Robotic Tutors for Nurse Training: Opportunities for HRI Researchers

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Introduction

As the largest hospital workforce, nurses are essential to the overall stability of healthcare organizations and play a vital role in delivering quality patient care. An ongoing nurse labor shortage threatens to disrupt the entire healthcare system and presents a complex challenge: there is a decreasing supply of nurses while the demand for nursing services continues to rise, **creating an ever-widening nurse labor deficit** (Smiley et al. 2021; Juraschek et al. 2012). According to the Bureau of Labor Statistics, the U.S. healthcare sector has lost approximately a half a million workers since February 2020, with nearly one in five healthcare workers leaving since the COVID-19 pandemic began (Wager et al. 2021). This alarming and dire nursing shortage is only projected to worsen in the next decade (Marć et al. 2019; Haddad, Annamaraju, and Toney-Butler 2020).

At the same time, today's hospitalized patients require more complex medical management and sophisticated nursing care than ever before. As a result, hospital-based nurses are required to undergo extensive, frequent training to ensure safe patient care is provided. The training includes education of nursing skills and periodic skill validation, both of which are currently conducted by expert nurses (Figure 1). A **growing challenge for healthcare facilities is sustaining the current nurse-to-nurse model of training** given the nursing labor shortage and large volumes of nurses who require ongoing educational support.

We anticipate that addressing these challenges in nursing (not unlike other fields of medicine) will involve interdisciplinary solutions that merge expertise from healthcare, human factors, and technology. In particular, we (a multidisciplinary team of nurses, nurse scientists, roboticists, and AI researchers) envision the development of **intelligent robotic tutors that assist expert nurses in both education and assessment of nursing skills** (Figure 2). In this paper, we translate our need-driven vision to research problems for human-robot interaction (HRI) researchers and practitioners. Our goal is to invite the HRI (and more broadly AI and robotics) community to address these research problems and enable development of robotic tutors for nurse training.

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Accepted at the Association for the Advancement of Artificial Intelligence Spring Symposium on HRI in Academic and Industry.

Figure 1: A nurse educator (human expert) training nurse trainees with the aid of humanoid robot patients.

Related Work: Robots in Nursing

Hospital-based nurses are no stranger to technology and already employ several technological solutions to triage patients, monitor patient health, and maintain electronic health records (Robert 2019; Stokes and Palmer 2020). Robots are also being introduced to assist nurses in hospitals, with considerable commercial activity in the field (Kirschling, Rough, and Ludwig 2009; Bloss 2011; Ackerman 2018; Kangasniemi et al. 2019; Ackerman 2020). These robots hold the potential to support nurses in some routine tasks, allowing them to spend more time on patient care, increasing quality of care, and improving patient health outcomes (Tietze and McBride 2020). In pilot studies, robots have been shown to successfully fetch items, disinfect rooms, and help reduce hospital associated infections (Li et al. 2017; Abubakar et al. 2020; Worlikar et al. 2021).

Our vision is informed by this growing work on robots in nursing but differs in its focus. While the aforementioned robots focus on assisting nurses as they are supporting patients, we consider robot-assisted *nurse training*. Recent survey articles highlight the challenges that robots could help address in nursing education (Maalouf et al. 2018; Romero, De La Hoz, and González 2019). Dante et al. (2022) in detailed survey identify that two main robotic technologies

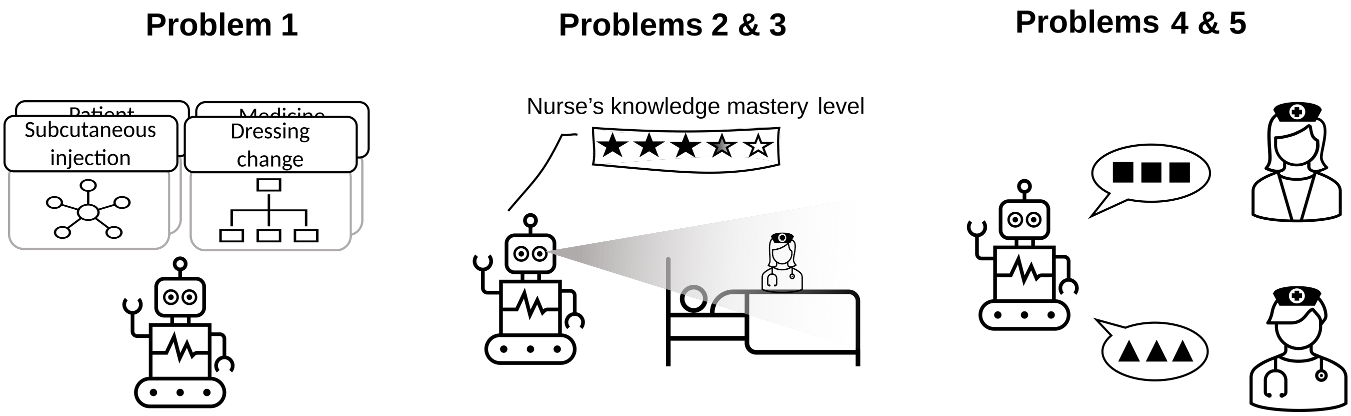

Figure 2: Schematic representing key research problems that will need to be addressed during the development of robot tutors for nurse training. We envision interactive robot tutors that maintain task models of nursing procedures (Problem 1), assess nurse trainees' skills using perception (Problem 2) and human modeling algorithms (Problem 3), and help accelerate nursing skill acquisition by providing personalized feedback (Problems 4 and 5).

are currently being explored in nursing education: humanoid robot patients and remote-presence robots. While important and synergistic, these systems differ from the proposed vision of robotic tutors. As detailed in the following sections, we propose research and development of interactive robot tutors that observe nurse trainees using their sensors, assess their skills using human modeling algorithms, and provide feedback to accelerate skill acquisition.

Such robot tutors hold the potential to reduce the time to acquire nursing skills and enable nurse educators to train a larger cohort of nurses. Currently, nursing pedagogy does not discuss robots or their potential influence on the nursing workflow (McAllister, Kellenbourn, and Wood 2021; Tietze and McBride 2020); instead nurses are expected to learn about new technology on the job. Along with their direct benefit for skill acquisition, we expect introducing robots in nursing education would also help the nursing community form more accurate mental models of prospective robotic assistants.

Robots for Skill Assessment

The ability to assess a trainee's skill is essential to effectively tutor them. Thus, first we describe potential of interactive robots for objective assessment of nursing skills.

Many important nursing procedures (such as central line dressing change, subcutaneous injection and others) require long sequences of subtasks in which nurses manipulate specialized medical objects and interact with patients. Currently, when validating a nurse's skill on such medical procedures, an expert nurse (human educator) observes and determines if a standardized protocol was followed by the nurse trainee. To ensure that assessments are done objectively, nurse educators typically utilize checklists and need to observe the trainee for the entire duration of the procedure. Nursing procedures can have multiple subtasks and involve off-nominal scenarios, thereby making the assessment process highly time-intensive. Moreover, many nursing skills are required to be validated annually which is especially challenging for larger hospitals. For instance, a hospital with over 2000 nurses will require up to 20 nurse educators daily for more than a month to observe every nurse's skills. Not only does this model require extensive specialty nurse resources, it removes the expert nurse from the patient's bedside for up to 4 hours each day.

We posit that an intelligent robot tutor – equipped with a task model of the nursing procedure, an appropriate perception module, and algorithms for modeling and monitoring task-oriented human behavior – can help in objective assessment of such physically grounded nursing skills. Our hypothesis is informed by other fields of medicine (e.g., surgery) that have already begun exploring AI-assisted objective assessment of skills using off-the-shelf sensors and machine learning algorithms. Robot-assisted nurse assessment would not only reduce the number of nurse educators needed for periodic assessment of nursing skills but also reduce the time nurses are away doing non-patient care activities. Next, we highlight three research problems that will need to be addressed to realize such a system.

Problem 1: Specifying Task Models of Nursing Procedures To objectively assess a trainee's ability to perform a medical procedure, a robot tutor will first require a computational model of the procedure. The robot will need to know the sub-tasks that constitute the procedure, the objects (e.g., medical instruments) relevant to the particular subtask, the sequence of actions that the nurse needs to take for completing the sub-task, and the appropriate response in off-nominal scenarios. The wide diversity of procedures, objects, actions and their relationship in the medical domain makes the problem of task representation for nursing procedures particularly challenging. We anticipate mathematical models and description languages used in the areas of planning and robotics – such as the Planning Domain Definition Language (PDDL) (McDermott et al. 1998), Markov Decision Processes (MDP) (Puterman 2014), Hierarchical Task Networks (HTN) (Erol, Hendler, and Nau 1994), and Petri Nets (Reisig 2012) – will be useful starting points.

For instance, PDDL-inspired models have been used to represent tasks in the nursing workflow (Abuazizeh, Kirste, and Yordanova 2020; Abuazizeh, Yordanova, and Kirste 2021). However, to capture the diversity in nursing procedures and hospital-specific practices novel techniques that enable nursing domain experts to translate their domain knowledge into robot-interpretable computational models will need to be developed. In the HRI community, there is already a strong and growing body of work on robot learning from human teachers (Chernova and Thomaz 2014), advances which can help address this need.

Problem 2: Perceiving the Nurse Training Environment and Activities Given the task model of a nursing procedure, a robot tutor can gain the understanding of its success criteria. However, to assess whether the criteria are met, it needs additional capabilities to observe a training session (both the nurse actions and the environment) and ground such observations to its task model, i.e., map the information obtained through its sensors to a known representation in the task model. Realizing this requirement can be viewed as a domain-specific case of the robot perception and grounding problem. To meet this requirement, solutions for nursing can utilize off-the-shelf sensors (e.g., cameras and physiological sensors) and build upon continued advances in machine learning algorithms for scene perception and activity recognition (Hutchinson and Gadepally 2021; Wang 2021). However, a critical bottleneck in direct application of existing techniques is the necessity of large datasets to train learned models (Kawaguchi et al. 2011).

We expect research on scene perception and activity grounding from *small datasets* through *multimodal and active sensing* particularly relevant for nursing. By utilizing sensors placed on the robot (e.g., cameras, LIDARs), on the nurse (e.g., heart rate monitors), and in the training environment, multimodal perception techniques can help provide a richer context. For instance, Inoue et al. provide a smartphone-based dataset for nursing activity and use it recognize nursing activities. Research on active sensing (Bajcsy, Aloimonos, and Tsotsos 2018), which utilize the ability of the robot to obtain measurements from multiple perspective and through human-robot communication, will also be important given that nursing activities can often be subject to occlusions from a single perspective.

Problem 3: Characterizing Learning Curves of Nurse Trainees Lastly, given the ability to model and perceive the nursing procedure, a robotic tutor will need to translate the perceived information into objective assessment of nurse trainees' skill level. To meet this requirement, we expect research on human modeling and, in particular, knowledge tracing to be particularly relevant. Knowledge tracing refers to when a machine models the knowledge of a student as they interact with computer-based tutors, such as an intelligent tutoring system (ITS). One of the most widely used techniques is Bayesian Knowledge Tracing (BKT) (Corbett and Anderson 2005). BKT models a learner's knowledge mastery level using a Hidden Markov Model (HMM), which updates the probability of a learner knowing the knowledge through the learner's response to questions from the tutor. Other dynamic probabilistic models have also been explored for knowledge tracing, such as Performance Factors Analysis (Pavlik, Cen, and Koedinger 2009), Learning Factors Analysis (LFA) framework (Cen, Koedinger, and Junker 2006), and Knowledge Graph (Yang and Zhang 2019). Recent work has also explored the use of neural networks in knowledge tracing (Piech et al. 2015; Minn et al. 2021). For using a robot as an objective evaluator of nursing skills, interactive knowledge tracing solutions that build upon these techniques and utilize human-robot communication seem particularly promising.

Robots for Skill Training

In addition to serving as an assessment aid, a robotic tutor can also help provide feedback to accelerate nurse trainees' skill acquisition. Currently, one nurse educator provides face-to-face education to up to 20 nurses at a time. This training model requires significant involvement of expert nurses when large volumes of nurse trainees need the identical education. For example, when a new device is introduced into the clinical environment, every nurse will require instruction on how to use it. Robot-assisted education would allow for more nurses to be educated in a shorter time frame and provide opportunities for personalized learning. Widespread utilization of the device impacting patient care and outcomes would happen sooner.

Related to robotic tutors, virtual intelligent tutoring systems are being explored for nursing education (Koutsojannis, Prentzas, and Hatzilygeroudis 2001; Hospers et al. 2003; Abuazizeh, Kirste, and Yordanova 2020; Abuazizeh, Yordanova, and Kirste 2021). Unlike traditional ITS which primarily provide audiovisual feedback, robotic tutors through their physical embodiment can endow both physical and audiovisual interactions. In other domains, the ability to provide multimodal feedback has been shown to produce significant cognitive benefits and achieving learning outcomes that are similar to those of human tutors on restricted tasks (Leyzberg et al. 2012; Leyzberg, Spaulding, and Scassellati 2014; Belpaeme et al. 2018). In this section, we discuss the additional challenges that need to be addressed to bring forth these benefits for training nursing skills.

Problem 4: Designing Personalized Feedback The fourth challenge is determining *what to teach*; in other words, determining how to generate instructions to improve nurses' knowledge of a task. This problem of selecting good examples and generating instructions to explain a task is highly related to the research field of explainable AI (XAI), especially task-oriented XAI which is often seen in explaining robot behavior. Solutions for describing sequential decision-making behavior of autonomous agents and (more recently) robots include providing users with local examples and/or a global summary of the behavioral policy (Zhan et al. 2014; Amir and Amir 2018; Huang et al. 2019; Lee, Admoni, and Simmons 2021; Qian and Unhelkar 2022). Such methods take a task model as input and output selected instructions. For example, authors in (Qian and Unhelkar 2022) describe the task using a Markovian policy and algorithmically select (state, action)-pairs that highlight the robot's strategies to complete a task. Similarly, given a nursing task, an essential problem to address is how to algorithmically generate instructions that can help nurses learn the optimal way of completing tasks as quickly as possible.

Research in pedagogy is also highly relevant, which categorizes teaching strategies based on the use of direct versus indirect instructions (Julien-Schultz, Maynes, and Dunn 2010; Nguyen et al. 2017; Ruutmann and Kipper 2011). Direct instructions are teacher-centered, involve clear teaching objectives and consistent classroom organizations; indirect instructions are student-centered and encourage independent learning. There is a rich body of work on intelligent tutoring system (ITS), which is developed to provide independent learning opportunities for students through expert-designed materials, as a combination of direct and indirect learning-and-teaching, that can help inform the development of robotic tutors for nurse training.

Problem 5: Communicating Feedback in a User-Interpretable Manner The second challenge, closely followed after *what to teach*, is *how to teach*. For tutoring of nursing skills, information can be delivered to humans using a variety of modalities (e.g., text, images, augmented/virtual reality) and types (e.g., natural language explanations, template-based explanations, demonstrations). The design space for delivering the instructions is rich. We envision three categories of help actions that a robot tutor can take: no action (observing the nurse's activities), giving a verbal hint, and performing a physical action (e.g., providing demonstrations or creating novel scenarios that require objects manipulation). To determine which help action is more effective and efficient, reward and cost functions are needed for evaluating the estimated learning outcomes of different help actions and the cost of each help actions (e.g., time, space, resource).

Unique to robot tutors – unlike other tutoring systems such as ITS – is their ability to perform actions that can modify the state of the world around the nurse trainee. This capability can be used to provide demonstrations of certain critical tasks and to physically create realistic scenarios in physically simulated environments, a feature that is currently limited only to human tutors. To realize such behavior, a robot needs to reason over both discrete decisions (what to do) and continuous parameters (how to do it). Task and Motion Planning (TAMP) (Dantam et al. 2018; Garrett et al. 2021) and multimodal planning (Hauser and Ng-Thow-Hing 2011) algorithms provide methods to tackle these problems through a layered planning approach. Discrete reasoning is performed through symbolic planning (McDermott et al. 1998), while continuous parameters (i.e., how to grasp or put down an object) are computed using motion planning (Kavraki et al. 1996).

Although tremendous advances have been made in the TAMP community, these techniques are still largely limited by modeling choices and assumptions, such as uncertainty in the robot's actions and perception, and limitations in the robot's capabilities. Further work along this direction will help enrich the space of tutoring modalities and enable effective communication of tutoring feedback.

Conclusion

In this position paper, we highlight a novel need-driven opportunity for HRI researchers: development of robotic tutors for nurse training. Towards this opportunity, we highlight specific research problems and application areas for researchers working on human activity recognition, human-robot communication, task and motion planning, interactive user interfaces, among others. Our goal is that this preliminary analysis will motivate novel solutions for training nurses (and more broadly addressing the nursing shortage) from the HRI community.

Developing mature and robust solutions for this novel application will require contributions from both the academia and industry. Preliminary work, particularly for Problems #1, #3, and #4, will largely involve academic research to demonstrate benefit of robotic tutors in proof-of-concept nursing scenarios. Problems #2 and #5 involve components that are already part of commercial robotic systems; increased focus on these components in the nursing context will help accelerate transition to practice. Moreover, the list of research problems described in the preceding sections is not meant to be exhaustive. We expect further work in this area will motivate additional problems (and solutions) across different technology readiness levels.

Concurrently, within the nursing community, there is growing interest in understanding and characterizing the role of AI and robots in nursing and nurses' perspective towards this novel technology (Robert 2019; Buchanan et al. 2021). We expect that this cross-disciplinary effort will contribute to this understanding and enable the next generation of nurses to better calibrate their trust in robotic systems.

Acknowledgments

This work was supported in part by NSF award #2222876, the Houston Methodist Hospital, and Rice University.

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