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Editorial

Man vs. machine? The future of emergency medical dispatching

The role of emergency medical dispatch (EMD) in out-of-hospital cardiac arrest is increasingly being recognized as an underutilized resource in a number of ways. From merely being the recipient of a bystander's call for an ambulance, we are recognizing that the EMD has a pivotal role in helping diagnose cardiac arrest, initiate resuscitation and support lay rescuers in optimizing resuscitation efforts.[1,2] As health care professionals they have access to increasing resources, and new technologies and innovations keep changing their role in the chain of survival.[3] Many EMD systems are now able to map out the nearest Automated External Defibrillators (AEDs), and some can even dispatch additional nearby volunteer lay rescuers to bring an AED to the caller. There is ongoing work to provide real-time video coaching to improve lay rescuer resuscitation, deliver AEDs by use of drones and develop technology to allow dispatchers to monitor real-time lay rescuer resuscitation quality.[4,5]

In this issue of Resuscitation, Blomberg and colleagues have ventured down yet another exciting path for emergency medical dispatch using machine learning to improve the recognition of cardiac arrest.[6] Their results are impressive, the machine learning network was better (72.5 vs. 84.1%) and faster (44 vs. 54 s) in recognizing cardiac arrest compared to their trained dispatchers, although at the cost of lower precision with lower specificity (97.1 vs. 98.8%) and lower positive predictive value (20.9 vs. 33.0%). As the authors recognize, there are systems that report even higher emergency medical dispatch recognition rates than that demonstrated by their machine learning network — but these are few and far between,[7–9] and any clinical decision support tool able to raise the bar well over 80% would be a welcome addition to most EMD systems.

The speed of recognizing cardiac arrest also deserves attention. Although to be fair, here the machine might have a slight technical advantage on the dispatcher. While the authors were able to determine exactly when the machine reached their predefined confidence level being "inside the head" of the machine, they were certainly not "inside the head" of the dispatchers. Time to recognition of cardiac arrest by the dispatchers was therefore defined as the dispatcher or caller verbally communicating the need for resuscitation or an AED, or explicitly stating that the patient appeared to be in cardiac arrest.[6] It is not unlikely that dispatchers occasionally recognized cardiac arrest without giving prompt verbal confirmation. For instance, any case where the caller would be considered unable or not ready to receive resuscitation instructions (language barrier, caller not in immediate vicinity, patient needing to be repositioned prior to resuscitation, perceived frailty of caller etc) would likely delay the verbal confirmation needed to pinpoint time to recognition without accurately reflecting delayed recognition by the dispatcher. The difficulty in defining the exact time point of dispatcher cardiac arrest recognition challenges both EMD research and quality improvement efforts.

The third objective of this study was exploring how machine learning performed differently compared to dispatchers. While very few arrests were only identified by dispatchers, there were some interesting differences in the arrests only identified by the machine that invites speculation. It is interesting that the machine outperforms the dispatcher where the caller witnesses the arrest.[6] One might speculate that a dispatcher might easily get distracted by the caller's description of the events leading up to the arrest while a machine might not. It is also encouraging that the machine seems to be able to recognize arrest in some of the cases where the dispatchers failed to explicitly clarify consciousness or breathing, factors previously been described to be important barriers to dispatcher recognition.[8,10–12] Regardless, identifying the sub-groups of cardiac arrest calls which the dispatchers are most likely to miss without additional help from the machine learning network, should increase the helpfulness and sophistication of the network, and has the potential to greatly improve overall performance. These subgroups could, however, vary largely between different EMD systems and perhaps also with time, and each system would likely need to continuously assess the networks performance.

The authors raise some important questions about how we would best implement this new technology into our EMD systems. Having completed a first step - a proof of concept, many questions remain. Perhaps most importantly, as the machine learning network has significantly lower specificity, it's warning of a possible cardiac arrest would likely prompt the dispatchers to activate cardiac arrest protocols more often than not, even when the dispatchers had not suspected the patient was in cardiac arrest. This over-triage might be within acceptable levels when taking into account the increased sensitivity — but it would likely result in increased utilization of limited pre-hospital resources. Additionally, as the authors also point out — it will be challenging to decide on a level of machine confidence.[6] Because although the end-result from the machine may be binary — cardiac arrest or no cardiac arrest, the likelihood of one prediction over the other will be a continuous assessment changing with time.

So the questions is not really man vs. machine, because the beauty of the proposed machine learning network is that "man" and "machine" would work in concert, that the machine learning network would provide additional support in the extremely challenging clinical decision making facing dispatchers every day. But with any new technology, comes the potential for unforeseen risk. Any machine learning network will only be as good as its training. They currently only operate within our pre-set parameters, meaning any bias or discriminations we are prone to as human beings will easily be transferred into our training algorithms. So exciting at this new avenue might be, it is important to remain vigilant and humble into any shortcomings we may not have foreseen. Although innovative businesses embrace new technology and constantly look to push boundaries, they have the luxury of time to review and reflect on their innovations, and perhaps choose to ignore their machine learning algorithms that consistently advise them against hiring women, or favoring anyone who has played high school lacrosse — our margins saving victims of cardiac arrest are infinitely smaller.

Conflicts of interest

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