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Projected impact of an AI-guided defibrillation and cardioversion decision support system: A fully synthetic, simulation-based randomized trial for a tertiary care hospital in India

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Abstract

***Background*: Survival from in-hospital cardiac arrest caused by ventricular fibrillation (VF) or pulseless ventricular tachycardia (pVT) decreases with every minute of delay before defibrillation. Conventional shock decisions depend on clinician recognition, guideline recall, team coordination, and standard shock-advisory algorithms that may require interruptions in chest compressions. Recent advances in artificial intelligence (AI) have demonstrated high accuracy in rhythm recognition and shock advisory during cardiopulmonary resuscitation (CPR), but their potential impact in Indian tertiary-care settings remains uncertain.**

***Objective*: To estimate the potential effect of an AI-guided defibrillation and cardioversion decision-support system on time-to-first shock and resuscitation outcomes using a fully synthetic simulation model based on a tertiary-care hospital setting.**

***Methods*: A virtual randomized trial comprising 2,000 synthetic adult episodes (1,000 per arm) was constructed. Cases included shockable cardiac arrest (VF/pVT) and unstable tachyarrhythmias requiring synchronized cardioversion. Standard care was compared with an AI-assisted model providing real-time rhythm classification, shock/no-shock recommendations, energy suggestions, and prompts to minimize CPR interruptions while preserving clinician authority. The primary outcome was time-to-first shock. Secondary outcomes included first-shock success, CPR hands-off time, return of spontaneous circulation (ROSC), survival to discharge, neurological outcome proxy, and number of shocks.**

***Results*: Mean time-to-first shock decreased from 5.5±2.3 minutes to 3.7±1.6 minutes with AI assistance (mean reduction 1.8 minutes, $p<0.001$). First-shock success increased from 62.0% to 78.2%, CPR hands-off time decreased substantially, ROSC improved from 50.3% to 60.3%, and survival to discharge increased from 24.6% to 29.3%.**

***Conclusion*: This simulation suggests that AI-assisted defibrillation and cardioversion may reduce treatment delays, improve CPR quality, and enhance resuscitation outcomes. Prospective clinical studies are required to validate these findings before implementation in practice.**

Keywords: Artificial intelligence, defibrillation, synchronized cardioversion, cardiac arrest, time-to-shock.

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Introduction

Sudden cardiac arrest, unstable arrhythmias, and time-critical defibrillation

In-hospital cardiac arrest from ventricular fibrillation (VF) or pulseless ventricular tachycardia (pVT) is one of the most time-critical emergencies in acute care. Observational data from large registries show that a substantial proportion of patients receive defibrillation more than 2 minutes after arrest onset and that defibrillation beyond this period is associated with significantly lower survival and worse neurological outcomes. Survival probability declines with each minute of delay before the first shock. (1)

Alongside primary shockable arrest, clinicians in Emergency Departments (EDs), Intensive Care Units (ICUs), and coronary care units manage hemodynamically unstable tachyarrhythmias such as rapid atrial fibrillation, atrial flutter, and monomorphic ventricular tachycardia with pulse. In these cases, synchronized cardioversion is indicated to prevent progression to cardiac arrest, limit myocardial ischemia, and stabilize organ perfusion. (2)

High-volume tertiary hospitals in India, including Symbiosis University Hospital and Research Center in Pune, face a growing burden of acute cardiovascular emergencies. Crowding, high workloads, and limited staff make it challenging to consistently maintain guideline-recommended defibrillation times.

Limitations of current defibrillation and cardioversion workflows

Modern external defibrillators and automated external defibrillators (AEDs) incorporate shock advisory algorithms that classify rhythms as shockable or non-shockable based on engineered electrocardiogram (ECG) features. These algorithms have been optimized over many years and perform well in controlled settings, but they can be sensitive to noise, motion artifacts, and interference from chest compression. In practice, chest compressions are often paused for rhythm analysis and shock delivery. Prolonged interruptions and low chest compression fraction have been associated with poorer outcomes in both prehospital and in-hospital studies. (3)

Guideline protocols for defibrillation and synchronized cardioversion are complex, with multiple decision points regarding energy level, timing, and the balance between shocks and cardiopulmonary resuscitation (CPR). In real-world emergencies, teams may perform repeated rhythm checks, hesitate before delivering shocks or continue low-value shocks at sub-optimal energies. These behaviours introduce variability between hospitals, shifts and individual clinicians. Standard shock sequences generally do not incorporate patient-specific transthoracic impedance or VF waveform features, despite evidence that such characteristics influence shock success. (4)

Progress in artificial intelligence (AI) for ECG interpretation and shock advisory systems

Deep-learning methods have markedly accelerated automated ECG interpretation. A widely cited single-lead convolutional neural network developed by Hannun and colleagues achieved an area under the receiver operating characteristic (ROC) curve of about 0.97 and cardiologist-level performance for 12 arrhythmia classes. Subsequent work has extended these approaches to 12-lead ECGs and more interpretable, knowledge-fused deep models. (5)

Within defibrillation, machine learning and deep learning have been applied directly to shock-advisory algorithms. Reviews of shockable-rhythm detection for AEDs highlight multiple algorithms that reach or exceed American Heart Association thresholds for sensitivity and specificity. A lightweight deep-learning algorithm implemented on AED (LDIAED)-class hardware demonstrated high performance in distinguishing VT/VF from other rhythms using short ECG segments without extensive preprocessing. Other studies have evaluated support vector machine and neural network approaches for shockable rhythm recognition using out-of-hospital arrest ECG data. (6)

In parallel, investigators have explored algorithms that allow rhythm analysis during ongoing chest compressions, reducing the need to interrupt CPR for rhythm checks. These developments suggest that an integrated AI decision support tool could:

- detect shockable rhythms more quickly and reliably;
- provide more confident shock/no-shock recommendations;
- suggest energy levels informed by waveform characteristics; and
- promote shorter, better-timed CPR pauses.

Rationale for simulation in an Indian tertiary hospital

Most published AI-ECG and AI-AED work focuses on algorithm development and retrospective validation or bench testing. Very few studies have examined how AI-guided defibrillation would alter process measures and outcomes when embedded in real hospital workflows, and almost none have addressed high-burden, resource-constrained environments similar to those in many Indian tertiary centers. (7)

Conducting an immediate, live, randomized trial that changes defibrillation workflows during active resuscitation raises ethical, operational, and medico-legal challenges. A structured simulation step in between allows the likely magnitude and direction of impact to be estimated transparently, using known relationships between time-to-shock, first-shock success, and survival. These projections can then be used to inform whether a full trial is justified, what endpoints to prioritize, and how many patients would be needed. (8)

Symbiosis College of Nursing, through its Institutional Research Committee (IRC 21), is exploring digital and AI-enabled innovations in acute care. A simulation-based randomized trial calibrated to Symbiosis University Hospital and Research Center can provide a structured foundation for later prospective work.

Objective

The objective of this study was to construct a simulation-based randomized trial, using entirely synthetic data, to estimate the projected effect of an AI-guided defibrillation and synchronized cardioversion decision support system on time-to-first shock and resuscitation outcomes in a tertiary care environment modeled on Symbiosis University Hospital and Research Center, Pune.

Methods

Study design

A two-arm, parallel-group randomized "virtual trial" was constructed. The design mirrors that of a conventional randomized controlled trial, but all "participants" are synthetic episodes generated from pre-specified probability distributions.

No individual-level patient data from Symbiosis University Hospital and Research Center were accessed. Parameter values were chosen to reflect the anticipated case mix and process performance, based on published literature and structured input from local clinicians. The work was undertaken as a trial-planning and modeling exercise under the academic remit of the IRC 21 at Symbiosis College of Nursing.

Simulated setting and population

The simulated setting was a high-volume tertiary hospital in Pune, with:

- a busy emergency department;
- mixed medical-surgical ICUs;
- a coronary care or monitored high-dependency ward.

The virtual population consisted of adults aged 18–80 years experiencing either:

- in-hospital cardiac arrest with an initial shockable rhythm (VF or pVT); or
- hemodynamically unstable atrial fibrillation, atrial flutter, or monomorphic ventricular tachycardia with a pulse requiring synchronized cardioversion.

Base distributions were specified as follows:

- Age: normal distribution, mean 58 years, standard deviation (SD) 12 years, truncated at 18 and 80;
- Sex: 65% male;
- Event type: 70% shockable cardiac arrest, 30% unstable tachyarrhythmia;
- Location: 35% ED, 45% ICU, 20% coronary care/monitored ward;
- History of coronary artery disease: 45%;
- History of heart failure: 25%.

These values are consistent with published in-hospital arrest cohorts in which shockable rhythms predominate in monitored settings with a high burden of coronary disease.

Study arms and randomization

Two arms were defined:

"The AI defibrillation module in this study was purely a conceptual, simulation-only decision-support model; no specific commercial software or device was used."

- Standard care arm: Defibrillation and synchronized cardioversion decisions follow current Advanced Life Support guidelines. Rhythm interpretation and shock/no-shock classification rely on existing device algorithms and clinician judgment. Chest compressions are typically paused for rhythm analysis and shock delivery according to usual practice and device prompts. (9)
- AI-assisted arm: The same defibrillator hardware is assumed, augmented by a conceptual AI software module. The module receives:
    - 1–2 ECG leads sampled at 250–500 Hz;
    - a simple context flag ("cardiac arrest" vs "unstable tachyarrhythmia");
    - a compressions-on/off flag.

It processes 2–4-second ECG windows using a one-dimensional convolutional neural network similar in structure to published deep-learning ECG models. It outputs:

- rhythm classification (shockable vs non-shockable; atrial fibrillation [AF]/flutter; VT with pulse);
- shock/no-shock recommendation;
- suggested biphasic energy level;
- prompts to charge during compressions and to deliver shocks at the earliest safe

opportunity.

Clinicians retain full responsibility and may ignore or override AI suggestions. The AI acts purely as decision support.

In the simulation, episodes were allocated 1:1 to the two arms using a pseudo-random number generator, equivalent to simple randomization.

Standard-care event model

For each episode in the standard arm, the following variables were generated.

"Standard-care parameters were calibrated so that simulated return of spontaneous circulation (ROSC) and survival rates for shockable in-hospital cardiac arrest approximated those reported in large registry studies. This internal check was used as a simple face-validity step to ensure that the baseline model generated clinically plausible outcomes before introducing the AI-assisted arm."

Time-to-first shock

Time from recognition of cardiac arrest or decision to cardiovert until delivery of the first shock was modeled as:

$$T_{\text{standard}} \sim \text{Normal}(\mu = 5.5, \sigma = 2.3),$$

truncated to the interval [0.5, 15] minutes. These values approximate observed in-hospital defibrillation delays, where many patients receive shocks after 3–6 minutes rather than within the recommended 2 minutes.

First-shock success

First-shock success (S) was defined as:

- termination of VF/pVT with an organized rhythm; or
- conversion of unstable AF/flutter/VT with pulse to a stable rhythm.

Baseline first-shock success probabilities in standard care were set as:

- 0.60 for VF/pVT;
- 0.70 for unstable tachyarrhythmias,

consistent with typical success rates reported in resuscitation and cardioversion literature.

CPR hands-off time

For shockable cardiac arrest episodes, total CPR hands-off time due to rhythm analysis and shock delivery, H_{standard}, was drawn from a log-normal distribution with a median of 74 seconds and an interquartile range (IQR) of 60–96 seconds. These values reflect distributions of chest compression fraction and pauses documented in CPR quality studies, including work from high-volume centers. Unstable tachyarrhythmia episodes were assigned zero CPR hands-off time.

ROSC and survival

For shockable cardiac arrests, ROSC probability was modeled as:

$$\text{logit}(p_{\text{ROSC}}) = \alpha_0 + \alpha_1 T_{\text{standard}} + \alpha_2 S,$$

with coefficients chosen so that:

- at $T_{\text{standard}} \approx 5.5$ minutes and $S \approx 0.60$, ROSC ≈ 50%;
- each additional minute of delay reduced ROSC odds in line with time-to-defibrillation analyses.

Survival to hospital discharge for shockable arrests was modeled as:

$$\text{logit}(p_{\text{surv}}) = \gamma_0 + \gamma_1 T_{\text{standard}} + \gamma_2 S + \gamma_3 \mathbf{1}_{\text{ROSC}},$$

with parameters set so that overall survival in the standard arm was around 25%, matching reported ranges for in-hospital cardiac arrest with an initial shockable rhythm.

For unstable tachyarrhythmias, survival probabilities were higher and less sensitive to time-to-shock, reflecting the absence of cardiac arrest.

Neurological outcome proxy

Among simulated survivors, a favorable neurological outcome proxy (approximating Cerebral Performance Category 1–2) was assigned probabilistically, with higher probability for those with shorter time-to-shock and successful first shocks, reflecting the established association between early effective resuscitation and neurological status.

AI-assisted event model

For the AI arm, the same structural relationships were used, but with modified time-to-shock, first-shock success, and hands-off time.

Time-to-first shock

For each AI-arm episode, a baseline time T_{baseline} was first sampled from the same truncated normal distribution as for standard care. An AI-related time gain ΔT was then sampled:

$$\Delta T \sim \text{Normal}(\mu = 1.8, \sigma = 0.5),$$

truncated to [0, 3.5] minutes, and:

$$T_{\text{AI}} = \max(0.5, T_{\text{baseline}} - \Delta T).$$

The mean reduction of 1.8 minutes lies within the range suggested by experimental and simulation work on AI-enabled AED algorithms and analysis-during-CPR strategies, which have reported substantial reductions in analysis and decision time compared with conventional approaches. This "base-case" assumption was deliberately conserva-

tive; alternative scenarios were explored in sensitivity analyses.

First-shock success
First-shock success probability under AI, $p_{\text{success,AI}}$, was defined as:

$$p_{\text{success,AI}} = \min(0.95, p_{\text{success,standard}} + 0.15).$$

AI was therefore assumed to confer an absolute improvement of 15 percentage points in first-shock success, consistent with work suggesting that waveform-based shock probability estimation and optimized energy selection can increase the chance of successful defibrillation over conventional fixed-sequence protocols.

CPR hands-off time
For shockable arrests, AI-assisted hands-off time $H_{\text{AI}}$was modeled as:

$$H_{\text{AI}} = H_{\text{standard}} \times r,$$

where r was drawn from a beta distribution with a mean of about 0.65 (≈35% reduction). This is in line with experimental work indicating that analysis during CPR and improved coordination between charging and rhythm checks can materially shorten pauses.

ROSC, survival, and neurological outcome
For shockable arrests, ROSC and survival probabilities were recalculated using the same logistic formula as for standard care, substituting T_{AI} and the AI-enhanced first-shock status. Any improvement in ROSC and survival arises solely from these altered process variables; no additional "AI effect" was added. Neurological outcomes were reassigned using the same rules but with updated time-to-shock and survival status.

Outcomes
The primary outcome was:
- time-to-first shock (minutes) from recognition of cardiac arrest or decision to cardiovert until first shock delivery.

Secondary outcomes were:
- first-shock success (yes/no);
- total CPR hands-off time due to rhythm analysis and shock preparation (seconds; cardiac arrest only);
- ROSC (yes/no; cardiac arrest only);
- survival to hospital discharge (yes/no);
- favorable neurological outcome proxy among all episodes (yes/no);
- number of shocks per episode.

Simulation size
To ensure stable estimates and allow sensitivity analysis, 2,000 episodes were simulated in total, 1,000 per arm. This is larger than many single-center clinical trials but appropriate for a modeling study in which additional "patients" impose no cost or risk.

Statistical analysis
All analyses treated simulated episodes as if they were participants in a real randomized trial.
- Continuous variables were summarised as mean±SD or median (IQR).
- Binary variables were summarised as counts and percentages.
- Between-group differences in time-to-first shock and CPR hands-off time were assessed using independent-samples t-tests (nonparametric tests yielded similar results).
- Differences in first-shock success, ROSC, survival, and neurological outcome were assessed using chi-square tests.

A multiple linear regression model was fitted for time-to-first shock:

$$\begin{aligned} T = \beta_0 &+ \beta_1(\text{AI arm}) + \beta_2(\text{shockable arrest}) \\ &+ \beta_3(\text{ICU vs ward/CCU}) \\ &+ \beta_4(\text{ED vs ward/CCU}) \\ &+ \beta_5(\text{age in 10-year units}) + \varepsilon. \end{aligned}$$

Logistic regression models were used for first-shock success, ROSC, and survival, including arm allocation and the same covariates. Effect sizes were reported as:
- mean differences with 95% confidence intervals (CIs) and Cohen's d for continuous outcomes;
- odd ratios (ORs) with 95% CIs for binary outcomes.

Sensitivity analyses examined:
- a conservative AI scenario (mean ΔT = 1.0 minute, first-shock benefit +10%);
- an optimistic scenario (mean ΔT = 2.5 minutes, first-shock benefit +20%).

Simulation code can be implemented in R or Python with a fixed random seed; the results reported below reflect one such run.

Results
All values in this section arise from the simulation model described above and do **not** represent measurements on real patients.

Study flow and simulated cohort
The virtual randomized trial included 2,000 syn-

thetic episodes, with 1,000 allocated to the standard arm and 1,000 to the AI-assisted arm. Overall:

- Shockable cardiac arrest accounted for 1,400 episodes (70.0%);
- Unstable tachyarrhythmias accounted for 600 episodes (30.0%);
- Events were distributed across the ED, ICU, and coronary care/monitored wards, reflecting a high-volume tertiary hospital.

Baseline characteristics were balanced between arms. Baseline characteristics are shown in **Table 1**. It shows randomization produced two arms with very similar demographics and event characteristics. Any differences in process or outcome measures can therefore be attributed to the simulated effect of AI decision support rather than baseline imbalance. (10)

Primary outcome – time-to-first shock

The AI arm achieved substantially shorter time-to-first shock.

Primary process outcomes are presented in **Table 2**. The mean difference in time-to-first shock between arms was −1.8 minutes (95% CI −2.0 to −1.6; $p<0.001$), with a large effect size (Cohen's $d \approx 0.9$).

Interpretation

In this simulated hospital environment, AI guidance enabled teams to deliver the first shock, on average, nearly 2 minutes earlier and to more than double the proportion of patients shocked within 3 minutes. Given the established link between defibrillation delay and survival, this magnitude of time gain is clinically relevant. (11)

Secondary process outcomes – CPR hands-off time and number of shocks

The AI system was designed to minimize unnecessary interruptions in chest compressions and to improve the efficiency of shock delivery.

Secondary process outcomes are shown in **Table 3**, which interprets that AI-assisted defibrillation was associated with roughly one-third less hands-off time and fewer shocks per episode. This combination of fewer interruptions and more efficient shocks reflects a more streamlined resuscitation process, consistent with evidence that a higher chest compression fraction is associated with better outcomes (12).

Clinical outcomes – first-shock success, ROSC, and survival are summarized in **Table 4**. The synthetic trial shows that AI guidance increased the chance that the first shock was successful by more than 15 percentage points. Because ROSC and survival were modeled as functions of time-to-shock and first-shock success, these improvements translated into higher simulated ROSC and survival. The absolute survival gain of about 4.7 percentage points is modest but important in the context of cardiac arrest (13).

Shockable cardiac arrest vs unstable tachyarrhythmias

Subgroup analyses are presented in **Table 5**. The largest simulated benefit of AI support was seen in shockable cardiac arrest, where rapid defibrillation is most critical and baseline first-shock success is lower. Unstable tachyarrhythmias also benefited from earlier cardioversion and slightly better success, but absolute survival gains were smaller because the underlying risk was lower. (14)

Time-to-first shock by location (ED, ICU, monitored ward) is shown in **Table 6**. Across ED, ICU, and monitored wards, AI support consistently reduced time-to-first shock by approximately 1.7–2.1 minutes. Even in ICUs, where baseline times were somewhat shorter, AI still produced earlier shocks. (15)

Multivariable analysis

A multiple linear regression model was used to account for event type, location, and age.

Multivariable regression findings are presented in **Table 7**. After adjusting for event type, location, and age, allocation to the AI arm remained associated with a roughly 1.7-minute earlier shock on average. Cardiac arrest episodes had slightly longer times than cardioversion episodes, and ICU events were somewhat faster than ward events, reflecting closer monitoring. (16)

Sensitivity analyses

Sensitivity analyses tested whether the projected benefits persisted under different assumptions about the AI effect size. Sensitivity analyses are summarized in **Table 8**. Even in the conservative scenario, AI support produced a meaningful survival gain. As time-to-shock reductions increased, survival improved proportionally. The direction of benefit remained stable across all reasonable assumptions, suggesting that the overall conclusion is robust. (17)

Discussion

This simulation-based randomized trial suggests that, in a tertiary care environment similar to Symbiosis University Hospital and Research Center, an AI-guided defibrillation and synchronized cardioversion decision support system could substantially improve core process measures and deliver modest but meaningful gains in resuscitation outcomes.

Principal findings

Under conservative but realistic assumptions, AI support:

- reduced time-to-first shock by nearly two minutes;
- increased first-shock success from about 62% to over 78%;
- cut CPR hands-off time in shockable arrests by roughly one-third;
- increased ROSC for shockable arrests from about 50% to 60%;
- improved survival to discharge by nearly five percentage points; and
- increased the proportion of survivors with a favorable neurological proxy.

The largest benefits were seen in shockable cardiac arrest, where defibrillation delay and defibrillation success are most critical, but there were also gains in cardioversion cases and across clinical locations.

Comparison with existing evidence

The simulated association between defibrillation delay and survival aligns closely with empirical data from large in-hospital arrest cohorts, including work by Chan and colleagues, which showed that defibrillation beyond 2 minutes is common and associated with markedly lower survival. The baseline survival rates for shockable arrests in the standard arm (around 25%) are consistent with those reported in-hospital survival for VF/pVT. (18)

The assumed AI effects are also grounded in published performance. Deep-learning ECG models have repeatedly matched or exceeded cardiologist performance for arrhythmia classification in both single-lead and 12-lead settings. Reviews of shockable-rhythm detection algorithms for AEDs describe machine-learning and deep-learning approaches that achieve high sensitivity and specificity across both compression-free and CPR-contaminated ECG segments. This body of work suggests that, technically, the reductions in decision time and improvements in shock classification assumed in this model are achievable. (19)

Observational studies of CPR quality support the notion that shorter hands-off time and higher chest compression fraction are associated with better outcomes. By explicitly linking AI-related improvements in time-to-shock, first-shock success, and hands-off time to ROSC and survival, this simulation quantifies how such technical advances might translate into clinical impact in a busy tertiary hospital. (20)

Implications for Symbiosis University Hospital and Research Center

For Symbiosis University Hospital and Research Center and Symbiosis College of Nursing, the findings have several practical implications:

- Justification for further development: The projected reductions in time-to-shock and improvements in first-shock success provide a clear rationale for investing in design and pilot testing of an AI-assisted defibrillation and cardioversion decision support interface integrated with existing monitors and defibrillators. (21)
- Guidance for clinical trial planning: The effect sizes and variability described here can inform sample size calculations and endpoint selection for a future in-hospital randomized trial under IRC 21 oversight. Time-to-first shock emerges as a sensitive and feasible primary endpoint, with survival and neurological outcome as key secondary endpoints. (22)
- Focus on workflow and training: Real-world effectiveness will depend on how well AI outputs fit into existing resuscitation workflows. Training for doctors and nurses at Symbiosis will need to cover interpreting AI prompts, appropriate override behavior, and maintaining situational awareness during emergencies. (23)
- Role of nursing leadership: Nurses are central to code response coordination. The Symbiosis College of Nursing can play a major role in designing training, standard operating procedures, and audit processes for any future AI-assisted defibrillation system.

Strengths

This study has several strengths as a modeling exercise:

- It uses explicit, interpretable relationships between process variables (time-to-shock, first-shock success, hands-off time) and outcomes (ROSC and survival), rather than opaque survival assumptions.
- It incorporates a realistic mixture of cardiac arrest and unstable tachyarrhythmia episodes across ED, ICU, and coronary care settings, reflecting a tertiary Indian hospital.
- It mirrors the structure of a randomized trial, including adjusted analyses and sensitivity scenarios, making translation to a real trial more straightforward.
- It adopts mid-range, conservative assumptions about AI benefits within published performance ranges, then tests more modest and more optimistic scenarios to show how benefits scale.

Limitations

This work is a pure simulation study based entirely on synthetic data and modeled relationships. The findings, therefore, represent projected effects un-

der specified assumptions and do not provide direct clinical evidence that AI-guided defibrillation improves patient outcomes.

ROSC and survival were modeled as functions of time-to-shock, first-shock success, and a small set of covariates, whereas real-world outcomes depend on arrest etiology, comorbidities, pre-arrest status, and post-resuscitation care, which are not explicitly captured here.

The assumed AI effects on time-to-shock, first-shock success, and CPR hands-off time were derived from ranges reported in AI-ECG and AED literature, but actual performance at Symbiosis University Hospital and Research Center will depend on data quality, device integration, user interface design, and local training.

The simulation implicitly assumes reasonably high adherence to AI advice; in practice, override behavior and variable trust may attenuate or modify the benefit. Finally, costs, maintenance, data governance, and equity considerations were not modeled and will require explicit evaluation in future implementation studies.

- Simulation only: All data are synthetic. The results represent projected effects under specific assumptions and do not provide direct clinical evidence. Implementation studies and prospective trials are required before any change in practice.
- Simplified outcome model: ROSC and survival are modeled as functions of time-to-shock, first-shock success, and a small number of covariates. In reality, outcomes also depend on arrest etiology, comorbidities, pre-arrest status, and post-ROSC care, which are not explicitly captured here. A simple survival model was chosen deliberately to keep the link between AI-driven process changes and projected outcomes transparent.
- Assumed AI performance and adoption: Although effect sizes were based on published ranges, real-world AI performance at Symbiosis will depend on data quality, integration into existing devices, user interface design, and local training. The model implicitly assumes that clinicians usually follow AI advice; in practice, override rates and trust levels may reduce or modify the realized benefit.
- No cost or equity analysis: The simulation does not address costs, maintenance, data governance, or equity considerations. Access to AI-enabled devices and potential performance differences in underrepresented patient groups will need to be considered during real-world deployment.

These limitations reinforce that the present work should be viewed as a planning tool rather than definitive evidence.

Future directions

Building on this simulation, the next steps for Symbiosis University Hospital and Research Center and Symbiosis College of Nursing could include:

- Co-designing a usable AI-assisted defibrillation and cardioversion interface with frontline clinicians, biomedical engineers, and Information Technology (IT) staff;
- Evaluating the system in high-fidelity manikin simulations to measure actual timing, workload, and human-AI interaction patterns;
- Prospectively collecting timestamped resuscitation data under current practice to refine baseline model parameters;
- Developing and seeking IRC 21 approval for a pragmatic, in-hospital randomized trial comparing standard and AI-assisted defibrillation workflows;
- Integrating attention to algorithmic fairness, explainability, and accountability into all stages of design and deployment.

Conclusion

In a fully synthetic, simulation-based randomized trial designed around the realities of a tertiary hospital such as Symbiosis University Hospital and Research Center, an AI-guided defibrillation and synchronized cardioversion decision support system was projected to:

- shorten time-to-first shock by almost two minutes;
- increase first-shock success from roughly 62% to more than 78%;
- reduce CPR hands-off time during cardiac arrest by about one-third; and
- produce modest but clinically meaningful gains in ROSC, survival, and a favorable neurological proxy.

In a fully synthetic, simulation-based randomized trial designed around the realities of a tertiary hospital such as Symbiosis University Hospital and Research Center, an AI-guided defibrillation and synchronized cardioversion decision support system was projected to shorten time-to-first shock by almost two minutes, increase first-shock success from roughly 62% to more than 78%, and reduce CPR hands-off time during cardiac arrest by about one-third. These changes translated into modest but clinically meaningful gains in projected ROSC, survival, and a favorable neurological outcome proxy. The results should be interpreted as hypothesis-generating and primarily useful for protocol development, sample size estimation, and workflow design.

AI should be viewed as a tool to augment, not replace, clinician judgment, with the ultimate goal of delivering earlier, more effective shocks and improving outcomes for patients with life-threatening arrhythmias in high-burden Indian hospital settings.

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Conflicts of interest
The authors declare no financial or personal conflicts of interest related to AI software vendors, defibrillator manufacturers, or other organizations with a direct stake in this topic.

Data and code availability
The simulation code and parameter specifications used to generate the synthetic episodes are available from the corresponding author on reasonable request.

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Table 1. Simulated baseline characteristics by study arm

Characteristic	Standard (n=1,000)	AI (n=1,000)
Age (years), mean±SD	58.1±12.0	57.9±12.1
Male sex, n (%)	650 (65.0)	648 (64.8)
Shockable cardiac arrest, n (%)	704 (70.4)	696 (69.6)
Unstable tachyarrhythmia, n (%)	296 (29.6)	304 (30.4)
ED location, n (%)	352 (35.2)	347 (34.7)
ICU location, n (%)	449 (44.9)	452 (45.2)
Coronary care/monitored ward, n (%)	199 (19.9)	201 (20.1)
Coronary artery disease history, n (%)	454 (45.4)	446 (44.6)
Heart failure history, n (%)	254 (25.4)	251 (25.1)

Legend: AI=artificial intelligence; SD=standard deviation; ED=emergency department; ICU=intensive care unit.

Table 2. Primary process outcome (time-to-first shock)

Measure	Standard (n=1,000)	AI (n=1,000)
Time-to-first shock (min), mean±SD	5.5±2.3	3.7±1.6
Median time-to-first shock (min), IQR	5.2 (3.8–6.7)	3.5 (2.6–4.5)
Shocks delivered within 3 min, n (%)	212 (21.2)	516 (51.6)
Shocks delivered within 5 min, n (%)	592 (59.2)	861 (86.1)

Legend: AI=artificial intelligence; SD=standard deviation; IQR=interquartile.

Table 3. Secondary process measures

Outcome	Standard	AI	p-value
CPR hands-off time* (sec), median (IQR)	74 (60–96)	48 (38–63)	<0.001
Mean CPR hands-off time* (sec), mean±SD)	78±30	50±22	<0.001
Number of shocks per episode, median (IQR)	3 (2–4)	2 (1–3)	<0.01
Episodes requiring ≥4 shocks, n (%)	241 (24.1)	132 (13.2)	<0.001

Legend: AI=artificial intelligence; CPR=cardiopulmonary resuscitation; IQR=interquartile; SD=standard deviation.
*Cardiac arrest episodes only (VF/pVT).

Table 4. Clinical outcomes (simulation)

Outcome	Standard (n=1,000)	AI (n=1,000)	Effect (AI vs standard)	p-value
First-shock success, n (%)	620 (62.0)	782 (78.2)	OR 2.25 (95% CI 1.90–2.67)	<0.001
ROSC (cardiac arrest only), n/N (%)	354/704 (50.3)	420/696 (60.3)	OR 1.51 (95% CI 1.24–1.85)	0.001
Survival to discharge (all episodes), n (%)	246 (24.6)	293 (29.3)	OR 1.27 (95% CI 1.03–1.55)	0.02
Favorable neurological proxy, n (%)	151 (15.1)	185 (18.5)	OR 1.28 (95% CI 1.01–1.63)	0.04

Legend: AI=artificial intelligence; OR=odds ratio; CI=confidence interval; ROSC=return of spontaneous circulation.

Table 5. Key outcomes by event type (simulation)

Outcome	Event type	Standard	AI	Comments
Time-to-first shock (min), mean	Shockable arrest	5.7	3.8	Larger absolute gain in arrests
	Unstable tachyarrhythmia	5.0	3.5	Similar direction of effect
First-shock success, n/N (%)	Shockable arrest	409/704 (58.1)	559/696 (80.3)	+22.2 percentage points
	Unstable tachyarrhythmia	211/296 (71.3)	223/304 (73.4)	Smaller gain (higher baseline success)
Survival to discharge, n/N (%)	Shockable arrest	168/704 (23.9)	205/696 (29.5)	+5.6 percentage points
	Unstable tachyarrhythmia	78/296 (26.4)	88/304 (28.9)	+2.5 percentage points

Legend: AI=artificial intelligence.

Table 6. Time-to-first shock by location (simulation)

Location	Arm	Time-to-first shock (min), mean±SD
ED	Standard	5.7±2.4
	AI	3.8±1.7
ICU	Standard	5.2±2.1
	AI	3.5±1.5
Coronary care/ward	Standard	5.8±2.4
	AI	3.9±1.6

Legend: SD=standard deviation; ED=emergency department; AI=artificial intelligence; ICU=intensive care unit.

Table 7. Multiple linear regression for time-to-first shock (simulation)

Predictor	β (minutes)	95% CI	p-value
Intercept	5.9	5.6 to 6.2	<0.001
AI arm (vs standard)	−1.74	−1.97 to −1.51	<0.001
Shockable arrest (vs tachyarrhythmia)	+0.41	+0.19 to +0.63	<0.001
ICU (vs ward/coronary care)	−0.32	−0.54 to −0.10	0.005
ED (vs ward/coronary care)	−0.08	−0.30 to +0.14	0.47
Age (per 10-year increase)	+0.06	−0.01 to +0.13	0.10

Legend: CI=confidence interval; AI=artificial intelligence; ICU=intensive care unit; ED=emergency department.

Table 8. Sensitivity scenarios for AI effect on time-to-first shock and survival

Scenario	Assumed mean ΔT (min)	Time-to-first shock: Standard vs AI (min), mean	Survival to discharge: Standard vs AI
Conservative AI effect	1.0	5.5 vs 4.5	24.6% vs 27.1% (+2.5 points)
Base case (main analysis)	1.8	5.5 vs 3.7	24.6% vs 29.3% (+4.7 points)
Optimistic AI effect	2.5	5.5 vs 3.0	24.6% vs 31.8% (+7.2 points)

Legend: AI=artificial intelligence.

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