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When artificial intelligence meets educational leaders' data-informed decision-making: A cautionary tale

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A R T I C L E I N F O

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A B S T R A C T

Artificial intelligence (AI) refers to a type of algorithms or computerized systems that resemble human mental processes of decision making. Drawing upon multidisciplinary literature that intersects AI, decision making, educational leadership, and policymaking, this position paper aims to examine promising applications and potential perils of AI in educational leaders' data-informed decision making (DIDM). Endowed with ever-growing computational power and real-time data, highly scalable AI can increase efficiency and accuracy in leaders' DIDM. However, misusing AI can have perilous effects on education stakeholders. Many lurking biases in current AI could be amplified. Of more concern, the moral values (e.g., fairness, equity, honesty, and doing no harm) we uphold might clash with using AI to make data-informed decisions. Further, missteps on the issues about data security and privacy could have a life-long impact on stakeholders. The article concludes with recommendations for educational leaders to leverage AI potential and minimize its negative consequences.

1. Introduction

This position paper aims to examine promising applications and potential perils of artificial intelligence (AI) in educational leaders' data-informed decision making (DIDM). As AI forges ahead in the era of DIDM and school accountability, what applications of AI could educational leaders leverage in their DIDM? What are the perils of misusing AI in leaders' DIDM? To seek answers to these questions, I turn to recent literature that intersects AI, decision making, and policymaking from multiple disciplines such as educational leadership, administrative science, educational policy, computer science, judgment and decision making, and neuroscience. Given the multidisciplinary nature of AI topic, this paper includes not only the very limited AI literature relevant to educational leadership, but also the AI literature published in the world's most prestigious multidisciplinary journals, including *Nature* and *Science*. Particular attention is paid to the potential impact of AI on educational leaders' AI-assisted DIDM. This position paper is better seen as an introduction for further thought on the role of AI in leaders' DIDM, rather than an exhaustive account.

2. What is artificial intelligence?

Artificial intelligence (AI) refers to a type of algorithms or computerized systems that resemble human intellectual processes, such as the ability to generalize, reason, uncover meanings, and learn from past experiences (Castelvecchi, 2016). The term "artificial" bears a close resemblance to the actual mental processes of decision making in human brains (Ullman, 2019). On the one hand, one brain region (i.e., a set of brain cells), which is connected neuroanatomically to multiple brain regions, supports multiple brain functions. For example, the ventromedial prefrontal cortex/orbitofrontal cortex (vmPFC/OFC) is the brain region above our eye sockets, and it is active when multiple emotions—such as empathy, guilt, and regret—are involved in our decision making (Damasio, 1994; Thomas, Croft, & Tranel, 2011). On the other hand, one brain function engages multiple brain regions (Gazzaniga, Ivry, & Mangun, 2013). For example, the tasks of mathematical reasoning and causal reasoning activate an important brain network called the task-positive network, which includes multiple brain regions that are associated with attention and cognition (Boyatzis, Rochford, & Jack, 2014; Fox, Corbetta, Snyder, Vincent, & Raichle, 2006). Inspired by how billions of brains cells (i.e., neurons) and different neural networks communicate with one another in human brains, AI adopts a similar approach to identify patterns in massive amounts of data to identify patterns, recognize speech, categorize images, process language, and make adaptive decisions based on often real-time data from sensors and digital data (Hof, 2013). Examples of AI include Amazon Alexa that interacts with human users, driverless cars that make navigational decisions based on real-time traffic (Waldrop, 2015), and

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AI-assisted medical diagnosis to detect diseases (Esteva et al., 2019).

In education, AI has been used in teaching and learning (Pearson, 2019), as we shall see in later sections. However, scant attention has been paid to a broad discussion on the role of AI in educational leaders' decision making. By contrast, in the broad field of administrative science, AI has evoked debates about its use for public administration (Agarwal, 2018; Fast & Schroeder, 2019; Reis, Santo, & Melão, 2019; Wirtz, Weyerer, & Geyer, 2019). This growing body of literature about the influence of AI on administrative science provides us with insights into how AI could potentially influence educational leaders' decision making. To this end, in this position paper I do not attempt to find new avenues for AI in educational leaders' DIDM, but rather discuss the impact of AI that has already been applied in the practices of educational leadership. These AI applications are full of both promises and potential perils, and we must prepare ourselves for both.

Given the very limited literature on AI in educational leadership, I draw upon multidisciplinary literature intersecting AI, decision making, and educational leadership from disciplines such as educational leadership, administrative science, educational policy, computer science, judgment and decision making, and neuroscience. The literature drawn upon in this position paper is not exhaustive but illustrative. In the following pages, I first present the potential benefits of using AI to assist educational leaders' DIDM. I then discuss the potential perils of AI in educational leaders' DIDM from three aspects. I conclude this position paper by offering recommendations for educational leaders who are interested in applying AI to assist their DIDM.

3. Benefits of AI-assisted data-informed decision making

AI can increase efficiency and accuracy in educational leaders' DIDM. DIDM acknowledges that data-driven decision making focuses only on instruction and student academic achievement, but pays scant attention to ethics and people's well-being (Hargreaves, Shirley, Wangia, Bacon, & D'Angelo, 2018(Wang, 2019). To that end, data can only inform, but "never completely drive decisions" (Schildkamp, Poortman, Ebbeler, & Pieters, 2019, p. 284). In line with this view, educational leaders make decisions informed by data—any information "collected and organized to represent some aspect of schools" (Lai & Schildkamp, 2013, p. 10). AI can improve efficiency and accuracy in leaders' DIDM. To reap such a benefit, it is important first to understand how AI works. For AI as intelligent systems with the ability to think and learn, there are different techniques that fall under the umbrella of AI, including rule-based expert systems, machine learning, neural networks, and deep learning (Davenport, 2018).

3.1. How AI works

The first technical approach of AI is *rule-based expert systems*. This approach follows the logical rules in the AI programs: If X, and then Y. A series of if-then rules manifest expertise and knowledge that works well for simple, well-defined problems. This approach, however, falls apart as the number of options grows exponentially in decision making and when the rules conflict with each other (Davenport, 2018).

To overcome the limitations of the rule-based expert systems, machine learning was developed. As a sub-set of AI, machine learning algorithms often use statistical techniques to adjust the algorithms to the situation and "learn" with data without being explicitly programmed to do so (Littman, 2015; Pearl, 2019). Grounded in the probabilistic framework, machine learning algorithms represent uncertainty—a fundamental part of decision making—through a probabilistic perspective. The state-of-the-art advances in probabilistic machine learning include probabilistic programming, Bayesian optimization, data compression, and automatic model discovery (see Ghahramani, 2015, for a detailed review). As a concrete example, consider a leader selecting a program from multiple alternatives to implement in an organization. Each of the multiple programs, proposed by the team members for consideration, has an unknown probability of success in the decision maker's (in this case, the leader's) organization. To make a decision, the leader evaluates the situation by considering an array of factors (e.g., the resources needed for implementing each program, the success rate of each program in other organizations, and the similarity between the leader's organization and other organizations). The data of all these factors are then used to calculate the probability of the success rate of each alternative program to inform the leader's decision making. Such a probabilistic approach could be very helpful for educational leaders who might not know how all the nuances of data collection and analysis influence data interpretation. Indeed, even statisticians sometimes make erroneous decisions using DIDM (Kahneman, 2013). With this probabilistic approach, AI algorithms generate useful information and provide recommendations for leaders' DIDM.

Another commonly used technique in AI is called *neural networks*. This approach was inspired by human brains' structure and function, hence the "neural network" moniker (Davenport, 2018; Ullman, 2019). The neural networks generally do not follow the if-then rules to make decisions. Rather, like the neurons in human brains, there are many artificial "neurons" that can receive, process, and transmit information, and then generate a decision. Without the if-then rules, the neural networks identify the patterns within the data by processing a torrential flow of information. For example, to identify whether a person is smiling in a picture, the neural network approach feeds the algorithms millions of sample pictures labeled "smiling" or "not smiling," and the algorithms identify what features in millions of pictures are most closely correlated to the "smiling" label.

To analyze the neural networks efficiently, we use a specific technical approach in neural networks called *deep neural learning*, also called deep learning (LeCun, Bengio, & Hinton, 2015). To enhance efficiency, deep learning allows multiple processing units and layers to process, learn, and represent data (Schmidhuber, 2015; Ullman, 2019). With its efficiency, deep learning AI programs can now outperform humans in identifying faces, recognizing speech, and many other tasks. A famous example is AlphaGo—the first program to defeat a world champion in the game of Go (Silver et al., 2017). Recently, a poker-playing AI took only eight days, instead of a world-class player's lifetime—to master a poker game and outperform a four-time World Series of Poker champion (Camero, 2019). AI programs can also learn to become a team player by predicting how others will behave, develop classic cooperative strategies, and even invent a completely novel strategy (Jaderberg et al., 2019).

Taken together, AI is an umbrella term that encompasses all of the above techniques. To produce accurate results, AI often requires massive amounts of data, as the data "trains" the algorithms to detect patterns by giving them an enormous number of examples (Lee, 2018). For example, to diagnose a disease, AI algorithms—which read x-rays, detect brain bleeds, and pinpoint tumors—are not based on one doctor's experience with patients, but millions of patients with the same disease (Allen et al., 2019). Taking a similar approach, to evaluate whether a teacher is effective in schools, AI algorithms are not based on one or two employers' evaluation records, but the data on tens of thousands of effective teachers, if not millions, from multiple data sources at multiple time points. Admittedly, any technology can have unintended consequences, a point I will return to shortly. If used in the right way, AI can shine a light on teacher effectiveness from multiple data sources and multiple time points. With those data, educational leaders then weigh the importance of different data sources to inform their decision making. More importantly, with more data used to train AI algorithms, AI can actually improve over time. The importance of data in AI is where AI comes into play in educational leaders' DIDM.

3.2. AI in education

To date, one of the most popular applications of AI in school is personalized learning. Personalized learning refers to "instruction that is focused on meeting students' individual learning needs while incorporating their interests and preferences" (Pane, Steiner, Baird, Hamilton, & Pane, 2017, p. 2). Departing from a one-size-fits-all approach, personalized learning prioritizes each student's learning needs and goals, allows a differentiated, flexible learning pace, and may even generate data of student learning in real time (Mandinach & Miskell, 2017). Delivered through accessible, affordable personal computing devices with software that supported student learning, an AI-powered tutoring system can detect and respond to students' emotions in a similar way that human tutors do (Yuksel, Collisson, & Czerwinski, 2017). One study reported that students' passing rates on state tests were 10 % higher after a week of lessons with the AI-powered tutor than they were with peers who spent the same amount of time learning geometry in a regular classroom (Woolf et al., 2009). The AI-powered tutor not only used real-world problem-solving tasks to teach geometry, but also picked up on students' emotional states through hundreds of sensors. The sensors embedded in the computers focused on the student's eyebrows, mouth, and nose, discerning whether the learner was smiling, frowning, or yawning. The wrist-worn sensors detected changes in students' pulse and moisture levels on the surface of the skin, which indicated students' stress level. The sensors embedded in the chair cushions identified different postures a learner might take. Leaning forward, for example, suggested engagement, while leaning to the side might indicate boredom or frustration. It was reported that an emotionally sentient tutoring system could function as a pedagogical conversational agent, providing students with social and emotional support, and enhancing the effectiveness of human-computer interaction (McDuff & Czerwinski, 2018). Recently, in the United Kingdom, robots—such as the ones that can carry on a conversation with humans, recognize faces, and make eye contact—have been used to help students with special needs (Wakefield, 2018).

Beyond instruction, AI has been re-shaping the future of jobs (Frank et al., 2019). Thanks to advances in AI, it was estimated that 47 % of the jobs in the United States could be under the threat of automation over the next two decades (Frey & Osborne, 2013). The pace of AI adoption in education shows no sign of slowing. By 2030, AI is expected to automate 40 % of the tasks that elementary school teachers now perform, especially non-instructional tasks such as tracking student progress (Herold, 2019b). Moreover, instructional tasks could be re-shaped by AI-powered classroom management tools and tutors that provide personalized instruction and adaptive testing (Etzioni & Schoenick, 2018; Sparks, 2017). Schools have been using AI to optimize routes of school buses (Klein, 2019a). Some schools have begun using AI to screen application materials for teacher hiring. Other schools have been using early warning systems that help identify which students were at the risk of dropping out (Sorensen, 2019). To address school safety concerns, some schools and districts have already or planned to invest in facial recognition software as part of efforts to beef up school safety (Klein, 2019c). Florida, in particular, has planned to build a massive database to identify students who are likely to suffer from mental health issues such as suicide or depression (Herold, 2019a).

These examples illustrate the impact of AI can have on education. The scope of AI applications in education will continue to grow, and AI algorithms will be more sophisticated. Though the aim of this paper is not to survey AI in education, it is important to discuss them as educational leaders may make a judgment call about how to use those AI tools to inform their decision making. This further reinforces the need for an enriched understanding of the role of AI in leaders' DIDM.

3.3. AI in leaders' DIDM

To unpack the role of AI in educational leaders' DIDM, it is important to note at the outset that any AI system is dependent upon the access to a large volume of data. The more data fed into AI, the more accurate AI systems are (LeCun et al., 2015). If the data on educational administration or student learning are not digitized yet (e.g., the data are still stored on paper, rather than stored in a computer), AI would yield little benefit to leaders' DIDM, as the data infrastructure for AI is not ready yet. Not surprisingly, most AI in education, as seen in the examples in the following pages, caters to the schools and districts that have already had a high volume of data. With automation, AI speeds up data collection, processing, analysis, and interpretation for leaders. To that end, AI has potential to enhance educational leaders' data literacy, which was defined as "the collection, examination, analysis, and interpretation of data to inform some sort of decision in an educational setting" (Gummer & Mandinach, 2015, p. 2). Many education leaders have received insufficient training on how to collect, analyze, and interpret data (Lasater, Albiladi, Davis, & Bengtson, 2019; Luo, 2008; Mandinach & Gummer, 2013). To enhance leaders' data literacy, AI can provide the leaders with expert knowledge in data analytics, such as the up-to-date statistical modeling and text mining analytical methods of probabilistic topic modeling, sentiment analysis, network analysis, and convolutional network analysis. The automated data analytical models are particularly valuable in schools and districts where the lack of data analytical knowledge may force a leader to make a less data-informed decision. This is similar to an individual with insufficient training in radiology would have inferior skills in examining medical imaging (e.g., X-rays and ultrasound) to diagnose and treat patients. As one might expect, educational leaders' data literacy may evolve with AI. For instance, leaders need to understand how AI works, identify and prioritize AI opportunities, as well as recognize the limitations of AI. This is because all tasks, AI-assisted DIDM included, should be aligned with an organization's vision and culture. For example, the introduction of an AI-algorithm to predict teacher retention and turnover needs to be accompanied by an organizational culture that builds a structure to support the professional growth of teachers, and empowers—instead of punishes—teachers when they innovate and fail.

In addition to data literacy at an individual level, to capitalizing on using AI to assist leaders' DIDM, it is important for leaders to develop a core team with the responsibilities to share effective practices with teachers and communities about whether and how to adopt AI, develop AI training strategies, and work with AI services and software providers. In educational systems, it takes multiple levels of efforts to build organizational capacity for data use, ranging from teachers, leaders in school buildings and district offices, policymakers at the district, state, and federal levels, communities, to researchers (Bowers, Bang, Pan, & Graves, 2019).

Leaders must also facilitate the discussion of the impact of AI on students and teachers, identify barriers to AI adoption, develop AI talent, and offer guidance on instilling the underlying organizational culture changes required. Without building organizational capacity, schools are likely to squander significant time and money on AI, only to abort it midway—with little or no benefits (Fountaine, McCarthy, & Saleh, 2019). With the increasing AI adoption in education and the fast-paced technological advancement in AI, it is expected that data literacy will evolve over time as well. Educational leaders' data literacy training thus requires a fast-evolving knowledge base that is not readily available or is still under development. Further, the field of AI takes a move-fast-and-break-things approach (Lee, 2018). It is likely that educational leaders' AI-assisted DIDM entails skills that go beyond data literacy. An example includes a leader's skills to understand others' emotional and mental states when the leader presents data about a teacher's instruction in a feedback session. A defensive teacher would not believe that the data reflect reality, whereas a receptive teacher treats the data as an opportunity to grow. To date, most AI applications in education have been developed on the improved efficiency and accuracy in data collection, processing, and analysis. Here I proceed to detail how increased efficiency and accuracy could assist educational leaders in making data-informed decisions.

3.4. Increased efficiency and accuracy in AI-assisted DIDM

Amid an increasing emphasis on school accountability, DIDM has been a prevailing approach for educational leaders to make decisions (Gummer & Mandinach, 2015; Mandinach & Gummer, 2015; Wang, 2019). Teachers use data to improve their instruction (Datnow & Hubbard, 2015; Mandinach, Friedman, & Gummer, 2015; Mandinach & Gummer, 2016; (Mandinach & Jackson, 2012). Educational leaders use data to inform their evidence-based decisions to enhance school effectiveness (Datnow & Park, 2014; Schildkamp, Poortman, & Handelzalts, 2016). With increasing accountability in education at the federal, state, and local district levels, schools are awash in data. What remains challenging is that educational leaders and teachers have been struggling with converting data into actionable information. Many educators felt that they were "flying blind" through the burgeoning amount of data, living in the paradox of being data-rich but information-poor simultaneously (Wayman & Stringfield, 2006). To overcome the challenge, many factors have been found to contribute to DIDM in schools. They include, but not limited to, (1) data characteristics such as data access, availability, and quality, (2) school organizational characteristics such as a shared goal, leadership support, and stakeholder engagement, and (3) individual and team characteristics such as the knowledge, skills, attitude, and collaboration of data at both individual and team levels (Jimerson, Garry, Schildkamp, & Poortman, 2019; Schildkamp & Poortman, 2015).

Regarding the data characteristics of leaders' DIDM, AI—with ever-growing computational data processing power and real-time data—can increase efficiency and accuracy in educational leaders' DIDM by turning data into actionable information in real time. Specifically, AI can assist in leaders' DIDM by improving the data characteristics such as enhancing data access and availability. For example, in addition to numeric data (e.g., test scores), there are also many other types of data that can be leveraged by educational leaders, including text, images, videos, audios, social media hashtags, posts, comments, likes, and retweets (Wang, 2016). Given the increasing availability of rich data from an array of data sources, the highly scalable AI thus holds great potential in improving efficiency and accuracy in educational leaders' DIDM. In the blink of an eye, AI can process vast amounts of data and produce information that educational leaders can act on (Stajic, Stone, Chin, & Wible, 2015). More importantly, the copious amounts of data in the educational system are generated constantly, laying a strong foundation for educational leaders to use AI to assist their DIDM in a timely manner.

In addition to the data characteristics, AI can assist in leaders' DIDM by improving the individual and team characteristics such as the knowledge, skills, attitude, and collaboration of data at both individual and team levels. As school districts invest in collecting ever-growing quantities of data, AI can efficiently sift through data, break down data silos, and produce timely AI-generated recommendations for leaders' DIDM. This is particularly important in large school districts where people in different departments collect data to fulfill their own needs, and where getting actionable data in the hands of leaders in a timely manner is a major challenge. Many school districts have their own data warehouse to store data from a wide variety of sources, including assessments of teaching and learning, the district's student information system, and the data on human resources, budgeting, and finances. All these data can be efficiently processed by AI. In fact, AI has been used to identify the risk of student dropout in a timely manner. In Denmark, researchers have conducted a research study to predict high-school dropout with machine learning, since students not finishing high schools were a big societal problem (Sara, Halland, Igel, & Alstrup, 2015). In the United States, using longitudinal student records data from the North Carolina Department of Public Instruction, researchers applied machine learning techniques and incorporated 74-predictor measures from Grades 3 through 8, including academic achievement, behavioral indicators, and socioeconomic and demographic characteristics to identify students at the risk of dropping out of school and provide intervention accordingly (Sorensen, 2019).

Another example of using AI to turn data into actionable information in a timely manner is teacher hiring. AI can assist educational leaders in teacher hiring by predicting the effectiveness and potential turnover before a teacher steps foot into a classroom (Will, 2019). To make hiring decisions, educational leaders' traditional approach is to pore over resumes, credentials, and recommendations, assemble a panel for job interviews, and even take into account personality test results. In an attempt to make better decisions about whom to hire among multiple applicants, a screening tool has been developed to suggest whether a job candidate is a good fit for the teaching position, based on teachers' resumes, teacher evaluations, and retention data (Jacob, Rockoff, Taylor, Lindy, & Rosen, 2019). With the screening tool, educational leaders score applicants based on the experience on resumes, the recommendations from references, and the district's history of all hired teachers, generating a ranking of all applicants. Then, school principals look at the applicants who have met a particular cutoff score and do another round of evaluations before bringing prospective teachers in for face-to-face interviews. Considering the fact that American urban school districts, on average, spend more than $20,000 on each new hire (Learning Policy Institute, 2017), AI can potentially assist educational leaders in making decisions on teacher hiring with efficiency and accuracy.

Third, AI can help us step away from over-obsession with using standardized test scores in teacher evaluation (Loewus, 2017). As of 2015, there had been at least 15 lawsuits related to different states' teacher evaluation systems that were sometimes unreliable, invalid, biased, nontransparent, unfair, and too arbitrary (Amrein-Beardsley & Close, 2019). Standardized test scores have been criticized as a narrowly defined measure of student learning and teacher instruction. In the state of New York, for example, students' standardized test scores over time were used to calculate a value-added indicator of teacher effectiveness, accounting for 50 % of a teacher's overall evaluation score. However, the value-added indicator overrode other indicators (e.g., the data of classroom observation) collected at the same time if they were in contradiction, yielding 100 % of a teacher's overall evaluation score (National Association of Secondary School Principals, n.d.). In January 2019, both houses of the state legislature in New York voted overwhelmingly to eliminate the requirement of using state standardized test scores to evaluate teachers (Lovett, 2019). This is because standardized test scores—along with value-added modeling in teacher evaluation—have been recognized by many researchers, policymakers, and even judges in court, as insensitive to teacher effectiveness (Close, Amrein-Beardsley, & Collins, 2019; Strauss, 2016; Tobiason, 2018). Since AI can assist in leaders' DIDM by improving the data characteristics such as enhancing data access and availability, teachers can be evaluated based on a variety sources of data, ranging from the assessment developed and given by teachers in class, the answers given by their students to judge teachers' curriculum competency, how well students are mastering the curriculum appropriate to that grade or course, the data on students as learners over time with samples of work and their own thoughts and reflections on the learning, administration observations, student surveys, to teachers' professional portfolios. Further, AI can analyze the data of multiple observations of instruction, classroom artifacts on multiple occasions to increase reliability for classroom observation. The addition of multiple data sources opens the door for innovative, reliable teaching evaluation techniques. The more data used to gauge teaching and learning at multiple time points, the more accurate the picture they can paint for educational leaders' DIDM for teacher effectiveness. More importantly, as AI provides personalized learning that is adaptive to students' learning needs, teachers' job will likely to be re-shaped to focus on coaching, mentoring, inspiring, as well as developing students' social-emotional skills, cross-cultural competency, and collaborative problem solving (Davis, 2019; Lee, 2018; Sparks, 2017).

In line with teacher evaluation, AI can also assist educational leaders in teacher retention. Consider, for example, an AI-powered management system predicts which employees are most likely to quit in the near future. Using the longitudinal data on employees in an organization, the AI-algorithms recommend actions—such as training or awarding an overdue promotion—to encourage employees to stay with the organization (Fisher, 2019). Notably, educational leaders' job is not to rubber-stamp AI-generated recommendations. AI can efficiently analyze massive amounts of data, but it takes a human to add context to the AI-generated results. To put data and results in context, educational leaders need to have close relationships with teachers and team members, listen to their goals and dreams, and understand their motivations. In doing so, educational leaders' role will evolve to be coaches, talent scouts, cheerleaders, and servants. Benefiting from the efficiency of AI, educational leaders can focus more on coaching teachers, rather than rating them. An educational leader's job is less about being a bureaucrat who carries out box-checking evaluations and uses them as a punitive tool. Instead, it is more about building people up and providing performance feedback for professional growth. Direct relationships with humans are better than algorithms. Most of the time, knowing a teacher well is enough to offer him or her a personalized, compelling incentive to stay with the organization.

4. Risks of AI-assisted DIDM

The potential of AI in assisting in educational leaders' DIDM warrants genuine enthusiasm. However, it would be negligent in downplaying the risks of AI-assisted DIDM. The single-minded excessive pursuit of efficiency could lead schools astray. As AI gallops ahead, people, educational leaders included, are grappling with its potential perils. Education is about students, teachers, parents, and communities. In this sense, education is inherently people-driven. Data, if misused, can be a bully, threatening and demotivating people (Muller, 2018). The thorny issues of DIDM—including unconscious biases, equity, morality, security, and privacy—are all centered around people in educational organizations. These issues pose risks of AI-assisted DIDM for educational leaders as well. As the potential perils of AI loom ahead, we take a step back here, looking into the risks associated with AI-assisted DIDM in order to be proactive to potential risks and perilous implications of AI-assisted DIDM for students, teachers, and communities.

4.1. Amplified biases

Many lurking biases in current AI, if used without human scrutiny, could be amplified in educational leaders' DIDM (Hutson, 2017). Biases refer to predictable, systematic errors in decision making, and they are mostly at work beneath the threshold of our consciousness (Kahneman, 2013). AI is created by humans who may not even be aware of their own unconscious biases. In education, classrooms with mostly English-language learners may not respond to recommendations generated by AI that was built on the data made up primarily of those who spoke English as their first language. Similar biases may arise regarding the difference between rural classrooms and urban classrooms (Herold & Schwartz, 2017).

Moreover, the data that feed into AI programs can be biased (Zou and Schiebinger, 2018). In making hiring decisions, AI programs may amplify gender bias. In the field of education, most teachers are female, but many school leadership positions are occupied by male. If we use AI to assist in deciding whom to hire, a lesson from Amazon.com Inc.'s hiring AI provides a cautionary tale. In 2014, to search for talented job applicants, the company used its received resumes over a 10-year period and built an AI program for hiring. The AI program reviewed applicants' resumes, gave applicants scores, and ranked the applicants by the scores. The company soon realized gender bias in its hiring AI, which was developed to review applicants by observing patterns in the existing resumes. Most resumes came from men, reflecting male dominance in the technology industry. The company's AI program taught itself that male candidates were preferable, penalizing resumes that included the word "women" and even downgrading graduates of women's colleges (Dastin, 2018). Another example is that facial recognition software, which has already been used for school safety, is notoriously inaccurate at identifying people of color, women, and children. More troubling, some risk-assessment AI algorithms that have been used to generate risk scores and calculate criminal sentences tend to make harsher predictions about black defendants than white ones (Dressel & Farid, 2018). Such biases can lead AI to discriminatory, biased decisions against the residents in impoverished or minority neighborhoods (Osoba & Welser, 2017).

In educational leaders' AI-assisted DIDM, AI may bias against students from minorities and from low socioeconomic families, and students with special needs. AI may also have racial and gender biases in teacher/staff hiring and over shared decision-making processes (Herold & Schwartz, 2017). Even worse, the biases, in turn, could exacerbate education inequities, generating a vicious circle that entrenches marginalized people as the victims of biases. Without transparency and oversight, AI is at particular risk of amplifying existing biases in educational leaders' DIDM. Being aware of the lurking biases in AI is the first step for educational leaders to contemplate how to use AI in their DIDM to counter biases, instead of amplifying them.

4.2. Moral and ethical decision making

Of more concern, the moral values (e.g., fairness, equity, honesty, and doing no harm) we uphold in educational leadership might clash with using AI to make data-informed decisions. Neuroscience research has consistently indicated that emotional engagement is essential in making moral decisions (Damasio, 1994; Greene, Sommerville, Nystrom, Darley, & Cohen, 2001). The vmPFC, the brain region noted earlier, is associated with social emotions, such as empathy, compassion, shame, and guilt. People with brain damage in this region make emotionally-detached decisions, such as choosing to kill one person—even a family member—to save five strangers (Greene, 2007). They justify the decision by maximizing the group interest (i.e., the greater good): the value of five lives is larger than that of one life. This approach to making moral decisions is utilitarianism, also called consequentialism. Focusing on the consequences and utility, utilitarian decision makers conduct a cost-benefit analysis for each option, and choose the option that generates maximum benefit. Brain damage to the vmPFC dampens the emotional effect on decision making, leading people to make highly analytical, utilitarian decisions.

AI programs can improve efficiency and accuracy in data processing and analysis, but they do not generate emotions over the decision-making processes. AI programs do not *feel* awe, excitement, empathy, gratitude, guilt, and shame. Current AI mostly has not taken into account the role of feelings and emotions in human mental processes in decision making (Damasio, 2019). Our feelings and emotions—from passion to compassion, from empathy to disgust, and from guilt and regret—are part of the intuitions we rely on when making fast decisions that follow our gut feelings (Wang, 2020). AI may be able to read human emotions through facial expression and body language, but AI has not been able to empathize with the suffering of others (at least, not yet), which is essential in moral decision making to uphold and restore justice (Decety & Cowell, 2015). Educational leaders ask, "What's the right thing to do?" AI programs, on the other hand, ask, "Based on the identified patterns in data and calculated probability of options, what is the most appropriate next action?" Unlike humans, AI programs are not motivated by compassion- or empathy-motivated altruism. For this reason, AI can only complement educational leaders' DIDM, but not supplant it.

Education is inherently people-driven. People cannot be reduced to data points. When we make decisions in social settings, complexity reins, and ambiguity grows. If data are the only factor taken into account in making moral decisions, AI may generate analytical, calculating, cold-hearted, and emotionally detached decisions, creating an ethical minefield. When making a decision about whether to close a school, if AI follows the utilitarian principle—maximizing the group interest and the greater good, the decisions of closing a school—due to the data on low student enrollment and low rating in a state's accountability system—could be interpreted by the community as a cold-hearted decision and injustice (Tieken & Auldridge-Reveles, 2019). To fulfill our moral obligations to students' well-being, we need a human touch, literally and figuratively. Educational leaders, rather than AI, should take the helm of caring for students and teachers, pouring our heart out, and empowering teaching and learning in schools.

4.3. Security and privacy concerns

Beyond biases and moral challenges, there are security and privacy concerns that imperil the adoption of AI-assisted DIDM in education. Missteps on the issues about cybersecurity and student privacy can have a life-long impact on students, teachers, and staff. Some school districts have already fallen victim to phishing scams, hacks, ransomware attacks, losing millions of taxpayer dollars and personal data about children and teachers being comprised. School districts, which are data-rich but often lacking robust cybersecurity, have emerged as an increasingly vulnerable target. Ill-intentioned hackers have learned that schools—with their large repositories of data—can be exploited. Take ransomware as an example. Ransomware is the malware that takes hold of victims' data, used by hackers to threaten to publish or delete the data if a ransom is not paid. In 2018, public K-12 schools in the United States reported 11 cybersecurity incidents that were connected to ransomware (The K-12 Cybersecurity Resource Center, 2018). In 2019, schools districts in at least eight states—including Idaho (Wood, 2019), Connecticut (Lambeck, 2019), New Mexico (Moya, 2019), New York (Mulder, 2019), Oklahoma (Hansen, 2019), Louisiana (The Associated Press, 2019), Alabama (Alabama Media Group, 2019), and Arizona (Klein, 2019c)—have been attacked by ransomware. In the United States, public schools are subject to federal laws (e.g., the Every Student Succeeds Act) and state laws to collect a large amount of data, ranging from student performance data to what medications students take. Losing access to these data not only can be devastating to stakeholders, but also creates legal liability for school districts.

In addition to cybersecurity, privacy repercussions are another concern over the AI-assisted DIDM. This is particularly important when schools use AI surveillance system to boost school safety and security. After Stoneman Douglas High School shooting that killed 17 people and injured 17 others in Florida in 2018, to prevent school shootings, Florida proposed a massive surveillance program that can label students as threats based on the data from multiple sources, including, but not limited to, people's social media postings, millions of records held by school districts, records for over 9 million people placed in foster care, information related to unverified tips and suspicious activity reports held by law enforcement, and the data on students identified as victims of bullying (Herold, 2019a). Some school districts have already hired social media monitoring companies to track the posts of everyone in the areas surrounding schools, including adults. Other companies scan the private digital content of millions of students using district-issued computers and digital service accounts. Those services are complemented with tip-reporting apps, facial recognition software, and other new technology systems. Some districts conceded that the system they had employed had generated thousands of "false positives." Abusing this system assaults on people's privacy.

Informed consent is another thorny issue in the age of AI. Take facial recognition AI as an example. In AI programs, our face is usually connected to those who interact with us. When we give informed consent to one entity, say a school district, there is no guarantee that the data of our face would not be used by other entities (e.g., technology companies who have a contract with the school district for the service of facial recognition). Facial recognition AI in schools thus should be subject to strict privacy regulations. Moreover, putting an Alexa in the classroom, we may give Amazon.com Inc. access to children's voices without parents' consent. One of the challenges to shore up informed consent is that in the United States, the Children's Online Privacy Protection Act (COPPA) requires operators of commercial websites, online services, and mobile apps to get permission from parents before gathering information about any child under the age of 13. Yet the U.S. Federal Trade Commission (FTC)—the agency that enforces and oversees the COPPA—stated that in some situations, schools could stand in for parents, giving consent for student data to be collected. In this case, technology companies often pass the burden of getting parental consent on to districts, which then either make decisions in lieu of parents, or spend a lot of time, money, effort, and energy in getting informed consent from individual parents for children's data to be shared (Klein, 2019b).

Lastly, to protect the privacy of students and teachers in our current digital age, educational leaders need to pay special attention to anonymized and aggregated data sets. This is because even after anonymizing identifiable information, individuals can still be identified within anonymized and aggregated data sets (Rocher, Hendrickx, & de Montjoye, 2019). It might put vulnerable individuals and minority groups—including undocumented immigrants, and members of ethnic and religious communities—at risk of being identified. They could be unfairly targeted by AI programs. To that end, educational leaders need to be proactive in policymaking and engage technology company vendors in protecting student data.

5. Recommendations

The benefits of AI-assisted DIDM come with risks. Educational leaders are inundated with data on a daily basis. AI can free up educational leaders' time, improving efficiency and accuracy in DIDM. As with all new technologies, constructive dialogue and necessary regulations are the preferred way forward to gain the maximum benefit and do the least harm. There will be an increasing number of educational leaders who navigate the uncharted waters and wrestle with thorny questions associated with leveraging AI-assisted DIDM in a data-rich world. While AI is making great strides in education, this position paper calls into mind the cautionary tale of the potential perils of using AI in assisting educational leaders' DIDM. Before jumping on the wagon of AI, here I lay out critical recommendations for educational leaders' AI-assisted DIDM to mitigate risks discussed above and to avoid unintended consequences.

5.1. Public scrutiny of AI

To ensure transparency of educational leaders' decision making, the effectiveness of AI needs to be under public scrutiny. Transparency is crucial for building public trust in schools (Hoy & Tschannen-Moran, 1999). Educational leaders face up some entrenched societal issues that have nothing to do with technology, but AI, as noted earlier, can potentially amplify existing biases. The public may ask, "Could you explain how AI reaches its decision?" Educational leaders might not be able to answer such a question. The problem may not lie with the leader, but that how the algorithms reach a decision could be a black box. It is difficult, even to those who develop the AI algorithms, to really know how a decision is made. AI algorithms process the immense streams of data in ways that human brains are incapable of computing and processing. To make matters worse, the better the AI system is, the more difficult it often is to explain (Courtland, 2018). Without public scrutiny, AI, as warned by an AI scientist Yoshua Bengio, "is a tool that can be used by those in power to keep that power, and to increase it" (Castelvecchi, 2019). But too often, the public ascribes objectivity and neutrality to algorithms and artificial intelligence. Recent research found that lay people were more likely to follow advice provided from an algorithm than from a person, whereas experienced professionals, who relied less on algorithmic advice, made less accurate judgment. People weighed algorithmic advice more heavily than human advice and chose algorithmic judgment over human judgment when given a choice. They even showed a willingness to choose algorithmic advice over their own judgment. That is, people have an "algorithm appreciation" (Logg, Minson, & Moore, 2019, p. 90). Authority, as Pasquale (2015) aptly put, "is increasingly expressed algorithmically" (p. 8). A jarring but true fact is that many algorithms are the closely guarded secrets, not open to the public. It is thus difficult to evaluate accuracy and risks, as well as assess fairness and equity in decision making. This is particularly problematic when AI algorithms entrench inequality and inequity in education.

To tackle the lurking biases in AI algorithms, educational leaders need to be cognizant of and remain vigilant of the biases, including racial bias, gender bias, confirmation bias, and many others. To do so, leaders need to first familiarize themselves with the biases, deepen their understanding of how the biases work, examine their own biases, be observant of the presence of the biases in others and AI algorithms, and then take action to minimize them. The more we understand our biases, the better we can overcome them (Soll, Milkman, & Payne, 2015). As human beings, we all have bias blind spot—failing to recognize our own biases is a bias in itself (Pronin, Lin, & Ross, 2002). Under the spell of our bias blind spot, we notice cognitive and motivational biases much more frequently in others than in ourselves (Pronin & Kugler, 2007). In this case, it is particularly important for educational leaders to proceed cautiously and engage relevant stakeholders to tackle the biases as a team. The stakeholders include those who have intimate knowledge of the data, those who will be influenced by the decisions (e.g., teachers, parents, students, communities), and those who develop AI algorithms. In order not to erode public trust in schools, student interest should always be the top priority, and they—along with their families—should not become the collateral damage over the process of optimizing AI in educational leaders' DIDM.

5.2. *Treat AI as a decision support, not a replacement*

With all the tools of AI at our disposal, educational leaders may mistake AI-generated recommendations as decisions. Educational leaders need to decide when it is appropriate to use AI-assisted DIDM about people. AI comes in many shapes and forms, ranging from algorithms detecting bullying and mental health on social media, identifying students who are at the high risk of dropping out of school, sifting through and recommending potential hire for teaching positions, to wearable devices monitoring employees' personal health risk factors (Russakovsky, 2016). Since AI resembles human intellectual processes of decision making, to use AI means educational leaders understand the context of the data, and prioritize people. AI is a tool that educational leaders can leverage for its efficiency and accuracy in DIDM. But AI should not replace humans in making decisions, particularly in a domain that is driven by student interest. For example, what should an educational leader decide with a statistical probability of 60 %—or even 98 %—that a student will drop out of a school? Should the leader invest more resources in that child, or less? If a teacher is labeled as "ineffective" in the teacher evaluation system, should leaders decide to terminate the teacher's employment or provide more coaching and professional development for the teacher?

Too often, technological advances have been hailed for staving off all problems in education. AI is not a magic wand that can cure all the woes we face in education. Neither is AI a plug-and-play technology with immediate returns. It could be perilous to rely solely on data to make decisions that would have a widespread influence on people. In the age of AI, blindly pursuing data without any thought to social impact may undermine our commitment to education and to promoting a kind-hearted, compassionate, and innovative organization where people thrive. For this reason, AI is a supplementary system—a tool that educational leaders use to serve people. AI can help with part of the data literacy required, namely with the data collection, examination, analysis, and interpretation. However, given people's "algorithm appreciation" as noted earlier, it is important to reiterate that AI does not make decisions. Rather, the decision-making power resides in educational leaders who make data-informed decisions to serve students.

It is important for education leaders to bear in mind that data work for people, not the other way around. The efficiency and accuracy of AI can liberate educational leaders from the daily grind of busily accumulating data. Are educational leaders willing to use the freed-up time to engage with people in schools, to understand the messy realities behind data, to treat people with respect? Are educational leaders willing to resist the temptation of merely looking for a quick fix that removes the messy details of building and maintaining social relationships? If we allow the value of data to override the value of people, we justify replacing ourselves with robot leaders who endow AI with all decision-making power. To avoid it, educational leaders are recommended to spend more time on what makes us human and what separates us from machines: caring for others, empathizing with others, expressing our compassion and gratitude toward others, and following our heart. In DIDM, data are the means to an end, but data are not an end in itself. In education, data are used to serve the interest of students. AI does the well-defined, data analytical tasks, whereas educational leaders wrap the analysis with a human touch filled with compassion. In a shared future between AI and leaders' DIDM, education leaders should consider AI as an advisor, rather than a decider. Educational leaders could hand their data analytical tasks off to algorithms and instead focus on communicating more with people and making them feel cared for. Leaders would not be able to compete with AI in their ability to crunch data and memorize facts. Leaders, however, can provide a human touch, kindness, care, and compassion in data-informed schools.

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