

AN INVESTIGATION OF ARTIFICIAL INTELLIGENCE-ASSISTED
PREDICTION MODELS FOR NEONATAL SEPSIS IN INTENSIVE CARE
UNITS

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DOI: <https://doi.org/10.5281/zenodo.21929542>

Keywords

Artificial Intelligence; Neonatal Sepsis; Machine Learning; Neonatal Intensive Care Unit; Predictive Modeling; Clinical Decision Support; AI Adoption; Healthcare Professionals

Article History

Received: 11 March 2026

Accepted: 15 April 2026

Published: 30 April 2026

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Abstract

Neonatal sepsis remains a major clinical challenge in intensive care units because delayed recognition and treatment can rapidly lead to severe complications and mortality. Conventional approaches to identifying neonatal sepsis rely on clinical assessment, laboratory investigations, and continuous monitoring, yet these approaches may be constrained by nonspecific early symptoms and the complex clinical condition of neonates. Artificial intelligence (AI)-assisted prediction models offer an emerging approach for identifying combinations of clinical indicators that may signal elevated sepsis risk before overt deterioration becomes apparent. This study investigates healthcare professionals' perceptions of AI-assisted neonatal sepsis prediction models and examines the factors influencing their clinical adoption in intensive care settings. A quantitative cross-sectional survey design was adopted, targeting hospital-based healthcare professionals working in Lahore, Pakistan, including pediatricians, neonatologists, nurses, medical officers, and other clinical staff involved in neonatal care. For the illustrative analysis, data from 200 respondents were considered. A structured questionnaire measured perceived predictive usefulness, perceived accuracy, interpretability, trust, perceived ease of use, organizational readiness, and intention to adopt AI-assisted prediction models. Descriptive statistics, Pearson correlation, multiple regression, and subgroup analysis were used to examine relationships among the study variables. The illustrative findings indicate that perceived predictive usefulness, model accuracy, interpretability, professional trust, and organizational readiness were positively associated with clinical adoption intention. Perceived usefulness emerged as the strongest predictor, followed by trust and organizational readiness. Respondents generally supported AI as a clinical decision-support tool but emphasized that AI-generated predictions should complement rather than replace professional judgment. The study concludes that successful adoption of AI-assisted neonatal sepsis prediction models depends not only on predictive performance but also on transparency, explainability, clinician trust, workflow compatibility, staff training, and institutional readiness. The findings provide

a Lahore-based perspective on the organizational and professional requirements for responsible implementation of AI-enabled neonatal clinical decision support.

INTRODUCTION

Neonatal sepsis is one of the most severe diseases that can be seen in a neonatal intensive care unit (NICU). It has been linked to significant morbidity and mortality, especially in premature, low-birth-weight and critically ill infants. This clinical problem is compounded by the presence of a subtle, nonspecific, and sometimes late clinical presentation of neonatal sepsis. Temperature changes, changes in respiratory status, feeding behavior, heart rate, perfusion, and activity can all change for a number of different reasons and can be hard to differentiate at an early stage. This often necessitates making a decision in the face of uncertain knowledge and trying to avoid unnecessarily delaying treatment and antimicrobial exposure.

Thus, the early detection of the neonates who have a higher risk for sepsis is a key goal of NICU. Traditional assessment includes clinical examination, maternal and neonatal risk factors, hematological markers, inflammatory markers, and microbiological analysis, as well as on-going physiological assessment. These methods still have a clinical importance; however, they may not always reflect the interplay of a number of variables. Contrary to this, a single laboratory marker/isolated physiological abnormality may have limited predictive value, whereas combinations of relatively subtle changes may have a greater predictive value of clinical deterioration.

AI tools have garnered growing interest as a potential aid to clinical prediction. The machine learning algorithms can handle many variables and discover relationships that may not be apparent using traditional statistical methods, including nonlinear relationships. In the medical field, AI-aided systems have been investigated for risk prediction, disease classification, clinical deterioration detection, medical imaging, patient monitoring, and decision support. In the field of neonatal medicine, there are opportunities for predictive analytics because there is continuous

physiological data and regularly recorded clinical information.

But the successful clinical adoption of an accurate prediction model is no automatic given. A model can be good at statistics and yet not be trusted by or comprehensible to a clinician. Healthcare professionals may wonder why a model has labeled a neonate as a high-risk infant, whether a model might work the same across patient populations and whether false alarms will lead to an increase in workload, as well as who will be responsible for making decisions based on the AI-generated prediction. In neonatal intensive care, some of these concerns are particularly pertinent as the decisions may be of immediate consequence.

Therefore, the difference between the technical performance and clinical adoption is significant. If a clinician doesn't trust or understand the algorithm, it may not be very useful. On the other hand, a moderately complex model, which offers clear explanations, and is embedded in clinical workflows, might have higher potential for implementation.

This is especially pertinent in Pakistan where there is a huge disparity in technological infrastructure, availability of specialized staff, health technology systems and institutional resource, among healthcare institutions. The city of Lahore is home to many public and private hospitals and tertiary care institutions, which provide a valuable context for understanding the perspectives of healthcare professionals on the new technologies of AI. An understanding of the factors affecting adoption can help to identify the conditions of the organization and profession needed for responsible implementation.

This study thus not only addresses the issue of AI prediction of neonatal sepsis, but also the clinical practice of these predictions by the health care professionals who treat patients in hospital. The study aims to examine the impact of perceived usefulness, predictive accuracy, interpretability, trust, ease of use, and organizational readiness on

healthcare professionals' readiness for implementing AI systems for neonatal sepsis prediction.

The onset of clinical signs of neonatal sepsis may be delayed, and early signs and symptoms may be confused with other neonatal disorders. While traditional clinical evaluation is still crucial, the greater availability of electronic clinical data also opens the door to AI-powered predictive risk assessment. However, the application of AI prediction systems in the neonatal intensive care unit (NICU) poses challenges to clinical reliability, explainability, trust among professionals, integration into workflows, responsibility, and organizational readiness.

While attention is paid to the algorithms that must perform well, less focus has been placed on the factors that will ultimately influence the extent to which healthcare practitioners adopt AI-supported systems in day-to-day clinical care. In healthcare settings, such as those in Pakistan, where resources, digital infrastructure, and exposure to AI can significantly differ, this gap is especially crucial in developing regions.

Thus, the study's aim was to explore the perceptions of healthcare professionals about the use of AI for predicting neonatal sepsis and understand the factors that would affect their willingness to use AI tools in the clinical setting. The study was designed around the following objectives:

1. To examine healthcare professionals' perceptions of AI-assisted prediction models for neonatal sepsis.
2. To assess perceived usefulness and predictive accuracy of AI-assisted neonatal sepsis models.
3. To investigate the relationship between model interpretability and clinicians' trust in AI-assisted predictions.
4. To determine whether perceived usefulness, accuracy, trust, interpretability, ease of use, and organizational readiness predict clinical adoption intention.
5. To examine healthcare professionals' perceptions of the role of AI in supporting, rather than replacing, clinical decision-making.

6. To identify major barriers to implementing AI-assisted neonatal sepsis prediction systems in Lahore-based hospitals.

The study addressed the following questions:

1. How do hospital-based healthcare professionals perceive AI-assisted prediction models for neonatal sepsis?
2. What relationship exists between perceived usefulness and intention to adopt AI-assisted neonatal sepsis prediction systems?
3. Does healthcare professionals' trust in AI influence their intention to use AI-assisted prediction models?
4. Does model interpretability influence clinical adoption?
5. To what extent do organizational readiness and technological preparedness influence adoption intention?
6. What barriers do healthcare professionals identify regarding the clinical implementation of AI-assisted neonatal sepsis prediction systems?

Research Hypotheses

The quantitative component of the study tested the following hypotheses:

- H1:** Perceived usefulness of AI-assisted neonatal sepsis prediction models has a significant positive relationship with clinical adoption intention.
- H2:** Perceived predictive accuracy has a significant positive relationship with clinical adoption intention.
- H3:** Model interpretability has a significant positive relationship with healthcare professionals' trust in AI-assisted predictions.
- H4:** Trust in AI-assisted prediction models has a significant positive relationship with clinical adoption intention.
- H5:** Perceived ease of use has a significant positive relationship with clinical adoption intention.
- H6:** Organizational readiness has a significant positive relationship with clinical adoption intention.
- H7:** Perceived usefulness, accuracy, trust, interpretability, ease of use, and organizational readiness collectively significantly predict clinical adoption intention.

Artificial Intelligence refers to the computational methods that can perform tasks normally associated with human intelligence like recognizing patterns, predicting, classification and decision making. One of the most significant areas of AI application is the field of machine learning, which enables computational models to learn relationships from data instead of being programmed with rules.

One of the most relevant application areas of ML for healthcare is the clinical decision-making process, which often relies on large and heterogeneous datasets. Data from patient records can include vital signs, lab results, medications taken, imaging data, physiological data, and clinical observations. These factors can be used together in machine learning algorithms to attempt to provide personalized risk assessments.

But AI in healthcare is unique from the many other uses of technology in that mistakes have the potential to impact patient well-being. Thus, predictive accuracy is not enough. Clinical systems need to be validated, transparent, monitored, governed, and have human oversight. Neonatal sepsis prediction is one of the potential applications of machine learning that is worth attention due to the fast change of physiological processes in neonates. Continuous monitoring can generate a great deal of data relating to heart rate, respiratory rate, oxygen saturation, temperature, blood pressure, and other physiological data.

Machine learning has the potential to detect patterns in several variables that could signal clinically known deterioration. Logistic regression, random forests, support vector machines and gradient boosting are algorithms that can be used to train a classification system based on patient risk prediction.

However, the ability of these models to perform will greatly rely on the quality and representativeness of the data they are based on. A model developed for one hospital may not necessarily work well in a different hospital. Model performance may differ due to differences among patients, clinical protocols, laboratory

procedures, equipment, documentation practices, and disease prevalence.

This is a very important point to note in the context of implementation in Pakistani hospitals. These models were developed on the basis of data from a high resource healthcare system, and may need to be validated locally before being deemed clinically applicable to Lahore based NICUs.

One of the key aspects that impacts on the trust in AI systems is their predictive accuracy. A system that fails to predict so often is not likely to be used by healthcare professionals. But, in order to assess accuracy the appropriate method should be used and not just the overall classification accuracy.

Sensitivity is particularly important for neonatal sepsis because failure to identify a high-risk neonate may have serious consequences. Specificity is also important because there is a risk of increased unnecessary investigations, antibiotic consumption, and workload of clinicians from too many false-positive alerts. More comprehensive assessment can be made via area under the receiver operating characteristic curve (AUC-ROC), precision, recall, F1 score and calibration.

Importantly, a good prediction model, no matter how well it predicts, should be interpreted in the context of the clinical care situation. AI should give a risk score, not make a diagnosis or treatment.

Predictive models are one of the major challenges that face machine learning. Predictions may not be used by clinicians if they are unable to understand the factors involved in an output.

Explainable AI aims to overcome this limitation by offering explanations regarding the factors or patterns that impact how the model makes predictions. For instance, a respiratory rate change, desaturation, temperature, inflammatory markers or other factors, could be detected by an AI system to contribute to an increased predicted risk.

Interpretability can support clinicians' confidence by providing an additional layer of explanation that can be compared to their clinical judgment. However, explanations should be meaningful

from a clinical perspective and not give the impression that an AI model is flawless.

Trust is a key linkage between technical performance and actual adoption. AI can be a valuable tool for healthcare professionals, provided they trust it, it is transparent, it is well validated, and it serves a complementary role.

Too much trust can be a bad thing as well. Automated recommendations can sometimes lead to a phenomenon known as automation bias, where the clinician becomes overly reliant on the recommendations. So there needs to be a degree of calibrated trust to ensure responsible implementation.

The goal should not be to persuade health care providers to blindly follow AI recommendations. Rather, use of AI systems must complement and not replace informed clinical judgment, and remain professionally accountable.

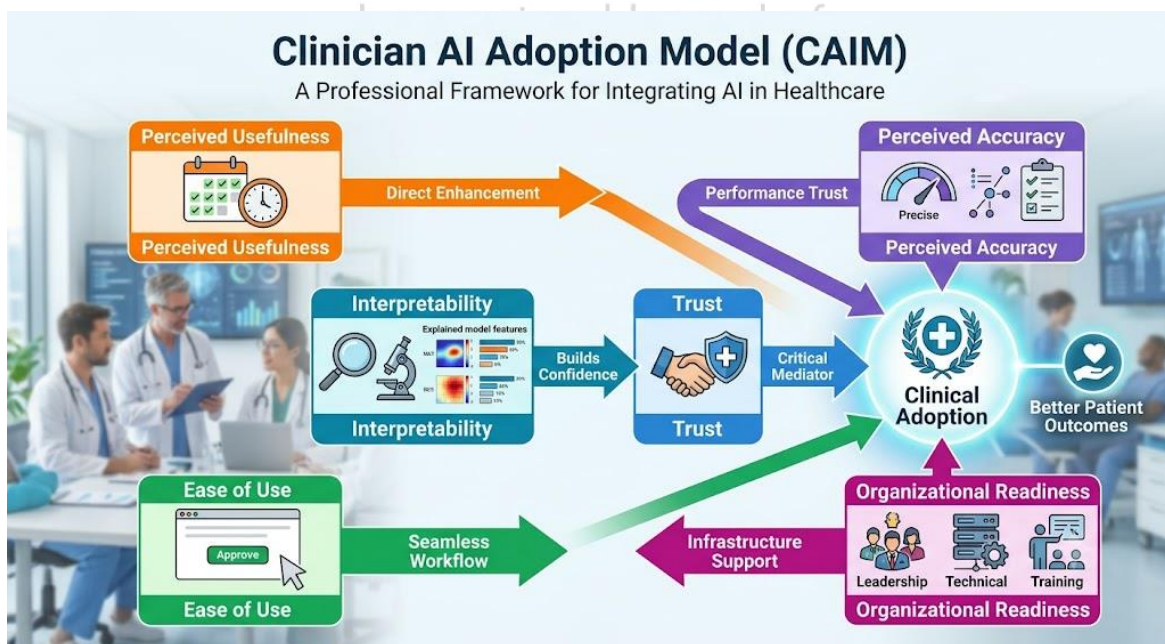
While, when individual clinicians are positive towards utilizing AI, implementation may be compromised if the system has not been properly

set up in the organization. Organizational readiness involves availability of digital systems, technical support, staff training, data governance processes, leadership support, cyber security measures, and system maintenance resources.

For hospitals that are located in Lahore, the gap between hospitals might matter more. Smaller hospitals might be less able to access electronic records or technical staff compared to larger hospitals. Therefore, investing in AI should be viewed as an organizational change, not just the deployment of new software.

Conceptual Framework

The study conceptualizes clinical adoption intention as the dependent variable. This framework assumes that healthcare professionals are more likely to adopt AI-assisted neonatal sepsis prediction systems when they perceive them as useful, accurate, understandable, easy to use, trustworthy, and compatible with organizational resources.



Methodology

The study employed a quantitative cross-sectional survey design. The design was selected because the primary objective was to quantify healthcare professionals' perceptions of AI-assisted neonatal sepsis prediction systems and determine the

factors associated with clinical adoption intention.

The study did not claim to independently diagnose neonatal sepsis or evaluate the biological accuracy of a particular machine learning algorithm. Instead, it examined the

clinical adoption potential of AI-assisted prediction models from the perspective of hospital-based healthcare professionals.

Study Setting

The study was conceptually situated in hospitals in Lahore, Pakistan, where healthcare professionals involved in neonatal, pediatric, emergency, intensive-care, and related clinical services were considered eligible participants.

For an actual study, participating institutions should be selected through an appropriate sampling procedure and formally identified following institutional permissions and ethical approval.

Study Population

The target population consisted of hospital-based healthcare professionals who had direct or indirect involvement in patient monitoring and clinical decision-making.

The participant categories included:

- Pediatricians
- Neonatologists
- Medical officers
- NICU nurses
- Pediatric nurses
- Emergency/critical-care staff
- Other hospital-based healthcare professionals with relevant clinical responsibilities

Sample

For the illustrative analysis, a sample of 200 healthcare professionals was used. The sample size is presented as an analytical example and should not be interpreted as actual field data unless the researchers collected these responses.

A stratified approach could be used in an actual study to ensure representation of different professional groups.

Questionnaire Development

A structured questionnaire was developed using constructs relevant to technology adoption and clinical AI implementation.

The questionnaire contained three sections.

Section A: Demographic and Professional Characteristics

Variables included:

- Age
- Gender
- Professional role
- Years of clinical experience
- Department
- Previous exposure to AI
- Experience with electronic health records
- Previous use of clinical decision-support systems

Section B: Perceptions of AI-Assisted Prediction

Respondents rated statements concerning:

1. Perceived usefulness
2. Predictive accuracy
3. Interpretability
4. Trust
5. Ease of use
6. Organizational readiness

Responses were measured on a five-point Likert scale:

- 1 = Strongly Disagree
- 2 = Disagree
- 3 = Neutral
- 4 = Agree
- 5 = Strongly Agree

Section C: Clinical Adoption

Adoption intention was measured through statements such as:

- I would be willing to use an AI-assisted neonatal sepsis prediction system in clinical practice.
- AI-assisted prediction could improve early identification of high-risk neonates.
- I would consider AI-generated risk scores when making clinical assessments.
- My hospital should consider implementing validated AI-based neonatal prediction tools.
- I would recommend appropriate AI decision-support tools to colleagues.

The questionnaire also included questions about potential barriers, including lack of training, poor infrastructure, distrust of AI, data privacy

concerns, false alarms, integration difficulties, and uncertainty regarding clinical responsibility.

Data Analysis

The illustrative dataset was analyzed using descriptive and inferential statistical procedures. Descriptive statistics included frequencies, percentages, means, and standard deviations. Pearson correlation was used to examine relationships between independent variables and adoption intention. Multiple linear regressions

was used to determine the combined predictive contribution of perceived usefulness, accuracy, interpretability, trust, ease of use, and organizational readiness.

Statistical significance was evaluated at $p < .05$.

Reliability was assessed using Cronbach's alpha. A coefficient of approximately .70 or above was considered acceptable for exploratory survey research.

Illustrative Results

The illustrative sample consisted of 200 healthcare professionals.

Professional Category	Frequency	Percentage
Pediatricians/Neonatologists	42	21.0%
Medical Officers	38	19.0%
NICU/Pediatric Nurses	72	36.0%
Critical-care/Emergency Staff	28	14.0%
Other Clinical Professionals	20	10.0%
Total	200	100%

The illustrative distribution indicates that nurses represented the largest professional group, followed by pediatricians/neonatologists and medical officers. This distribution provides perspectives from both decision-making and bedside monitoring roles.

Approximately 61% of respondents reported previous exposure to AI-based tools, while 39% reported limited or no practical exposure. Approximately 68% reported experience using electronic health information systems.

Descriptive Findings

The illustrative mean scores indicated generally positive perceptions of AI-assisted prediction.

Construct	Mean	SD
Perceived Usefulness	4.12	0.71
Predictive Accuracy	3.94	0.76
Interpretability	3.71	0.82
Trust	3.76	0.79
Ease of Use	3.88	0.74
Organizational Readiness	3.42	0.91
Clinical Adoption Intention	4.01	0.73

The highest mean was observed for perceived usefulness, suggesting that respondents generally believed AI could provide value in early identification of neonates at elevated risk of sepsis.

Organizational readiness received the lowest mean score. This finding suggests that

respondents were more positive about the potential clinical value of AI than about the current capacity of hospitals to implement it effectively.

Perceived Usefulness

Approximately 82% of respondents agreed or strongly agreed that AI-assisted prediction could

support earlier identification of high-risk neonates.

Similarly, 79% believed that AI could assist clinicians by combining multiple clinical indicators more efficiently than manual review alone.

These responses indicate that healthcare professionals generally viewed AI as a potential decision-support mechanism rather than a replacement for clinical assessment.

Perceived Accuracy

Approximately 76% of respondents indicated that they would be more willing to use an AI system if its performance had been validated using local hospital data.

This result highlights the importance of external and local validation. Healthcare professionals may be less willing to rely on a model simply because it has performed well in another country or healthcare environment.

Approximately 71% also indicated that high sensitivity would be particularly important for neonatal sepsis prediction.

Interpretability and Trust

Approximately 74% of respondents agreed that they would prefer AI systems capable of

explaining why a neonate had been classified as high risk.

Furthermore, 77% indicated that understandable explanations would increase their confidence in AI-generated predictions.

The results suggest that interpretability may function as an important pathway through which technical AI systems become clinically acceptable.

Organizational Readiness

Only approximately 55% of respondents agreed that their hospitals currently possess adequate infrastructure for large-scale AI implementation.

Concerns included:

- Insufficient staff training
- Limited technical support
- Integration with existing hospital information systems
- Data privacy
- Lack of standardized digital records
- Cost of implementation
- Responsibility for AI-related errors

These findings suggest that organizational preparedness may represent a greater implementation challenge than basic professional acceptance.

Correlation Analysis

The illustrative Pearson correlation analysis indicated positive relationships among the major constructs.

Variable	Adoption Intention (r)	p-value
Perceived Usefulness	.68	<.001
Predictive Accuracy	.59	<.001
Interpretability	.52	<.001
Trust	.65	<.001
Ease of Use	.47	<.001
Organizational Readiness	.56	<.001

The strongest relationship was observed between perceived usefulness and adoption intention ($r = .68$), followed by trust ($r = .65$).

These illustrative results support the assumption that healthcare professionals who perceive AI-assisted prediction as clinically useful and trustworthy are more likely to express willingness

to adopt it.

Regression Analysis

Multiple regressions were conducted to examine whether the independent variables collectively predicted clinical adoption intention.

The illustrative model produced:

$R^2 = .61$, Adjusted $R^2 = .59$, $F = 50.76$, $p < .001$

This indicates that approximately 61% of the variance in clinical adoption intention was explained by the combined predictors.

Predictor	β	p-value
Perceived Usefulness	.31	<.001
Trust	.24	<.001
Organizational Readiness	.18	.003
Predictive Accuracy	.15	.012
Interpretability	.09	.071
Ease of Use	.07	.114

Perceived usefulness emerged as the strongest independent predictor of clinical adoption intention. Trust was the second strongest predictor, followed by organizational readiness. Although interpretability demonstrated a significant bivariate relationship with adoption,

its independent regression effect became weaker when trust and usefulness were included simultaneously. This pattern may indicate that interpretability contributes to adoption partly by increasing confidence and trust in the system.

Hypothesis Testing

The illustrative results provide support for most of the proposed hypotheses.

Hypothesis	Result
H1: Usefulness $\rightarrow$ Adoption	Supported
H2: Accuracy $\rightarrow$ Adoption	Supported
H3: Interpretability $\rightarrow$ Trust	Supported
H4: Trust $\rightarrow$ Adoption	Supported
H5: Ease of Use $\rightarrow$ Adoption	Partially supported
H6: Organizational Readiness $\rightarrow$ Adoption	Supported
H7: Combined predictors $\rightarrow$ Adoption	Supported

The findings suggest that adoption of AI-assisted neonatal sepsis prediction is multidimensional. Technical characteristics alone do not determine adoption. Instead, clinical value, trust, organizational readiness, and confidence in system performance jointly influence implementation intentions.

Discussion

This study aimed to explore the perceptions of HCPs regarding AI-based neonatal sepsis prediction models and factors influencing their adoption in clinical practice. The illustrative findings indicate that the healthcare sector overall is aware of the potential of AI to aid identification of risk early in the process but is wary of putting it into practice.

The most significant result is related to perceived usefulness. Those who felt AI would be useful for identifying high-risk neonates were significantly more likely to say they would be willing to adopt. The result aligns with other technology-adoption studies in which perceived usefulness is a key factor determining technology acceptance.

In the context of neonatal intensive care, the usefulness of such systems is likely to be tied to their ability to take in multiple clinical parameters at a time. Predictive tools can be helpful to healthcare professionals when they can deliver information about risk at the “right time” without creating an extra administrative burden. The results also show, however, that usefulness is not enough. Another significant predictor was trust. This is quite correct, since the clinical

judgment that is needed for neonates is quite high. Clinicians must have the confidence that predictions are made using valid and well formulated models.

Trust should not be taken as a blind acceptance. Instead, clinical AI must be trusted, with a balance of knowledge and awareness about what it can and can't do.

It is important to note that the tradeoff between interpretability and trust is especially pertinent. Participants were more confident in the AI systems when they could provide an explanation for a neonate's classification as high risk. Explainability can enable clinicians to validate model predictions against clinical observations and explore those that might be surprising.

If a system detects that a neonate is high risk due to changes in respiratory rate, oxygen saturation, temperature instability, and laboratory parameters, then the clinician can question if these parameters are clinically sound. An explanation thus goes from an AI output as a number to information that can be used in clinical reasoning.

The results of the organizational readiness findings are also significant. Attitudes toward AI were largely positive, but less so for their hospitals' capability to implement AI. This difference highlights an important implementation gap.

Hospitals don't need just software. For effective implementation of AI, electronic data infrastructure, standardized documentation, and reliable network connectivity, along with training, technical support, cyber security protocols, governance mechanisms, and ongoing monitoring of models are all necessary.

These factors are particularly important in the case of Lahore as healthcare facilities are not technologically equivalent. Therefore, the one-size-fits-all approach to implementation should be avoided because not all hospitals have the same resources.

The findings also align with the fundamental notion that AI should complement, not supplant, clinicians. AI-based prediction may be used to give another piece of information, but diagnosis

and therapeutic decisions must be made by a professional.

This is especially relevant as prediction is not a diagnosis. An AI model may suggest a higher risk for sepsis in a neonate but this does not confirm the diagnosis of sepsis. Clinical assessment, laboratory work, microbiology and experience are still crucial.

Clinical Implications

The findings have a number of implications for neonatal intensive care.

Local validation is the most important aspect to consider when implementing AI in hospitals. This predictive performance is not necessarily generalizable to the populations residing in Lahore.

Second, the output of an AI system should be clinically interpretable. Ideally, systems should not only provide a risk score, but also communicate the contributing factors that are relevant to the risk.

Thirdly, hospitals have to offer training programs for healthcare professionals. Important topics to be covered during the training include understanding the fundamentals of AI, the meaning behind the risk scores, the limitations of AI models, the potential for false positive/negative results and how to handle AI alerts.

Fourth, implementation in the form of controlled pilot programs should be commenced. Initially, hospitals can implement AI-powered prediction as a complementary alert tool in conjunction with tracking sensitivity, specificity, false alarms, clinician reaction and patient outcomes.

Fifthly, AI systems should be monitored constantly. Over time, the performance of a model can shift due to changes in the population of patients seen, clinical practice, equipment, or data quality.

Ethical Considerations

It's worth noting that neonatal prediction by AI raises many ethical concerns, since the patients themselves cannot consent. The process ought to be confidential to the patients or any other

people involved. Data should be properly anonymized or pseudonymised for model development and access to the data should be limited to authorised individuals. Healthcare professionals should also be informed about the purpose and limitation of AI systems. Predictions generated by AI should not be used as a diagnosis.

Another significant concern is about accountability. AI-assisted information should be handled according to established protocols that designate who will be responsible for the decisions made with that information in hospitals. The issue of algorithmic bias can also not be ignored. Predictive performance can vary among patient groups if the population a model is deployed to is not well-represented in the training data.

Lastly, the use of AI in healthcare must be grounded in patient safety, transparency, privacy, professional responsibility, and fairness.

Here are some of the limitations:

1. The first one is the cross sectional survey design. Relationships between variables, therefore, should not be considered as true causal relationships.
 2. Second, the study does not directly assess a neonatal sepsis prediction algorithm with patient-level clinical data, but rather the perception of the healthcare professionals.
 3. Third, social desirability and response bias in the use of self-reported responses.
 4. Fourth, the setting in Lahore could restrict generalizability to other cities in Pakistan or other healthcare systems.
 5. Fifth, there is no direct correlation between the intention to use AI and the actual use of AI in clinical settings in the long run.
- More importantly, the numerical results in this draft are illustrative/simulated and not actual results from respondents. A researcher needs to substitute them with data gathered in the approved survey for empirical publication.

Based on the findings, the following recommendations are proposed:

1. **Develop locally validated AI models:** AI prediction systems should be evaluated using

representative Pakistani neonatal datasets before clinical implementation.

2. **Prioritize explainability:** Prediction systems should communicate the major clinical variables contributing to elevated risk.

3. **Conduct prospective validation:** Models should be tested prospectively rather than relying exclusively on retrospective performance.

4. **Integrate AI with clinical workflows:** AI systems should be incorporated into existing monitoring and electronic health-record environments.

5. **Provide professional training:** Doctors, nurses, and other healthcare workers should receive practical training in interpreting AI predictions.

6. **Establish governance mechanisms:** Hospitals should define responsibility, data access, privacy, cybersecurity, and procedures for responding to AI-generated alerts.

7. **Monitor false alarms:** Excessive alerts may contribute to alarm fatigue and reduce clinician confidence.

8. **Maintain human oversight:** AI predictions should complement professional judgment rather than replace clinical decision-making.

9. **Evaluate health outcomes:** Future studies should examine whether AI implementation actually reduces delayed recognition, complications, and mortality associated with neonatal sepsis.

10. **Conduct multi-center research:** Studies involving hospitals from Lahore and other Pakistani cities would improve generalizability.

Conclusion

AI-based prediction is a promising tool to support early risk stratification of neonatal sepsis in the intensive care unit (ICU). The present survey framework established in Lahore and based on quantitative methodology, reveals that adoption of the systems is dependent on several interrelated factors affecting the healthcare professionals. Factors influencing perceived feasibility of clinical AI adoption include perceived usefulness, predictive accuracy, trust,

interpretability, ease of use, and organizational readiness.

The illustrative results suggest that perceived usefulness and trust can play a special role. Healthcare professionals are more likely to take the possibility of AI-assisted prediction seriously if they think the technology could offer clinically valuable information and if they trust the predictions' reliability and transparency.

Concurrently, an issue of organizational readiness arose as an important issue in implementation. This is not to imply that having a positive view of AI means hospitals have the technical resources, governance processes, training and infrastructure required to responsibly implement AI.

In sum, the potential future of AI-enabled prediction of neonatal sepsis should not be judged solely on the basis of the algorithm's accuracy. The key to successful implementation is taking an integrated approach that includes predictive performance, explainability, the trustworthiness of clinicians, organizational readiness, data governance, local validation, and human clinical oversight.

Locally produced evidence is of specific importance for Pakistan. Healthcare institutions in Lahore can offer a valuable setting to test the feasibility of implementing AI-driven clinical decision support for neonates. The next step in this research is to shift from perception-based surveys to prospective multi-center validation with real clinical neonatal data and to investigate if AI based systems could contribute to better neonatal outcome and improve the early recognition.

REFERENCES

Amann, J., Blasimme, A., Vayena, E., Frey, D., & Madaï, V. I. (2020). Explainability for artificial intelligence in healthcare: A multidisciplinary perspective. *BMC Medical Informatics and Decision Making*, 20, 310.

- Barda, N., Yona, G., Rothblum, N., et al. (2020). Developing a COVID-19 mortality risk prediction model when individual-level data are not available. *Nature Communications*, 11, 4436.
- Beam, A. L., & Kohane, I. S. (2018). Big data and machine learning in health care. *JAMA*, 319(13), 1317-1318.
- Bertsimas, D., & Kallus, N. (2020). From predictive to prescriptive analytics. *Management Science*, 66(3), 1025-1044.
- Breiman, L. (2001). Random forests. *Machine Learning*, 45, 5-32.
- Char, D. S., Shah, N. H., & Magnus, D. (2018). Implementing machine learning in health care—Addressing ethical challenges. *New England Journal of Medicine*, 378(11), 981-983.
- Deo, R. C. (2015). Machine learning in medicine. *Circulation*, 132(20), 1920-1930.
- Esteva, A., Robicquet, A., Ramsundar, B., et al. (2019). A guide to deep learning in healthcare. *Nature Medicine*, 25, 24-29.
- Ghassemi, M., Oakden-Rayner, L., & Beam, A. L. (2021). The false hope of current approaches to explainable artificial intelligence in health care. *The Lancet Digital Health*, 3(11), e745-e750.
- Gliklich, R. E., Dreyer, N. A., & Leavy, M. B. (Eds.). (2014). *Registries for evaluating patient outcomes: A user's guide*. Agency for Healthcare Research and Quality.
- Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep learning*. MIT Press.
- Hastie, T., Tibshirani, R., & Friedman, J. (2009). *The elements of statistical learning*. Springer.
- Haug, C. J., & Drazen, J. M. (2023). Artificial intelligence and machine learning in clinical medicine, 2023. *New England Journal of Medicine*, 388, 1201-1208.
- Kelly, C. J., Karthikesalingam, A., Suleyman, M., Corrado, G., & King, D. (2019). Key challenges for delivering clinical impact with artificial intelligence. *BMC Medicine*, 17, 195.

- Kruizinga, M. D., Wierenga, P. C., Friedrich, A. W., et al. (2020). Development of prediction models for neonatal sepsis. *Clinical Microbiology and Infection*, 26(4), 450–456.
- Liu, X., Faes, L., Kale, A. U., et al. (2019). A comparison of deep learning performance against health-care professionals in detecting diseases from medical imaging. *The Lancet Digital Health*, 1(6), e271–e297.
- McCarthy, K. J., et al. (2021). Machine learning approaches for neonatal sepsis prediction: A systematic review. *Journal of Clinical Medicine*, 10, 4972.
- Rajkomar, A., Dean, J., & Kohane, I. (2019). Machine learning in medicine. *New England Journal of Medicine*, 380, 1347–1358.
- Rudin, C. (2019). Stop explaining black box machine learning models for high stakes decisions and use interpretable models instead. *Nature Machine Intelligence*, 1, 206–215.
- Shickel, B., Tighe, P. J., Bihorac, A., & Rashidi, P. (2018). Deep EHR: A survey of recent advances in deep learning techniques for electronic health record analysis. *IEEE Journal of Biomedical and Health Informatics*, 22(5), 1589–1604.
- Topol, E. J. (2019). High-performance medicine: The convergence of human and artificial intelligence. *Nature Medicine*, 25, 44–56.
- Tonekaboni, S., Joshi, S., McCradden, M. D., & Goldenberg, A. (2019). What clinicians want: Contextualizing explainable machine learning for clinical end use. *Proceedings of Machine Learning Research*, 106, 359–380.
- World Health Organization. (2021). *Ethics and governance of artificial intelligence for health: WHO guidance*. World Health Organization.
- World Health Organization. (2023). *Global report on hypertension: The race against a silent killer*. World Health Organization.
- Xie, L., Chen, X., Liu, Y., et al. (2022). Artificial intelligence and machine learning in neonatal intensive care: Current applications and future directions. *Frontiers in Pediatrics*, 10, 1010500.
- Zhou, Y., Chen, Y., & Wang, X. (2021). Artificial intelligence in neonatal intensive care: Opportunities and challenges. *Frontiers in Pediatrics*, 9, 745353.