

# Wireless monitoring and artificial intelligence: A bright future in cardiothoracic surgery

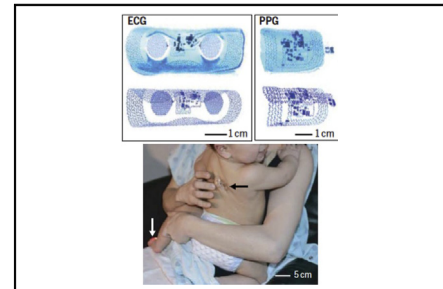


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Current vital sign monitoring systems in neonatal intensive care units are based on rigid and wired interfaces that can lead to iatrogenic skin injury, make basic clinical tasks challenging, and prevent skin-to-skin parent/neonate bonding. Chung and colleagues<sup>1</sup> describe a wireless, skin-like flexible electronic platform that when used in a time-synchronized fashion can reconstruct multipoint full vital signs information with clinical-grade precision (Figure 1).

New technologies have to be carefully understood in terms of the tradeoffs between added value and limitations. An example is pulse oximetry, the technology of which began in the early 1970s, took 5 years to commercialize, and at least 15 years to become the fifth vital sign.<sup>2</sup> In that time, multiple studies showed the benefits of having this continuous bedside tool that estimates oxygen saturation in such pathologies as chronic lung disease and premature infants. However, we learned that ambient light, skin pigmentation, poor perfusion such as in low output states, and hypothermia can produce inaccurate readings.<sup>3</sup> Additionally, peripheral capillary oxygen saturation values below 80% do not correlate nearly as well to arterial blood oxygen values,<sup>4</sup> knowledge important in the care of single ventricle patients or those with mixing lesions. The binodal device by Chung and colleagues<sup>1</sup> will additionally require further understanding in clinical scenarios outside of normal, such as its performance during arrhythmias and low output states, its ability to trend and transmit data during cardiopulmonary resuscitation, and trends in plethysmography in lower saturations.

That being said, this innovative wireless monitoring system for neonates is a remarkable example of what wireless



Wireless, skin-like systems for vital signs monitoring in neonatal intensive care.

### CENTRAL MESSAGE

Machine learning and AI techniques have the potential to be used in conjunction with wireless monitoring systems to transform our specialty. Cardiothoracic surgeons should not miss this opportunity.

The Invited Expert Opinion provides a perspective on this topic based on the following paper: Science. 2019;6430. <https://doi.org/10.1126/science.aau0780>.

monitoring technology can bring to patients with thoracic and cardiovascular diseases. Indeed, the most recent wireless monitoring technologies are advanced wearable sensors that enable secure and effective communication between the clinician and patient. Such monitoring systems can help with many health care challenges, including ageing, chronic diseases, low cost-effectiveness, overutilization, inadequate patient care, and high readmission and mortality rates.<sup>5</sup> Creating a more seamless health care system experience through the implementation of wireless monitoring technologies can significantly decrease the health care costs related to clinical follow-up by decreasing the workload needed for this task and also enhances the involvement of patients in chronic disease management.<sup>6</sup> This technology will also lead to the generation, storage, and analysis of new extremely large data sources that need parallel computing tools to handle them (so-called big data), and that will ultimately increase our medical knowledge base.

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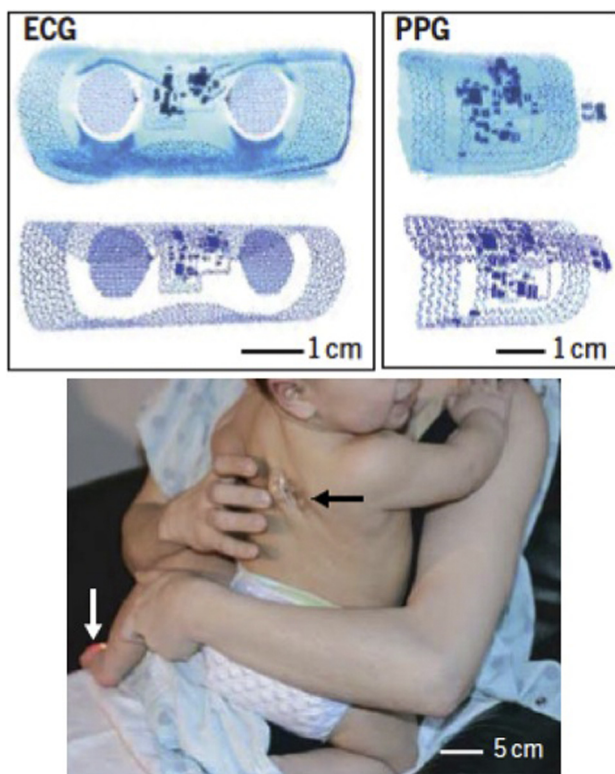
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**FIGURE 1.** Images and finite-element modeling results for electrocardiograms (*ECG*) and photoplethysmograms (*PPG*) devices bent around glass cylinders (*top*). A mother holding her infant with a *PPG* device on the foot and an *ECG* device on the back (*bottom*).

Many recent advances in engineering science serve as foundations for wireless platforms. These include real-time data analytics and signal processing through efficient algorithms; high-speed and time-synchronized data communication systems and wireless power transfer via radio-frequency; soft-electronics-based flexible sensors; and advances in polymer science and soft, light, and low-modulus biomaterials. Moreover, the combination of wireless monitoring systems with nanotechnology enables manipulation of materials at the nanoscale that can increase sensitivity, selectivity, and lower the cost of a diagnostic system.

The main medical areas of application of wireless monitoring systems are rehabilitation, long-term condition and chronic care management, cardiovascular diseases, falls, and mental health.<sup>5</sup> Many wireless monitoring-based technologies have been applied to cardiothoracic surgery. The CardioMEMS Heart Failure System (St Jude Medical, St Paul, Minn) comprises a wireless pressure sensor that is implanted percutaneously in the pulmonary artery and transmits real-time measurements of pulmonary artery pressures.<sup>7</sup> A wireless electronic esophageal stethoscope was designed for continuous auscultation of heart and lung sounds in anesthetized patients.<sup>8</sup> Zheng and

colleagues<sup>9</sup> developed an *in vivo* self-powered wireless cardiac monitoring system via implantable triboelectric nanogenerator.

The raw data collected from wearable sensors provide data that did not exist before. Machine learning and artificial intelligence techniques have the potential to be used in conjunction with wireless monitoring systems to transform big data into meaningful and actionable information that physicians and surgeons can use to improve the quality of care and quality of life of patients with thoracic and cardiovascular diseases. Artificial intelligence (AI) can be defined as the development of computer algorithms to perform tasks typically associated with human intelligence.<sup>10</sup> In medicine, AI technologies can aid in diagnosis generation and therapy selection, risk predictions and stratifying disease, reduce medical errors, and improve productivity.<sup>11</sup> Today, money is being increasingly invested in the field of medical AI. The US government's investment in research and development in AI-related technologies was ~\$1.1 billion in 2015 and the National Science and Technology Council's Committee on Technology estimated that this amount will increase during coming years.<sup>12</sup> Medical institutions such as Mayo Clinic, Memorial Sloan Kettering Cancer Center, Massachusetts General Hospital, and the UK National Health Service have developed AI algorithms.<sup>13</sup> At Columbia and NewYork-Presbyterian/Weill Cornell Medical Center, we have initiated several implementation initiatives in AI to streamline clinical operations underlying the delivery of cardiac care. Academic AI-related research is booming, too: 212 AI-related publications were indexed globally in 1990, increasing to 1153 in 2014. Large technology companies such as IBM and Google, and startups such as Welltok and Ayasdi, have developed AI algorithms for health care. By 2021, growth in the AI market is expected to reach \$6.6 billion.<sup>14</sup>

AI algorithms for learning can be classified as supervised, unsupervised, or reinforced.<sup>15</sup> In supervised learning, algorithms use a dataset that has to be labeled by humans, whereas unsupervised learning aims to find hidden patterns in the data without feedback from humans. Reinforcement learning can be viewed as a hybrid of supervised and unsupervised learning. All these algorithms have been mostly used in the fields of imaging, clinical-risk stratification, and precision medicine.<sup>16</sup> Two of the supervised learning techniques are neural networks and deep learning. Neural networks that process solutions as a brain would do, have been used successfully to classify cardiac abnormalities. Singh and colleagues<sup>17</sup> developed a neural network-based system called the effective heart disease prediction system that uses 15 medical parameters such as age, sex, blood pressure, cholesterol, and obesity to predict the likelihood of patients getting heart diseases. Recent machine learning studies in cardiac imaging have made significant progress in autointerpretation and

autoquantification in echocardiography, single-photon emission computed tomography, and cardiac magnetic resonance imaging (MRI). Our hospital has deployed a Food and Drug Administration-approved cloud-based deep learning platform (Arterys; Arterys Inc, San Francisco, Calif) to accelerate the clinical workflows in cardiac MRI and increase access to cardiac MRI and cardiac care in general. DeepVentricle (Arterys Inc), a deep-learning application for cardiac MRI images, received Food and Drug Administration clearance for clinical use.<sup>18</sup> Deep learning has also been used to predict outcomes in heart failure<sup>19</sup> and to identify out-of-hospital cardiac arrest in emergency telephone calls in Denmark.<sup>20</sup> A network model using an AI-enabled electrocardiogram was successful in screening patients for asymptomatic left ventricle dysfunction.<sup>21</sup>

The integration of AI technology and biosensors with the wireless capabilities through Bluetooth, Wi-Fi, and global positioning systems have led to the development of point-of-care (POC) diagnosis. POC, which represents fast, cheap, and effective processes to diagnose conditions by bringing a health expert or laboratory to a patient's home, has a huge influence on the quality of care and health care costs in developing countries. Along with the advancements in digitalization and the development of user interface devices such as smartphones and smartwatches, microfluidics-based POCs can have a profound influence on global cardiovascular and thoracic health and on the ability to process massive health data streams. Steinhubl and colleagues<sup>22</sup> developed and validated a portable, deployable system for continuous vital sign monitoring using a multiparametric wearable sensor and personalized analytics in an Ebola treatment center.<sup>22</sup>

Despite the huge recent progress in the field of wireless monitoring and AI, there are still some barriers that limit the wider clinical adoption of such technologies in medicine in general and in cardiothoracic surgery. Most of the current clinical decision support technologies based on AI and sensors use data related to a specific disease or specific medical knowledge and therefore can analyze the collected data from a small dataset only. Further improvement in scalability and wider integration is a challenge for the future of AI and wireless monitoring in cardiothoracic surgery. The next generation of wearable monitoring systems will need to integrate real-time machine learning techniques into the hardware or in the cloud computing platforms for real-time processing. Other current limitations and challenges of AI in cardiothoracic surgery include the need for extensive data labeled by humans, better data sharing across multiple institutions and potentially across nations, full transparency of data and AI algorithms, the implementation of a specific regulatory framework for AI applications in medicine (the Food and Drug Administration has recently defined a new category called Software as Medical Device (the regulatory pathway for which still needs to be updated),

full data standardization and integration into existing clinical workflows, and probably some effort in educating the medical community in computer science and health informatics.<sup>10</sup> Finally, our community will also need to face clinical acceptance challenges. Cardiothoracic physicians and surgeons will have to consider wireless monitoring systems not only as systems that can collect in a flexible and integrated way more data, but also—and more importantly—as a new technology that can engage the patient and the care team. User-engagement and user-interaction of patients for wearable technologies will ultimately increase the quality of life of our patients.

Cardiovascular surgery is well suited to use wireless monitoring technologies and AI methods for a smart analysis of continuous and massive data streams in this new era of wearable sensors. The logical next step in the application of wireless monitoring systems as platforms of AI in cardiothoracic surgery will be to integrate health big data into a medical Internet of things between medical devices and global analytic systems that would improve outcomes in the era of personalized medicine. AI will not replace cardiothoracic surgeons, but it is important that cardiothoracic surgeon-based multidisciplinary teams learn how to use AI to support real-time clinical decision making, improve outcomes, and decrease health care costs in cardiothoracic surgery to bring on the era of precision cardiovascular medicine and cardiothoracic surgery in developed and developing countries. The new Comprehensive American Association for Thoracic Surgery Quality Program includes machine learning and AI technology for automated data collection and real-time data analysis. In an ideal world, cardiothoracic surgeons would need to understand the construction of algorithms; comprehend the datasets underlying their outputs; and, importantly, understand their limitations. Otherwise, our specialty would miss the boat of AI-driven personalized medicine. As the American College of Radiology has done with the creation of the Data Science Institute, our community and our learned societies should also create a task force committee to deal specifically with AI implementation in our specialty.

### Conflict of Interest Statement

Authors have nothing to disclose with regard to commercial support.

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