

# Characteristics of out-of-hospital cardiac arrest calls unrecognised by machine learning versus medical dispatchers: a nationwide observational study

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# Abstract

## Background

Early recognition of out-of-hospital cardiac arrest (OHCA) during emergency medical calls is critical, yet nearly one-quarter of cases are missed by dispatchers. Machine learning (ML) models offer promise but require evaluation regarding their specific failure patterns. The aim of this study was to describe and compare the characteristics of OHCA calls with discordant recognition by medical dispatchers and an ML model.

## Methods

This observational study analysed a predefined sub-cohort of unrecognised emergency 112 calls from a representative nationwide sample of Swedish OHCA cases in 2018. Audio logs were systematically audited using standardised Cardiac Arrest Registry to Enhance Survival (CARES) criteria. Calls missed by either the ML model or medical dispatchers were analysed using univariate logistic regression to identify characteristics associated with recognition by either ML or by dispatchers.

## Results

Ninety calls met the inclusion criteria. OHCA was recognised by the ML model but missed by medical dispatchers in 58% (52/90) of calls, while medical dispatchers recognised OHCA missed by the ML model in 42% (38/90). ML recognition was positively associated with the caller knowing the patient (OR 1.69, 95% CI 1.08 to 2.70), being a layperson (OR 2.98, 95% CI 1.20 to 7.64), being alone (OR 8.33, 95% CI 2.93 to 35.01), OHCA occurring at home (OR 1.78, 95% CI 1.08 to 3.02), and calls occurring in the evening (OR 4.29, 95% CI 1.09 to 21.82). Conversely, medical dispatchers were more likely to recognise OHCA when CPR was already in progress (OR for ML recognition 0.07, 95% CI 0.004 to 0.33) or when the caller was not alone (OR for ML recognition 0.09, 95% CI 0.02 to 0.28).

## Conclusions

Among discordant OHCA calls, medical dispatchers and ML models showed different recognition patterns. These findings support further evaluation of whether ML-based decision support may complement dispatcher recognition of OHCA.

## BACKGROUND

Out-of-hospital cardiac arrest (OHCA) remains a primary cause of mortality worldwide, with more than 350,000 cases annually in the United States and 340,000 in Europe.[1–5] Survival depends critically on the chain of survival, in which early recognition of OHCA, immediate bystander cardiopulmonary

resuscitation (CPR), and prompt use of an automated external defibrillator (AED) are key determinants.[6–8] Emergency Medical Dispatch Centres (EMDCs) represent the initial entry point in OHCA management. Rapid recognition of OHCA by dispatchers enables immediate activation of emergency medical services (EMS), provision of dispatch-assisted CPR (DA-CPR), and referral to the nearest public-access AED.[9–12] However, up to 25% of OHCA cases are not recognised by dispatchers during the emergency call.[10] Common barriers include agonal breathing, often mischaracterised as gasping or snoring, and seizure-like activity at onset.[13–17]

Machine learning (ML) decision-support tools have emerged as promising approaches to improve OHCA recognition and reduce time to recognition.[19–21] Nevertheless, ML models also experience false negatives, particularly in calls containing features that complicate accurate classification, such as complex acoustic environments or ambiguous clinical descriptions.[19–22]

Understanding the distinct and potentially complementary failure modes of medical dispatchers and ML models is necessary to optimise real-time AI integration.[13, 22]

In a previously published nationwide cohort underlying the present study, the ML model recognised 729 of 851 OHCA calls, compared with 715 recognised by medical dispatchers. Discordant recognition between the machine-learning model and medical dispatchers was identified in 90 OHCA calls. These cases allowed comparison of the characteristics of calls recognised by each approach. (20)

The primary objective of this study was to describe and compare the characteristics of OHCA calls recognised by medical dispatchers but not by a machine-learning model and those recognised by a machine-learning model but not by medical dispatchers.

## **METHODS**

### **Study Design and Setting**

This was a retrospective observational study performing a detailed manual audit of emergency 112 audio logs in Sweden. Sweden utilises a single national emergency number (112) operated by SOS Alarm AB. During the study period, dispatchers used the criteria-based Swedish Index for Medical Emergency Assistance rather than a script-based dispatch protocols such as the Medical Priority Dispatch System (MPDS).[23] Ethical approval was obtained from the Swedish Ethical Review Authority (Dnr 2019-01998).

### **Data Sources and Cohort Selection**

The original cohort comprised a representative random sample of 1000 OHCA calls from 2018 extracted from the Swedish Registry of Cardiopulmonary Resuscitation (SRCR) and SOS Alarms audio databases (CoordCom), as previously described by Byrsell et al. [20]

After excluding EMS-witnessed arrests, inaccessible audio recordings, and cases where resuscitation was not attempted, 851 calls were eligible for analysis. Archived audio recordings were retrospectively

reviewed by trained reviewers using predefined audit criteria.(24) Dispatchers recognition of OHCA during the original emergency call was compared with retrospective OHCA classification by the ML model. The present study focused on a predefined sub-cohort of 90 emergency calls in which OHCA was not recognised (false negative) by either the medical dispatcher or the ML model (Figure 1). Analysing this dataset provides a mechanistic comparison of error sources under controlled, ethically approved audit conditions. The underlying communication dynamics and human operational barriers (e.g., agonal breathing interpretations) remain fundamentally stable despite incremental software updates.

## **ML Framework**

The ML software (Corti ApS) consisted of an automatic speech recognition (ASR) module paired with a real-time OHCA classification model.[20] To reflect real-world operational thresholds, the model's false-positive rate was fixed at 1.5%.[20]

## **Data Extraction and Variables**

Audio recordings were audited independently by two experienced reviewers using an adapted version of the Cardiac Arrest Registry to Enhance Survival (CARES) Dispatcher-Assisted CPR Dictionary (Supplementary File 1).[24] Dispatcher recognition of OHCA was defined as the point at which the dispatcher verbally identified cardiac arrest or indicated that CPR should be initiated.

Variables included caller characteristics, presence of bystanders, patient location, communication barriers (e.g., emotional distress and language barriers), and physical limitations.

## **Statistical Analysis**

Categorical data are reported as counts and percentages (n, %). Continuous variables are reported as medians with interquartile ranges (IQRs). Differences in continuous variables were assessed using the Wilcoxon rank-sum test. Univariable logistic regression was used to evaluate associations between call characteristics and OHCA recognition by the ML model versus medical dispatchers. Results are presented as odds ratios (ORs) with 95% confidence intervals (CIs). Statistical significance was defined as  $p < 0.05$ . Missing, unknown, or not applicable (N/A) data were excluded from the regression analyses. Analyses were performed using R version 4.4.1.

# **RESULTS**

Out of the 851 reviewed calls, 90 met the criteria for OHCA recognition failure by either the medical dispatcher or the ML model. The ML model recognised OHCA in 58% (52/90) of calls missed by dispatchers. Conversely, medical dispatchers recognised OHCA in 42% (38/90) of calls missed by the ML model.

Patient and call characteristics are summarised in Table 1. The median patient age was 70 years (interquartile range [IQR] 52–80) among OHCA calls not recognised by the ML model and 73 years (IQR

65.0-79.8) among calls not recognised by medical dispatchers, with no significant difference between groups.

Across all 90 calls, dispatchers assessed patient consciousness in 91% (n = 82) and breathing in 97% (n = 87) of calls. Abnormal breathing was present in 84% (n = 76) of analysed cases and probable cardiac aetiology was present in 93% (n = 78) of calls. Identified barriers are detailed in Table 2. Statistically significant associations between call characteristics and OHCA recognition are shown in Fig. 2.

Table 1  
Characteristics of unrecognised OHCA calls

| Patient age (years), median [IQR]                                                | All<br>(n = 90)     | Recognised by<br>medical dispatcher,<br>not ML<br>(n = 38) | Recognised by ML, not<br>medical dispatcher<br>(n = 52) |
|----------------------------------------------------------------------------------|---------------------|------------------------------------------------------------|---------------------------------------------------------|
|                                                                                  | 73 [58.5-<br>80.25] | 70 [52.00–80.00]                                           | 73 [65.00–79.75]                                        |
| <b>CPR in progress</b>                                                           |                     |                                                            |                                                         |
| Yes                                                                              | 16 (18)             | 15 (39)                                                    | 1 (2)                                                   |
| No                                                                               | 74 (82)             | 23 (61)                                                    | 51 (98)                                                 |
| <b>Consciousness is addressed</b>                                                |                     |                                                            |                                                         |
| Yes                                                                              | 82 (91)             | 34 (89)                                                    | 48 (92)                                                 |
| No                                                                               | 8 (9)               | 4 (11)                                                     | 4 (8)                                                   |
| <b>Breathing is addressed</b>                                                    |                     |                                                            |                                                         |
| Yes                                                                              | 87 (97)             | 37 (97)                                                    | 50 (96)                                                 |
| No                                                                               | 3 (3)               | 1 (3)                                                      | 2 (4)                                                   |
| <b>Abnormal breathing is addressed</b>                                           |                     |                                                            |                                                         |
| Yes                                                                              | 4 (4)               | 2 (5)                                                      | 2 (4)                                                   |
| No                                                                               | 56 (63)             | 14 (38)                                                    | 42 (81)                                                 |
| N/A                                                                              | 29 (33)             | 21 (57)                                                    | 8 (15)                                                  |
| Missing                                                                          | 1                   | 1                                                          | 0                                                       |
| <b>Patient is breathing normally</b>                                             |                     |                                                            |                                                         |
| Yes                                                                              | 3 (4)               | 0 (0)                                                      | 3 (7)                                                   |
| No                                                                               | 76 (96)             | 35 (100)                                                   | 41 (93)                                                 |
| Missing                                                                          | 11                  | 3                                                          | 8                                                       |
| <b>Delayed recognition due to<br/>deviation from cardiac arrest<br/>protocol</b> |                     |                                                            |                                                         |
| Yes                                                                              | 23 (28)             | 7 (18)                                                     | 16 (36)                                                 |
| No                                                                               | 60 (72)             | 31 (82)                                                    | 29 (64)                                                 |
| Missing                                                                          | 7                   | 0                                                          | 7                                                       |

| <b>Patient age (years), median [IQR]</b> | <b>All<br/>(n = 90)</b>     | <b>Recognised by<br/>medical dispatcher,<br/>not ML<br/>(n = 38)</b> | <b>Recognised by ML, not<br/>medical dispatcher<br/>(n = 52)</b> |
|------------------------------------------|-----------------------------|----------------------------------------------------------------------|------------------------------------------------------------------|
|                                          | <b>73 [58.5-<br/>80.25]</b> | <b>70 [52.00–80.00]</b>                                              | <b>73 [65.00–79.75]</b>                                          |
| <b>CPR in progress</b>                   |                             |                                                                      |                                                                  |
| <b>OHCA witnessed</b>                    |                             |                                                                      |                                                                  |
| Yes                                      | 55 (71)                     | 21 (64)                                                              | 34 (76)                                                          |
| No                                       | 23 (29)                     | 12 (36)                                                              | 11 (24)                                                          |
| Missing                                  | 12                          | 5                                                                    | 7                                                                |
| <b>Probable cardiac etiology</b>         |                             |                                                                      |                                                                  |
| Yes                                      | 78 (93)                     | 34 (92)                                                              | 44 (94)                                                          |
| No                                       | 4 (5)                       | 1 (3)                                                                | 3 (6)                                                            |
| Trauma                                   | 2 (2)                       | 2 (5)                                                                | 0 (0)                                                            |
| Missing                                  | 6                           | 1                                                                    | 5                                                                |
| <b>Call continued until EMS arrival</b>  |                             |                                                                      |                                                                  |
| Yes                                      | 21 (27)                     | 11 (30)                                                              | 10 (24)                                                          |
| No                                       | 57 (73)                     | 26 (70)                                                              | 31 (76)                                                          |
| Missing                                  | 12                          | 1                                                                    | 11                                                               |
| <b>Caller's gender</b>                   |                             |                                                                      |                                                                  |
| Male                                     | 40 (44)                     | 14 (37)                                                              | 26 (50)                                                          |
| Female                                   | 50 (56)                     | 24 (63)                                                              | 26 (50)                                                          |
| <b>Patient's gender</b>                  |                             |                                                                      |                                                                  |
| Male                                     | 54 (60)                     | 24 (63)                                                              | 30 (58)                                                          |
| Female                                   | 36 (40)                     | 14 (37)                                                              | 22 (42)                                                          |
| <b>Location of call</b>                  |                             |                                                                      |                                                                  |
| Home                                     | 64 (71)                     | 23 (61)                                                              | 41 (79)                                                          |
| Public place                             | 14 (16)                     | 7 (18)                                                               | 7 (13)                                                           |
| Other                                    | 12 (13)                     | 8 (21)                                                               | 4 (8)                                                            |

| <b>Patient age (years), median [IQR]</b> | <b>All<br/>(n = 90)</b>     | <b>Recognised by<br/>medical dispatcher,<br/>not ML<br/>(n = 38)</b> | <b>Recognised by ML, not<br/>medical dispatcher<br/>(n = 52)</b> |
|------------------------------------------|-----------------------------|----------------------------------------------------------------------|------------------------------------------------------------------|
|                                          | <b>73 [58.5-<br/>80.25]</b> | <b>70 [52.00–80.00]</b>                                              | <b>73 [65.00–79.75]</b>                                          |
| <b>CPR in progress</b>                   |                             |                                                                      |                                                                  |
| <b>Caller knows the patient</b>          |                             |                                                                      |                                                                  |
| Yes                                      | 78 (88)                     | 29 (78)                                                              | 49 (94)                                                          |
| No                                       | 11 (12)                     | 8 (22)                                                               | 3 (6)                                                            |
| Missing                                  | 1                           | 1                                                                    | 0                                                                |
| <b>Caller is a healthcare provider</b>   |                             |                                                                      |                                                                  |
| Yes                                      | 29 (33)                     | 17 (47)                                                              | 12 (23)                                                          |
| No                                       | 59 (67)                     | 19 (53)                                                              | 40 (77)                                                          |
| Missing                                  | 2                           | 2                                                                    | 0                                                                |
| <b>Caller is alone</b>                   |                             |                                                                      |                                                                  |
| Yes                                      | 28 (32)                     | 3 (8)                                                                | 25 (50)                                                          |
| No                                       | 60 (68)                     | 35 (92)                                                              | 25 (50)                                                          |
| Missing                                  | 2                           | 0                                                                    | 2                                                                |

Reported as number (%) unless otherwise specified (e.g. patient age). OHCA, out-of-hospital cardiac arrest; ML, machine learning; EMS, emergency medical services.

Table 2  
Barriers present in unrecognised OHCA calls

| <b>Caller hangs up the phone</b>   | <b>Total<br/>(n = 90)</b> | <b>Recognised by medical dispatcher, not ML<br/>(n = 38)</b> | <b>Recognised by ML, not medical dispatcher<br/>(n = 52)</b> |
|------------------------------------|---------------------------|--------------------------------------------------------------|--------------------------------------------------------------|
|                                    | <b>7 (8)</b>              | <b>5 (13)</b>                                                | <b>2 (4)</b>                                                 |
| <b>Language barrier is present</b> | 4 (4)                     | 4 (11)                                                       | 0 (0)                                                        |
| <b>Caller not with patient</b>     | 9 (10)                    | 4 (11)                                                       | 5 (11)                                                       |
| <b>Overly distraught</b>           | 9 (10)                    | 2 (5)                                                        | 7 (15)                                                       |
| <b>Caller cannot move patient</b>  | 12 (13)                   | 1 (3)                                                        | 11 (24)                                                      |
| <b>Patient's status changes</b>    | 1 (1)                     | 1 (3)                                                        | 0 (0)                                                        |
| <b>Patient is obviously dead</b>   | 2 (2)                     | 2 (5)                                                        | 0 (0)                                                        |
| <b>Other</b>                       | 5 (6)                     | 3 (8)                                                        | 2 (4)                                                        |
| <b>No barrier</b>                  | 41 (46)                   | 21 (55)                                                      | 20 (43)                                                      |
| <b>Missing</b>                     | 6 (7)                     | 0 (0)                                                        | 6 (13)                                                       |

Reported as number (%). Some calls had more than one barrier. OHCA, out-of-hospital cardiac arrest; ML, machine learning.

## Caller Characteristics

Machine learning model recognition was positively associated with the caller knowing the patient personally (odds ratio [OR] 1.69, 95% confidence interval [CI] 1.08 to 2.70), being a layperson rather than a healthcare professional (OR 2.98, 95% CI 1.20 to 7.64), and being alone at the scene (OR 8.33, 95% CI 2.93 to 35.01). Conversely, dispatcher recognition was positively associated with the caller not being alone (OR for ML recognition: 0.09, 95% CI 0.02 to 0.28).

## Situational Characteristics

Ongoing CPR prior to or during the emergency call was associated with dispatcher recognition rather than ML recognition of OHCA (OR for ML recognition 0.07, 95% CI 0.004 to 0.33). Conversely, ML model recognition was positively associated with OHCA occurring in residential settings (home vs public

location: OR 1.78, 95% CI 1.08 to 3.02), callers reporting an inability to move the patient (OR 9.93, 95% CI 1.80 to 185.83), and calls occurring during the evening rather than the morning (OR 4.29, 95% CI 1.09 to 21.82). Detailed regression results are presented in Table 3. No other call characteristics were significantly associated with OHCA recognition.

Table 3  
Time of day of unrecognised OHCA calls

| <b>Morning</b>   | <b>All (n = 90)</b> | <b>Medical dispatcher, not ML<br/>(n = 38)</b> | <b>ML, not medical dispatcher<br/>(n = 52)</b> |
|------------------|---------------------|------------------------------------------------|------------------------------------------------|
|                  | <b>25 (28)</b>      | <b>14 (37)</b>                                 | <b>11 (21)</b>                                 |
| <b>Afternoon</b> | 26 (29)             | 12 (32)                                        | 14 (27)                                        |
| <b>Evening</b>   | 18 (20)             | 3 (8)                                          | 15 (29)                                        |
| <b>Night</b>     | 21 (23)             | 9 (24)                                         | 12 (23)                                        |

Reported as number (%). Hours corresponding to each time of day: morning (6–12), afternoon (12–18), evening (18–22), night (22–6). OHCA, out-of-hospital cardiac arrest; ML, machine learning.

## DISCUSSION

In this study of OHCA calls with discordant recognition between medical dispatchers and a ML model, we identified distinct characteristics associated with recognition by either the dispatchers or the ML model. The findings suggest that medical dispatchers and ML models possess complementary recognition profiles, supporting the potential value of AI-assisted emergency medical dispatch systems.

### Characteristics associated with ML-only recognition among discordant calls

The ML model demonstrated superior sensitivity in residential settings and in calls where callers knew the patient, were laypersons, or were alone at the scene. One possible explanation is that such situations may provide clearer and more focused descriptions, potentially facilitating automated speech recognition (ASR) transcription of diagnostically relevant information.

The ML model was less likely to recognise OHCA when the caller was a healthcare professional, consistent with previous findings.[20, 22] One possible explanation is that important information may be communicated differently during calls from healthcare professionals than during calls from laypersons, potentially reducing the ML model’s ability to identify patterns associated with OHCA. These findings highlight the importance of maintaining a structured assessment process regardless of the caller’s professional background. Communication-related factors are known barriers to OHCA recognition during emergency calls.[13]

We also observed improved ML recognition during evening calls. The explanation remains uncertain but may reflect temporal differences in call volume, dispatcher workload, or caller behaviour. However, given the wide confidence interval, this association should be interpreted cautiously and requires confirmation in larger studies.

Machine learning recognition was also more likely when callers knew the patient. Familiarity with the patient may enable callers to provide more specific descriptions of the collapse, breathing abnormalities, or deviations from normal status, generating linguistic cues that are more readily captured by the model.

## **Characteristics associated with dispatcher-only recognition among discordant calls**

Medical dispatchers were more likely than the ML model to recognise OHCA when CPR was already in progress and when the caller was not alone.[22] One possible explanation is that high ambient noise and chaotic multi-party interactions degrade current ASR performance, leading to transcription omissions. Similar communication and operational barriers have previously been identified as important obstacles to effective emergency call management and bystander CPR initiation.[25–27] These findings suggest that AI may currently be most valuable as a decision-support tool that complements, rather than replaces, medical dispatchers.[21]

## **Clinical and operational implications**

The findings support further evaluation of whether ML-based decision support and dispatcher assessment have different failure modes.[18] They do not establish that an integrated system improves recognition or patient outcomes. Such systems require prospective evaluation under operational conditions, including assessment of false alerts, alarm fatigue, automation bias, workflow effects, and time to CPR. This perspective aligns with recent proposals for an "AI dispatcher copilot", in which AI functions as an integrated decision-support system that complements rather than replaces dispatcher expertise.[28] Future development of such systems may benefit from training and validation on acoustically challenging emergency calls, including noisy environments, multi-speaker conversations, and background distress signals. At the same time, maintaining a structured and standardised assessment of consciousness, breathing, and patient status remains essential for consistent OHCA recognition across diverse caller and patient characteristics. Within this framework, AI could potentially function as a real-time background monitoring tool, alerting dispatchers in situations such as quieter, single-caller scenarios where subtle verbal cues indicating abnormal breathing might otherwise be overlooked.

## **Limitations**

This study has several limitations. First, the sample size was relatively limited ( $n = 90$ ), reflecting the small subset of calls with discordant OHCA recognition between the ML model and human dispatchers identified within the original cohort. Consequently, several regression estimates were associated with wide confidence intervals, indicating statistical imprecision and reduced estimate stability. Secondly,

auditor classification of dispatcher recognition relied on explicit verbal instructions (e.g., DA-CPR guidance); dispatchers who recognised OHCA internally but omitted verbalisation due to logistical constraints were classified as non-recognitions. Finally, while audio logs from 2018 were used due to ethical and resource constraints, it is important to realise that the fundamental human communication barriers in emergency resuscitation remain largely unchanged.[10, 13]

## CONCLUSION

Among discordant OHCA calls, human dispatchers and ML models showed different recognition patterns. These findings support further evaluation of whether ML-based decision support may complement dispatcher recognition of OHCA.

## Abbreviations

|      |                                     |
|------|-------------------------------------|
| AED  | Automated External Defibrillator    |
| CI   | Confidence Interval                 |
| CPR  | CardioPulmonary Resuscitation       |
| EMDC | Emergency Medical Dispatch Centre   |
| EMS  | Emergency Medical Services          |
| IQR  | InterQuartile Range                 |
| ML   | Machine Learning                    |
| OR   | Odds Ratio                          |
| OHCA | Out-of-Hospital Cardiac Arrest      |
| SRCR | Swedish Registry of Cardiopulmonary |

## Declarations

### Acknowledgements

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### Author contributions

A. N, A. W., F. B., A. C., and S. F. conceptualized and designed the study. A. N, A. W., F. B were responsible for data collection, A. W. and M. J. performed statistical analyses. A. N and A. W. drafted the manuscript.

S. F., F. B., A. C., S. R., M. J. and J. H. contributed to the interpretation of the data and critically revised the manuscript for important intellectual content.

All authors contributed to the study design, reviewed the manuscript, and approved the final version.

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## **Availability of data**

The datasets generated and/or analysed during the current study are not publicly available because they contain sensitive personal data and are subject to legal and ethical restrictions. Data may be made available upon reasonable request, provided that all applicable ethical, legal, and data protection requirements are met and permission is obtained from SOS Alarm AB.

## **Ethics approval and consent to participate**

Ethical approval was granted by the Swedish Ethical Review Authority (Dnr 2019-01998). The requirement for informed consent was waived because of the retrospective nature of the study. This research has been conducted in accordance with the declaration of Helsinki.

## **Consent for publication**

Not applicable.

## **Competing interests**

The authors declare that they have no competing interests.

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## Figures

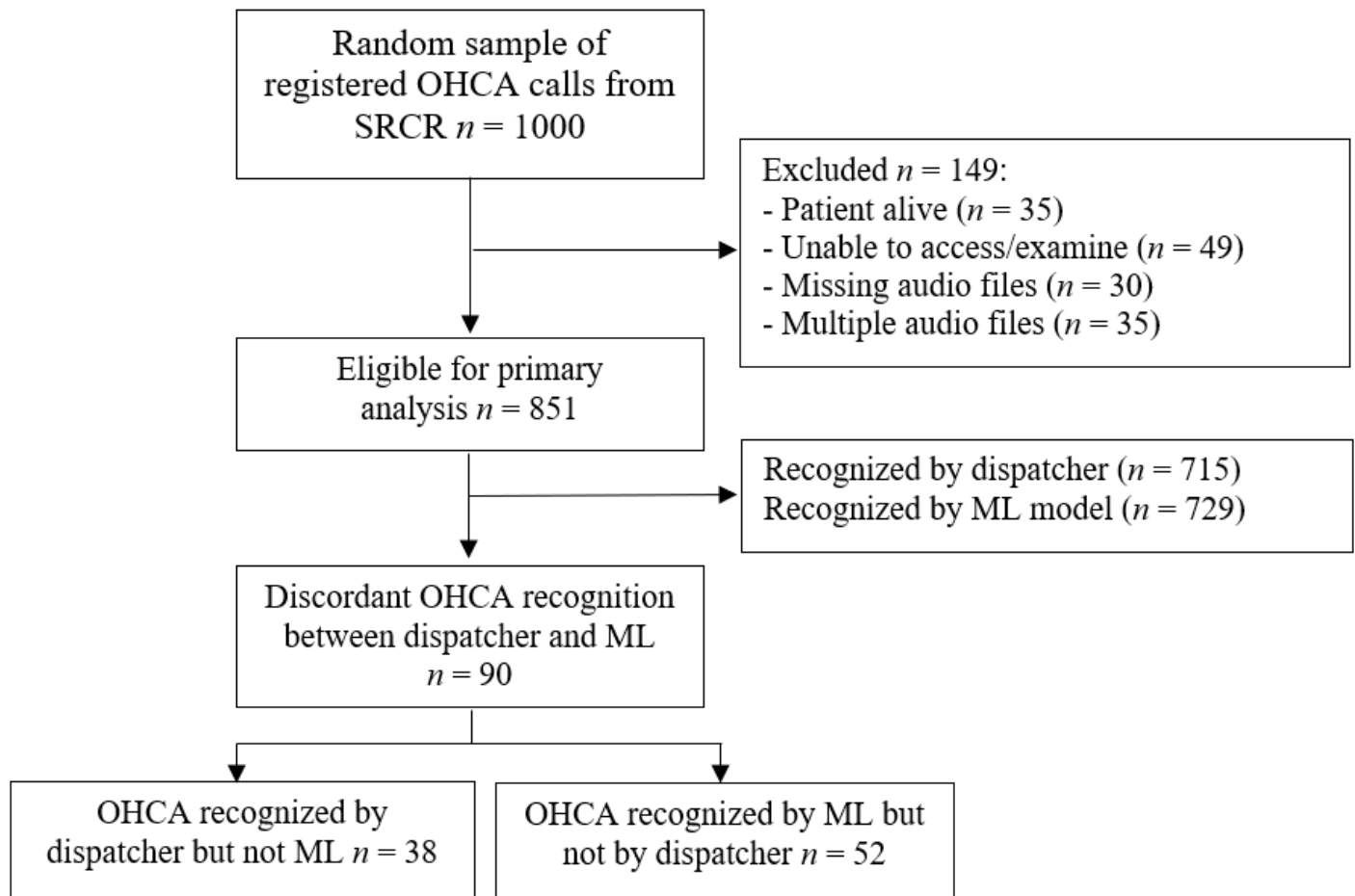


**Figure 1**

Flowchart of data collection. OHCA, out-of-hospital cardiac arrest; SRCR, Swedish Registry of Cardiopulmonary Resuscitation; ML, machine learning.

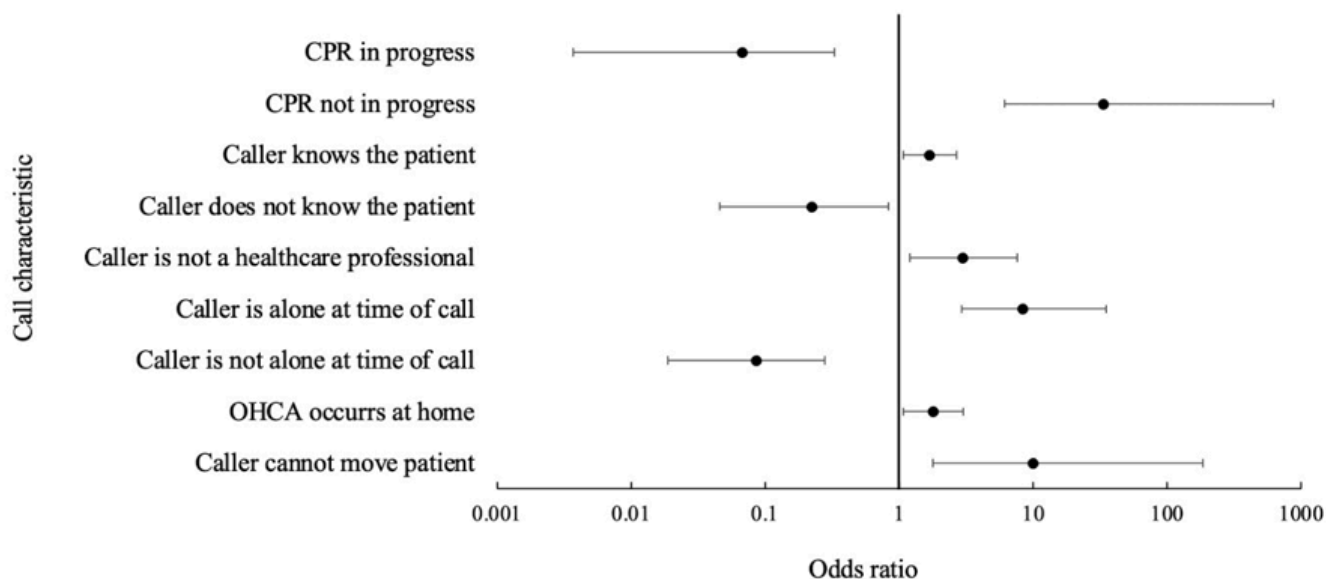


**Figure 2**

Statistically significant associations between call characteristics and OHCA recognition by the ML model versus dispatcher recognition, analysed using unadjusted logistic regression. Odds ratios (95% CI) are shown on a logarithmic scale. Only significant associations ( $P < 0.05$ ) are presented. OHCA, out-of-hospital cardiac arrest; ML, machine learning; CPR, cardiopulmonary resuscitation; CI, confidence interval.

## Supplementary Files

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- [SupplementaryFile1.pdf](#)