

TITLE PAGE

Title: Bridging the Global Digital Health Divide for Cardiovascular Disease

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Bridging the Global Digital Health Divide for Cardiovascular Disease

“Big data” approaches have been lauded as gamechangers in healthcare. Exponential growth of telecommunications and mobile phone ownership have presented new possibilities for digital health (use of data to drive healthcare), e-health (use of electronic processes in healthcare) and m-health (use of mobile technologies in healthcare). From machine learning and natural language processing to genomics and metabolomics, advanced analytics are being developed to improve health outcomes.

Health inequalities are well-documented within and across countries, and the role of social determinants is increasingly recognized as an important factor driving these differences. Could digital technologies and their associated healthcare strategies improve these health inequalities by making information and expertise more scaleable and widely available? Or will they perpetuate or even worsen these widespread differences?

Cardiovascular diseases (CVD), the cause of greatest morbidity and mortality worldwide, are the ideal lens through which to explore these issues and the future of global health in the era of digital health. According to the Global Burden of Disease (GBD) Study(1), which celebrated its 20th anniversary in October, CVD disproportionately affects low- and middle-income countries (LMICs) but technologies are widely transforming societal trends across many LMICs. In this article, the potential associations between digital health and inequalities in CVD are reviewed.

Inequalities in CVD

There have been several calls for greater attention and action for the CVD epidemic, recognising the disparities between countries and within countries at every stage of the patient journey. In terms of diagnosis, individuals from lower socioeconomic status (SES) and from LMICs, have less access to screening programmes and testing, whether laboratory, imaging, or interventional-based. Preventive strategies, from lifestyle to medical interventions, are less likely to be implemented in these settings. Evidence-based treatment, including drugs and invasive therapies such as surgery, are less widely available and less likely to be recommended or prescribed by health professionals in LMICs. Moreover, adherence and persistence to drugs are lower in

low-income settings. Social gradients also exist for the risk factors for CVD. Any strategy to tackle health inequalities (including big data approaches) must consider these issues to avoid inadvertently creating and worsening health gaps (2).

It is widely acknowledged that the volume, variety, velocity, veracity and value of data have increased to the extent that new ways of practising healthcare are not only possible, but necessary. The role of big data technologies, techniques and technicalities in health inequities in CVD will be examined (Box 1).

Technologies

E-health approaches have not necessarily included “hard-to-reach” populations. M-health is the most widely used big data technology in research in LMICs(3), but m-health and e-health tend to be implemented in certain diseases with specific applications and not in integrated patient management. Genomics and applications of -omics have not been widely translated or available for care even in high-income countries, and are unlikely to be applicable to many LMIC health systems, where even basic epidemiology is poorly characterised, as illustrated by the case of diabetes in sub-Saharan Africa(4). There are huge inequities in capacity to conduct genomic research, with concentration of funding, expertise and resources in centres which may not be representative of the majority of the disease burden(5). A consequence could be a focus on research, whether basic or translational science, which may not be applicable to the populations most in need of change in health system approaches. There is also optimism about the impact of wearables on management of CVD. However, low socioeconomic status (SES) individuals need to be included in research and practice, otherwise there is potential to divert limited healthcare resources away from the individuals who need them most; an effect which would be heightened in LMICs.

Relatively little research concerning CVD (among other non-communicable diseases) in LMICs has been done to-date(6), including digital technologies. The reasons are complex and multifactorial, but include financial resource, human capacity, lack of research culture and inattention to non-communicable diseases in LMICs. The main consequence is the poor generalisability and applicability of research to the countries where the majority of the CVD burden is seated. To test the transformational potential

of big data technologies, research must be done in these settings. The Precision Medicine Initiative in the United States has focused on “precision” and “personalisation”, but perhaps at the expense of the population. Even in the US, there is potential to increase inequalities due to lack of wide availability of universal basic healthcare coverage, let alone detailed genomic and other -omic testing. The situation is magnified when we consider the world’s poorest populations.

Even in domains where research is being conducted in digital health (e.g. SMS to improve drug adherence for secondary prevention of CVD), there is insufficient evidence to recommend large-scale roll-out and more data is required from LMICs(7). Overall, the evidence base and the culture of evaluation in health informatics needs to be greatly strengthened, particularly in LMICs. Large sums of money are being spent in Europe and North America on electronic health records (EHR) but often without evidence to support impact on outcomes and/or quality of care. Implementation must include evaluation of impact on health inequalities. In LMICs, the ramifications of poor evaluation are greater due to constrained financial, infrastructural and human resources.

Three shifts are required in culture. First, local capacity in data science needs to be increased alongside calls for more health professionals so that local datasets are sustainably produced and applied. Second, patient-centred and problem-based uses of technology work better than finding problems to “fit” the technology (technology-centred), and therefore the health system and research needs of LMICs must be prioritised and addressed with technology as a facilitator. Third, big data and technology have to be considered in the context of the health system in LMICs and not for isolated applications.

Techniques

Machine learning and analytics are potentially useful but not widely available or applied in LMICs. Without big data analytics, the health system will be potentially “data-rich but knowledge-poor”. The rate-limiting steps are more likely in computing and human capacity, as well as quality and scale of collected healthcare data. Research evaluating and implementing analytic strategies must consider how to include low-income individuals and settings. Otherwise, in one world, we will move

towards artificial intelligence and augmented intelligence, while another world struggles with basic data analysis and biased algorithms derived from training datasets which are unrepresentative of the populations they are eventually used in.

The big data approach could lead to health data that are aggregated automatically, with little effort and decreasing cost(8). Registries and data-driven quality improvement are possible in LMICs in CVD(9), but a major limitation is the lack of real-time data currently collected and monitored for CVD in many settings. Therefore, data for research occurs in a totally different silo to care delivery with resulting waste. The human and technology capacity for data analyses is currently concentrated in affluent settings rather than where the burden of CVD lies(10).

The three strategies for techniques are similar to those for technologies: (1) improve local capacity in advanced data analytics and local datasets; (2) a shift of motivation and emphasis from showcasing machine learning to solving pressing healthcare problems where data analytics may help; and (3) consideration of applications in a holistic and a system perspective. For example, the high profile criticism of “Watson and Oncology”, IBM’s initiative to apply machine learning to cancer management, has received criticism(11) which may be quelled by these strategies that focus on expansion to real-world challenges of improving access to cancer drugs in developing countries(12).

Technicalities

The most disenfranchised people in any society are least likely to have access to digital health technologies, as with other aspects of healthcare. Moreover, they are least likely to have education and knowledge to use these technologies, and may be more vulnerable to biased evidence, especially with direct-to-consumer advertisement and sales. The digital health industry has not capitalised on the “fortune at the bottom of the pyramid”(13). Whether wearables or apps, the target population is neither low-income individuals, nor low-income countries. If this trend changes, there can be real impact on global health and profits to boot.

The digital revolution has potential to empower patients in their own care, but there is no country where patients yet have full access to their seamless EHRs. Interoperability

standards will accelerate healthcare towards this vision, but at the moment, the poorest patients and the poorest countries face the least patient-centred care, where digital approaches are currently not being optimally used to change healthcare delivery. Concerns about data and cyber-security, and legal frameworks around data sharing will need to be addressed for truly patient-centred digital healthcare to be a reality.

The eleventh version of the WHO International Classification of Diseases (ICD) is expected in 2018. In the EHR era, ontologies such as SNOMED-CT (Systematized Nomenclature of Medicine-Clinical Terms) and FHIR (Fast Healthcare Interoperability Resources) will be increasingly used in high-income countries to enable greater interoperability of healthcare data, and consequently greater opportunities to employ big data analytics for patient benefit will ensue. However, even ICD-10 is variably used in the poorest settings, and therefore, large-scale, representative, up-to-date data poses challenges in many countries, limiting the scalability of quality improvement(14). Again, capacity and training in clinical ontologies, which are increasingly open-source, will aid implementation.

Consensus clinical practice guidelines are generally developed in high-income countries and not LMICs, partly due to lack of evidence from the latter. These countries therefore often develop health system guidance for digital technologies on the basis of data which may not be relevant to their own populations, since availability, accessibility and usability differ within and between countries. If local research and practice data are properly curated, there will be major opportunities to develop, monitor and improve adoption of locally relevant guidelines.

These technicalities can to be addressed by: (1) urgent development of international consensus, open-source, inter-operable ontologies, standards and guidelines for evaluation; (2) North-South partnerships which leverage expertise in high-income countries in technologies and techniques to populations in LMICs; (3) detailed modelling of the health impact of poor access to digital health technologies.

Next Steps

There are opportunities and justified excitement about applications of technology to healthcare. However, there is also a history, perhaps more in CVD than in other branches of medicine, where hype and a clamour for early adoption can sometimes come at the expense of medical errors and patient safety. If global health inequalities may be created by such strategies, the stakes are even higher, and there is therefore a need for proper evaluation of new technologies, in terms of effectiveness, cost-effectiveness and value to public health. In science, evidence and care, an integrated approach is needed at planning, design and implementation phases. Examples of good practice must be gathered and should be used to strengthen and cement the potential of digital health technologies to democratise healthcare.

Digital solutions, like any area of healthcare, will benefit from being (i) locally- rather than externally-driven; (ii) patient- rather than technology-centred; (iii) driven by science, evidence and care(15); and (iv) evaluated not just implemented. Big data approaches are enablers but not an end in themselves, and they must not be an expensive distraction for health systems – particularly those working in environments with existing resource constraints.

FIGURES AND TABLES

<p><u>Technology</u></p> <p>Telecommunications Electronic health records Genomics and -omics Drugs and treatments Diagnostics</p> <p><u>Techniques</u></p> <p>Machine learning Natural language processing Artificial intelligence Intelligence augmentation Deep learning</p> <p><u>Technicalities</u></p> <p>Privacy Confidentiality Ethics and law Interoperability Trust Patient-centredness</p>
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Box 1. A framework for big data approaches in healthcare

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