

Authoring Negotiation Content and Programming Simulated Patients

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Abstract Competent negotiation with simulated patients can save expenses in medical education and improve outcomes for all parties involved. The use of simulated agents is beneficial for a study of human behaviour and cognition due to the possibility to create and manage a wide range of specific social situations. Building plausible cognitive models underlying the agent's intelligent behaviour from scratch is challenging and costly. Interaction designers and cognitive engineers require sufficient background knowledge to decide which domain information, resources and activities are important. Domain experts require sufficient understanding of human interaction and social cognition. All may lack advanced software development skills and an access to sufficient amount of authentic data. This paper presents a methodology to author cognitive agents and interactions with them. Authors can easily encode agents' knowledge and equip them with different sets of preferences and decision making strategies. This offers abundant opportunities for various social simulations: to create and control situations in which doctor's decision making and negotiation skills can be applied and assessed; employ and relate specific action patterns to various strategies and sociopragmatic variables of interactional power, social distance and degree of imposition; predict outcomes and explain why the choices made lead to what specific outcomes. The proposed approach also enables efficient collection of significant amount of annotated dialogue data and can be applied to model various medical and not medical negotiation scenarios.

1 Introduction

Currently, large amounts of data became available to advance the state of the art in many research fields. Researchers in social disciplines, however, struggle with an issue how to aggregate appropriate data to answer their research questions. The

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analysis of *authentic interactions* occurred in real social environments is expected to deliver the most satisfactory degree of understanding of natural human behaviour, but researchers do not always have an access to the authentic sites and real participants to be able to collect sufficient number of instances of various phenomena. Authentic data collection in some domains is not always possible for ethical reasons and is even not always desirable due to a loose experimental control. For some use cases, restrictions need to be imposed to be able to investigate a controlled set of communicative activities and related phenomena without having to deal with unrelated details. Therefore, researchers may opt for various forms of specifically arranged interaction such as *elicited interactions*, open and closed *role plays* and *simulations*. Such data collection methods can be effective for eliciting and examining authentic interactive behaviour [20, 3]. The role-playing method is frequently used in interactive data collection efforts [7], and underpins simulations of communicative situations featuring many real-life scenarios.

In medical encounters, focus of this study, the ability to communicate can be one of the greatest assets of health care providers, but also one of their greatest liabilities [6]. Regular practice in efficient, professional and socially competent dialogue with patients often takes place in a patient-simulated setting, where Simulated Patients (SPs) are involved to portray a particular set of symptoms or roles [21, 19]. Simulation with human actors or lay persons are at rather high cost, high fidelity, but may be poorly accessible. Alternatively, artificial agents are used for training various human skills and are successfully integrated into intelligent tutoring systems and intelligent narratives [33, 34, 12]. It has been showed that even very simple agents can exhibit complex emergent behavioural patterns [15]. Advanced agents are able to produce detailed simulation of human learning, prediction, adaptation and decision making [28, 39]. They are also perfectly capable to play the role of a believable human-like agent in various human-agent settings [27, 30].

Cognitive models underlying agent's intelligent behaviour represent rather complex research objects, and despite of their acknowledged potential are not very often integrated into interactive systems. The main impediment is rooted in their ease of the authoring. Creation of plausible cognitive models from scratch is challenging, time-consuming and requires considerable multidisciplinary expertise. For instance, doctor-patient communication is an activity that, in the first place, involves an understanding of behaviour motivated by certain therapy related goal(-s) and medical task(-s). Medical experts are the only ones who have sufficient background knowledge to decide which information, resources and activities are important for which settings. Medical experts can share this information with technical experts or can better directly program agents, however lack skills to do this. Since the success of interactive processes often depends not only on the medical competence of the doctor, but also on his/her linguistic, social and cultural competences [43, 25], the design requires expertise in social interaction and cognition.

In this paper, we propose a solution which produces variable, robust and plausible agents with little efforts. We designed an authoring tool that facilitates an easy (co-)creation of multiple simulated actors for various scenarios and contexts. Agents can be built using limited interactive data: they are supplied with initial au-

thored state-action templates encoding domain knowledge, the agent's preferences concerning issues under discussion and expected outcomes, and decision making strategies. The agent collects interactive experiences and learns from them. An example showcased in this paper demonstrates therapy planning negotiations training. However, the method can be applied in a wide range of other negotiation scenarios, e.g. negotiation of employment terms and conditions, or a mobile deal.

The paper is structured as follows. Section 2 discusses the related work performed in the authoring of dialogue systems and content. In Section 3, key characteristics of medical asymmetric negotiations are specified (negotiation content). Subsequently, in Section 4, we discuss the design aspects related to the human-agent interaction giving a global outline of a set of negotiation tasks with increasing scenario complexity and performed interactive actions, and decision making strategies (negotiation logic). Section 5 presents the authoring tool and interface to program baseline cognitive interaction agents which simulate patients exhibiting various negotiation behaviour in settings of various complexity. In Section 6, we present the simulated dialogue data and demonstrate how the tool can be used to author agents for new negotiation domains. Finally, we summarize our findings and outline directions for the future research and development.

2 Related Work: Authoring Dialogue Exchanges

In few past decades, many toolkits and authoring environments have been developed to build and experiment with dialogue systems – see Table 1 for an overview of the main paradigms in dialogue modelling and available authoring toolkits.

Many existing dialogue systems represent a set of possible dialogue state transitions for a given dialogue task. Dialogue states are often defined in terms of dialogue actions, e.g. question, reply, inform, and slot filling goals. Finite State Machines (FSMs) are applied to represent states and transitions, and are attractive in that they can be easily visualized, the flow is easy to understand and adjust. A toolkit to build, research and experiment with FSMs is CSLU tool [44]. Another FSM based formalism for defining complex, reactive, event-driven systems is based on statecharts [14], e.g. Deal system [8] and IrisTK system [41].

In frame-based dialogue systems, the dialogue manager extracts the necessary information from the user response and fill out the necessary slots while remembering not to ask questions for slots already filled out. Authoring a frame-based dialogue system typically involves authoring/generating or collecting (web-based) templates. CMU Communicator [36] is a toolkit to design frame-based and agenda based dialogue systems. VoiceXML [47] became the standard language used for developing interactive frame-based speech applications.

Con conversationally plausible dialogue models are based on rich representations of dialogue context for flexible dialogue management, e.g. information-state updates (ISU, [45, 10]. Several ISU development environments are available, such as TrindiKit [22] and Dipper [5].

Other approaches to dialogue modelling are built as full models of rational agency accounting for planning and plan recognition. RavenClaw [4] is a dialogue

architecture where designers can specify hierarchical domain tasks. ViewGen [2] is a system for modelling agents, their beliefs and their goals as part of a dialogue system, which uses a planner to simulate agents' plans.

Certain robustness has been achieved when applying statistical methods to dialogue modelling. OpenDial toolkit [26] relies on an information-state architecture where the dialogue state is represented as a Bayesian network and acts as a shared memory for all system modules. Alex Dialogue Systems Framework (ADSF, [18]) provides a modular platform for experimenting with statistical methods, e.g. based on Partially Observable Markov Decision Processes (POMDP, [49]), in the area of spoken dialogue systems. Similarly, PyDial toolkit [46] provides implementations of statistical approaches for all dialogue system modules.

Recently, deep neural networks have gained a lot of attention. PyOpenDial [16], a Python-based domain-independent, open-source toolkit for spoken dialogue systems design, re-implements OpenDial in Python and provides Python bindings to interface with popular deep learning frameworks such as Tensorflow or PyTorch, for neural dialogue state tracking and action planning.

Dialogue Modelling approach	Example task	Toolkit/Authoring environment
Finite state machines	Long-distance calling	CSLU [44]
Statecharts	Virtual receptionist	SCXML [9]; IrisTK [41]
Frame-based	Getting travel information	CMU Communicator [36]; VoiceXML [47]
Information State Update	Human-robot interaction	TRINDI [22]; Dipper [5]
Plan-based	Medical diagnosis	RavenClaw [4]
Agent-based	Collaborative planning and acting	ViewGen [2]
Probabilistic approaches	Car driving assistant	OpenDial [26]
Neural approaches	Various information-seeking tasks	Alex DSF [18]; PyDial [46]
Chat-oriented;	Negotiations	PyOpenDial [16]
interactive pattern-matching	Retail 'chat commerce'	AIML [48]
information-retrieval techniques	Personal assistant	Facebook: Botsify, Chatfuel, Chatsuite, etc.
	Question-answering	NPCeditor [24]

Table 1 Toolkits and authoring environments for various dialogue modelling approaches.

Although the above mentioned toolkits and architectures have been successfully used for building multiple dialogue systems, using them requires considerable knowledge in the dialogue theories, expertise in software development and dialogue systems design. There have been efforts in the area of question-answering, proposing authoring tools which can be used by non-experts for rapidly building a dialogue system, e.g. NPCeditor [24]. Designers were allowed to author questions and the corresponding answers. However, the approach suffers from the inability to maintain coherence over large turn sequences. There are a dozen authoring tools to help non-experts to design dialogue exchanges with chatbots. All have graphical interfaces, and most of them require no programming. They, however, offer a rather limited set of dialogue actions, are stateless and not able to provide guarantees about content coherence. They are problematic in managing task-oriented interactions.

To author coherent dialogue interactions, methods have been proposed in the area of tutoring dialogue, interactive storytelling and games. For example, TuTalk [17] is an authoring tool which allows educational researchers to rapidly prototype dialogue systems. In digital storytelling, methodologies have been proposed to (semi-) automatically generate coherent dialogue exchanges exploiting a small base of annotated

human-authored dialogue exchanges, e.g. combinatorial dialogue authoring [37]. In game design, where branching dialogue is the dominant approach to implement Non-Player Character (NPC) conversations [13], authoring interactions are largely based on scripting in-game behaviour, e.g. authoring (multi)branching dialogue as a tree or directed graph. The approach guarantees content coherence, but authoring becomes complex and costly; many states may not be anticipated at authoring time. The construction of conversational threads for NPCs using pattern matching and employing transition graph representations as the main interface for authoring has been proposed [42]. In [38], a fully procedural alternative to branching dialogue is presented. Rather than specifying not easy manageable directed graphs, an author composes individual lines of dialogue and annotates them with respect to the central selection policy: once a conversation turn is allocated to an NPC, an ISU-based dialogue manager requests for a line of a dialogue from the authored content that performs a targeted dialogue move or addresses a targeted topic.

Numerous studies show that participants of real-life dialogues happen to get involved in rather dynamic non-linear interactions where past and future events are out of chronological order, several parallel including disrupted or disjointed lines in the cause of events and no causality/dependency patterns between events are observed, strict directionality disappears revealing large jumps forward or backward in achieving dialogue (sub-)tasks. Good example of a non-linear interaction is negotiation, in particularly multi-issue bargaining. Negotiators may delay making complete agreements, previously reached agreements can be cancelled. Parties have the possibility to simultaneously bargain over several goods and attributes. They also may revise their past offers, accept or decline any standing offer, make counter-offers, etc. The agenda, i.e. order in which the issues are negotiated, might influence on the overall outcome. We offer a tool for authoring dialogue content and programming cognitive agents that are involved in non-linear interactions. Domain experts, e.g. medical professionals, author dialogue content and select the type of agent they would like to interact with.

3 Negotiation Content

3.1 *Asymmetries in interactions*

Many real-life interactive situations are characterised by a clear division of roles and an asymmetric distribution of knowledge and interactional power. e.g. at home between parents and children, in school between teachers and students, at work between supervisors and subordinates. Asymmetries are consistently observed in participant's individual attitudes towards behaviour and its outcomes. Large-scale asymmetries are detected in institutional settings where interactions are structured through institution-specific tasks and goals, which make certain institutional roles, topics, and actions available and impose constraints on others. Compared to mundane conversation, institutional discourse is often more predictable and therefore offers abundant opportunities for authoring of various social simulations.

In medical encounters, doctors exert control over the concerns expressed by their patients, and patients defer to the authority of the doctor by refraining from battling for control themselves. This may hinder patient participation in joint medical decision making as regards taking more informed decisions, but also leads to a decrease in patients' therapy adherence [50]. Therefore, the form of the interaction such as negotiation plays an important role, and doctors who show convincing persuasion and negotiation skills achieve better results for their patients [40]. In order to reach an efficient agreement, doctor should propose regimen that are feasible to follow, show an appropriate understanding of patient's desires, expectations and fears, and exercise the right influence on patient's beliefs taking patient's social, cognitive and economic constraints into account [11]. In [30], an integrative bargaining model for shared decision making in medical consultations is proposed in terms of a balancing of values as the patient's best interest and patient autonomy. The patient's best interest is modelled by taking the professional (doctor's) view on a patient's best interest. The patient's autonomy is respected based on an assessment of whether the patient is willing and able adhere to the treatment. Parties reason about the interests (preferences) of each other and negotiate the best possible *mutual agreement*.

3.2 Authoring negotiation profiles

Individual preferences involve participant's beliefs about perceived importance and desires concerning certain behaviour and its outcomes (attitudes) and participant's beliefs about his abilities to perform this behaviour (self-efficacy beliefs). Using the designed tool, preferences can be specified by an author (e.g. domain expert), human participant and/or generated automatically by the system dependent what type of partner the human participant wants to negotiate with. A graphical user interface was designed where an author can specify negotiation options, their preferences and select partner's preference profile, either identical, conflicting, matching or overlapping defined as (Figure 1): (1) *identical*: negotiators' preferences are completely identical; (2) *conflicting*: negotiators' preferences are completely the opposite to each other; (3) *matching*: preferences are of the same polarity, but different in strength; and (4) *overlapping*: some preferences are of the same polarity and strength.

Fig. 1 Authoring negotiation values and setting a preference profile.

3.3 Use case

The use case domain selected concerns diabetes. The patient-doctor negotiation scenario was designed based on the recommendations for patients who have diabetes of Type 2 of the International Diabetes Federation (IDF, 2017) addressing four issues:

(1) medication, (2) diet, (3) activity and (4) exercise recommendations. Each of these issues involves four important negotiation *options* with preferences assigned representing parties negotiation positions, i.e. preference profiles. Preferences are weighted in order of importance (strength) and defined as the participant's beliefs about *attitudes* towards certain behaviour and *abilities* to perform this behaviour. The goal of each partner is to find out preferences of each other and to search for the best possible mutual agreement.

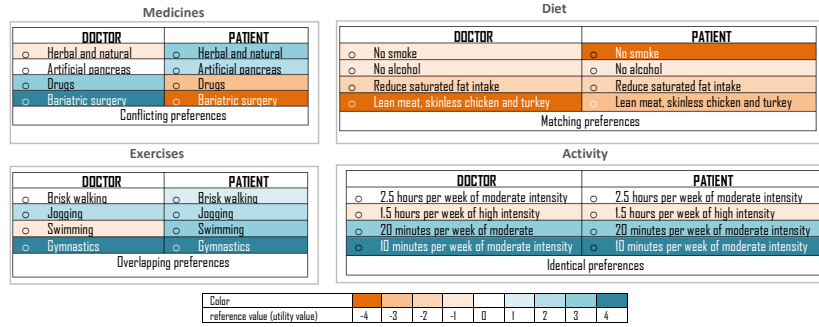


Fig. 2 Example of a participant's preference profiles.

Differences in preferences result in four scenarios of various complexity. The preferences strength is communicated to the human negotiator through colours, see Figure 2. The human participant - doctor - negotiates with various agents who simulates various types of patients, selecting one option per issue. Further, simulated patients have different preferences and are equipped with a basic set of negotiation and decision-making strategies, see next Section.

4 Negotiation Logic

In integrative and problem solving negotiations, the better all possible actions and parties experiences are explored and discussed, the better agreements are reached. Interacting with our simulated patients, doctor is prompted to elicit description of preferable actions, to encourage patient to share his experiences, to match those with his professional expertise, and to adjust his behaviour accordingly. Doing this, doctors train their Theory of Mind skills [32].

4.1 Negotiation actions

In negotiations, parties typically exchange offers expressing different levels of commitments, see [29]. Parties may propose trade-offs across issues in order for both sides to be satisfied with the outcome. Parties can give up more on one issue, but can receive in exchange for a larger share on another. They can postpone making an agreement or make a partial agreement on one issue, until the agreement on the

second one is secured. They may exit agreements during the interaction and revise their past offers, accept or decline any standing offer, make counter-offers.

Medicines	Diet
<input type="radio"/> Herbal and natural therapies	<input type="radio"/> No smoke
<input type="radio"/> Artificial pancreas	<input type="radio"/> No alcohol
<input type="radio"/> Drugs	<input type="radio"/> Reduce saturated fat intake
<input type="radio"/> Bariatric surgery	<input type="radio"/> Lean meat, skinless chicken and turkey

Exercises	Activity
<input type="radio"/> Brisk walking	<input type="radio"/> 2.5 hours per week of moderate intensity
<input type="radio"/> Jogging	<input type="radio"/> 1.5 hours per week of high intensity
<input type="radio"/> Swimming	<input type="radio"/> 20 minutes per week of moderate intensity
<input type="radio"/> Gymnastics	<input type="radio"/> 10 minutes per week of moderate intensity

Reaction to partner's offer

My action

Fig. 3 Example of a preference profile for a 'diabetes' scenario and an action selection menu.

The successful medical negotiation involves adequate disclosure by both parties indicating their values as well as other relevant matters. It is enabled that participants express the importance, desires and abilities concerning the certain behaviour and its outcomes, i.e. global attitudes and self-efficacy assessments in their preference profiles as discussed above, and 'modalising' their reactions and counter-offers with respect to dynamically changed preferences, abilities, necessity and acquiescence performing, see Figure 3.

In any medical interaction, many acts are produced not so much for the purpose to exchange information or influence each other's behaviour, but to establish a certain bond between the dialogue participants. Successful partnership building actions promote better cooperation. Patients are often anxious about their medical condition, express concerns or worry, and seek reassurance or special attention. In the future, we will incorporate Interpersonal Relations Management acts, but also affected state and personality related aspects added to the agent's profile, based on the Roter Interaction Analysis System (RIAS, [35]), widely used for analysis of medical interaction. Table 2 provides an overview of actions used by the implemented agents and the categories proposed for future extensions (marked *).

After the agent has made a decision to perform a certain dialogue act, a corresponding linguistic pattern is selected from a database. Patterns are extracted from a comparable negotiation corpus - Multi-Issue Bargaining Corpus (MIB, [31])¹. From the MIB corpus, lexicalised patterns tagged with communicative functions were ex-

¹ The MIB corpus is released in the Linguistic Data Consortium catalogue under the reference number LDC2017S11 <https://catalog.ldc.upenn.edu/LDC2017S11>

Table 2 Taxonomy of the agent's actions. Adapted from the ISO 24617-2 dialogue act taxonomy and the RIAS categories proposed for future extensions(*).

Interpersonal Relations Management (*)	Task	Semantic content			Global affect/personality (*)
		Modality	Negotiation Move	Issue(options)	
compliment	(open-ended) set question	preference	(final) offer	Figure 2 related to:	uncertainty
empathy	(forced) choice question	ability	exchange	therapeutic regimen	anxiety
compassion	propositional questions	necessity	concession	lifestyle recommendations	dominance
concern/worry	check questions	acquiescence	deal		attentiveness
reassure/encourage	inform/answer		withdraw		engagement
legitimize	(dis-)agreement				friendliness
self-disclosure	suggest				anger
criticism	request/instruct				openness
	offer				

tracted and stored as templates with the variable fields for modalised semantic content as slots values. In total, 679 communicative functions patterns were extracted and 64 slot values specified. Although an initial set of patterns was rather small, the combination of sentence patterns with the ability to change individual values, allows the generation of utterances, broader than the target corpus (5,781 MIB utterances vs 43,453 automatically generated utterances).

4.2 Negotiation strategies

Negotiators apply different strategies to reach acceptable outcomes. We experimented with two basic strategies: cooperative and non-cooperative. We consider negotiators as *cooperative* if they share information about their preferences with their opponents and prefer options that have the highest shared utility. If not enough information is available to make this determination, a cooperative negotiator will elicit this information from his opponent. He will not hold on to a fixed set of preferences regardless the interests of others, instead, he will attempt to find issues where a compromise is possible. *Competitive* negotiators prefer to assert their own preferred positions rather than exploring the space of possible agreements. They ignore partner's interests and information requests, instead insist on their own ideal positions making the opponent concede. The competitive negotiator will threaten to break the negotiation if he cannot gain a significant number of points from it.

5 Simulated patients

5.1 Agent's knowledge and memory

The agents are designed using the ACT-R cognitive architecture². Agent's knowledge is encoded in instances (Table 3) stored in an ACT-R declarative memory which is represented as traces of experiences.

The ACT-R mechanisms account for the effects of recency - more recent memory traces are more likely to be retrieved, and frequency - if a memory trace has

² A Java Simulation and Development Environment for the ACT-R was used <http://cog.cs.drexel.edu/act-r/about.php>

Table 3 Instance definition. Adopted from [30].

Slot	Value	Explanation
Strategy	e.g. cooperative	the strategy associated with the instance
Agent-move-value-agent	$[-4, 4]$	the number of points the agent's gets from his own move
Partner-move-value-agent	$[-4, 4]$	the number of points the partner's move brings to the agent
Partner-move-greater	$[true false]$	true if the partner's move brings at least as much as the agent's one, otherwise - false
Next-move-value-agent	$[-4, 4]$	the number of points that the next best move can bring to the agent
Utility	$[0, 17]$	how valuable are the partner's suggestions made by now
Shared utility	$[0, 1]$	how valuable are the partner's suggestions for both negotiators
Agent-move	(M_1, \dots, M_n)	the move that the agent should make in this context
Partner-move	(M_1, \dots, M_n)	the move that the agent believes the partner should make in this context
Compensation	$[1, 4]$	if the agent's move is of the concession or exchange type, what is the minimum utility that the agent should look for choosing an alternative option

been created or retrieved more often in the past it has a higher likelihood of being retrieved. The agent is also able to retrieve past instances even when a particular situation has not been encountered before, 'blending' is proposed as a generalization of the retrieval mechanism, allowing to retrieve values from multiple instances. An instance does not have to be a perfect match to a retrieval request to be activated. ACT-R can reduce its activation to compute partial matching, see [23, 1].

To simulate repetitive negotiations assessing doctor's behaviour over time³, cross-rounds agent's performance is modelled taking multi-dialogue negotiation history into account. The agent is however able to forget about his experiences, the memory decay rate can be set using the interface (0.5 set as default).

5.2 Agent's decision making strategies

Authors can choose from three decision-making strategies (Figure 4): *matching coordination*, *compensatory*, and *non-compensatory*. All three strategies are proven plausible to simulate situations where different alternatives will be selected by the agent in a certain context in order to achieve acceptable outcomes [30].

Fig. 4 Decision making strategies selection.

The *matching coordination* agent mirrors decision making behaviour of their opponents: the agent is competitive if it experiences the partner as competitive; it switches to a cooperative mode, if it thinks the partner is cooperative. The *compensatory* agent compensates for his losses: the agent starts with his highest offers,

³ In real life, doctors and patient often do not meet only once, but share certain interaction history with each other.

it continues in a competitive mode until it collects enough points (threshold is adjustable and default set at 0.5 standing for the half of the maximum possible scores) switching after to a cooperative mode; acting cooperatively, if the agent starts losing too much, so that its utility score becomes lower than pre-defined threshold, it will switch to the competitive mode. To simulate *non-compensatory* decision-making, the agent insists on the options beneficial for it: the agent sticks to his preferred options with the hope that partner concedes (position bargaining); if they are not accepted by the partner, the agent breaks the negotiation proposing the final offer playing ‘take-or-leave-it’ strategy. The time (number of moves) until the agent breaks the negotiation is configurable via GUI.

6 Data collection and domain shift

Using the tool we constructed the **LICA** dialogue corpus⁴. Human-human and human-agent dialogues were collected. In human-human setting, one participant was randomly assigned the role of a doctor, the other participant the role of a patient. The tool is used to automatically generate preference profiles for scenarios of various complexity. The goal of each partner is to find out the preference of each other and to search for the best possible mutual agreement. In human-agent negotiations, each human trainee in the doctor’s role negotiated with the simulated patient (agent) who has different attitudes (preferences) and exhibit either cooperative and non-cooperative behaviour and uses different decision-making strategies. In total, we collected 25 human-human negotiations comprising about 575 speaking turns, and 75 human-agent negotiations were collected comprising 2049 turns. Table 4 summarizes the core corpora properties.

Table 4 Comparison of human-human and human-agent negotiation performance.

Evaluation criteria	Human vs human	Human vs agent
Number of dialogues	25	75
Collection time (in min/per dialogue)	9:40	3:50
Annotation time (in min/per min of dialogue)	25	0.0
Mean dialogue duration (in #turns)	23.0	21.3
Number of offers/per round	16.0	14.3
Dialogue Acts (# unique acts)	29	10
Vocabulary size (# unique tokens)	1864	517
Agreements (in %)	78.0	86.3
Pareto efficient agreement (in %)	82.4	90.3
Negative deals (in %)	21.0	34.3
Cooperativeness rate (in %)	39.0	61.9

Automatically generated dialogues are not rated as highly as human-human ones: human-agent dialogues do not have as rich vocabulary as human-human ones and the agents still cannot deliver human-like interactive behaviour delivering a rather scarce repertoire of dialogue acts; human use different tactic which agent do not yet possess, namely they tend to justify most of their offers explaining why it is important to accept a certain option. Agents, however, show task-related negotiation and decision making behaviour comparable to humans in terms of the number of agreements reached and their Pareto efficiency, the number of the accepted negative

⁴ LICA stands for Learning Interactive Cognitive Agents.

deals and the cooperativeness rate. Provided with a set of agent’s profile parameters and database of behavioural (linguistic) patterns, however relatively small, the tool instantly generates many full exchanges that are semantically annotated and evaluated. In Appendix, there are human-human and human-agent dialogue examples provided.

We envision immediate practical use of our method for a study of social cognition and for collection and exploration of behavioural and functional data. For example, dependencies between pragmalinguistic forms, strategies and socio-pragmatic variability and their role for the efficient decision making process can be assessed in a systematic controlled way. Our primary observations showed that human participants facing different types of agents used different negotiation tactics which resulted in different outcomes: delayed making complete agreements; frequently revised their past offers; vary the order in which the issues are negotiated; adjust the alacrity to reveal or hide their preferences. It has been also noticed that not only asymmetries in preferences and participant’s status may influence the decision making process, but participants of different gender and personality, and in different emotional state may adopt divergent strategies under identical conditions. We see that our simple agents equipped with various decision making strategies offer plenty of opportunities to investigate relationships between participant’s intrinsic characteristics and various dependent variables.

Medicines	Diet
<input type="radio"/> Nicotine patches	<input type="radio"/> Chew gum or hard candy
<input type="radio"/> Nicotine gum and/or lozenges	<input type="radio"/> Drink lots of water
<input type="radio"/> Non-nicotine medication, e.g. varenicline	<input type="radio"/> Skip cigarette after meal or coffee
<input type="radio"/> Hypnosis or acupuncture	<input type="radio"/> Reduce alcohol consumption

Exercises	Activity
<input type="radio"/> Get out house for a walk or run	<input type="radio"/> Distract yourself, e.g. watch TV, take a shower
<input type="radio"/> Do breathing or relaxation exercises	<input type="radio"/> Go to movie or read a book
<input type="radio"/> Do yoga stretches or meditate	<input type="radio"/> Keep hands busy, e.g. brush teeth
<input type="radio"/> Join a fitness group	<input type="radio"/> Meet non-smoking friends

Fig. 5 Example of a set participant’s preference profile and action selection menu for ‘ceasing smoking’ scenario.

To test the transferability across domains, the tool was used to encode domain knowledge for ‘stop smoking’ negotiation scenario. For this, the recommendations presented on WebMD⁵ were extracted addressing the same four issues: (1) medication, (2) diet, (3) activity and (4) exercise recommendations, but involving different four negotiation *options* each, Figure 5. The doctor’s task was then to help a patient to develop positive attitudes towards ceasing smoking, and strengthen his self-efficacy beliefs that he is capable to maintain this behaviour. Parties negotiate about what is desirable, possible and mandatory.

⁵ <https://www.webmd.com/>

7 Conclusions and future work

In this study, we presented an approach to author simple cognitive agents that produce plausible simulations of human decision making and negotiation performance acting as believable agents in human-agent interactive learning setting. Agents are not restricted to a specific domain, but can be authored to be situated in wide range of negotiation scenarios. An author who is either a domain expert, a human negotiator/trainee, a cognitive model or dialogue system designer, can easily create various agents proving them with minimal domain knowledge, setting preferences, specifying the scenario complexity and choosing appropriate decision making strategy.

The designed baseline agents as well the authoring functionality will be extended for a comprehensive analysis and well-founded computational models of adaptive decision making behaviour in asymmetric patient-doctor interactions while accounting for the interwoven relationship between multimodal language-specific schemes and emotional, social and cultural determinants. For this, participant-specific models capturing characteristics of prototypical and personalised settings will be built. The patients' age, gender, cultural background, personality and their level of knowledge/expertise aspects will be incorporated into the agents' knowledge. This will allow for the creation of patient agents with different personality profiles, increasing the realism and complexity of the interaction. Further, baseline and participant-specific models will be extended to enable the agents to exhibit plausible context-aware human behaviour. For example, doctors are often situated in so called 'unfavourable environments' characterised by multi-tasking, time pressure, distractions, physical and psychological exhaustion. By simulating such environments, we will be able to create unique social interactive and training situations.

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Appendix

Table 5 Human-human and human-agent dialogue example. (*D* stands for doctor; *HP* - for human patient; and *SP* - for simulated patient)

ID	Human vs Human	ID	Human vs Agent
D1	Hallo		
D2	My name is John Smith and I am your doctor		
D3	Today I would like to discuss		
D4	our treatment plan for your diabetes of Type 2		
D4	So, are you aware of the seriousness of this disease?		
HP1	No		
HP2	Tell me more		
D5	tell more ...		
D6	This is very serious and if we do not act now it increases the risk of heart disease, stroke, high blood pressure and narrowing of blood vessels		
HP3	oh, no		
D7	So, I'd like to discuss a few things with you	SP1	What medicines will work the best for me?
D8	A treatment concerns medicine, diet, exercise and activities	SP2	What can you offer?
D9	For instance, I suggest we start with medicines		
D10	The most efficient therapy from my experience are drugs	D1	We could try drugs
D11	Metformin shows 99% recovery rate		
HP4	well ...		
HP5	This sounds like a great idea. I would go for it	SP3	I agree, lets do this
D12	Moving further, I would like to talk about is your diet		
D13	We need to make several adjustments		
D14	I would propose to reduce saturated fat intake	D2	For diet, you need to reduce saturated fat intake
D15	That's the most effective strategy fighting diabetes		
HP6	It doesn't sound like a good idea	SP4	I don't like to reduce saturated fat intake
HP7	I really like all fatty stuff and it will be hard to resist		
D16	OK		
D17	But you need to make sacrifices, otherwise we will be not successful		
	You need to do something with your diet		
HP8	OK		
HP9	What do you think if I give up smoking or alcohol, would this be enough?	SP5	I think no smoke or no alcohol is more efficient
D18	Well ...		
D19	This is a good start		
D20	Maybe you can give up smoking and spend time on physical activities which can be of varied intensity	D3	OK, let's do no smoke and one and half hour per week of high intensity
D21	I am afraid that in your case there is no other option than one and half hour per week of high intensity		
HP10	well ...		
HP11	I think it's a doable thing	SP6	That would be nice
	If I split this in a couple of days, it seems doable		
D22	Exercising can help manage your blood sugar and weight		
D23	My personal suggestion would be brisk walking	D4	How about brisk walking?
D24	I recommend brisk walking often to my patients, it's ...		
HP12	Actually I do not have any objection against it	SP7	I think I can live with that
HP13	Swimming would be a problem, but brisk walking I can do		
D25	OK ...	D5	So, to summarize, we agreed on drugs, to reduce fat intake, 20 minutes per day of moderate intensity and brisk walking
D26	In 5 month we ...		
HP14	Tell me Doctor, am I going survive?	SP8	No, we agreed on drugs, to reduce fat intake, one and half hour per week of high intensity and brisk walking
D27	and still enjoy life with my wife and kids <i>laugh</i>	D6	Right, that's a deal
	Of course <i>laugh</i> just follow my recommendations		