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Alexa, Can You Help Me Solve That Problem? – Understanding the Value of Smart Personal Assistants as Tutors for Complex Problem Tasks

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Abstract. In recent decades, the number of students per lecturer at universities has constantly risen. In these learning scenarios, individual lecturer support for helping students actively acquiring new knowledge is hardly possible. However, active student behavior is necessary for successful learning. Smart Personal Assistants such as Amazon's Alexa or Google's Home promise to fill this gap by being students' individual tutors. In order to understand what students expect from Smart Personal Assistants as tutors and how they interact with them, we will carry out an experiment. In this research in progress paper, we present our experiment design, where we observe the individual interaction between students and a Smart Personal Assistant tutor and between students and a human tutor applying the same methods in both cases. Drawing on the concepts of parasocial interaction and trust, we derive hypotheses, present the Smart Personal Assistant development and explain the experiment process in detail.

Keywords: computer tutor, Smart Personal Assistant, education, experimental design,

1 Introduction

In recent decades, the number of students per lecturer at universities has constantly risen [1, 2]. In these learning scenarios, lecturers are often forced to present their learning content to the students in a one-directional way with nearly no support for students before and after the lecture. However, the predominant constructivist learning theory states that learning only occurs when students actively acquire new knowledge [3]. This happens best in learning environments where lecturers individually scaffold students' understanding of new learning content [4]. This kind of support is hardly possible due to universities' financial and organizational restrictions. According to the

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OECD, the number of students at universities rose from 2005 to 2014 by 15 percentage points in the US and 29 in Germany while public spending for education decreased in the same period by 7 percentage points in the US and 1 in Germany [5]. Smart Personal Assistants (SPA) such as Amazon's Alexa or Google's Assistant that are based on current technological developments in artificial intelligence and natural language processing have the potential to fill this gap. SPAs are software programs that communicate with an individual via natural language (voice and text) helping users to perform tasks [6]. Until now, there is no empirical evidence whether and under what conditions students accept SPAs as their personal tutors. Moreover, in past research, SPAs have been mostly used for rather simple and short tasks such as setting an alarm, restaurant reservations, etc. We therefore try to answer the following research questions:

RQ1: How do students accept Smart Personal Assistants as their tutors in complex problem task environments?

RQ2: How does interaction mode (voice vs. text) influence the acceptance of Smart Personal Assistants as tutors in complex problem task environments?

We employ a 2 x 2 (human vs. SPA and voice vs. text) between-subject experiment design with an actual SPA powered with current technology to address these research questions. By this means, our study contributes to literature in the following ways: (1) To the best of our knowledge, this study is amongst the first that empirically investigate the value of SPAs as personal tutors within complex problem task environments. (2) We extend past research of human and computer tutoring by directly comparing four types of tutoring (human text vs. human voice vs. computer text vs. computer voice).

2 Theoretical Background and Hypotheses

2.1 The ICAP-Framework in the Context of Tutoring

The ICAP-Framework is based on the constructivist learning theory. It helps classifying students' cognitive engagement behaviour during learning with four categories: *interactive, constructive, active, or passive* and predicts that they can be ordered by effectiveness *(better learning outcomes)* as **interactive > constructive > active > passive**. A *passive* student behaviour would be attending to the presented instructional information without additional physical activity (e.g. reading a text). An *active* student behaviour includes "doing something physically" (e.g. taking notes). A *constructive* student behaviour requires "producing outputs that contain ideas that go beyond the presented information" (e.g. self-explaining a text). An *interactive* behaviour requires "dialoguing extensively on the same topic, and not ignoring a partner's contribution [7]. One-on-one tutoring with human tutors mostly elicit interactive student behaviour including co-construction and other collaborative spoken activities leading to an increased understanding of learning content and an increased learning process satisfaction [8]. This way of interaction is currently beyond the state of the art in computer tutoring. Nevertheless, recent developments in artificial intelligence, natural language processing and machine learning let us believe that Smart Personal Assistants are able to replace human tutors to some extent. We therefore propose:

H1. There is no difference in acceptance levels between Smart Personal Assistants and human tutors.

2.2 Voice-based vs. Text-based Smart Personal Assistants

Voice-based discourse is the primary form of human-human communication, hence, computer interfaces that communicate via voice provide a more efficient, meaningful, and naturalistic interaction experience [9]. Within the context of tutoring, there are a lot of theoretical positions supporting that spoken interaction is important in tutorial dialogue, compared to communication through typing and printing [10, 11]. One reason for that might be that the gap between thought and speech is much less than the gap between thought and writing, because voice-based discourse is the language of the “mother tongue” [12]. However, studies also showed that people feel uncomfortable when talking with SPAs in public [13]. Nevertheless, voice-based interactions have the potential to foster relationship building between students and tutors [14]. We therefore propose:

H2. Voice-based Smart Personal Assistants show increased acceptance levels compared to text-based Smart Personal Assistants.

2.3 The mediated role of Parasocial Interaction and Trust

The concept of parasocial interaction was first introduced by Horton and Wohl [15], ahead of ubiquitous interactive computer technology. When computers such as robots or AI came to have human-like interfaces, researchers have started to use this concept to investigate the existence of emotional relationship (e.g. feelings of friendship) between people and computers [16]. Furthermore, Trust is vital in one's acceptance of technology [17]. Many studies found out that users must have trust in a technology before they show willingness to adopt it [17, 18]. Especially the affective dimension of trust may be very important for tutors’ acceptance. It explains the confidence one places in a partner on the basis of feelings generated by the level of care and concern the partner demonstrates [19]. We therefore hypothesize that type of tutor as well as interaction mode can be mediated by these constructs.

H3a. The effect of type of tutor on tutor’s acceptance is mediated by parasocial interaction.

H3b. The effect of type of tutor on tutor’s acceptance is mediated by trust.

H3c. The effect of interaction mode on tutor’s acceptance is mediated by parasocial interaction.

H3d. The effect of interaction mode on tutor’s acceptance is mediated by trust.

3 Overall Experiment Procedure and Treatment Design

To test our hypotheses, we run a laboratory experiment where participants have to individually conduct a 30-minute complex problem task with the help of a SPA or a human tutor. Table 1 shows our treatment design. The human tutor can be perceived as an expert in tutoring (gold-standard). We include a control group that has no tutor. The sample consists of graduate and undergraduate students attending a Swiss business school.

Table 1. Treatment Design (randomly assigned groups)

		Type of tutor		
		No tutor (control)	**SPA tutor**	**Human tutor**
Interaction mode	**Voice-based**	T0 (N=35)	T1 (N=35)	T2 (N=35)
	Text-based		T3 (N=35)	T4 (N=35)

4 Task Design and SPA Development

We decided to choose a complex problem task comparable to the types of problems people face every day. We therefore first derived task requirements from complexity theory and problem-based learning theory [20, 21]. By this means, we chose a task that was already tested in a study on the effectiveness of problem-based learning [22]:

Increasing traffic flow has led to a significant increase in the number of accidents at a major intersection in your city. Several deaths have occurred in recent years. What should the city do about it?

We used Amazon's Alexa and its Skill Development Kit 2.0 with nodeJS to develop our voice-based and text-based SPA. The interaction model and the corresponding instructions of Alexa is based on the problem-solving steps of Kim and Hannafin [23]: *(a) problem identification, (b) problem exploration, (c) problem reconstruction, (d) presentation and communication, (e) reflection and negotiation*. We conducted a pretest with twenty students in order to test the functionality of our programmed SPAs and noted their change requests.

5 Measurement, Analysis and Conclusion

This experiment will be measured with the help of a posttest-questionnaire. *Tutors' acceptance* will be measured with the help of the technology acceptance model proposed by Davis et al. [24]. In specific, we will adapt items from perceived usefulness and perceived ease of use. Furthermore, we will measure the construct *parasocial interaction* with Rubin et al.'s [25] PSI (Parasocial Interaction) Scale. The construct *trust* will be measured with items proposed by Lee and Choi [26]. For analysis, we will use traditional t-tests to show mean differences between the treatment groups.

We are currently analyzing the data of the experiment. First results show that audio-based SPAs are significantly better than text-based SPAs in terms of acceptance. Our expected results from the experiment have a twofold contribution. To the best of our knowledge, this study is amongst the first that empirically investigate the value of SPAs as tutors for complex problem tasks. As this kind of task support has the potential to increasingly enter education in future, it is important to understand how students accept SPAs as their tutors. Moreover, we extend past research on human and computer tutoring that mainly focused on one type of tutoring.

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