Temporal Transformer Networks for Continuous Life-Saving Intervention Prediction in Trauma Care

Using continuous vital signs to anticipate blood, airway, and chest interventions during the golden hour

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Disclosure

The content presented does not necessarily reflect the position or policy of the U.S. Government, and no official endorsement should be inferred

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Background: The Tactical Challenge

Paramedics and combat medics often under extreme environmental stress and limited information.

- Critical tasks include airway management, hemorrhage control, and treating severe thoracic injuries.
- Sole providers frequently become **task-saturated**, hindering the synthesis of complex physiological data.
- Rapid, sequential resuscitation decisions dictate survivability.

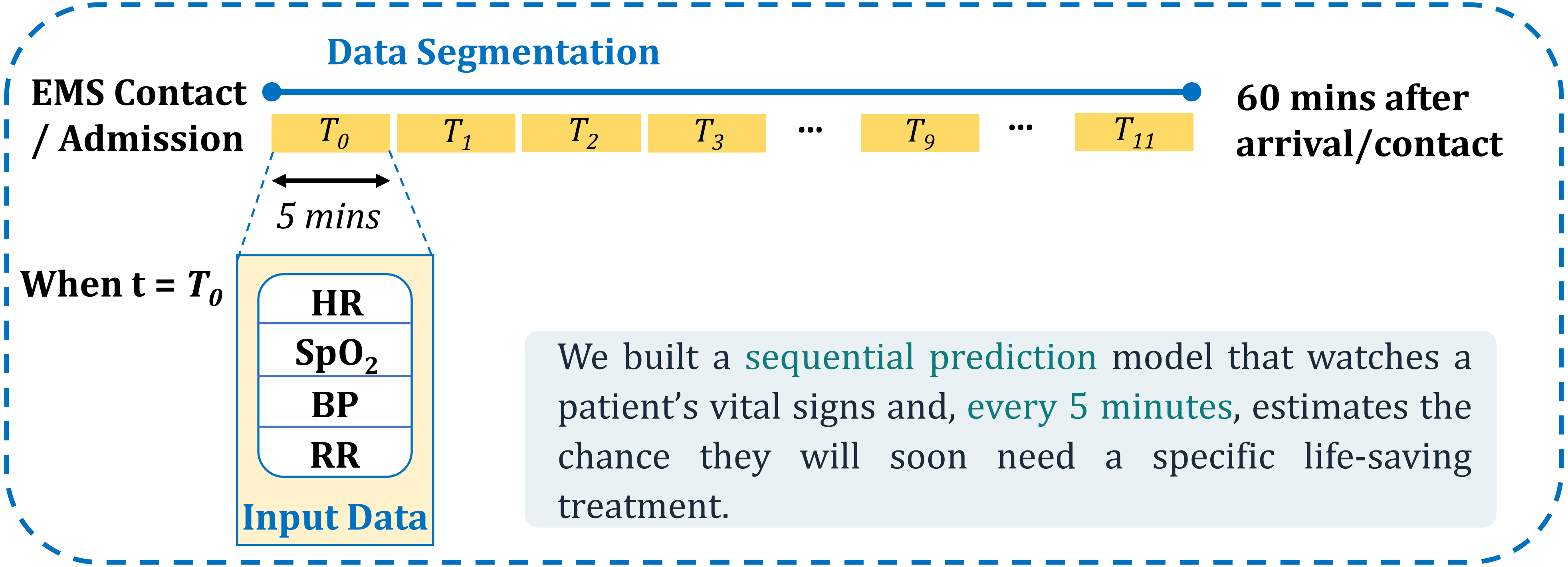
Three Critical, Time-Sensitive Interventions

These life-saving interventions (LSIs) are exactly the calls that must be made quickly, and that AI can help anticipate.

LSIs needs	Relevant actions
Critical Transfusion Needs	Prepare blood; Activate hemorrhage response
Chest Tube	Anticipate thoracic decompression need
Intubation	Prepare airway team, equipment, evacuation communication

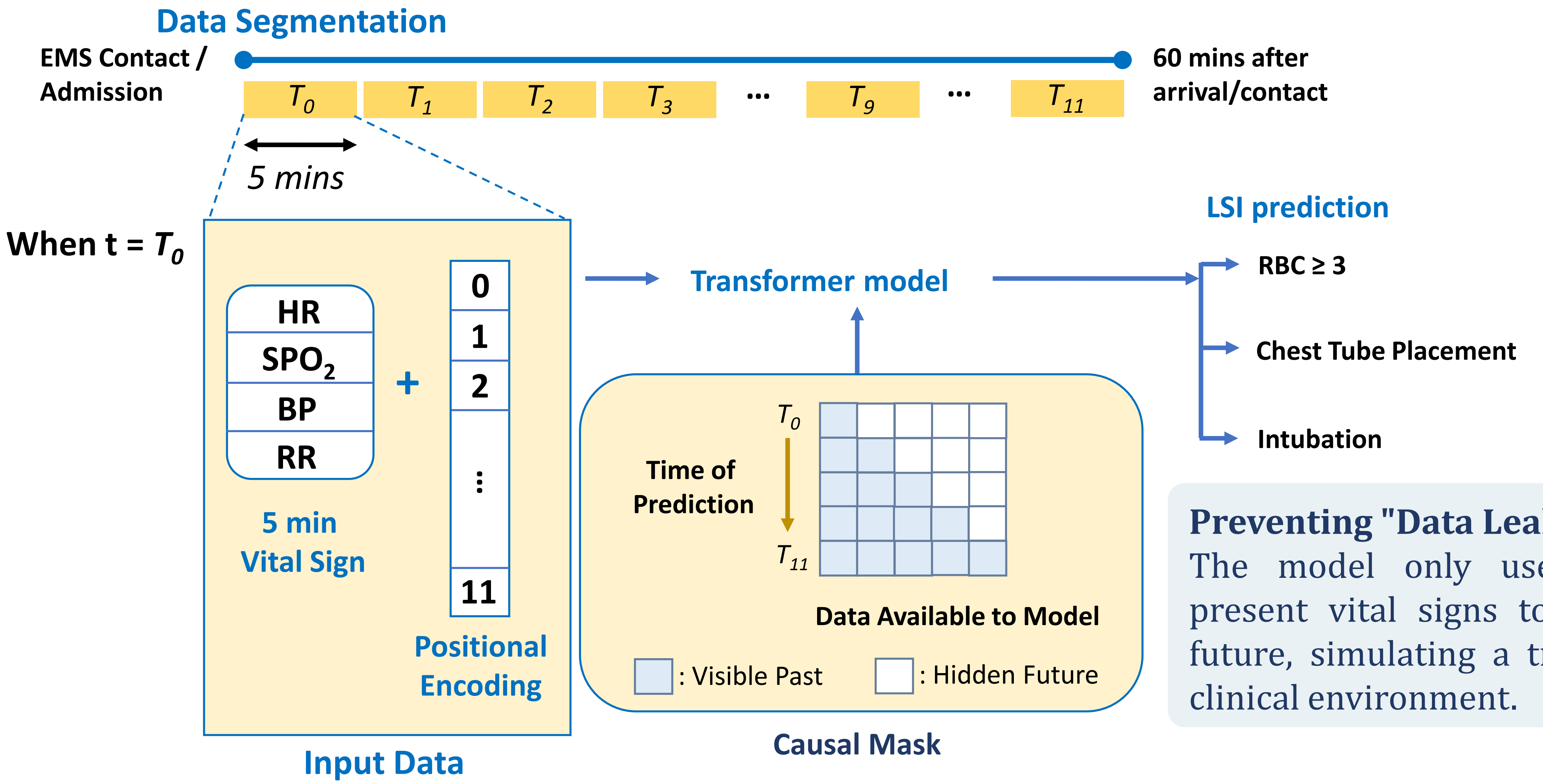
Methods: An AI "Early-Warning" System

Trauma Center Admission → **Vital Sign Monitoring** → **AI Predictive Model** → **LSIs Prediction**



We built a sequential prediction model that watches a patient's vital signs and, every 5 minutes, estimates the chance they will soon need a specific life-saving treatment.

Detailed Model Structure



Preventing "Data Leakage"

The model only uses past and present vital signs to predict the future, simulating a true real-time clinical environment.

Study Population

- Direct from scene

	All (N=3336)	Train(N=2466)	Validation(N=577)	Test (N=293)
Age (Years) – Mean (SD)	39.1(14.2)	39.0(14.2)	40.4(14.5)	38.0(13.5)
Male n (%)	2427(72.8%)	1787(72.5%)	428(74.2%)	212(72.4%)
Blunt n (%)	2728(81.8%)	2033(82.4%)	462(80.1%)	233(79.5%)
Penetrating n (%)	561(16.8%)	400(16.2%)	106(18.4%)	55(18. 8%)

Outcomes Prevalence:

- Critical transfusion needs (RBC ≥3 units): 4.4%
- Chest tube placement: 5.1%
- Endotracheal intubation: 15.7%

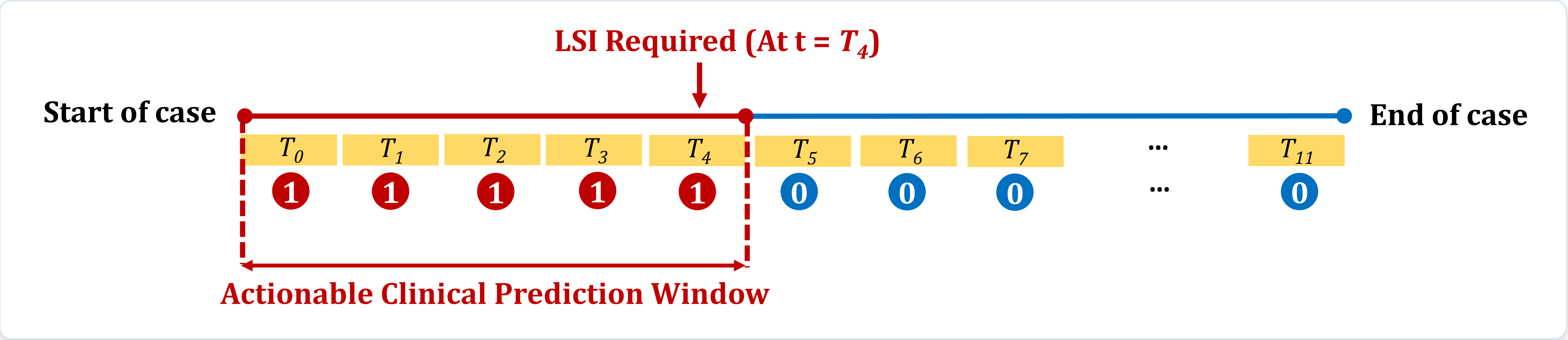
Model Design

- **Model Type:** Deep learning **transformer-based** time series model
- **Rationale:** Architecture selected for its ability to capture complex, long-range temporal dependencies within the 60-minute sequence
- **Prediction Frequency:** Update risk predictions every 5 minutes to track rapid physiological changes
- **Timeframe:** The first 60 minutes
- **Vital Signs:** Heart Rate (HR), peripheral oxygen saturation (SpO_2), blood pressures (SBP, MBP, DBP), and Respiratory Rate (RESP)
- **Temporal Segmentation:** Twelve 5-minute windows

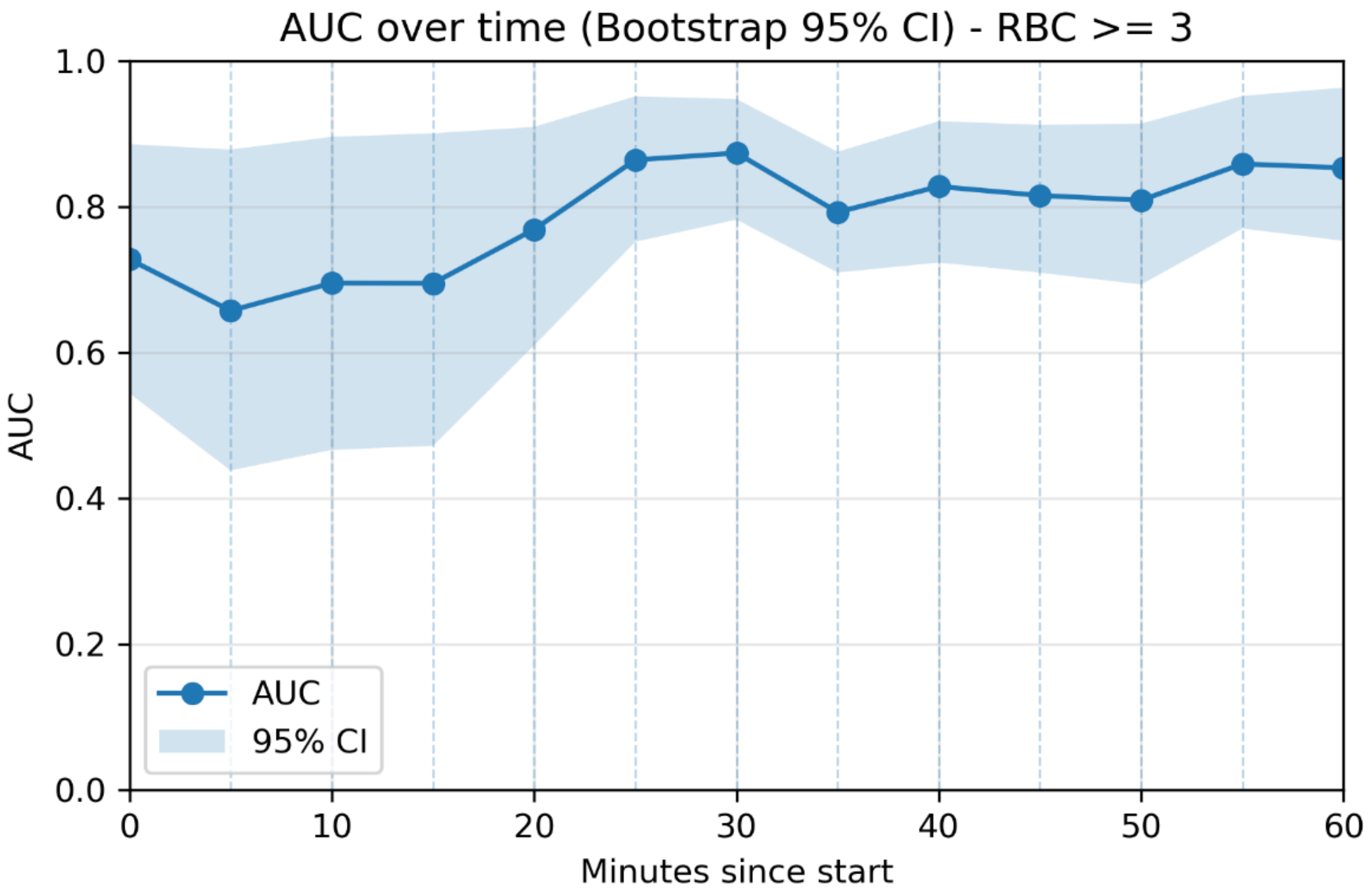
Like a language model reading a sentence, the transformer reads the vital-sign sequence and learns which patterns predict deterioration.

Defining the Prediction Target for Early Warning

- Creating an **Actionable Window** for Medical Resource Allocation.
- **Labeling Rule:** If an LSI occurs (e.g., at t = T_4), that window and all prior windows are labeled Positive.
- **Clinical Goal:** Predicts deterioration before the crisis, creating a time buffer for tactical preparation.



Results: Transfusion >=3 units of pRBC



pRBC: Packed Red Blood Cell

Results

Three LSI Outcomes Prediction AUROC (first hour average)

- Critical Administration: (RBC ≥3 units): 0.85 (95%CI 0.83 to 0.87)
- Chest tube placement: 0.97 (95%CI 0.94 to 1.00)
- Endotracheal intubation: 0.73 (95%CI 0.69 to 0.77)

Limitations and Next Steps

- **Limitations**
  - Single-center retrospective cohort
  - Rare outcomes, especially transfusion and chest tube
  - Intubation prediction needs improvement
- **Next steps**
  - External validation in prehospital, en route, and military-relevant settings
  - Device/noise robustness testing
  - Human-factors evaluation with medics

Operational Use Case

How This Could Help a Combat Medic

- At minute X: vitals are abnormal but not yet catastrophic
- AI risk update: rising probability of need for chest decompression
- Suggested action: reassess breath sounds, prepare chest tube/needle decompression kit, alert receiving team
- Provider remains in control: AI supports, does not decide

Conclusion

- **Feasible:** standard vital signs can support early LSI prediction
- **Timely:** Useful performance emerges in the first 25-30 minutes
- **Operationally relevant:** Can reduce cognitive burden and support medics in austere trauma care.

This is not intended to replace clinical judgment
It is a second set of eyes during the highest-risk minutes.

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Questions & Discussion

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