Z-inspection® Use Case

On Assessing Trustworthy AI in Healthcare. Machine Learning as a Supportive Tool to Recognize Cardiac Arrest in Emergency Calls

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Use Case

On Assessing Trustworthy AI in Healthcare. Machine Learning as a Supportive Tool to Recognize Cardiac Arrest in Emergency Calls

Front. Hum. Dyn., Human and Artificial Collaboration for Medical Best Practices, 08 July 2021 |

Health-related emergency calls (112)

Image https://www.expatica.com/de/healthcare/healthcare-basics/emergency-numbers-in-germany-761525/

The problem

- In the last years, the Emergency Medical Dispatch Center of the City of Copenhagen **has failed to identify approximately 25% of cases of out-of-hospital cardiac arrest (OHCA),** the last quarter has only been recognized once the paramedics/ambulance arrives at the scene .

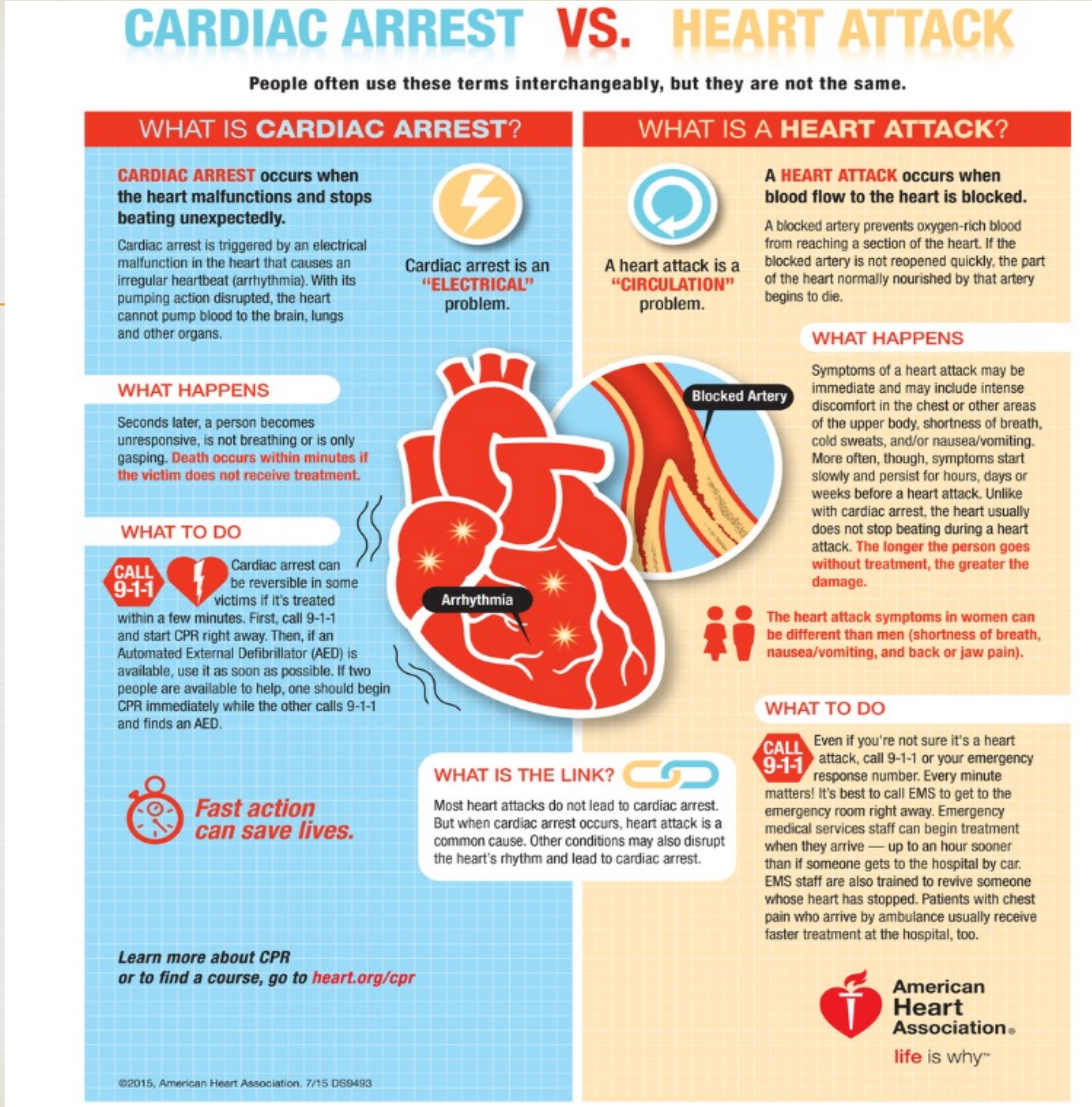

CARDIAC ARREST VS. HEART ATTACK
People often use these terms interchangeably, but they are not the same.
WHAT IS CARDIAC ARREST?
CARDIAC ARREST occurs when the heart malfunctions and stops beating unexpectedly.
Cardiac arrest is triggered by an electrical malfunction in the heart that causes an irregular heartbeat (arrhythmia). With its pumping action disrupted, the heart cannot pump blood to the brain, lungs and other organs.
Cardiac arrest is an "ELECTRICAL" problem.
WHAT HAPPENS
Seconds later, a person becomes unresponsive, is not breathing or is only gasping. Death occurs within minutes if the victim does not receive treatment.
WHAT TO DO
CALL 9-1-1
Cardiac arrest can be reversible in some victims if it's treated within a few minutes. First, call 9-1-1 and start CPR right away. Then, if an Automated External Defibrillator (AED) is available, use it as soon as possible. If two people are available to help, one should begin CPR immediately while the other calls 9-1-1 and finds an AED.
Arrhythmia
Fast action can save lives.
Learn more about CPR or to find a course, go to heart.org/cpr
©2015, American Heart Association. 7/15 DS9493
WHAT IS A HEART ATTACK?
A heart attack is a "CIRCULATION" problem.
A HEART ATTACK occurs when blood flow to the heart is blocked.
A blocked artery prevents oxygen-rich blood from reaching a section of the heart. If the blocked artery is not reopened quickly, the part of the heart normally nourished by that artery begins to die.
Blocked Artery
WHAT HAPPENS
Symptoms of a heart attack may be immediate and may include intense discomfort in the chest or other areas of the upper body, shortness of breath, cold sweats, and/or nausea/vomiting. More often, though, symptoms start slowly and persist for hours, days or weeks before a heart attack. Unlike with cardiac arrest, the heart usually does not stop beating during a heart attack. The longer the person goes without treatment, the greater the damage.
The heart attack symptoms in women can be different than men (shortness of breath, nausea/vomiting, and back or jaw pain).
WHAT TO DO
CALL 9-1-1
Even if you're not sure it's a heart attack, call 9-1-1 or your emergency response number. Every minute matters! It's best to call EMS to get to the emergency room right away. Emergency medical services staff can begin treatment when they arrive — up to an hour sooner than if someone gets to the hospital by car. EMS staff are also trained to revive someone whose heart has stopped. Patients with chest pain who arrive by ambulance usually receive faster treatment at the hospital, too.
WHAT IS THE LINK?
Most heart attacks do not lead to cardiac arrest. But when cardiac arrest occurs, heart attack is a common cause. Other conditions may also disrupt the heart's rhythm and lead to cardiac arrest.
American Heart Association.
life is why™

Image: CPR

The Problem (cont.)

- Therefore, the Emergency Medical Dispatch Center of **the City of Copenhagen loses the opportunity to provide the caller instructions for cardiopulmonary resuscitation (CPR), and hence, impair survival rates.**
- OHCA is a life-threatening condition that needs to be recognized rapidly by dispatchers, and recognition of OHCA by either a bystander or a dispatcher in the emergency medical dispatch center is a prerequisite for initiation of cardiopulmonary resuscitation (CPR).

Cardiopulmonary resuscitation (CPR)

Image :http://developafrika.org/compress-airways-breath-a-guide-to-performing-cardiopulmonary-resuscitation-cpr/?utm_source=ReviveOldPost&utm_medium=social&utm_campaign=ReviveOldPost

Liability

- Who is responsible is something goes wrong?
- Medical Dispatchers are liable.

The AI "solution"

- A team of medical doctors of the Emergency Medical Services Copenhagen, and the Department of Clinical Medicine, University of Copenhagen, Denmark worked together with a start-up and examined whether a **machine learning (ML) framework could be used to recognize out-of-hospital cardiac arrest (OHCA) by listening to the calls** made to the Emergency Medical Dispatch Center of the City of Copenhagen.

Context and processes, where the AI system is used

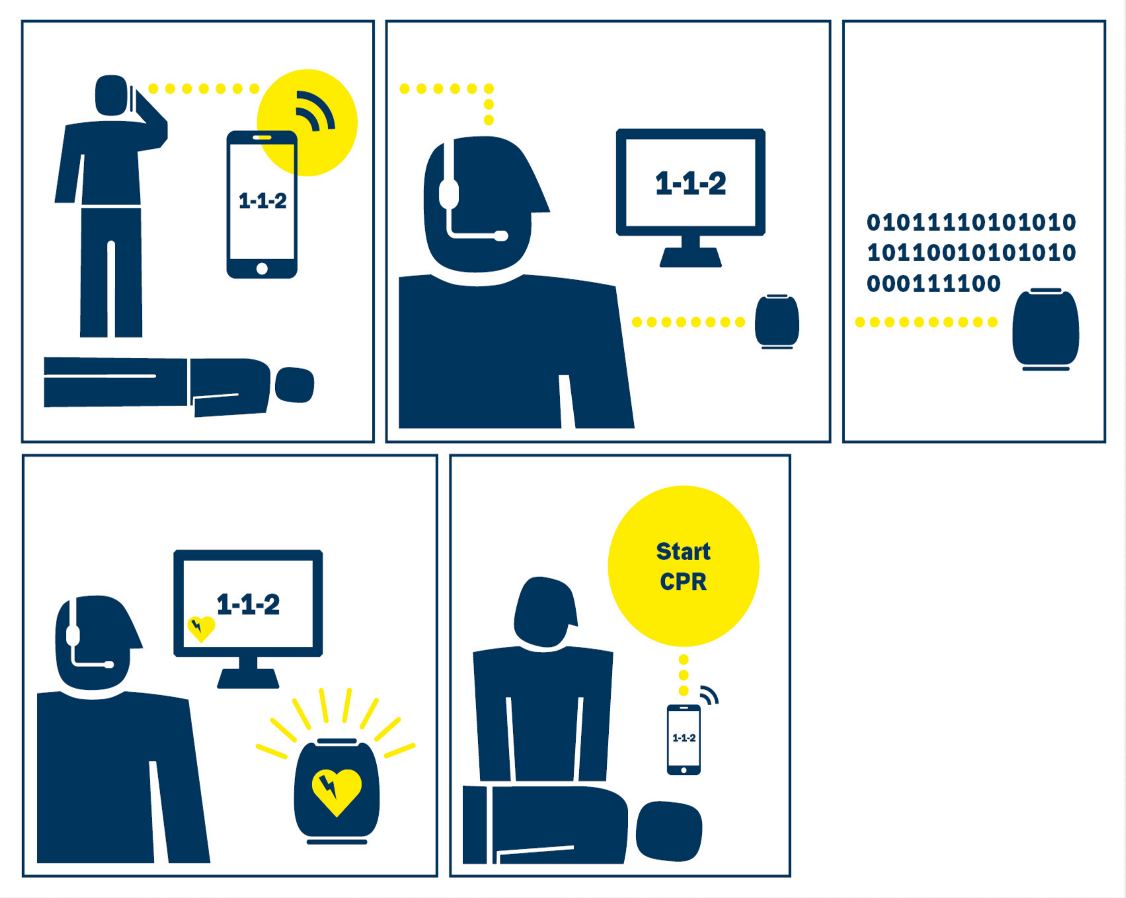


Figure . Ideal Case of Interaction between Bystander, Dispatcher, and the ML System. (with permission from Blomberg, S. N

Retrospective study

- The AI system **performed well in a retrospective study** (AI analyzed 108,607 emergency calls audio files in 2014)

Retrospective study

- The machine learning framework had a significantly **higher sensitivit**y (72.5% vs. 84.1%, p < 0.001) with **lower specificity** (98.8% vs. 97.3%, p < 0.001).
- The machine learning framework had a **lower positive predictive** value than dispatchers (20.9% vs. 33.0%, p < 0.001).
- **Time-to- recognition** was significantly shorter for the machine learning framework compared to the dispatchers (median 44 seconds vs. 54 s, p < 0.001).

- Source RESUSCITATION 138(2019)322–329 Published 2019

Randomized clinical trial

- In 2020 it was conducted a **randomized clinical** trial of 5242 emergency calls, a machine learning model listening to calls could alert the medical dispatchers in cases of suspected cardiac arrest.

Published January 2021, *JAMA Netw Open*. 2021;4(1):e2032320. doi:10.1001/jamanetworkopen.2020.32320

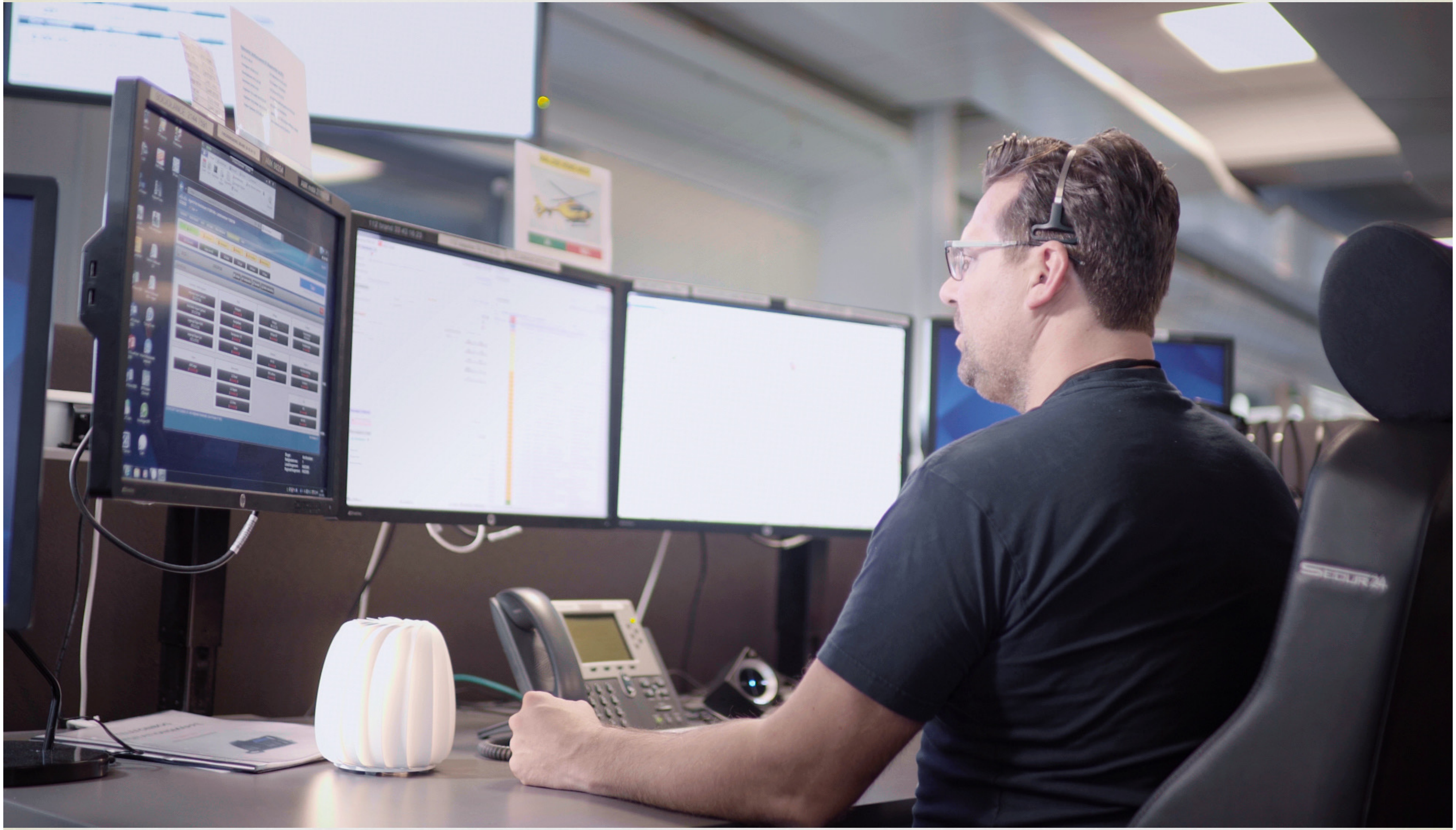
Randomized clinical trial (Cont.)

- **There was no significant improvement in recognition of out-of-hospital cardiac arrest during calls on which the model alerted dispatchers vs those on which it did not;** however, the machine learning model had higher sensitivity that dispatchers alone.

The AI system was put in production

- **The AI system was put into production during Fall 2020.**

- Note: A responsible person at the Emergency Medical Dispatch Center **authorized the use** of the AI system.



- https://cordis.europa.eu/project/id/823383/reporting

Motivation

- We agreed to conduct a *self-assessment* jointly by our team of independent experts together with the prime stakeholder of this use case.
- The main motivation of this work is to study if the rate of lives saved could be increased by using AI, and at the same time to identify ***how trustworthy is the use of the AI system*** assessed here, and to provide recommendations to key stakeholders.

Tensions in the evidence base

- There is **a tension** between:

- The conclusions from the **retrospective study** (Blomberg et al., 2019), indicating that **the ML framework performed better than emergency medical dispatchers** for identifying OHCA in emergency phone calls - and therefore with the expectation that the ML could play an important role as a decision support tool for emergency medical dispatchers- ,

Tensions in the evidence base

- and the results of **a randomized control trial** performed later (September 2018 – January 2020) (Blomberg et al., 2021), **which did not show any benefits in using the AI system in practice.**

Possible lack of trust

- For our assessment, it was important to find out **whether and how the ML system influences the interaction between the human actors,**
- i.e., how it influences the conversation between the caller/bystander and the dispatcher, the duration of the call, and the outcome, and why during the clinical trial the use of the AI system did not translate into improved cardiac arrest recognition by dispatchers (Blomberg et al. 2021).

Lack of Trust?

- Some possible hypotheses that needed to be verified:

- **The dispatcher possibly did not trust the cardiac arrest alert.** It might depend on how the system was introduced – how the well-known cognitive biases were presented/labeled – if the use of the system was labeled as a learning opportunity for the dispatcher, and not as a failure detection aid, that would disclose the incompetence of the dispatcher.

Lack of Trust?

- But it could be that **dispatchers did not sufficiently pay attention to the output of the machine**.
- It relates to the principle of ***human agency and oversight*** in trustworthy AI .
- Why exactly is this?

Lack of Trust?

- If one of the reasons why dispatchers are not following the system to the desired degree is that **they find the AI system to have too many false positives**, then this issue relates to the challenge of achieving a satisfactory interaction outcome between dispatchers and system.

Lack of Trust?

- Another tension concerns **whether dispatchers should be allowed to overrule a positive prediction made by the system and not just merely overrule a negative prediction by the system**.
- In particular, what exactly is the right interplay or form of interaction between system and human, given the goals of using the system and the documented performance of human and system?

Medical benefits – risks versus benefits

- *Possible risks and harm: false positives and false negatives*

- One of the biggest **risks** for this use case is **where a correct dispatcher would be overruled by an incorrect machine.**

Medical benefits – risks versus bene*fits*

- We could not find a justification for choosing a certain **balance between sensitivity and specificity.**

- **If *specificity* is too low,** CPR is started on people who do not need it and administered CPR over a longer period of time can break the rib cage. However, it is unlikely that CPR would be performed on a conscious patient for a longer time, as the patient probably would fight back against it.

Ethical tensions related to the design of the AI system

- ***Lack of explainability***

- The main issue here is that it is not apparent to the dispatchers how the system comes to its conclusions. **It is not transpa**rent to the dispatcher whether it is advisable to follow the system or not. Moreover, it is not transparent to the caller that an AI system is used in the process.

Diversity, non-discrimination, and fairness: possible bias, lack of fairness

- It was reported in one of the workshops that if the caller was not with the patient, such as in another room or in a car on their way to the patient, the AI system had more false negatives.
- **The same was found for people not speaking Danish or with a heavy dialect.**

Bias,Fairness

- For this use case, concepts such as “**bias**” and **“fairness”** are domain-specific and should be considered at various levels of abstractions (e.g., from the viewpoint of the healthcare actors down to the level of the ML model).

Bias, Fairness

- We look at possible bias in the use of the AI system. The AI system was only trained on Danish data, but the callers spoke more languages (i.e., English, German).
- **Here, there is a risk of bias, as the system brings disadvantages for some groups, such as non-Danish speaking callers, callers speaking dialects, etc.**

Discrimination

- When we looked at the **data used to train the ML model,** we observed that the dataset used to train the ML system was created by collecting data from the Copenhagen Emergency Medical Services from 2014.
- The AI system was tested with data from calls between September 1, 2018, and December 31, 2019. **It appears to be biased toward older males, with no data on race and ethnicity.**

Liability

- For this use case, a problem is the **responsibility and liability of the dispatcher.**
- **What are the possible legal liability implications for ignoring an alert coming from a ML system?**

- The consequences of refuse or acceptance of an alert are central.

Risk of de-skilling

- There is a need of justification of choice: in this field, **the risk of de-skilling is possible (technological delegation also in order not to be considered reliable for ignoring/refusing it);** we also need to think about the cultural level of a dispatcher and the ethical awareness of the consequences of his/her choice:
- How could he/she decide against the machine? Sometimes it could be easier to accept than to ignore/refuse for many reasons.

Risk of alert fatigue

- In the randomized clinical trial it was reported that less than one in five alerts were true positives.

- **Such low sensitivity might lead to alert fatigue, and in turn, ignoring true alerts.**

- "The term **alert fatigue** describes how busy workers (in the case of health care, clinicians) become desensitized to safety alerts, and as a result ignore or fail to respond appropriately to such warnings"
- Source: https://psnet.ahrq.gov/primer/alert-fatigue

The legal framework

- Since the AI system processes personal data, the **General Data Protection Regulation** (GDPR) applies, and the prime stakeholder must comply with its requirements.

- From a data protection perspective, **the prime stakeholder** of the use case is in charge of fulfilling the legal requirements.

- From a risk-based perspective, it would be desirable if the **developers** of the system would also be responsible as they implemented the AI system. **But the responsibility of the vendors or developers of a system is not a requirement of the GDPR.**

Societal and environmental well-being

- We consider here broader implications, such as additional costs that could arise from an increase in false positives by the AI/ML system, resulting in unnecessary call taker assisted CPRs, and dispatching ambulances when they are not necessary, and trade-offs, by detracting resources from other areas.

Example of mapping

- **Dispatcher Accept/Reject Prompt**

ID Ethical Issue: E1, Dispatcher Accept/Reject Prompt

- **Description:**

It is unclear whether the dispatcher should be advised or controlled by the AI, and it is unclear how the ultimate decision is made.

MAP TO ETHICAL Pillars/Requirements/Sub-requirements (closed vocabulary):

- Respect for Human Autonomy > Human Agency and Oversight > Human Agency and Autonomy.

NARRATIVE RESPONSE

- Importantly, any use of an AI system in the healthcare system needs to be accompanied by a clear definition of its use. In the current setting, it is unclear how the decision support tool, should be used by the dispatchers. Should they defer to the tool's decision (especially since the performance seems to surpass human capabilities)?
- And if they do not defer to the tool, do they need to justify the decision? We also need to take into account that the dispatchers in Denmark are highly trained professionals that will not easily defer to an automated tool without a certain level of clinical validation and trust in the system. Despite the fact that the dispatchers are the primary users, they were not involved in the system design.

ID Ethical Issue: E5, Potential Harm Resulting From Tool Performance

- **Description**

The tool's characteristic performance, such as a higher rate of false positives compared to human dispatchers, could adversely affect health outcomes for patients.

Map to Ethical Pillars/Requirements/Sub-Requirements (Closed Vocabulary)

- Prevention of Harm > Technical Robustness and Safety > Accuracy.

Narrative Response

- The algorithm did not appear to reduce the effectiveness of emergency dispatchers but also did not significantly improve it. The algorithm, in general, has a higher sensitivity but also leads to more false positives. There should be a firm decision on thresholds for false positive vs. false negatives. The risk of not doing CPR if someone needs CPR exceeds the risk of doing CPR if not needed. On the other hand, excessive false positives put a strain on healthcare resources by sending out ambulances and staff to false alarms. This potentially harms other patients in need of this resource. The gold standard to assess whether the tool is helpful for the given use case is to analyze its impact on outcome. Given, however, the low likelihood of survival from out of hospital cardiac arrest, there wasn't an analysis attempting to assess the impact on survival, as it would take years in a unicentric study.

ID Ethical Tension (Open Vocabulary): ET4

- Kind of tension: True dilemma.
- Trade-off: *Fairness vs. Accuracy.*
- Description: The algorithm is accurate on average but may systematically discriminate against specific minorities of callers and/or dispatchers due to ethnic and gender bias in the training data.

Recommendations to the key stakeholders

- The output of the assessment is a report containing recommendations to the key stakeholders. Such recommendations should be considered as a source of qualified information that help decision makers make good decisions, and that help the decision-making process for defining appropriate trade-offs. They would also help continue the discussion by engaging additional stakeholders in the decision-process.

Example of Recommendation

- *Recommendation 1*: **It is important to ensure that dispatchers understand the model predictions so that they can identify errors and detect biases that could discriminate against certain populations.**
- Here, the model is a statistical black-box, and the clinical trial conducted with the model showed an important lack of trust that had an impact on the outcome of the trial. An improvement to the model would include interpretable local approximations [such as SHAP (Lundberg and Lee, 2017)], which are easy for stakeholders to understand and provide different levels of interpretation for judging the relevance of an individual prediction. In our example, explanation may involve words that were more predictive, tone of voice, or breath sounds.

What to do with recommendations?

Monitoring