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Human-centered artificial intelligence in education: Seeing the invisible through the visible

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ABSTRACT

The inevitable rise and development of artificial intelligence (AI) was not a sudden occurrence. The greater the effect that AI has on humans, the more pressing the need is for us to understand it. This paper addresses research on the use of AI to evaluate new design methods and tools that can be leveraged to advance AI research, education, policy, and practice to improve the human condition. AI has the potential to educate, train, and improve the performance of humans, making them better at their tasks and activities. The use of AI can enhance human welfare in numerous respects, such as through improving the productivity of food, health, water, education, and energy services. However, the misuse of AI due to algorithm bias and a lack of governance could inhibit human rights and result in employment, gender, and racial inequality. We envision that AI can evolve into human-centered AI (HAI), which refers to approaching AI from a human perspective by considering human conditions and contexts. Most current discussions on AI technology focus on how AI can enable human performance. However, we explore AI can also inhibit the human condition and advocate for an in-depth dialog between technology- and humanity-based researchers to improve understanding of HAI from various perspectives.

1. Introduction

The research trend on artificial intelligence (AI) is shifting from technology-oriented applications, which focus on increasing production and performance, to humanity-oriented applications, which focus on augmenting human intelligence with machine intelligence (Yang, 2021). The shifting of AI research trend has brought about new challenges, including shifts from general-purpose to transfer intelligence, computation to cognition, customization to adaptation, known to unknown, one-size-fits-all to precision, and technology to humanity (Yang, 2019).

1.1. AI research trends and challenges

The first shift in AI research trends was from general-purpose to transfer intelligence; specifically, early efforts to identify points of common sense and knowledge transformed into natural language processing based on pre-training and fine-tuning to enable knowledge transfer between domains for value creation. AI has comparatively better performance on computing and decision-making than humans (Banerjee et al., 2018), AI research now focuses more on perception and human audio-visual literacy, which is the ability to see, hear, read, and write. Therefore, we should focus on cultivating students' cognitive thinking in addition to their computational thinking. From prior customization to real-time adaptation, Google Maps is a prime example. Google Maps can determine whether a driver is approaching traffic congestion and suggest an alternative route. Moreover, when we make big data inferences, we know what we do not know (known of unknown) and can subsequently employ reasoning for insight; it is more difficult to reveal what we do not know (unknown of unknown), and AI can help identify many hidden values and unknown results (Krittanawong et al., 2017). In terms of the shift from a one-size-fits-all to precision approach, precision education refers to the use of machine learning and learning analytics of AI to improve teaching quality and learning effectiveness by addressing at-risk students and enabling timely interventions. The use of AI and other related technologies to diagnose learning conditions could enable teachers to intervene in real time to enhance students' learning outcomes. In terms of the shift from technology to humanity, AI can enhance human productivity through technology. However, AI designs should

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consider human conditions and have a human-oriented approach when attempting to augment human intelligence with machine intelligence.

The shifting of AI research trends has brought new applications of AI in education, one example of the transfer intelligence is the generation and adoption of new deep learning algorithms in natural language processing such as BERT (Bidirectional Encoder Representations from Transformers) (Devlin et al., 2018) and GPT-2 (Generative Pre-Training) (Klein and Nabi, 2019), they apply pre-trained knowledge to fine-tune domain, and have been shown to be more effective than previous generation of deep learning and traditional machine learning algorithms. These new algorithms can achieve performance that is closer to humans. In addition, the promise of precision education commit to apply AI research to intelligent tutoring for precise adaption and personalization, to precise profiling, diagnosis, prediction, treatment, and prevention for smart assessment and evaluation (Yang, 2021). In addition, potential ethical issues involved as AI requires large amount of learner data, sometimes sensitive information for model training; and also how to make AI educational systems theoretically and educationally sound (Chen et al., 2021).

1.2. Human-centered AI

Kant's determinant judgment and reflective judgment provide crucial guidance to explain human-centered AI (HAI). HAI can be interpreted from two perspectives; one is AI under human control (Shneiderman, 2020), and the other is AI on the human condition (Stanford HAI, 2020). AI under human control (or human-controlled AI) is a determinant judgment distinguished according to the degree of human control over AI. At one end is AI that is completely controlled by humans and only assists automation; at the other end is the autonomy that is completely determined by AI. The Human control AI leverages the collaboration between human control and AI automation to empower human productivity with a high level of reliability, safety, and trust (Shneiderman, 2020). AI on the human condition (Stanford HAI, 2020) is a type of reflective judgment. AI on the human condition refers to the design of AI algorithms with humanity as the main consideration; this type of AI requires explainable and interpretable computation and judgment processes as well as continuous adjustments of AI algorithms through human context and societal phenomena to augment human intelligence by using machine intelligence, thereby enhancing human welfare.

2. Humanity and technology for human-centered AI

After we understand the topics of HAI, we must investigate the societal impact of AI and how to target these topics by advocating research toward sustainable AI.

2.1. Societal impact of AI

Vinuesa et al. (2020) demonstrated that AI can help achieve sustainable development goals (SDGs) from two perspectives. AI can be an enabler and inhibitor to our society, economy, and environment. As an enabler, the development and operation of AI has had considerable benefits in achieving several SDG goals. However, as an inhibitor, AI could be abused or misused by human such as the misuse of personal information to identify citizen scores which breach human right. AI could be biased because of the data and algorithm used for training are with societal bias. These inhibitors often undermine our social cohesion, democratic principles, and human rights. Table 1 lists the possible societal impact of AI as enablers and inhibitors to our society and environment.

The development of AI has had great benefits for human well-being, including food, health, water, education, and energy, all of which are positively affected by the development and operation of AI (Vinuesa et al., 2020). AI can help promote the development of the circular economy and smart cities and facilitate more efficient human use of Earth's resources. With the advent of the 5G era, AI can enable connections between driverless cars and smart home appliances to realize the so-called smart life (Nerini et al., 2019). Smart grids are also a crucial topic. The main significance of smart grids in renewable energy management is that the current power generation is diverse considering the uncertainty of natural factors such as solar, wind, and tide etc., it needs smart grids to reach the best planning and managing of renewable energy.

Table 1
Societal impact of AI as enablers and inhibitors.

AI as enablers	AI as inhibitors
1. AI in agriculture 2. AI in medicine 3. AI in education 4. AI in energy 5. AI in circular economy 6. AI in smart cities 7. AI enabled smart grids 8. AI enabled driverless cars 9. AI enabled smart home appliances	1. Increase of electricity consumption because of high volume of computing 2. Bias and misuse of AI algorithms result in damage to human rights 3. Racial and gender biases and inequality because of societal stereotypes in AI training datasets 4. Obstacles and burdens for low- and middle-income countries for AI development 5. Job inequality because of required AI knowledge and concepts

These are suitable applications of AI as enablers. However, these applications have consequences. First, the application of AI requires computing, and a large amount of computing consumes a lot of energy. ICT is expected to require 20% of the planet's electricity supply by 2030, which is extremely high compared with the current requirement of 1% (Jones, 2018). Without a comprehensive power and energy solution, this will cause a global energy crisis. Green growth is seen as one of the most valuable solutions (Karnama et al., 2019). Green growth, which refers to the more efficient and widespread use of renewable energy, is also on its way to being implemented by industries and governments. For example, numerous data centers have moved to cold places, such as Finland to take advantage of the local natural environment to achieve the cooling effect because cooling systems are highly power consuming.

AI can also be abused or misused because of the biases on data and algorithm, which often undermine our social cohesion, democratic principles, and human rights. AI can be influenced by the societal stereotypes imparted by data sets and engineers, resulting in the creation of data biases. Algorithms operate with some predetermined subjective values, as is the case with humans and human-developed algorithms. For example, current training data sets in natural language processing is based on regular news, pre-trained with general news or articles and then fine-tuned. However, unfair reports on women or minorities or those based on misconceptions are common in these news articles. Therefore, this training could cause data bias, which is a type of societal bias (Vinuesa et al., 2020). Another example of misuse of AI is citizen scores (Nagler et al., 2019). AI can calculate a score based on each citizen's social behavior. However, this use leads to the following questions: What is the significance of citizen scores? What is the purpose of citizen scores? This is a classic case of misuse of AI that has severely damaged human rights. Although citizen scores are technically feasible, they are ethically impermissible and should be carefully considered by both the government and the general public.

2.2. Toward sustainable AI

To understand this societal impact, we should consider combining technology and humanity. Through repeated reinforcement learning, algorithms pursue perfect results, which is a determinant judgment. These determinant judgments often lead to extremes because of the pursuit of perfection. It is thus easier to form biases in the algorithm and then guide or even expand false biases, especially in terms of ethnicity and gender. AI scientists are working on explainable AI and interpretable machine learning (ML), hoping that when making complex decisions, AI can explain the reasons for each decision to increase the credibility of AI.

Underlying research of explainable AI and interpretable ML can explain how AI algorithms make decisions. AI governance can reduce the risk of algorithmic bias and misuse of AI by enhancing AI risk management, accountability, and self-surveillance. As indicated in Table 2, research topics on humanity and technology that focus on sustainable AI include governance, policy, technology, and practice. First, researchers must consider how to avoid algorithmic bias and the misuse of AI, understand its impact and influence on society, and determine approaches to perform AI risk management, accountability, and AI self-surveillance and achieve explainable AI and interpretable ML (Conati et al., 2018). AI and ML both must have sufficient interpretability, and the current AI algorithms are inadequate in this regard. Therefore, explainable AI is necessary to enable explanation and comprehension so that humans can understand how AI algorithms make decisions.

3. Smart learning environments for human-centered AI

Learning technology is different from pure technology. Learning technology must be human-centered because it involves teaching and interacting with people. Therefore, smart learning environments must not only focus on performance; human feelings and outcomes should be the main concern. Therefore, we must start with a discussion of ethics and norms and further explore the impacts of smart learning environments on the current technological environment, current learning platform, and learning communities.

3.1. Precision education

Precision education shares the same inspiration as precision medicine (Kuch et al., 2020; Yang, 2019). Precision medicine was proposed by former US President Barack Obama. He discussed the problems with a one-size-fits-all approach because people differ in various respects, including in terms of genes, living environments, and lifestyles (Lin et al., 2021). Therefore, precision medicine must be applied in four steps: diagnosis, prediction, treatment, and prevention. The core thinking of precision education is also built from these four steps. For instance, people can develop various diseases and face various difficulties or risks in learning, including poor grades and learning disabilities. Therefore, students' learning behaviors, learning environments, and learning strategies can be analyzed and discussed through the four steps of diagnosis, prediction, treatment, and prevention to identify solutions (Yang, 2021). Research topics concerning precision education, including governance, policy, technology, and practice, are detailed in Table 3.

As demonstrated by Yang (2021), pedagogical models will change, and a digital platform will produce numerous qualitative changes due to differences in learning strategies or teaching strategies (Quadir et al., 2020). The platform is constant, but the strategies are diverse. The value of teacher lies in their ability to apply strategies and teaching methods wisely. Pedagogical models and tools can be used to design comprehensive learning activities to enhance students' learning outcomes and help them develop learning strategies (Tempelaar et al., 2021). Learning analytics and assessments must also be considered (Alyahyan and Düştegör, 2020). Smart learning analytics and smart assessments are also needed, which will change when AI is added. The prerequisites of appropriateness must be satisfied to meet the standards of precision education (Luan and Tsai, 2021). All of these topics in learning originate from the integration of AI and warrant more attention.

Table 2
Topics regarding humanity and technology focusing on sustainable AI.

AI governance and policy	AI technology and practice
1. Use and misuse of AI 2. Biases in AI Algorithms 3. AI on societal impact 4. AI accountability and self-surveillance 5. AI governance and risk management	1. Explainable AI for explanation and comprehensible by humans 2. Interpretable ML for flexibility and contextual understanding by humans 3. Intelligent agent (assistants) 4. Intelligent conversational robot (Chabot)

Table 3
Research topics concerning precision education.

Governance and policy	Technology and practice
1. The impact of precision education to emerging pedagogical environments such as MOOCs, eBook, coding, AR/VR, robotics, games et al. 2. Ethical and other concerns relating to precision education 3. The design of pedagogical models and tools for precision education 4. The design of learning strategy and learning activity for precision education 5. Exploring the critical factors affecting students' learning performance based on precision education 6. Exploring the influence of teachers' intervention on students' learning performance based on precision education	1. Diagnosis of students' engagement, learning patterns and behavior 2. The design of evaluation and assessment methods for precision education 3. Prediction of students' learning performance and the improvement of predictive models 4. Treatment and prevention with teachers' timely intervention 5. Data analytics for precision education, such as text analytics, audio analytics, image analytics, video analytics 6. Data visualization for precision education, such as dashboard, simulation

3.2. Smart learning analytics

Essential research of smart learning analytics is the application of big data and AI to identify at-risk students and provide timely interventions. The goal is to improve teachers' teaching quality and students' learning outcomes. As indicated in Table 4, research on smart learning analytics is needed to improve the quality of teaching (i.e., teachers must identify and address topics of concern to students, such as inadequate feedback from learning environments), identify which students are struggling with a particular topic, and understand how their content has been used and how effective it is (Zawacki-Richter et al., 2019). Smart learning analytics enables teachers to continually enhance educational content so that it can be tailored to students' level of understanding as they progress and monitor the performance of students so that teachers can then adapt their teaching. Smart learning analytics enables students to take control of their learning, know how they are performing in comparison with peers, and complete assessments to keep up with the learning progress of their peer group and helps teachers to identify gaps in students' prerequisite knowledge and key study skills. Smart learning analytics can help students develop skills and knowledge in a more personalized and self-paced way, providing students with better information on how they are progressing and what they must do to meet their educational goals. Smart learning analytics also provides student consent services, which helps to ensure privacy by enabling students to decide whether to give their

Table 4
Research topics concerning smart learning analytics.

How to improve teachers' teaching quality	How to improve students' learning outcome
1. Identify and address topics of concern to students such as inadequate feedback 2. Identify that students are struggling with a particular topic 3. Provide educators better understanding of how their content is being used and how effective it is, and enable its continual enhancement 4. Enabling the educational content to be tailored to student's level of understanding as they progress through it 5. Monitor the performance of students so teachers can then adapt their teaching	1. Enable students to take control of their own learning 2. Help students develop skills and knowledge in a more personalized and self-paced way. 3. Give students better information on how they are progressing and what they must do to meet their educational goals 4. Provide student consent service helps to ensure privacy by enabling students to give their permissions for data capture and use

permission for data capture and use.

3.3. Smart assessment

As displayed in Table 5, findings on smart assessment, including defining and evaluating students' learning outcomes using a good grading policy (Lu et al., 2021), evaluating students' learning behaviors using a good learning strategy, and evaluating students' learning difficulties, enable teachers to adjust their teaching strategies and materials according to students' learning effectiveness, behaviors, and difficulties (Lu et al., 2018). Categorizing students' learning patterns and predicting their learning effectiveness is useful in exploring the correlation between learning effectiveness and learning patterns (Wong, 2019). Timely counseling can be provided on the basis of students' learning patterns. Defining and assessing students' motivation, attention, and engagement and designing learning activities for improving these areas could enhance their learning (Huang et al., 2019).

Smart assessment can be improved through increased evaluation of students' learning activities, such as preclass preview, reflection, oral reports, assignments, special topics, and program writing, and introduction of an examination mechanism into the smart evaluation system (Hsiao et al., 2019). Teachers provide teaching materials (e.g., textbooks and slides), AI extracts the key concepts in texts through text summarization, and the system automatically generates test questions and reference answers (automatic question generation) to evaluate the key concept (Kurdi et al., 2020). Test questions can be in Cloze (Das and Majumder, 2017), multiple-choice, yes/no, fill-in-the-blank, essay, or short-answer format (McDermott et al., 2014). For short-answer questions, the system can automatically compare students' answers and reference answers with deep learning technology and provide scores and feedback. For smart evaluation, teachers provide textbooks and slides. The system uses natural language processing technology for text summarization to extract key concepts of the textbook and produce a knowledge map. Each node on the knowledge map represents a key concept, and each edge represents the contextual relation between two connected nodes. On the basis of the key concept represented by each node on the knowledge map, the system automatically generates test questions and reference answers (automatic question generation) to evaluate the mastery of a key concept. If students' answers are in written form, then the system can automatically compare the students' answers with the reference answers and give scores (short-answer grading) using deep learning technology and provide feedback. Through repeated testing and practice (Stenlund et al., 2016), students can enhance their memory retention of the learned content, improve the mastery of key concepts, and achieve better performance than if they had simply restudied the learning content.

Table 5
Smart assessment research topics.

Assessment of learning behavior, patterns and strategy	Automation and AI-enabled intelligence
1. Evaluate students' learning behavior with good learning strategy	1. AI-enabled conversational robot (Chabot)
2. Adjust teaching strategies and teaching materials design according to students' learning effectiveness	2. AI-enabled personalization
3. Categorize students' learning patterns	3. Smart content, learning pathway, and recommendation
4. Predict students' learning effectiveness and find out the correlation between learning effectiveness and learning patterns	4. Automatic evaluation of students' learning outcome with grading policy
5. Define and assess students' motivation, attention, and engagement	5. Intelligent assessment and evaluation
6. Differentiated and individualized learning	6. Automatic question generation
	7. Automatic grading
	8. AI-enabled plagiarism detection

4. Discussion: From cold technology to warm humanity

As AI algorithms become more powerful, their ability to aid human judgment and decision-making improves. In such cases, creating an algorithmic bias that can cause and even amplify false biases, especially those concerning ethnicity and gender, is the easiest approach. The problem of gender inequality should also be addressed. Our social environment also lacks adequate representation of women and minority groups in the workforce. Failing to promote the inclusion of female scientists and engineers in the AI field would exacerbate inequality.

The future job market will rely more on data analysis, and to obtain a good job, future job seekers will be required to possess a great deal of technical skills and preparatory knowledge, especially knowledge and concepts related to AI. Furthermore, wealth inequality has been exacerbated by the COVID-19 pandemic. Wealth has been moving from workers to investors, with the rich getting richer and the poor getting poorer. Each crisis engenders a redistribution of wealth, illustrating the different forms that inequality takes.

As AI becomes increasingly powerful, only large countries and companies will have the ability and financial resources to develop it, which will lead to competition between large countries or companies and will create obstacles and burdens for low-income and middle-income countries. Furthermore, if these technologies fall into the hands of dictators or unscrupulous corporations, then they will be as dangerous to the future of humanity as destructive weapons or addictive commodities are today.

The greater the impact that AI has on humans, the greater the need is for us to understand it. The primary difference between machines and humans, or what we think of as humans, is that humans possess free will, consciousness, and emotions that sometimes contain irrational conflicts. Humans are sometimes irrational, agreeing with a person but not with what they do. Humans can hold multiple contradictory mentalities at one time, whereas the thought processes of machines can only follow a logical series. Therefore, to maintain self-awareness and autonomy, humans should possess self-knowledge and self-determination. When AI technologies can make better decisions than humans or better know individuals than they know themselves, then what is left for humans do? AI has indeed far surpassed human capabilities in computing and decision-making. However, humans have some characteristics that AI cannot match. These characteristics are their abilities regarding perception, emotion, feeling, and cognition. Although AI algorithms have evolved to imitate human behavior, these human characteristics are still difficult to imitate in a short time. The last line of defense for humans should be philosophical thought and ethics because only through self-regulation at the ideological and spiritual level can we transcend material constraints.

The movie "The Imitation Game" is mainly about the mutual imitation of humans and machines. The main character of the movie is Alan Turing, a crucial figure in computer science history. Alan Turing believed in the difference between humans and machines, particularly in terms of their modes of thinking. Alan Turing questioned whether the fact that a machine thinks differently from humans means that it does not think. As individuals, we may perceive those who think differently from us as "not thinking" and believe that others are wrong when their thought process differs from ours. Alan Turing famously said "Sometimes it is the people no one can imagine anything of who do the things no one can imagine." This belief has inspired numerous scientists. Numerous elites may have been in the middle class when they were in school but were prone to becoming the unexpected elite of society.

5. Conclusion

Humans always have an awareness of potential dangers and can react with timely correction and even timely braking, whereas machines can only move forward to maximize profits. Therefore, an individual must set "specific, measurable, agreed upon, realistic, and time-based" goals to conduct smart AI research (Yang, 2019). Research trends must be specific and always point in the right direction. Moreover, research topics must be measurable, always general enough to have wide-ranging implications but specific enough to yield meaningful results. Research collaboration requires agreement, alertness, catching on, and refocusing. Research expectations must be realistic and focus on enjoyment; Finally, regarding research time, time is not measured by a watch but by moments, so the time spent researching AI should be cherished.

Love may be among the human characteristics that cannot be replaced by machines or algorithms. Love is accompanied by a series of biochemical reactions and hormonal changes in the body and brain. It may be driven by irrational thoughts or feelings and involve a combination of imagination and reality. AI may be a current trend, but humanistic beauty is eternal. You have to live like a human to see the beauty of the world. When you are busy, remember that you are still human. When you see beauty, you will feel that the world is worth living in. With beauty comes love and expectations. Therefore, HAI is based on human feelings and rethinks human reflective judgments. Humans are imperfect; they should accept that the present version of their self is the best, adjust their emotional state to feel the beautiful state of the soul, and develop an understanding of the invisible mind through the visible world.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

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