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Artificial Intelligence for Humans: Finding the Interplay

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Abstract

This article explores the complex interplay between Artificial Intelligence (AI) and Human Intelligence (HI), underscoring the need for a nuanced understanding of both. AI, once the domain of fiction, now significantly influences various aspects of human life, from daily conveniences to advanced medical diagnostics. The paper posits that while AI aims to replicate and surpass HI, our grasp of HI remains incomplete. Historical perspectives on HI, from ancient philosophical inquiries to contemporary scientific methods, illustrate its multifaceted nature. The discussion extends to the evolution of AI, highlighting milestones from early neural network models to current deep learning innovations. The paper emphasizes the importance of rigorous research on HI to effectively guide AI development, ensuring beneficial coexistence rather than dystopian outcomes.

Keywords:

Artificial Intelligence, Human Intelligence, Neural Networks, Deep Learning, Cognitive Science

Introduction

One of the most vital topics that has ignited popular imagination and speculation in the first quarter of the Twenty-first Century is the persistent discussion of Artificial Intelligence (AI) and its role in the public sphere. What used to be the material of fiction and film some years ago, it seems, is now the reality of lived experience as the specter of an "all engulfing" artificial entity hovers over humanity. This is the new monster that the collective Frankensteins have created that would surpass the dystopia visualized by Orwell in 1984 where the totalitarian state would have people watching under the euphemism of "big brother." In the current dialog about AI, particularly in the way the warning is sent out, it is not just a big brother but a network of big data that, in totality, creates the new eye that watches over us, albeit we are the creators of the watcher. The other view of AI has been more kind to the new technologies, and it promises the open-ended potential of technology (see, e.g., Castell 2010) where he suggests that the outcome of technology is indeed: "the final outcome depends on a complex pattern of interaction." In the more hopeful view, as presented within the popular sphere, AI would offer opportunities that can greatly improve the quality of life with its magical efficiencies.

Within these discussions there is embedded the notion of connecting AI with traditional intelligence which used to be the quintessential aspect of being human. This ontological element, the very essence of being human, was the fact that the species could claim intelligence that was superior to all other species. The preliminary goal of AI is to replicate the intelligence that humans possess, which will have to be now named "human intelligence (HI)" to be distinguished from AI. This distinction is important to where AI goes, since the goal is to reach a level of AI where it becomes "like HI," and then in some future moment it will surpass HI offering the possibility of a favorable or dystopic future for humans and their HI.

While this debate remains central to much of the available discourse on AI there remains the need for humans, who created AI, to learn more about it to actually move it towards the condition where it will surpass its creator. This apparently suicidal move has been compared to the way in which the developments of nuclear science led to the atomic bomb and there are concerns about the way the AI technology is developing and could develop (see, e.g., Hawkins, 2015; Musk, 2017 and Tegmark, 2018). The focus of learning about AI has, however, focused on AI itself and not necessarily the ways in which AI could connect with HI. In this paper, I posit that there is a need to fill the gap where the connection of AI with HI needs to be explicitly laid out. To begin with, it is instructive to see how HI has been conceptualized.

Human Intelligence (HI)

The supposition that humans possess a quality that is different from all other species has been recognized from the early days of civilization and this quality has defied any specific definition given the amorphous notion of the idea of what has eventually been called, intelligence. In most cases, this quality is operationalized in human behavior where specific things that people do are supposed to demonstrate different levels of intelligence. This notion of difference has been central to the thoughts on intelligence.

Consider for instance the way in which the notion of intelligence was addressed by Greek philosophers who had diverse and profound views on human intelligence, exploring its nature, origins, and implications. Their discussions laid foundational concepts that continue to influence modern thought on cognition and intelligence. Socrates, for example, emphasized the importance of self-knowledge and critical thinking in the well-known method of dialectic inquiry, which involves asking probing questions to stimulate critical thinking and illuminate ideas. The notion of "critical thinking" still remains central to contemporary conversations about HI. The ideas of Socrates are carried forward by Plato, a student of Socrates, who suggests that intelligence is a virtue that could be cultivated through philosophy and education. This idea is centered around the tripartite soul, where reason (*logistiko*n) was the highest part and should govern the spirited (*thymoeides*) and the appetitive (*epithymetikon*) parts. This bifurcation of HI into parts continues in the debates today as well just as the Greeks further refined the notion of HI though the work of Aristotle, a student of Plato, who offered a more empirical and biological view of intelligence. He believed that intelligence was tied to the biological life force and differentiated between the active mind (*nous poietikos*), which was immortal and divine, and the passive mind (*nous pathetikos*), which was involved in the processing of sensory information. Here too the notion of differentiation and the acknowledgment that HI must be considered to be a complex notion with many aspects became central to the discussion.

These early musings about HI are continued centuries later with the notions of positivism and the scientific approach gaining centrality in considering many of the phenomenon that made up the practice of everyday life. For example, in the nineteenth century, the study of human intelligence underwent significant transformations, moving from philosophical discourse to more empirical and scientific approaches. It was becoming important to be able to consider the notion of HI in a more pragmatic and measurable way so that decisions could be made about humans based on the best understanding of the level of I a H possessed. Galton, for instance, offered statistical methods to study human differences, introducing tools such as the correlation coefficient and regression toward the mean. This approach also led to the development of eugenics: A controversial field concerned with improving human population quality through controlled breeding based on desirable traits. His methods and approaches to studying individual differences significantly influenced subsequent psychological research and the development of psychometric testing. What was significant about the research in this time period was the move to a "scientific" way to study HI with the experimental methods conducted in laboratory settings by different pioneers across the Western World. Laboratories were established, such as the one at the University of Leipzig in 1879, where the work of Wundt emphasized introspection, where trained observers would report their thoughts and mental processes under controlled experimental conditions. In a similar way, Simon and Binet developed the first practical intelligence test in 1905. This test, initially created to identify schoolchildren requiring special education services, laid the foundation for future standardized testing. Binet's earlier investigations into cognitive faculties like memory and attention during the 1890s shaped his understanding of intelligence as a composite of various mental abilities, which could be measured and quantified. This approach to HI laid the foundation for contemporary measures of intelligence that show up in the proliferation of "entrance" examinations for colleges and universities across the world.

However, this period was also one where human physiology was under examination and there was careful examination of the brain, spawning fiction like *Frankenstein* published in the early 1800s where the centrality of the brain to life is exemplified. This is also the time when HI and the brain is getting connected in the work of neurologists like Paul Broca and Carl Wernicke who identified specific brain regions involved in language processing, establishing links between brain structures and cognitive functions. Their work contributed to a broader understanding of the brain's role in intelligence and cognition.

These programs of research were continued in the post-World War II era when there was a frenetic effort to understand human behavior carefully following the horrors of the war and the genocides that accompanied the global conflicts. There was also a simultaneous faith in the adoption of the methods of "natural sciences" to the humanities and study of societies giving rise to the study of humans through a "social science" perspective. This tendency permeated all disciplines including communication, sociology, psychology, etc. Consequently, HI became increasingly quantified through psychometric approaches that began with Binet and was developed by many other scholars such as Charles Spearman, all of whom focused on “measuring” intelligence through standardized tests such as the Stanford-Binet Intelligence Scales and the Wechsler Adult Intelligence Scale (WAIS). This was also the period when there was recognition that began to distinguish between fluid intelligence, which he defined as "the ability to solve novel problems," and crystallized intelligence, "the use of acquired knowledge and experience (Cattell, 1963).” This bifurcation of HI from a monolithic construct to a variegated and nuanced understanding is furthered by those who begin to see the restrictions of assuming HI can be measured by the standardized tests alone.

Many suggest that there are multiple intelligences. Gardner posits eight distinct intelligences, including linguistic, logical-mathematical, spatial, musical, bodily-kinesthetic, interpersonal, intrapersonal, and naturalistic intelligence. Similarly, Robert Sternberg's triarchic theory of intelligence proposes three interrelated components: analytical (componential), creative (experiential), and practical (contextual) intelligence. Sternberg's model emphasizes the adaptability of intelligence, highlighting how individuals apply their cognitive abilities to real-world contexts and problems. Sternberg (1985) suggested that "intelligence is not a single trait but a combination of three components that work together," underscoring the practical applications of intelligence in daily life (Sternberg, 1985). He later elaborated that "successful intelligence involves using all three components in harmony (Sternberg, 1999).” This is connected to the debates about emotional intelligence, popularized by Daniel Goleman, who focuses on the ability to recognize, understand, and manage one's own emotions and those of others. Emotional intelligence is argued to play a crucial role in social interactions, leadership, and overall mental health. What emerges is a more complex description of HI with some ambiguity of its understanding and the processes that govern the expression of HI. Thus, the advances in neuroimaging techniques have provided deeper insights into the neural correlates of intelligence. Studies have identified specific brain regions, such as the prefrontal cortex, which are associated with higher-order cognitive functions laying a physiological foundation for HI focusing on the neural networks that operate in the brain to facilitate what is termed as HI.

This brief treatise on HI demonstrates the complexities in understanding an essential element of being human. The study of HI is a dynamic and interdisciplinary field, integrating perspectives from psychology, neuroscience, education, and beyond. Current scholarship emphasizes the complexity of intelligence, recognizing the interplay between genetic, environmental, and socio-cultural factors. It is within this backdrop that it is important to understand AI because much of the goal of AI is to replicate and improve upon HI, where there are still ongoing debates about clearly understanding HI. In the next section I offer an overview of AI mirroring the discussion of HI.

Artificial Intelligence (AI)

The technology that is currently called AI has been a concern and point of inquiry for quite some time. Engineering aspects have developed more recently, but the notion of tools that would complement HI has been around for a good length of time, at least within the realm of popular culture. The idea that something other than humans would possess cognitive capabilities was imagined by the Greek as mechanical servants and automata, most notably in the works attributed to Hephaestus, the god of craftsmanship, who created mechanical servants to assist him. Additionally, the myth of Talos, a giant bronze man, reflects an early conceptualization of robotic guardianship (Mayor, 2018). The notion of life-like machines was also considered in Asia suggesting a sophisticated understanding of mechanical engineering in early Chinese civilization (Needham, 1986). This idea of creating tools that could be human-like was explored in the Renaissance period in Europe when Leonardo da Vinci designed a mechanical knight, capable of basic human-like movements, demonstrating an advanced integration of art and engineering that typified the Renaissance man's pursuit of knowledge (Rosheim, 2006).

It is only in the early part of the 20th century that there were more elaborate plans for tools that would possess intelligence and behavioral capabilities like humans. For instance, in the 1920s, the term "robot" originates from Karel Čapek's 1920 play "R.U.R.", where it was used to describe artificial people created in factories. Čapek's work not only introduced the word robot but also set a narrative for the ethical and practical implications of autonomous machines (Čapek, 1920). This is followed by other works of fiction where some essential elements of AI are established, as in the three rules of robotics established by Asimov. Although these rules are challenging to implement in current technology, the principles behind Asimov's laws do inspire current discussions about AI ethics and regulation. Organizations and policymakers consider similar objectives when designing ethical guidelines for AI, such as ensuring AI systems do not harm humans, maintaining human oversight, and safeguarding user privacy and autonomy.

The imagination of authors finds implementation with the developments of technology and a careful understanding of the interplay between AI and HI. Perhaps one of the vital moments in the emerging conceptualization of AI is presented in Alan Turing's 1950 paper which laid the foundational framework for modern artificial intelligence. His propositions regarding machine intelligence and the 'Turing Test' have significantly influenced the philosophical and technical pursuits in AI (Turing, 1950). This is the point at which the idea of "mimicking" HI is carefully presented, and Turing argues that AI must be able to replicate HI with such degree of efficiency that HI would not be able to distinguish between AI and HI when involved in a communication episode with an entity that could either be HI or AI.

The pathway to the engineering and technology of AI begins in the post-World War II era when there are advances in solid state technology, binary mathematics and Boolean logic systems. Such approaches relied on symbolic representations of problems and logic-based methods to solve them. One of the earliest AI programs, the Logic Theorist, developed by Allen Newell and Herbert A. Simon, was designed to mimic human problem-solving skills and successfully proved several mathematical theorems (Newell & Simon, 1956). In the 1960s, Joseph Weizenbaum created ELIZA, an early natural language processing program that simulated a Rogerian psychotherapist. Although limited in its capabilities, ELIZA demonstrated the potential for machines to interact with humans using natural language (Weizenbaum, 1966).

The theoretical foundations began to take shape in applications that were propelled by the development of increasingly powerful interconnected digital devices that were capable of taking the "analog" experiences and creating vast amounts of digital representations. It is this representation, which begins to be called "Big Data," that begins to form the foundation of AI. Much like humans use information to make decisions and create new information, machines were expected to do that. Consequently, there was development of machine learning and connectionist approaches, inspired by the human brain's neural networks. Systems such as artificial neural networks (ANNs) and the backpropagation algorithm, enabling ANNs to learn from data by adjusting their weights through gradient descent (Rumelhart, Hinton, & Williams, 1986). This direction of research and development was aimed continuously at creating systems that would offer humans the supplemental resource to make better decisions. To a great extent the interest was in developing systems, such as MYCIN and DENDRAL, which used rule-based approaches to emulate the decision-making abilities of human experts in specific domains, such as medical diagnosis and chemical analysis (Feigenbaum et al., 1971; Shortliffe, 1976).

The rules needed information to make decisions just as the narrower notion of HI has focused on the relative merits of decisions to compare intelligence of humans such as the completion of patterns and number series. Consequently, there was increasing focus on development such as “deep learning,” a subset of “machine learning,” that involves training large neural networks with many layers (deep networks) on vast amounts of data. This approach led to significant breakthroughs in various AI applications, including image and speech recognition. One of the landmark achievements in deep learning was the development of AlexNet by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton, which won the ImageNet Large Scale Visual Recognition Challenge (ILSVRC) in 2012 with a substantial margin, demonstrating the power of deep convolutional neural networks (CNNs) (Krizhevsky, Sutskever, & Hinton, 2012). Another notable development was the creation of Generative Adversarial Networks (GANs) by Ian Goodfellow and his colleagues, which opened new possibilities in generative modeling and unsupervised learning (Goodfellow et al., 2014). The availability of big data and increased computational capabilities of digital devices offered the machine to create efficient decisions that mimicked or exceeded the capabilities of humans to make decisions only because the digital system had the capability of handling large amounts of data at a pace that would physiologically be impossible for humans.

This is the ability that has received the most amount of attention and application as in the case of popular tools such as virtual assistants to advanced applications in healthcare, finance, and autonomous vehicles. Natural language processing (NLP) models, such as OpenAI's advancing versions of GPT, have demonstrated remarkable capabilities in generating human-like text and understanding context, pushing the boundaries of what AI can achieve (Brown et al., 2020). This is the tendency that has received the greatest degree of attention and sets the stages for the fictional future of AI where it will graduate from generation of human-like data to support humans to the different positive and negative evolution of AI. It is important to note that these are yet to come, and the way they may develop could be related to the way in which HI and AI will work together. This is the focus of the last section of this essay.

AI and HI Interplay

There is certainly a need to understand the ways in which the two forms of intelligence will work together in the future. However, the need is more than at the level of application and answering the question “what can it do?” with respect to AI. That being said, I would suggest that there is a need to explore the connection between the two forms of intelligence. As of now, the focus has been on “mimicking.” Consider for instance the following quote about developments in spiking neural networks:

> In the last decade, artificial neural networks (**ANNs**) have become increasingly powerful, overtaking human performance in many tasks. However, the functioning of ANNs diverges strongly from the one of biological brains. Notably, ANNs require a huge amount of energy for training and inferring, whereas biological brains consumes much less power. This energy greediness prevents ANNs to be used in some environments, for instance in embedded systems. One of the considered solutions to this problem is to replace the usual artificial neurons by spiking neurons, mimicking the function of biological brains (Geeter, et.al.).

What is notable about this quote, from the introductory section of a purely mathematical paper, is the need to produce a mathematical model and its application whose value and efficiency is pegged against the "function of biological brains." This is precisely the concern because, as demonstrated in this essay, the "standard" against which AI is being measured itself remains an amorphous construct which scholars are still grappling with.

The interplay that could develop between AI and HI must need to be concerned with a few grounding principles, all of which need further exploration. That research, and its outcomes, could begin to address the anxiety and hope related to AI in terms of the harm it could do and the opportunities it would present.

First, there needs to be a sense of the description of HI. There are sufficient debates about the understanding of HI, methods of measurement, and the source of HI. These concerns need to be addressed because there is an attempt to make an artificial system which also needs to be described, whose effectiveness will need to be measured and whose functions will need to be understood, and perhaps manufactured. Humans are not able to "manufacture" the human brain in a laboratory yet, but there is the aspiration to manufacture the biological brain in verisimilitude. Thus, there needs to be a more concerted effort to understand HI in its fullness. That understanding may be as far away, in scientific times, as the achievement of "singularity" in AI which predicts that the era of humans would be over, and thus the end of HI, and the era of machines will begin with this fictional form of intelligence (see, e.g., Kurzweil, 2005; Vinge, 1993). Consequently, the thrust in understanding HI needs to be amplified to be able to answer the next concern about the interplay.

As the next concern and research interest, it would be important to enumerate the methods of measuring the effectiveness of AI. As of now, there are a set of metrics that are used for this measurement that include elements such as accuracy of information, how well systems are able to recall data, the overall efficiency of the AI system, the scalability of AI, and the general satisfaction of the human users of AI systems (see, e.g., Goodfellow, et. al 2016; Russel, et. al. 2020). Notably, these are similar to the ways in which HI is also measured. Yet these measurements of HI have been called into question, for instance, in the way that tests that create Intelligent Quotients have been criticized (e.g., Dorans, 2002; Fischer, et. al., 2006; Gould, 1996; Santelices, et. al., 2010; Soares, 2014). If indeed, there are concerns about testing HI, then there needs to be a more careful examination of the measurement of AI, which is being designed to mimic HI.

The third concern that could be addressed is the way in which the current AI systems are being designed. Earlier in the essay, I have offered an overview of the stages of development of AI. The underpinning principle of all the design mechanisms relies on humans, and thus HI, that actually train the systems, as well as develop the algorithms and rules that define the way in which AI products would offer the outcomes. There has always been evidence that these human-made designs are inherently biased. Consider the following:

> Asked to show “normal women,” the tools produced images that remained overwhelmingly thin. Midjourney’s depiction of “normal” was especially homogenous: All of the images were thin, and 98 percent had light skin (Tiku and Chen 2024).

Similar biases have been reported by others such as Crawford and Paglen (2019) where they claim, “There is a stark power asymmetry at the heart of these tools.” These asymmetries are a product of human culture. There are long-standing debates about what is considered “normal” within popular culture as exposed in the work of those like Gramsci who have argued for the notion of hegemonic systems that define what is ideologically acceptable at any moment in time within any socio-cultural system. It is important to examine how much of such hegemonies will creep into AI and their outcomes on the way HI and AI work together.

Conclusion

There is much to be done in understanding the connection between HI and AI. Both the areas need further examination to find the point of congruence in the interplay. Rapidly developing

AI, without the necessary explorations of the interconnection, may lead to the fictional Artificial General Intelligence (AGI) and the eventual singularity. However, it is important now, at this juncture, to see what degree of verisimilitude is possible and acceptable. That answer could influence not only training the machines but also reconsidering what we may call education – training humans – to be able to work with AI.

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