Artificial Intelligence and its role in surgical care in low-income and middle-income countries

The barriers that prevent access to safe, affordable, and timely surgical care for 5 billion people are myriad, including shortfalls in workforce, infrastructure, and financing. These barriers mainly affect health systems in low-income and middle-income countries. In many high-income countries, artificial intelligence (AI) is viewed as a promising tool for transforming health systems. AI has a role to play in optimising health systems and supporting clinical judgement, because it can be used to search for patterns and insights across a patient population when human cognition alone is limited. However, is AI a luxury in low-resource settings, or a required tool? Low-income and middle-income countries are a heterogeneous group of countries when it comes to data and technological expertise. Countries such as Brazil, China, India, Turkey, and South Africa have large datasets at the institutional and national levels and have the technological capacity to implement the technology. Exploring the possible use of AI could be considered a distraction, especially when major barriers to health-care delivery exist, but we argue that precisely because of these barriers, AI presents an exciting opportunity for some low-income and middle-income countries. We believe that the potential of AI to build more robust surgical systems lies in appropriately applying it to health system processes, to augment clinical judgment.

In 2015, WHO member states adopted a resolution that emphasised the crucial role of surgery in Universal Health Coverage. Surgically treatable conditions contribute to more deaths each year than HIV, tuberculosis, and malaria combined (appendix)—a burden inequitably borne by low-income and middle-income countries. AI tools could help augment clinical judgment regarding patients and will probably eventually improve surgical care through stronger surgical diagnostics, prognostics, and therapeutics. However, for low-income and middle-income countries, we believe that AI tools should be developed to target the most substantial factor limiting surgical care: weak health systems with severe resource shortages and operational challenges, all of which undermine patient-level surgical care.

The core problems in many low-income and middle-income countries are operational, managerial, and process challenges that reflect faults in the surgical system, rather than poor decision making by clinicians. Faulty supply chains result in inadequate surgical supplies; poor infrastructure—for example, electricity blackouts—causes delays in operating theatre lists; insufficient workforce foments physician burnout, inattention, and clinical errors; and weak governance and management results in impaired service delivery and overall institutional decay.

Ineffective management of processes can be made more efficient within this realm of system function through AI systematically applied to answer questions within the domains of the National Surgical, Obstetric, and Anesthesia Planning (NSOAP) framework. Low-income and middle-income countries have implemented NSOAPs to develop country-specific strategies to improve their surgical system within six functional domains of a health system—governance, financing, workforce, infrastructure, service delivery, and information management. NSOAPs are integrated into country national health strategic plans and within the other strategic health objectives of the Ministry of Health. For each country, data drives strategic decisions within each NSOAP domain, to which AI can be applied to data to answer process-related questions and reveal inferences that help policy makers and administrators advance surgical systems. The application of AI could overcome bureaucratic inefficiency for more efficient surgical system development in these countries, helping to optimise the production, distribution, and use of the health workforce and infrastructure; allocate system resources more efficiently; and streamline care pathways and supply chains.

However, how can the issue of low-quality data in low-income and middle-income countries be addressed? With regards to data, not all low-income and middle-income countries are the same. Many countries, including South Africa, have large sets of data that pertain to both the health system and the broader context that together influence health service delivery at the national and sub-national levels.
Countries with targeted national programmes have rich datasets to which AI could be applied to help policy makers gain insights into the provinces and challenges that should be prioritised. In addition to government data, dedicated networks of health-care providers offer specialised surgical care with comprehensive data repositories in both the private and public sectors. With appropriate data cleaning, rigorous coding, and transfer from one format to another to produce reliable and interoperable databases, growing surgical systems can leverage the large datasets they already possess.

Most data in low-income and middle-income countries are not of low quality—they are more frequently asymmetric, asynchronous, varied in type, and spread across locations. These datasets are dormant and underutilised in these countries. Expert-driven AI using smaller data sets that are combined—for example, at the institutional level—can be equally as powerful as large amounts of data. Data scientists working closely with clinicians have already applied this approach in AI to address specific clinical questions. Experts in health service delivery in low-income and middle-income countries can navigate asynchronous and asymmetric data sets through different applications of AI instead of relying only on bottom-up methodologies, although this has not yet been applied to health systems to answer questions on the inputs and outputs that determine the state of their health system.

Developing transparent AI is possible through leveraging a combination of small data sets. When developers and experts are aware of the algorithms, its biases, and the results produced at each step in the application process, the AI algorithm becomes explainable and therefore minimises the ethical and functional issues caused by blind results. Although the method holds promise, AI is not a panacea for improved surgical care. Broader challenges affecting AI policy include concerns around employment; ethics; privacy; and whether countries ought to immediately invest in other proven, cost-effective interventions before seeking out AI solutions. More specifically, regulatory and ethics boards will be needed to uphold the principles of transparency, accountability, privacy, and fairness in the use of data. This will require a careful assessment of both the challenges and potential benefit at institutional and national levels. Although the return on investment is unclear, the magnitude of the potential impact warrants the development of a receptive environment for AI adoption. This entails evaluating the AI innovation itself (AI utilised via the NSOAP framework), the adoption system (including stakeholders), and the broader health system context (appendix). The adoption system must encompass individuals and institutions that implement AI within the health system and those entities that influence or create the AI technology itself, each of which is crucial for successful adoption and scale-up.

The potential for AI to improve access to effective and efficient surgical care in low-income and middle-income countries could be substantial. Urgent action is needed to develop the required technical skills for appropriate AI technologies and to create a receptive environment to test and scale AI. These countries must nurture local talent, bringing together a triad of AI developers, policy makers and clinicians, to understand the potential of AI that leverages asynchronous data sets; improve the pooling of data; develop context-appropriate regulatory and ethical frameworks; and apply appropriate AI technologies to answer questions within the domains of a surgical system. Failing to do so will almost guarantee the passive transfer of clinical AI tools to low-income and middle-income countries not ready to adopt and implement them in the contextual reality of a weak health system. Through a fair and inclusive process and method of analysis framed by NSOAPs, these countries could make substantial improvements in the application of AI to help expand surgical services to those who require it the most.

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SA declares patents pending in relation to software unrelated to the submitted work.

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