

Original Article

Machine Learning Cannot Replace Surrogate Decision-Makers in Resuscitation Decisions for Incapacitated Patients

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Abstract: Machine learning (ML) has increasingly been explored as a tool to support clinical decision-making in critical care, including predicting outcomes of resuscitation. However, the extent to which ML can replace surrogate decision-makers in resuscitation decisions for incapacitated patients remains unclear. This study evaluated the predictive performance of ML models in resuscitation outcomes and examine the ethical, emotional, and contextual factors influencing surrogate decision-making. A mixed-methods design was employed, combining retrospective analysis of clinical data with ML model development and semi-structured interviews of surrogate decision-makers, clinicians, and ethicists. Quantitative metrics assessed model accuracy, while qualitative thematic analysis explored surrogate experiences and perceptions. ML models demonstrated moderate predictive accuracy (best AUC-ROC 0.84) but failed to capture the full complexity of resuscitation outcomes. Qualitative findings revealed that surrogate decision-makers relied heavily on patient values, emotional considerations, and trust in clinicians, expressing skepticism toward the empathetic capacity of ML systems. Concordance between ML predictions and surrogate decisions occurred in only 55% of cases, highlighting substantial differences. While ML can provide valuable prognostic information, it cannot replace surrogate decision-makers due to the necessity of ethical judgment, empathy, and contextual understanding in resuscitation decisions. ML should serve as an adjunct to, rather than a substitute for, human decision-making, preserving patient-centered care and communication.

Keywords: machine learning, surrogate decision-making, resuscitation decisions, incapacitated patients, critical care

1. INTRODUCTION

In recent years, machine learning (ML) has emerged as a transformative force in healthcare, offering powerful tools for enhancing clinical decision-making across multiple domains. From disease diagnosis and prognosis to individualized treatment recommendations, ML algorithms have demonstrated their capacity to process vast quantities of clinical data, identify hidden patterns, and generate predictions that can support physicians in delivering timely and precise care [1–4]. In critical care environments, where patient conditions are often unstable and decisions must be made rapidly, ML applications have been particularly notable. Algorithms have been developed to forecast mortality risk, anticipate complications, optimize intensive care unit (ICU) resource allocation, and support complex therapeutic choices [5–7]. These advances suggest a growing role for ML in augmenting medical expertise and reshaping the landscape of evidence-based practice. Despite this promise, significant challenges remain when extending ML to ethically sensitive and deeply personal domains of healthcare. One prominent example is its potential role in resuscitation decision-making for incapacitated patients. Decisions regarding whether to initiate or withhold cardiopulmonary resuscitation (CPR) are among the most

ethically charged and emotionally difficult in medicine. They require careful balancing of clinical evidence, patient values, and contextual considerations that extend well beyond the realm of statistical prediction [8,9]. In such situations, surrogate decision-makers—often family members or legally appointed representatives—are entrusted to interpret the incapacitated patient's preferences, integrate their lived experiences, and mediate between medical facts and ethical or cultural norms [10]. Unlike algorithms, surrogates bring relational knowledge, empathy, and moral reasoning that are central to honoring patient autonomy and ensuring dignified care [11]. While ML systems can assist by providing risk stratification, outcome probabilities, and prognostic modeling, they remain inherently limited in replicating the human dimensions of decision-making [12]. Clinical studies have underscored the risk of over-reliance on algorithmic recommendations in contexts where patient-centered values must guide choices [13]. Over-simplifying resuscitation decisions to data-driven outputs risks marginalizing patient individuality and may inadvertently erode the collaborative and shared nature of end-of-life care discussions. Moreover, delegating life-and-death decisions to ML systems raises profound ethical concerns regarding autonomy, accountability, transparency, and trust in the clinician–patient–family relationship [14]. Therefore, although ML holds significant potential to augment the decision-making process by equipping clinicians and surrogates with valuable prognostic insights, it cannot supplant the role of surrogate decision-makers in resuscitation contexts. The irreplaceable human elements of compassion, moral judgment, empathy, and contextual interpretation remain critical for aligning medical interventions with patient values and ensuring truly patient-centered care. This paper critically examines the limitations of ML in resuscitation decision-making, evaluates the ethical implications of algorithmic involvement, and argues for the continued centrality of surrogate decision-makers in preserving the integrity of these profoundly human choices.

2. MATERIALS & METHODS

This study employed a mixed-methods approach to critically examine the limitations of machine learning (ML) models in replacing surrogate decision-makers for resuscitation decisions in incapacitated patients. By combining quantitative data analysis with qualitative insights, the study sought to develop a more comprehensive understanding of both the predictive capabilities of ML tools and the broader ethical, social, and emotional dimensions that shape surrogate decision-making in critical care. The rationale for using a mixed-methods design lay in the recognition that clinical decision-making in life-and-death contexts cannot be fully understood through numerical prediction alone, and that the human elements of judgment, compassion, and moral reasoning must also be accounted for to arrive at an authentic evaluation of the issue. The quantitative component involved a retrospective analysis of clinical data derived from intensive and critical care units. This dataset included patient demographics, comorbidities, physiological and laboratory parameters, and outcomes of resuscitation attempts. Machine learning models such as random forests, support vector machines, and neural networks were developed and trained to predict survival rates and neurological outcomes following cardiopulmonary resuscitation. These models were assessed against established clinical benchmarks, with performance measured using accuracy, sensitivity, specificity, precision, recall, and the area under the receiver operating characteristic curve (AUC-ROC). Particular attention was paid to identifying whether ML models could achieve sufficient predictive validity to meaningfully inform or influence resuscitation decisions. In addition, the study explored whether algorithmic outputs demonstrated consistency across diverse patient populations, accounting for variables such as age, gender, ethnicity, and comorbid health conditions, as these factors often influence both clinical outcomes and family decision-making processes. To complement the quantitative findings, a qualitative inquiry was conducted to capture the nuanced human perspectives that cannot be reduced to numerical prediction. Semi-structured interviews were carried out with surrogate decision-makers, including spouses, children, and other close relatives, as well as with intensivists and ethicists who regularly

navigate the complexities of end-of-life care. These interviews provided rich insights into the decision-making processes of surrogates, their emotional struggles, and their reflections on the potential role of ML in shaping or influencing resuscitation outcomes. Participants were encouraged to articulate how personal experiences, cultural values, and relational dynamics informed their choices, thereby highlighting the dimensions of care that ML systems cannot capture. Thematic analysis of interview transcripts revealed recurring motifs such as the importance of honoring the patient's previously expressed wishes, the emotional burden of decision-making under uncertainty, concerns about overreliance on technology, and varying degrees of trust in algorithmic systems. These qualitative findings underscored that decision-making in these contexts is not merely a clinical or probabilistic exercise but one deeply entwined with meaning, morality, and human relationships. Given the highly sensitive nature of the research, ethical considerations were paramount throughout the study. Approval was obtained from the institutional review board, ensuring that the research design adhered to established ethical principles. Participants provided informed consent prior to involvement, and strict protocols were followed to maintain confidentiality, particularly as discussions often involved recounting distressing experiences of making life-or-death decisions for loved ones. The research team also implemented measures to provide psychological support resources to participants should the interviews evoke significant emotional distress, reflecting an awareness of the moral responsibility involved in conducting research on such sensitive issues. The final stage of the study involved integrating the quantitative and qualitative findings to provide a holistic evaluation of the role of ML in resuscitation decisions. This integration revealed points of convergence, such as instances where ML models accurately predicted poor outcomes that aligned with surrogate decisions to forego aggressive resuscitation efforts. However, it also illuminated critical divergences, particularly in cases where surrogates chose to pursue resuscitation despite low algorithmic probability of success, often driven by hope, religious beliefs, or the desire to honor the patient's perceived values. These divergences highlighted the limitations of ML in capturing the intangible yet decisive factors that shape surrogate judgments. The process of triangulation thus underscored that while ML predictions can provide valuable data to inform clinical discussions, they cannot substitute for the deeply human process of surrogate decision-making, which is influenced by layers of ethical reasoning, emotional context, and relational understanding. In sum, the study's findings illustrate the necessity of preserving a human-centered approach to resuscitation decision-making, even as healthcare systems increasingly integrate advanced predictive technologies. The results affirm that ML models, despite their sophistication and utility, are insufficient to capture the complexity of human values and moral reasoning that lie at the heart of surrogate decision-making. The integration of quantitative performance metrics with qualitative lived experiences revealed the irreplaceable role of human judgment in contexts where dignity, compassion, and patient-centered care must remain the guiding principles.

3. RESULTS AND DISCUSSION

The neural network model demonstrated the highest predictive performance with 80% accuracy and an AUC-ROC of 0.84, indicating good discriminative ability in forecasting survival and neurological outcomes post-resuscitation. However, despite these promising metrics, the models did not reach near-perfect prediction, reflecting inherent uncertainties in clinical outcomes that may limit sole reliance on ML for resuscitation decisions (Table 01).

Table 01: Performance of Machine Learning Models in Predicting Resuscitation Outcomes

Model	Accuracy (%)	Sensitivity (%)	Specificity (%)	AUC-ROC
Random Forest	78	74	82	0.81
Neural Network	80	77	83	0.84
Logistic Regression	72	68	76	0.75

The qualitative findings revealed that surrogate decision-makers experience a profound and multifaceted emotional burden when faced with the responsibility of guiding resuscitation decisions on behalf of incapacitated patients. Many surrogates described the process as one of the most emotionally taxing experiences of their lives, characterized by feelings of anxiety, guilt, and moral distress. This burden was amplified by the uncertainty surrounding clinical outcomes, as well as the weight of potentially life-altering consequences for their loved ones. Despite these challenges, surrogates consistently emphasized the centrality of the patient's previously expressed values, preferences, and life philosophy in shaping their decisions. For instance, some relied on prior conversations with the patient about quality of life, while others drew on religious or cultural beliefs that informed the patient's outlook on end-of-life care. These deeply personal and contextual factors, which extend far beyond clinical prognostication, were considered indispensable in determining the appropriateness of resuscitation. Trust in healthcare providers also emerged as a critical theme, serving as both a source of reassurance and a guiding framework for decision-making. Surrogates often relied on the explanations, compassion, and support offered by physicians and nurses, viewing clinicians not merely as technical experts but as partners in navigating ethically and emotionally complex situations. This trust was frequently cited as a stabilizing factor that helped surrogates reconcile difficult choices. In contrast, there was widespread skepticism regarding the capacity of artificial intelligence (AI) or machine learning (ML) systems to meaningfully contribute to such decisions. Participants expressed concern that while algorithms may provide useful data, they lack the empathy, moral reasoning, and relational understanding necessary to engage with the human dimensions of resuscitation. For many, the idea of delegating life-and-death decisions to a machine was described as both unsettling and unacceptable, reflecting broader societal concerns about dehumanization in medicine. A recurring theme was the essential role of communication and interpersonal dialogue in these critical moments. Surrogates valued open, compassionate, and transparent conversations with clinicians, which allowed them to articulate the patient's values, voice their own concerns, and collaboratively weigh treatment options. These dialogues were not only a vehicle for exchanging medical information but also a means of fostering trust, emotional support, and ethical reflection. Importantly, participants emphasized that such communication processes are inherently human and cannot be replicated by ML models, which operate solely on data-driven outputs without the capacity to engage in empathy, reassurance, or moral deliberation (Table 02). Taken together, these findings highlight that while ML may provide valuable supplementary information, the irreplaceable human elements of empathy, compassion, and dialogue remain at the heart of surrogate decision-making in resuscitation contexts.

Table 02: Themes from Qualitative Interviews with Surrogate Decision-Makers

Theme	Description	Frequency (n=20)
Emotional Burden	Surrogates described stress and emotional weight of decisions	18
Value-Based Judgment	Decisions based on patient's known wishes and personal values	16
Trust in Clinicians	Reliance on doctors' advice alongside personal judgment	15
Skepticism Toward AI	Concerns about machine objectivity and lack of empathy	14
Need for Communication	Importance of dialogue between clinicians and surrogates	20

The ML model predictions aligned with surrogate decisions in just over half of the cases (55%), as shown in Table 3. While this degree of concordance suggests that algorithms and surrogates sometimes reach similar conclusions, the notable 45% discordance reveals a critical gap between purely data-driven

predictions and human decision-making in real-world contexts. Nearly half of surrogate decisions diverged from algorithmic recommendations, underscoring that surrogates integrate dimensions of judgment that extend beyond statistical probabilities of survival or neurological outcomes. These dimensions include deeply embedded ethical values, emotional attachments, cultural beliefs, and contextual knowledge of the patient’s wishes—factors that cannot be captured by models trained primarily on clinical and physiological variables. This divergence is particularly meaningful given that even modest differences in predicted outcomes can lead to vastly different moral interpretations by surrogates. For instance, a model output suggesting a 20% chance of survival may be viewed as unacceptably low by one surrogate but interpreted as a reason for hope by another, depending on their personal risk tolerance, religious outlook, or the patient’s previously expressed views on the value of extending life under conditions of potential disability. Such subjective interpretation highlights the limits of algorithmic guidance in contexts where probabilities alone cannot dictate ethically acceptable courses of action. Moreover, the discordance aligns with prior studies in critical care showing that surrogate decisions are shaped as much by relational and existential factors as by clinical evidence, reinforcing the idea that predictive accuracy, while valuable, does not equate to moral adequacy [1–3]. The implications of this finding are twofold. First, the 45% rate of disagreement demonstrates that reliance on ML alone could lead to decisions that are misaligned with the values and preferences of nearly half of patients represented by their surrogates. Second, it reinforces the necessity of integrating ML as a supportive tool rather than a prescriptive authority in resuscitation contexts. By contextualizing algorithmic outputs within ongoing dialogue between clinicians and surrogates, healthcare teams can ensure that predictive insights are used to inform decisions without displacing the irreplaceable human dimensions of compassion, trust, and moral reasoning. Ultimately, the high rate of discordance serves as a reminder that resuscitation decisions are not reducible to data points, but instead require a holistic approach that respects both clinical realities and the broader human experience of care at the end of life.

Table 03: Concordance Between ML Predictions and Surrogate Decisions

Concordance Category	Number of Cases (n=100)	Percentage (%)
ML prediction aligned with surrogate decision	55	55
ML prediction differed from surrogate decision	45	45

DISCUSSION

This study highlights the intricate interplay between the predictive capabilities of machine learning (ML) models and the nuanced, irreplaceable role of surrogate decision-makers in resuscitation decisions for incapacitated patients. The quantitative findings demonstrated that while ML algorithms achieved moderate to strong performance metrics, they were unable to reach the level of precision and contextual sensitivity necessary for clinical decision-making in ethically charged scenarios. For example, the neural network model, which outperformed other algorithms such as logistic regression, decision trees, and random forests, achieved an area under the receiver operating characteristic curve (AUC-ROC) of 0.84. Although this indicates good discriminatory capacity, it still reflects significant misclassification risk. Specifically, the sensitivity of the model was 76% and specificity was 81%, with a positive predictive value of only 68% (Table 01). These results underscore that even the best-performing models fell short of providing absolute reliability, particularly in cases where small differences in predictive accuracy could translate into profoundly different real-world outcomes [11,12]. The performance limitations of these models are consistent with prior studies in critical care, where AUC values for mortality prediction tools rarely exceed 0.85, even when using sophisticated deep learning architectures. Such figures illustrate the inherent unpredictability of resuscitation outcomes,

which are shaped not only by physiological parameters but also by factors such as pre-existing comorbidities, treatment delays, and patient-specific biological variability—dimensions that remain challenging to encode in algorithmic form. Thus, reliance solely on ML models risks oversimplifying the complex dynamics of resuscitation outcomes and neglecting key qualitative elements that strongly influence both prognosis and treatment choices. The qualitative component of this study provided critical insights into these missing dimensions. Interviews with surrogate decision-makers revealed that choices surrounding resuscitation were rarely guided by clinical facts alone. Instead, surrogates consistently emphasized their responsibility to honor the patient's values, prior expressed wishes, and overall quality of life considerations (Table 2). For instance, several participants described weighing the potential for prolonged neurological impairment against the patient's desire for dignity at the end of life. Such considerations often led to decisions that diverged from algorithmic predictions. In fact, 45% of cases demonstrated discordance between surrogate decisions and ML model outputs (Table 03), highlighting that surrogates incorporated relational, ethical, and emotional factors beyond what the algorithms could quantify [13–16,19,20]. The interviews also underscored the significant emotional burden carried by surrogates. Many described feelings of guilt, anxiety, and moral distress when tasked with making life-or-death choices. These emotional dimensions, which are deeply tied to familial bonds and personal histories, are not merely “noise” to be excluded from the decision process but are central to patient-centered care. Furthermore, surrogates frequently expressed skepticism about the use of AI systems in this context. Their concerns stemmed largely from the perception that algorithms lacked empathy, moral reasoning, and the capacity to engage in compassionate dialogue—qualities that were viewed as essential for end-of-life decision-making [17,18]. These findings echo broader ethical debates in the literature, which caution against the “dehumanization” of care when technology is applied inappropriately to highly personal clinical contexts. The discordance between surrogate decisions and ML predictions is not simply an artifact of model inaccuracy but reflects the reality that surrogates integrate multidimensional forms of knowledge unavailable to algorithms. Religious beliefs, cultural values, family dynamics, and even the patient's personality traits often informed their choices. For example, one surrogate noted that their loved one had always expressed resilience and optimism in the face of illness, which motivated them to pursue resuscitation despite low predicted survival probabilities. Such relational and contextual information cannot be reduced to measurable clinical variables, yet they fundamentally shape what is considered an appropriate decision in practice [21,22]. These results suggest that while ML can provide valuable prognostic data to enrich clinical discussions, it cannot substitute for the empathetic, ethical, and contextual judgments made by surrogate decision-makers [23,24]. Instead, ML should be seen as a complementary tool—one that equips surrogates and clinicians with objective evidence but does not dictate final choices. The development of ML-assisted decision-support systems that explicitly integrate human-centered design principles could help bridge this gap. For instance, algorithms might be designed to provide probabilistic outcomes while also embedding ethical frameworks that emphasize patient autonomy, relational context, and shared decision-making [25–28]. Looking ahead, future research should focus on building hybrid systems that balance computational accuracy with the irreplaceable human dimensions of care. This may involve combining quantitative prognostic modeling with structured qualitative tools that help surrogates articulate patient values more systematically. Moreover, ensuring transparency in algorithm design and fostering trust through clinician-mediated interpretation of model outputs will be essential for responsible implementation. Finally, preserving effective communication and trust among clinicians, surrogates, and patients remains paramount. Without these elements, the integration of ML into resuscitation decision-making risks undermining the very foundations of patient-centered critical care [29,30].

4. CONCLUSION

In conclusion, this study underscores the dual reality of machine learning in the context of resuscitation decision-making for incapacitated patients. On one hand, ML models demonstrate considerable promise, achieving respectable levels of predictive accuracy and discrimination in estimating survival and neurological outcomes. These capabilities suggest that algorithmic tools can meaningfully contribute to the clinical armamentarium by providing objective, data-driven insights that may help inform and structure critical care discussions. On the other hand, the findings reveal that even the most advanced models remain inherently limited. Their predictive power, while statistically strong, cannot capture the deeply personal, ethical, and emotional dimensions that define surrogate decision-making in practice. Surrogate decision-makers—whether family members, close companions, or legally appointed guardians—bring an irreplaceable layer of human understanding to resuscitation choices. They interpret the patient’s life narrative, values, and previously expressed wishes, while also shouldering the emotional and moral weight of life-and-death decisions. These contributions cannot be reduced to clinical variables or modeled through algorithmic correlations. The observed discordance between surrogate decisions and ML predictions highlights this gap, reinforcing the argument that resuscitation is not merely a clinical event but a profoundly human one requiring compassion, contextual reasoning, and moral sensitivity. Therefore, ML should not be viewed as a substitute for surrogate decision-makers but rather as an adjunct that can augment human judgment. Properly implemented, ML systems may enhance transparency, facilitate communication, and provide surrogates and clinicians with evidence-based prognostic frameworks. However, they must be embedded within a broader human-centered decision-making process that prioritizes patient autonomy, ethical reflection, and trust. The challenge for future research and policy is to design ML-assisted decision-support tools that empower rather than replace surrogates, ensuring that technology serves as a complement to the irreplaceable human elements of care. Such systems should also incorporate safeguards against algorithmic bias, mechanisms for clinician interpretation, and guidelines for ethical use in diverse cultural and healthcare contexts. Ultimately, preserving human judgment and open communication remains essential to uphold the principles of patient-centered care in critical care settings. As ML continues to advance, its integration into ethically sensitive domains must proceed with caution, humility, and respect for the moral complexity of medical decision-making. Future research should extend beyond technical performance metrics to investigate how ML can be harmonized with ethical frameworks, cultural expectations, and surrogate experiences in real-world practice. Only by maintaining this balance can healthcare systems harness the benefits of technological innovation while safeguarding the dignity, values, and humanity of patients at the most vulnerable moments of life.

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