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Artificial Intelligence in the 21st Century: Unveiling the Strengths and Weaknesses

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Abstract

Artificial Intelligence (AI) is a transformative technology that brings forth a diapason of advantages and challenges. On the positive side, AI offers unknown effectiveness, allowing tasks to be performed briskly and more directly than mortal capabilities. robotization, a crucial point of AI, reduces the burden of repetitious and mundane tasks, enabling mortal coffers to concentrate on further creative and strategic trials. AI excels at data analysis, recycling vast datasets to prize precious perceptivity, serving fields from healthcare to finance. also, AI operates lifelessly,24/7, without succumbing to fatigue. Again, AI has its downsides. robotization's effectiveness can lead to job relegation, particularly in diligence where mortal labor is substituted by machines. Bias and fairness enterprises arise as AI systems learn from poisoned literal data, potentially immortalizing societal inequalities. sequestration becomes a concern with the eventuality for invasive surveillance and data abuse. Ethical dilemmas crop when AI is assigned with making life- or- death opinions in independent vehicles and healthcare. Security pitfalls are current, as AI can be exploited for cyberattacks and the creation of satisfying deepfake.

The past 20 years have seen a dramatic shift in educational policy toward a concentration on socio-emotional competencies and other 21st century abilities. Technological progress, machine learning, and AI ethics provide the background for this article's discussion of 21st-century soft skills, which include social and emotional intelligence. The paper defines these skills as non-epistemic competence components. However, there are significant societal issues that may arise from using data-driven AI technologies to model and quantify them. These challenges will have enormous ramifications for educational policies and practices. We recommend waiting to incorporate data on these skill components into machine learning systems until we have a clearer grasp of the societal impact.

Keywords: AI, AIED, Regulation of AI, Machine Learning.

1. Introduction

"Are thoughts capable of being generated by machines?" In his seminal work "Computing, Machinery, and Intelligence," Alan Turing raised this same subject.1 He thinks we need to define thinking in order to get the solution to this question. Thinking is a subjective behavior, making it difficult to define properly. The Turing test, which Turing later developed, is an indirect way to check if a machine can think; it looks at how well a machine can mimic human intelligence. A machine can be called artificially intelligent (AI) if it passes the test.

Artificial intelligence (AI) is the ability of computers or other systems to mimic human intelligence.

Artificial intelligence aims to create a machine that can simulate human intelligence and perform tasks such as perception, reasoning, learning, planning, prediction, and more. One of the most striking differences between humans and other animals is our level of intelligence. As long as there are industrial revolutions, more and more machines will do the work of humans in every industry; the next great obstacle will be to prevent machine intelligence from eventually replacing humans as a resource. Research in the area of artificial intelligence is rich and varied because many scientists are concentrating on it. Search algorithms, expert systems, knowledge graphs, natural language processing, evolution algorithms, ML, DL, and many more areas of artificial intelligence study are all part of the field.

Multiple forms of intelligence, including visual, cognitive, and decision-making, are involved in AI development. What we call "perceptual intelligence" in computers refers to their ability to mimic human senses like sight, sound, touch, etc. The capacity for higher-level reasoning, induction, and knowledge acquisition is known as cognitive intelligence. The goal is to provide computers human-level reasoning and cognitive abilities, drawing inspiration from fields like cognitive science, neuroscience, and brain-like intelligence. It is commonly believed that machines would be able to make the best judgments for people, factories, and the environment once they develop the capacity for perception and cognition, much like humans. For decision intelligence to work, data science must be expanded through the use of social science, decision theory, management science, and applied data science. Intelligence in perceiving, thinking, and making decisions requires an AI infrastructure layer that is backed by data, storage, processing capacity, ML algorithms, and AI frameworks. After that, it can understand the data's inherent rules to support and implement AI applications through model training. Our jobs and lifestyles are being significantly altered by the increasing breadth and depth of AI's application layer, which is being linked with basic sciences, industrial manufacturing, human existence, social governance, and cyberspace.

2. History of AI

John McCarthy, speaking at a symposium at Dartmouth College in 1956, first used the phrase "artificial intelligence (AI)," marking the beginning of current AI research. Such an event marked the beginning of the artificial intelligence (AI) academic discipline. The subsequent years saw incredible advancement. Automated reasoning and the use of AI to prove mathematical theorems and solve algebraic problems have attracted a lot of attention from researchers and scientists. Logic Theorist, developed by Allen Newell, Herbert A. Simon, and Cliff Shaw, is a well-known example. It proves 38 out of the first 52 theorems of "Principia Mathematica" and offers more sophisticated proofs for a few more [1]. Many early adopters of AI were quite hopeful as a result of these achievements, which supported the idea that completely intelligent machines will be created soon. But they quickly learned that there was a long way to go before their ultimate aim of creating machines with intellect comparable to that of humans could be achieved. It turned out that logic-based programs couldn't handle many nontrivial tasks. The increasing complexity of the problems and the limited computing power to solve them posed additional challenges. Organizations and financiers ceased backing these AI projects that failed to produce as expected.

In the 1980s, artificial intelligence (AI) saw a renaissance thanks to the invention of a model by a number of academic institutions and universities. This model aims to assist non-experts in making judgments by summarizing a set of fundamental rules derived from expert knowledge. We call these setups "expert systems." Carnegie Mellon University's XCON and Stanford University's MYCIN are two such examples. Finally, an expert system was able to handle real-world problems by deriving logic rules from expert knowledge. This era's AI research revolved around the understanding of how to make machines "smarter." Privacy technologies, inflexibility, low versatility, high maintenance costs, and so on were among the expert system's many flaws that became apparent over time. Also, the Fifth Generation Computer Project, which the Japanese government poured a lot of money into, fell short of most of its initial objectives. Artificial intelligence hit rock bottom when, once again, funding for AI research dried up.

A method for constructing deeper neural networks and a strategy to prevent gradient vanishing during training were proposed by Geoffrey Hinton and colleagues [2,3] in 2006, marking a significant advance in artificial intelligence. This sparked a new wave of interest in artificial intelligence, and deep learning algorithms are now among the most promising areas of study. In artificial intelligence (AI), machine learning (ML) refers to the process by which computers or programs can learn and gain intelligence without human involvement, while deep learning (DL) is a subset of ML based on many layers of neural networks with representation learning [4]. Therefore, "learn" is the buzzword in artificial intelligence right now. The efficiency of obtaining characteristics and information from enormous data samples has been greatly enhanced by big data technologies and the advancements in computing power. The representational learning capability of DL and its subsequent expansion into wider applications have been the focus of numerous novel neural network architectures and training methods. On some datasets, current DL algorithms in computer vision (CV) and natural language processing (NLP) can match or even surpass human capabilities. Artificial intelligence (AI) technologies have revolutionized various industries and domains, and they have consistently proven their worth as foundational tools for both academic study and practical use.

As ML methods have been developed to analyze high-throughput data to obtain useful insights, categorize, predict, and make evidence-based decisions in novel ways, it is having a substantial broad effect across many aspects of technology and science within artificial intelligence. This includes computer science, geoscience, materials science, life science, medicine, chemistry, physics, economics, psychology, and management science, among other data-intensive empirical fields. It may be far quicker to train a system by showing it instances of the intended input-output behavior than to manually program it by anticipating the desired response for every possible input. In order to promote the advancement of science and accelerate its applications for the benefit of humans, society, and the planet, the following sections provide a survey of eight basic sciences: mathematics, chemistry, information science (informatics), geoscience, medicine, materials science, physics, life science, and geoscience.

3. Structural Updation of AI in 21st Century

Competence has been used in several areas in recent decades. Since its 1990s use in strategic management literature, it has extended to numerous core competence frameworks used to develop work and life skills. The OECD Core Competence Framework for financial literacy (2015), the UNESCO Core Competency Framework for staff (2016), and the EU Key Competence Framework for Lifelong Learning (2018) are examples.

Despite its prevalence, competencies are rarely discussed completely. The current UNESCO Competence Framework for Cultural Heritage Management (UNESCO, 2020) lists skills and knowledge as areas of competence. UNESCO's Competency Framework for Employees (UNESCO, 2016) defines competences as a set of related knowledge, skills, and abilities that lead to key employee behaviors. Technical competences are separated from core competences that are essential to all OECD employment in the internal Competency Framework (OECD, 2014). Analytical thinking, accomplishment focus, flexible thinking, teamwork and leadership, diplomatic sensitivity, influencing, negotiation, and strategic thinking are OECD competencies. The European Commission states that “competences include more than knowledge and understanding and take into account the ability to apply that when performing a task (skill) as well as how – with what mind-set – the learner approaches that task (attitude)” (EC, 2018, p. 4 Thus, competence in EU literature is generally defined as a combination of knowledge, skills, and attitudes.

Technical domain-specific skills and functional or general abilities are commonly distinguished in skills and competency literature. Attewell (1990) links skills to people, occupations, and employment, as well as technology. Competence includes cognitive, conative, and emotive components (Snow et al., 1996).

Knowledge and intelligence are cognitive elements. The conative dimension collects motivational and purposeful traits including attention, grit, and executive control, while the affective dimension captures emotional and temperamental traits.

Squicciarini & Nachtigall (2021) and other AI-based systems use broad skill taxonomies based on natural language processing of online job ads. The European Skills, Competences, Qualifications, and Occupations (ESCO) skills pillar currently has 14,000 skills (EC, 2022). Job-related basic content skills, basic process skills like critical thinking and active learning, and cross-functional skills like social, complex problem solving, and technical skills are covered by the widely used US government-sponsored occupational information resource website O*Net OnLine (O*NET, 2022).

We can simplify this complex picture by showing competence as two qualitatively different components. The epistemic component contains knowledge, domain-specific expertise, and experience. Expertise summarizes this. Education, vocational training, and intelligent tutoring systems in AIED have focused on competence as new knowledge and domain-specific abilities can be learnt and experience obtained. This epistemic component needs non-epistemic ingredients to form an articulated ability to get things done. Attitudes, dispositions, noncognitive, soft, and 21st-century abilities make up the "behavioral repertoire" (Hoekstra & Van Slujis, 2003). Cognitive aptitudes and capacities are also included, as explained in the next section. Analytical and critical thinking, communication, emotional intelligence, leadership, curiosity, openness to experience, grit, and learning skills are among these non-epistemic components. The list is long. It might be condensed to '21st century skills' or 'social and emotional skills.' This article calls such abilities the non-epistemic components of competence to describe how they differ from standard 20th-century education.

Competent action typically arises when material and cultural contexts are assumed. Social institutions, such as education, work organization, and knowledge and expertise, have stabilized after new technologies were introduced (Freeman & Louçã, 2001), allowing skills and competences to be distinguished. Thus, domain-specific skills and knowledge often reflect the technological and material background (Tuomi, 2020; Kotamraju, 1999). An anvil develops a blacksmith, an automobile creates a car mechanic, and a programmable computer creates a software programmer and computational thinker. Industrial skill sets were stable enough to be linked to professions, specialties, and education. Thus, occupational skills, as listed in taxonomies like O*Net and ESCO for the US and Europe, are conceptually similar to modern technologies. Many of these talents become outmoded as technology advances, and policy focus switches to '21st century competences,' or social, emotional, and transversal abilities. Task completion depends on material, technical, and human collaboration and coordination. At one extreme, actor-network theory and science and technology studies advocated human-non-human symmetry (Callon et al., 1986).2 Socially distributed and situated cognition and cultural-historical activity theory highlighted the linkages between human cognition, culture, and action instruments and technologies. A sociological and organization theoretic view of competence emphasizes the social and cultural constraints, norms, rules, and resources needed for human action and agency, while sociology of technology and science agrees with Vygotsky (Vygotsky & Luria, 1994) that instruments, tools, and technology are necessary to get things done.

Culture provides value systems that make action meaningful and socially intelligible and valuable in activity theory and sociology. In a world where cultural settings change and activities are connected across cultures, communication, collaboration, and intercultural skills are crucial. Cultural change is closely connected to technical change, especially communications technology. Intercultural collaboration is no longer limited to cross-border commerce (Durkheim, 1933) or global information flows (Castells, 1996), according to classical sociological ideas of modernization. Actors must mobilize social resources across cultures and meanings to behave properly. Due to this process and its ongoing evolution, technological and cultural contexts, previously taken for granted, become visible.

The following summary indicates that non-epistemic skill components are receiving more attention for social, economic, and historical reasons. Thus, the concentration on 21st-century competencies was a response to the information or knowledge society, a disruptive historical time before AI breakthroughs. Personal qualities can be linked to non-epistemic competency components. Education and policy must recognize that competence comes from shifting social, technological, epistemic, and nonepistemic factors.

It is no coincidence that non-epistemic components are called '21st century competences.' Labeling these as skills is confusing because skills are usually domain-specific or practice-oriented competency components linked with 'know-how,' procedural, and tacit knowledge. Calling these person-related parts "competences" ignores cultural and technological settings and makes it hard to appreciate how continuing changes in these contexts necessitate addressing these non-epistemic competence components. Figure 1 shows competence domains graphically. Left-hand expertise is knowledge, skill, and experience. The right side includes inclinations, traits, and generic capacities needed for competent action. Technology and cultural norms and values restrain and permit action, which demands social and material resources. The left-to-right movement from 20th-century capabilities to 21st-century competences is accompanied by the increased visibility of changing cultural and material circumstances.

4. AI and the emerging world order

AI could lead to a variety of technological improvements, but they may not require major organizational or war-fighting reforms. AI technology is still young and its uses are unpredictable, therefore it's too early to draw analogies with huge technological changes like World War I tanks. This purpose is best served by examining major powers' capabilities and placing them within the organizational attributes most likely to position nation-state entities like the government and military to adapt fastest to a major technological change and gain an edge.

The Adoption Capacity Theory states that militaries' organizational and budgetary factors determine technological innovation dissemination and power balance. Financial considerations include hardware and other investment costs, while organizational considerations include the military mindset, such as how it would view war-fighting changes or bureaucratic practices that may prevent technology adoption. Technological breakthroughs alone do not affect the balance of power, but how they are applied can distinguish a military.

The British Royal Navy designed the aircraft carrier for battleship observation. Traditionalists in the Royal Navy considered carriers as battleship aids. However, growing naval powers Japan and the US quickly realized that aircraft carriers were best as mobile attacking platforms. Commanders would have struggled to think creatively, putting the UK at a disadvantage. The developing US and Japanese navies were less concerned with such matters. Countries with formidable battle-hardened militaries may be at a disadvantage when adopting AI, whereas developing nations may have the benefit.

As mentioned above, three elements determine how much AI can affect the global balance of power: technical development and spread, manner of use and institutionalization, and domestic issues. After an AI breakthrough like AGI, diffusion patterns may shift the balance of power. The rate of technology diffusion is important here. An AI innovation may lead to a hegemon if the state that pioneered it can maintain the first mover advantage. The breakthrough innovation's military or civilian nature may define such trends. Understand nuclear technology dispersion patterns after World War II to show this argument. Breakthroughs in nuclear sciences like civilian nuclear fission in the 20th century led to new technologies and applications. However, military R&D like the nuclear bomb and its delivery technologies revolutionized global power dynamics. After the hierarchical NPT system was established in 1968, nuclear technologies spread under tight supervision and verification. This has made it harder for non-NWS to acquire nuclear weapons. Only India, Pakistan, and North Korea have tested nuclear weapons post-Cold War, excluding the NWS. The

NWS used their special status and collective first mover advantage to maintain a strategic advantage in international affairs.

ICT is a commercialized military innovation. Several countries become international poles due to low production costs and easy imitation in a globalized geopolitical framework. Global Positioning System (GPS) technology also spread from military to consumer. The U.S. Air Force began building the first Navistar satellites in 1974, starting GPS development. The Reagan government made GPS free for civilians in 1983. GPS-equipped handhelds were accessible in 1989 when the US government spread the technology. Selective Availability (SA) was added to NAVSTAR satellites to combat GPS-using adversaries. SA purposefully inserted satellite data faults to reduce civilian users' accuracy “by a factor of 10”.

China wants to use AI and robotics to catch up to the US, which is the most technologically sophisticated nation. China must win the AI weapons race to overtake the US as the most advanced nation. According to the prediction that AI masters rule the world, China would have leveraged its AI advantages to equal the US. This situation is achievable if China's ruling dispensation can maintain control over all public and private machines and keep dissent to AI minimal. China is conscious that AI may take employment from its enormous population, but other efforts to open up its markets can create more chances for an upwardly mobile citizenry. Since the US military is older and more experienced, adopting AI may require overcoming bureaucratic hurdles. While it is impossible to predict who will dominate the AI race, both nations will gain from being at the forefront and motivate other nations to follow.

AI parity between China and the US may evolve like nuclear technology did during the Cold War. Both countries may exchange technology with friendly nations through commerce or alliances, with some information seeping out through espionage, to obtain strategic advantages. These nations seeking global prominence can follow in the footsteps of China, the US, and Russia, which should continue to lead the race assuming commercial AI information remains open source. The three powers may also build countermeasures to protect against and anticipate adversary operations, multiplying technology applications like confounding AI with pictures or generating illogical replies. War strategies may also incorporate asymmetric methods to counter an opponent's AI technology. However, achieving military parity is unlikely or would take time.

5. Conclusion

Naturally, the above-mentioned findings do not imply that our investigation into nonepistemic competency components, their evolution, or AI as a means to identify and enable noncognitive learning should come to a halt. This is definitely the twenty-first century. One of the most exciting potential applications of AI in education going forward is AI-supported non-epistemic learning.

On the other hand, it could be helpful to reframe the situation. Evidence from Vygotsky's 1920s research on the function of objects and implements in the mind (Luria & Vygotsky, 1992) supports the idea that technological advancements can supplement human intellect. From the perspective of our own personalities, we are all unique, and AI has proven to be an effective tool in helping pupils with special needs.

Research and development of future AIED for AI in education (AIED) may benefit from using hybrid person-technology complexes as the appropriate unit of analysis. It may be feasible to supplement and enhance social and emotional abilities with AI-based systems, when necessary, even if it is challenging to change person-related 21st century capabilities. All aspects of our lives are shaped by technology, and the way artificial intelligence (AI) is evolving is a direct result of this. Technology has permeated every aspect of our lives to the point that it may be appropriate to study it in isolation.

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