OPEN LETTER

New technologies to improve healthcare in low- and middle-income countries: Global Grand Challenges satellite event, Oxford University Clinical Research Unit, Ho Chi Minh City, 17th-18th September 2019 [version 1; peer review: 1 approved, 1 approved with reservations]

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Abstract
We report the outputs of a satellite event in Ho Chi Minh City, Vietnam, organized as part of the “2nd Global Grand Challenges of Engineering Summit”. The event considered challenges and potential solutions for improving low- and middle-income country (LMIC) healthcare systems, with particular reference to critical care. Participants from key regional and local stakeholders in healthcare and engineering discussed how new advances in technology, especially in the field of Artificial Intelligence, could be of potential benefit. This article summarizes the perspectives and conclusions of a group of key stakeholders from LMICs across South and South East Asia.

Keywords
LMIC, healthcare, machine learning, artificial intelligence, technology, engineering

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Introduction

In September 2019, The UK, US and Chinese academies of engineering co-hosted the 2nd Global Grand Challenges Summit in London. This event, inspired by the ‘14 Grand Challenges of Engineering’ involved engineers, researchers, innovators, entrepreneurs, and policymakers from around the world to discuss the theme ‘Engineering in an Unpredictable World’. As part of the summit, satellite events were held in India, Kenya, Mexico, Thailand, Uganda and Vietnam to discuss globally relevant topics related to the principle theme. In this report, we summarize the outputs of the Vietnamese event, which brought together key regional and local stakeholders in healthcare and engineering to discuss challenges and potential benefits of introducing new technologies to improve healthcare in low- and middle-income countries (LMICs).

Care quality in low- and middle-income country healthcare systems

Healthcare systems in many LMICs have undoubtedly improved over the last few decades. Areas such as maternal health and preventative medicine have benefited from a sustained drive to implement universal standards of care. Nevertheless, a recent report by the Lancet Global Health Commission estimated that almost 9 million lives and $1.6 trillion in productivity are lost each year as a result of poor quality medical care, the majority of which occurs in LMICs. Important limitations in diagnosis and treatment were identified as causes of this, in addition to systems-level problems with safety, integration and continuity of care. Overall quality of care was worst in vulnerable groups, such as the low-income groups, and those with stigmatized conditions.

The Lancet Commission argues that providing any health system that is not of high quality is unethical. However, in improving care quality, LMIC systems face many challenges, particularly with regard to critical illness, where providing healthcare is most complex, requiring highly-trained staff and expensive equipment for diagnostics and treatment.

This satellite event focused on the provision of high-quality care to critically ill patients and enabled a wide variety of engineering and healthcare stakeholders from the region to share perspectives on the potential for new technologies to improve health care and particularly critical care in LMIC settings.

Challenges to providing high quality care of critically ill patients in South and Southeast Asia

Access to care

In many LMICs, there is wide variation in access to healthcare services, and particularly large differences between care available to urban and rural communities. In critical illness, where rapid assessment and treatment are necessary, ensuring timely access to services for remote communities is a particular challenge. Even if there are rural health stations, staff may often have limited medical training and few options to safely transfer their patients to larger centres.

Appropriate diagnosis and treatment

Timely identification of critical illness and prompt implementation of treatment are vital in improving outcome in seriously ill individuals. Indeed, delayed diagnosis and slow initiation of treatment were both identified as the main reasons for poor quality of care by the Lancet Care Quality Commission. However, there are important contextual differences between LMICs and high-income settings, which necessitate innovative solutions to these challenges. For example, the causes of critical illness themselves are often different. In low-income countries, more than half of all deaths are due to maternal causes, nutritional deficiencies or communicable diseases compared to just 7% in high-income settings. This means diagnosis may often require more highly developed laboratory infrastructure and equipment in LMICs. Performing and evaluating diagnostic tests is time-consuming and requires further expertise. In almost all critical illness, once a diagnosis has been reached, treatment requires expensive equipment and careful monitoring to assess response to treatment and anticipate complications early. Whilst these may be available in LMICs, usually this is only in a limited number of specialist centres.

Health systems

LMIC health systems themselves are often different from those in high income settings and vary widely between countries. Increasingly, private providers provide critical illness care in LMICs, but standards are variable, and lack of comprehensive regulatory systems are a further challenge to implementation of high-quality care. Corruption within some healthcare systems has been cited as a major barrier to advancement and sustainability of quality care. An estimated 10–25% of global health spending is lost to corruption with unquantifiable impact on lives, communicable disease control or antimicrobial resistance. In most healthcare systems, about 70% of recurrent healthcare resources are spent on people, thus improving management, distribution and training can have a huge impact on healthcare quality and outcomes. As lack of knowledge amongst healthcare providers has been identified as a factor in itself preventing further development, improving training and knowledge should be a priority.

Cost of care

Critical care is costly due to the expensive treatments, sophisticated equipment and labour-intensive care required. Although healthcare coverage is increasing, in LMICs, many of these expenses are still passed directly as out-of-pocket costs to patients and their families. Currently about 100 million people are pushed into extreme poverty every year as a result of out-of-pocket medical costs. Additionally, many survivors are left with long-term disability which, in addition to costs of hospitalization, puts huge economic strain on families and communities.

Until now, intensive care units (ICUs) in LMICs have adopted similar models of care used in high income settings. However, the associated requirement for staff, equipment and
training is limiting if not prohibitive in most LMICs. Recent advances in engineering and technology, however, offer disruptive and novel alternatives to conventional care approaches.

**Recent advances in engineering and technology in the healthcare context**

Artificial Intelligence and Machine Learning: definitions and applications in healthcare

“Artificial Intelligence” (AI) refers to a field of computer science that accentuates the creation of intelligent machines that operate and react like humans. Such intelligence can be measured as how a machine produces responses that are indistinguishable from those of a human, as defined in the famous Turing Test (Figure 1). Early applications of AI in healthcare included expert systems, such as MYCIN, which assisted physicians in diagnosing blood infections, and DENDRAL, which aided chemists in determining the structure of organic molecules. Unfortunately, these expert systems, which relied on static sets of predefined rules, failed to address the dynamic and the probabilistic nature of medical phenomenon and human activities.

Recently, Machine Learning (ML) and Deep Learning (DL) have gained more attention as principled frameworks to implement AI in the age of Big Data. ML focuses more on improving the learning and the adaptation capability of machines and computer systems, given the continuing changes in its operational context, while DL introduces the neural network-based methodology where the learning process loosely emulates the information processing and distributed communication nodes in biological systems. Figure 2 puts AI, ML and DL into perspective, in which ML is a subfield of AI and DL is a specific methodology to improve the machine’s capacity to learn. ML is seeing gradual acceptance in the healthcare industry thanks to the capacity to analyze large sets of medical data in order to provide timely risk scores, precise resource allocation, and illness diagnosis. We review some major applications of AI and ML in improving the state-of-the-art in healthcare.

**Enhanced diagnosis.** AI, and DL in particular, are well-suited to pattern recognition and consequently are increasingly being used in interpretation of medical imaging. AI has been applied to MRI or CT imaging to look for early signs of cancer. For example, DL systems improved accuracy of lung cancer detection from low-dose CT and a ML system for MR breast cancer detection has received FDA approval. An important advantage of such systems is that, even if they perform similarly to an experienced radiologist, AI systems do not suffer from human fatigue – a potential cause of significant error in busy real-life situations. Figure 3 shows an example of a decision tree for diagnosing dengue.

**Decision support.** ML offers a framework for analysis of high-dimensional multimodal data, which is of particular advantage in examining complex biomedical data, and shows promise in improving detection, diagnosis, and monitoring of disease. Examples include startups such as Face2Gene, which combines facial recognition software with ML to help clinicians detect phenotypes that correlate with rare genetic diseases diagnose, and PathAI, which develops solution to help pathologists to make quicker and more accurate diagnoses and to help guide the right treatment for patients.
Figure 2. From Artificial Intelligence to Deep Learning.

Figure 3. A decision tree for dengue diagnostics[^1], reproduced under a Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original author and source are credited.
particular reference to sepsis, ML has been used to predict risk of sepsis, and using reinforcement learning has shown to be supportive in making difficult clinical decisions\textsuperscript{21}.

**Healthcare systems.** To aid healthcare management, ML applications can be developed to better identify and track chronic disease states and high-risk patients, design appropriate interventions, and reduce the number of hospital (re)admissions and claims. For example, BERG’s Interrogative Biology platform uses ML to identify the molecular basis of efficacy and adverse events in order to map disease with and treatments on oncology, neurology and other rare conditions\textsuperscript{22}. Such technology allows healthcare providers to take a more predictive approach rather than relying on trial-and-error.

**AI healthcare potential for critical care in LMICs.** The above mentioned AI systems have potential for significant impact in LMICs and address many of the barriers to providing high quality ICU care as identified by the event participants. Reducing the cost and expertise needed to monitor and treat critically ill patients is an important step not only in improving patient outcomes per se, but also in reducing inequalities in service provision. For example, the requirement for highly trained radiology staff can be reduced with DL systems. Busy and less well-trained staff can be supported by ML clinical decision support systems trained or optimized on relevant contextualized data. Furthermore, as more countries embrace electronic health records, data from these could be used either for clinical decision support or healthcare service optimization.

There are already examples from event participants of initiatives towards using these technologies in LMICs. In Vietnam, ML-based clinical decision support tools for tetanus and dengue are being developed as well as DL image-analysis in tuberculous meningitis and dengue as part of the VITAL (Vietnam ICU Technology Applications Laboratory) project.

Nevertheless, despite these potential advantages there remain several challenges and limitations to the adoption of AI technologies.

**Other emerging technologies in healthcare**
A new generation of information technologies including internet of things (IoTs), big data, cloud computing, and crowdsourcing, has transformed healthcare to become not only more efficient and more convenient, but also more personalized, yet deliverable at low-costs. For example, patients can be equipped with wearable devices to monitor their health constantly. Another example is that of low-cost mobile devices can be used as live source of data for monitoring spread of diseases. We identify several trends in which healthcare systems, and in particular critical care, in LMICs can benefit.

**Smart healthcare.** The smart healthcare model focuses on enabling real-time monitoring and immediate feedback of health data in order to deliver timely intervention of medical behavior. This model drives on the emergence of implantable/wearable devices, and smart health information platforms, which are connected by IoT technology. In particular, by integrating advanced sensors with high-performance microprocessors, wearable/implantable devices can continuously sense and monitor various physiological indicators of patients in an intelligent manner. The primary challenges for such systems are the limited battery life and maintaining a wireless network connection. Nevertheless, these technologies have shown to be improving comfort, while allowing sensed data to be combined with health information for better and more timely medical intervention.

Such technologies are particularly attractive in LMIC critical care settings where wearable monitoring systems may be much cheaper and even allow remote monitoring and clinical decision tools to support patient care in isolated communities. There are many other uses beyond the ICU. For example, the HCMC University of Technology and Education, Vietnam, demonstrated IoTs-based fall detection system, in which data collected from tri-axial accelerometer sensors and/or Kinect camera systems are transferred continuously to a cloud server for processing and detecting fall states\textsuperscript{23}. Fall detection and alerts can be sent to relatives or healthcare personnel for immediate medical assistance.

**Crowdsourcing and Big Data.** The concept of Crowdsourcing is to utilize the vast wealth of the public data to address social challenges including healthcare. For example, collecting and analyzing geolocation data from sensor-based and mobile devices allows monitoring the spread of diseases or levels of air pollution. Such capacity provides data to better understand causes of disease or can enable prevention and control. Other uses of crowdsourcing data with geolocation technologies include measuring and predicting network performance and coverage, monitoring emergency responders’ locations, tracking and backtracking disease carriers, and determining the effectiveness of quarantine and isolation.

In the critical care setting, large amounts of data are already routinely collected. In high income countries, national-level datasets are routinely gathered and are an invaluable resource for improving care quality and patient outcomes\textsuperscript{24}. Improving the quality of these data in LMICs would facilitate similar improvements in these countries. One example of a successful platform is in Sri Lanka where an ICU registry provides accurate real-time data for network partners using a cloud-based platform\textsuperscript{25}. This platform has been expanded and adopted by 9 countries as part of the CRIT CARE Asia network and adopted in over 44 sites across the region\textsuperscript{26}. Data from the registry allows quality improvement initiatives and audit, with demonstrable benefits in ICU patient outcomes\textsuperscript{1}.

**mHealth and telemedicine.** To date, smartphone ownership worldwide surpasses three billion and continues to grow in the next few years. In 2018, 48% of the global population were connected to the internet, and in LMICs mobile phones were the primary medium for this\textsuperscript{27}. South and Southeast Asia notably have amongst the world’s most affordable mobile internet
making these countries ideal sites for telemedicine services. In Vietnam 40% of the population are expected to have a smartphone by 2021. Such uptakes introduce the opportunity for mHealth, which focuses on improving the quality, efficiency and cost of healthcare via mobile platforms (see Figure 4). For example, a Cloud Telemedicine Information system, which consists of 100 devices to measure blood pressures and heart rate, can obtain live patient data to enable physicians to monitor patient’s blood pressures online\[28\]. This pilot cyber medical system, developed by the School of Biomedical Engineering of International University - Vietnam National Universities in Ho Chi Minh City, was successfully implemented in Binh Duong province (Vietnam) to test its efficacy. At the University of Medicine and Pharmacy Ho Chi Minh City, the Department of Family Medicine leads a project connecting family doctors and patients through telemedicine. Whilst currently these projects mainly focus on non-acute care, there is potential for similar technologies to be used to support ICU care in remote sites, or for patients after discharge from hospital.

Issues of adopting emerging technologies in healthcare

Despite much interest and enthusiasm in the technologies described above, the application in patient care has some limitations. Compared to traditional statistical analysis tools, many AI solutions (particularly DL) are considered ‘black boxes’ because outputs from AI models lack transparency and their rationale cannot be clearly explained. Using systems without clear biologically-plausible reasoning concerns many clinicians and regulators, especially if results have direct impact on patient care. There are critical questions around ethics, such as who is responsible for biases produced by AI. Finally, some practitioners consider AI a ‘hype’ because its recent success in other disciplines mainly due to the advent of brute-force computing power and the availability of more data. This sentiment generates caution in adopting AI and ML solutions in patient care and clinical practices. For mHealth and Big Data technologies there are concerns about data privacy and ownership. These issues may be particularly pertinent in LMIC settings where regulation and control may be lacking (Table 1).

Conclusions and next steps

Improving the provision and quality of critical care in South and Southeast Asia is a significant step towards achieving sustainable development goals and improving quality of life in the region. Heterogeneity of health systems, remote rural populations and cost of providing critical care are significant barriers to achieving this.

During the satellite event in Vietnam, we identified a range of technology advances that are beneficial to healthcare systems in LMICs. However, these may have significant disruptive potential to conventional models of care provision, but ultimately offers cost-effective solutions for LMICs in the region. This multidisciplinary meeting enabled professionals from relevant backgrounds to discuss key elements of this. Attendees made a firm commitment to maintaining working together in the future. This includes activities such as an international meeting in 2020, shared student projects and new research initiatives.

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Figure 4. mHealth infrastructure to support online monitoring of patient’s condition.
Table 1. Barriers to adoption of Artificial Intelligence (AI) in low- and middle-income country healthcare settings.

| Barriers to adoption of AI | |
|---------------------------|--|
| Poor quality of data or insufficient volume due to data, especially healthcare data, is often in inconsistent formats and consists of a lot of noise and bias | |
| Integration into existing clinical workflows | |
| Lack of skilled staff to lead and use AI because it is challenging to find and employ staffs with both healthcare background and Machine Learning skills | |
| No clear benefits from using AI because medical doctors often found AI outputs lack transparency to support medical decisions | |
| Regulatory and legal requirements | |

Data availability

No data is associated with this article.

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Reason for conference: focus on the provision of high-quality care to critically ill patients, enable various interested parties to provide input on potential for new technologies to improve health care (critical care specifically).

Challenges:

Access to care:

○ Rapid assessment and treatment are necessary
  In most developed countries, roughly 30% of critical care involves the management of non-acute patients requiring peri-operative care or patients with multiple comorbidities who are at higher risk of complications than other cohorts. I am unsure of the percentage in LMIC but it is probably reasonable to note that not all critical care patients are those that require rapid assessment and management plans.

○ ...for remote communities, it is a particular challenge
  This is also the case for developed countries, and we get around this issue by funding expensive and skill dense retrieval services. The point being that I don't think this is an issue that is unique to LMIC. What may be worth commenting on is that these countries (may?) have a higher proportion of their populations in rural settings, making the logistics of servicing the population more onerous. A retrieval logistics are very expensive!

○ Even if there are rural health stations, staff may often have limited medical training and few options to safely transfer their patients to larger centres
  Retrieval services are very expensive (as mentioned above) and they have a very specific process of acquiring and maintaining skills (the details of which I am not knowledgeable). In Australia, the process of stabilising a critical patient in a remote location is often left to a non-critical care trained person until the retrieval service arrives. This is a hypothesis, but for this small aspect of critical care service provision perhaps LMIC countries are not as challenged as in other aspects?
**Appropriate diagnosis and treatment:**
- In low-income countries, more than half of all deaths are due to maternal causes, nutritional deficiencies or communicable diseases compared to just 7% in high-income settings. This means diagnosis may often require more highly developed laboratory infrastructure and equipment in LMICs.

I am concerned about this statement. I don't understand how maternal, nutritional and communicable disease critical care presentations require more developed lab infrastructure than, for example, trauma or cardiothoracic presentations which are very prevalent in developed countries? I'm not sure how this is distinctive for LMIC. They probably require different lab infrastructure. It may be worth emphasising this point. Or it may be worth emphasising that lab infrastructure is not as widely available (if that is the case, which I assume it might be).

Likewise, diagnostic tests being time-consuming doesn't seem a key issue in LMIC where the cost and availability of labour may be less of an issue than it is in developed countries. I don't think that is a major barrier to good care being provided. It certainly requires further expertise. Overall, my best guess (having had no experience in such a setting I must emphasise this it is a guess) is that a significant challenge is the provision and maintenance of highly trained clinicians and laboratory scientists/technicians working in concert in a timely manner for critical unwell patients. That is expensive both materially and in terms of human capital and is difficult to achieve when the social structures within which hospitals exist are not sufficiently developed. This involves extremely complex manufacturing, engineering and educational supply chains (about which I know very little) but may warrant mentioning and/or exploring. I’d certainly be interested to learn more.

**Health systems:**
- Private health care provision is growing in LMIC, which is unregulated and standards vary. Additionally, they are prone to corruption (paraphrased). That seems very important but a broad description of the health systems as they currently exist in both settings and setting out a clear and concise description of the main differences and why that matter clinically in the critical care setting. A table would be intuitive and would help the reader. And there is no description of how/when/why corruption is more damaging to health systems in LMIC than in developed countries. I’d be very interested to know more.

- Recognising the need to invest in the development, training and knowledge of clinical staff (paraphrased). This seems logical and important, but this statement is true of all health systems, developed or otherwise. How are their distinctions in the LMIC setting? How can these be targeted? With specific discussion around emerging technologies?

**Costs of care:**
- Currently about 100 million people are pushed into extreme poverty every year as a result of out-of-pocket medical costs. Additionally, many survivors are left with long-term disability which, in addition to costs of hospitalization, puts huge economic strain on families and communities...

This statement is startling and is of huge importance. One hypothesis might be that private
health care provision (as mentioned above) is filling the gaps left by struggling publicly funded health systems – which is possibly a ‘double edged sword’? I.e. because these private health systems are financially motivated, insufficient consideration and regulation is being adopted to prevent serious financial hardship post critical care. This raises important ethical/moral questions that might be useful to touch on briefly. It would seem logical to think such families in need of critical care support (which is usually life threatening) are vulnerable to predatory providers whose primary motivation is making money. How can we quantify this? Use technology to defend against this? Perhaps this opens an interesting line of thought around financial/tax data being used to indirectly improve critical care provision in LMIC? I.e. Maybe we need to think outside the box a bit?

...Recent advances in engineering and technology, however, offer disruptive and novel alternatives to conventional care approaches. This is encouraging but the author has provided no further detail on the matter. What disruptive and novel alternatives? Having been informed on the above issue, this would be useful to know. Little of what follows in the paragraphs below explores that in great detail.

Recent advances in engineering/tech in Healthcare:

AI/ML definitions:
○ The descriptions of AI/ML are slightly confusing. These paragraphs are lacking a clear focus.

Enhanced Diagnosis:
○ The author makes the point that AI/DL are particularly well adapted to pattern matching in radiology (although the 2 examples are for cancer detection, which has little or no relevance to most critical care imaging requirements). They then go on to mention that this might be helpful in terms of negating fatigue. That does seem useful but wouldn't a major challenge in LMIC be accessing highly trained medical staff? As such, a more obvious advantage might be the use of AI systems that quickly and reliably interpret radiological images in place of a doctor/under the remote supervision of a doctor (if indeed that AI can function at a similar level of accuracy). There are many caveats to that statement because the interpretation of an image also requires an understanding of the clinical context. This is particularly true in critical care, where the rapid evolution of pathologies need to be regularly reviewed, and forward and backward comparisons made to enable decision making. I would also guess that remote radiology might be highly applicable to LMIC where the availability of expertise might be limited? Figure 1 is also somewhat confusing.

Decision support:
○ As above, these two examples have little or no relevance to helping decision making in critical care. The example provided (Komorowski) is highly relevant and it might be helpful to expand on exactly what they did, which was extremely interesting, innovative and exciting. It was slightly limited in certain ways and expanding on the positives and negatives of this example might be useful.

Healthcare systems:
○ As above, examples not highly relevant to critical care. There are many applications of ML being used for the deteriorating patient (Churpek in particular). It might be worth mentioning those.
AI healthcare potential for critical care in LMICs:
The above-mentioned AI systems have potential for significant impact in LMICs and address many of the barriers to providing high quality ICU care as identified by the event participants.

In light of what has been mentioned above, this statement needs to be better reinforced. I don’t think the examples mentioned above demonstrably show potential to address the barriers to providing good critical care. Although I concede this might be open to interpretation. Regardless, I would also add that those barriers (described in the first section) have not been described sufficiently clearly and that would make a nice addition to the paper. Perhaps a table? E.g. Barriers to the provision of critical care in LMIC:

1. It’s very expensive – how expensive? What is the comparison? Where might savings be made? What are the potential advantages of LMIC?
2. It’s reliant on complex supply chains? Perhaps describe one or two as examples? Like a blood gas machine, a CT machine and an Infectious Diseases lab?
3. It’s reliant on highly trained personnel – what are the barriers here?
4. Retrieval is challenging.
5. Public Health Service provision is limited.
6. Private Health Service provision is patchy and ethically ambiguous – this seems very important. Are there data to further inform this point in the paper?

Other emerging technologies:

Smart healthcare:
- *Timely intervention of medical behaviour*
  This sentence is confusing. Perhaps try it another way. Wearables are still in the early stages but are evolving fast. Perhaps some critical care relevant examples in this paragraph. There is considerable work being done in Oxford on this. You mention trends where LMIC might benefit. Please describe them.

- *Such technologies are particularly attractive in LMIC critical care settings where wearable monitoring systems may be much cheaper.*
  Can you provide examples of the cost comparison? This would be informative and relevant.

- *...and even allow remote monitoring and clinical decision tools to support patient care in isolated communities.*
  This is an interesting point. The logistics of such an exercise would be very interesting to learn about. Perhaps consider expanding on this briefly.
  You then expand on non-critical care related research – this is not relevant to the remit of this paper.

Crowdsourcing and Big Data:
- Good points.

mHealth and telemedicine:
- Good points. However, critical care medicine is a particularly ‘hands on’ specialty making it difficult to extract benefit from telemedicine without careful planning. Was there anything
in the conference discussion around this point?

**Issues of adapting emerging tech into health care:**
- You have mentioned: 1. Black box issues 2. Lack of clinician ‘buy in’ 3. Ethics 4. Data privacy – each of these seem to have merit but my best guess is that these four issues are not the key rate-limiting-steps when it comes to adapting tech into the LMIC critical care setting.
- I hypothesise the following are at least as or more important: ongoing technical limitations, the real difficulties around merging data-driven algorithmic outputs with health care systems that are (essentially) run by people, data inaccuracy, data delay, software/hardware maintenance, lack of data science expertise. I hasten to add I am not an expert in the LMIC domain so these are just guesses.

**Conclusions:**
- The barriers you mention were not really mentioned above. I think the conclusion should be a brief synopsis of the above points followed by your subjective interpretation of what this means.

**Summary statement by the Reviewer:**
- Thanks for the opportunity to review this interesting and important paper. It is an important topic that requires the attention and resources of the international critical care community. I have made suggestions which may help the author but I hasten to add I am not an expert on LMIC critical care provision so please interpret these comments with that in mind. There are some grammatical issues that need to be addressed. The headings are helpful but I’d argue that the examples provided are often not relevant to critical care, and those that are not sufficiently explored. The overall format of the paper might be worth simplifying and the author may consider adding in a table or two to summarise the key points. It also gives the impression that the discussions were very broad but not specific. This seems reasonable, but it might be helpful to mention that in the paper.

**Is the rationale for the Open Letter provided in sufficient detail?**
- Partly

**Does the article adequately reference differing views and opinions?**
- Partly

**Are all factual statements correct, and are statements and arguments made adequately supported by citations?**
- Yes

**Is the Open Letter written in accessible language?**
- Partly

**Where applicable, are recommendations and next steps explained clearly for others to follow?**
- Partly
**Competing Interests:** No competing interests were disclosed.

**Reviewer Expertise:** The deteriorating ward patient

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard, however I have significant reservations, as outlined above.

C Louise Thwaites, Oxford University Clinical Research Unit, Ho Chi Minh City, Vietnam

The article is meant to reflect the proceedings of an event focused around LMICs rather than provide a comprehensive review of the field. Nevertheless, the comments have allowed us to include a high-income setting perspective into the article and many of the challenges faced by critical care services in LMICs are also present in resource-rich settings. We have reflected this in the second version of our article. Answering Specific points:

1. The reviewer raises an important point about the use of ICU beds for routine surgery or planned admissions. The participants however mainly wanted to discuss critically ill patients, not necessarily in ICU. We have clarified this by changing the sentence from critical illness to ‘critically ill patients when rapid access and treatment are necessary’.

2. Ensuring access to care in rural communities is challenging in all communities and the text has been modified. However we feel in resource restricted settings challenges are more pronounced. Regarding rural health stations, our meaning here is that in LMICs, many rural health stations are staffed by non-health professionals with no or limited medical (certainly not critical care training) and transfers are done by foot, taxi or at best ambulances, usually accompanied by relatives only. Our participants felt that these were indeed different to HIC services.

3. Our section about differences in diagnosis was not a clear and the reviewer correctly queries this. The statement and has been revised in line with the comment and our original meaning. The group was trying to convey that the necessary infrastructure was different.

4. The section regarding private healthcare and corruption was also not clearly written and we have rephrased it to convey our meaning, i.e. that health care systems are variable and therefore difficult to compare and that the increased use of private healthcare makes it difficult to institute or evaluate quality improvement. Again the reviewer has correctly noted that this is not necessarily different in LMICs. The section on corruption has been expanded, but the article by Garcia (citation number 5) provides an excellent summary of the impact of corruption from the perspective of somebody directly involved in LMIC health service provision.

5. Concerning staff and training, these of course are problems in all healthcare settings, but our group felt that the difference in LMICs is that there are less resources to start with, therefore less staff, and that these staff are also much less equally distributed. This has been clarified in the text and readers can refer further to the WHO report specifically on this
issue (citation number 6).

6. In many LMICs, private health providers are actively encouraged to develop to increase health system capacity. I am not aware of countries looking at the issues of financial hardship and many will rely on insurance companies to regulate cost of services. Generally private hospitals cater for more wealthy people with health insurance and it is not the private hospitals which are pushing people into poverty, sometimes the very poor will use them for convenience and speed. The approach in most countries is to aim for universal healthcare coverage. It is an interesting point that data may be useful to improve care and many countries are implementing electronic healthcare records which is very often driven by the need to provide medical insurance companies with accurate data. We have expanded the section on ‘big data’ to include this as a possibility.

7. We have expanded the sentence on potential roles of new technologies as an introduction to the latter sections.

8. The introductory paragraph on AI and ML have been altered. The first paragraph discusses AI as a field of study. The following paragraphs are on the application of AI in healthcare.

9. The enhanced diagnosis has been modified to include more ICU examples, but also note their limitations regarding LMIC application at present.

10. The decision support section has been expanded and further critical care examples included. Limitations regarding LMIC application are added.

11. Health systems in this section and our event, aimed to look at the larger scale health systems (mainly hospitals). Examples of critical care systems have been included in the above section. The value of ML applied to electronic health records and resource allocation/costs of ICU care has been added.

12. A table of barriers to critical care provision has been added.

13. Examples of smart healthcare systems have been expanded, although as this section is meant to be more broad and less focused on critical care this has been reflected in the examples. As there are many different examples, an exact cost comparison is not possible but an approximate percentage estimate has been added.

14. We have expanded on the potential application of remote monitoring. We leave the more broad examples of local applications in this document but included why the examples, for example the fall-monitoring systems, are still relevant to ICU populations.

15. The section on telemedicine in ICU has been expanded and clarified with ICU examples added.

16. Regarding barriers to AI, this was not meant to be a comprehensive list but reflected views of participants. We have included infrastructure in the table. The other points are
covered already in the table.

17. The conclusion represents the conclusion to the meeting. We have therefore expanded
and re-titled this section to address the comments and be more clear.

**Competing Interests:** None
Does the article adequately reference differing views and opinions?
Yes

Are all factual statements correct, and are statements and arguments made adequately supported by citations?
Yes

Is the Open Letter written in accessible language?
Yes

Where applicable, are recommendations and next steps explained clearly for others to follow?
Yes

**Competing Interests:** No competing interests were disclosed.

**Reviewer Expertise:** Development of medical technology.

I confirm that I have read this submission and believe that I have an appropriate level of expertise to confirm that it is of an acceptable scientific standard.

Author Response 23 Jul 2020

C Louise Thwaites, Oxford University Clinical Research Unit, Ho Chi Minh City, Vietnam

We have clarified Figure 1 to make it less confusing.
Unfortunately we did not as a group make any recommendations for future research. This would be a valuable component of any future meeting and is an excellent suggestion.
We have expanded the section about data security/ ethics in line with the comment.

**Competing Interests:** None