
Endorsement, Prior Action, and Language: Modeling Trusted Advice in Computerized Clinical Alerts

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Abstract

The safe prescribing of medications via computerized physician order entry routinely relies on clinical alerts. Alert compliance, however, remains surprisingly low, with up to 95% often ignored. Prior approaches, such as improving presentational factors in alert design, had limited success, mainly due to physicians' lack of trust in computerized advice. While designing trustworthy alert is key, actionable design principles to embody elements of trust in alerts remain little explored. To mitigate this gap, we introduce a model to guide the design of *trust-based* clinical alerts—based on what physicians value when trusting advice from peers in clinical activities. We discuss three key dimensions to craft trusted alerts: using colleagues' endorsement, foregrounding physicians' prior actions, and adopting a suitable language. We exemplify our approach with emerging alert designs from our ongoing research with physicians and contribute to the current debate on how to design effective alerts to improve patient safety.

Author Keywords

Clinical alerts; health; health informatics; trust in socio-technical systems; design.

ACM Classification Keywords

H.5.2. User Interfaces: User-centered design.

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Introduction

Clinical alerts—a kind of clinical decision support—are routinely used in prescribing patient medications via computerized physician order entry (CPOE) systems [5]. The most common type of clinical alerts is Drug-drug interaction (DDI) alerts (Figure 1). Although intended for safe prescribing of drugs, studies found that up to 95% of DDI alerts are ignored by physicians [2, 13]. Nonadherence to DDI alerts increases the risk of prescribing unsafe medications that often leads to adverse events—especially to vulnerable populations, such as the elderly. Reasons for physicians' poor adherence to DDI alerts include the lack of specificity in alert messages, fatigue from receiving numerous alerts of questionable clinical importance, disruption to workflow, and human factor issues [14].

Incorporating different human factor principles while redesigning alerts have showed mixed results. For example, integrating contextual cues into alerts failed to improve physicians' adherence significantly (reported at 15% [4]). But 43% fewer prescribing errors were reported when Creatinine Clearance alerts (for patients with impaired renal function) were redesigned in terms of the interface layout and timing of the alert [11]. Overall, physician adherence continues to remain low—and increasingly attributed to a lack of satisfaction and trust in clinical alert systems [9].

Other than the common approach toward improving presentational elements of clinical alerts—visually, temporally, or contextually—recent work has explored when and why physicians trust their medical colleagues and mentors in clinical settings. A focus has been primarily on the elements of trusted peer discussions around prescribing medications. Prior empirical work


Drug Interaction	Risk of Hemorrhage and Increased Anticoagulant Effect
Drug Interaction	Warfarin interacts with Erythromycin Details > Patient on Erythromycin 500.0MG Details > 
Cancel Warfarin Order Continue Order	

Figure 1. Although intended for safe prescribing of drugs, override rates of drug-drug interaction (DDI) alerts remain as high as reported over a decade ago (about 88% in 2002 [13] and 95% in 2014 [2]).

has foregrounded the emerging themes of trusted advice that included physicians' expertise, role in the medical hierarchy, empathy, understanding of patients' situation, and use of collaborative language [3]. Drawing on these drivers of trusted advice in clinical settings, we propose a model to guide the design of *trust-based* alerts. Our model consists of three fundamental dimensions: using endorsement of colleagues, foregrounding physicians' prior actions, and adopting a suitable language. In this paper, we first characterize our model and its key design dimensions. Then, we exemplify our approach with emerging alert designs from our ongoing research with physicians. Finally, we discuss our evaluation plans to test the efficacy of our alert designs. Our work contributes to the ongoing debate on how to design effective computerized clinical alerts that can ultimately improve patient safety on a daily basis.

Related Work

Trust has been researched extensively in social sciences and economics for over the past five decades.

In human-computer interaction, issues of trust have also been explored in socio-technical systems—such as in automated systems, online shopping, security systems, internet applications, and more recently, computerized clinical decision support systems (CDSS) [1]. Although a lack of trust has been found to be a major detriment in the adoption of CDSS [1], improvements in DDI alerts have primarily relied on organizational, presentational, and contextual factors. For example, research on safe prescribing practices suggested educating physicians about clinical alerts by local experts [7]; and incorporating human factor principles, such as presenting alerts in tabular formats, embedding links to additional laboratory information, literature supporting alert messages, and further information on medication risks [11]. Recommendations to improve the usability of DDI alerts included improving design features, such as consistent use of color and visual features, consistent terminology and brevity in alert messages, requiring physicians to mention alert override reasons, and making less severe alerts non-interruptive to physicians' current workflow [12].

Although improving DDI alerts continue to focus on advancing knowledge bases to trigger more effective alerts and bettering presentational elements, incorporating trust in alert designs is a crucial requirement. Trusted advice is crucial because medicine lacks rules that can generally and unambiguously be applied to every case at hand [10], thus increasing physicians' belief in personal or trusted experiences above scientifically rigorous, impersonal data—especially in instances of uncertainty. While the medical field has sought to embrace evidence-based medicine over anecdotal decision-making [15], the influence of

anecdotal evidence, along with peer-to-peer discussions, still plays a major role in clinical decision making [6, 8, 10].

Modeling Trusted Advice in Clinical Alerts

Incorporating trust in computerized clinical alerts is a complicated endeavor—primarily due to the challenge of distilling broad user requirements into simple, tractable design guidelines. To that end, we propose a model for trusted advice that establishes three fundamental dimensions for designing *trust-based* clinical alerts (Figure 2). Each of these three dimensions, endorsement, physician's prior action, and the language used to craft alert messages, have different sub-dimensions, which can be variously parameterized to design a wide range of *trust-based* clinical alerts.

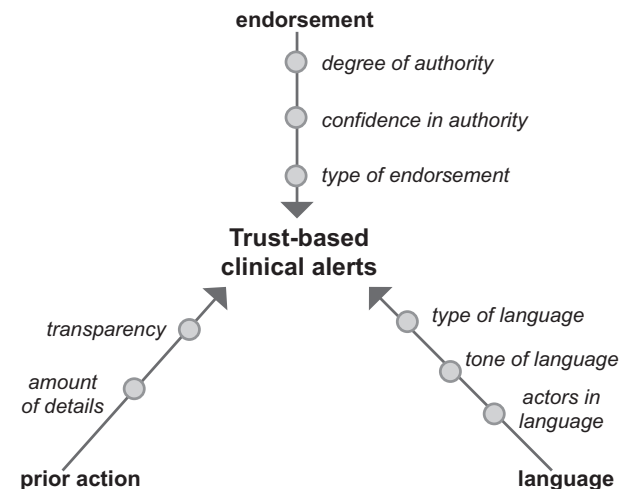


Figure 2. The three fundamental dimensions of the trust-based alert model can be parameterized along different sub-dimensions to generate a rich design space (see example parameters in Tables 1–3; see design prototypes in Figure 3).

Endorsement

An endorsement is a sponsorship of a clinical alert to increase powers of persuasion. For instance, endorsements can come from a local or trusted expert, a colleague in a position of authority, or a reference from the literature. We propose three design dimensions of endorsement (Table 1): degree of authority (e.g., chief of surgery or a colleague), type of endorsement (e.g., specialty physician, current attending, or a manager), and the physician's confidence in authority (e.g., professional or personal).

Endorsement Dimensions	Example parameters
Degree of authority	chief of surgery, chief of medicine, resident, attending, union president
Type of endorsement	specialty, authority figure in medical or management hierarchy, individual with demonstrated experience, references from literature, hospital protocol, federal/state regulations
Confidence in authority	professional (e.g., field expert), or personal (mentor, local expert)

Table 1. The three dimensions of endorsement.

Prior action

Awareness of their prior actions (e.g., earlier treatment decisions) can enable physicians to make an informed choice about complying with an alert or not. Similarly, when physicians' decision to accept or reject an alert is documented in the patient note (and later conveyed along the alert), it can lead to an increased consideration of the alert and also serve as a trusted reference for other physicians during decision making. How transparent would be these prior actions (e.g., to peers, to patients, or both) and how much details would be available (e.g., mere comply/override or

associated reasons) are the two relevant dimensions when foregrounding physicians' prior actions (Table 2).

Prior action Dimensions	Example parameters
Transparency	to oneself, peers, managers, authority figures, patients, or both peers and patients
Amount of details	action noted, or detailed reason recorded in patient notes

Table 2. The two dimensions of physicians' prior actions.

Language

The language adopted while crafting alert messages can elicit trust and empathy from physicians. Choosing an appropriate type of language (e.g., descriptive, prescriptive, or reflective), tone of language (e.g., neutral or negative), and implied narrators (e.g., computer, authority figure, or peers) is essential to generate or tailor different trust-based alerts (Table 3).

Language Dimensions	Example parameters
Type of language	descriptive, prescriptive, reflective
Tone of language	neutral, negative, implying personal responsibility
Actors in language	computer, authority, patient, peer

Table 3. The three dimensions of language.

Designing Trust-Based Clinical Alerts

The function of our model is to guide the design of trust-based clinical alerts by parameterizing the different dimensions—for example, as shown in Figure 3. Alerts can be modeled using any one, two, or all of the three dimensions. However, all possible

combinations of the different sub-dimensions would not generate trust-based designs. For example, using authoritative language to portray another colleagues' overrides could come off as their directive—not as awareness or transparency. Thus, we recommend that designers first establish design directions for trusted

advice, such as endorsed alerts, transparent alerts, or empathic alerts [3], and then parametrize the available dimensions to craft design prototypes. The three trust-eliciting elements in our model, which can be alternated and modified, opens up a rich design space of trust-based alerts, thus not habituating physicians with alerts that look the same.



Figure 3. Example prototypes of trust-based alerts designed using our proposed model. Alerts can be designed combining any one, two, or all of the three dimensions. Example parameters of the different sub-dimensions are listed in Tables 1–3.

Conclusion

Low physician adherence to computerized clinical alerts hinders safe prescribing of medications. To improve adherence, we proposed a model that embodies elements of trust in alerts, such as using endorsement from colleagues, foregrounding physicians' prior actions, and adopting a suitable language. Our model provides actionable design guidelines to craft trust-based drug-drug interaction (DDI) alerts. We exemplified our approach with emerging alert designs from our ongoing research with physicians. Our work contributes to the current debate on how to design effective alerts to improve patient safety.

Future Work

Our next step is to evaluate trust-based clinical alerts with physicians. We are planning a two-stage evaluation. First, we have an ongoing survey on our design prototypes (e.g., see Figure 3) to evaluate physicians' likelihood of alert compliance and their perceived value of the alerts. For instance, we are measuring how much physicians find the alerts trustworthy, unconvincing, helpful, annoying, and manipulative. This survey is currently sent out to physicians in Indiana University Health and Eskenazi Health. Second, we are planning controlled in-lab studies to evaluate physicians' cognitive load during decision making (e.g., using secondary tasks) and measure attention to different trust cues using gaze duration and gaze trajectories. Identifying reliable and valid outcome measures to gauge the efficacy of clinical alerts, however, is still a challenge.

Possible outcome measures for evaluating DDI alerts range from interaction cost of the physicians (e.g., cognitive load, time) to the cost of adverse drug

events. It is, however, suggested that effectiveness should be defined as a combination of measured and perceived values, such as clinical outcomes, clinician satisfaction, or process efficiency measures [12]. Furthermore, demographic of the physicians may also play a role in the perceived helpfulness of DDI alerts, and thus, alert override rates would not solely determine the effectiveness of alerts. Research on integrating human factor principles in computerized clinical alerts is still in its infancy. Thus, the field lacks standardized metrics to measure the effectiveness of DDI decision support and could benefit from a broader participation of human-computer interaction researchers and practitioners.

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References

1. Gregory L. Alexander. Issues of trust and ethics in computerized clinical decision support systems. 2006. *Nursing administration quarterly* 30, 1: 21–29. Retrieved January 7, 2016 from http://journals.lww.com/naqjournal/Fulltext/2006/01000/Issues_of_Trust_and_Ethics_in_Computerized.5.aspx
2. A. D. Bryant, Grant. S. Fletcher, and Thomas H. Payne. Drug interaction alert override rates in the Meaningful Use era: no evidence of progress. 2014. *Applied clinical informatics* 5, 3: 802–813. <http://dx.doi.org/10.4338/ACI-2013-12-RA-0103>
3. Debaleena Chattopadhyay, Romisa R. Ghahari, Jon D. Duke, and Davide Bolchini. 2015. Understanding

- Advice Sharing among Physicians: Towards Trust-Based Clinical Alerts. *Interacting with Computers*. Advance Access published August 27, 2015. <http://dx.doi.org/10.1093/iwc/iwv030>
4. Jon D. Duke and Davide Bolchini. A successful model and visual design for creating context-aware drug-drug interaction alerts. 2011. *AMIA Annual Symposium Proceedings*, 2011: 339–348. Retrieved January 7, 2016 from <http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3243201/>
 5. Jon D. Duke, Justin Morea, Burke Mamlin, Douglas K. Martin, et al. Regenstrief Institute's Medical Gopher: A next-generation homegrown electronic medical record system. 2014. *International journal of medical informatics* 83, 3: 170–179. <http://dx.doi.org/10.1016/j.ijmedinf.2013.11.004>
 6. Murray W. Enkin and Alejandro R. Jadad. Using anecdotal information in evidence-based health care: heresy or necessity? 1998. *Annals of Oncology*, 9, 9: 963–966.
 7. Adrienne Feldstein, Steven R. Simon, Jennifer Schneider, et al. How to design computerized alerts to ensure safe prescribing practices. 2004. *Joint Commission Journal on Quality and Patient Safety* 30, 11: 602–613. Retrieved January 7, 2016 from <http://www.ingentaconnect.com/content/jcaho/jcqs/2004/00000030/00000011/art00003>
 8. Trisha Greenhalgh. Narrative based medicine in an evidence based world. 1999. *BMJ: British Medical Journal* 318, 7179: 323–325.
 9. James Hayward, Fionagh Thomson, Heather Milne, et al. "Too much, too late": mixed methods multi-channel video recording study of computerized decision support systems and GP prescribing. 2013. *Journal of the American Medical Informatics Association* 20, e1: e76–e84. <http://dx.doi.org/10.1136/amiajnl-2012-001484>
 10. Kathryn Hunter. "Don't think zebras": Uncertainty, interpretation, and the place of paradox in clinical education. 1996. *Theoretical medicine* 17, 3: 225–241. <http://dx.doi.org/10.1007/BF00489447>
 11. Brittany L. Melton, Alan J. Zillich, Scott A. Russell, Michael Weiner, M. Sue McManus, Jeffrey R. Spina, and Alissa L. Russ. Reducing Prescribing Errors through Creatinine Clearance Alert Redesign. 2015. *The American journal of medicine* 128, 10: 1117–1125. <http://dx.doi.org/10.1016/j.amjmed.2015.05.033>
 12. Thomas H. Payne, Lisa E. Hines, Raymond C. Chan, Seth Hartman, Joan Kapusnik-Uner, Alissa L. Russ, Bruce W. Chaffee, et al. Recommendations to Improve the Usability of Drug-Drug Interaction Clinical Decision Support Alerts. 2015. *Journal of the American Medical Informatics Association* 2015: ocv011. <http://dx.doi.org/10.1093/jamia/ocv011>
 13. Thomas H. Payne, W. Paul Nichol, Patty Hoey, and James Savarino. Characteristics and override rates of order checks in a practitioner order entry system. 2002. *AMIA Annual Symposium Proceedings*, 2002: 602–606. Retrieved February 13, 2016 from <http://www.ncbi.nlm.nih.gov/pmc/articles/PMC2244252/>
 14. Alissa L. Russ, Alan J. Zillich, Brittany L. Melton, Scott A. Russell, Siying Chen, Jeffrey R. Spina, Michael Weiner, et al. Applying human factors principles to alert design increases efficiency and reduces prescribing errors in a scenario-based simulation. 2014. *Journal of the American Medical Informatics Association* 21, e2: e287–e296. <http://dx.doi.org/10.1136/amiajnl-2013-002045>
 15. David L. Sackett, William M. Rosenberg, J. A. Gray, R. Brian Haynes, and W. Scott Richardson. Evidence based medicine: what it is and what it isn't. 1996. *BMJ: British Medical Journal* 312, 7023: 71–72. <http://dx.doi.org/10.1136/bmj.312.7023.71>