COPALZ: A Computational Model of Pathological Appraisal Biases for an Interactive Virtual Alzheimer's patient

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ABSTRACT

Confronted with patients suffering from Alzheimer's disease, professional caregivers must be aware of their own non-verbal communication as well as the patient's non-verbal communication in order to respond to the behavioural disorders which are frequent in this disease (e.g. apathy, aggression, anxiety, etc...). Virtual patients, which are interactive animated characters that simulate the behaviors of a patient, are increasingly used to train caregivers to interact with patients. The virtual patient needs to dynamically generate multimodal expressions of pathological behaviors consistent with the pedagogical goals. In this article, we introduce COPALZ (COmputational model of Pathological appraisal biases for a virtual ALZheimer's patient), a new model that supports the generation of pathological behaviors identified as pedagogically relevant for caregivers interacting with Alzheimer's patients. This model is based on the theory of appraisal biases and on interaction data that we collected using a partially simulated version of our virtual patient with 31 caregivers. We describe initial evaluations and explain how we intend to evaluate the fully automatic virtual patient during training sessions.

KEYWORDS

Multimodal User Interfaces; Virtual Patient; Non-verbal behavior; Training simulation; Emotions

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1 INTRODUCTION

Apathy, irritability, aggression, anxiety, and inappropriate emotional behaviors are common in Alzheimer's patients. They are something that professional caregivers (nurses, physician, ...) need to know how to manage [36], especially since approximately one out of two patients exhibits challenging behaviors [18]. A study on geriatric caregivers highlights the protective role of training about the disease against burnout among caregivers [56]. It is also recommended to help caregivers become aware of the importance of non-verbal communication and to develop their skills to better communicate, reassure and manage difficult patients [32, 54]. In the field of healthcare staff training, it is recommended not to train on a real patient the first time [23]. Medical personnel traditionally train with human actors who play the role of so-called "standardized" patients [53]. However, this approach is costly and limits opportunities to learn how to interact with patients. One solution consists in using "virtual patients" [6, 29, 45]. These are interactive virtual characters allowing caregivers or medical students to practice communicating with patients in interactive pedagogical situations. This solution, less expensive than standardized human actors, allows to target pedagogically relevant situations while confronting users with interactive verbal and non-verbal behaviors that are supposed to be close to those displayed by patients, while remaining in a secured and controlled environment.

In this article, we explain how we designed a virtual patient and its emotional model aimed to train caregivers to interact with Alzheimer's patients. The autonomous interactive virtual patient must be able to display behaviors similar to those of an Alzheimer's patient, in a pedagogical situation and take into account the verbal and non-verbal behaviors displayed by the user (the caregiver).

The remainder of the article is organized as follows. Section 2 summarizes relevant research on the topic of virtual patients and computational models of emotions. Section 3 describes the interactive system that we designed, which allows care-givers to practice their interacting skills in a controlled and safe environment and interact with our virtual patient. Section 4 describes our emotional model which allows the virtual patient to simulate pathological symptoms. Finally, in Section 5, we conclude by describing the future set-up in the hospital and our objectives towards the evaluation of the fully automated system.

2 RELATED WORK

Virtual Patients. A virtual patient is a specific type of virtual agent. A virtual agent is an interactive software designed to perform a task and which can be visually represented by an animated character (humanoid or not) [14]. A virtual agent is conversational when it has communication capabilities, which allow it to simulate human communicative skills (e.g. turn-taking) and interactions by generating verbal and/or non-verbal behaviors, such as facial expressions, gestures, postures and can be endowed with features such as personality or mood [10]. Some virtual agents are also able to interpret their environment and the behaviors of a human user in order to generate an interactive response adapted to the situation. Depending on the application and its requirements, virtual agents can be more or less expressive and more or less interactive. They can be found in many application domains and in particular in training and healthcare [9, 25, 44]. In the context of medical education, a virtual patient refers to any software that enables case-based training [30]. It can be represented graphically as a virtual agent to portray a patient. Our work focuses on virtual agents used to simulate a patient's behavior. The advantage of such virtual patients is that they address the availability and cost issues of standardized patients (human actors), as they can be accessed in multiple locations at once and as many times as desired, while reproducing in a controlled manner and in a specific context, clinical situations identified as pedagogically relevant. For example, in the Sick Call Project, a virtual patient simulates a military patient with Post Traumatic Stress Disorder [44]. Other researchers have designed a virtual patient simulating depressive disorders to train medical personnel in the diagnosis of depression [16]. Another virtual patient trains physicians to deliver bad news to patients [39]. This virtual patient detects social cues expressed by the user-physician, interprets them, and adapts its behavior in order to train physicians to use their verbal and non-verbal behavior appropriately during these interactions.

Regarding virtual Alzheimer's patients, to our knowledge, there is currently only one system allowing a virtual agent to simulate non-verbal behaviors. However, the pathological behaviors of this virtual patient are not automatically generated and are controlled in part by a human experimenter who has a graphical user interface proposing a set of possible sentences, each accompanied by associated non-verbal behaviors [46]. Currently, virtual patients rarely include a model of the pathologies they are supposed to simulate and which impact communication with these patients. Instead, virtual patients are mostly based on manual writing of scripts that are not scalable and that limit training situations [1, 4]. It therefore seems necessary to propose an appropriate level of representation and interaction allowing to make the link between, on the one hand, the trainee's behaviors and her progression in the pedagogical scenario, and on the other hand, the possible pathological reactions of the virtual patient.

Computational models of emotions. The relationships between emotions and facial expressions are complex, unsystematic, and modulate how well a person is able to infer or not infer another person's emotions from their facial expressions [5]. Emotion theories have been used as a basis for several computational models. Computational models were inspired by three main approaches to emotions [34]: the categorical approach, in which each independent emotion is considered to be the result of a unique circuit; the dimensional approach, in which emotions are distributed in a continuous multidimensional space; and the cognitive approach, in which an emotion is defined as the result of a process of evaluation of the situation by an individual.

For the categorical approach, a limited number of emotions are defined, with for example facial expressions that are often prototypical, possibly mixed. For the dimensional approach, emotions are often represented in a finite two- or three-dimensional space. Regarding cognitive approaches, their popularity in computational models is explained by the evaluation process, which makes it relevant for interactive systems. In several models resulting from these cognitive approaches, an event is evaluated through a set of criteria, called "appraisal variables", which vary according to the theories [2, 19, 31, 42, 49]. For example, in the Component Process Model (CPM) [49], there are four categories of evaluation criteria applied successively: relevance (how relevant is the event to the individual, new and/or pleasurable?), involvement and goal conduciveness (how will the event affect short- and long-term goals?), coping potential (to what extent is it possible to cope with the consequences of the event?) and agreement with standards (what is the impact on the individual's social and personal values and norms?). Each group includes several sub-criteria, each of which may result in physiological and behavioral changes depending on the outcome of the assessment, and require resources of attention, memory, reasoning, and self-awareness. Cognitive models are described as an assemblage of interacting components, each describing an aspect of the emotional process.

In [34], the authors propose a generalized architecture of computational models based on these cognitive theories. The first component of this architecture, the "Agent-Environment Relationship" component, describes the relationship between the agent and its environment. The Belief Desire Intention (BDI) model [43] is often used in this component to represent how the agent perceives its environment and its motivations with three variables: Beliefs (knowledge of the environment and its state), Desires (often identified with the agent's goals) and Intentions (actions and desires that the agent wishes to achieve). It is used in the emotional models EMA [35] and WASABI [7].

This representation of the agent's environment is then transformed into a set of variables during the transition via the "Appraisal Derivation Model" into the second component "Appraisal Variables". In the case of models that do not integrate the agent-environment relationship component, such as the ALMA model

[21], each event or situation is explicitly described in terms of appraisal variables (e.g., desirability). The set of appraisal variables depends on the underlying theoretical basis. The one proposed in the OCC model [42] is commonly used in the design of computer models, such as Flame [17] and InFra [11]. The appraisal variables proposed by Lazarus (1968) are also included in the model of [55] and in the EMA model. The appraisal variables proposed by Klaus Scherer [49] are used in the WASABI model.

The third component of this architecture is a representation of the agent's emotional state. It is obtained by transforming the appraisal variables during the transition through the "Affect Derivation Model" and the "Affect Intensity Model", specifying how the appraisal variables will induce emotional reactions and their intensity. The underlying theoretical basis is decisive to perform this operation, because the emotional state can be described as an emotion label, as in the AR model, or a position in a multidimensional space as in the WASABI model with the PAD (Pleasure Arousal Dominance) space [48], or even as a combination of both in the ALMA model. This emotional state will finally induce behaviors and/or cognitive changes, through the Affect Consequent Model transition, modifying the agent's environment model and thus closing the loop. These modifications are the consequence of the evaluation and lead to external changes such as facial expressions, physical actions or internal changes such as a change of evaluation strategy.

In order to design a pathological computer model of emotions and their expressions by a virtual patient, we need to select an appropriate theoretical framework, allowing us to take into account the emotional disorders and dysfunctions that have been identified as pedagogically relevant for caregivers.

Appraisal Bias Model (ABM). The ABM model [28, 50] considers individual characteristics as appraisal biases. Individual differences in memory and cognitive abilities are thus explicitly taken into account in the evaluation of the CPM criteria. Disorders of these abilities will imply an inappropriate evaluation of the situation. The ABM model allows to consider inter-individual differences in the cognitive evaluation process, interpreting them as a filter by perception and evaluation processes, increasing the probability and frequency of being in specific emotional states. When the frequency and intensity of these emotional episodes are abnormally high, they are considered to be due to emotional pathologies (e.g. apathy and paranoia). [28] propose links between each evaluation criterion of the CPM model and clinical characteristics of emotional disorders [28]. A symptom is a sign felt by a patient such as pain. A syndrome is the set of symptoms that can evoke the presence of a disease. These authors link for example apathy to an inability to judge the importance of events and to a low motivation, which would be caused by a poor evaluation of the Goal relevance sub-criterion of the Relevance detection dimension.

Alzheimer's patients. We identified several behavioral disorders of Alzheimer's patients that are pedagogically relevant. According to DSM-5 (Diagnostic and Statistical Manual of Mental Disorders 5)[3], the emotional disorders that Alzheimer's patients may exhibit are: depression, apathy, irritability, psychotic disorders, agitation, aggression, and ambulation. Behavioral impairments, such as apathy and emotions in general might not be a major factor in the definition provided in the DSM-5 but it can be considered a major complication for caregivers and informal caregivers as the neurocognitive disorder progresses [37]. It should also be noted that as the pathology evolves, cognitive capabilities as a whole but also the cognitive component of emotions deteriorate. This component is negatively impacted and leads to dysfunctional emotional non-verbal behavior as a whole [22, 47]. In our study, caregivers reported that handling their own non-verbal behaviors while facing patients suffering from Alzheimer's disease is a great challenge that needs to be tackled. Accordingly, we chose to direct our research project towards the design of a pathological model of emotions (rather than other cognitive processes) to support the caregivers training needs. The ABM makes it possible to represent the disorders identified in the DSM-5. In our work, we focus on the following appraisal criteria: suddenness, familiarity, intrinsic pleasure, goal conduciveness, and coping potential. We selected these criteria because the ABM considers the following emotional disorders which are relevant for Alzheimer's patients: Irritability (suddenness and familiarity criterion); Anhedonia (intrinsic pleasantness criteria); Apathy (goal conduciveness criterion); Chronic dissatisfaction/frustration (goal conduciveness criterion) ; Depression (coping potential criterion); mania (aggressiveness) and panic (coping potential criterion). In addition, Alzheimer's patients often display mood changes [20].

3 ARCHITECTURE OF THE VIRTUAL ALZHEIMER'S PATIENT

In this section, we present our system which enables a user-caregiver to interact with a virtual patient simulating Alzheimer's disease. The virtual patient is animated with Unity and runs on a computer. It is displayed on a 43-inch (109.22 cm) screen oriented in portrait mode. The user clicks on the menus displayed on a graphical user interface with a remote control. Using a remote allows the user to remain at a proper distance from the virtual character displayed on the large screen, thus partly simulating interactions with a real human patient. The system features three modules :

User module (caregiver): It allows the user to interact with the virtual environment which includes an animated character, as well as a camera to record and analyze the non-verbal behavior displayed by the user. At specific moments of the interaction, the user is asked to select an action from a list displayed on a graphical interface on the screen (Figure 1) (for example: enter the room, give the medication), and/or a sentence (called "dialogue" on the interface) from a list of choices to guide the course of the interactions. He then stops using the remote and performs his choice by interacting naturally through the use of its verbal and non-verbal behaviors (facial expressions, posture, prosody, gestures) towards the virtual patient.

Virtual Patient module: this module receives as input the user data collected by the caregiver module (choice of actions and sentences selected by the user and videos of the user's verbal and non-verbal behaviors), which will be analyzed by the emotional model. As a result, the emotional model produces a set of behaviors to simulate the behavior of an Alzheimer's patient.

Animation Module: It receives the description of the virtual patient's behavior, then transforms it into animation parameters in order to execute the behavior on the 3D model of the virtual character.

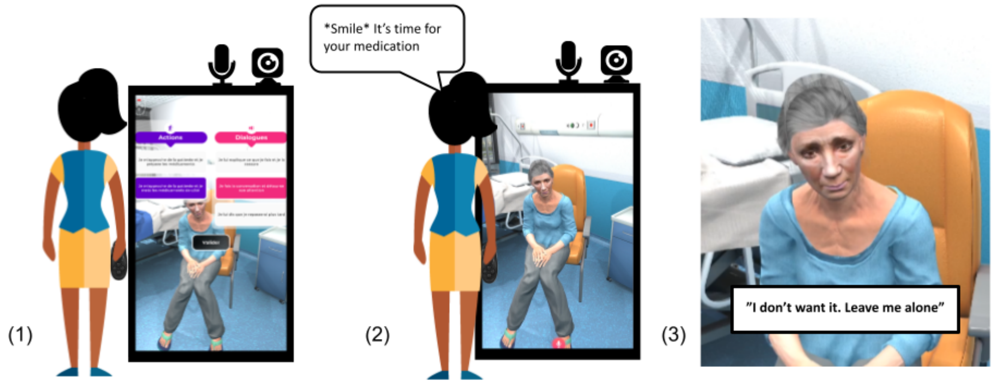

Figure 1: Interaction with the virtual Alzheimer's patient (1) User selection in the dialog and action menu on the graphical user interface (2) User performing the selected action selected (verbal and non-verbal behaviors) (3) The virtual patient's reaction (verbal, facial expressions and gaze)

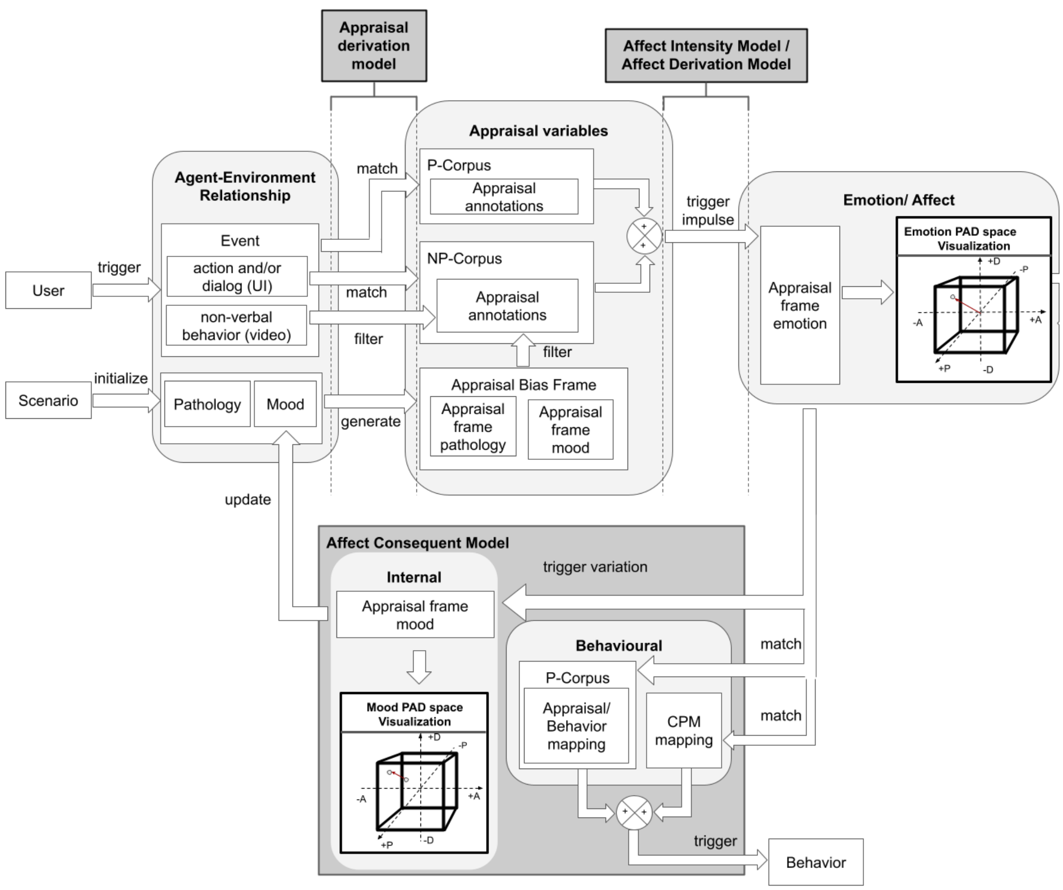

Figure 2: COPALZ model based on different sources of knowledge: the Appraisal Bias Frame module represents knowledge from the literature ; the NP-Corpus (Non Pathological Corpus) module represents data collected from non-pathological participants ; the P-Corpus module represents data collected with our simulated virtual patient.

4 COPALZ: A MODEL OF PATHOLOGICAL EMOTIONS AND EXPRESSIVITY

We introduce COPALZ, a new model for a virtual Alzheimer's patient based on two elements: 1) the ABM [50], derived from the CPM model [49], and 2) a corpus of interaction data collected during experiments between caregivers and a simulated version of our virtual patient [8]. Drawing on the theoretical model of appraisal biases, we represent in our model the current mood of the virtual patient and some of her pathological evaluations during her emotional process. These components of the model influence the way the agent evaluates some criteria of the CPM model. In our model, the mood of the virtual patient is represented by a configuration of the state of appraisal variables. This configuration will evolve during the interaction according to the successive evaluations made by the virtual patient.For simulating pathological emotional appraisals, we draw on the mapping between appraisal patterns and emotional disorders proposed in the ABM model [50]. In order for our virtual patient to express an emotion, it proceeds to an evaluation of the situation. It will, for each evaluated criterion, 1) trigger facial expressions and verbal behaviors, and 2) update the current mood of the patient.

We will now detail the architecture of the COPALZ model (Figure 2), inspired by the framework proposed by [34]. The module "Affect Consequent Model" will not be presented here and is beyond the scope of this article.

Appraisal frame

We consider an appraisal frame as a vector af containing n values $val_{dimension}$, with n the number of selected dimensions of the underlying considered appraisal theory. Our model COPALZ is based on the CPM appraisal variables set [49]. We thus consider the following subset of dimensions that are relevant for training caregivers to interact with a virtual Alzheimer's patient: suddenness, familiarity, intrinsic pleasantness, goal conduciveness, and coping potential. In our case, an appraisal frame will have the following structure:

$$af = [val_{suddenness}, val_{familiarity}, val_{pleasantness}, val_{goalconduciveness}, val_{copingpotential}] \quad (1)$$

Each appraisal value can take one of the following values: Low (-1), Neutral (0) or High (+1). We consider an appraisal probability frame as a vector of the same form as an appraisal frame, where the values $val_{dimension}$ are represented using probability density functions $density_{dimension}$ in the range $[-1;1]$ and for each dimension, we have the following expression:

$$\int_{-1}^{1} densite_{dimension}(x)dx = 1 \quad (2)$$

The function $density_{dimension}(x)$ allows us to represent the probability that $val_{dimension} = x$. We can thus compute a value x for each dimension and assign to $val_{dimension}$ one of the values of the set {-1, 0, 1} :

$$val_{dimension}(x) = \begin{cases} -1 & \text{if } x \in [-1;-0.3] \\ 0 & \text{if } x \in]-0.3;0.3[\\ 1 & \text{if } x \in [0.3;1] \end{cases} \quad (3)$$

Agent-Environment Relationship

The agent's environment is represented in our system by four elements (Figure 2):

Scenario: The scenario defined by the pedagogy and medical researchers contains elements concerning the agent. These elements can be related to the history of the virtual patient, such as its name and age, or recent events experienced. They are used to define an initial mood and pathology.

Mood: The initial mood of the virtual patient is defined according to the interaction scenario and described through an appraisal probability frame apf_{mood}. We explain later how it is represented and how it evolves during the interaction.

Pathology: It is described through an appraisal probability frame $apf_{pathology}$. We use this frame to specify, using the ABM correspondences, the disorders that we want to simulate. It is possible to decide this in advance for a specific scenario phase or the entire scenario. For example, we can simulate apathy in the first step of the scenario, then mania in the remaining steps. It is also possible to represent more than one disorder at a time. Alzheimer's patients can indeed display in a single interaction multiple symptoms. These symptoms can appear simultaneously, for example with apathy and depression symptoms. It is also possible that in the same interaction, a patient will first display symptoms of apathy and later in the interaction display symptoms of mania and no more symptoms of apathy. Our model enables us to simulate several symptoms happening at the same time or in sequence.

Event: Each event is encoded in a vector event:

$$event = [phase, user\_choice, user\_behavior_1, user\_behavior_2, ..., user\_behavior_n], with :$$

- $phase$: the phase of the scenario during which the event occurs
- $user\_choice$: the user's choice on the menu from the graphical user interface. At the beginning of each phase of the scenario, the user chooses on the GUI a combination of action and dialogue that will represent her communication strategy at this moment of the scenario [41].
- $user\_behavior_i$: with $i \in 1, ..., n$ the n non-verbal behaviors expressed by the user and detected by the system (for example a smile).

An event corresponds to an action of the user, i.e. the combination of the choice on his graphical interface (for example: "I reassure the patient") and her associated verbal and non-verbal performance. The resulting vector will contain all the user's behavioral activations during this time window.

Appraisal-derivation model / Appraisal variables

As mentioned above, in the initial state of the scenario, two probability frames have already been defined: apf_{mood} which represents the patient's mood (defined according to the scenario), and $apf_{pathology}$ which represents pathology from the point of view of our pedagogical approach. Our model combines these two probability frames by assigning to each of them a weight m for the mood and p for the pathology, to obtain an appraisal bias frame abf :

$$abf = m.apf_{mood} + p.apf_{pathology}\ , \quad \forall m, p \in [0,1], with\ m + p = 1 \quad (4)$$

The weights p and m modulate the influence of the pathology on the agent's mood. This appraisal bias frame represents the tendency of the agent to evaluate the situation. This frame evolves during the session with each update of the mood and/or the pathological evaluations.

In order to make explicit the link between events and their evaluations, we used a corpus of appraisal annotations. A Non-Pathological corpus (NP-Corpus) is used to produce appraisal annotations (Figure 2), represented as appraisal probability frame apf_{NP}. We are currently collecting the NP-Corpus through a questionnaire filled by random participants with no known neuropathology. We ask each participant to imagine himself or herself in a hospital (For example after a digestive problem). We then ask them to evaluate, according to our selected dimensions of the CPM (see Appraisal frame section) a list of actions and dialog acts. This list corresponds to every choice available on the graphical interface of the user in our system. We will then obtain with these data an average non-pathological evaluation of every choice available on our system and independently of user's behaviors.

When an event is detected during the interaction, it is evaluated by the virtual patient using the NP-Corpus that we described above, while taking into account the appraisal bias frame abf. We represent the appraisal bias frame as a filter to be applied to the vector produced by the NP-Corpus, which will bias the initially planned evaluation.

Our model also considers user's behaviors: we focus on the identified elements of the pathology that we want to represent and that we want to emphasize during the pedagogical scenario. For example, according to [15], small changes in the caregiver's posture and a more sustained eye contact lead to better interactions with Alzheimer's patients. These identified behaviors are associated with an appraisal frame, corresponding to an evaluation according to CPM dimensions. For example smiles are associated with a positive value of the intrinsic pleasantness and the goal conduciveness dimensions. These information will be encoded into an appraisal probability frame $apf_{user\_behavior}$, applied as a filter on the filtered apf_{NP} appraisal probability frame. We thus obtain a new appraisal probability frame $apf_{biasedNP}$ defined as :

$$apf_{biasedNP} = apf_{user\_behavior} * (abf * apf_{NP}) \quad (5)$$

This probability frame corresponds to the pathological and contextual evaluation of the agent. It takes into account the user's action and behaviors.

We complete this estimation of the evaluation with another corpus of data, the P-Corpus Appraisal Annotations (Figure 2) which contains data from interactions between 31 caregivers and a simulated version of the virtual patient using a Wizard of Oz (WOZ) experiment as described in Section 3, where the Virtual Patient Module is controlled by an experimenter [8]. The data collection allowed us to observe and analyze these interactions in the specific context of our pedagogical scenario. This data collection includes a detailed analysis of professional caregivers' reactions and strategy choices when dealing with difficult behavior of the simulated Alzheimer's patient. We identified different strategies, their impact and outcomes on the patient's behavior. Few works have been able to identify clear strategies to adopt when interacting with Alzheimer's patients in terms of non-verbal behaviors. With our experiment and thanks to automatic annotations made by the log files and the post-experiment detection of the user's non-verbal behavior, we can more easily identify, in this particular scenario, explicit non-verbal behaviors that have an impact on the patient's reactions. This corpus allows us to obtain mappings between the choices and behaviors made by the users in the interactions and the pathological evaluations expressed by the virtual patient. This translates into a probability of evaluating the event in a specific way, which will take the form of a appraisal probability frame called apf_P. This frame represents the evaluation probabilities of an event from the video corpus in the pedagogical context. This context and pathology information is thus directly encoded in the statistical correspondences resulting from these data. We therefore have two appraisal frames: one frame corresponding to the evaluation based on the literature (ABM model) applied on non-pathological appraisal data, and one frame corresponding to the data from the video corpus of interactions. These two frames are combined in the model by assigning a weight np for the first one and a weight p for the second one. We obtain a new probability frame apf_{result}:

$$apf_{result} = np.apf_{biasedNP} + p.apf_P\ , \quad \forall np, p \in [0,1], with\ p + np = 1 \quad (6)$$

It is possible to vary the p and np weights to give more or less importance to one of the two frames. This appraisal probability frame will be used, as described in the Appraisal variable part, to generate the values of the final appraisal frame apf_{result}. The possible combinations may not all be represented by the available dataset and by the annotations made beforehand. During a new interaction, if we are faced with a combination that does not exist in the video corpus, we will only use annotations from the NP-corpus.

Affect-intensity model / Affect-derivation model

For the representation of intensity we limit ourselves to mere activations of the appraisal variables {1, 0 or 1} as described in the "Appraisal variables" section. This results in the following number of possible emotional states $n^35 = 243$ combinations.

Once the final appraisal frame is obtained, as described above in the section about the Appraisal derivation model, the COPALZ model makes a mapping from the evaluation criteria of the CPM model (in 5 dimensions) to a PAD space (in 3 dimensions) to simplify the visualization of mood evolution. To our knowledge, there are no direct correspondences between the criteria of the CPM model and the PAD space. In [27],the authors calculated activation patterns (prototypes) of the CPM model's appraisal variables for 13 emotions from the data in [51]. We also consider the mapping between 22 emotions and their location in the PAD space as proposed in the ALMA model [21]. We then identified the 9 emotions present in both works (e.g. rage, disgust, sadness), in order to obtain a mapping between the activations of the appraisal variables and the location on the PAD space for each of these dimensions. To do this, we applied a linear regression model, with the dependent variable being the PAD variables and the independent variable being the CPM dimensions, to get a position on a 3 dimension PAD space from the 5 dimension appraisal frame, according to the equivalences for these 9 emotions. We were able to determine the linear coefficients that allow us to go from a PAD space to the CPM dimensions activation pattern. The small amount of data and the non-linearity of the distribution of these data on the two spaces makes the coefficients obtained by the linear regression approximate, and allows us to obtain insights about how the selected CPM variables could be related to each of the PAD space dimensions. We thus set these correspondences:

$$\begin{aligned} P &= 0.6 * pleasantness + 0.4 * conduciveness \\ A &= 0.25 * suddenness - 0.25 * familiarity + 0.5 * |conduciveness| \\ D &= 0.3 * conduciveness + 0.7 * power \end{aligned} \tag{7}$$

We then checked the consistency of the distribution formed by all the possible points obtained following formula (7). By varying each of the 5 CPM dimensions variables values between -1 and 1 with a step of 0.1, all combinations of the three dimensions of the PAD space (between -1 and 1 with a step of 0.1) were tested, resulting in a 97% matching level. This proposed mapping between moods and appraisal tendencies is one of the original contributions of our work. Another objective of the CPM space to PAD space derivation is to formalize appraisal tendencies of an agent in a particular mood state.

Illustration

The formulas we propose are our attempt at formalizing the pathological mechanisms identified in the ABM [50]. In the ABM, the authors define an appraisal bias as a perception and evaluation filter that increases the frequency of specific emotional states. Mood and emotional disorders can be represented as appraisal biases. For example, an agent in a sad mood will have a tendency to evaluate a situation in a more pessimist way, whereas an agent in a happy mood will have a tendency to evaluate this same situation in a more positive way. It is the same principle for emotional disorders. For example, according to this model, someone presenting depression symptoms will be more likely to evaluate situations in a pessimist way and experience sadness more frequently. The authors also propose links between other emotional disorders and biases in the evaluation of specific dimensions of the CPM. We represent this by defining a filter to apply to the evaluation of a non-pathological agent. As described in the article, we define with the NP-Corpus for each choice on the user's interface, the evaluation made by a random person with no pathology. This is represented as a density probability function as described in formula (2), in order to provide the probabilities to evaluate each dimension in a specific way. For example, for a choice C, the NP-Corpus gives us indications about how a random person with no pathology would evaluate this choice for each dimension of the CPM. If the participants of the NP-Corpus experiment evaluated the intrinsic pleasantness dimension for the choice C on average as 0.9 (very pleasant), we represent the probability to evaluate this choice as a gaussian function with a mean of 0.9. This will result in an evaluation for the intrinsic pleasantness around 0.9 (but not always 0.9). This brings some variability to the emotional evaluations. This evaluation will then be filtered by the appraisal bias frame abf, which combines the mood and the pathology. We will choose to use a simple example where only the mood and no pathology is represented to understand the intuition behind the filter. When we add a pathology, the filter gets more complex by a mixture of the gaussian functions representing the mood in one hand and the pathology in another hand, as described with formula (4).

Once the filter is defined, we apply a convolution filter on the choice C for each dimension. Let's say for example that the agent has no pathology and is in a very bad mood, represented as a tendency to evaluate the intrinsic pleasantness dimension as very unpleasant (-1). The filter will then be applied to the non pathological appraisal of the choice C, moving the density probability function towards a lower value. After the filter is applied, the agent will then have a tendency to evaluate an event as less pleasant than the initial evaluation.

In formula (6), we propose to combine in the same way as formula (4) the filtered evaluation and the pathological evaluation from our WOZ experiment for the same choice. To our knowledge, this is the first proposition to adapt computationally the ABM.

Model evaluation method

For the evaluation of the model, we rely on the concept of "didactic situation". This concept was elaborated jointly by simulation specialists and field practitioners using a methodology based on analyzing training needs and simulation results.

First, challenging situations were identified from observing and interviewing actual professionals. A simulation scenario was designed using the data from this work and from the scientific literature. In parallel, an instructional analysis revealed three use-cases in our context: a task completion-focused communication strategy, a relationship-focused communication strategy, and a patient-focused communication strategy. A "didactic situation" is then a pedagogical relevant part of an interaction, represented by a description of the mobilized communication strategy, the moment of the interaction and the patient's mood at this moment. Second, an analysis of the recorded simulations was conducted to annotate didactic situations.

The validation goal is to obtain outputs of the model (the virtual patient's appraisal of the situation and the facial expressions) similar to the observed data. First, we need to initialize our model to run it. We propose to select video extracts from the Wizard of Oz experiments, where the patient's behavior, the behavior of the caregiver, and the observed didactic situations were annotated. Each choice of the user will lead to reactions on the patient, which will depend on several variables (e.g. the level of cooperation of the patient (decided by the experimenter), the intensity of the disorders presented by the patient). In our model, we can represent these variables by initialization elements. We can for example make the patient more or less cooperative according to her initial mood or by presenting more or less pathological disorders. The reaction will also depend on how the users interpreted the selected action with their non-verbal behavior. We will then use the NP-Corpus annotations of the model in order to simulate a situation. The patient's mood (which evolves during the interaction), the represented disorders and the user's non verbal behavior will then be used to filter the NP-Corpus annotations.

Our evaluation method includes two steps. The first step is to present the four selected extracts from the simulation videos to the neuropsychologist who controlled the virtual patient (called wizard) in our previous experiment, in order to acquire from him an explanation of the mood and emotional disorders he made the virtual patient express. Each extract is separated in blocks. A block is the combination of the user's choice on his interface, his verbal and non-verbal behaviors used to perform his selection, and the virtual patient's reactions. We first showed the wizard the video from the beginning of the session to the start of our extract. We then asked him to evaluate the goal and the initial mood of the patient. We finally show him the complete extract, block by block. Knowing the context, he has to annotate the situation according to the selected CPM criteria, for each block. For example, he has to tell if the patient, in her current state, would find the situation as highly familiar, lowly familiar, or neutral. In the end of each extract, he also has to identify the pathological disorder(s) presented by the patient during the video. The objective of this method is to collect, from the wizard, the set of input values required to initialize our model. This initialization allows us to compare the outputs of the model simulation (appraisal frame and possible expressions obtained by the appraisal frame) with the annotations made by the wizard during the interview about the four extracts considered as representative by our pedagogy researchers partner. The second step involves obtaining from additional neuropsychologists their perception of the mood and the emotional disorders observed in the videos in order to confirm the performance of the wizard.

The data collected during the Wizard of Oz experiment will also enable us in future works to evaluate our automatic model. One of our evaluation goals is to compare outputs from our automatic model simulations with more data from our corpus. We also intend to use the collected data to evaluate the generative power of our automatic model. For instance, we will study how the appraisal biases can modulate the reactions of the virtual patient by comparing the reaction of the virtual agent without emotional disorders (only the mood and the user's behavior will bias the appraisal) and the reactions of an agent with one or more emotional disorders. The evaluation will consist of a qualitative evaluation by experts of the compared outputs.

The evaluation of such an automatic model raises several problems [24]. It is difficult to evaluate the internal mechanisms responsible for emotional pathologies and only feedback from medical and pedagogy experts concerning the pedagogical relevance of the simulation can validate our system. Additionally, in the evaluation method we described above, we only focused on small extracts from a limited interaction corpus, and we still have to test the model on more different cases. We also can point out the fact that we only evaluated the resulting appraisal frames, and since the mapping between the appraisal and the facial expressions could lead to multiple configurations, it is difficult to make a validation concerning the relevance of facial expressions. We also have to keep in mind that Alzheimer's disease is very complex, thus the variability of the symptoms and of their intensity makes it difficult to properly evaluate the relevance of the simulated behaviors of our model and it is preferable to focus on the reproduction of interesting pedagogical situations considered as such by medical experts.

5 CONCLUSIONS AND FUTURE DIRECTIONS

In this article, we introduced COPALZ, a new pathological model of emotions that we designed for controlling an automatic virtual Alzheimer's patient. Regarding the modeling of emotions, our model is inspired by several existing computational models. As in WASABI [7], FAtiMA [13] and the work of [33], we rely on the appraisal variable set from the CPM model [49]. The concept of appraisal frame, used in the FatiMA and EMA models [35], allows us to describe the evaluation of a situation according to these variables. These appraisal frames are then transformed into a 3D representation in a PAD space, as in WASABI, to represent the emotion felt by the agent. The mood, defined in the same way as in the EMA model, i.e. an accumulation of emotional episodes, is also represented on a PAD space and will undergo a variation induced by this emotion, with a dynamic similar to the one defined in the ALMA model [21] and in the model proposed by [52]. The location in the PAD space that represents the emotion decreases following an exponential decay, as in the EEGS model [40] and in the WASABI model [7].

The originality of our work is based on the introduction of the appraisal biases [50] to represent the influence of the pathology on the agent's behaviors. In the same way as in the TAME model [38] with the concept of dispositions, and in the MAMID model [26] with the concept of traits, we represent tendencies to be in certain specific emotional states with the concept of appraisal bias, which will influence the agent's evaluation process. The originality of our work is also based on the integration of data collected during a Wizard of Oz experiment involving interactions between 31 members of the nursing staff and a partially simulated virtual patient. These data gather information such as the user's actions on the graphical intercace, the non-verbal behaviors of the caregiver, the current state of the simulation (phase of the scenario) and the verbal and non-verbal behaviors selected by a medical expert of Alzheimer's disease and expressed by the virtual patient. They will then be completed with manual annotations describing the evaluation of each situation made by the virtual patient according to criteria of the CPM model. To do so, we plan to annotate all the collected videos according to a coding scheme and an annotation guide that we have already defined and tested [8]. Additionally, our automatic model could be a valuable source of knowledge for inspiring similar works and understanding other pathologies. The next step will be to integrate all this data into the design of the automatic model, in order to perform an evaluation of the automatic virtual patient with caregivers. For the evaluation, we also intend to consider existing studies about reverse appraisal theory [12], which argues that people can infer, from emotion displays, how others are appraising a situation. In our virtual patient, reverse appraisal is involved when the caregiver is interpreting the facial expressions displayed by the virtual patient. It is also involved in our corpora when we annotate appraisals thanks to the behaviors displayed by the virtual agent.

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