

ARTIFICIAL INTELLIGENCE IN NEONATAL CARE

18th Hot Topics in Neonatal Medicine

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OBJECTIVES

- How has NON-AI been used in Neonatal Care?
- What can AI bring to Neonatal Care?
- What are some examples of use?
- Where is AI headed in NICU?

NON-ARTIFICIAL INTELLIGENCE

- Humans ponder what sort of known and perhaps unknown risk factors may predict outcomes
- Therefore restricted to a limited set of identified risk factors typically using logistic regression to apply risk



NON-ARTIFICIAL INTELLIGENCE

Extremely Preterm Birth Outcomes Tool

[Overview](#)[Use the Tool](#)[About the Data](#)[References](#)

Use the Tool

This tool provides a range of possible outcomes for infants born extremely preterm. The outcomes are based on data from infants born at specific U.S. hospitals between 2006 and 2012. "Hospital range" in the tool results represent outcomes for 80% of hospitals included in this study (10th to 90th percentiles). Please note that the tool describes outcomes for groups of infants with similar characteristics. It does not predict outcomes for any individual infant. Visit [About the Data](#) to learn more.

Please enter information available at the time of birth to use the tool.

* Indicates required field

***Gestational Age**
(Best estimate in completed weeks)

Select ▼

***Birth Weight**
(from 401-1000 grams)

* **Infant Sex**

Male Female

* **Singleton Birth**

Yes No

* **Antenatal Steroids**

Yes No

Clear

Submit

Have feedback on the tool?

[Email us](#) with your ideas for improvement. Be sure to include your role/profession and how you used the tool. We cannot give medical advice or diagnoses.

Use of antenatal Vermont Oxford data for predictions

24 WEEKS

* Indicates required field

*Gestational Age
(Best estimate in completed weeks)

24 ▼

*Birth Weight
(from 401-1000 grams)

570

* Infant Sex

Male Female

* Singleton Birth

Yes No

* Antenatal Steroids

Yes No

Clear

Submit

Infants Receiving Active Treatment

Average Survival: 52%
Hospital Range: 37 - 66%

All Infants, Including Infants Not Actively Treated

Average Survival: 50%
Hospital Range: 34 - 65%

Outcomes At 18-26 Months' Corrected Age Among Infants Who Survive: (About the Data)

Profound Neurodevelopmental Impairment	Moderate-Severe Neurodevelopmental Impairment	Blindness	Deafness	Moderate-Severe Cerebral Palsy	Cognitive Developmental Delay
3 - 6%	32 - 52%	< 1%	1 - 5%	6 - 15%	31 - 46%

SEPSIS – KAISER PERMANENTE

- Developed in 2016
- 608,014 newborns born at 34 weeks' gestation or later at 14 hospitals in the United States
- Antenatal data + clinical patient data

Escobar GJ, Puopolo KM, Wi S, et al. Stratification of risk of early-onset sepsis in newborns 34 weeks' gestation. *Pediatrics*. 2014;133(1):30-36

Probability of Neonatal Early-Onset Sepsis Based on Maternal Risk Factors and the Infant's Clinical Presentation

The tool below is intended for the use of clinicians trained and experienced in the care of newborn infants. Using this tool, the risk of early-onset sepsis can be calculated in an infant born ≥ 34 weeks gestation. The interactive calculator produces the probability of early onset sepsis per 1000 babies by entering values for the specified maternal risk factors along with the infant's clinical presentation.



Please enter details below.

Predictor	Scenario
Incidence of Early-Onset Sepsis ⁺	<input type="text" value=""/>
Gestational age ⁺	<input type="text" value=""/> weeks <input type="text" value=""/> days
Highest maternal antepartum temperature ⁺	<input type="text" value=""/> Fahrenheit <input type="text" value=""/>
ROM (Hours) ⁺	<input type="text" value=""/>
Maternal GBS status ⁺	<input type="radio"/> Negative <input type="radio"/> Positive <input type="radio"/> Unknown
Type of intrapartum antibiotics ⁺	<input type="radio"/> Broad spectrum antibiotics > 4 hrs prior to birth <input type="radio"/> Broad spectrum antibiotics 2-3.9 hrs prior to birth <input type="radio"/> GBS specific antibiotics > 2 hrs prior to birth <input type="radio"/> No antibiotics or any antibiotics < 2 hrs prior to birth

Calculate »

Clear

Risk per 1000/births			
EOS Risk @ Birth			
EOS Risk after Clinical Exam	Risk per 1000/births	Clinical Recommendation	Vitals
Well Appearing			
Equivocal			
Clinical Illness			

Classification of Infant's Clinical Presentation [Clinical Illness](#) [Equivocal](#) [Well Appearing](#)

REAL LIFE IMPACT

Deshmukh M, Mehta S, Patole S. Sepsis calculator for neonatal early onset sepsis—a systematic review and meta-analysis. *J Matern Fetal Neonatal Med.* 2021;34(11):1832-1840

TABLE 1

Results of Meta-Analysis Comparing Use of Kaiser Permanente Neonatal Early-Onset Sepsis Calculator with Standard Care

Outcome	Number needed to treat using calculator to prevent one outcome
Antibiotic use in neonates	37
Laboratory testing in neonates	8
Neonatal intensive care unit admission	7
Readmissions to the neonatal intensive care unit	No difference
Culture-positive sepsis	No difference

Information from references 1 and 2.

BPD - NICHD

Neonatal BPD Outcome Estimator (2022)
 Infants with GA 23-28 weeks & Birth Weight 501-1250g

Information at Time of Birth		
Postnatal Day	-- Select --	Please select.
Gestational Age (Weeks)	-- Select --	Please select a value between 23 and 28.
Birth Weight (Grams)	<input type="text"/>	Please enter a value between 501 and 1250.
Sex	-- Select --	Please select.
ANS	ANS should only be entered for postnatal day 1.	
	-- Select --	Please select
Surgical Necrotizing Enterocolitis	Surgical necrotizing enterocolitis should only be entered for postnatal days 14 and 28.	
	-- Select --	Please select
Respiratory Support Type	-- Select --	Please select.
FIO2 ¹	<input type="text"/>	Please enter a value between 21 and 100.

¹Enter the FIO2 content in percent, e.g., enter 23.22% as 23.22.

Neonatal BPD Outcome Estimator (2022)
 Infants with GA 23-28 weeks & Birth Weight 501-1250g

Postnatal Day	3
Gestational Age (Weeks)	24
Birth Weight (Grams)	570
Sex	Male
ANS	N/A
Surgical Necrotizing Enterocolitis	N/A
Respiratory Support Type	HFV (high frequency ventilation)
FIO2	32

Probability of Outcome
 (expressed as a percent)

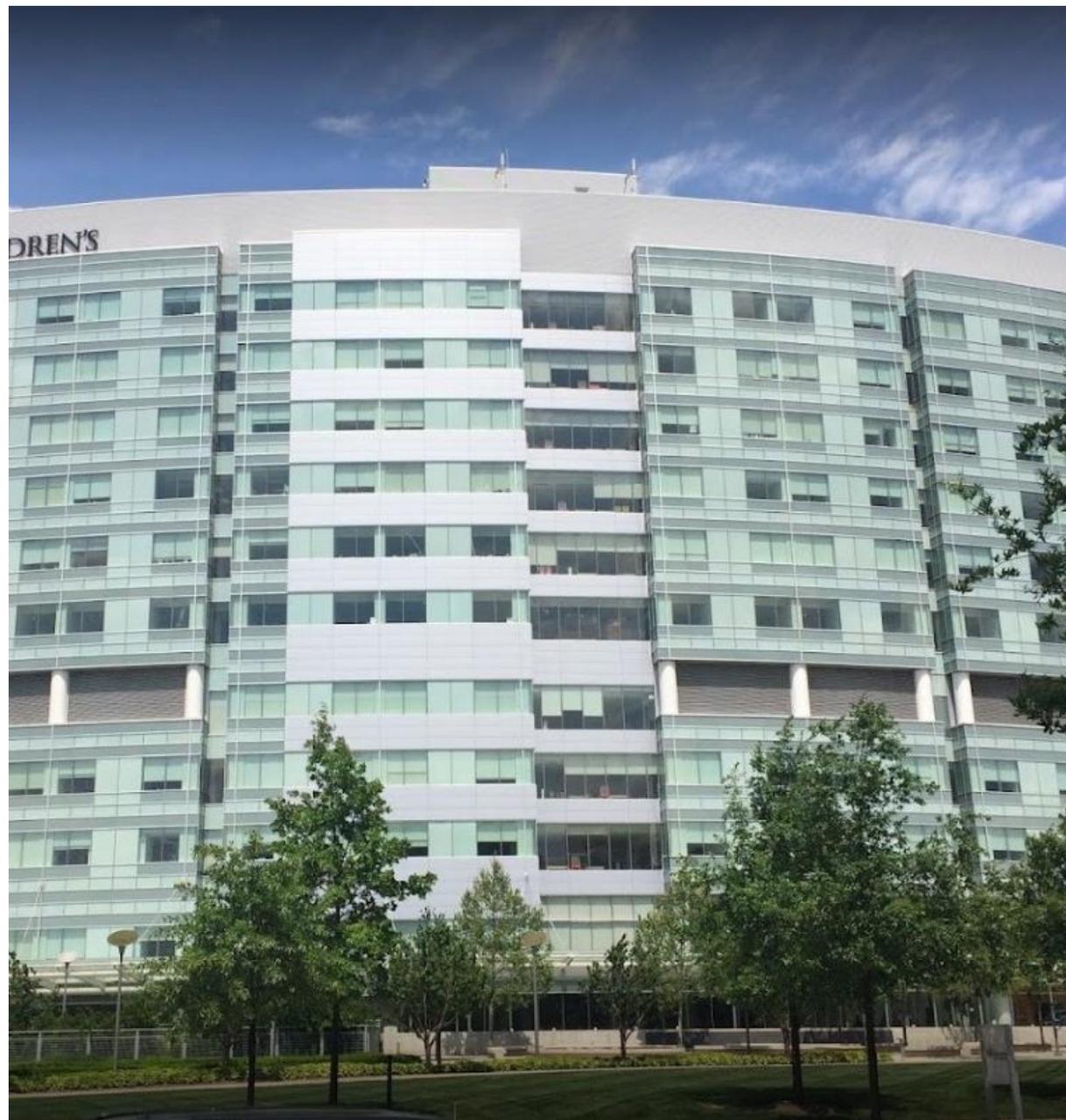
Death	Grade 3 BPD	Grade 2 BPD	Grade 1 BPD	No BPD
19.28	14.49	39.22	23.71	3.31

Laughon MM, Langer JC, et al Eunice Kennedy Shriver National Institute of Child Health and Human Development Neonatal Research Network. Prediction of bronchopulmonary dysplasia by postnatal age in extremely premature infants. Am J Respir Crit Care Med. 2011 Jun 15;183(12):1715-22. doi: 10.1164/rccm.201101-0055OC. Epub 2011 Mar 4



AI VS NON-AI

- NON-AI relies on limited factors to determine risk
- Practices in place at time of calculator development change over time
 - NIPPV, nHFOV, high flow
 - Conventional ventilation vs high frequency
- Organism virulence and diversity vary depending on country
- ELGANS
 - When outcomes are variable between sites calculators may fail!



Journal of Perinatology (2019) 39:39–47
<https://doi.org/10.1038/s41372-018-0248-y>

ARTICLE

Outcomes following a comprehensive versus a selective approach for infants born at 22 weeks of gestation

Carl H. Backes^{1,2,3} · Fanny Söderström⁴ · Johan Ågren⁴ · Richard Sindelar⁴ · Christopher¹
Brian K. Rivera³ · Courtney C. Mitchell³ · Heather A. Frey⁶ · Edward G. Shepherd^{3,7} · Leif D. Ne

Received: 20 June 2018 / Revised: 20 September 2018 / Accepted: 28 September 2018 / Published online: 23 October 2018
© Springer Nature America, Inc. 2018

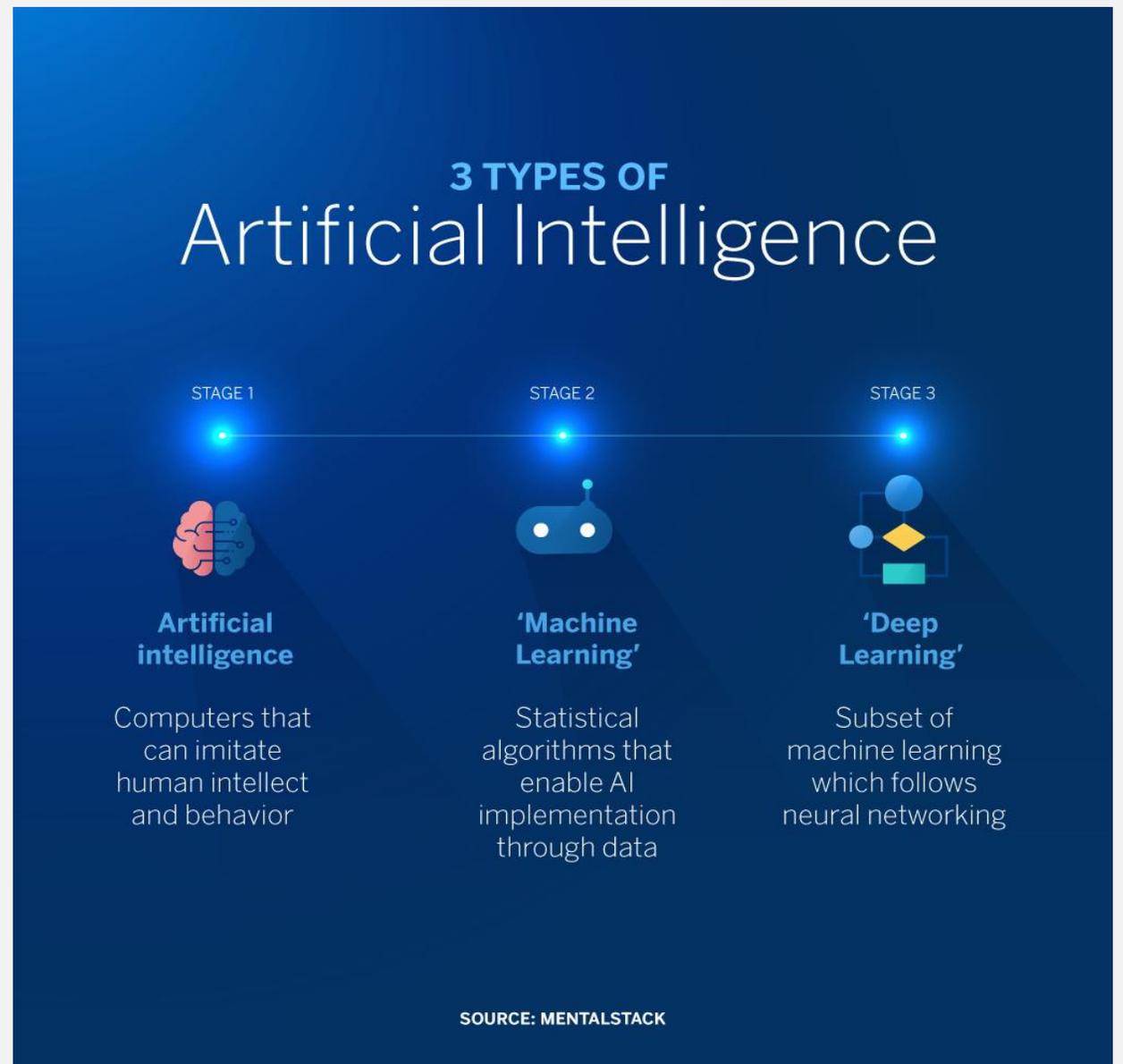
SURVIVAL

Delivery room:
(38/40, **95%** vs
12/16, **75%**; $P =$
0.049)

24 h (37/40, **93%**
vs. 9/16, **56%**; $P <$
0.01).

1 year (21/40,
53% vs. 3/16,
19%; $P < 0.05$)

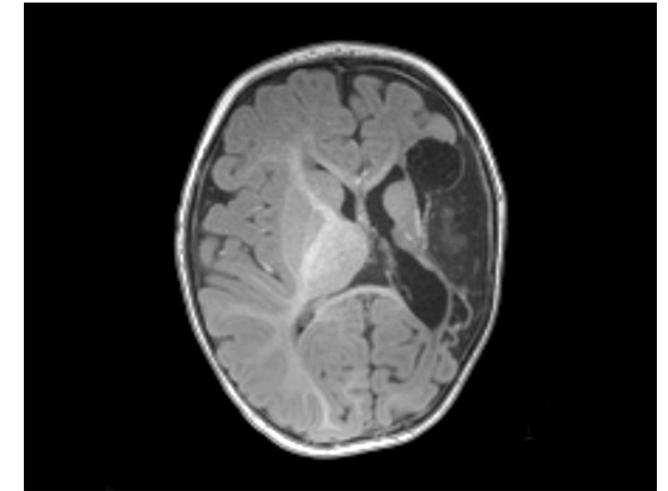
FUNDAMENTALS OF AI



Supervised vs unsupervised learning

HOW MIGHT AI BE USED IN NEONATAL CARE

- 1. Early Diagnosis and Monitoring:** AI analyzes data from monitors, sensors, and records to detect signs of complications or deteriorating conditions in infants, tracking vital signs and anomalies faster than humans.
- 2. Predictive Analytics:** By analyzing historical and real-time data, AI predicts complications, aiding in preventive measures or targeted interventions.
- 3. Image Analysis:** AI interprets diagnostic scans swiftly and accurately, aiding in identifying conditions or anomalies.
- 4. Treatment Optimization:** AI suggests personalized treatments, dosages, and identifies potential drug interactions, considering infants' unique physiological aspects.



Drug Allergy Alert

Allergic to **Unasyn** (ampicillin / sulbactam) ⓘ
Reaction hives, itching, facial swelling

Prescribed **Augmentin** (amoxicillin / clavulanate)

Stop

Order

[Feedback](#)

CLINICAL DECISION SUPPORT SYSTEM (CDSS)

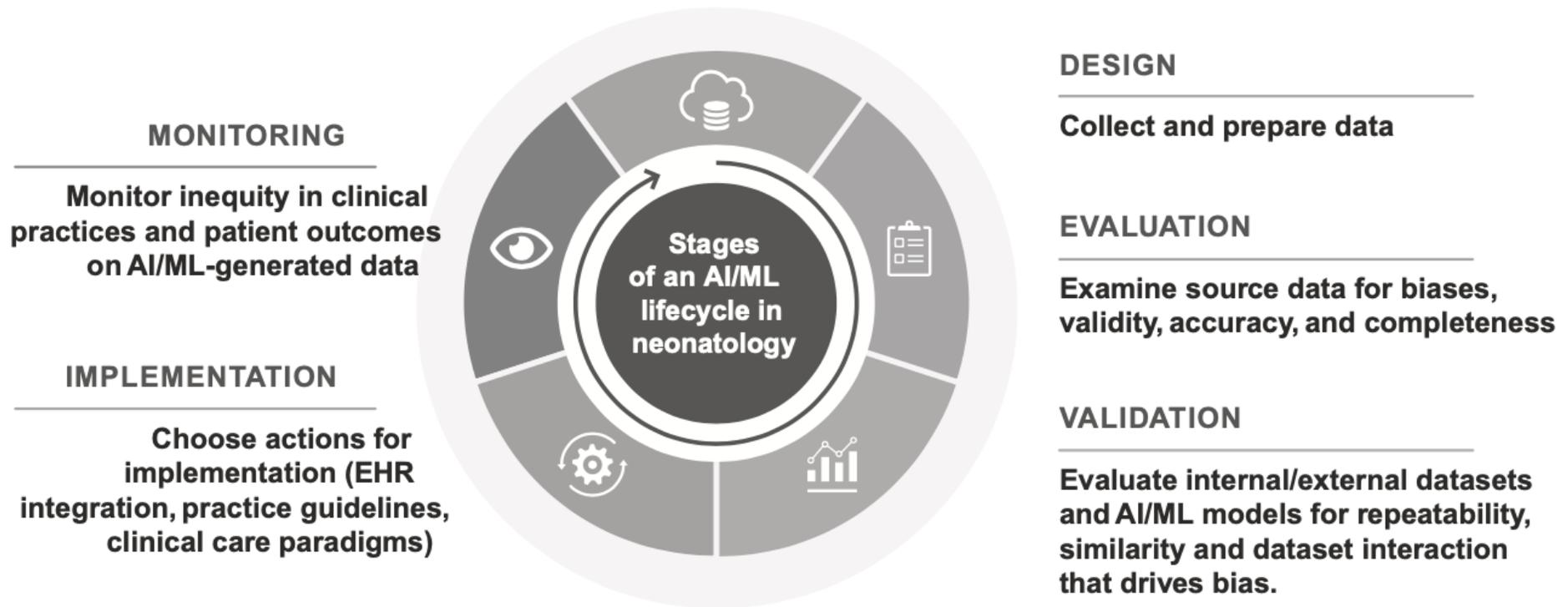
HOW MIGHT AI BE USED IN NEONATAL CARE

5. Clinical Decision Support: AI offers real-time guidance and evidence-based recommendations, aiding in decision-making and reducing errors.

6. Family Support and Education: AI platforms provide educational resources for parents, aiding them in understanding their child's condition and care options.

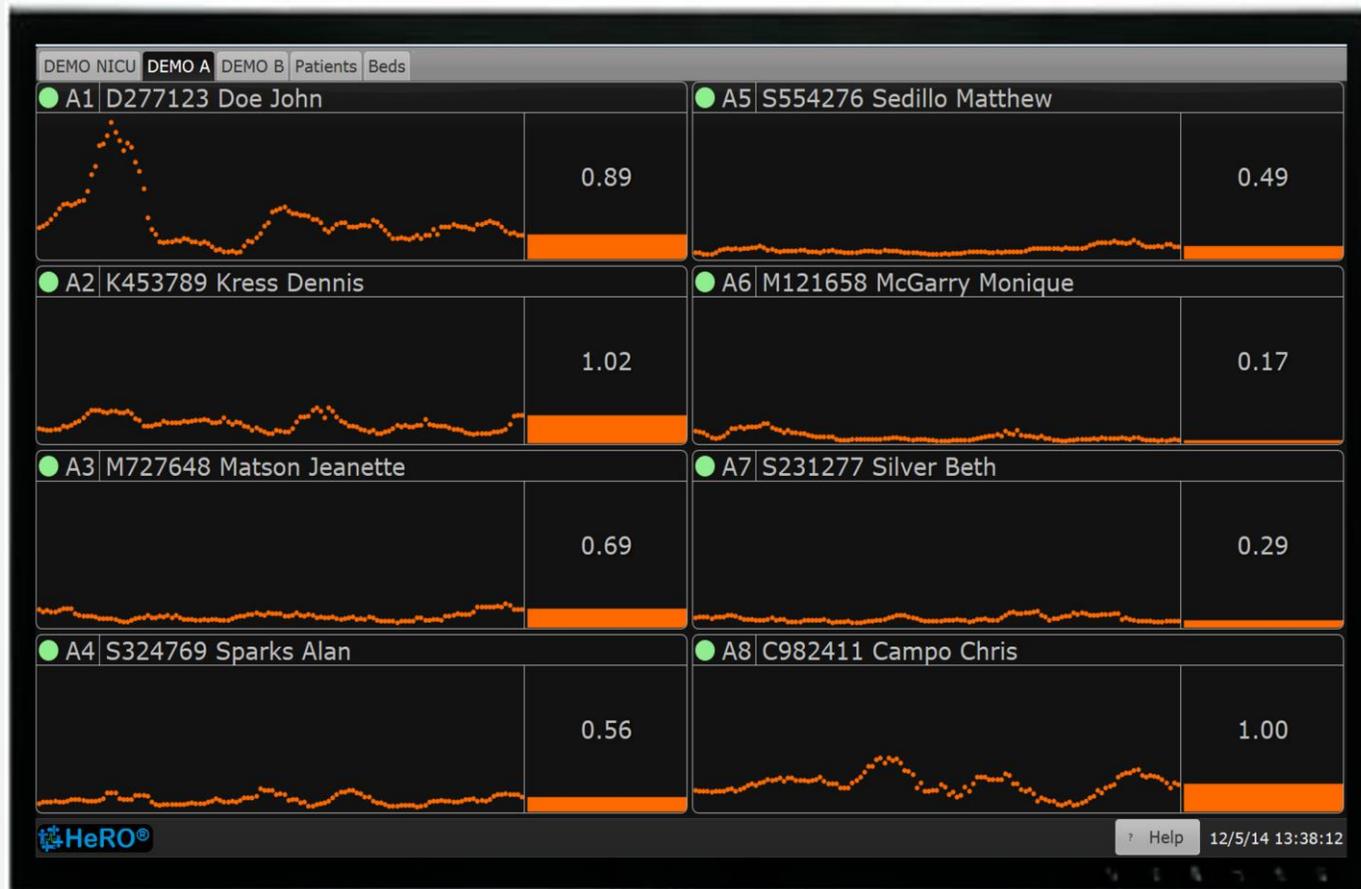
7. Research and Development: AI analyzes NICU data to aid research, understand diseases, improve treatments, and develop interventions.

THANK YOU CHAT GPT!



ENSURING ETHICAL AI

CURRENT EXAMPLE OF AI



Basis for HeRO
Heart rate variability and declines in HR precede sepsis

Mortality reduction by heart rate characteristic monitoring in very low birth weight neonates: a randomized trial

J. Randall Moorman, M.D., Waldemar A. Carlo, M.D., John Kattwinkel, M.D., Robert L. Schelonka, M.D.*, Peter J. Porcelli, M.D., Christina T. Navarrete, M.D., Eduardo Bancalari, M.D., Judy L. Aschner, M.D., M. Whit Walker, M.D., Jose A. Perez, M.D., Charles Palmer, M.D., George J. Stukenborg, Ph.D., Douglas E. Lake, Ph.D., and T. Michael O'Shea, M.D.

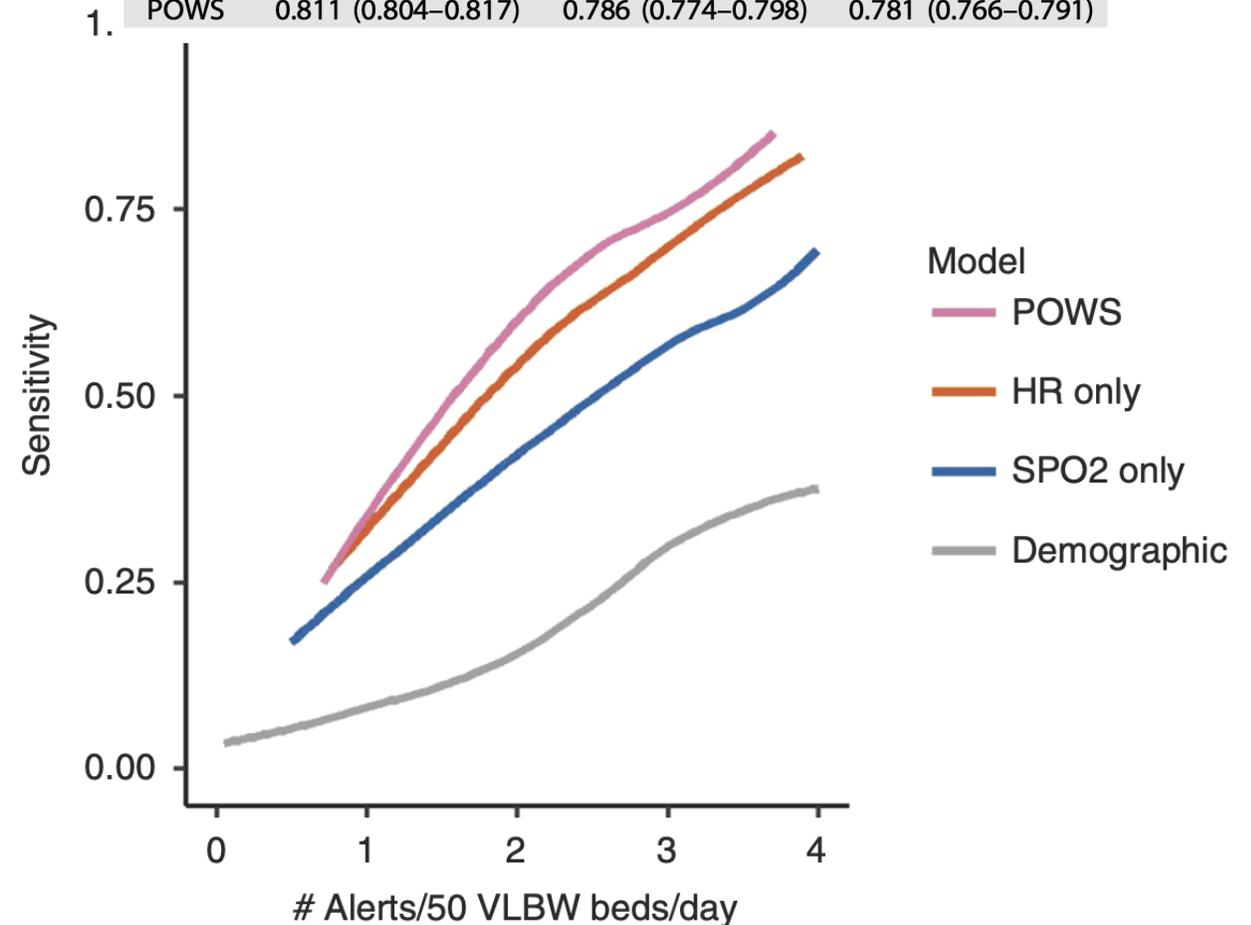
- The incidence of proven sepsis was not different in the infants whose heart rate characteristics monitoring results were displayed (358/1500 compared to 379/1489, P=0.34).
- **Mortality overall reduced by 20%**, number needed to monitor = 48
- **Mortality rate in the 30 days following the first episode of proven sepsis** was 10.0% in the infants whose heart rate characteristics monitoring results were displayed compared with 16.1% in the control infants
 - **38% reduction in mortality**
 - ARR of 6.1% (36/358 vs. 61/379, P=0.01).
- **Mortality benefit was concentrated in infants with birth weight <1000g** (HR=0.74, 95% CI 0.57 to 0.95, P=0.02, number needed to monitor 23)

APPLYING MACHINE LEARNING

- HR variability alone inferior to combo of findings
- Changes in O2 saturation
- POWS = combo O2 sat & HR from oximeter
- LOS def'n: blood culture +ve & treated with ≥ 5 days of abx, & culture was preceded by at least two days with no antibiotics.
- Excluded -ve blood cultures, +ve blood cultures obtained within 7d of a prior positive blood culture, & +ve blood cultures treated as contaminants (defined as <5 days of antibiotics).

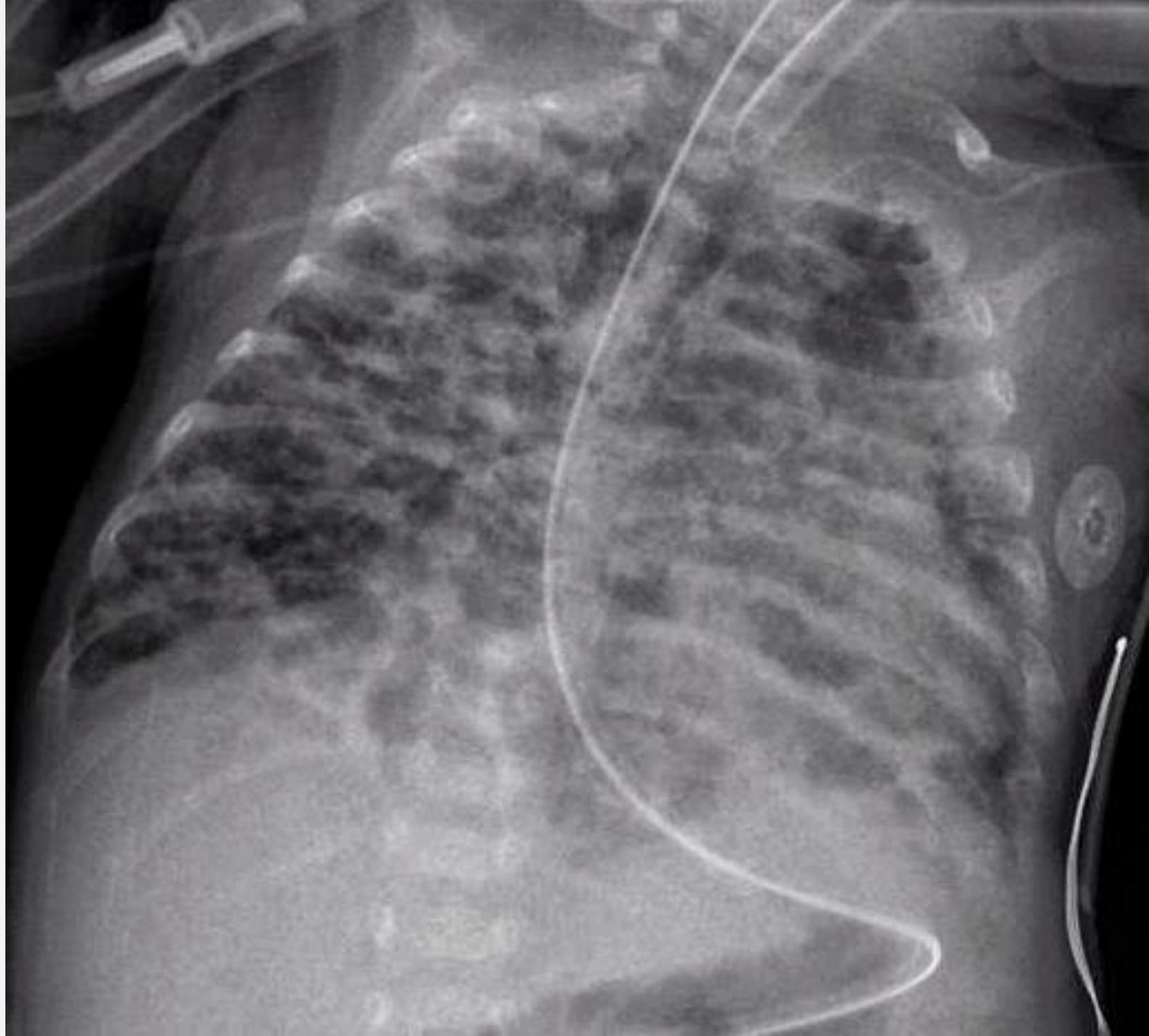
Table 3. Performance at NICU 1, 2, and 3 using features derived from pulse oximetry for Predicting Sepsis within 24 h.

Model	AUC		
	NICU 1 (train)	NICU 2 (test)	NICU 3 (test)
POWS	0.811 (0.804–0.817)	0.786 (0.774–0.798)	0.781 (0.766–0.791)



PREDICTING BPD

- First described by Northway in 1967
- Even with calculators how good are we at answering the question...
 - **“Doctor will my baby have BPD?”**



REFINING PREDICTIONS

- External validation of the BPD calculator had an AUC for prediction of BPD of 0.73-0.76
- Machine learning study
 - Patients recruited from 2013 – 2020
 - Less than or equal to 30 weeks & 3 days
- BPD-free survival outcome was defined as survival until at least 36 weeks PMA and no respiratory support needs at 36 weeks PMA.

Leigh RM et al. BMC Pediatrics 2022

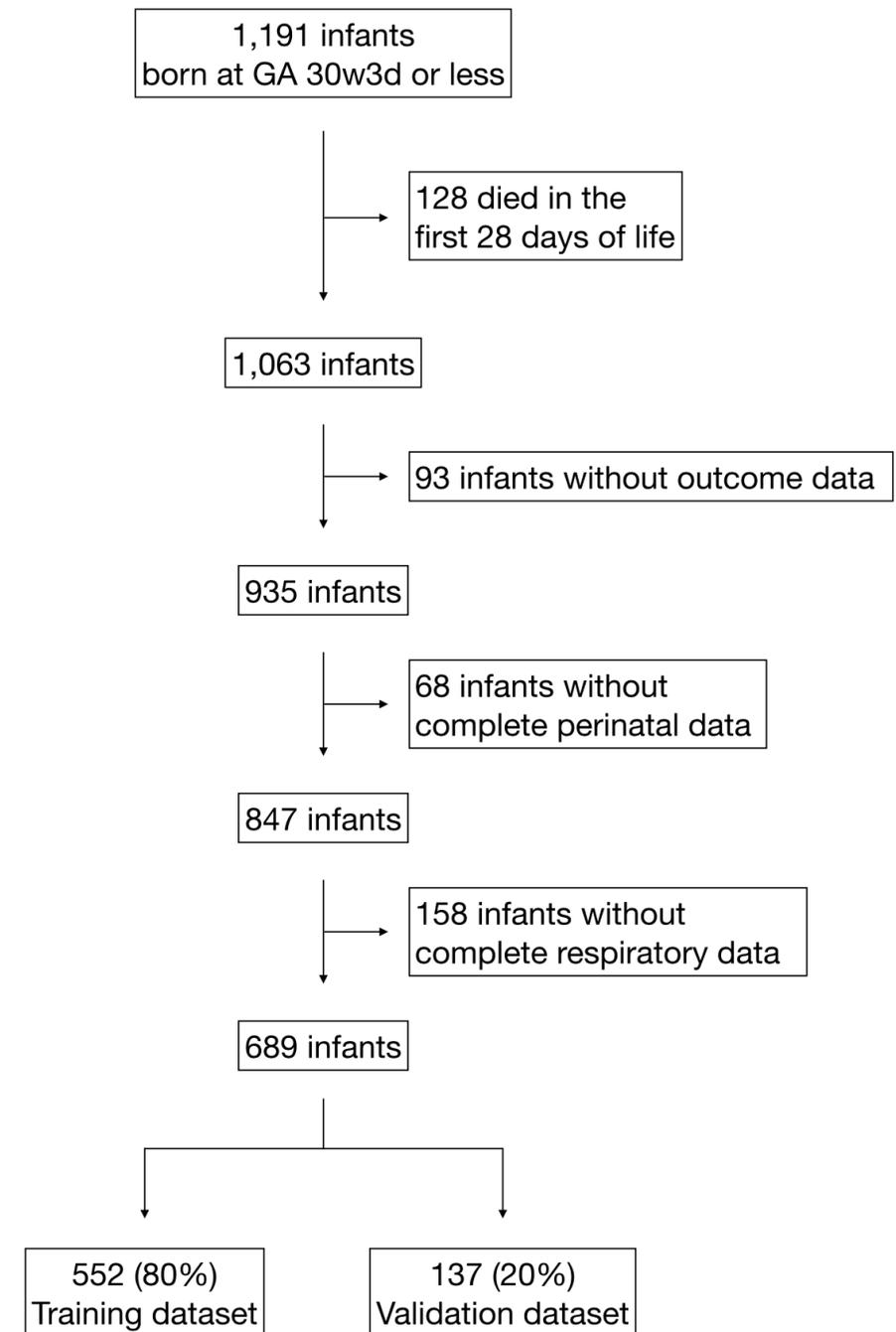


Fig. 1 A flow chart depicting the selection of study participants

Table 3 A table detailing performance measures for various random forest models predicting bronchopulmonary dysplasia-free survival. The training dataset was used for model development. The testing dataset was used for model validation

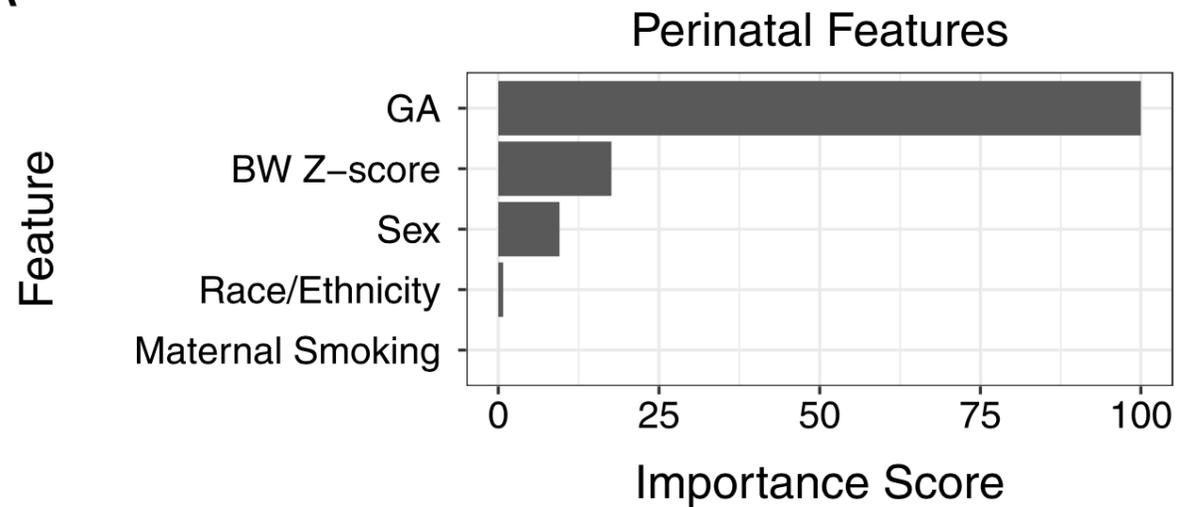
Model ID	Data included in model training	ROC AUC (95% CI)	Cutoff threshold	Youden's J value	Accuracy (95% CI)	PPV	NPV
Training Dataset							
1	Perinatal features only	0.861 (0.831–0.891)	0.550	0.571	0.786 (0.750–0.820)	0.773	0.802
2	DOL1 respiratory feature	0.724 (0.684–0.764)	0.537	0.395	0.699 (0.659–0.737)	0.680	0.726
3	DOL1-7 respiratory features	0.866 (0.836–0.896)	0.341	0.618	0.808 (0.773–0.840)	0.849	0.773
4	DOL1-14 respiratory features	0.900 (0.875–0.926)	0.510	0.676	0.839 (0.805–0.869)	0.816	0.866
5	Ensemble of Models 1 & 2	0.875 (0.847–0.904)	0.521	0.624	0.812 (0.776–0.843)	0.827	0.796
6	Ensemble of Models 1 & 3	0.911 (0.887–0.934)	0.494	0.662	0.832 (0.798–0.862)	0.829	0.834
7	Ensemble of Models 1 & 4	0.921 (0.899–0.943)	0.488	0.702	0.851 (0.819–0.880)	0.850	0.853
Testing Dataset							
1	Perinatal features only	0.841 (0.774–0.908)	0.550 ^a	0.507 ^a	0.752 (0.671–0.822) ^a	0.810 ^a	0.709 ^a
5	Ensemble of Models 1 & 2	0.867 (0.806–0.928)	0.521 ^a	0.576 ^a	0.788 (0.710–0.853) ^a	0.789 ^a	0.788 ^a
6	Ensemble of Models 1 & 3	0.884 (0.827–0.940)	0.494 ^a	0.622 ^a	0.810 (0.734–0.872) ^a	0.844 ^a	0.781 ^a
7	Ensemble of Models 1 & 4	0.899 (0.848–0.949)	0.488 ^a	0.623 ^a	0.810 (0.734–0.872) ^a	0.855 ^a	0.773 ^a

DOL Day of life, ROC AUC receiver operating characteristics area under the curve, CI confidence interval, PPV positive predictive value, NPV negative predictive value

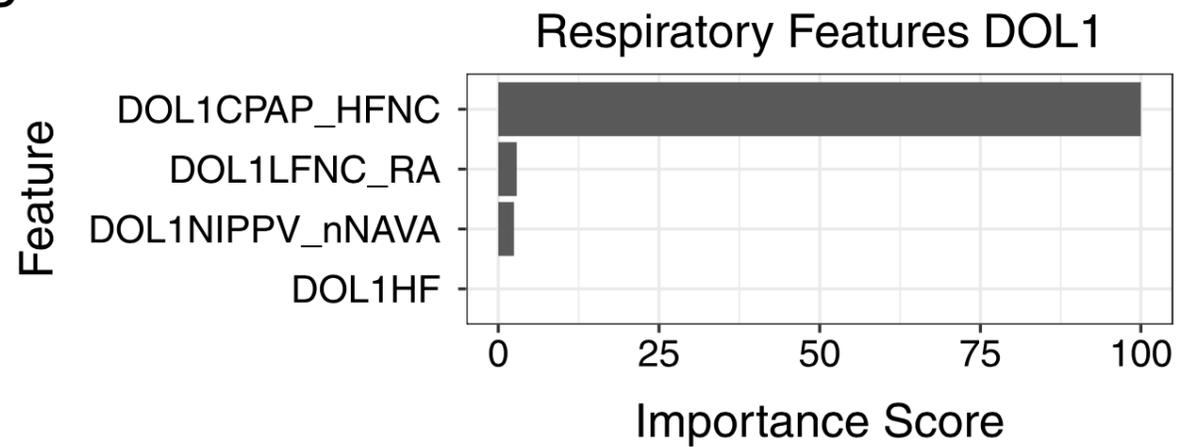
^a Based on the cutoff threshold generated using the training dataset

WHAT MATTERS MOST TO OUTCOME?

A



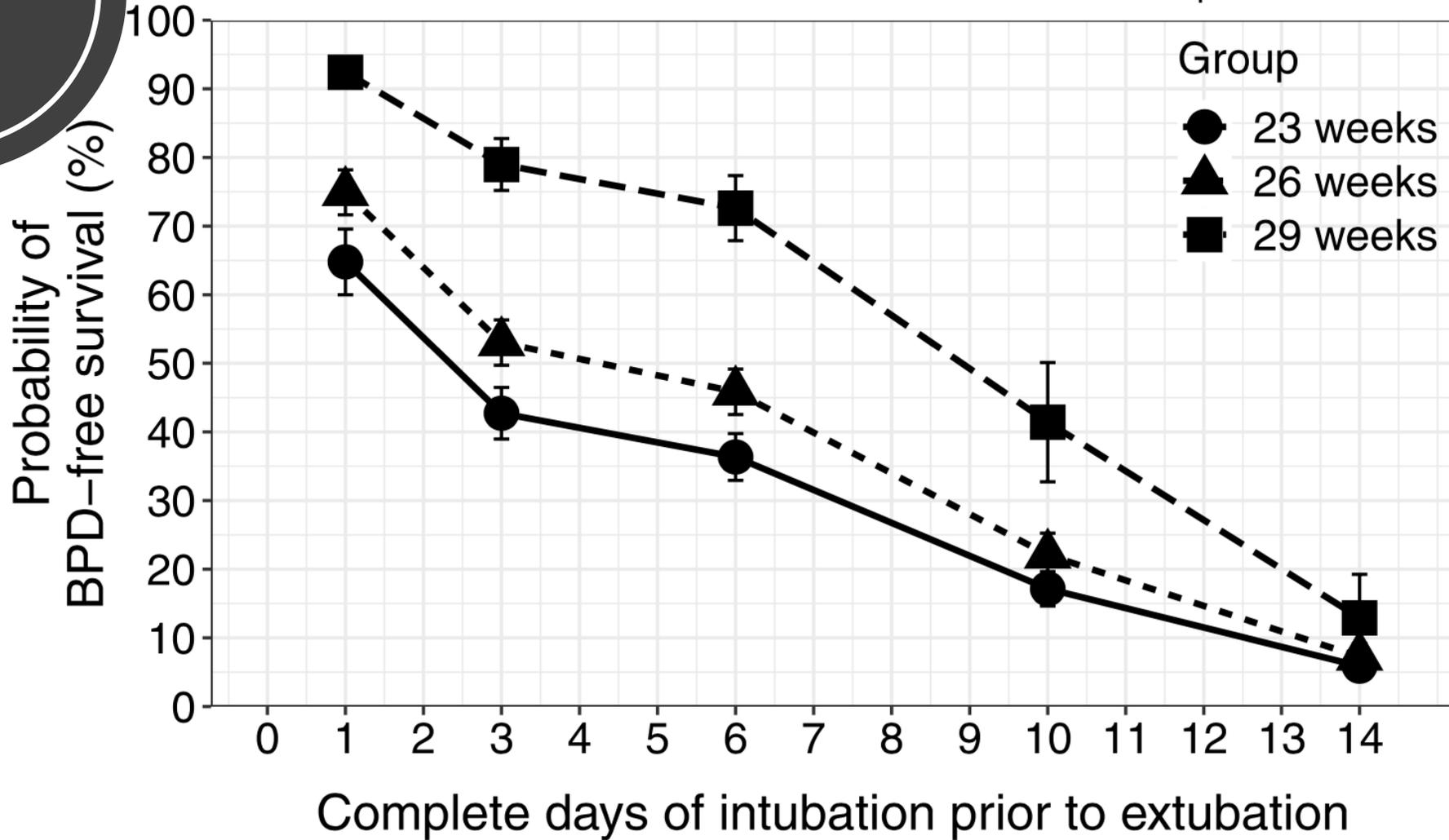
B





Impact of Gestational Age and Intubation Duration on BPD-Free Survival

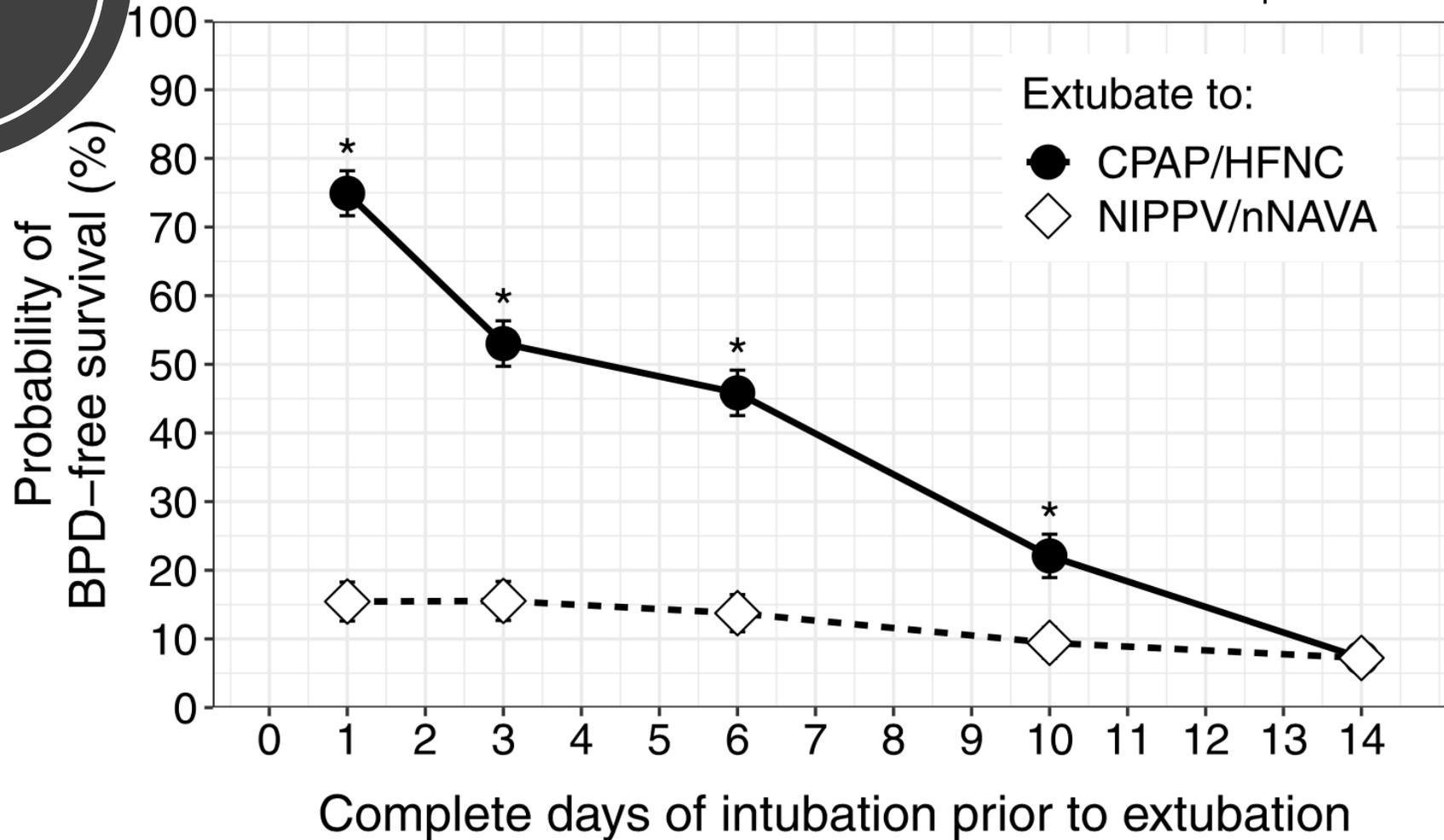
Female White AGA newborn without in utero smoke exposure

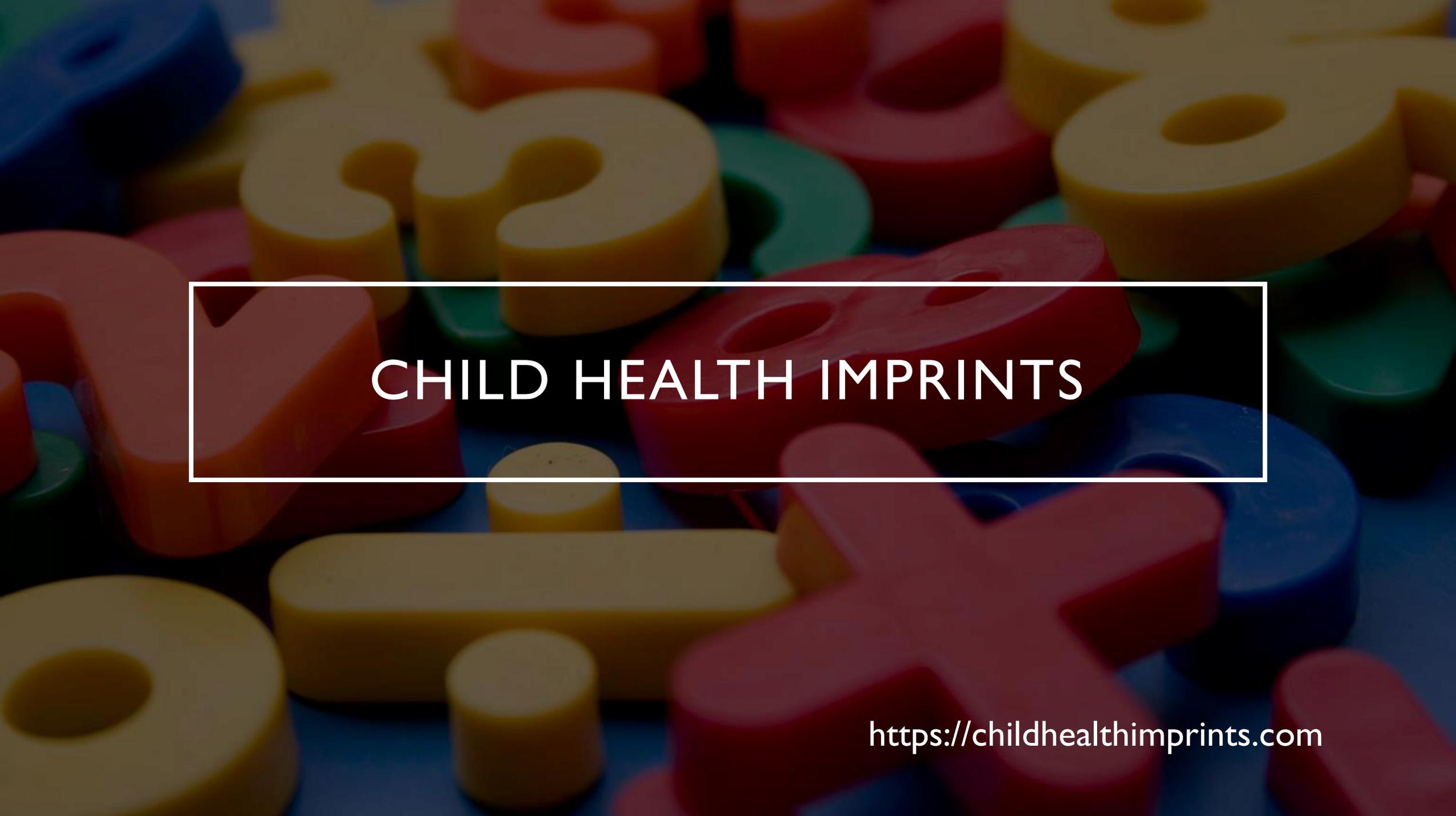


SPECIFIC
QUESTION
2

Impact of Respiratory Mode Following Extubation on BPD-Free Survival

26 week female White AGA newborn without in utero smoke exposure



A collection of colorful wooden blocks and letters scattered on a blue surface. The blocks are in various colors including yellow, red, blue, and green. Some are shaped like letters (A, B, C, X, Y, Z) and others are simple geometric shapes like cylinders and rings. The background is a dark blue gradient.

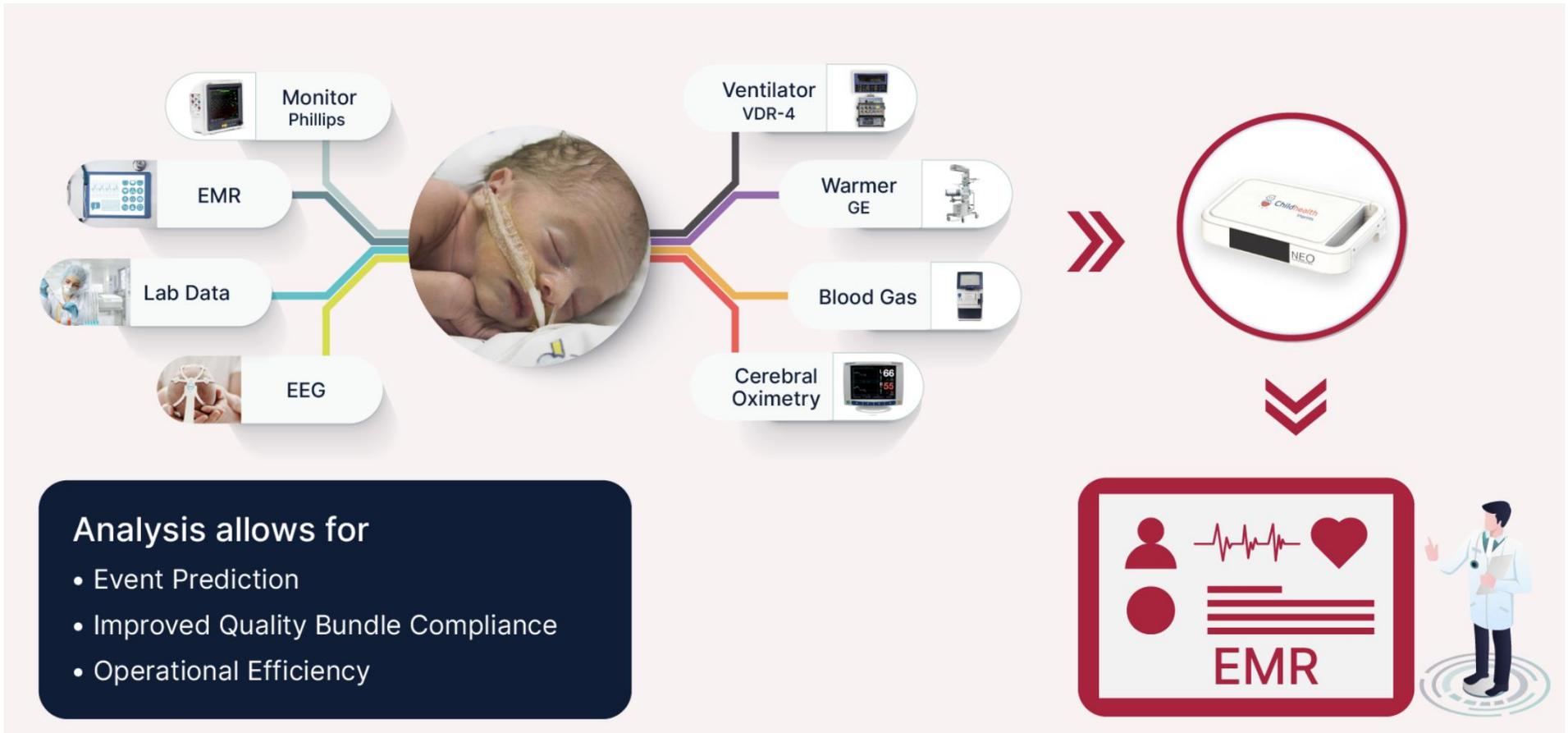
CHILD HEALTH IMPRINTS

<https://childhealthimprints.com>

PREDICTING OUTCOMES

- What is the likelihood of sepsis every day?
- Patient with an initial low prediction of BPD but then becomes septic.
 - Does this increase risk and if so by how much?
- Pulmonary hemorrhage at day 5 of life in an ELGAN.
 - How does this impact risk of IVH?





NEXT STEP IN AI

Thermo-Regulation Bundle

Pre Delivery

Delivery Room

NICU

Total Babies
Qualified
633

Overall
Temp
43%

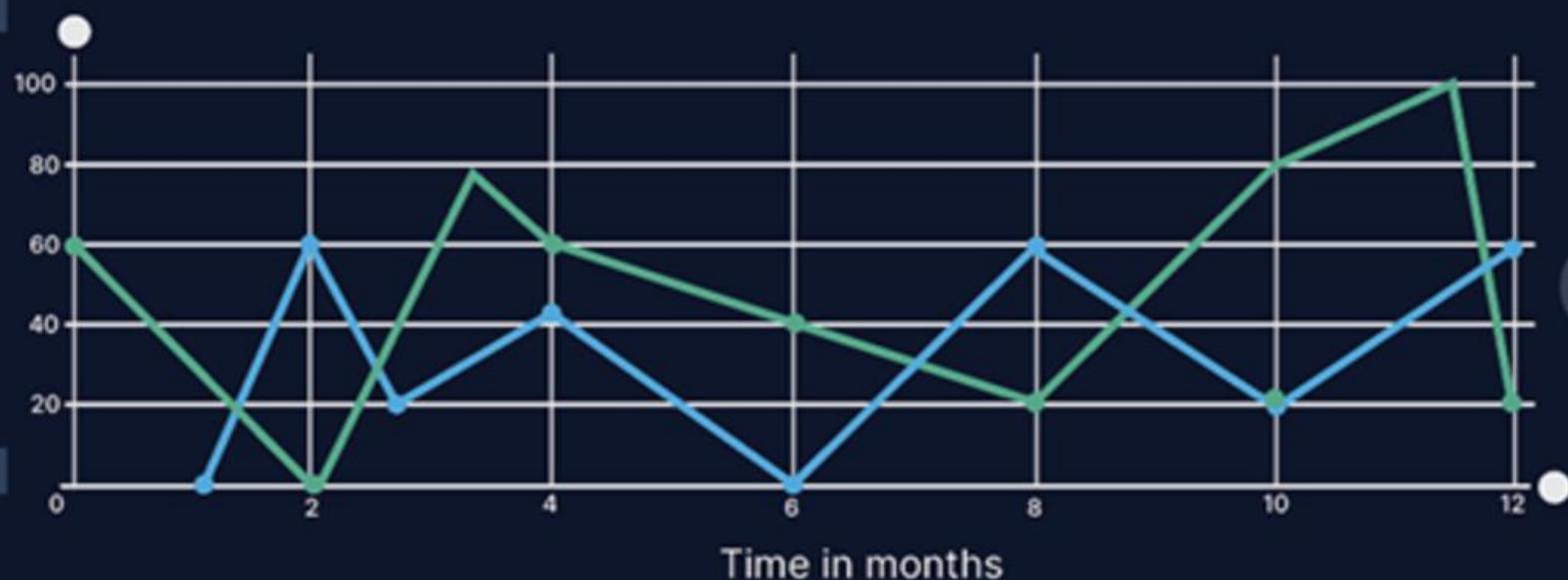
Room
Temp
85%

Compliance Percentage

< January 2023 >

S M T W T F S

						1
2	3	4	5	6	7	8
9	10	11	12	14	15	16
17	18	19	20	21	22	23
24	25	26	27	28	29	30
31						



AI IN ITS INFANCY IN NICU



Search ("Artificial Intelligence"[Mesh]) AND "Intensive Care Units, Neonatal"[Mesh] X

Advanced Create alert Create RSS

User Guide

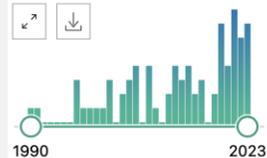
Save Email Send to Sort by: Most recent Display options

MY NCBI FILTERS

73 results

Page 1 of 8

RESULTS BY YEAR



1 [Early Prediction of Neonatal Sepsis From Synthetic Clinical Data Using Machine Learning.](#)
Cite Lyra S, Jin J, Leonhardt S, Luken M.
Share Annu Int Conf IEEE Eng Med Biol Soc. 2023 Jul;2023:1-4. doi: 10.1109/EMBC40787.2023.10341082. PMID: 38082722

2 [Early prediction of need for invasive mechanical ventilation in the neonatal intensive care unit using artificial intelligence and electronic health records: a clinical study.](#)
Cite Kim Y, Kim H, Choi J, Cho K, Yoo D, Lee Y, Park SJ, Jeong MH, Jeong SH, Park KH, Byun SY, Kim T, Ahn SH, Cho WH, Lee N.
Share BMC Pediatr. 2023 Oct 23;23(1):525. doi: 10.1186/s12887-023-04350-1. PMID: 37872515 **Free PMC article.**

TEXT AVAILABILITY

- Abstract
- Free full text
- Full text



Search ("Artificial Intelligence"[Mesh]) AND "Intensive Care Units"[Mesh] X

Advanced Create alert Create RSS

User Guide

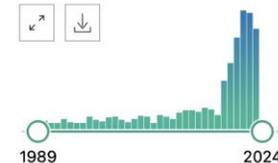
Save Email Send to Sort by: Most recent Display options

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905 results

Page 1 of 91

RESULTS BY YEAR



1 [Continuous Risk Estimation of Acute Kidney Failure with Dense Temporal Data for ICU Patients.](#)
Cite Wu K, Chen EH, Wirth F, Vitanova K, Lange R, Burschka D.
Share Annu Int Conf IEEE Eng Med Biol Soc. 2023 Jul;2023:1-5. doi: 10.1109/EMBC40787.2023.10340113. PMID: 38083688

2 [A Pilot Study of Deep Learning Models for Camera based Hand Hygiene Monitoring in ICU.](#)
Cite Huang W, Huang J, Wang G, Lu H, He M, Wang W.
Share Annu Int Conf IEEE Eng Med Biol Soc. 2023 Jul;2023:1-5. doi: 10.1109/EMBC40787.2023.10341146. PMID: 38083035

TEXT AVAILABILITY

- Abstract
- Free full text

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Pediatrics > General Pediatrics

ChatGPT Misdiagnosed Most Pediatric Cases

— Older version of the chatbot was wrong in 83% of kids' clinical scenarios

by [Jennifer Henderson](#), Enterprise & Investigative Writer, MedPage Today January 2, 2024

Barile J et al. Diagnostic Accuracy of a Large Language Model in Pediatric Case Studies. JAMA Pediatr. 2024 Jan

Table. Representative Cases and Diagnostic Outcome for a Large Language Model (LLM)

Representative case	LLM diagnosis	Physician diagnosis	Artificial intelligence diagnosis outcome	Outcome frequency (N = 100)
15-y-old girl with unexplained intracranial hypertension	Adrenal insufficiency (Addison disease)	Primary adrenal insufficient (Addison disease)	Correct	17
Rash and arthralgias in a teenager with autism	Immune thrombocytopenic purpura	Scurvy	Incorrect	72
Draining papule on the lateral neck of an infant	Branchial cleft cyst	Branchio-oto-renal syndrome	Did not fully capture diagnosis	11

CONCLUSIONS

- AI is going to become an important part of daily clinical work
- Refinements needed to bring AI to the institutional level to provide real-time local data and patterns to help with decision making
- Will not replace Neonatologists and at least for the moment our diagnostic abilities are superior to AI!