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Introduction

Health communication meets artificial intelligence

1. Introduction

This special section of Patient Education and Counseling on artificial intelligence (AI) and health communication, presents 14 (out of 24) submitted papers. The call for papers to this special section was motivated by discussion at the Association for the Advancement of Artificial Intelligence (AAAI) Spring Symposium on Artificial Intelligence and Health Communication held at Stanford University, CA in 2011, co-organized by three editors of the special section Nancy Green, Sara Rubinelli, and Donia Scott [1]. A number of the submissions to this special section are extended versions of papers presented there.

This collection of papers responds to the large and growing interest in the development of automated systems to provide health services to patients and consumers. In the last two decades, applications informed by research in health communication have been developed, e.g., for promoting healthy behavior and for managing chronic diseases [2,3]. While the value that these types of applications can offer to the community in terms of cost, access, and convenience is clear, there are still major challenges facing design of effective health communication systems.

Communicating health information is a challenging task. For example, the sender often comes from the expert domain of medicine, while its receiver consists of patients who for the most part do not have expertise in medicine, but who may have the lived experience of a health condition. Thus, what is relevant from a medical point of view might not be relevant from the patient's perspective, and vice versa. Communication is not a one-way activity, and so it is necessary for a health communication source to be able to engage the patient's interest and trust, to elicit and interpret information from the patients, to monitor their comprehension and state of mind, and to tailor the on-going exchange appropriately [4]. Designing an automated system for health communication that can engage in this type of interaction is thus far from trivial, and the challenge is being addressed by the use of AI techniques in combination with empirically-based theoretical frameworks from the field of health communication and related areas. In general, the field of AI attempts to simulate one or more human capabilities: e.g., reasoning, problem-solving, language production, language comprehension, emotion. Much basic research remains to succeed in this endeavor, although numerous carefully focused applications of AI are beginning to emerge. This special section aims to provide a platform of discussion from theory to practice, bridging the gap between health communication and artificial intelligence.

2. The AI perspective for health communication

What counts as AI? In addition to having the goal of simulating human behavior, a computer program is considered to use AI if it is engineered in a certain way. In many AI systems, application-specific information is represented in symbolic forms (e.g., logical formulae, production rules, ontologies, etc.) instead of as computer programming language instructions (or "computer code"). With this design approach, it is possible to change the system's behavior, not by changing the computer code but rather by adding knowledge based on theories from the social sciences, psychology, linguistics, philosophy, etc. The motivation for this design approach is to enable multiple different applications to be developed more quickly and to lower the overall cost of building new applications; see the paper by Bickmore et al. [5] for more on the rationale for this type of approach. This so-called *symbolic AI* or *knowledge-based* design approach is embodied in some of the AI papers appearing in this issue. For example, the paper by Bickmore et al. [5] describes use of an *ontology* (a sort of hierarchical classification system) representing knowledge from health behavior change theory. In the paper by Green and Stadler [6], knowledge used to construct arguments is represented as *argumentation schemes* (abstract structures based on argumentation theory). The paper by Scott et al. [7] describes use of a *semantic network* to represent the causal and temporal relationships between the events in a patient's medical history.

An important type of information for tailoring interaction that is used in many symbolic AI systems for health communication is called a *user model*. User models in AI may be *static*, i.e., filled with information about the target audience before using the system, or *dynamic*, i.e., updated with the system's inferences about characteristics of the particular user, based upon his or her interaction with the system. For example, the paper by Green and Stadler [6] illustrates use of a static user model, in which it is assumed that parents of a child with a deleterious mutation will negatively assess the type of information to be presented to them. On the other hand, the papers of Bickmore et al. [5] and of Hudlicka [8] describe use of a dynamic user model to acquire progressively more information about the user over time.

The type of audience and mode of communication of the AI systems represented in this special section is another dimension by which they can be organized. Both the systems described by Scott et al. [7] and by Green and Stadler [6] communicate via written documents. However, the target audience of the former is the physician whereas the primary audience of the latter is the healthcare client.

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Most of the other AI systems in this special section support user interaction with an *embodied conversational agent* (ECA), a visual avatar that holds a simulated conversation with the user. The motivation for use of ECAs in HC is to increase user engagement and effectiveness of the intervention. For example, the paper by Bissett et al. [9] describes the importance of engaging its users in order to get them to hear the message about the risk of binge drinking. The paper by Hudlicka [8] describes the use of an ECA to maintain user engagement while they learn to apply the practice of mindful meditation. Similarly, the paper by Bickmore et al. [5], describes the use of an ECA to counsel users with a view to promote healthy behaviors such as increasing physical activity and consumption of fruit and vegetables. Taking this notion a level further, Henkemans et al. [10] present in their paper a personalized robot that engages with children with diabetes, helping them to become more knowledgeable about their condition and to learn how to self-manage it. Song et al. [11], on the other hand, shows that AI communication systems can also be effective even without personalization or the use of ‘high tech’ interventions. He describes a low-cost, automated advisory service that delivers health information to low-income pregnant mothers through a two-way text messaging system that operates on a mobile phone. Similarly, Rupert et al. [12] present and evaluate an online AI-enabled clinical decision support tool for identifying and counseling women at increased risk for hereditary breast and ovarian cancer syndrome.

Following the statistical approach in AI, Hamon and Gagnayre [13] present a system that automatically analyzes messages posted in online discussions to extract information about patients’ self-management skills and map them to an established existing taxonomy.

3. The health communication perspective for AI

The user-experience with any AI system aimed at patients is of course a critical factor in its uptake and efficacy, and a common thread of the paper of this special section originating from the health communication perspective is the concern to make the interaction with the system a pleasant one, enhancing the user’s experience by making the system not just informative but also engaging. On this topic, Kreps and Neuhauser [14] provide a compelling overview of the deficiencies of many ehealth communication systems that fail to properly engage their target users. They introduce the notion of ‘immediacy’ and describe how AI methods can be used to improve health communication systems by increasing immediacy. Putting theory into practice, they describe the design and use of two mobile ehealth applications aimed at helping people with Crohn’s disease to manage their care, where the immediacy of the communication is enhanced through the use of AI.

Within a related context, the paper by Neuhauser et al. [15] illustrates the value of joining design science and AI components to enhance the acceptability and efficacy of health communication interventions. According to the authors, in order to develop engaging tools for health communication it is essential, alongside theoretical models, to involve users in reflecting on the nature and purpose of the systems that they will ultimately use.

Considering the concept of relevance of information provided to users of automated health advisory systems, Rubinelli et al. [16] propose that the design of such systems should be informed by theories of argumentation that operationalize the reasoning process at the basis of health behavior. What is relevant is not necessarily appropriate, however, and there is a need to identify criteria to guide individuals in the selection of appropriate information for decision-making. Schulz and Nakamoto [17] address the topic of the potential of the internet as a source of health information. By exploring the relationship between health literacy, empowerment and improved health outcomes they identify ways to enhance the quality of internet search engines by means of AI tools.

Addressing the link between engagement and efficacy of AI-driven systems, Camerini et al. [18] argue for the value of theory-based evaluation studies and present as a case in point a model-driven evaluation of an Internet-based patient education intervention for fibromyalgia patients.

4. Conclusion

As opposed to recently popularized statistical-based AI applications, such as computer programs that can beat humans at quiz show games, the majority of AI applications covered in this special section illustrate the continued usefulness of knowledge-based or symbolic AI approaches to health communication. As one of the papers here shows, statistical AI indeed may play a role in the field of health communication by providing insight into patient populations. However, the other papers in this special section show that knowledge-based AI, embodying models from linguistics, psychology, social science, argumentation theory, and other fields relevant to health communication, supports applications that are patient-centered, i.e., that communicate about or communicate with and engage patients as individuals.

Health communication is a key field of study that can inform AI technology in the development of effective systems to communicate with patients and their healthcare providers and to influence individuals’ health behaviors. Theories and models of health communication highlight barriers to behavior change and limitations in technology-driven health interventions, and thus suggest areas where the efficacy of AI-supported systems can be enhanced. They can also instruct on aspects to consider when designing and evaluating AI systems. On the other hand, the use of AI poses the challenge to the field of health communication to provide validated theories and models, as well the opportunity to use AI to engage in more thorough testing of as yet unvalidated health communication theories and models.

Overall, what emerged from this special section is that the integration of AI technology and health communication can be very beneficial. As editors we will have achieved our aim if this special section of Patient Education and Counseling inspires discussions and further joint ventures in the fields of health communication and AI, a starting point in the evolution of AI-supported healthcare information systems that can address pitfalls in the current practice of health communication.

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