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**Can AI detect  
cardiac arrest  
before the  
dispatcher?**

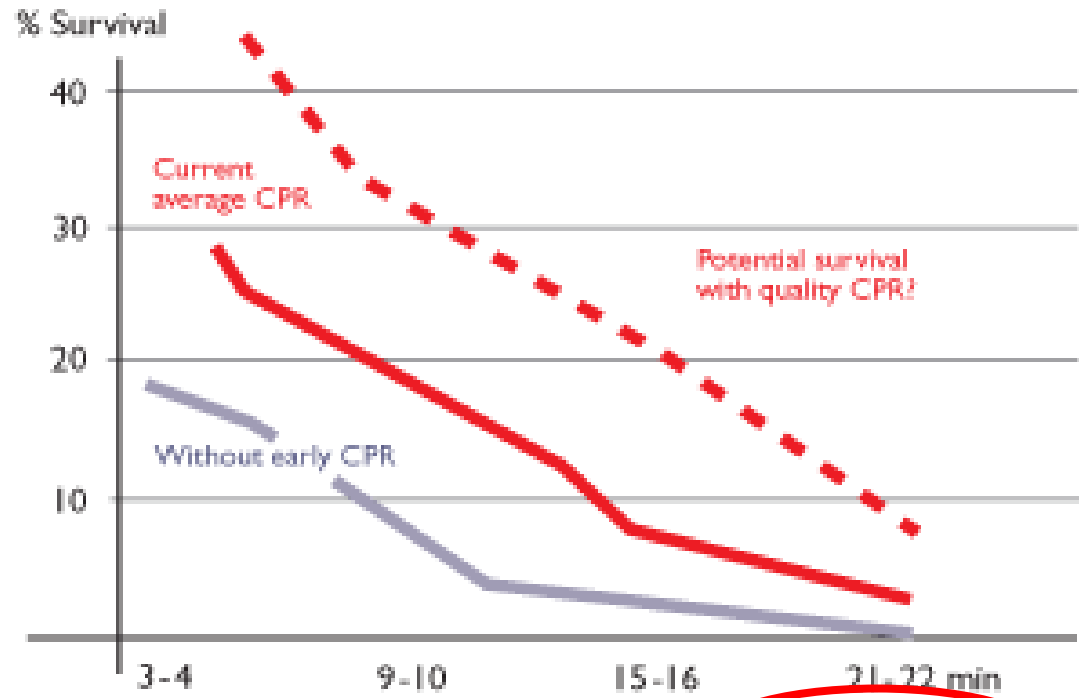


DET MEDICINSKE SELSKAB  
I KØBENHAVN

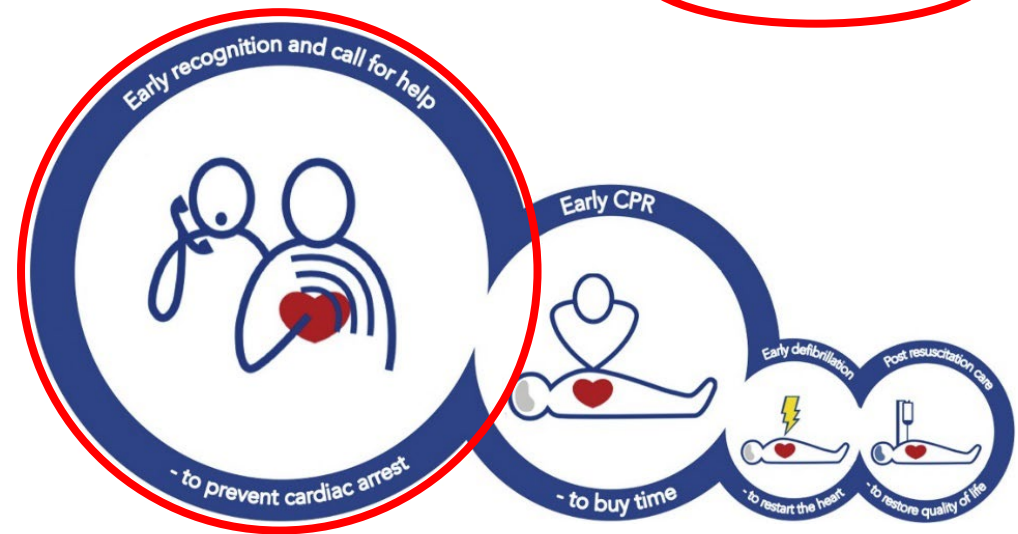
# Declaration of interest

- **Received research grants from:**
  - The Danish TrygFonden
  - The Danish Heart Foundation
  - Novo Nordisk Foundation
  
- Copenhagen EMS has received unrestricted research grant from the Laerdal Foundation

**Time is critical  
in cardiac  
arrest  
survival!**



Time to first Shock



# The challenge for cardiac arrest recognition

1 % of all emergency calls are cardiac arrests

25 % of cardiac arrest identified by caller

Another 50 % identified by call taker during the call

25 % initially missed until arrival of ambulance

Early recognition is **VERY** important to outcome!

# Solutions

Public awareness and education to identify cardiac arrest

Dispatcher training in identifying cardiac arrest

Can artificial intelligence / machine learning do better?

THOMAS VINTERBERG'S

# FESTEN



ALLE FAMILIER HAR EN HEMMELIGHED



THOMAS VINTERBERG'S  
**FESTEN**



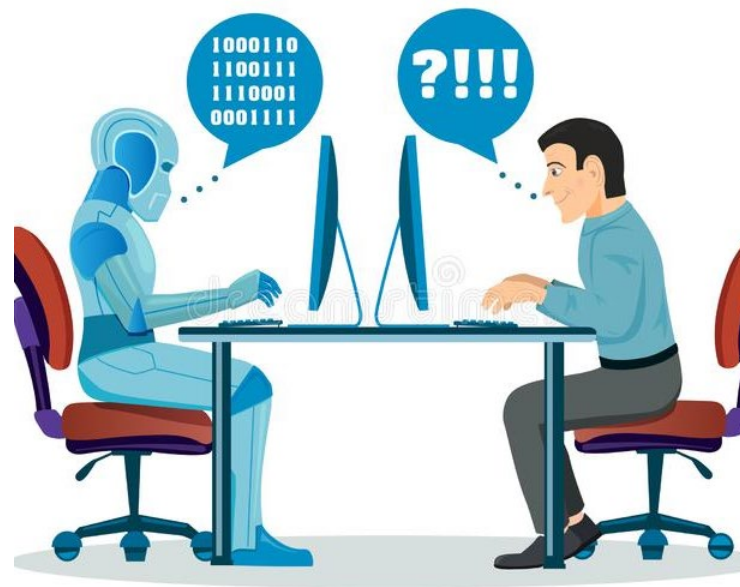
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Green  
Talks



# Human vs. Machine



Use pattern  
recognition

Remember  
every case

Years of  
experience in  
one model

Processed  
in no time

No human  
bias

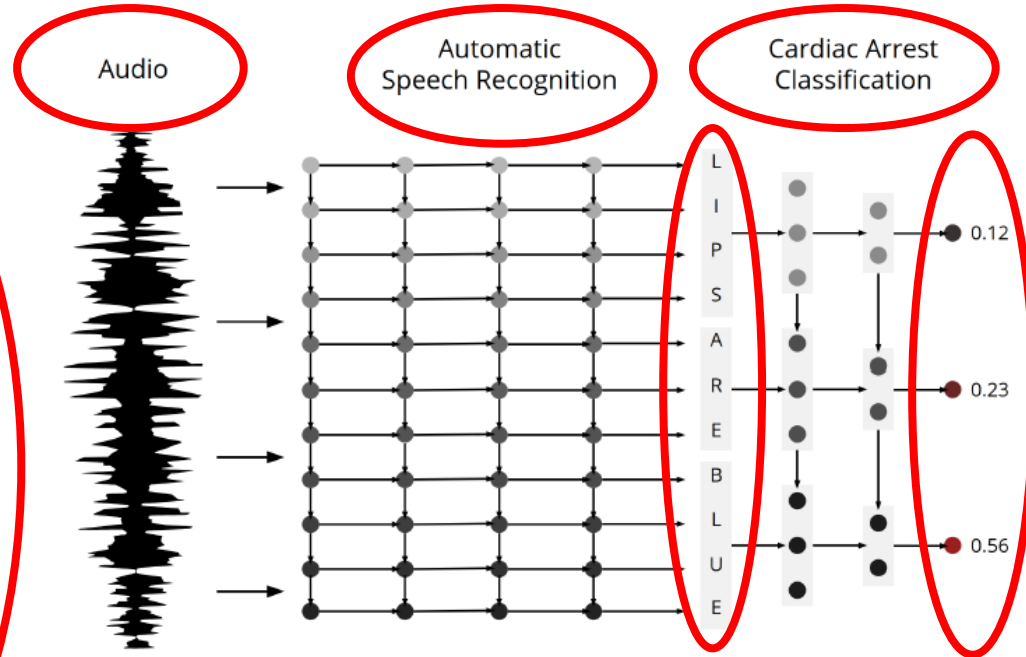
AI better in  
cardiac arrest  
recognition?

# Machine Learning in Cardiac Arrest Recognition

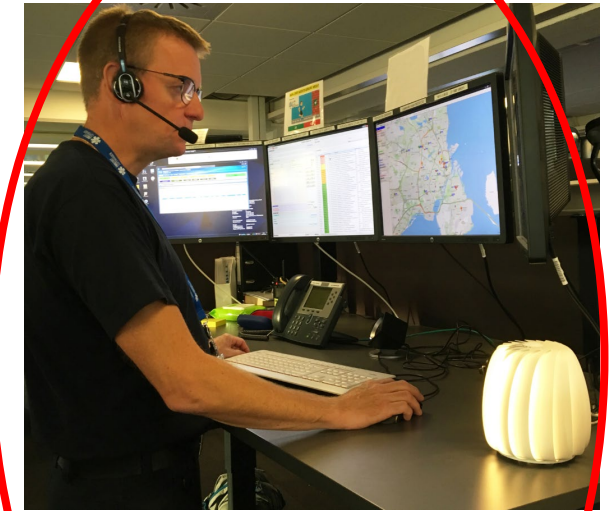
## - Artificial Intelligence -



1-1-2 call regarding potential OHCA



Neural network (AI)



Alerting dispatcher



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**Resuscitation**

journal homepage: [www.elsevier.com/locate/resuscitation](http://www.elsevier.com/locate/resuscitation)



**Clinical paper**

## **Machine learning as a supportive tool to recognize cardiac arrest in emergency calls**

**Stig Nikolaj Blomberg<sup>a,b,\*</sup>, Fredrik Folke<sup>a,b,c</sup>,  
Annette Kjær Ersbøll<sup>d</sup>, Helle Collatz Christensen<sup>a</sup>,  
Christian Torp-Pedersen<sup>e,f</sup>, Michael R. Sayre<sup>g</sup>,  
Catherine R. Counts<sup>g</sup>, Freddy K. Lippert<sup>a,b</sup>**

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RESUSCITATION 162 (2021) 218 –226



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**Clinical paper**

## **Machine learning can support dispatchers to better and faster recognize out-of-hospital cardiac arrest during emergency calls: A retrospective study**



**Fredrik Byrsell<sup>a,b,\*</sup>, Andreas Claesson<sup>a</sup>, Mattias Ringh<sup>a</sup>, Leif Svensson<sup>a</sup>,  
Martin Jonsson<sup>a</sup>, Per Nordberg<sup>a</sup>, Sune Forsberg<sup>a</sup>, Jacob Hollenberg<sup>a</sup>, Anette Nord<sup>a</sup>**

<sup>a</sup> Department of Medicine, Centre for Resuscitation Science, Karolinska Institutet, Solna, Sweden

<sup>b</sup> SOS Alarm AB, Stockholm, Sweden



# What did the observational studies show?

 Sample: 108,607 emergency calls, 918 (0.8%) were cardiac arrests

 Sample: 43,832 emergency calls, 3944 (9.0%) were cardiac arrests

Machine learning model had a significantly higher sensitivity (72.5% vs. 84.1%,  $p < 0.001$ ) than dispatchers in OHCA recognition 

Machine learning model recognized 36% within 1 min compared with 25% by dispatchers, and recognition rate at any time during the call was 86% for ML and 84% for dispatchers 

AI surpassed humans in detecting cardiac arrest during live emergency calls (faster and higher sensitivity) – but with lower specificity  

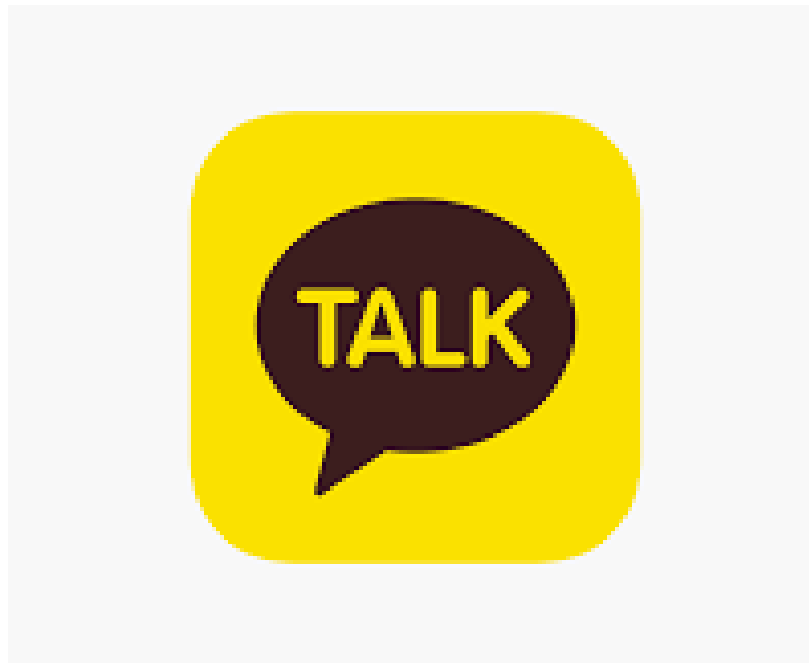




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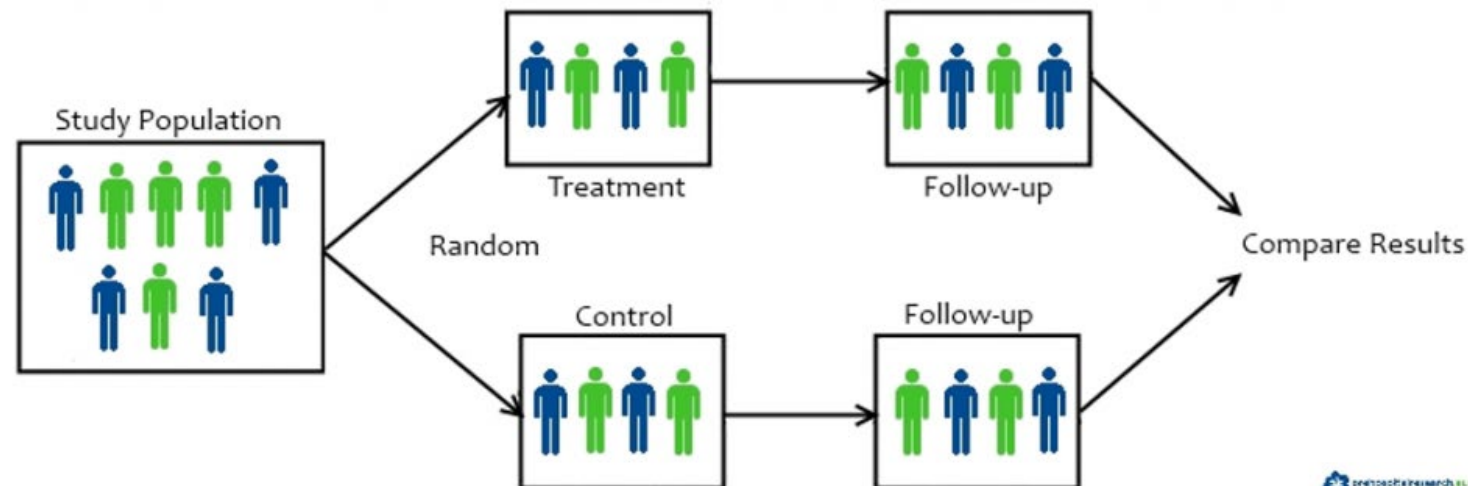


Original Investigation | Emergency Medicine

# Effect of Machine Learning on Dispatcher Recognition of Out-of-Hospital Cardiac Arrest During Calls to Emergency Medical Services

## A Randomized Clinical Trial

Stig Nikolaj Blomberg, MSc; Helle Collatz Christensen, MD, PhD; Freddy Lippert, MD; Annette Kjær Ersbøll, MSc, PhD; Christian Torp-Petersen, MD, PhD; Michael R. Sayre, MD; Peter J. Kudenchuk, MD; Fredrik Folke, MD, PhD



# What did the randomised study show?

The machine learning model assessed all 112-calls. Identified OHCA calls were randomized 1:1 to be shown or not

169 049 emergency calls were examined, 654 confirmed OHCA (336 control vs. 318 intervention)

AI surpassed humans in detection cardiac arrest during live-calls: **85.0% vs. 77.5%**, but **NO** improvement for dispatcher recognition in the AI assisted group

**No** improvements in CPR instructions started in the AI assisted group vs. in control: **64.8% vs. 61.9%** ( $P = .47$ )

The alert from AI did **not** result in an increased number of correct recognitions of OHCA by dispatchers or improved bystander CPR instructions



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# Resuscitation

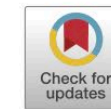
journal homepage: [www.elsevier.com/locate/resuscitation](http://www.elsevier.com/locate/resuscitation)



EUROPEAN  
RESUSCITATION  
COUNCIL

## Clinical paper

# When the machine is wrong. Characteristics of true and false predictions of Out-of-Hospital Cardiac arrests in emergency calls using a machine-learning model



Stig Nikolaj Blomberg<sup>a,b,\*</sup>, Theo W. Jensen<sup>a,b</sup>, Mikkel Porsborg Andersen<sup>f</sup>,  
Fredrik Folke<sup>a,b,d</sup>, Annette Kjær Ersbøll<sup>a,e</sup>, Christian Torp-Petersen<sup>f,g</sup>,  
Freddy Lippert<sup>a,b,h</sup>, Helle Collatz Christensen<sup>a,b,c</sup>



Clinical paper

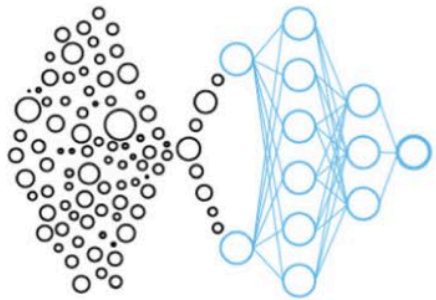
**When the machine is wrong. Characteristics of true and false predictions of Out-of-Hospital Cardiac arrests in emergency calls using a machine-learning model**



169,068 calls

A blue bracket is positioned to the right of the text "169,068 calls", spanning the vertical height of the text.

# Conclusion



## Training Data & ML Model

- Training data availability, accessibility, quality, etc.
- Quality of real-world modelling
- ML model's performance and focus

## System Integration & Data Used

- Integration with existing technical infrastructure and workflows
- Real-world data availability, accessibility, quality, etc.

## User Interface

- Output representation
- Visualisation
- Contextual information
- Explanations

## User & System Use

- Attitude towards the system
- Diverse needs
- Training
- Perception of usefulness

## Workflow & Organisation

- Workflow differences
- Available healthcare resources
- A team-based approach to work
- Operationalisation costs

## Healthcare Institution & Political Arenas

- Clinical efficacy
- Cost-effectiveness
- Political and legislative factors
- Ethics

Hubert D. Zając, Dana Li, Xiang Dai, Jonathan F. Carlsen, Finn Kensing, and Tariq O. Andersen. 2023. Clinician-Facing AI in the Wild: Taking Stock of the Sociotechnical Challenges and Opportunities for HCI. *ACM Trans. Comput.-Hum. Interact.* 30, 2, Article 33 (March 2023), 39 pages.