User-Models to drive an Adaptive Virtual Advisor*

Demonstration

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ABSTRACT

Agents that adapt to their user need to have knowledge of their user and expertise on how best to adapt to that type of user. In this paper we describe the addition of an agent's expertise and collection of machine-learnt user profiles to the proposed extended FAtiMA (Fearnot AffecTive Mind Architecture) cognitive agent architecture. A study to evaluate the extended architecture is presented which compares the benefit (i.e. reduced stress and increased rapport) of tailoring dialogue (i.e. empathic or neutral) to the specific user.

CCS CONCEPTS

• Computing methodology → Distributed artificial intelligence → Intelligent agents

KEYWORDS

Virtual Humans, Virtual Advisor, Agent's Expertise, User Model

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1 Introduction

Intelligent interaction requires the agent to consult a knowledge base to adapt to the user, based on real-time understanding of the context including the user. Many agent architectures, such as FAtiMA (Fearnot AffecTive Mind Architecture) [1], allow the agent to have their own emotions and autobiographical memories gained through past interaction(s) that allow them to respond in a humanlike and socially believable way. Our focus, however, is not on agent believability but on responding in ways that are appropriate to each user. For the agent to be able to adapt to different users, not just to different user inputs, we need to include understanding of the user and knowledge of how to respond to different types of users as part of the agent architecture. To achieve this, we have extended FAtiMA with an agent's expertise and a collection or repository of User Models, one for each user, and an Agent expertise module that represents what the agent has learnt by interacting with a range of users in the past. The User Model can include complex elements such as the user's verbal and non-verbal responses, personality, preferences, emotional state.

In this paper we present our proposed adaptive engine, an implementation and a study to evaluate the adaptive behavior using three variations of a scenario (empathic, neutral, tailored/adaptive) aimed at Reducing Study Stress. In the three scenarios, the dialogue differs according to the 10 empathic dialogue cues identified by Bickmore ([2]), where the neutral scenario uses no empathic cues; the empathic scenario uses all 10 cues and in the adaptive scenario the dialogue is adapted to include or omit one or more of the empathic cues according to the agent's knowledge of the individual user and the agent's expertise gained from dealing with users over time. The evaluation seeks to answer these research questions:

- Do users feel less stressed after interacting with a virtual human when it uses tailored, empathic or neutral dialogue?
- Do users establish more sense of rapport with a virtual human when it uses tailored, empathic or neutral dialogue?
- Does increased rapport lead to less study Stress?

2 Proposed Extended Architecture

We have extended FAtiMA to support capture of a collection of user models (one for each user) and agent expertise developed using machine learning of dialogue preferences elicited from previous users. Figure 1 shows the modules of FAtiMA toolkit which we used to develop the system. The three modules at the bottom are our extensions to support the agent's adaptive behaviour. The *user model* consists of 18 factors such as the user's demographics, personality, emotional state and study goals and attitude. The adaptive rules which form the agent's expertise are implemented in the *knowledge base* to provide the adaptive responses to the user based on those 18 parameters.

Integrated authoring tool is composed of different libraries designed to create the *role play characters* with emotional and social intelligence in the *world model.* The character integrates the functionality of the other libraries and has their own *decision making* process to take actions based on defined logical rules.

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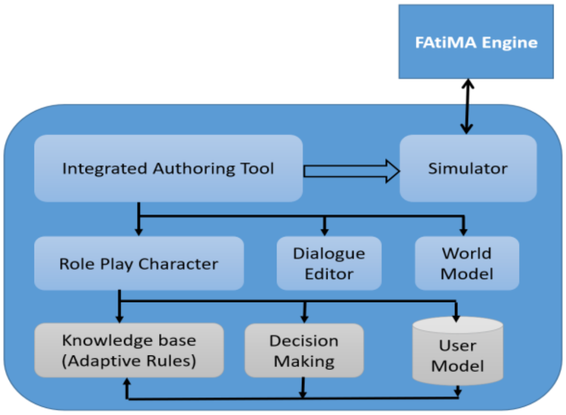

Figure 1: Extended FAtiMA

3 Methodology

The aim of this study is to compare the results of user interactions with 3 different types of virtual advisor: neutral (Group 1), empathic (Group 2) and adaptive (Group 3). We designed a scenario "Reducing Study Stress" where Sarah talks to the user and provides study tips using neutral, empathic or tailored dialogue. Sarah provides tips to reduce study stress derived from our campus wellbeing (e.g. work, study and life balance, exercise and healthy eating, exam and socialising tips). For empathic Sarah's dialogue, we modified neutral Sarah's dialogue to include Bickmore's 10 empathic (relational) cues [2]. The cues with related examples are shown in Table 1.

Data for Groups 1 and 2 were collected in 2018. From these previous studies, we used machine learning to develop user models based on features such as student gender, age, personality and ethnicity[3].

Table 1: Empathic cues used in the dialogue

Relational Cues (RC)	Example	
Social	"How are you going?"	RC1
Meta-Relational	"As a last thing together,..."	RC2
Empathic Feedback	"I am here for you."	RC3
Humor	"If I actually have a mouth, I think I'd eat healthy food."	RC4
Continuity behaviors	"I am waiting here for you."	RC5
Self-Disclosure	"I got the tip from my friend."	RC6
Mutual/sharing knowledge	"We think alike."	RC7
Solidarity & mirroring	"So you are a day person like me."	RC8
Politeness	"Please make yourself comfortable."	RCS9
Inclusive pronoun	"It's nice to have our own time."	RC10

In the following adaptive conversations, RC2, RC3 & RC6 are triggered for Agent 1. In the second one only RC10 is triggered and in the last one there is no RC triggered.

Adaptive Agent 1: Let's talk about socializing which is good for our mental health (RC2 & RC10) That's why I'm here (RC2 & RC3). It helps reduce the symptoms of depression and anxiety. I'm supported by my friends and family (RC6). Do you feel supported in your life?

Adaptive Agent 2: Let's talk about socializing which is good for our mental health (RC2 & RC10) It helps reduce the symptoms of depression and anxiety. Do you feel supported in your life?
Adaptive Agent 3: Socializing is good for your mental health. It helps reduce the symptoms of depression and anxiety. Do you feel supported in your life?

4 Evaluation & Conclusion

To evaluate the extended architecture, we reran our 2018 studies to collect data for Group 3. Across the three groups, we collected data from 154 participants' data aged between 18-57 (mean age=20.20, SD=4.05). Comparison of the results of the three groups, revealed no apparent benefits of tailoring and the results for the adaptive version of Sarah were similar to the fully empathic character. In answer to the research questions, while all groups significantly reduced their stress levels, there were no significant differences between the three groups and the highest rapport was reported with the neutral character. No relationship was found between level of rapport and change in stress levels.

The higher reported rapport by the neutral group is consistent with findings that participants who feel less emotional intensity about problems they are facing will build more rapport with a character that uses neutral language, whereas participants with high emotional feelings will build more rapport with an empathic character [4]. Perhaps if participants had been more highly stressed, the benefit of using empathic language (either fully or partially/tailored empathic) would have been evident.

Limitations include the short duration of the study (15 -20 minutes) and lack of non-verbal behaviours that may affect rapport building. The agents' non-verbal behaviours have been intended to create believability and more sense of rapport [5, 6]. All adaptive, empathic and neutral Sarah did not have any non-verbal behaviours except a smile.

We have analysed the rules triggered for each individual and their preferences for each cue. We found that accuracy was low (around 20%). While true positives (cue triggered correctly) were around 100%, false negatives (cue did not trigger correctly) were very high. This meant that most participants did not receive many empathic cues. It appears our rules were overfitted for Groups 1 and 2 used in training and testing and did not cover Group 3, This highlights the importance of getting the user model right. Improving accuracy would require larger datasets and improved machine learning algorithms. Since this is not viable, we are currently conducting a study that first captures preferences and then uses these to adapt the dialogue. In future we aim to improve the agent's expertise by receiving feedback from the user in real time to find out if they like or do not like certain language and update the user profile and expertise engine accordingly by using incremental knowledge acquisition methods, such as ripple-down rules [7].

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