User Needs Inquiries for Explainable Clinical Decision Support Interfaces

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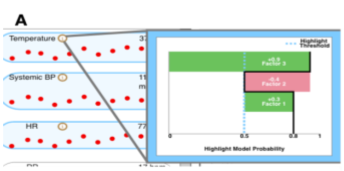
Introduction

Clinical Decision Support Systems (CDSS) are powerful tools which can leverage state-of-the-art machine learning (ML) models to enhance health and health care. Convincing clinicians to adopt these tools can be difficult, even when they have relatively high accuracy[1]. User-centered concerns including lack of trust[2] and difficult-to-understand designs can lead clinicians to ignore recommendations made by CDSS. Explainable Artificial Intelligence (XAI) has been proposed as a potential pathway to address the trust concerns of clinicians[3]. Some XAI approaches have been shown to increase clinician trust in CDSS[4]. However, current explanation displays have also been shown to not be a reliable method for clinicians to distinguish between correct and incorrect ML model predictions[4]. This may be due to common visualizations for XAI being too complex. In this study we aim to assess clinicians' explanatory needs by developing preliminary CDSS displays which use XAI to aid them in assessing whether a prediction is correct. To achieve our aim, we are designing these displays (see Figure) in collaboration with potential users through semi-structured interviews and think-aloud sessions.

Methods

Participants are clinicians or clinicians in training familiar with CDSS. Initial participants were identified through professional contacts of the investigators, followed by snowball sampling based on referrals from participants. Participants are being engaged in a single study session consisting of a semi-structured interview, a think-aloud exploration of a proposed interface design, and an unstructured interview that will last from 15-30 minutes each. Audio recordings of each session will be analyzed using an Emergent Coding Approach for this study. The preliminary interfaces are updated after each interview.



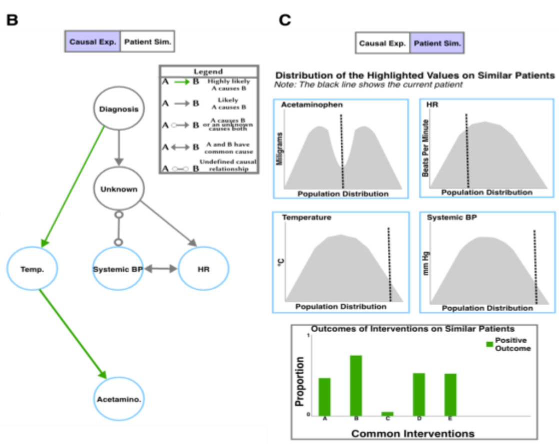


Figure. Preliminary interfaces after feedback. **A**. Example of feature attribution-based explanations. **B.** Causal graphs of how predictions may relate to diagnosis. This may help clinicians incorporate their knowledge to assess which predictions are correct. **C**. Distributions of the important information on similar patients.

Results

Participants who we have interviewed to date have reported needing access to evidence that our explanations are accurate; a desire for explanations that help them justify interventions; and interest in an explanation which elucidates the causes of their patient's state.

Conclusion

Our study of clinicians' explanatory needs may help design CDSS interfaces which reduce potential instances of automation bias caused by XAI while increasing clinicians' understanding of how these explanations relate to their patient's state. Insights from our clinician needs interviews could form the basis for other developers to create Explainable CDSS tools.

References

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Pilot Study: User Needs Inquiries for Explainable Clinical Decision Support Interfaces

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Background

- Clinicians often ignore Clinical Decision Support Systems (CDSS) recommendations:
  - Lack of Trust in System's Accuracy
  - Difficult-to-understand Designs
- Potential Solutions:
  - Explainable Artificial Intelligence (XAI)
  - Participatory Design

Aim

- To explore clinician's perspectives on:
  - Preliminary XAI displays for CDSS.
  - Explainable CDSS in general.

Methods

- Semi-Structured Interviews & Focus Group.
- Review preliminary XAI displays for an EMR-based CDSS.
- Focus on participants' critiques and preferences.
- Emergent coding to extract insights from interview transcripts.

Figure 1. Display for a CDSS that highlights patient information predicted to be of interest for a clinician. Highlighted information is shown in blue.

Preliminary Designs

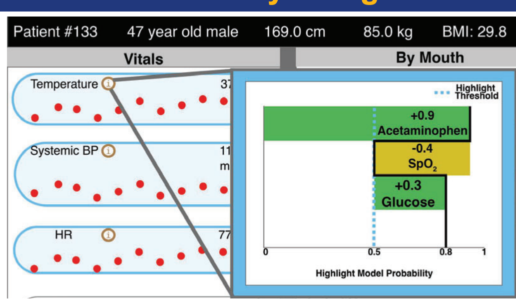


Figure 2. Design #1 Feature Importance Plot. Display of impact of features on highlight model's probability. Positive numbers (green) increase the probability of a piece of information to be highlighted. Negative numbers (yellow), decrease the probability of information being highlighted. The horizontal line at 0.5 of the X-axis (blue) shows the threshold for highlighting. The black line tracks the highlight model's probability after accounting for each feature.

Preliminary Designs

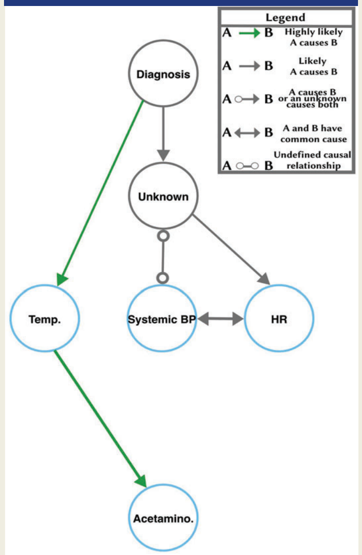


Figure 3. Design #2 Causal Graph: Causal depiction linking Diagnosis to highlighted information.

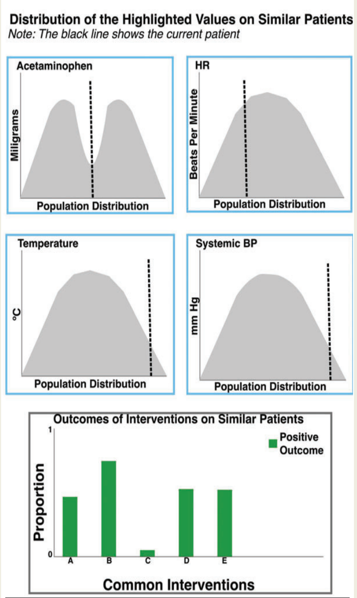
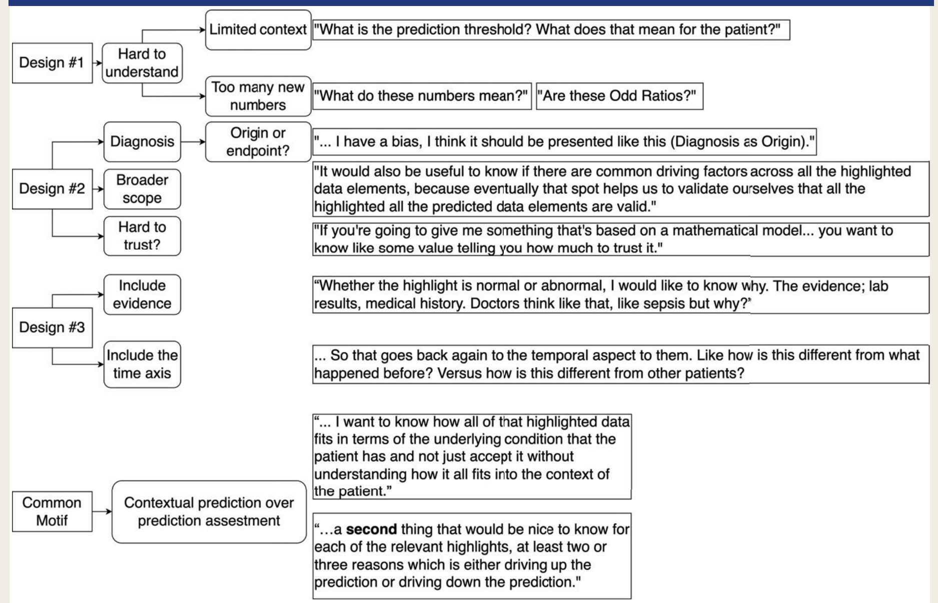


Figure 4. Design #3 Supporting Information. Comparison of highlighted information that of similar patients.

Results



Conclusions

- Clinicians preferred:
  - Evidence of importance rather than estimated feature importance values.
- Contextualizing predictions (Highlights) more important than
  - Assessing prediction correctness
  - Feature importance
- Assessment of prediction correctness should be integrated such that it occurs as part of clinician workflow.
- Modification to Designs #2 and #3 should include workflow improvements like:
  - Providing shortcuts to relevant lab results and medical history.
  - Non-Highlighted information that is clinically relevant to the highlighted information.
- Limitations:
  - Sample Size (Only 5 clinicians / clinicians in training).

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