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Human Complexity vs. Machine Linearity: Tug-of-War Between Two Realities Coexisting in Precarious Balance

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ABSTRACT

Are machines smarter than humans? What will happen of our species if artificial intelligence (AI) becomes so advanced that it can no longer be controlled? Is the uniqueness of human beings at risk? These are just some of the questions that grip computer science experts as much as ordinary people who experience technological development day in and day out. In our paper, the current scenario will be analysed, from the search for a definition of human intelligence to the historical stages marking the birth and development of technologies capable of emulating many of its facets. The discussion will focus on the main differences between man and machine in the interpretation and replication of the concept of intelligence, highlighting the diversity of approach between an inherently complex entity (man) and a linearly functioning system (machine). The purpose will be trying to provide insights to answer the initial questions, by analysing possibilities and limitations of the main AI emulation techniques. The optimistic view offered by our work suggests that the machine's highest aspiration can only come down to the sheer emulation of our behaviours: machines' linearity will always remain in the service of human complexity, never vice versa.

Keywords: Artificial Intelligence, Complexity, Emergence, Human Intelligence, Machine Learning.

1. INTRODUCTION

The present era of computer science is characterized by a series of trends and developments that have radically transformed the way we engage with technology and how it influences our daily lives: it involves a constant interaction of man with machine, to the point that the reality around us can hardly be separated from the virtual world [1]. With the rise of the Internet of Things (IoT), modern machines have boundless amounts of data to analyse in real time through increasingly fast and efficient processing techniques [2]. Technological growth in performance is exponential, such that modern society must dynamically readjust to keep up with the times. Such a scenario poses no small challenge to human beings, who in an effort to take advantage of the new opportunities offered by scientific progress must acquire the ability to reinvent themselves quickly. This sort of forced coexistence has meant that, in recent decades, the interest of computer science has shifted mainly toward the study of cognitive abilities and the development of systems capable of performing complex tasks typical of the human intellect [3]: it is a sort of gold rush, in which computer scientists try to simulate human intelligence through increasingly sophisticated and high-performance algorithms, while ordinary people trudge along trying to understand the potential of such innovations.

Artificial intelligence (AI) is the child of all this, and it marks our age by splitting public opinion in two: on the one hand, those who support technological progress with a drawn sword, and on the other, those who see the rise of machines as the enemy to be fought. When viewed optimistically, the advancement of AI promises to lead to a significant improvement in the quality of life, pointing to the introduction of new scientific breakthroughs and innovative solutions to complex problems. In addition, with the automation of many processes, particularly tedious and time-consuming work tasks could be entrusted to machines, allowing humans to focus on more meaningful activities [4]. The negative view on AI, on the other hand, sees a future in which humans will be replaced in various areas of work by much higher-performance machines, capable of carrying out the same tasks in a better way and much reduced timelines. The common feeling of many people is one of helplessness in the face of rapid technological development, due to a lack of understanding of the new processes introduced by AI. This sense of distrust leads people to see AI as a risk to the uniqueness of human beings, who are likely to find themselves alienated once machine emulation reaches a level of precision that exceeds their capabilities [5]. The consequence would be a true dystopian scenario in which the increasing autonomy of machines will lead to a loss of control by humans and AI will be in charge, with unpredictable and potentially harmful consequences.

Although the line between risks and benefits of AI would seem to be much thinner than it appears, an important gap between human thinking and machine functioning must be acknowledged: humans are inherently complex beings, machines in contrast operate through linear processes. Complex systems, by definition, are composed of a large number of elements that interact with each other through a whole range of different relationships. The peculiarity is that while it is possible to analyse all the elements, it is in no way possible to go and determine the overall behaviour of the system from that of the individual parts [6]. The behaviour of complex systems is defined by flock theory, which defines the concept of "emergence" [7]: until one observes the flock as a whole, it is not possible to make sense of the movement of individual birds within it; another practical example is provided by the set of human beings within society, whose laws and rules cannot be deduced by observing the behaviour of individual citizens.

The human being can be considered an innately complex system because the subsystems that comprise it (think of cells, tissues, and organs), themselves exhibit a high degree of complexity. Human's ability to harness the capacity to perceive context, integrate disparate information and draw conclusions that are not necessarily obvious from available data is an expression of complex thinking, characterized by a wealth of nuances, connections and intuitive understandings that lead to emergent-type behaviours [8]. Our minds do not follow a linear path in solving problems or formulating ideas, but rather rely on experience, creativity, and intuition. Unlike humans, machines operate by using defined algorithms and instructions, performing operations in sequence without deviations. The linearity of such an approach does not allow machines to discern deeper meanings, make unexpected connections or grasp the essence of concepts beyond the data provided [9].

The aim of our study is to analyse both sides of the coin, trying to draw a sharper line between the risks and benefits of AI diffusion, based on the substantial difference between human complexity and machine linearity. The research seeks to go into specifics on the concept of intelligence starting from its definition and the transformation it has undergone over the centuries, and ending with an analysis of the different AI techniques that enable the emulation of different aspects of the human cognitive spectrum. The purpose is to provide the reader with a tool that can be food for thought in order to gain a more conscious stance regarding the ethical issue of AI attempting to mimic, or even surpass, the human intellect.

The paper is structured as follows: in the next section, the historical path that led to the development of a multisectoral definition of intelligence and the emergence of AI will be analysed; in the third section, starting with Howard Gardner's theory of multiple intelligences [10], the substantial differences between humans and machines in different domains will be examined, with reference to the application possibilities and operational limitations of different AI techniques; finally, in the concluding section, we will try to draw conclusions on the basis of the presented analysis, also offering our personal point of view on the issue at hand.

2. HISTORICAL BACKGROUND

The complexity of human beings is reflected in most of their characteristic aspects. Intelligence, whose varied nature generates particular controversy, is no exception. The very definition of intelligence is not universally recognized in the scientific community and varies significantly depending on the cultural, social, and disciplinary context in which it is described [11]. Numerous psychologists and distinguished scholars in cognitive science agree in understanding intelligence as the ability to understand, learn, solve problems, and adapt to new situations [12]. However, this is a rather vague definition that does not allow for a thorough understanding of the different facets that characterize the human intellect. The origin of intelligence itself is a rather debated topic between those who argue that it is largely hereditary and depends heavily on genetic factors and those who believe that environmental causes play a more significant role in the development of cognitive abilities [13].

The following section will explore in detail the historical stages that led modern scholars to argue for the complexity and multifactorality of intelligence, as well as the milestones that marked the birth and development of AI.

2.1 History of human intelligence

Although the definition of intelligence is not unambiguously recognized in science, the organ within which all the processes relatable to intelligence reside is the brain. Human brain is composed of about 85 billion neurons, units capable of processing large amounts of information simultaneously and in parallel. They communicate through electrical impulses and chemical signals, called synapses; each neuron has about 5000 to 10000 synapses, forming complex networks that enable various cognitive functions such as perception, learning, memory, and decision making [14]. The brain's storage capacity is often estimated in terms of the number of synapses: each synapse can store information in the form of synaptic strength, which reflects the effectiveness of communication between neurons. In addition, the brain's ability to reorganize and create new connections, known as synaptic plasticity, enables it to adapt to new experiences and learn throughout life. Such a structure gives the human brain potentially unlimited computational power and storage capacity and, although they are not precisely quantifiable in terms of traditional computing metrics, some estimates suggest that its parallel processing capabilities far exceed those of even the most powerful supercomputers [15].

While we cannot establish with certainty the possibilities of the brain, the high potential of the instrument was already known to the most ancient peoples, from the dawn of time. The Egyptians and Mesopotamians, for example, attributed roles of power to the people they considered the most intelligent; all the way to the Greeks who, with the birth of philosophy (love of knowledge), made intelligence a real discipline [16]. In general, for Greek philosophers, intelligence was not simply the ability to process information or solve problems, but it was also closely related to the pursuit of truth, wisdom, and happiness. It was considered a virtue that guided the individual toward a good and meaningful life, to such an extent that illustrious names such as Plato, Aristotle and Socrates based their method on it [17].

The use of intelligence, understood as the ability to deal with situations creatively and to exploit available resources wisely aimed at obtaining maximum yield has guided man throughout the ages. All the innovations that have marked the development and flourishing of modern civilization, right up to the era of cybernetics that we are experiencing today, are the result of the application of our knowledge through intelligence. The subject of intelligence has become a central topic of study, especially in the fields of psychology and sociology, since the late 19th and early 20th centuries, to such an extent that we have come to the need to develop models for assessing or "measuring" it. Among the pioneers of the scientific inquiry that allowed to shape our understanding of intelligence was Francis Galton, in the late 1800s; he was among the first to study human intelligence through psychometric testing and statistical analysis, laying the groundwork for the development of intelligence testing [18].

It was only in the early 20th century, however, that prominent psychologists such as Alfred Binet and Lewis Terman, developed the first standardized intelligence tests: these played a crucial role in quantifying and measuring intelligence, though they were initially focused on cognitive abilities such as memory, reasoning, and problem-solving []. Binet himself is considered the forerunner of the modern IQ measurement scale, a term later coined by psychologist William Louis Stern to denote the relationship between an individual's mental age and his or her biological age [19]. Along these lines, British statistician Charles Spearman introduced the concept of the “g factor” (general intelligence), which suggests that intelligence can be measured and described by a single primary factor [20]. However, the limitation of the theoretical models of assessing and measuring intelligence levels in the early 1900s soon became quite apparent: only specific aspects of individuals' intellectual capacity were being assessed, with reference to individual aspects, and not to intelligence as a whole.

The first to realize this was Louis L. Thurstone, who sharply criticized Spearman's view, pointing to it as simplistic; instead, taking up Galton's psychometric studies, he proposed a model of intelligence composed of multiple factors, known as the “primary factor theory.” According to Thurstone's view, human intelligence was composed of seven primary mental abilities: verbal comprehension, verbal fluency, arithmetic ability, spatial visualization, associative memory, inductive reasoning, and speed of perception [21].

Throughout the 20th century, numerous researchers like Jean Piaget and Lev Vygotsky supported Thurstone's view by emphasizing its multidimensional nature, including emotional, social, and practical intelligences [22,23].

More recent contributions to the study of cognitive psychology include Stenberg's triarchic theory, for which he suggests that intelligence is composed of three aspects (analytical, creative, and practical), and John Bissel Carroll's hierarchical pyramidal organization of intelligence [24,25]. Breakthroughs in neuroscience, cognitive psychology, and artificial intelligence have further enriched our understanding of human intelligence, highlighting the intricate interplay between biological, environmental, and cultural factors in shaping cognitive abilities. Today, although the study of human intelligence remains a dynamic and interdisciplinary field, with ongoing research exploring topics such as cognitive development, the most accredited Theory is Howard Gardner's Theory of Multiple Intelligences, according to which intelligence cannot be reduced to a single parameter, but there are different forms of intelligence, such as verbal, logical-mathematical, spatial, musical, bodily, interpersonal, and intrapersonal intelligence [10].

2.2 History of Artificial Intelligence

Before the birth of the first calculators at the dawn of the 19th century, all logical-mathematical operations could not be carried out automatically but required active participation of the human being: the only tool available was the intellectual capabilities of our species. Several issues led scholars along the years to develop new technologies capable of performing such operations faster and more efficiently (from the first rudimentary calculators to modern supercomputers). First, while the human brain's computational power and storage capacity are extraordinary, human mental processes are not uniform and each brain works differently; this is related to the complexity of the human being, who is not able to handle all operations, voluntary or not, that take place within his or her body in a linear manner. While it is true that the performance of the brain is potentially extraordinary, it is also true that mental resources are not totally under our control and cannot be allocated at will as it can be in the case of a programmable computer. Second, the utilization of mental resources requires an enormous expenditure of energy and time. AI’s goal is precisely to protect the most precious resource of the human species: our time. The development of automatic systems that can perform tasks requiring human intelligence in less time is the leitmotif that led to the birth of computers first, and AI later. Beyond the creation of the first computer prototypes and the development of increasingly complex computational tools, the earliest work that can be considered precursors of AI can be traced back to the studies of Turing and McCulloch and Pitts, who in 1943 developed the first computational model based on artificial neurons, the ancestor of the artificial neural networks (ANN) that will play a significant role in the later development and establishment of AI [26]. Based on this model, in 1950, Minsky and Edmonds, created what is recognized as the first ANN, known as SNARC (Stochastic Neural Analog Reinforcement Calculator) [27]. Six years later, in 1956, at the famous Dartmouth Conference, Minsky himself championed the initiative that would lead to the actual birth of AI as a distinct field: he gathered a team of experts with the (rather ambitious) goal of creating in two months a machine capable of simulating every aspect of human learning and intelligence [28]. The following decade was marked by the scientific community's great enthusiasm for the new discipline, to such an extent that numerous scholars took the cause to heart, producing important steps toward research; among the notable discoveries were several new AI techniques including the General Problem Solver (GPS) by Herbert Simon [29] and the SHRLDU, the first program for understanding human language that effectively began the study of natural language processing (NLP) [30].

After an initial boom, enthusiasm for AI was interrupted as the first difficulties began to arise at the programming level and numerous practical limitations of the machines came to light. Many of the algorithms that, at least at the theoretical level, should have quickly led computers to emulate human behaviours and perform most of their tasks, proved unworkable in practice; the approaches taken to training the machines were considered “weak” by the U.S. government, so much so that in the early 1970s the funds allocated to AI research and development were reallocated differently [31].

The turning point came in the early 1980s when backpropagation, the learning algorithm for neural networks devised by Bryson and Ho, made a comeback [32]. The application of backpropagation completely revolutionized the scientific landscape, enabling a whole plethora of new uses of neural networks not only in AI but in computer science in general. Rumelhart's work in 1986, thanks to which the back-propagation algorithm found wide scientific acceptance, effectively marks the birth of the modern ANNs and AI as we know it today [33]. The late 20th and early 21st centuries saw exponential growth in AI research and application, fueled by the IoT era, characterized by advances in computing power, data availability and algorithmic innovation. In addition, the advent of deep learning (DL) techniques, particularly convolutional neural networks (CNNs) and recurrent neural networks (RNNs), has revolutionized several fields, including computer vision, NLP, and robotics. Today, AI continues to evolve rapidly, with ongoing research focusing on areas such as explainable AI and the integration of AI with other nascent technologies such as robotics.

3. IS AI REALLY INTELLIGENT?

The limitation of psycho-cognitive theories that define intelligence as a single, general ability that can be measured through standardized tests is the lack of a criterion that can consider the complexity of human beings and the inherent differences that define each person's way of being. The theory of multiple intelligences, proposed by Howard Gardner in 1983, succeeded in revolutionizing the traditional concept of intelligence by recognizing that each person has a unique mix of abilities and talents that cannot be fully measured and described by a single numerical indicator. Gardner's theory makes it possible to recognize the existence of cognitive diversity whereby none of us can be called intelligent in an absolute sense but can demonstrate a propensity to use his or her intellect effectively in certain situations or relative to specific activities rather than others. The holistic approach to intelligence predicts the existence of eight different main aspects of the human intellect (Figure 1), which reflect the complexity of human experiences and mental processes that enable us to process thoughts and ideas.

With this in mind, AI's attempt to emulate human behaviour aims to design systems that can mimic each of the different types of intelligence that characterize our cognitive spectrum, rather than just performing certain tasks in place of humans. The great unknown on which our work is intended to provide food for thought is whether AI is able to simulate the mechanisms of the human brain to such an extent that it can develop authentic intelligence in all respects; in other words, the question is if the technological use of different linear-type approaches can somehow go on to result in a system capable of developing an intrinsic complexity similar to that characterizing us humans.
In the remainder of this section, all eight forms of multiple intelligence proposed by Gardner will be described and the different techniques used by AI to emulate distinct aspects of each will be analysed. The order in which the different forms of intelligence will be presented reflects, on an ascending scale, the level of difficulty (and failure) in emulation by AI: it will start from logical-mathematical intelligence in which AI algorithms have achieved even better performance than humans, all the way down to intrapersonal intelligence for which an AI-based approach capable of emulating it is at present hardly conceivable.

3.1 Logical-mathematical intelligence

When the first calculators began to appear between the beginning and the first half of the 20th century, the goal was clear: technological progress was heading in a direction in which digital entities would perform mathematical-type operations instead of humans, saving them a great deal of time and labour. Therefore, the first computational algorithms can be considered the ancestors of modern AI, having arisen to simulate the logical-mathematical functions of our intellect [34].

Generally, logic smartness refers to the capacity of drawing conclusions from new or existing information, through rational processes; according to Gardner himself, logic-mathematical intelligence is among all those most associated with the use of reason. What are the mechanisms on which human reason is based is a topic widely debated by psychologists, philosophers, and cognitive science experts; in any case, reason in the strict sense involves the mental transition from one idea to another through logical-type criteria, based on causal relationships, inductive or deductive approaches. The logical type of approach leaves no room for intuition but is based on a mere mechanical method in which decisions are made almost automatically, based on objective rules and criteria [35].

Figure 1: Wheel representation of the eight frames of mind by Gardner’s theory of multiple intelligences. Source: Gardner, H. (1983). Frames of mind: The theory of multiple intelligences. Basic Books.

Logic smartness, being reason-based, inherently leaves little room for complexity: an underlying linearity is evident in all processes involving logic reasoning, which limits the possibility of generating emergent behaviours [36]. The action of extracting knowledge from specific input data through the use of logic reasoning-based models and algorithms is the exact definition of knowledge discovery in databases (KDD), the ultimate goal of machine learning (ML) [37]. Not surprisingly, there are a myriad of AI approaches, primarily based on ML and DL, that can apply deductive and inferential logic rules and accurately emulate human logical-mathematical intelligence.

The areas of computer science mainly aimed at studying and emulating the processes underlying human logical-mathematical intelligence are computational logic and automated reasoning. Computational logic originated in the 1970s with the aim of analysing the theoretical basis of psychology and cognitive science for the realization of algorithms capable of imparting logical thinking to machines, applicable to various tasks that are not simply limited to computational operations [38]. Automated reasoning is aimed at the use of fuzzy logic or Bayesian inference algorithms, based on the ability to use analog-type thinking, based on induction and abduction; this finds wide application in science especially for automated theorem proving and automated proof checking tasks [39].

In summary, reason as an expression of our logical-mathematical intelligence represents the linear side of our thinking, and it is no coincidence that it is probably the aspect of our intellect that machines have been able to emulate best over the years. Counter-evidence of the excellent effectiveness of AI in emulating linear thinking can be seen in the ability of modern supercomputers to play chess; in chess, a player's skill lies principally in planning a strategy based on calculating all possible combinations of moves of individual pieces. This is a logical problem, based on logical reasoning of a causal type (if a player moves a particular piece, the opponent may move accordingly) and the ability to memorize as many scenarios as possible. It is just the kind of operations in which machines excel, since they are based on linear solving strategies that require only computing power and efficient search algorithms. Beginning with Deep Blue defeating chess champion Garry Kasparov for the first time in 1997, to the present day in which computers, thanks in part to new approaches based on reinforcement learning have achieved scores unreachable by humans [40], it shows how the potential of AI to emulate or even surpass human capabilities with respect to logical-mathematical tasks has reached incredible levels.

3.2 Verbal-linguistic intelligence

The ability to speak and express oneself is the main element that distinguishes humans from other intelligent forms of life. The ability to connect words to certain sounds and to understand that the latter are used to describe the world around us is something that is acquired from the very first years of life: for humans, linguistic-verbal intelligence is developed from an early age [41]. Language allows people to communicate their thoughts and feelings permitting the development of the interpersonal relationships that are the basis of society. Without the ability to perform actions such as listening, speaking, reading, and writing, the very act of reasoning would be an end in itself because it would not be possible to share the fruit of it with others. Radicalizing the subject, one might say that linguistic-verbal communication is the basis for the survival of our species, since as complex beings we need to explicate our nature through dynamics of sharing and social interaction [42]. Verbal intelligence, while almost innate in humans, is nevertheless something that needs to be cultivated and refined. It is not only limited to the ability to read, write, or express oneself, but also influences more complex skills related to the use of language in different contexts. Some people with distinct verbal intelligence, for example, are able to learn new language, explain relatively complex concepts effectively, intervene in debates persuasively, and tell or write stories and anecdotes, better than others. The very ability to produce literature, be it short stories, novels, or poems, is a clear sign of the presence of a marked verbal intelligence that distinguishes the leading literary artists in history [43].

When it comes to emulating verbal intelligence through AI, the techniques and algorithms utilized mainly aim at a system that allows machines to understand and generate human language in a similar way as a human would. The skills to be mimicked refer to the development of systems with heightened sensitivity to meaning, structure and order of the words and ability to effectively use language, both spoken and written. This is done within a field of computer science called natural language processing (NLP): here, through approaches including natural language analysis, natural language understanding, and natural language generation, based primarily on ML algorithms, machines are trained on large amounts of text to learn grammatical rules, word meaning, and language coherence patterns [44,45]. Numerous text generation techniques also fall under the umbrella of NLP, which are among the generative AI algorithms. The combination of machine learning and text generation techniques within NLP has, over the past few years, resulted in the architecture model that has disrupted the world of computer science and AI by giving birth to the Generative Pre-trained Transformer (GPT) [46]. GPT model is based on transformers, a particular type of DL architecture capable of processing sequential type input data with frightening efficiency. Ultimately, large language model (LLM) algorithms, of which GPT is the major exponent, are perfectly capable of performing language-related tasks and generating human-like text based on patterns in data: they are programmed for understanding and generating text across a wide range of topics, making connections between words and concepts, and assisting users with various language-related tasks [47]. The text production offered by LLMs is grammatically correct and consistent in any language and its content can be inherent in a wide range of topics, and even mimic different writing styles [48].

The level of emulation offered by AI seems to be beyond the actual capabilities of the human intellect, both in speed of execution and variety of skills. However, there are limitations that still do not allow AI-generated texts to be as compelling or impactful as those written by humans. These fall, once again, in the realm of complexity: for a text, be it a scientific work or a literary tale, to be engaging, there is a need to understand the specific needs of the audience and go on to generate in them a kind of emergent behaviour that is expressed in their emotional response. This is only possible by including in the text such qualities as creativity, originality, emotional depth that derive from the passion and cultural context of the writer and that AI may not fully replicate for the time being [49].

3.3 Visual-spatial intelligence

From a purely descriptive point of view, visual-spatial intelligence is related to the ability to perceive and analyse shapes, spaces, and dimensions of objects around us. It can be considered a mechanical form of intelligence, which we humans acquire from the earliest moments of life, almost spontaneously, through the use of our senses (particularly touch and sight). From this primary ability are then derived numerous other skills that determine the individual's level of intelligence, from a keen sense of orientation to the ability to recognize and remember images or to mentally manipulate objects around us, even creating new ones [50]. Beyond the basic cognitive skills that describe visuo-spatial intelligence, the most obvious product of this form of intelligence is art. Although it is not easy to find an effective definition of visual art, it can be understood as a representation of the forms and spaces of reality, mediated by the interiority of the author. In other words, the encounter between the linear process of analysing forms and the complexity of human beings generates art, understood as an expression of emotions, ideas, experiences, and worldviews [51].

The artistic process stems from the linear operation of acquiring morphological patterns that describe existing structures in nature. AI is perfectly capable of emulating such pattern acquisition processes through various algorithms and ML or DL techniques. CNNs, for example, were designed specifically for image processing and to enable the extraction of relevant features from them, such as edges, textures, and shapes [52]. More modern technologies see the use of RNNs and Long Short-Term Memory (LSTM) for processing temporal sequences of data, which is necessary for contextual analysis of spatial and temporal information [53]. Recently, the same transformer technology used by GPT models for natural language elaboration has been applied to images, with the goal of segmenting them into a series of patches useful for classification and replication [54]. The latest frontier in AI-generated visual arts is Generative Adversarial Networks (GAN): this is a particular type of framework in which two neural networks are trained simultaneously, in a competitive way; starting from the initial dataset, the competition mechanism allows the system to artificially generate new data, very similar to the real data, on which to build very realistic images and content [55]. At present, the operational possibilities of AI in the field of visual-spatial intelligence are frightening, to the point that the creation of hyper-realistic multimedia content (so-called "deepfakes") is at the centre of numerous ethical controversies. The dissemination of material that is bogus but, given the remarkable accuracy of image generation algorithms, difficult to distinguish from the real thing, risks generating misinformation by manipulating public opinion or damaging the reputation of the individuals involved resulting in a violation of privacy [56].

Beyond the ethical implications, it is undeniable that modern technologies enable machines to recognize, analyse, and generate images and spaces in similar (sometimes indistinguishable) ways to how a human being would. The only limitation of AI, again, is related to the lack of the element of complexity that determines the difference between art and representation: a true work of art must be able to inspire and excite the viewer, not merely reproduce shapes, colours, and dimensions accurately. The visual-spatial intelligence of human beings also lies in being able to recognize a work of art by the emotion it can convey, to appreciate the difficulty of the creative process, and to understand the deeper meaning the work is intended to transmit. We could conclude that generative AI, accurate as it is, is able to offer an excellent emulation of the end result of visuo-spatial intelligence without being able to reproduce the complex processes that characterize its artistic explication.

3.4 Musical intelligence

Music, in the same way as painting or sculpture, is considered to all intents and purposes an art form. Any kind of artistic process starts from the mechanism of acquiring natural patterns, in this case rhythms and sounds, which are reworked through creative processes to produce the final result [57]. Just like visual arts, music is the product of the encounter between a linear mechanism related to hearing, which is almost spontaneous, and processes of a complex nature related to the creative and emotional part of our brain. Musical intelligence is nothing more than the ability to interact with this type of art, whether through composition and performance or simple listening. In fact, individuals with high musical intelligence present a high sensitivity in the recognition of tones, rhythms, timbres and melodies: they can understand and appreciate elaborate musical structures and different musical styles and, in the best of cases, produce original music by singing or playing instruments.

From the AI perspective, the emulation of musical intelligence starts by reproducing the same linear pattern acquisition mechanism used by humans: the machine collects sound data and extrapolates features that can be used for generation, recognition, and classification [58]. The techniques used by AI are roughly the same as those described in the case of visuo-spatial intelligence: the mechanisms underlying the emulation process are the same, but they work on sound-type input instead of images. The features replicated by AI are mainly song and melody recognition and music generation. Most software and mobile applications for recognition and classification are based on CNNs, used for analysing audio signals and spectrograms, or RNNs and LSTMs, used on audio time sequences for tone and rhythm detection [59]. For music generation, however, much more extensive training is required, which can be done by technologies such as RNNs and transformers [60]. Another very recent technology is related to the use of special neural networks that can identify notes by going to transcribe audio tracks directly into musical notation [61].

The emulative capabilities of AI, even in this area, turn out to be astounding. It is no coincidence that the problem of deepfakes, which was the prerogative of the visual arts, is now extending to the field of music as well. The reason is related to the spread of AI-based speech synthesis models, which are able to simulate extremely realistic human voices [62]. The limitation of AI, again, is dictated by the inability of machines to operate complex dynamics: music is an art and as such requires a good deal of creativity and emotionality. The quality of a musical product cannot be measured by objective criteria but depends on the emotional response it generates in listeners. Music cannot be understood (and appreciated) solely on the basis of the recognition of sounds and rhythms, but is linked to emergence through the ideas, memories, and feelings it is capable of arousing. AI ensures an emulation (albeit an excellent one) of the result leaving behind the creative process that characterizes its artistic nature.

3.5 Interpersonal intelligence

Interpersonal intelligence refers to the uniquely human ability to understand and interact effectively with others. Underlying it is the ability to recognize and interpret the feelings, motivations, and behaviours of others, based on one's personal experience: be able to engage in emotions and feelings is the prerequisite on which to understand those of others and generate empathy in different contexts of interaction [63]. Given these premises, AI starts at quite a disadvantage in its attempt to emulate this specific aspect of human intellect compared to the ones analysed before. As is well known, machines are unable to feel emotions (typical expressions of human complexity), which is why there are several limitations in AI's possibilities of understanding human feelings. In any case, while AI is unable to generate genuine empathy, it is making great strides in emulating interpersonal intelligence, thanks in part to the scientific community's renewed interest in human computer interaction (HCI) and affective computing (AC) [64]. These disciplines deal with the specific task of applying computer science to the human emotional spectrum by going to use statistical and ML approaches for classifying and recognizing the state of mind of individuals and obtaining optimal interactions, as similar as possible to natural ones. The main task of AC is definitely emotion detection, which aims to classify human emotions from the analysis of facial expressions, posture, or tone of voice. However, AI's recognition possibilities are limited to Ekman's six emotions (anger, happiness, sadness, disgust, fear, surprise), which are the primary mood states according to many psychologists and cognitive science scholars [65]. The great effectiveness of emotion detection algorithms, especially in the area of facial emotion recognition (FER), is due to Ekman himself, who in 1978 introduced the Facial Acting Coding System (FACS), an international coding system of facial expressions based on the position and movement of specific facial points during the action of a particular emotion [66]. Thanks to FACS, it has been possible to classify facial expressions objectively, managing to compose a large number of datasets on which to train DL and ML algorithms for FER. Indeed, it is no coincidence that in the field of emotion detection, FER is the approach that determines the best results in terms of accuracy and efficiency. CNN first and foremost [67], but also other algorithms such as Support Vector Machines (SVMs) work excellently for FER, while they find enormous difficulty for other types of investigations, because of the lack of adequately detailed datasets on which to train the models [68]. Other techniques for emotion detection and HCI are based on the use of NLP algorithms aimed at creating chatbots and virtual assistants capable of understanding and responding to user requests in a natural, conversational way [44]. Statistical approaches, on the other hand, are used in digital marketing for social data analysis and user profiling. This particular focus on public sentiment allows for the personalization of interactions based on the preferences and the mood of the consumer based on their previous consumption pattern [69].

The progress of AI in this area is evident, but again, since these are dynamics belonging to complexity, the limitations related to the full understanding of the context of interaction, the lack of intuitiveness that can guarantee a genuine empathic response, and the impossibility of feeling authentic emotions, significantly limit the potential of machines.

3.6 Naturalistic intelligence

Man has always been part of nature since the birth of the species. At the same time, being part of it, he has always harboured a feeling of curiosity and respect, almost of fear, toward nature itself. For human beings, naturalistic intelligence stems from the need to understand their origin through the observation of natural phenomena. Admiration of natural power has characterized the development of the species since the time of primitive humans to the point that illustrious philosophers such as Heraclitus or Thales discussed natural elements profusely, making them the central topic of their thought [70]. Naturalistic intelligence is thus something innate in humans; it is not limited to the observation of nature and classification of different items (flora, fauna, rocks, and landscapes), but is also related to the ability to create close contact with nature itself by interacting with and manipulating natural elements through the full awareness of being an integral part of them.

Regarding the task of identifying and classifying natural features, the level of efficiency of AI is quite high. The mechanisms it uses are based on computer vision techniques already analysed earlier: thanks to the presence of satellite systems that constantly observe every corner of our planet, we now have at our disposal a potentially unlimited number of images on which to train ML and DL algorithms for the classification of flowers, animals, or geographic locations [71]. There are plenty of software or applications for mobile devices that can classify an image (possibly acquired in real time through the smartphone camera) and associate a description with it. This is possible through the association of a series of image recognition algorithms (mainly based on CNNs) with natural language generation techniques, which produce a description in real time once the image has been classified [72]. Another recent innovation, mainly related to climate change alarm, is the introduction of predictive modelling technologies capable of forecasting the effects of natural phenomena on the behaviour of animal populations; again, the technology is based on the use of ML techniques for extracting patterns from the vast amount of environmental data available and statistical analysis of climate and geographic data [73].

What AI lacks to fulfil all the tasks related to naturalistic intelligence is the feeling of curiosity that moves human beings to question the world around them. The empathetic relationship between humans and nature that stems from human awareness of being the single element in a more complex ecosystem is something totally inconceivable to machines. They stop at a basic level of interaction with nature, related to linear mechanisms of pattern extraction and element recognition: they lack a deeper level of sensitivity, given by active participation within the natural ecosystem, manipulation and sharing of personal experience with other natural elements, and a self-awareness that allows the machine to feel part of the nature itself.

3.7 Bodily-kinesthetic intelligence

The nature of the connection between mind and body gives rise to a debate that has accompanied the development of human philosophical thought for centuries. On one side are the proponents of Cartesian dualism who see the mind and body as separate and independent entities [74], and on the other side is the self-awareness-based approach for which each human being is unique and different from others on both the mental and physical sides [75]. Beyond philosophical digressions, a more scientific approach based on neuroscience shows how the brain is plastic, meaning it is able to adapt in response to experiences and physical stimuli [76]. Similarly, psychosomatics, the manifestation of physical symptoms in response to negative mental conditions, is an expression of the inescapable link between the mind and our bodies [77]. Bodily-kinestethic intelligence begins with knowledge of one's body, understood not only as the ability to control its movements and perform a variety of physical skills, but also in the ability to use gestures and to express our inner selves. People who excel in this type of intelligence are particularly good at actions that require high physical coordination and/or manual dexterity, harmony in movements and balance, or possess a marked expressiveness in gestures or facial expressions.

The emulative limitation of AI in this case is not only functional, but also structural: the presence of a physical substrate capable of acting as a support for the mind (whether natural or artificial) is the minimum necessary requirement for the expression of kinesthetic intelligence. The emulation of bodily intelligence for machines cannot, therefore, disregard technologies that can overcome this structural limitation by going to the development of a body for AI software. Robotics, at least in its initial conception, was born with the aim of creating machines capable of automatically performing rather simple human tasks that require specific motor functions; in the present day, technological advances brought about by advanced robotics have made it possible to create humanoid robots, which, through the implementation of machine learning algorithms, advanced sensors, and actuators, are capable of performing increasingly precise and complex tasks [78]. The very design of robots is evolving in directions that lead them to be increasingly human-like in form as well as function, as a response to the growing interest of high-tech industrial giants in the topic of HCI. Training techniques based on reinforcement learning are making it possible to progressively improve the motor performance of androids through repeated trial-and-error processes. Although there is still plenty of room for improvements, today we have robots that can dance, run, or perform sports activities [79].

Having overcome the structural limitation, the emulative power of AI can take advantage of the fact that motor functions are based on linear criteria that describe the movements of the individual joints forming our bodies. The biomechanics of the human body can be entirely described by physical laws that AI software can recreate, provided it has sufficiently adequate mechanical supports with which to reproduce them [80]. The insurmountable limitation of AI in emulating bodily intelligence, on the other hand, is on the level of self-awareness: humans, as complex beings, are masters of their bodies and aware of the functionalities they may be able to express; an android, on the contrary, no matter how sophisticated its functionalities may become in the coming years and no matter how human-like its appearance, is unlikely to achieve this level of awareness.

3.8 Intrapersonal intelligence

The phrase “Know thyself,” historically engraved on the pediment of the ancient temple of Apollo at Delphi and later taken up by Socrates, is an invitation to all men to self-interrogate and recognize their own limitations [81]. Intrapersonal intelligence is aimed precisely at this purpose and is, of all eight Gardner's frames of mind, the one most representative of human complexity. Man is such a complex being that he cannot, in most cases, fully understand himself and know his inner self. The goal of introspection is the achievement of deep self-reflection that enables to recognize and understand one's moods, feelings, and the reason behind them. The concept of intrapersonal intelligence is entirely based on self-awareness that is derived from human experience and the trials that characterize the growth of each of us. The ability to control impulses, as well as the spirit of enterprise and the tendency to achieve goals, derive precisely from the objective awareness of one's own possibilities, acquired as a result of the careful analysis of experienced events. In the absence of genuine life experience and knowledge of human emotions, to think that AI is capable of developing genuine empathy toward itself is rather difficult [82]. The mimicry of intrapersonal intelligence undoubtedly proves to be the most difficult obstacle for AI to overcome in achieving a degree of total emulation of humans. As a counterevidence, algorithms and linear approaches to machines can simulate the human intellect as a whole, yet without getting into the innermost aspects of its complexity.

4. CONCLUSIONS

The notion of intelligence encompasses a plethora of facets that fully reflect the complex nature of human beings. Each functionality of our brains can be conjugated into a myriad of different operations that go into determining the cognitive abilities and talents that characterize the personality of each of us. The idea that an individual's intelligence can be measured in an absolute sense turns out to be rather sloppy, given and considering the different forms that smartness itself can take. AI's attempt to create systems that can simulate human intelligence as a whole must contend with each of these frames of mind, with more or less accurate results depending on the degree of complexity required for the representation. Among the different types of intelligence hypothesized by Gardner, the one closest to the modus operandi of machines is certainly the logical-mathematical: it is based exclusively on causal criteria, following a linear approach. Other types of intelligence, on the other hand, although based on logical-linear operations, involve instinctive and emotional aspects that fall within the realm of complexity. The circle closes with intrapersonal intelligence, based on the concept of self-awareness, which is totally unrelated to machine functioning. The level of accuracy in emulation by AI is summarized in Figure 2, as a function of the degree of complexity involved, relative to each of the eight frames of mind analysed above.

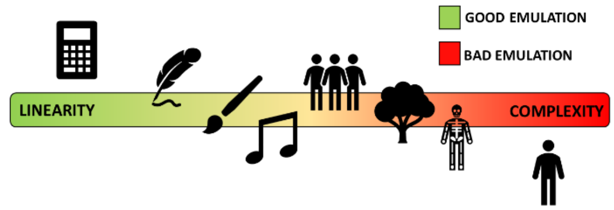

Figure 2: AI emulation level of the different Gardner’s type of intelligence as a function of the degree of complexity (from left to right: logical-mathematical, verbal-linguistic, visual-spatial, musical, interpersonal, naturalistic, bodily-kinesthetic, intrapersonal).

In conclusion, the idea that AI can go on to perform any task of the human intellect with such accuracy that it will come to replace us in the future seems rather ambitious. The obstacle of complexity represents an insurmountable structural limit for machines, which, while offering constant technological improvements and increasingly satisfactory results, remain rooted in linear processes.

Human history, since the origin of the species, is made up of discoveries and innovations that changed reality as we know it and provided a new perspective on life: they may be frightening at first, before we get used to them, but they promise a better future once integrated into society. AI is only the latest of these innovations and as such should be welcomed, without undue fear, knowing that complexity is the guarantee of the uniqueness of our species.

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