Artificial Intelligence and Risk Communication

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Abstract

The challenges of effective health risk communication are well known. This paper provides pointers to the health communication literature that discuss these problems. Tailoring printed information, visual displays, and interactive multimedia have been proposed in the health communication literature as promising approaches. On-line risk communication applications are increasing on the internet. However, potential effectiveness of applications using conventional computer technology is limited. We propose that use of artificial intelligence, building upon research in Intelligent Tutoring Systems, might be able to overcome these limitations.

Introduction

Through recent advances in medicine, it is possible to compute a person's risk of developing adult-onset diseases (e.g., coronary heart disease, type 2 diabetes) and to predict how changes in lifestyle factors (e.g., obesity, smoking) can lower that risk. However, the problem of effectively communicating risk information to lay audiences remains a challenge. And, while accurate comprehension of risk may not be sufficient to motivate a person to change his behavior, it is a necessary condition for making an informed decision about whether to accept arguments for making changes in lifestyle (Weinstein 1999). Furthermore, patients need to comprehend risks to make informed decisions on testing (e.g. BRCA gene testing) and treatment (e.g. whether to undergo surgery after receiving a positive PSA test result, or which postoperative breast cancer adjuvant therapy to select).

A major challenge for effective risk communication to a lay audience is "health numeracy", i.e., having the quantitative skills necessary for understanding and making effective use of health information (Ancker and Kaufman 2007). Basic computational skills required for understanding risk include the ability to perform quantitative comparisons. For example, low-numeracy individuals may mistakenly assess fractions with larger denominators as greater than those with smaller denominators, e.g. 1/10 vs. 2/5 (Dewdney 1993). Another basic skill is "representational fluency" (Ancker and Kaufman 2007), the ability to understand different representations of the same quantity, e.g., as a percentage, rate, or proportion. Such numeracy issues cannot be circumvented by substituting qualitative expressions (e.g. 'very likely') for quantitative expressions, since different people may interpret the same terms differently, or the same person may interpret the same term differently in different contexts (Druzdzel 1996). Nevertheless, Gigerenzer argues that presentation of risk using "natural frequencies" instead of conditional probability statements can improve risk comprehension (Gigerenzer 2002).

The National Adult Literacy Survey (Kirsch et al. 2002, cited in Rothman et al. 2008) found that 26% of the participants lacked the most basic numeracy skills. Although numeracy has been correlated with literacy, Rothman et al. (2006) found that among patients with literacy skills assessed at ninth-grade level or above, 36% had less than sixth-grade level math skills and 18% were at the seventh-to-eighth-grade level in math skills. Dieckmann (2008) cites several studies that showed that even the highly educated have problems in comprehending probability.

Tailored printed information, visual displays, and interactive multimedia have been proposed by health communication researchers as promising approaches to improving risk communication (Lipkus and Hollands 1999; Strecher et al. 1999; Rimer and Glassman 1999). Although not yet addressing risk communication per se, there has been AI research on automatic generation of tailored patient documents and hypertext, e.g., see surveys in (Bental et al. 1999; Cawsey et al. 1997; Hüske-Kraus 2003). Recent research has addressed automatic tailoring of information for patients considering surgical options (DiMarco et al. 2008) and for family and friends of neonatal intensive care patients (Moncur and Reiter 2007).

Argumentation-based AI systems have been developed to provide explanations and justification to users in risk-related biomedical applications. The RAGs (Risk Assessment in Genetics) system provides physicians with

a list of reasons for and against its assessment of the qualitative risk that the patient has a genetic predisposition to cancer (Fox et al. 2007). REACT supports a physician in planning medical interventions together with his patient (Fox et al. 2007). REACT displays a dynamically updated graph of the patient's quantitative risk over time for the proposed plan of action; in addition, it displays a list of reasons for and against the proposed intervention. An argumentation-based document generation system, the GenIE Assistant generates first-draft letters for patients of genetic counselors (Green et al. 2011). However, none of these systems were designed for communication with low-numeracy audiences.

Ancker et al. (2006) reviewed research on effective design of graphs for health risk communication. However, they note that patients may need instruction to interpret less familiar types of graphics and that instruction may improve comprehension of familiar types of graphics. Lipkus (2007) summarizes current best practices on numeric, verbal, and visual formats for health risk communication. He notes that more research is needed to explore the role of numeracy in making use of numeric risk information, the reasons for certain numerical risk formats' superiority compared to other formats, and how graphical displays affect risk perception. The health communication field has begun to deploy interactive computer applications with graphics for conveying risk, e.g., <http://www.nhlbisupport.com/bmi/bmicalc.htm>, <http://www.healthcalculators.org/index.html>, <http://hp2010.nhlbihin.net/atpiii/calculator.asp?usertype=pub>, <http://www.yourdiseaserisk.wustl.edu/>, and <http://www.cbssm.org/doms/how-much-will-chemotherapy-really-help-you>. However, the potential effectiveness of risk graphics in systems using conventional computer technology is limited. Our proposal for use of AI to overcome the limitation of current technology is presented in the next section.

Potential Contribution of AI

Following current best practice guidelines, the designer of a risk communication computer application determines the requirements of the target audience, the goal of the presentation, and the appropriate design for this audience and purpose. Ideally, the project involves interaction design professionals who design a prototype, which undergoes formative evaluation and is iteratively refined (Wright et al. 2002). However, at the end of this process the design of the graphics (and accompanying text) is more or less fixed. Interactivity may support a limited amount of tailoring. For example, the user may be given a questionnaire to elicit his risk factors. The system then uses the responses to calculate the user's level of risk and display it in the graphical format created by the application designers. In addition, interactivity may support navigation by the user through the presentation. The designers may even try to anticipate the user's questions and provide navigation to supplementary information to address those questions. If the user still does not comprehend his risk, there is nothing more that the application can provide. Furthermore, the user may not realize that he has misunderstood the information.

We suggest that this limitation could be addressed by research building upon techniques developed in the field of AI and education, i.e., the intelligent tutoring systems (ITS) field. Typically an ITS includes a *domain model*, *student model* and a *pedagogical model* (Woolf 2010). The domain model consists of subject matter to be learned. The student model represents the student's current state of knowledge, skills, and/or affect. A student model is updated by the system as it makes inferences about the student's current state based upon her actions in the ITS. The pedagogical model reasons about teaching strategies to control the presentation of topics or provision of feedback. In addition, some ITS use synthetic humans to guide the student in use of the system, provide empathy, and maintain engagement.

Because of the known difficulties that many people face in understanding risk information, it would be beneficial for a risk communication application to maintain a dynamically-updated fine-grained user model, analogous to the student model of an ITS, of the healthcare client's risk comprehension. While presenting tailored information about the client's risk, the system would interact with the client to assess his comprehension of each part of the presentation. Based upon his actions or answers, the system would reason about which graph comprehension and numeracy skills that the client had not yet acquired that could hinder his comprehension of risk information. A risk presentation component, analogous to the pedagogical model of an ITS, would use the model to design or select, on the fly, graphics and explanations that are appropriate to the current state of the user model.

In an ITS, the student model may include a model of student affect (e.g., is the student currently frustrated, bored, or engaged?). Inferred student affect can be used by the pedagogical model. Furthermore in some ITS, a synthetic human (*pedagogical agent*) may address the student's negative affective state directly by communicating empathy. Given the role of affect in risk perception, it may be helpful to select presentation strategies based upon a model of user's affective state. For example, if the user is inferred to be worried about his risk, the system could employ presentation strategies that are not believed to exacerbate worry. An approach to probabilistic reasoning about the user's affective state for genetic counseling systems is proposed in (Green 2005).

This is not the first proposal for an educational intervention to improve risk communication. Schwartz et al. (1999) propose a written tutorial to help people

understand basic probability concepts and evaluate risk information. The five subjects it would cover are

- How risk is described, e.g., ways to quantify risk, and common sources of confusion
- Questions to ask about risk statements such as what is the time frame (e.g. five years or lifetime), what is the risk of (e.g. a disease or death), who is at risk (e.g. all women or women with a certain family history).
- Putting risk into context, e.g., how does the risk compare to the risk of familiar events.
- Changing risk, e.g., in presentations on the risk/benefit of different treatment options, understanding the distinction between absolute and relative risk, and framing effects.
- Evidence, e.g., evaluating the strength of evidence such as whether it comes from a randomized clinical trial or observational study, understanding the confidence interval, etc.

Taking a more ITS-like approach to risk communication, the above topics could be covered in a user-tailored presentation with the goal of helping him understand and make use of information about his particular case. Note that instead of sequencing the information in the order given in the above list, the information could be presented at any point in the presentation where it is needed, and tailored to the model of the user's current level of understanding.

Schwartz et al. discuss several potential problems with use of a tutorial that might apply to our proposal as well. First, a patient may say that he is not interested in using the tutorial. However, Schwartz et al. argue, in some cases a professed lack of interest may really indicate a fear of not being able to understand the information, and that the tutorial could make the quantitative information accessible to that audience. The same defense applies to our ITS-like proposal as well. Second, they note that a patient facing a serious diagnosis or decision may feel too distressed to use a tutorial. We agree. However, as noted above, synthetic humans have been used in ITS to mitigate negative student affect. Employing models from the counseling literature, synthetic humans have been used to help clients learn skills to cope with stress (Marsella et al. 2000). Thus, given empirical research on how to communicate risk in such situations, an AI-based system could include a synthetic human to embody that approach. Furthermore, for patients who prefer to have a thorough understanding of their condition and options, knowledge gained through use of our proposed system may provide some emotional relief.

References

Ancker, J.S. and Kaufman, D. 2007. Rethinking Health Numeracy: A Multidisciplinary Literature Review. *Journal of the American Medical Informatics Association* 14(6):713-721.

Ancker, J.S., Senathirajah, Y., Kukafka, R., and Starren, J. 2006. Design Features of Graphs in Health Risk Communication: A Systematic Review. *Journal of the American Medical Informatics Association* 13:608-618.

Bental, D.S., Cawsey, A., and Jones, R. 1999. Patient Information Systems that Tailor to the Individual. *Journal of Patient Education and Counseling* 36: 171-180.

Cawsey, A., Webber, B.L., and Jones, R.B. 1997. Natural Language Generation in HealthCare. *Journal of the American Medical Informatics Association* 4(6): 473-483.

Dewdney, A.K. 1993. *200% of Nothing*. New York: John Wiley and Sons, Inc.

Dieckmann, N. 2008. *Numeracy: A Review of the Literature*. Decision Research Report No. 08-2. Decision Research and University of Oregon.

DiMarco, C., Bray, P., Covvey, H.D., Cowan, D.D., DiCiccio, V., Hovy, E., Lipa, J. and Yang, C. 2008. Authoring and generation of individualised patient education materials. *Journal on Information Technology in Healthcare*.

Druzdzel, M. J. 1996. Qualitative Verbal Explanations in Bayesian Belief Networks. *Artificial Intelligence and Simulation of Behavior Quarterly*, 94:43-54.

Fox, J., Glasspool, D., Grecu, D., Modgil, S., South, M., and Patkar, V. 2007. Argumentation-based inference and decision-making – a medical perspective. *IEEE Intelligent Systems* 22(6): 34-41.

Gigerenzer, G. 2002. *Reckoning with Risk: Learning to Live with Uncertainty*. London: Penguin Books.

Green, N. 2005. Affective Factors in Generation of Tailored Genomic Information. *User Modeling 2005 Workshop on Adapting the Interaction Style to Affective Factors*, Edinburgh.

Green, N., Dwight,R., Navoraphan, K., and Stadler, B. 2011. Natural language generation of transparent arguments for lay audiences. *Argument and Computation*, to appear.

Hüske-Kraus D. 2003. Text Generation in Clinical Medicine – A Review. *Methods Inf Med* 42:51-60.

Lipkus, I.M. 2007. Numeric, Verbal, and Visual Formats of Conveying Health Risks: Suggested Best Practices and

Future Recommendations. *Medical Decision Making* 27: 696-713.

Lipkus, I.M. and Hollands, J.G. 1999. The Visual Communication of Risk. *Monographs of the Journal of the National Cancer Institute* 25: 149-162.

Marsella, S.C., Johnson, W.L., and LaBore, C. 2000. Interactive Pedagogical Drama. In *Proceedings of the 4th International Conference on Autonomous Agents*, 301-308.

Moncur, W. and Reiter, E. 2007. How Much to Tell? Disseminating Affective Information across a Social Network In *Proceedings of the Second International Workshop on Personalisation for e-Health*.

Rimer, B.K. and Glassman, B. 1999. Is There a Use for Tailored Print Communications in Cancer Risk Communication? *Monographs of the Journal of the National Cancer Institute* 25: 140-148.

Rothman, R.L., Montori, V.M., Cherrington, A., and Pignone, M.P. 2008. Perspective: The Role of Numeracy in Health Care. *Journal of Health Communication*, 13:583-595.

Schwartz, L.M., Woloshin, S., and Welch, H.G. 1999. Risk Communication in Clinical Practice: Putting Cancer in Context. *Monographs of the Journal of the National Cancer Institute* 25: 124-133..

Strecher, V.J., Greenwood, T., Wang, C., and Dumont, D. 1999. Interactive Multimedia and Risk Communication. *Monographs of the Journal of the National Cancer Institute* 25: 134-139.

Weinstein, N. D. 1999. What Does It Mean to Understand a Risk? Evaluating Risk Comprehension. *Monographs of the Journal of the National Cancer Institute* 25: 15-20.

Woolf, B. 2009. *Building Intelligent Interactive Tutors*. Burlington, MA.: Morgan Kaufmann.

Wright, P., John, C., and Belt. S. 2002. Designing an interactive decision explorer. *Information Design Journal* 11(2/3): 252-260.