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The Convergence of the Internet of Things and Artificial Intelligence in Medicine: Assessing the Benefits, Challenges, and Risks

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The adoption of the Internet of Things and artificial intelligence in health care has the power to advance diagnosis and treatment delivery in medicine. This article delivers an overview on the progress, benefits, and challenges of this convergence.

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The integration of tools into health care from emerging technologies, such as the Internet of Things (IoT) and artificial intelligence (AI), has advanced medicine and will continue to do so as their adoption accelerates. There already exist IoT systems that use AI algorithms to help patients manage chronic conditions, assist physicians in diagnosis and treatment, as well as help hospitals track and manage the use of medical equipment and devices.

While the use of AI in health care has received considerable attention over the last decade, its initial use can be traced to the expert knowledge systems of the late 1960s and early 1970s. AI has made tremendous advancements in the medical field and is now promising to continue to transform health care. Still, society should be cautious given the implications of unintended consequences. Diagnoses from predictive machine learning (ML) models trained on highly personalized data and the application



of pattern recognition for medical imaging anomaly detection carry more risk than consulting Internet search engines to learn more about medical conditions. These are critical systems and need validation, verification, and regulation. This article adds to the unfolding discussion on the benefits of integrating AI and IoT in health care, as well as its inherent challenges.

improves day-to-day management of the condition.

Moreover, IoT and AI have united to form the Artificial Intelligence of Things (AIoT). AIoT is frequently, and increasingly, seen in the medical industry.¹ In general, medical AI assistance can decrease stress on both patients and physicians. A patient with a chronic condition can use an

data but requires further human interpretation (for example, CGM). Level II involves more advanced algorithms that can draw conclusions and deliver a treatment or a diagnosis that may still be overruled (for example, AID). Finally, Level III exhibits algorithms that can manage diseases independently (for example, radiologic interpretation). The use of ML, which includes algorithms classified as Levels II or III, is gaining popularity in medicine. ML algorithms learn patterns from the data they use, thus enabling them to make inferences and predictions.⁸ Most autonomous medical technologies operate using ML algorithms. These algorithms, in turn, use electronic medical data to make predictions and determine treatments.⁹ Innovations such as the artificial pancreas, or closed-loop insulin delivery, have been incorporated into treatment to improve drug delivery using ML algorithms and other such technologies.¹⁰

Autonomous (Level III) technologies have reached impressive capabilities. They can interpret medical imaging faster and more accurately than medical experts.¹¹ In Level II and III technologies, these predictions are communicated to the system and acted upon accordingly. However, bias and imbalance in data can degrade the algorithms' predictions and potentially cause inaccurate interventions¹² and thus compromise reliability. In autonomous systems that are used to monitor and control patient health, these inaccuracies may lead to harm and adverse events. These critical systems must be highly reliable in that they not only complete their missions but also causes no harm.¹³ Therefore, the use of ML in critical systems is a challenge that will need continuous monitoring. With safety and trust being two of the most important requirements of a critical system, the adopted ML algorithms must also be reliable.

AI and humans learn from each other and improve reciprocally. Clearly,

A patient with a chronic condition can use an AI-enabled IoT system to administer treatment without having to be monitored in real time by a physician.

THE CONVERGENCE OF IOT AND AI

The IoT architecture has been well-received in the medical domain because of its ability to support communication among numerous medical devices, including decision triggers that are AI-enabled.¹ Tethered by vast amounts of data, improvements in AI, and capabilities of analytics, the many possibilities of convergence in these technologies are rising in modern medicine.² IoT is defined as the collective network of connected devices and the technology that allows them to communicate with each other. In the medical industry, IoT is sometimes referred to as the Internet of Medical Things (IoMT). However, there are clear limitations to adoption in the medical field that may not always be apparent, especially in terms of safety and ethics.

One example of an IoMT device is the continuous glucose monitor (CGM), which measures a patient's glucose level through a sensor, sends the reading to the transmitter, and then communicates the reading to the patient's smartphone. At such time, if the reading is out of range the patient will be alerted so a decision can be made on how to treat the glucose reading.³ Such technology not only assists in treatment but

AI-enabled IoT system to administer treatment without having to be monitored in real time by a physician. Medical instruments such as smart stethoscopes, thermometers, and blood pressure monitors can connect to the Internet and use AI to assist health-care professionals in accurate diagnoses and treatment decisions.⁴ Smartwatches and fitness trackers can collect vitals to make determinations and give feedback about a person's overall health. The automated insulin delivery system (AID) uses blood sugar readings to adjust insulin delivery.⁵ These devices have the ability to improve the overall quality of life for patients.

CATEGORIZING AI RISK

The level of AI integration in medicine delineates its risk. In 2021, the American Medical Association (AMA) classified AI applications into three categories: assistive (Level I), augmentative (Level II), and autonomous (Level III).⁶ Similarly, the European Union (EU) classified AI applications into three categories based on the risk that the model presents: unacceptable risk, high risk, and limited/minimal risk.⁷ These three levels differentiate the critical nature of the medical applications: Level I classifies technology that produces its own

medical professionals need to problem-solve even when automation is present in order to identify and mitigate adverse situations that arise. Thus, implementing a feedback loop that leads to resolving algorithmic imperfections and improving the outcome of technology is required. This creates a cycle of continuous enhancements that impact research, development, deployment, testing, and adaptation. Consequently, as technological solutions advance, so do medical treatments.

QUANTIFYING THE BENEFITS

Technological infrastructure has always been the bedrock of health-care advancements. However, the powerful tools of AIoT are now playing a much more transformative role in this industry, elevating the present-day medical domain much faster than ever before. The benefits of AIoT are multifaceted. These include improved decision-making, extended medical access, early prediction and detection, reduced stress for patients and physicians, and lowered costs. Additionally, convenient data storage is made possible by AIoT devices and enables physicians to store voluminous data with easy access.¹⁴

ML technology helps clinicians improve decision-making by detecting patterns in large health-care datasets that may not be identified by the clinicians alone. In epidemiology, ML algorithms were able to accurately predict the transmission of infectious diseases in West African populations.¹⁵ The novel predictive model analyzed infection patterns in a distinct African population. As a result, the algorithm accurately predicted transmission of the Ebola virus during the 2013 outbreak in Africa. IoT in epidemiology can utilize these predictive models more actively, thus creating an opportunity for AI to intervene. For example, wearable AIoT devices that measure physiological symptoms have been used to identify and evaluate contagious diseases, such as COVID-19.¹⁶

Integrating these predictive modeling techniques with data from IoT devices will lead to significant improvements in epidemiological models.

AIoT in medical care allows technology to work more efficiently with less risk and at a lower cost,¹⁷ thus expanding medical access. Clustered

demonstrating AI's potential to save lives with minimal intervention. AI and ML software systems already assist in the treatment and management of stomach and liver diseases. In a 2012 study, AI/ML models were used to identify patients with ulcerative colitis and Crohn's disease from

With safety and trust being two of the most important requirements of a critical system, the adopted ML algorithms must also be reliable.

regularly interspaced short palindromic repeats (CRISPR), a technology to improve existing therapies and test drug candidates, is an example of this that uses ML/AI. Specifically, AI is used in gene editing for target prediction, designing genomes, genomic analysis, and optimizing editing efficiency. By combining AI and CRISPR technology, researchers can make gene editing more precise, efficient, and reliable.¹⁷

Additionally, the recent application of AIoT in diabetes control highlights the potential of combining IoT technology with predictive models. The AID system is a way of delivering insulin through a pump that communicates with a CGM. ML algorithms analyze the blood glucose reading, predicts what the blood glucose will become based on the current trend, and automatically adjusts insulin delivery based on that prediction.⁵ Such a closed-loop system has been proven to greatly improve the quality of life for Type 1 diabetics by reducing the burden of constant blood sugar monitoring. The decisions of the AID system can be overruled by the patient, making it a Level II critical system. As a result, technologies similar to this are becoming popular in the medical industry due to their partial independence.

Gastroenterology, the study of the digestive system, and hepatology, the study of the liver and gallbladder, also have their own examples

endoscopy images, with an average accuracy of 90%. These systems can also identify high-risk patients who are unable to be identified with standard screening,¹⁸ underscoring AI abilities' over prevailing technology. Another example is in anesthesiology, which requires the analysis of complex data, where ML algorithms read patients' electroencephalography signals to examine their status under anesthesia.¹⁹ The algorithms used in anesthesiology include deep learning neural networks, which work together to improve accuracy in predicting the patient's status.¹⁹

Additionally, AIoT has had a fundamental position in cardiovascular disease prevention. ML uses data collected from a vast number of patients to create a precise algorithm capable of identifying factors that predict hypertension and coronary artery disease. The AI then uses this data to create a predictive model that prompts the IoT technology to alert the subject. This AIoT communication allows patients and physicians to precisely manage cardiovascular risk factors.²⁰

Though not perfect, the ability of AI to interpret complex signals and make predictions is extremely promising. Furthermore, the convergence of IoT with AI has created a paradigm shift by enabling the kind of smart machinery decision-making that reduces the burden of physical intervention for doctors and patients.

A NEED TO ADDRESS CURRENT CHALLENGES

While AIoT presents new and promising opportunities in health care, there remain challenges to be addressed. Research, development, and regulatory efforts to address concerns regarding reliability, generalizability, safety, and sustainability are underway.¹⁴ It is evident that transformative innovations are fueling autonomous medical technologies; however, current technological limitations are a drawback. These limitations include data privacy, limited data availability, biased data sets, patient injury, and machine error.²¹

Patient privacy is of utmost importance in health care. Patients want to know that their data are safe, secure, and not at risk of breach. When novel

external factors, making it difficult to adapt.²² Therefore, the reliability of AIoT can be degraded because of changes in the patient's environment that are difficult for the algorithms to detect. The AID system used in Type 1 diabetes is an example of an AIoT device used in medicine with limitations that can be attributed to its algorithm. Given the closed-loop insulin delivery system is designed to adjust insulin rates based on glucose levels, the algorithm does not know what the patient is actively doing or how it may affect their future blood glucose readings.⁵ For example, it cannot measure the amount of exercise of the patient or the type of food they are eating, so it may administer the incorrect amount of insulin. This type

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AIoT systems are deployed in health care, the potential for patient data being compromised is far greater than most patients understand or are willing to tolerate because of the complexities of these systems.⁸ Not only does unprotected patient privacy increase the possibility of patient discrimination by increasing data bias, but it also impacts long-term health care costs.²¹

The massive amounts of data and the deduced patterns by AIoT systems embody within them the biases of our society, making their use in health care a potential for ethical implications. Therefore, such solutions may not be viewed as trustworthy as those deduced by trained physicians. Predictions from AIoT systems are only as good as the data they receive. When that data are shown to have biases, the resulting predictions are not optimal.¹²

Another challenge is that current technology cannot measure or control

of error can cause hypo- or hyperglycemia, which can be fatal.

AIoT in medical care also has legal limitations. Injury and error are unavoidable in medicine, but when a problem does occur due to technology, legal measures must be taken. When physicians are held accountable instead of the technology, they may become liable.²³

AIoT is developing fast and is increasingly being adopted in medical care. It goes without saying that caution should continue to be used with AIoT-based technology. Due to their critical nature, health-care systems must be assured to be reliable and maintain such reliability throughout their usage. AIoT has the potential to make medical care safer, more efficient, affordable, and less stressful for physicians and patients alike, thereby improving health-care

delivery. However, despite their promise to assist physicians in disease diagnosis and treatment recommendation, AIoT systems have greater associated risk than prevalent technology. Furthermore, medical technology still has a long way to go before it can be fully trusted by clinicians. In the meantime, researchers are continuing to work on making AIoT more reliable by developing novel approaches to overcoming their limitations. ■

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