25th IEEE International Symposium on
Robot and Human Interactive Communication (RO-MAN)
August 26-31, 2016. Columbia University, NY, USA

Exploring Elicitation Frequency of Learning-Sensitive Information by a Robotic Tutor for Interactive Personalization*

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Abstract— **We formalize and analyze a robotic tutor's elicitation of learning-sensitive information to be leveraged by interactive machine learning methods for personalized education. The user study presented in this paper is an initial exploration of elicitation frequency of learning sensitive information, and the social and computational implications thereof. Our results, evaluated using a variety of subjective measures, demonstrate that a humans-in-the-loop approach positively benefits the human-robotic tutor interaction, while minimizing the computational complexity of personalization.**

I. INTRODUCTION

Personalization is a long-standing research interest in the field of human-robot interaction, aiming to quickly and effectively adapt robot behaviors to individual users [1]. Traditionally, personalization is carried out without the user's direct involvement (e.g., a robot observes that a user consistently chooses to play Tetris, and predicts that Tetris is the user's favorite game). In this paper, we consider the case in which personalization leverages information directly elicited from a user about his or her state and/or preferences (e.g., a robot asks a user if Tetris is his or her favorite game). We explore this problem of *interactive personalization* in the context of a robot acting as a tutor to a human.

Individuals vary greatly in terms of their personal abilities, special needs, and learning styles and preferences [2]. The innate diversity among human learners poses many computational complexities in modeling users for personalized education. To mitigate this challenge, many intelligent tutors leverage domain knowledge to pre-define the dependencies between learning goals (i.e., a fixed or strong prior probability that a learner understands one concept given that he or she demonstrated understanding of some other related concept).

The computational challenges inherent to intelligent tutoring can also be mitigated by direct input about the human learner's state or ability. This human-in-the-loop approach – parallel to the research in learning from demonstration [3], interactive machine learning [4], machine learning using privileged information [5], and recommendation systems [6] – enables an agent to obtain ground truth about a human learner, minimizing the need for repetitive interaction and/or rigid, literature-based models.

However, while explicit information about a human learner's state is powerful, it is also likely to be sensitive. The questions posed by an intelligent tutor about a learner's state may expose and highlight the weaknesses of that learner. *In this work, we explore how the frequency of learning-sensitive questions posed by a robotic tutor, for the purposes of interactive personalization, affects a human learner's impression of and overall interaction with the robot.* Our work offers the following contributions:

1) We define **interactive personalization** as a specific case of interactive machine learning.
2) We define **learning-sensitive information**, and formalize it in terms of observability, sensitivity, and computational gain. We also provide a specific set of learning-sensitive questions posed by a robotic tutor in our study.
3) We formalize **elicitation frequency** in terms of an intelligent tutoring agent eliciting learning-sensitive information from a human learner.
4) We observe and discuss the relationships between the frequency of learning-sensitive questions posed by a robotic tutor and the user's experience, impression, and overall interaction with the robot in a small exploratory study. Our observations support the potential of **social and computational gains** to a robotic tutor frequently eliciting learning-sensitive information from a human learner.

II. RELATED WORK

In this section, we situate our work within the research areas of personalized human-computer and human-robot interaction, intelligent tutoring systems, user modeling, and statistical machine learning.

A. Intelligent Tutoring

The benefits of personalized education are well-supported by research across the disciplines of psychology [7], human-computer interaction [8], and human-robot interaction [1], [9], [10]. Intelligent Tutoring Systems (ITS) have been shown to replicate, if not exceed, the benefits of human one-on-one tutoring [11], [12]. The embodiment of robotic tutors has been shown to further increase these learning gains [13], [14]. We are motivated by this strong research foundation to further explore the personalization of robotic tutors through the application of interactive machine learning.

B. Interactive Machine Learning

User modeling applied to intelligent tutoring offers many computational challenges, including but not limited to the amount of data available (i.e., the number of human learners and/or the length of their interactions with a robot), feature

* Research supported by National Science Foundation grant IIS-1139148.
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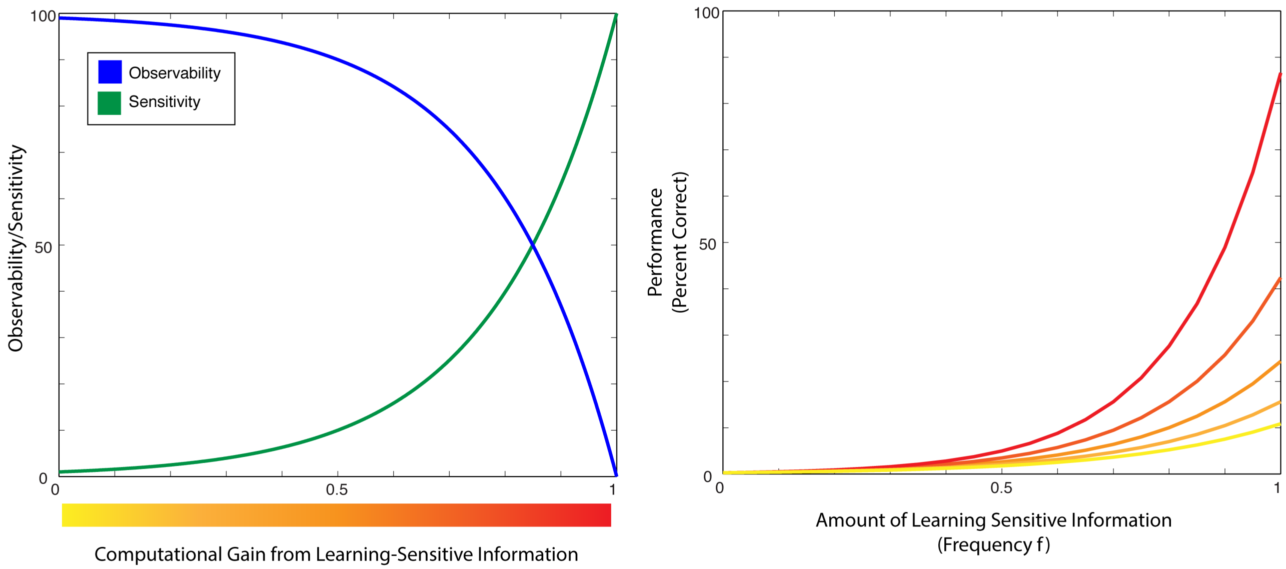

Fig. 1. The leftmost figure shows our proposed relationship between the observability, sensitivity, and computational gain of learning-sensitive information. The information with the greatest computational gain for an agent is the least observable and typically the most sensitive to obtain from a human learner. However, as the rightmost figure depicts, the more learning-sensitive information obtain, the better an agent may personalize to an individual.

noise (e.g., reliability of a robot's perception), data labeling (e.g., annotation of learners' states), and concept drift (i.e., learners' fluid aptitude and preferences) [15]. Generally, the state of human users is non-deterministic and partially observable at best, and such problems have been shown to be hard theoretically and experimentally [16]. However, these specific challenges can be alleviated by including humans-in-the-loop.

Interactive machine learning (IML; see [4] for a review) enables humans, an untapped source of guidance and knowledge in classical machine learning, to provide direct observations and ground truth to guide the learning process of an agent [17]. Some of the simplest and most familiar examples of IML include recommendation systems such as Pandora and Netflix. These systems allow the user to directly input their preferences as binary (i.e.,"liking" or "disliking") or ordinal (i.e., five-star rating) values.

The success of any machine learning approach depends on the amount of data available and the observability and noisiness of the features of those data. Interactive machine learning strives to reduce the challenges that accompany real-world problems, such as partial observability, limited data, and excessive noise. As shown in Fig. 1, an increase in human input should serve to further reduce those challenges.

However, in any application of interactive machine learning, it is important to keep in mind that human users are not oracles, and thus, they can and often do provide misinformation [18]. Additionally, it is equally important to consider the effects interactive machine learning may have on the user's experience, including user acceptance, attachment, and survey fatigue. In this paper, we thoroughly consider the later to formulate and test interactive personalization, defined as a specific case of interactive machine learning.

III. FORMALIZING INTERACTIVE PERSONALIZATION

So far, we have provided the motivation and background for personalization in intelligent tutoring, with a specific focus on intelligent robotic tutors. Here, we further define interactive personalization, and formalize the related concepts of learning-sensitive information and elicitation frequency.

A. Interactive Personalization

Definition 1: **Interactive personalization** is the process by which an intelligent agent adapts to the needs and preferences of an individual user through eliciting information directly from that user about his or her state.

Some features that could be elicited about a user's state include objective information such as the user's desired time on task, subjective information such as the user's comfort with a particular task, abstract information such as the user's learning style and preferences, and personal and sensitive information such as the user's aptitude and special needs.

B. Learning-Sensitive Information

In the case of intelligent tutoring, information about a human learner's state is largely hidden and may only be observable through direct input by the learner, or through interactive personalization. However, this important information is also typically sensitive in nature as it may expose the learner's weaknesses.

Definition 2: **Learning-sensitive information** includes any measurable data about an individual that effects his or her ability or style by which to achieve some learning goal.

The most important information about a human learner may often be the most occluded and challenging to postulate through indirect observations, and also the most sensitive to elicit directly, such as a learner's special needs. Thus, we assume there exists some relationship between the observability, sensitivity, and computational gain of learning-relevant information similar to the distribution shown in Fig. 1.

For the purposes of the study presented in this paper, the information elicited by the robotic tutor is fairly observable and minimally sensitive to the participant.

C. *Elicitation Frequency*

This paper presents an initial exploration of the *frequency* of learning-sensitive questions posed by a robotic tutor for interactive personalization.

Definition 3: **Elicitation Frequency** is the number of of learning-sensitive questions q posed by a robotic tutor over the number of user tasks T.

$$f = \frac{q}{T} \tag{1}$$

The higher the frequency, the more input is being asked of the user. We hypothesize that frequency is an important measure in interactive personalization.

IV. GENERAL HYPOTHESES

Our first general hypothesis comes from our subjective experience: interactive personalization will provide social gains in addition to computational gains, i.e., a robotic tutor that elicits learning-sensitive information ($f > 0$) will be considered more social, interactive, and intelligent than one that does not ask the human learner about his or her state.

Our second hypothesis is that too much elicitation ($f > 0.5$) will cause discomfort or annoyance to the human learner with minimal computational gains.

V. STUDY DESIGN

Given our definitions for interactive personalization, learning-sensitive information, and elicitation frequency, we conducted a small user study with a convenience population to explore the implications of f on a human-robot tutoring interaction. The purpose of this study is to explore the social costs and benefits relative to the frequency of learning-sensitive questions posed by a robotic tutor. The interaction is designed to evaluate the participant's aptitude rather than tutor the participant, as is the common form of pre-assessment in ITS.

A. *Experimental Setup*

1) System Setup: We used the Aldebaran NAO humanoid robot as a fully autonomous one-on-one robotic tutor to undergraduate and masters students at a United States university. The robot was positioned next to a touch tablet on which the student could provide answers to questions, connected via ethernet (see Fig. 2).

2) Educational Content: The interaction involved a set of 20 questions, presented in randomized order for each participant. The set of questions was an equal combination of trivia, SAT/GRE mathematics and science, and SAT/GRE grammar and vocabulary questions[1].

[1]The SAT and GRE are standardized undergraduate and graduate entrance exams, respectively, for United States colleges and universities.

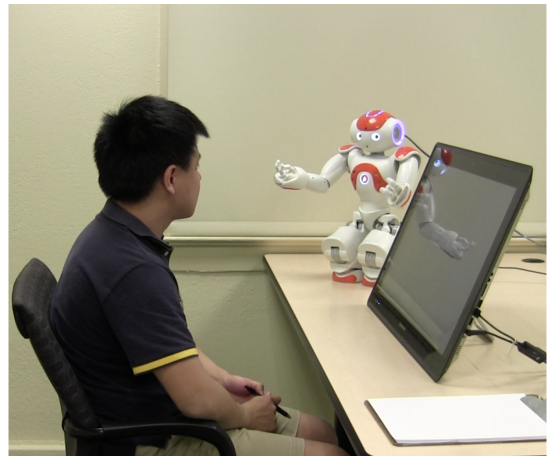

Fig. 2. In our study, the Aldebaran NAO robot acted as a tutor to undergraduate and graduate students. The students entered their answers on a touch tablet, or responded verbally to the robot directly when it elicited learning-sensitive information.

3) Robot Behavior: The fully autonomous robot verbally asked each question as it appeared on the tablet in front of the participant. As the robot asked the questions, it provided some natural, narrative gestures and shifted its gaze between the tablet and the participant.

After the participant submitted his or her answer, the robot responded accordingly, as follows. If the participant answered correctly, the robot provided a congratulatory statement randomly selected from a set of 15 such statements, with accompanying affective gestures. If the participant answered incorrectly, the robot stated "Let's try something else.", and then moved on to the next question.

If the robot tried to elicit learning-sensitive information from the participant, it only shifted its eye gaze, providing no embodied expression of emotion. The robot then waited until the participant responded verbally, and stated "Okay." before moving on to the next question.

4) Learning-Sensitive Information: The learning-sensitive questions posed by the robotic tutor randomly followed one of the schemas below, with a random selection of the optional words in brackets:

1) "Did you [struggle, have a hard time] [with, answering] [that one, that question, that last question, the previous question]?"
2) "Was [that one, that question, that last question, the previous question] [hard, difficult, challenging, tough, a challenge] [for you, for you to answer, to answer]?"

B. *Conditions*

We designed and tested three discrete conditions for frequency f. In each condition, the robot's elicitations were evenly distributed among the 20 questions such that there were no consecutive elicitations. We only consider frequency conditions up to $f = 0.5$ because we assume our user model performs at least as well as random before leveraging interactive personalization.

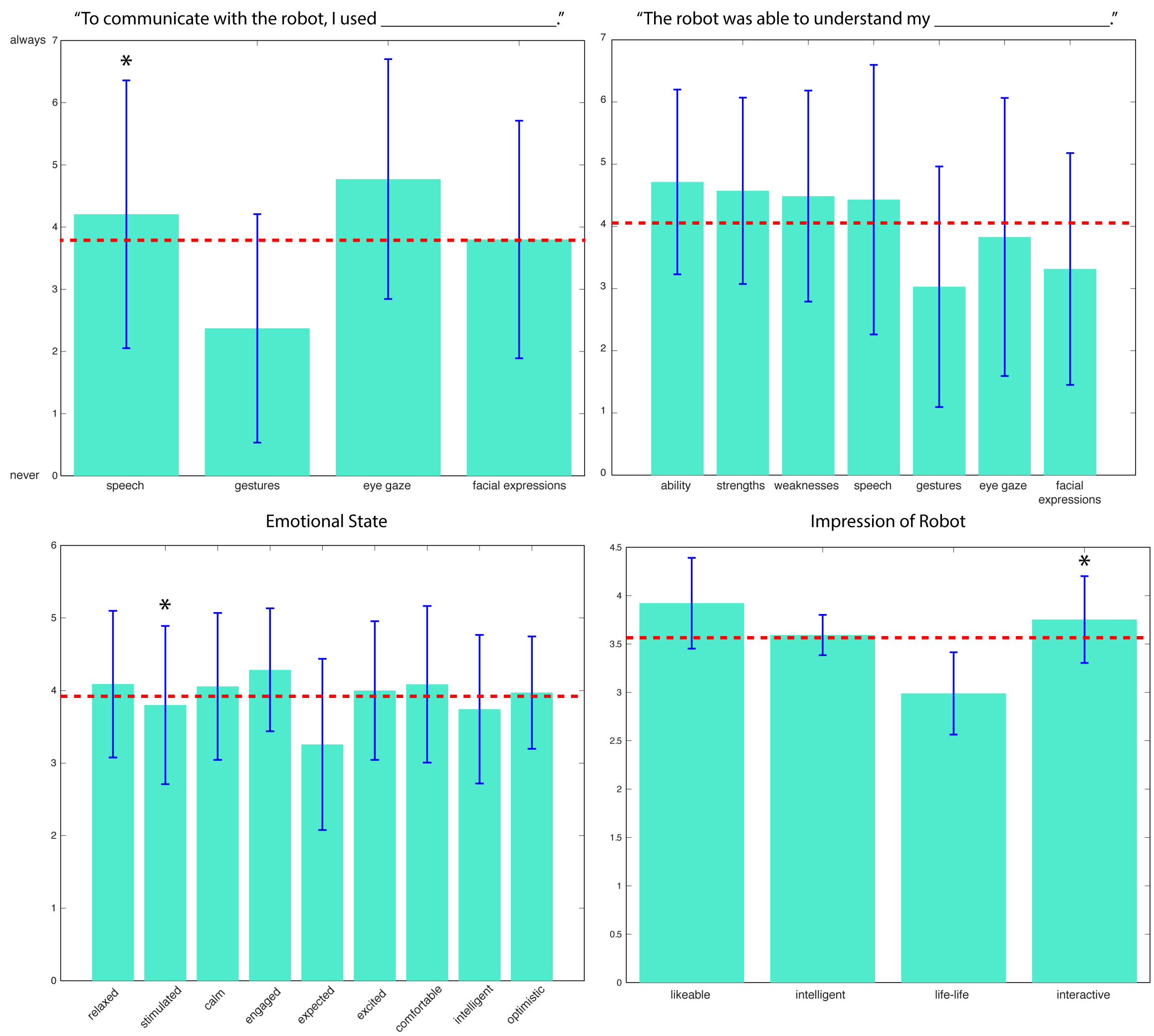

Fig. 3. A collection of subjective measures was taken to evaluate how participants felt about the robotic tutor and interaction among the three conditions. Overall, the impression of the robot was positive across conditions. Significant results are marked with an asterisk and explained in more detail in Section VII-B

1) f=0.0: In this condition, the robot never elicited learning-sensitive information from the participant. Thus, the interaction consisted of a series of questions, followed by the robot's response as to whether the participant answered correctly or incorrectly.

2) f=0.25: In this condition, the robot elicited learning-sensitive information 25% of the time, evenly distributed. Thus, in our short interaction, the robot asked the user a learning-sensitive question every 5 problems.

3) f=0.5: In this condition, the robot elicited learning-sensitive information 50% of the time, evenly distributed. Thus, in our short interaction, the robot asked the user a learning-sensitive question in every other problem.

C. Procedure

Participants were asked to answer a series of educational questions with a robotic tutor. They were instructed to answer to the best of their abilities and as honestly as they could, entering their answers on the tablet screen and/or responding verbally to the robot. They were also provided with a pen and paper to work any problems out as necessary. Participants were given no further information about the robot or what questions it would ask. For methodological reasons, we chose to use a very neutral formulation of the task and how to respond to the robot to not influence the judgment of the participant.

D. Participant Statistics

Using flyers and word-of-mouth, we recruited current undergraduate and masters students at the University of Southern California to participate in the study. We offered a $10 Amazon gift card to those willing to participate. In total, 38 participants engaged in the study. The sample population consisted of 14 female (37%) and 24 male participants (63%). Participants' age range was 18-29; average age was 22 (S.D. = 2.74); 18 participants held Bachelors degrees (47%) and 20 were current undergraduate students (53%). 79% of participants were of Asian descent, 8% of Hispanic/Latino descent, 8% of Caucasian descent, and 5% of African American descent. The average "experience working

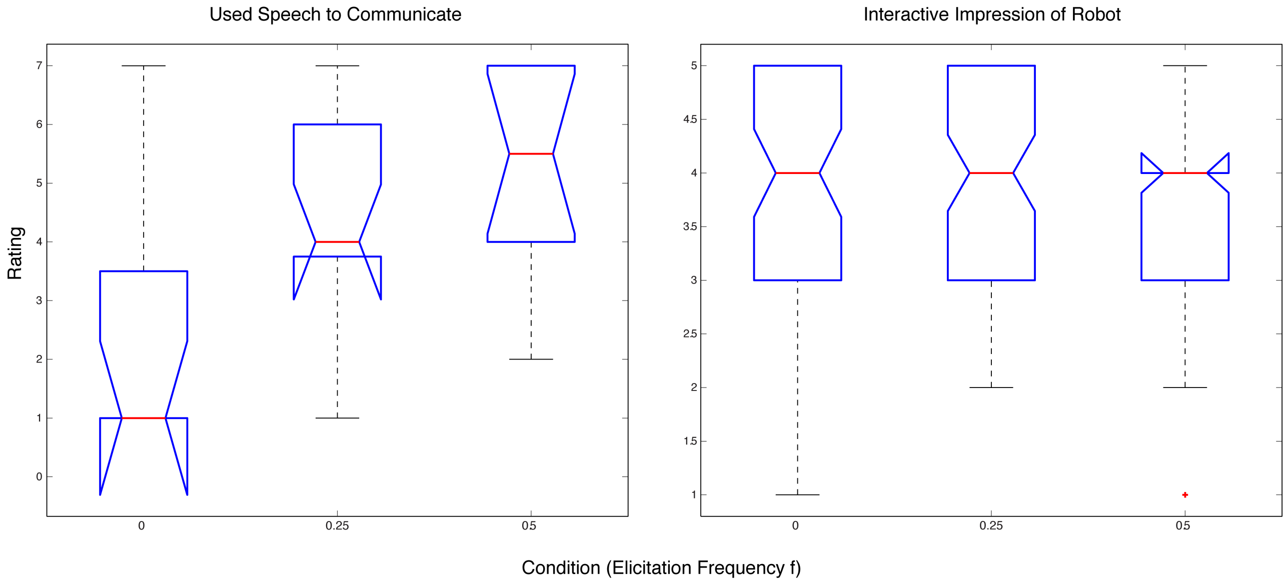

Fig. 4. Participants reported that they communicated and interacted more with the robotic tutor in conditions with a non-zero elicitation frequency. The computational benefits of such interaction are clear, and these results show that they do not impact the participants' overall impressions and comfort with the robotic tutor.

with robots", measured on a 1-4 scale, was 1.77 (S.D. = 0.88).

There were no statistically significant differences between conditions in participants' self-rated attitude towards robots and personalities (see pre-study subjective measures in Section VI). Participants in our study had a generally positive prior attitude towards robots (4-point NARS [19] Mean = 1.8, S.D. = 0.34).

VI. MEASURES

Before each session of the study, the participants were asked to fill out two surveys: (1) the Negative Attitude towards Robots Scale (NARS) developed by Nomura et al. to capture their prior experience with and/or attitude towards robots [19], and (2) the Big 5 traits: Neuroticism, Extraversion, Openness, Agreeableness, and Conscientiousness [20].

After each session, the participants were asked to fill out four Likert-type scales and answer five open-ended questions to capture their ratings of the interaction as well as their perceived ease of use of the robot system. Additionally, the participants were asked to fill out the Almere questionnaire to measure their acceptance of the robot as an assistive social agent [21]. We discuss these subjective measures and their implications in more depth in the following Section VII.

VII. RESULTS

We performed a mixed-design analysis of variance to examine the effects of elicitation frequency on our subjective dependent variables. Subjective data have been analyzed with MATLAB, using a combination of one-way analysis of variance (ANOVA) and two-sample t-test.

A. *General Impression of Robot*

Results indicate that participants had a generally positive impression of the robot that did not vary significantly with elicitation frequency (Fig. 3). Participants felt the robot communicated to and understood them through multiple modalities.

Participants also had a generally positive emotional state after working with the robotic tutor, even in the $f = 0.5$ condition in which participation took an average of twice as long to complete the study as compared to in the $f = 0$ condition.

Lastly, participants felt that the robotic tutor was generally likeable, intelligent, and interactive in all conditions. However, participants did not generally feel that the robotic tutor was very life-like.

B. *Statistically Significant Differences*

While the overall impression of robotic tutor was similarly positive among the three conditions, there were a few significant differences.

1) Emotional State: Participants felt they were more stimulated ($p < 0.05$) in the third condition ($f = 0.5$), in which the robotic tutor elicited learning-sensitive information more frequently. This indicates that there may not be a negative impact to eliciting more learning-sensitive information, which has positive implications for mitigating computational challenges through interactive personalization.

2) Communication: Participants reported that they communicated significantly more ($p < 0.005$) with the robotic tutor in the second ($f = 0.25$) and third ($f = 0.5$) conditions. While this result is intuitive, as a higher elicitation frequency requests the participants to communication with the robot more frequently, it indicates that the participants willingly responded to the robot's requests without any negative impact on the overall interaction. Participants were not required to respond to the robot's elicitations; however, participants consistently offered up learning-sensitive information without feeling frustrated (Section VII-B.1).

3) Interactivity: Another strong result from our small study was that participants felt the robotic tutor was generally more interactive in the second ($f = 0.25$) and third ($f = 0.5$) conditions ($p < 0.05$). We subjectively measured interactivity by how "active", "lively", "reactive", "interactive", and "responsive" the participants found the robot on a 5-point scale. This implies that that their are social benefits, such as engagement, to a non-zero elicitation frequency, supporting our first hypothesis (Section IV).

4) Almere: According to the Almere survey [21], participants were more likely to report that the robotic tutor had feelings ($p < 0.05$) and that they were more likely to trust the robot's advice ($p < 0.01$) in the case in which the robot posed the most learning-sensitive questions ($f = 0.5$).

VIII. DISCUSSION

The results presented in Section VII offer a number of insights about humans preference toward a robotic tutor's elicitation frequency of learning-sensitive information.

A. First Hypothesis

Subjective measures concerning participants' impression of the robotic tutor were found to be positive across conditions. Participants reported greater stimulation and interaction with a robotic tutor that elicited learning-sensitive information more frequently. This supports our primary hypothesis that interactive personalization may have social as well as computational gains.

B. Second Hypothesis

Our second hypothesis, that an elicitation frequency $f \geq 0.5$ would correlate with a negative user experience with a minimal computational gain, was not supported by the study data, the rejection of which provides further support interactive personalization. We found that elicitation frequency between 0 and 0.5 is beneficial to both the interaction and computation. We chose not to explore a frequency greater than 0.5 because we felt most models are capable of at least 50% accuracy.

C. Limitations & Implications

The study presented in this paper was small, and constructed to validate the concepts of elicitation frequency and learning-sensitive information in interactive personalization in the most general and convenient context. We believe our results support the joint social and computational benefits of interactive personalization.

IX. FUTURE WORK

We intend to continue to explore and define more features of interactive personalization for intelligent robotic tutors. The information elicited in the study presented in this paper was minimally sensitive. Next, we plan to explore the scaffolding (e.g., empathy) necessary for a robotic tutor to elicit more sensitive learning information from a human learner. We are also inspired to explore the scale of the questions asked by the robotic tutor (e.g., a question with an answer along an ordinal scale). Lastly, we will leverage insights about interactive personalization gained with convenience populations and apply them to an assistive domain such as young children with special needs.

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