Examining the Usability of a Machine Learning Enhanced Patient Safety Event Reporting System

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SAFETY, EQUITY, & DESIGN

Background

- Patient safety events (PSEs) describe **instances of avoidable harm** in healthcare [1]
- 1 in 17 hospital stays results in a harmful event [2]
- Most hospitals have implemented PSE reporting [2]
- **Issues**: 50-96% of PSEs go **underreported** [3], **misclassification** & errors are common [4,5,6], **barriers** due to time constraints & usability [7,8]
- Results in **delays, burdens** of reclassification, and hindered learning [9]
- **Machine learning (ML)** can be used to automate classification of event types, & has been successful with increased accuracy [10,11,12]
- **Human-AI collaboration (HAIC)**, which describes humans and AI complementing each other to enhance decision making, can enhance PSE reporting [10,13]
- **Explainability** techniques can be integrated to build trust & transparency in ML [14]

Goal: Evaluate the usability of a PSE interface with an integrated ML classifier for event types & LIME explainability

Methods

System Development

- Used 861 obstetric PSE reports (2019-2020) [10]
- SVM Roberta-base model (75.4%) accuracy [10]
- Integrated LIME explainability [14] to show highlighted words influencing ML classification
- Interface with 4 sections, built using Gradio [15]

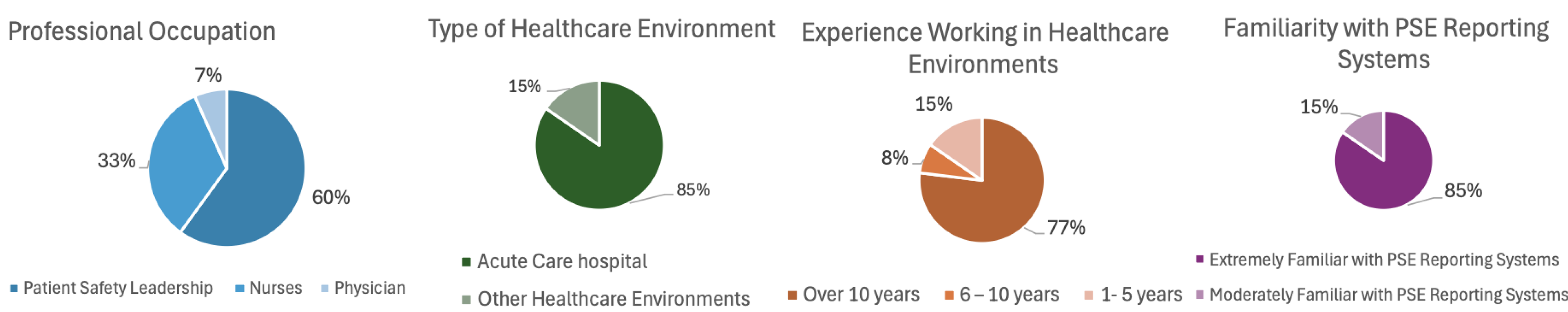
Usability Testing (3 parts, 2 scenarios each)

- Part 1 (P1): Full PSE report with ML
- Part 2 (P2): Classification with ML (50% reliability)
- Part 3 (P3) : Manual classification

Measures

- Reporting & classification time (min), classification accuracy (%), agreement with predictions & recommendations selected (%), SUS scores [16], qualitative debriefing interview feedback

Results & Key Points



Measure	With ML (P1, P2)	Without ML (P3)
Completion Time (min)	5.66 min (SD = 1.80)	N/A
Classification Time (min)	1.96 min (SD = 0.90)	1.19 min (SD = 0.59)
Classification Accuracy (%)	P1: 92.3%, 92.3% P2: 23.1%, 46.2%	31%, 62%

- **Mean SUS Score**: 87.9
- **High confidence**: mean 4.54/5 on SUS question about confidence
- **Agreement with ML predictions**: 76.9–100%
- **Explainability**: relevant in 7.7–38.5% of cases in P1, 0% in P2
- **Speed-accuracy tradeoff**: increased classification time was manageable, support of ML predictions worth minor time cost [17]
- **Calibration of trust issue**: some users agreed with incorrect predictions, however others responded to the shift in reliability accordingly
- **Explainability gaps**: LIME is often unstable [18]
- **HAIC improved classification accuracy and user confidence**

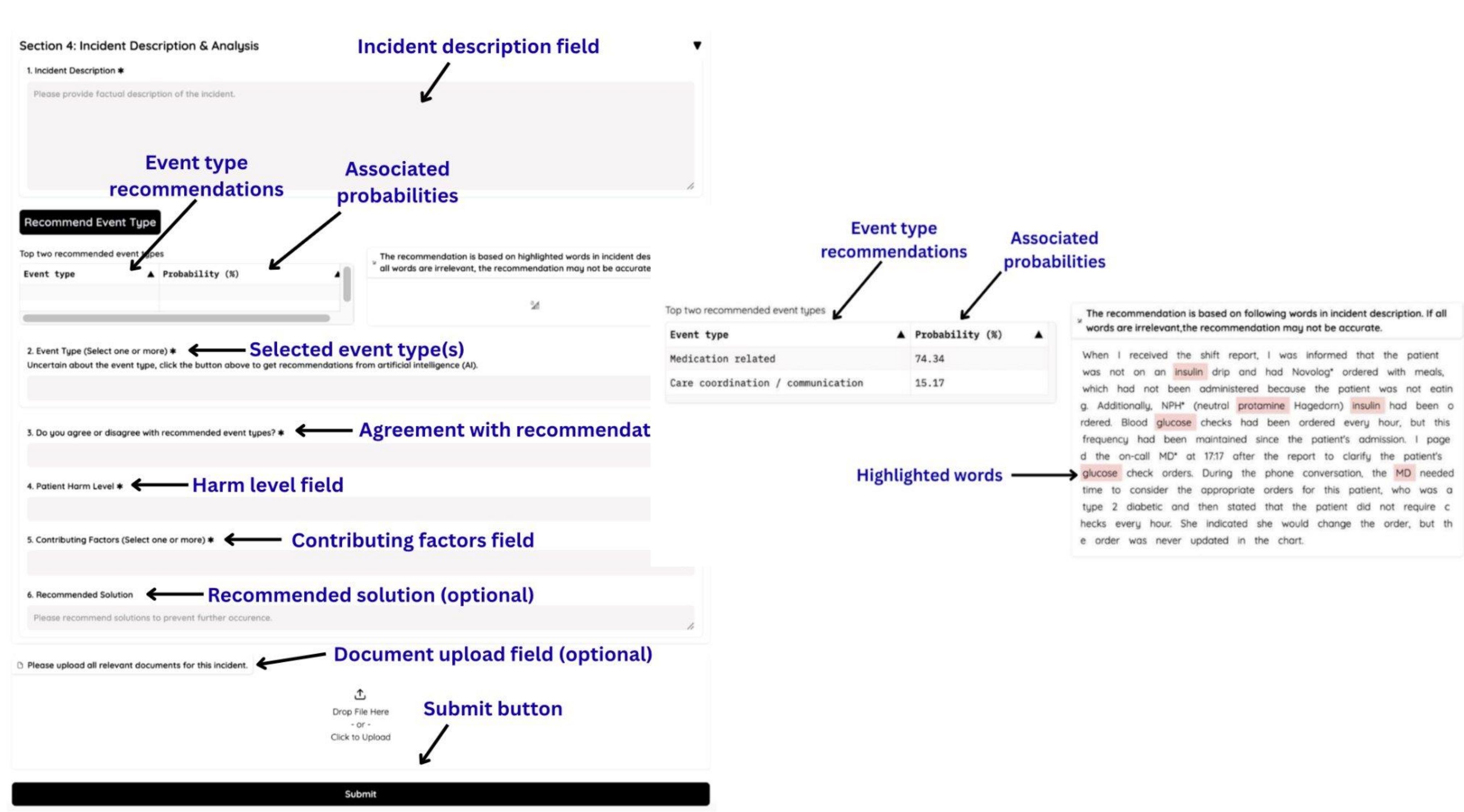


Figure 1. Event description & analysis section of PSE interface (Section 4)

Limitations & Next Steps

- Trained with a small dataset
- LIME feature not robust
- Small participant group
- Some scenarios possibly easier to classify

Future directions:

- Expand ML integration other PSE reporting categories & text generation
- Test alternative explainability methods
- Conduct additional usability testing

Conclusion

- Integration of ML into PSE reporting systems is a relatively new area of research that has potential to optimize & streamline the reporting process through HAIC
- This study demonstrates the integration of an ML classifier in PSE reporting systems shows potential to mitigate challenges related to the completion & quality of reporting

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