Evaluating the impact of explainable RL on physician decision-making in high-fidelity simulations: insights from eye-tracking metrics

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Abstract

Explainable reinforcement learning (XRL) is crucial for reinforcement learning (RL) algorithms within clinical decision support systems. However, most XRL evaluations have been conducted with non-expert users in toy settings. Despite the promise of RL in healthcare, deployment has been especially slow in part because of safety concerns which XRL might be able to attenuate. In our study, we observed doctors interacting with a clinical XRL in a high-fidelity simulated medication dosing scenario. Using eye-tracking technology, we analyzed these interactions across safe and unsafe XRL suggestions. We find that there cognitive attention devoted to XRL during unsafe scenarios is similar to during safe scenarios (despite doctors more frequently rejecting unsafe XRL suggestions). This suggests that XRL does not lie in the causal pathway for doctors to reject unsafe AI advice.

1 Introduction

Healthcare is a high-stakes domain with recurrent decision-making in pursuit of a long term objective (typically maximising patient health/survival); in other words, the perfect setting in which to exploit the benefits of reinforcement learning (RL) algorithms. In practice, despite promising proof of concept papers (Komorowski et al., 2018), there are no widely deployed clinical RL decision support systems even though these are most likely to be supportive rather than autonomous in the near future (Festor et al., 2021).

Therefore, optimizing the interaction between healthcare practitioners and RL-driven AI clinical decision support systems (AI-CDSS) becomes vital for broad acceptance and influence, something that has been relatively overlooked to date (van de Sande et al., 2021). Explainable RL (XRL) has been proposed as a potential strategy by providing intelligible justifications for RL-driven recommendations to human users (Barredo Arrieta et al., 2020). Apart from fostering trust in RL, XRL has been proposed as a mechanism to prevent the inadvertent implementation of unusual or even detrimental AI advice (Jia et al., 2022; Gordon et al., 2019; Antoniadi et al., 2021). The urgency for this is heightened by the emergence of generative AI (such as large language models) which occasionally generate hallucinatory (and thus, if used clinically, unsafe) suggestions (Lee et al., 2023). Nonetheless, the extent to which XRL can serve as a guard against unwitting adherence to unsafe (i.e., hallucinatory) AI advice is still unclear (Evans et al., 2022; Jacobs et al., 2021; Ghassemi et al., 2021).

When it comes to the real-world application of clinical XRL, there is a paucity of clinical evaluations involving XRL with specialist end-users, and even fewer in a high-fidelity setting (Schoonderwoerd et al., 2021). Current evidence indicates a weaker than expected correlation between physicians' actual prescribing behaviors

and self-reported utility of XRL (Nagendran et al., 2022). Importantly, other investigators have highlighted that both self-reports and actual behaviors can only be recorded after the event (Cao & Huang, 2022), limiting the effectiveness of these retrospective metrics as part of a reinforcement learning feedback loop, in contrast to real-time clinical attention indicators like eye-tracking (Ball & Richardson, 2022; Harston & Faisal, 2022). This technique has been widely utilized in non-hospital scenarios to ascertain an individual's attention focus (Auepanwiriyakul et al., 2018; Makrigiorgos et al., 2019; Ranti et al., 2020; Harston et al., 2021). High-fidelity simulation environments offer an opportunity to investigate XRL in a setting that closely mirrors real clinical practice and is often used in medical education (Cato & Murray, 2010; Cook et al., 2011). By incorporating eye-tracking into a high-fidelity setting, our methodology attempts to address the limitations of previous research (non-clinical participants, surrogate tasks, low fidelity environments) and gain a more accurate understanding of the clinician-XRL interaction dynamic.

In this work, we explored the influence of four distinct AI explanation types on clinicians within a high-fidelity simulation environment, as they performed a routine hospital task: determining the appropriate medication dosage for a patient after evaluation. Our aim was to quantify the impact of XRL on clinicians' prescription decisions, with a specific focus on whether doctors' attentional engagement (as measured by eye-tracking) differed between safe and unsafe AI scenarios.

2 Methods

Experimental Setup and XRL – Our investigation consisted of an observational analysis of how humans interact with AI within a simulated environment. Medical professionals were presented with one of six patient situations under two conditions: a recommendation from AI that was deemed safe or one that was potentially unsafe. The classification of safe and unsafe was based on exceptionally high or low prescriptions of fluids and vasopressors, as defined in prior research (Festor et al., 2022). The AI suggestions were artificially generated, with the main aim of our research being to assess the dynamics of interaction between healthcare professionals and AI. We constructed four unique explanations for the simulated AI system, all grounded in techniques we've utilized in reinforcement learning decision support systems. The first provided a natural language description of the Q-value difference between the recommended action and alternative actions. The second clarified the projected short-term changes in mortality following dosage adjustments as predicted by the AI. The third emphasized the five most influential aspects of the input data that steered the AI's recommendation. Finally, we identified the three most impactful training examples during the Q-learning process.

Eye-tracking for Gaze Detection – Eye-tracking was used to detect gaze, thereby determining clinicians' attention profile during simulations and their fluctuation. Participants wore unobtrusive, off-the-shelf eye-tracking glasses (Pupil Labs Core) featuring three cameras (Figure 2b), with the main camera capturing the wearer's viewpoint and the remaining two recording the eyes (Figure 2a). Pupil Labs software (Pupil Capture, version 3.5.7) used these cameras to identify the pupil and deduce the gaze direction (Figure 3a). Prior to the experiment, a two-stage 2D calibration exercise was conducted. Eye-tracking glasses were connected to a laptop (Lenovo Thinkpad) worn in a lightweight backpack, allowing unrestricted movement.

We delineated four primary regions of interest (ROIs) (Figure 1a): the patient mannequin, the vital signs monitor, the ICU data chart, and the AI display screen, the latter having four sub-regions tied to the XRL types. Using pre-set QR codes (April tags, Figure 3a), ROIs were defined during post-processing. This allowed

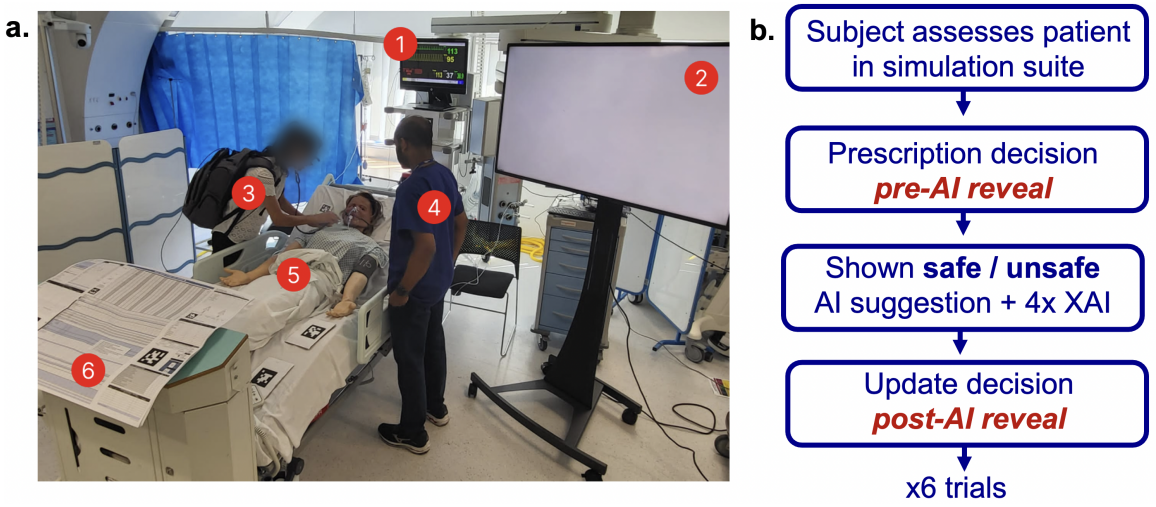

Figure 1: **Unfolding of a single simulation trial -** Left-hand image shows a picture of the simulation suite with a clinician assessing the mannequin. (1) Vital signs monitor, (2) AI screen, (3) Subject, (4) Bedside nurse, (5) Patient mannequin, (6) ICU bedside paper chart.

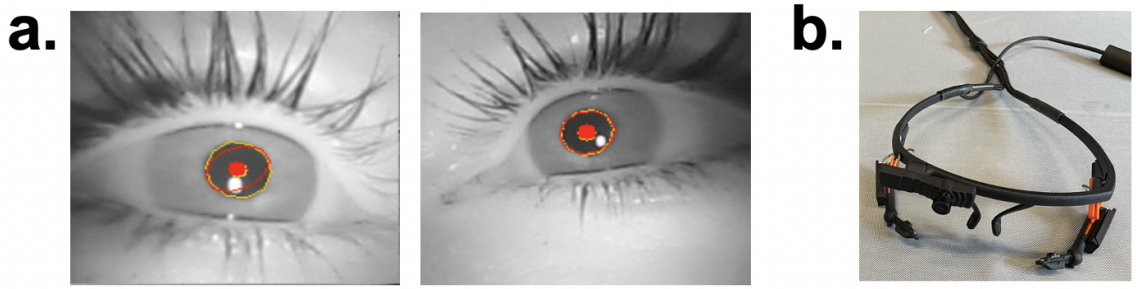

Figure 2: **Eye-tracking glasses (a) and pupil detection (b)** – Automatic pupil detection -> triangulates gaze position after calibrating software for each subject. Eye-tracking glasses have 3 cameras ('ego-centric' world-view camera plus one camera for each eye).

analysis of gaze-time per ROI, fixation count per ROI, and blink rate per minute per ROI - an indicator of concentration level.

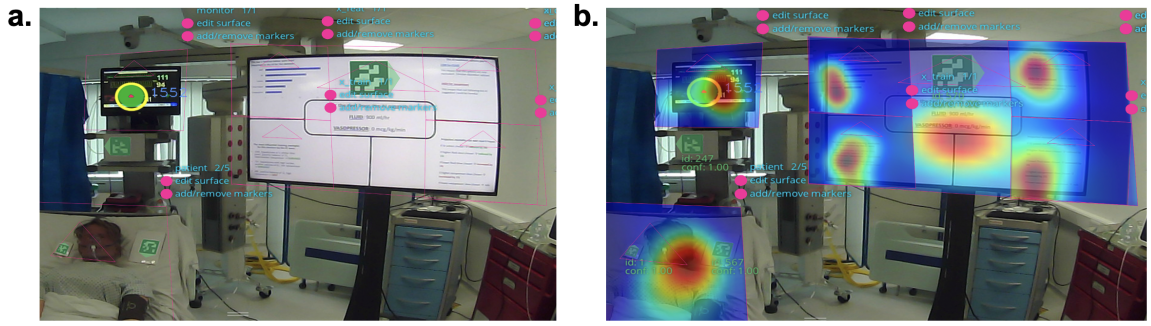

Figure 3: **Post-processing of eye-tracking data -** Left-hand image shows bounding boxes around regions (surfaces) of interest (ROIs). Right-hand side shows gaze density per ROI as heatmaps.

We further devised a distinctive method for gauging behavioural attention that adjusts for the percentage of the visual field an ROI occupies. To illustrate, if an ROI constitutes 50% of the visual field for half the time, based on randomness alone, the gaze should land within the ROI 25% of the time. By comparing this 'random gaze' figure of 25% with the actual gaze proportion, we can calculate a surrogate measure of the relative importance of ROIs, contrasting the rates of random and actual gaze into a ratio. The higher the ratio, the more purposeful the attention is on any given ROI (versus chance gaze).

Simulation Experiment – Participants first underwent a standard experiment briefing and completed a pre-experiment questionnaire regarding AI perceptions and demographic information. After familiarising themselves with the simulation suite and performing eye-tracking calibrations, they began the simulated scenarios. An individual role-playing an ICU bedside nurse assisted. The doctors evaluated six simulated ICU patients with sepsis. Each of the six scenarios required clinicians to perform an assessment, including data review and patient examination. Subsequently, they were asked by the nurse to provide their prescription for fluid and vasopressors for the next hour, indicate their confidence in the prescription, and state if they would seek higher advice or a second opinion. Afterward, AI recommendations and explanations were displayed near the patient bedside, prompting doctors to affirm or amend their prescriptions and reassess their answers regarding confidence and the need for senior advice (Figure 1b).

Subject recruitment – ICU doctors were recruited via targeted promotion and convenience sampling within a local hospital area. Eligibility requirements included: (i) currently practising as a doctor, (ii) possessing at least two months of adult ICU experience, (iii) current ICU involvement or ICU employment in the previous six months. Participants received compensation, and each session lasted around 60 minutes. The local research governance team at our institution and the UK Health Research Authority approved the study.

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3 Results

Cohort recruited – In total, 19 ICU doctors with eye-tracking data available were included (13 male, 6 female). Mean doctor age was 33 years (standard deviation (SD) 6 years). Mean ICU experience was 3.6 years (SD 4 years, range 2 months to 14 years).

Eye-tracking metrics on ROIs – During unsafe scenarios, gaze fixations on the AI screen were notably higher (mean 962 compared to 704, p=0.002, displayed in Figure 4a. However, no significant differences in gaze fixations were observed across various XRL modalities in either safe or unsafe scenarios (Figure 4b), with the disparity in the AI screen primarily attributed to the AI recommendation.

he blink rate was lowest when viewing the ICU chart (6.1 blinks per minute (bpm), SD 4.1), and was comparable for both the vital signs monitor and patient mannequin (average 15.2 bpm and 14.7 bpm, SD 8.7 and 9.2 respectively), with a significantly higher rate noted on the AI screen (average 19.9 bpm, SD 10.7). A comparison between all conventional clinical ROIs (chart, patient mannequin, monitor; depicted by blue bars in Figure 5) and all AI ROIs (including XAIs; shown by red bars in Figure 5) revealed a significantly lower mean blink rate for the conventional clinical ROIs compared to the AI ROIs (12.0 bpm vs. 23.7 bpm, p=0.002).

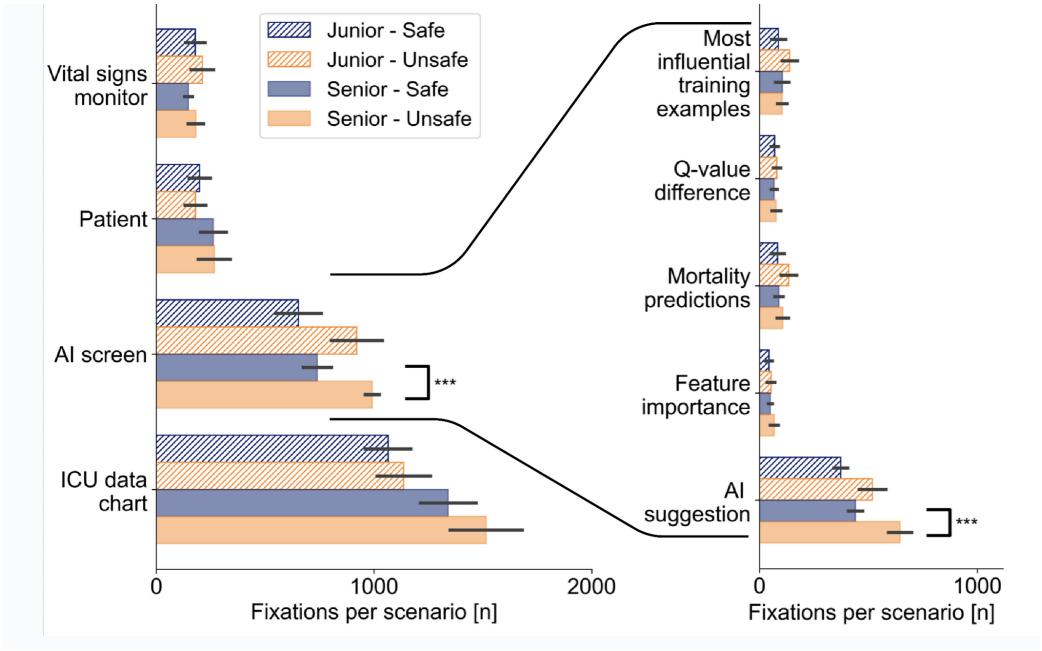

Figure 4: **Gaze fixations distribution:** Average number of gaze fixations per trial for safe and unsafe AI recommendations. The right plot expands the "AI screen" region into its four corners with explanations and the recommendation in the centre.

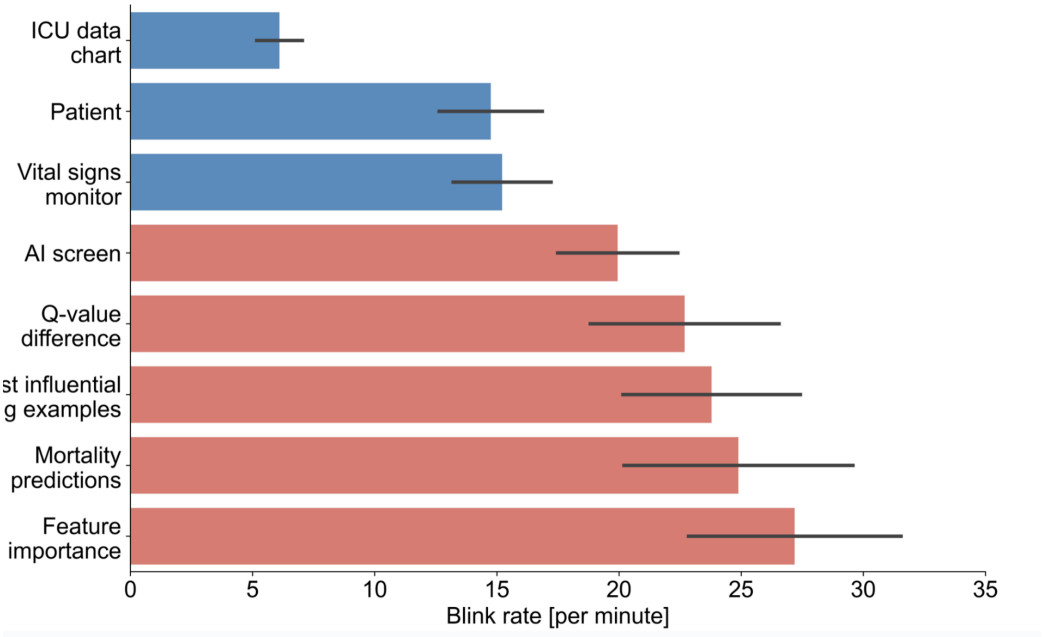

Figure 5: **Blink rate for each ROI:** Average blink rate for each region of interest across trials, error bars are standard deviations. Red bars are the AI-related ROIs, blud bars are the standard ones.

For every ROI except the patient mannequin, there was a significantly higher actual gaze proportion than random chance gaze proportion ($p<0.001$ for all seven comparisons). For the major ROIs (AI screen, ICU chart, vital signs monitor, patient) the

ratio of actual gaze to random gaze was 6.2, 1.6, 12.9 and 1.3 respectively. For the XRL ROIs (training examples, Q-value difference, mortality, feature importance) the ratio of actual gaze to random gaze was 5.4, 3.9, 4.9 and 3.1 respectively (see Figure 6).

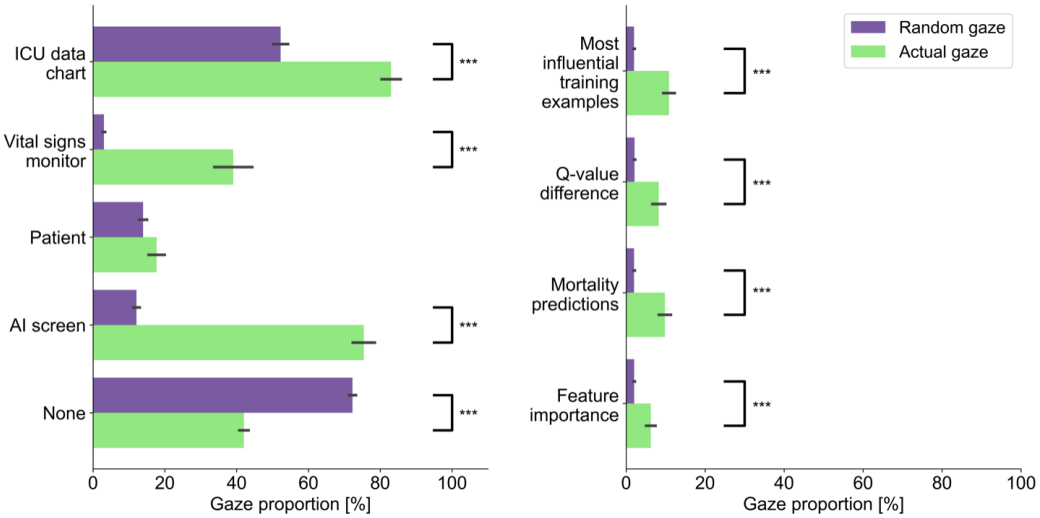

Figure 6: **Random gaze comparison:** Proportion of actual gaze time spent on each surface against the time a perfectly random gaze would have spent on it (mean and standard error).

Self-reported XRL usefulness – We here report self-reported data on the utility of XRL for 10 of the 19 subjects (Figure 7). The overall mean post-experiment usefulness rating for the XRL was 3.0 (SD 1.1) on a zero to four scale with higher value implying the XRL was more useful. The training examples explanation was the only one of the four to be rated significantly lower than the overall rating for explanations in general (mean 1.0, SD 1.1, $p<0.001$). When comparing the 'objective' marker of how many fixations there were on the four different types of XRL to the 'subjective' marker of how clinicians rated the usefulness of the four XRLs, we found no significant correlation for any of the four XRLs.

Adherence to AI suggestions among doctors – We defined adherence to AI as the distance between a doctor's final prescription (having had the opportunity to view the AI suggestion) and the value of the AI suggestion for any given trial/scenario (higher distance suggesting that the doctor was less adherent to AI and vice versa). There was no evidence of correlation between eye-tracking metrics (blink rate or number of gaze fixations) and AI adherence regardless of safety status or drug. Nor was there a significant association between number of fixations specifically on XRL ROIs and drug (either fluid or vasopressor) for either AI scenario (safe or unsafe). We however found that the spread of clinical decisions was different in computer-based and physical simulations (see Figure 8)

4 Discussion

Our study contributes several insights to our understanding of clinician interaction with XRL decision support tools. We demonstrated the efficacy of gaze fixations and blink rate as proxy attention indicators in a high-fidelity simulation, with the real-world clinical application pending less intrusive eye-tracking hardware and privacy considerations. We found no significant attention increase towards any explanation type when dealing with unsafe versus safe AI suggestions, challenging the assumption of heightened reliance on explanations in unsafe scenarios. There was

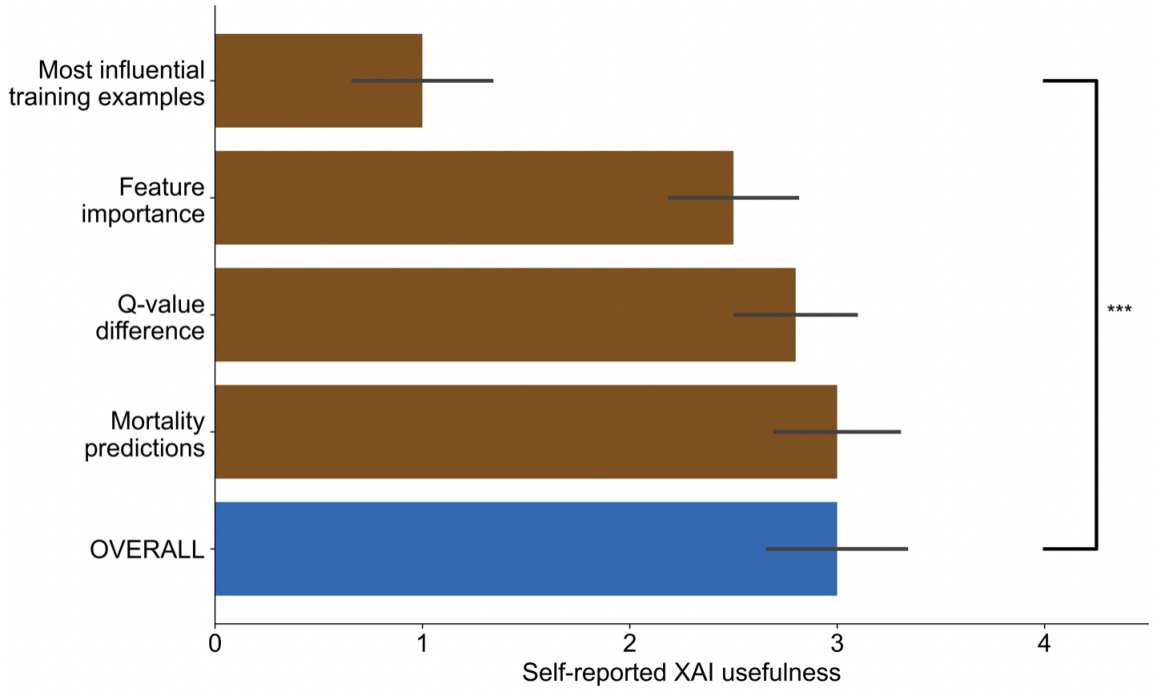

Figure 7: **Usefulness rating for each type of explanation as well as overall rating** – Mean and SEM error bars. The only significantly different explanation type compared to overall was the 'most influential training examples'.

no correlation between self-rated explanation usefulness and attention received, indicating that self-reports alone may not sufficiently evaluate XRL tools. Blink rate suggested less cognitive effort was required to interpret the AI data compared to the ICU chart. Lastly, no consistent links were found between eye-tracking metrics and variations in clinical practice or adherence to AI suggestions.

These findings must be viewed considering several limitations. The simulation suite couldn't fully emulate a real hospital environment's complexity, such as dynamic patient examination or team interactions. Real-world experiments require substantial sample sizes to standardise, making simulation studies crucial in exploring human-AI dynamics. Our small sample size could limit the validity of certain comparisons. Also, the categorisation of AI suggestions into safe or unsafe creates an arbitrary boundary on a continuous spectrum. Variations in explanation format could confound comparisons: some were primarily graphical, and others were text-heavy, potentially confounding comparisons between explanations.

Despite these limitations, our findings offer key insights for optimizing XRL-based medical decision support tools. We examined the assumption that explanations should help users reject poor AI advice, and corroborated that an increased rejection rate of unsafe advice wasn't driven by higher reliance on, or attention to, explanations. Evidence from other studies suggests a breakdown in the process of discarding unsafe advice, indicating potential automation bias (Shafti et al., 2022). The risk of such automation bias is also well documented in other medical investigations (Micocci et al., 2021; Panigutti et al., 2022). Another piece of evidence is an experiment assessing a mental health drug decision support tool, where explanations failed to prevent clinical users from following intentionally subpar AI recommendations (Jacobs et al., 2021). Our study corroborates these findings.

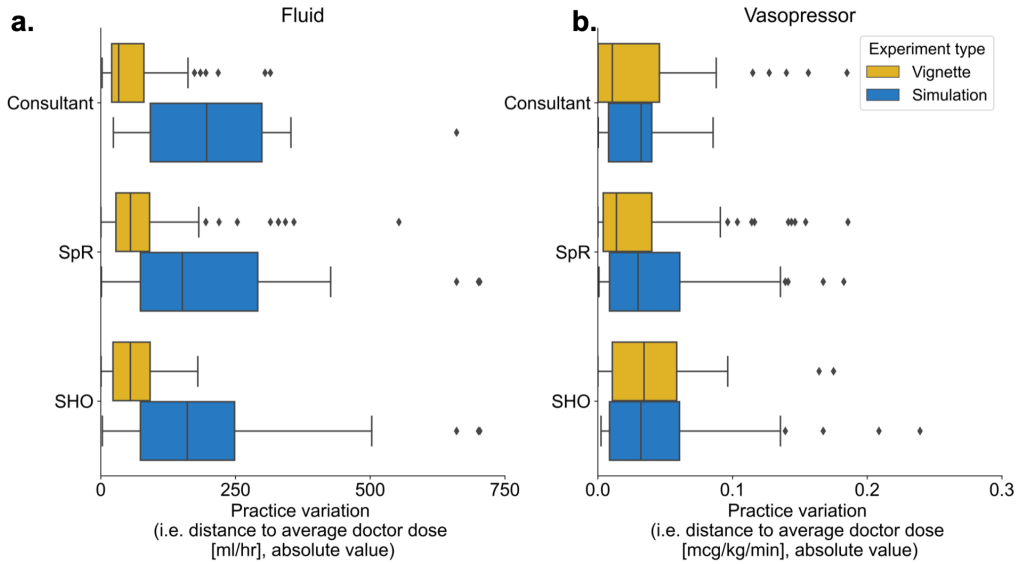

Figure 8: **Comparing online to physical simulation -** variability in prescription decisions (fluids on the left, vasopressors on the right) for depending on whether the experiment has happened on a computer on in a physical simulation suite.

The use of eye-tracking in AI-user studies remains limited. A notable example by Cao and colleagues found a positive association between gaze percentage on the AI suggestion and perceived user reliance and agreement with AI suggestions, but not with perceived trust (Cao & Huang, 2022). Similarly, we found no correlation between subjective explanation ratings and gaze fixations on the AI explanation. While eye-tracking may form the basis of a real-time feedback loop for human-AI interactions (Cao & Huang, 2022)., our results caution that we must first establish reliable eye movement patterns to accurately categorize users and predict their AI interactions.

5 Conclusion

In summary, our results indicate that eye-tracking is a viable technique to assess clinicians' engagement with reinforcement learning explanations (XRL). We illustrate that clinicians' reactions to safe and unsafe AI recommendations are distinctly different. Yet, the absence of a 'rescue' effect presented by XRL is of importance to note when designing clinical XRL systems. Our insights emphasize the necessity for future AI decision-support tools to customise not just their recommendations, but also their interaction style and explanation delivery for clinician users.

Acknowledgments If needed, acknowledgments can be included right before the references in the camera-ready version. They must be hidden in the submitted paper.

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