the contrary, AI should consider the imperfect formal features of human intelligence and how many times it is adaptively better to be biased than to be formally perfect.

In the following paragraphs I will present some theoretical and empirical reasons in support of this argument. The two main theses that will be developed are (1) The current programs of emulative AI, based on the processing of Big Data through machine and deep learning programs, are flawed in many contexts and in particular they manage to find patterns of past data, but they are not able to forecast future unstable events, such as financial ones, characterized by complexity and uncertainty; (2) The Simulative AI, also called Psychology AI (Gigerenzer, 2022), despite being more suited to grasping more realistic aspects of human intelligence, in fact has not been able to achieve this goal due to the lack of the body dimension of the simulated cognitive experience. In any case, according to some philosophers, the construction of machines that have the same intelligence as man is an a priori impossible undertaking.

BIG DATA FOR DUMB PREDICTIONS

The AI was born at Dartmouth College with the intent to simulate human intelligence. Nowadays Big Data algorithms and machine learning no longer have anything to do with the original project. The current AI has nothing to do with human intelligence, indeed, as some experts in the field claim, it no longer even makes sense to call it Intelligence. According to Kate Crawford,[2] AI is neither artificial nor intelligent. "Machine learning"—a sort of concrete subfield within the more nebulous quest for AI—has invaded numerous fields of human endeavor, from medical diagnosis to searching for new subatomic particles. Thanks to its most powerful incarnation—known as deep learning—machine learning's repertoire of skills now includes recognizing speech, translating languages, identifying images, driving cars, designing new materials and predicting trends in the stock market, among uses in many arenas. A proliferation of new papers on machine learning, deep learning and AI have flooded the scientific literature in recent years. Reviews of this new research have covered such topics as health care and epidemiology, materials science, fundamental physics, quantum computing, simulations of molecular interactions, fluid mechanics, clinical psychology, economics, vision science and drug discovery. But most such reviews also remark on intelligent machines' limitations. Some impressive successes, for instance, reflect "shortcut" learning that gets the right answer without true understanding. Consequently, apparently smart machines can be easily tricked into error. And much of today's so-called machine intelligence is narrowly focused skill, effective for a specific task, but without the flexibility of the general cognitive abilities possessed by people. A computer that can beat grandmasters at chess would be mediocre at poker, for example.

Fears of superintelligent machines taking over the world are therefore misplaced. The behavioral scientist Sendhil Mullainathan wrote:[3] "We should be afraid not of intelligent machines. But of machines making decisions that they do not have the intelligence to make. I am far more afraid of machine stupidity than of machine intelligence."

Let's see some examples (from Gigerenzer, 2022). To protect their citizens, government all around the world experiment with face recognition surveillance systems. These systems recognize faces when tested in laboratory using visa photographs or similar with people's heads held in similar positions. Are the recognitions effective and useful? Many times yes, especially when there is recognition based on the direct vision of the face, such as when we use it instead of the numeric PIN of our cellular phone. On the other hand, it becomes harmful and dangerous when mass surveillance is required and the information on the face is not clear and defined. This leads to often incorrect identifica-

tion results and dangerous consequences on the level of individual freedom. During the final football match of the Champion League in Cardiff between Juventus and Real Madrid in 2017, the English police tried to identify possible dangerous subjects among the fans who flocked to the stadium by screening 170,000 fans. The result was 2,470 matches with photos of criminals, but with a 93 percent error (2,297 false positives). Similarly, the Amazon face recognition algorithm compared photos of the 535 members of the U.S. Congress with a criminal data base and it reported 28 members that matched, all falsely (Gigerenzer, 2022).

Similarly, it was found in a pilot mass surveillance action carried out in Germany to prevent terrorist attacks in Berlin in 2017 that the presence of false positives amounted to only 0.1 percent. Let's imagine what would happen in a mass surveillance where millions of facial acknowledgments are made, such as face matching with a directory of criminals. Thousands of false attributions with the need to stop suspicious people and control them. An inconceivable result from the point of view of citizens' well-being and civil rights (Gigerenzer, 2022).

Another case in point is IBM's AI program called Watson. After his successes in TV quizzes and as a sentient box to interact with Bob Dylan, Serena Williams and other celebrities, IBM tries to adapt him to the world of health. Its target is very ambitious: the treatment of cancer patients. IBM's marketing was very aggressive and creates a lot of expectations in the health care world leading to many conventions from the U.S., to Germany to India. The payment for Watson's consultation per patient ranges from $200 to $1,000. Many of the program's treatment recommendations proved to be incorrect and inadequate. IBM announced that Watson's medical knowledge was at the level of a first-year medical student and, as some medical institutions had spent millions on the program it turned out to be an extremely expensive medical student (Gigerenzer, 2022). Watson's decisions proved that Artificial Intelligence does not always stand up to its name but it can sometimes become a blind and not very smart automatic procedure.

A case that has also been widely discussed in the media is that of the Google Flu Trends algorithm launched by Google to predict the development of flu epidemics. Referring to the observation of peaks in visits to doctors during peaks of flu, Google has thought by analogy to process the Big Data of the use of Google as a search engine for diagnosing the flu symptons and seeking treatment and advice. In 2009 Google Flu Trends failed to predict the otbreak of the swine flu which was the first flu pandemic since the Russian flu of 1977 (Katsikopoulos et al., 2020). Google increased from 45 to 160 cues to the model. This model fared poorly in prediction as well. From 2011 to 2013 the new model overestimated the proportion of flu-related doctor visits in 100 out of 108 weeks. In 2015 Google Flu was shut down (Katsikopoulos et al., 2020).

Why did Google Flu Search Algorithm fail? The main reason is that epidemics are not stable phenomena that follow the same pattern. There is a change in the start period. Swine flu started in April and the outbreak peaked in October whereas the seasonal flu typically starts in October and peaks between December and February. The symptoms are different in relation to the age. Moreover, the media changes the number of queries. The flu-related searches of people that have no symptoms but are simply curious may be triggered by media.

UNSTABLE WORLD

In the early twentieth century, Frank Knight stated unequivocally that it was impossible to represent complex phenomena, like economic and financial ones, as risk models, rejecting the arguments of many colleagues who seemed to overlook their intrinsic characteristics. Knight himself had developed an approach to formally characterize and evaluate the unknown characteristics of a situation. In his view, evaluation can be based on *a priori probability*, which corresponds to the propensities embedded in the structure of an object or phenomenon, for example, the probabilities of an outcome when flipping a coin, rolling dice or playing roulette. It is widely known that if the coin is not deformed, the probability of heads (or tails) is 50 percent. It is the design of the object that determines the probability, not the amount of past observations about its behavior. Another option for evaluation is *statistical probability*, that is, an evaluation based on the collection of empirical data, on an observational or experimental basis, about a phenomenon that shows a certain level of homogeneity. However, Knight notes that "the actual basis for action in a large number of cases is based on estimates" (1921, p. 223), which is the type of evaluation that should be the primary concern of the business world as well as among professors of economics. In some cases, evaluation is no longer based on a probabilistic assessment, but on an intuitive heuristic approach that is applied when no frequency can be reliably estimated, especially because of its complexity, or when the set of alternatives and their consequences are unknown. Frank Knight warns us about the difficulty of attributing probability to most events in the social, economic and political world as well as those related to health and the environment. In other words, a large part of our life is characterized by uncertainty. Uncertainty is present when we are unable to define the possible options of our choice and give them an estimated probability. There are two types of uncertainty. In the first, called *epistemic*, we know that we do not know the probabilities, but we are also aware that this ignorance can be reduced through an informative action to move to a risk situation. If, for example, we have in front of us an urn with black and white balls and we do not know their relative distribution, we are in a situation of

epistemic uncertainty: if we have the possibility to extract sample balls, this can give us additional information about the hypothetical relative percentages of black versus white. The other wider category of uncertainty is the *ontic* one. This category seems to correspond well to the situations described by Knight, where only an estimate or intuition on probability is possible. If we consider again the example of the urn, this is the condition in which we don't even know exactly what is inside and we have no chance of finding out by extracting samples. In general, in this type of situation we are aware that we do not know the probabilities and that we will never know them. Another example comes from the Covid-19 pandemic, where epistemic uncertainty manifested itself at the beginning of the outbreak, when the behavior of the SARS-CoV-2 coronavirus was not known and it was not possible to make predictions about its infectiousness, pathogenesis, immunization and resistance to physical and chemical agents, or the therapeutic action of a number of drugs (Viale, 2020). Progressively, through observation and experimentation, relevant data have been accumulated, which made the situation shift from epistemic uncertainty to statistical risk. However, a different scenario concerns the evaluation of the probability of future pandemics deriving from a virus spillover from animals to human beings. This is a typical *ontic uncertainty* situation where viral options are unknown and no relative probability can be attributed.

In the real world, however, choices are hardly ever similar to lotteries. Some time ago, the great economist Jimmy Savage (1954) made an unequivocal statement along the lines of Knight's affirmation. In his view, there are two types of worlds: the *small* one, like the game of dice, where it is possible to reason in terms of risk; and the *large* one, like the economic and political world, where this is not possible because of uncertainty.[4] Uncertainty is therefore not limited to disruptive events like the Lehman Brothers' bankruptcy or Brexit, but extends to "normal" political and economic life. Unpredictability, complexity, instability and non-linearity are, for example, the structural characteristics of finance, regardless of any particular situation of risk. In these contexts of choice, any attribution of probability to future events is incorrect and misleading (Kay and King, 2020).

If this is the case, then the question that we should ask is the following: are we sure that any behavior that does not meet economic rationality requirements when the situation is uncertain can be regarded as a bias and error?

Herbert Simon leaves no room for doubt about the impossibility for the normative application of neoclassical rationality in situations where the risk cannot be calculated, such as economic and social ones. Simon (1979, p. 500) in his Nobel Memorial Lecture stigmatized how the classical models of rationality required knowledge of all the relevant alternatives, their consequences and probabilities. This rarely happens in social and economic reality. Real life is like Savage's "*large worlds*": part of the relevant information is unknown

and must be estimated through small samples that are not reliable. Therefore, the conditions for the application of rational decision theory are not met and it is inappropriate to apply it as the norm for optimal reasoning. And, as Joe Stiglitz (2010) points out, even if we think we possess almost perfect information, we cannot consider this condition as equal to possessing perfect information. And yet, unfortunately, according to Stiglitz (2010), the business world makes these mistakes. For example, financial institutions continue to approach the *large world* of finance using the conceptual tools of the *small world*, with the disastrous results that we can all see before our eyes.

FROM SIMULATIVE AI TO EMBODIED COGNITION AI

When the term AI was introduced at Dartmouth College in 1957, the approach was to simulate human intelligence. In those days the computational model of the mind was predominant. They believed that minds were like computers and vice versa. The philosophy of mind was the functionalist explanation of mental activity. It relied on a *property dualism* that considered the mental activity as the software of the brain (but not identified with the neural states). Cognitive processes are information-symbols elaborated on the basis of precise rules. Both the information and the rules are represented in the mind and the elaborations are comparable to calculations realized serially. The metaphor of the mind as a computer relied on the theory of the Turing machine.

From the post-war period to today, the study of reasoning, judgment and decision processes has mainly been carried out within the classic cognitive model, which can also be defined as "Information Processing Psychology." It has three characteristics (Viale, 2012, 2018, 2021b, 2022). First, thought takes place as a form of computation. Every mental activity is performed by algorithms similar to the computer's machine language. Cognition derives from computational procedures that are carried out on abstract symbolic structures. The rules are formal (syntax or software) and are applied to symbols without influencing their semantic property. This idea is not new. The concept of reasoning as a form of calculus dates back to Aristotelian philosophy and subsequently to the thought of Thomas Hobbes, for whom reasoning was comparable to arithmetic calculus, to Leibniz, for whom thought was a symbolic process of combining signs, and to Descartes, according to whom the ideal of reasoning was the deductive chains of geometry.

Second, thought has as its objects mental images that are representations of external reality, deriving from perceptual activity, or its elaborations. It is a position very similar to that of Descartes for which every thought has as its object images projected into an internal space, called the mind. When we perceive something from the outside, the stimulus is translated into these amodal representations that become the real content of the experience and cognitive

activity. These mental entities, which can be in the form of images, propositions or a mix of the two, are the content of the inferential and decision-making activity.

Third, the psychological activity takes place independently or can be explained independently of the physical substrate that carries it out. The study of how we reason on a logical or probabilistic level, of how we represent external reality, of how we store and retrieve data from memory and how we decide on the basis of our knowledge and preferences does not require an understanding of the central nervous system, let alone of the peripheral one and of the remaining part of the body. Research and hypotheses on the thinking and decision processes of the human mind can be compared to the research activity of a computer scientist who develops software programs. This can happen independently of how the reference hardware is structured. According to the *computer metaphor*, the mind is to the software as the brain is to the hardware. The theoretical support for this model is varied. In the philosophy of mind, according to the functionalist approach (Fodor, 1975; Putnam, 1975), mental states have been functional to the brain in the same way that the states generated in the computer by the software have been functional to its hardware. This is the position of "Properties Dualism" (in its version of "anomalous monism" see Davidson, 1970; in its version of "biological naturalism" see Searle, 1983) which supports the thesis that mental properties described by cognitive psychology are different from those of any kind of hardware, for example, from those of the brain, capable of implementing them. This is the theory of the *multirealization* of mental properties by various types of physical substrate, inspired by Hilary Putnam and Jerry Fodor. Linked to this philosophical position, cognitivism has developed a series of theories that hypothesize different levels of analysis of cognitive reality. Among the most popular theses of a multi-level ontology is David Marr's (1982) tripartite level between a computational level (e.g. the result of a computation), an algorithmic one (e.g. the ways in which the computation is done) and physical implementation (e.g. the type of material structure that executes it). Cognitivism is interested in studying above all the first two levels, that is, how mental representations are generated and computed after the sensory organs transfer data from the outside.[5]

The classic cognitivist approach just described represents the theoretical central pillar of Simulative Artificial Intelligence. This cognitivist psychology-driven AI allowed some interesting and effective simulation of expert decision making (e.g. expert systems in games like chess or in professional decision making as medical diagnosis and therapies) but it was unable to simulate the real human psychology.

What is the human intelligence? Not the formal ability to apply formal rules to abstract symbols, but the *common sense*, that is, the ability to interpret the meaning of the environment that surrounds us, both physical and social.

To have this ability, human beings rely on what John Searle (1992) calls Background knowledge. It represents the set of abilities, capacities, tendencies and dispositions that humans have that are not themselves intentional states but that generate such states on demand. Thus, when someone is asked to "cut the cake," they know to use a knife and when someone is asked to "cut the grass," they know to use a lawnmower (and not vice versa), even though the request did not mention this. The Background fills the gap, being the capacity always to have a suitable interpretation to hand. To give an example, two chess players might be engaged in a bitter struggle at the board, but they share all sorts of Background presuppositions: that they will take turns to move, that no one else will intervene, that they are both playing to the same rules, that the fire alarm won't go off, that the board won't suddenly disintegrate, that their opponent won't magically turn into a grapefruit, and so on indefinitely. As most of these possibilities won't have occurred to either player, Searle thinks the Background is itself unconscious as well as non-intentional.

Background knowledge is made up of a series of social, ethical and epistemological norms and acquired values. Among these there is the linguistic *cooperative principle* that allows us to communicate and understand the meaning of language in our social interactions. It describes how people achieve effective conversational communication in common social situations—that is, how listeners and speakers act cooperatively and mutually accept one another to be understood in a particular way (Grice, 1989). Accordingly, the cooperative principle is divided into Grice's four *maxims of conversation*, called the Gricean maxims—quantity, quality, relation and manner. These four maxims describe specific rational principles observed by people who follow the cooperative principle in pursuit of effective communication. Applying the Gricean maxims is a way to explain the link between utterances and what is understood from them. The principle is intended as a description of how people normally behave in conversation. Grice's maxims encapsulate the assumptions that we prototypically hold when we engage in conversation. The assumption that the maxims will be followed helps to interpret utterances that seem to flout them on a surface level; such flouting often signals unspoken *implicatures* that add to the meaning of the utterance.[6]

The biological basis of the Backgound Knowledge, however, is given by those inferential principles of a hereditary type with which we are endowed from birth (Viale, 2013). In the past, philosophers used to put infants and children on the opposite side from science in the spectrum of cognitive rationality. Their supposed cognitive immaturity did not allow them to approach the ideal

image of rational beings. On the contrary, two psychologists, Alison Gopnik and Andrew Meltzoff, declared, at the end of the introduction to their book:

> Ultimately, our reason for watching and talking to children is the same as Socrates'. The most central questions in cognitive science are questions that only they can answer. (Gopnik and Meltzoff, 1997, p. 9)

One of the questions that children seem to answer in their book is about the analogy of the child as a little scientist. The central idea of the book is that "the processes of cognitive development in children are similar to, indeed perhaps even identical with, the processes of cognitive development in scientists" (Gopnik and Meltzoff, 1997, p. 3).

Infants are endowed with an innate set of principles that allows them to begin to interact with the world. Among these principles, one of the most important allows a causal attribution to relations between physical events.[7] At around the age of six months, the infant is able to apply the principle of cohesion—a moving object maintains its connectedness and boundaries; the principle of continuity—a moving object traces exactly one connected path over space and time; and the principle of contact—objects move together if and only if they touch (Spelke et al., 1995). Moreover, there is the theory of biology and the theory of psychology. These theories show that infants individuate some theory-specific causal mechanisms to explain interactions among the entities in a domain. A child has an intuition of what characterizes a living being from an artifact or an object. Between the ages of two and five, the child assumes that external states of affairs may cause mental states and that there is a causal chain from perception to beliefs to intentions and to actions (see Sperber et al., 1995).

What are the features of these principles? Data from developmental studies and a certain universality of causal perception in cross-cultural studies seem to support the hypothesis that we are endowed with early-developed cognitive structures corresponding to maturational properties of the mind-brain (Viale, 2013). They orient the subject's attention towards certain types of clues, but they also constitute definite presumptions about the existence of various ontological categories, as well as what can be expected from objects belonging to those different categories. Moreover, they provide subjects with "modes of construal," different ways of recognizing similarities in the environment and making inferences from them.

The common sense that derives from hereditary and acquired principles is the basis for human interaction in complex and uncertain environments. However, its implementation can only be achieved in a dimension of embodied cognition. The inferential capacity of man does not occur in the abstract, but through the interaction of the body with the environment. We decide and adapt

to the environment using our sensory, motor and visceral apparatus. Going back to Simon's fortunate metaphor of the scissors, the two blades of cognition and environment can interact and be successful if the pivot that allows them to coordinate is present (Viale, 2019, 2020; Gallese et al., 2021). The pivot is represented by the body. From the perspective of *embodied cognition*, cognition is not in a separate bubble from the body, but it is in fact embodied with it and our capacity for thought and judgment is intimately linked and shaped by action. It is no longer the body that is at the service of the brain as traditional cognitivism claims, but rather the opposite, that is, the brain is the tool that allows the individual to interact physically with the environment. The same center of gravity of the decision-making process at this point is no longer located in the cognitive computational part, but moved to the pragmatic part, of the possible actions that the environment allows.

On the contrary, cognitivism represented the mind that thinks and decides as if it were separate from the body and the environment. The mind is "disembodied" from the body that carries it and "disengaged" from the environment in which it interacts. The new perspective introduced by neuroscience refers instead to "embodied" and "grounded" cognition. That is, a cognition integrated with the body through action and shaped by the environment with which the body interacts. The acting body should no longer be understood as a mere physical instrument guided by the mind, as if it were the physical structure of a robot guided by its software. Instead, the body is one with cognitive activity, and together they interact with the environment (Viale, 2020; Gallese et al., 2021). Through this interaction we acquire motor and perceptual experiences that are subsequently reactivated by cognition. Bodily states are, therefore, necessary for cognition also to simulate perceptive and motor experiences, sensorimotor models ("*patterns*") that are extrapolated from their motor function and exploited in cognitive processes different from those for which they were created (Gallese and Goldman, 1998). Consider, for example, the importance of simulation in our social activity, in our interaction with others, in decisions about what to do in group work or on a market where several subjects operate. In these cases, we decide after having read the minds of others through simulation in our bodies of their possible actions and the consequent affective and emotional results. These simulations are based on the reactivation of sensorimotor experiences previously acquired by the individual in similar contexts (Gallese et al., 2004; Iacoboni, 2008). The core of the decision-making process is, therefore, no longer situated in the computational and cognitive part, but has moved to the pragmatic part, of the possible actions that the body-environment interaction allows. This position that places the constraints of the rational activity of choice and decision not so much in the computational possibilities of the human mind as rather in the mind-body-environment interaction represents a further development of Herbert Simon's theory of Bounded Rationality.

The environment cannot be analyzed only as the framework of the task based on its computational cognitive variables. The physical and social environment also generates sensory, visceral and motor constraints that influence reasoning and decision making (Damasio, 1994). In determining a choice, possible and simulated body actions influence the range of potential options and the value attributed to them. Based on these considerations, it is appropriate to extend the concept of bounded rationality by adding the *embodied dimension*.[8]

A closely related position to embodied cognition is that of *Enactivism* (Gallagher, 2017). Cognition arises through a dynamic interaction between an acting organism and its environment. The environment of an organism is brought about, or enacted, by the active exercise of that organism's sensorimotor processes.

> The key point, then, is that the species brings forth and specifies its own domain of problems … this domain does not exist "out there" in an environment that acts as a landing pad for organisms that somehow drop or parachute into the world. Instead, living beings and their environments stand in relation to each other through mutual specification or codetermination. (Varela et al., 1991, p. 198)

"Organisms do not passively receive information from their environments, which they then translate into internal representations. Natural cognitive systems … participate in the generation of meaning … engaging in transformational and not merely informational interactions: *they enact a world*" (Di Paolo et al., 2010, emphasis in original). The introduction of the term *enaction* in this context is attributed to Francisco Varela, Evan Thompson and Eleanor Rosch in (1991), who proposed the name to "emphasize the growing conviction that cognition is not the representation of a pre-given world by a pre-given mind but is rather the enactment of a world and a mind on the basis of a history of the variety of actions that a being in the world performs." Experience of the world is a result of mutual interaction between the sensorimotor capacities of the organism and its environment. In the enactive view, knowledge is constructed by an agent through its sensorimotor interactions with its environment, co-constructed between and within living species through their meaningful interaction with each other. In its most abstract form, knowledge is co-constructed between human individuals in socio-linguistic interactions.[9,10]

WHY SHOULD AI MEET HUMAN "STUPIDITY"?

The judgment of rationality of human behavior depends on its ability to adapt to specific environmental tasks. This ecological adaptability happens if the decision maker is successful in coping with the cognitive requirements of a specific environmental task. The requirements may be different. When

one has to solve an abstract task like Tower of Hanoi[11] or Missionaries and Cannibals,[12] the requirement is to find a solution. The same problem-solving requirements may be found in many tasks of everyday life, from replacing a tire to dealing with the failures of our computer software. When one has to make a financial investment, the requirement seems different, that is to say, making good predictions about the future value of one's investments. The same requirement seems to apply also when one is engaged in a negotiation, or needs to find a reliable partner or has to decide which approach may be better suited to pursue one's research. According to some authors (Schurz and Hertwig, 2019), cognitive success should be analyzed only in terms of the predictive power of the cognitive method used to deal with a task. Does the reduction of cognitive success to successful predictions include most successful adaptive answers to environmental tasks? According to Schurz and Hertwig (2019, p. 16), the answer is yes:

> The core meaning of the cognitive success of a system (including algorithms, heuristics, rules) is defined in terms of successful predictions, assuming a comprehensive meaning of prediction that includes, besides the predictions of events or effects, predictions of possible causes (explanatory abductions) and in particular predictions of the utilities of actions (decision problems). (Schurz and Hertwig, 2019, p. 16)

In fact, this reduction of cognitive success to successful prediction excludes a number of cognitive human abilities to adapt to complex environments (Viale, 2022). In 1986 Herbert Simon wrote:

> The work of managers, of scientists, of engineers, of lawyers—the work that steers the course of society and its economic and governmental organizations—is largely work of making decisions and solving problems. It is work of choosing issues that require attention, setting goals, finding or designing suitable courses of action, and evaluating and choosing among alternative actions. The first three of these activities—fixing agendas, setting goals, and designing actions—are usually called *problem solving*; the last, evaluating and choosing, is usually called *decision making*. (Simon, 1986, p. 1)

In dealing with a task, humans have to frame problems, set goals and develop alternatives. Evaluations and judgments about the future effects of the choice are the final stages of the cognitive activity. This is particularly true when the task is an ill-structured problem. When a problem is complex, it has ambiguous goals and shifting problem formulations, cognitive success is characterized mainly by setting goals and designing actions. Herbert Simon offers the example of design-related problems:

> the work of architects offers a good example of what is involved in solving ill-structured problems. An architect begins with some very general specifications

of what is wanted by a client. The initial goals are modified and substantially elaborated as the architect proceeds with the task. Initial design ideas, recorded in drawings and diagrams, themselves suggest new criteria, new possibilities, and new requirements. Throughout the whole process of design, the emerging conception provides continual feedback that reminds the architect of additional considerations that need to be taken into account. (Simon, 1986, p. 15)

Most of the problems in corporate strategy or governmental policy are as ill-structured as problems of architectural and engineering design or of scientific activity. Reducing cognitive success to predictive ability is the product of the decision-making tradition and in particular of the theory of subjective expected utility (SEU). It deals solely with analytic judgments and choices and it is not interested in how to frame problems, set goals and develop a suitable course of action (Viale, 2022). On the contrary, cognitive success in most human activities is based precisely on the successful completion of those problem-solving phases. Problem solving is not based on the computation of a decision based on an analytical prediction activity on data, but on a pragmatic recursive process made up of many attempts and related positive or negative feedback from the environment. The role of embodied simulation is fundamental in this pragmatic activity. It is possible to construct the meaning of one's attempts at a solution and in the end to select the final solution only through the enacting interaction of the problem solver with environmental affordances. In reality decision making, including the predictive success of judgments, may be reduced to an irrealistic abstraction and simplification of problem solving (Viale, 2023).

Ultimately, if AI programs want to simulate human intelligence they must emulate the cognitive success obtained in most situations of daily life. It depends, however, not on the applications of formal rules of a logical and probabilistic type, but on the often intuitive use of simple rules of thumb also called heuristics. These rules sometimes seem too simplistic to the point of being perceived as stupid. The term heuristic, from the Greek, means, "serving to find out or discover" (Todd and Gigerenzer, 2000, p. 738). In the context of problem solving, heuristics are experientially derived cognitive "rules of thumb" that serve as guides in problem-solving processes. Heuristics guide problem solvers by helping them simplify choices regarding the numerous immensely complex and imperfectly understood factors that act simultaneously to shape problems. For example, Allen Newell and Herbert Simon (1972) had identified some fundamental heuristics in problem solving. The heuristics that guide search derive from properties of the task (e.g. in chess, "Ignore moves that lose pieces without compensation"). If a domain has strong mathematical structure (e.g. is describable as a linear programming problem), strategies may exist that always find an optimal solution in acceptable computation time. In

less well-structured domains (including most real-life situations) the heuristics follow plausible paths that often find satisfactory (not necessarily optimal) solutions with modest computation but without guarantees of success. In puzzles, the problem space may be small, but misleadingly constructed so that plausible heuristics avoid the solution path. For example, essential intermediate moves may increase the distance from the goal, whereas heuristics usually favor moves that decrease the distance. *Due esempi di queste euristiche sono la means-end analysis e la hill-climbing* [Two examples of these heuristics are the means-end analysis and hill-climbing]. According to *means-ends analysis* (Newell and Simon, 1972), differences between the current situation and the goal situation are detected, and an operator selected that usually removes one of these differences. The differences are eliminated or decrease after recursive application of the operator. If the selected operator is not applicable to the current situation, a subgoal is established of applying the operator. Means-ends analysis is powerful and general, but is not useful in all problems. Hill-climbing is a technique which belongs to the family of local search. It is an iterative algorithm that starts with an arbitrary solution to a problem, then attempts to find a better solution by making an incremental change to the solution. If the change produces a better solution, another incremental change is made to the new solution, and so on until no further improvements can be found.

Gigerenzer and his group (Gigerenzer et al., 1999) have identified others to apply when faced with situations of uncertainty and complexity. Since we live in a world characterized mainly by uncertainty rational decision-making rules cannot derive from probability theory, deductive logic and utility theory. How can we know that we are making good decisions?

Studies in evolutionary psychology have tried to reconstruct the decision-making environment of our ancestors and how this explains the effectiveness of today's decision-making styles. In particular, efforts were made to explain (in an abductive way) why our inferential and decision-making activity has certain characteristics and why they are effective. For example, the need to decide quickly on the basis of very few elements seems to correspond to an important selective quality of survival in environments characterized by sudden aggression by predators. The lesson that comes from evolutionary psychology (Cosmides and Tooby, 2006) is that the most advantageous solution to improve our ability to survive is not too much calculation, too much time to make the decision, too much information gathering, especially in conditions of uncertainty (e.g. no reliable information on the probability of impending predators or poisonous foods that may be confused with safe ones). In these cases, the best solution to increase our adaptability is the application of simple, frugal and fast decision-making rules, even at the risk of making mistakes. These are the so-called *decision-making heuristics* that increase our *ecological rationality* (Gigerenzer et al., 1999; Todd et al., 2011).

Being *ecologically rational* means following *heuristic decision-making* procedures that in most cases do not guarantee an optimal solution, but only a satisfactory one. However, it means, above all, deciding in this way because the rational alternatives available do not seem feasible due to time limits, limited computational capacity and, above all, the uncertainty of the decision-making environment. And even if they were feasible with respect to time constraints and computational capacity, the result of their application would often be inferior to that of heuristic procedures.

Faced with the descriptive and regulatory failure of optimizing algorithms in decision making under conditions of uncertainty, a comprehensive heuristics research program was developed at the end of the 1990s that sought to formalize and test them empirically in situations of uncertain choice (Gigerenzer et al., 1999). The basic principle was that of *simplicity*. The greater accuracy of the results obtained in comparison with statistical decision methods can also be summarized as the "*less-is-more*" standard. There was an inverted-U ratio between the level of accuracy of the results and the amount of information, computation or time. Above a certain threshold "more is harmful," that is, the greater amount becomes harmful to the result (Gigerenzer and Gassamaier, 2011). The methods tested were powerful optimization algorithms.[13] Simon, in the back-cover commentary of Gigerenzer et al.'s book (1999), talks about a "revolution in cognitive sciences that represents an extraordinary impulse in favor of common sense in the approach to human rationality." However, in the 1970s the importance of simplicity in decision-making models had already been demonstrated[14] (Dawes and Corrigan, 1974; Einhorn and Hogarth, 1975).

The study of heuristics based on the "*less-is-more*" principle has been, in the past, mainly descriptive. As the examples above show, there is an interesting prescriptive aspect to heuristics that aims to determine when their use is preferable to the use of more complex strategies in uncertain environments. In other words, it is a question of understanding which characteristics of the decision-making environment point to the use of heuristics instead of optimization algorithms and when a heuristic allows us to make better predictive inferences, especially in situations of uncertainty where we have little time and limited computing power. In other words, when it is better to be a little stupid and simplistic according to the sophisticated standards of economic rationality and decision making. The answer to this question allows us to understand when a heuristic is adaptive, that is, when it improves our *ecological rationality*. The answer to this question might supply useful models to simulate human cognitive success in AI programs.

CONCLUSIONS: MAY AI GO OUT OF THE CHINESE ROOM?

Work in AI has produced computer programs that can beat the world chess champion, control autonomous vehicles, complete our email sentences, and defeat the best human players on the television quiz show *Jeopardy*. AI has also produced programs with which one can converse in natural language, including customer service "virtual agents," and Amazon's Alexa and Apple's *Siri*. Our experience shows that playing chess or *Jeopardy*, and carrying on a conversation, are activities that require understanding and intelligence. Does computer prowess at conversation and challenging games then show that computers can understand language and be intelligent? Will further development result in digital computers that fully match or even exceed human intelligence? Alan Turing (1950), one of the pioneer theoreticians of computing, believed the answer to these questions was "yes." Turing proposed what is now known as "The Turing Test": if a computer can pass for human in online chat, we should grant that it is intelligent. By the late 1970s some AI researchers claimed that computers already understood at least some natural language. In 1980, U.C. Berkeley philosopher John Searle introduced a short and widely discussed argument intended to show conclusively that it is impossible for digital computers to understand language or think.

Searle (1999, p. 108) summarized his Chinese Room Argument concisely:

> Imagine a native English speaker who knows no Chinese locked in a room full of boxes of Chinese symbols (a data base) together with a book of instructions for manipulating the symbols (the program). Imagine that people outside the room send in other Chinese symbols which, unknown to the person in the room, are questions in Chinese (the input). And imagine that by following the instructions in the program the man in the room is able to pass out Chinese symbols which are correct answers to the questions (the output). The program enables the person in the room to pass the Turing Test for understanding Chinese but he does not understand a word of Chinese.

Searle goes on to say, "The point of the argument is this: if the man in the room does not understand Chinese on the basis of implementing the appropriate program for understanding Chinese then neither does any other digital computer solely on that basis because no computer, qua computer, has anything the man does not have."

Thirty years after introducing the Chinese Room Argument, Searle (2010) describes the conclusion in terms of consciousness and intentionality:

> I demonstrated years ago with the so-called Chinese Room Argument that the implementation of the computer program is not by itself sufficient for consciousness

or intentionality (Searle, 1980). Computation is defined purely formally or syntactically, whereas minds have actual mental or semantic contents, and we cannot get from syntactical to the semantic just by having the syntactical operations and nothing else. To put this point slightly more technically, the notion "same implemented program" defines an equivalence class that is specified independently of any specific physical realization. But such a specification necessarily leaves out the biologically specific powers of the brain to cause cognitive processes. A system, me, for example, would not acquire an understanding of Chinese just by going through the steps of a computer program that simulated the behavior of a Chinese speaker. (2010, p. 17)

The narrow conclusion of the argument is that programming a digital computer may make it appear to understand language but could not produce real understanding. Hence the "Turing Test" is inadequate. Searle argues that the thought experiment underscores the fact that computers merely use syntactic rules to manipulate symbol strings, but have no understanding of meaning or semantics. The broader conclusion of the argument is that the theory that human minds are computer-like computational or information processing systems is refuted.

Searle shows us how the computational approach of AI about syntactic reduction of semantics is a claim empty of content. Computational reduction fails to explain the intentional dimension of human cognition. According to Searle, intentional activity directed towards the world (as in the case of a belief) and that of the world directed towards the individual (as in the case of desires) is possible only on the basis of a dimension of pre-intentional knowledge, called Background knowledge. It, as we explained before, is composed of non-representational mental capacities, skills, tendencies, dispositions, in other words know-how. It allows the functioning of intentional phenomena such as meanings, understandings, interpretations, beliefs, desires and experiences (Searle, 1992). Background knowledge has both a hereditary biological basis and a cultural basis linked to socialization. As regards the first dimension, the endowment of inferential principles of the newborn was described first. As for the second, it refers to conversational, social, religious and moral values, and norms that we learn in our socialization processes. The basic problem, however, is how this pre-intentional identity of the subject emerges. The answer can only refer to the embodied and embedded dimension of the subject who has been interacting with the human and physical environment from birth. From birth the subject through his body is situated in a world and with his body tries to act in an adaptive way. In other words, he tries to have cognitive success, in the sense of solving the practical problems of daily life that the environment places before him. Sometimes this attempt at a solution fails and the environment sends negative feedback (such as emotional or practical failures) to the subject. They are generally incorporated into subsequent

actions that are aimed at avoiding them. The degree of behavioral change of the action depends on various reasons related to the personality, intelligence and psychophysical state of the subject.[15]

Merleau Ponty offers a non-representational account of the way the body and the world are coupled. According to Merleau-Ponty (1962 [2002]), as an agent acquires skills, those skills are "stored," not as representations in the mind, but as a bodily readiness to respond to the solicitations of situations in the world. If the situation does not clearly solicit a single response or if the response does not produce a satisfactory result, the learner is led to further refine his discriminations, which, in turn, solicit more refined responses. Merleau-Ponty calls this feedback loop between the embodied agent and the perceptual world the *intentional arc*. He says: "the life of consciousness—cognitive life, the life of desire or perceptual life—is subtended by an 'intentional arc' which projects round about us our past, our future, our human setting, our physical, ideological and moral situation, or rather which results in our being situated in all these respects" (Merleau-Ponty, 2002, p.157). Describing the phenomenon of everyday coping as being "geared into" the world and moving towards "equilibrium" suggests a *dynamic* relation between the coper and the environment. Timothy van Gelder (1997) calls this dynamic relation *coupling*. He explains the importance of coupling as follows:

> The fundamental mode of interaction with the environment is not to represent it, or even to exchange inputs and outputs with it; rather, the relation is better understood via the technical notion of coupling. … The post-Cartesian agent manages to cope with the world without necessarily representing it. A dynamical approach suggests how this might be possible by showing how the internal operation of a system interacting with an external world can be so subtle and complex as to defy description in representational terms—how, in other words, cognition can transcend representation. (Van Gelder, 1997, p. 439)

Van Gelder (1997) shares with Brooks the idea that thought is grounded in a more basic relation of agent and world. Also, when abstract thought such as mathematics of theoretical philosophy is involved it relies on a basic dimension of being in the world. As van Gelder puts it:

> Cognition can, in sophisticated cases, [such as failure, problem solving and abstract thought] involve representation and sequential processing; but such phenomena are best understood as emerging from [i.e. requiring] a dynamical substrate, rather than as constituting the basic level of cognitive performance. (Van Gelder, 1997, p. 448)

And Dreyfus remarks "that this dynamical substrate is precisely the skillful coping first described by Heidegger and worked out in detail by Todes and Merleau-Ponty" (Dreyfus, 2007, p. 256).

Hubert Dreyfus (1972) was right when in 1972 he was criticizing AI because of its disembodied dimension. Without body, mind is not able to work and to feel to be situated in the world ("dasein"). Human beings are somehow already situated in such a way that what they need in order to cope with things is distributed around them where they need it, not packed away like a trunk full of objects, or even carefully indexed in a filing cabinet. This system of relations which makes it possible to discover objects when they are needed in our home or our world. (Dreyfus, 1972, p. 172)

This originary situation of the subject is also an important point to differentiate between how man and computer relate to the world. The computational approach considers the context irrelevant to the data with which a computer operates. For a computer to be able to respond to a problem, it needs to operate with a set of determined data to which it should assign a set of determined values. Unlike the computer, man has the possibility of processing holistically the information in the world, operating even with undetermined data. This is possible owing to the intentional arc and embodied skills by means of which we have direct access both to what is going on in the world and to the available solutions to solve our tasks (Negru, 2013).

The environment in which the individual operates is very different from that of games in which AI is so effective. The information is scarce and the future is uncertain and unstable. On the other hand, the environment in which the subject interacts is not the same both diachronically (i.e. for him over time) and synchronously with the individuals with whom he interacts. Ecological adaptation and cognitive success depend on the specific subjective "umwelt" (environment) of each individual (Uexkull, 2010). Each of us has a different "umwelt," that is, we see and consider different aspects of the environment as relevant. The environment is not stable and fixed, but is perceived by the subject in a dynamic and unstable way in relation to the momentary perceptual, sensorial, emotional, motor, visceral and cognitive characteristics of the individual. In other words, we see the environment differently at different times of our life and compared to what others observe. The salience and attention to some aspects changes in the same subject and between different subjects. We have a partial view of the environment similar to the frog that does not see an insect if it is immobile but only one in motion. The "umwelt" of the frog is made up only of moving objects. We can, however, coordinate our actions (speech and decisions) by the common characteristics we share. The current AI, on the other hand, lacks any "umwelt." The environment of these machines is composed of the data they obtain to adapt to their parameters. But a deep neural network isn't even aware that an environment exists. Alpha Zero can beat any human in chess and Go, but it doesn't know that it is playing a game called chess, or that there is a human opponent playing against it.

To conclude, this chapter attempts to analyze and explain how unrealistic the predictive and explanatory claims of AI are in both the past simulation and the current connectionistic machine learning versions. These claims are therefore to be treated with skepticism when they are heralded in the world of finance and create unrealistic expectations on the part of savers and investors.

This chapter has highlighted a number of critical issues on the possibility of creating intelligent machines like humans. In summary they are:

(1) Indeterminacy and uncertainty of knowledge: the empirical reality is made up of unstable and uncertain phenomena that cannot be predicted.

(2) Computational non-replicability of Background Knowledge: the BK is of a pre-intentional type and has non-representational characteristics so it cannot be simulated at the computational level.

(3) Syntactic irreducibility of semantics: computational theory of the mind underlying AI reduces intelligence to the application of syntactic rules on symbols. This fails to include the intentional and meaningful dimension of human thought and action.

(4) Absence of the embodied dimension of cognition: AI proposes Cartesian agents without a body while human intelligence and action are possible as embodied and embedded in phenomenic reality.

(5) "Dasein" in the situational context: the primitive dimension of the subject that cannot be replicated by AI is his being-in-the-world. "Dasein is its world existingly" (Heidegger, 1962, p. 416). We are in the world and part of it.

(6) Absence of the "umwelt" dimension: the environment and the context through its affordances stimulate specific and different perceptual, sensory and motor responses depending on the subjects and depending on the moment in the same subject. In AI there is no umwelt and we tend to consider the answers as context-free.

The embodied and embedded cognition approach together with the considerations on the heuristic ways of adapting in situations of uncertainty and complexity have already highlighted what should be the tentative path of an AI that simulates human cognition. The ideas of enactivism regarding how organisms engage with their environment have interested those involved in robotics and man-machine interfaces. The analogy is drawn that a robot can be designed to interact and learn from its environment in a manner similar to the way an organism does, and a human can interact with a computer-aided design tool or data base using an interface that creates an enactive environment for the user, that is, all the user's tactile, auditory and visual capabilities are enlisted in a mutually explorative engagement, capitalizing upon all the user's abilities, and not at all limited to cerebral engagement. In these areas it is common to

refer to affordances as a design concept, the idea that an environment or an interface affords opportunities for enaction, and good design involves optimizing the role of such affordances.

In theory if AI wants to simulate how human being adapts to the uncertain environment it has to follow the following recommendations:

(a)   To create a map of the human heuristics that are ecologically rational in given tasks and environmental settings.
(b)   To incorporate the heuristics in evolutionary computation techniques, which are stochastic algorithms whose search methods model some natural phenomena: genetic inheritance and Darwinian strife for survival.
(c)   Developing robots that mirror the structure of the human body, not only at perceptual or motor level, but also at visceral and sensorial level.

In a nutshell, it would involve equipping a robot with a toolbox of adaptive heuristics, a learning module that helps match heuristics to environments, and a discovery module that recombines the building blocks to create new adaptive heuristics. And we would need to create a body that gives the machine a purpose, for example, in the first place to act socially or to survive.

If these progresses were accomplished might we reach the *singularity phase*? According to the most popular version of the singularity hypothesis, an upgradable intelligent agent (such as a computer running software-based artificial general intelligence) would enter a runaway reaction of self-improvement cycles, with each new and more intelligent generation appearing more and more rapidly, causing an intelligence explosion and resulting in a powerful superintelligence that would, qualitatively, far surpass all human intelligence. The concept and the term were popularized by Vernor Vinge in his 1993 essay "The coming technological singularity," in which he wrote that it would signal the end of the human era, as the new superintelligence would continue to upgrade itself and would advance technologically at an incomprehensible rate. He wrote that he would be surprised if it occurred before 2005 or after 2030. Four polls, conducted in 2012 and 2013 among AI experts, suggested that the median estimate was a 50 percent chance that artificial general intelligence (AGI) would be developed by 2040–50.

In reality the answer to the previous question is negative. According to Dreyfus (2007), we would not only need a model of the brain functioning but we would also need a model of *our particular way of being embedded and embodied* such that what we experience is significant for us in the particular way that it is. That is, we would have to include in our program a model of a body very much like ours with our needs, desires, pleasures, pains, ways of moving, cultural background, etc. I agree with Dreyfus that "If we can't make our brain model responsive to the *significance* in the environment *as it shows*

up specifically for human beings, the project of developing an embedded and embodied Heideggerian AI can't get off the ground" (Dreyfus, 2007, p. 265, emphases in original).

And I conclude quoting Dreyfus: "The idea of supercomputers containing detailed models of human bodies and brains may seem to make sense in the wild imaginations of a Ray Kurzweil[16] or Bill Joy,[17] but they haven't a chance of being realized in the real world" (Dreyfus, 2007, p. 265).

NOTES

1. Publication realized within the MUSA – Multilayered Urban Sustainability Action – project, funded by the European Union – NextGenerationEU, under the National Recovery and Resilience Plan (NRRP) Mission 4 Component 2 Investment Line 1.5: Strengthening of research structures and creation of R&D "innovation ecosystems," set up of "territorial leaders in R&D."
2. Interview with Kate Crawford (Tom Simonite, Wired, April 26, 2021).
3. https://www.edge.org/conversation/jaron_lanier-the-myth-of-ai#25986 (accessed November 5, 2021).
4. Large worlds also include choice environments that can be classified as risk environments a priori, but whose complexity of calculation makes them comparable to an uncertain environment. Think of board games like chess or Go where the calculation of moves presents a typical combinatorial explosion.
5. According to another metaphor, that of the "*mental sandwich*" introduced by Susan Hurley (1998), the cognitive processes are the tasty and protein internal part of the sandwich, while the sensory and motor parts are the two tasteless external slices of bread. Therefore what is interesting is to concentrate on the side dish and let go of the bread.
6. For example, if Mario asks Maria if she will come to the beach the day after and Maria answers that her grandmother is ill, Mario will understand that Maria may not come beacause the grandmother is ill. This is an example of conversational implicature that adds to the meaning of the utterance.
7. According to Viale (1999), these results on causal cognition in infants seem to justify the anti-Humean thesis of causal inferences based on synthetic a priori principles.
8. For a discussion about embodied bounded rationality see the special issue edited by R. Viale, S. Callagher and V. Gallese, "Bounded rationality, enactive problem solving and the neuroscience of social interaction," *Frontiers in Psychology* (forthcoming).
9. McGann and Torrance (2005) argue that enactivism attempts to mediate between the explanatory role of the coupling between cognitive agent and environment and the traditional emphasis on brain mechanisms found in neuroscience and psychology. In the interactive approach to social cognition developed by De Jaegher and Di Paolo (2007), the dynamics of interactive processes are seen to play significant roles in coordinating interpersonal understanding, processes that in part include what they call *participatory sense-making*. Recent developments of enactivism in the area of social neuroscience involve the proposal of *The Interactive Brain Hypothesis* (Di Paolo and De Jaegher, 2012) where social

cognition brain mechanisms, even those used in non-interactive situations, are proposed to have interactive origins.

10. In the enactive view, perception "is not conceived as the transmission of information but more as an exploration of the world by various means. Cognition is not tied into the workings of an 'inner mind', some cognitive core, but occurs in directed interaction between the body and the world it inhabits." Alva Noë (2010) in advocating an enactive view of perception sought to resolve how we perceive three-dimensional objects, on the basis of two-dimensional input. He argues that we perceive this solidity (or "volumetricity") by appealing to patterns of sensorimotor expectations. These arise from our agent-active "movements and interaction" with objects, or "object-active" changes in the object itself. The solidity is perceived through our expectations and skills in knowing how the object's appearance would change with changes in how we relate to it. He saw all perception as an active exploration of the world, rather than being a passive process, something which happens to us. Another application of enaction to perception is analysis of the human hand. The many remarkably demanding uses of the hand are not learned by instruction, but through a history of engagements that lead to the acquisition of skills. According to one interpretation, it is suggested that "the hand [is] … an organ of cognition," not a faithful subordinate working under top-down instruction, but a partner in a "bi-directional interplay between manual and brain activity" (Hutto and Myin, 2013, p. 46).

11. The Tower of Hanoi is a mathematical game or puzzle. It consists of three rods and a number of disks of different diameters, which can slide onto any rod. The puzzle starts with the disks stacked on one rod in order of decreasing size, the smallest at the top, thus approximating a conical shape. The objective of the puzzle is to move the entire stack to the last rod, obeying the following simple rules: (1) Only one disk may be moved at a time. (2) Each move consists of taking the upper disk from one of the stacks and placing it on top of another stack or an empty rod. (3) No disk may be placed on top of a disk that is smaller than it.

12. The Missionaries and Cannibals problem is a classic river-crossing puzzle. It is a well-known toy problem in AI, where it was used by Herbert Simon as an example of problem representation. In the Missionaries and Cannibals problem, three missionaries and three cannibals must cross a river using a boat which can carry at most two people, under the constraint that, for both banks, if there are missionaries present on the bank, they cannot be outnumbered by cannibals (if they were, the cannibals would eat the missionaries). The boat cannot cross the river by itself with no people on board.

13. For example, multiple linear and non-linear regression, connectionist algorithms, Bayesian analysis algorithms, etc.

14. Kahneman et al. (2021) recently emphasized the important role of simplicity and intuition in decision making: "I think there is actually evidence of situations where deliberation doesn't help you. There is a study that when you're choosing a poster, then spending too much time analyzing why you like it, why you like it more than another poster, actually may not pay off. That you may be happier when you have a bunch of posters and you pick one. So, I would say for decisions where ultimately the criterion is whether you will like it and it's simple and relatively small, the evidence suggests that intuitive judgment may be better than analysis" (Nesterak, 2021).

15. On the contrary, one of the main features of psychotic disturbances is to be impermeable to the environmental feedbacks (Viale, 2021b). Threfore their behavior is not able to adapt to the signals coming from the environment.
16. Raymond Kurzweil is an American inventor and futurist. He is a public advocate for the futurist and transhumanist movements and gives public talks to share his optimistic outlook on life extension technologies and the future of nanotechnology, robotics and biotechnology.
17. William N. Joy is an American computer scientist, commonly defined by the US magazine *Fortune* as Bill Joy, the "Thomas Edison of the Internet." He can be considered the true scientific mind of Sun Microsystems.

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